FIW Working Paper N° 107
March 2013

Wage effects of U.S. service offshoring by skills and tasks

Julia Püschel[1]

Abstract

In this paper, I estimate the impact of service offshoring on the real wages of U.S. workers by controlling for workers' skill levels and the offshoring susceptibility of different tasks. Matching individual-level wage data with input-output tables over the period from 2006 to 2009, I am further able to account for unobservable individual-level heterogeneity. The results from a Mincerian wage regression indicate that within skill groups, the impact of service offshoring on real wages depends on the task content of the respective occupation. The real wages of medium- and high-skilled workers employed in the least offshorable occupations were positively affected by service offshoring. However, within the groups of medium- and high-skilled workers, service offshoring negatively affected the real wage of the most tradable occupations.

JEL: F14, F16, J31, F20
Keywords: Offshoring, services, tasks, wages

Author

[1] Graduate School of North American Studies (GSNAS), Free University Berlin, Lansstrasse 5, 14195 Berlin, Germany. Email: Pueschel@gsnas.fu-berlin.de

Wage effects of U.S. service offshoring by skills and tasks*

Julia Püschel†

Freie Universität Berlin, Graduate School of North American Studies

Abstract

In this paper, I estimate the impact of service offshoring on the real wages of U.S. workers by controlling for workers' skill levels and the offshoring susceptibility of different tasks. Matching individual-level wage data with input-output tables over the period from 2006 to 2009, I am further able to account for unobservable individual-level heterogeneity. The results from a Mincerian wage regression indicate that within skill groups, the impact of service offshoring on real wages depends on the task content of the respective occupation. The real wages of medium- and high-skilled workers employed in the least offshorable occupations were positively affected by service offshoring. However, within the groups of medium- and high-skilled workers, service offshoring negatively affected the real wage of the most tradable occupations.

Keywords: Offshoring, services, tasks, wages

JEL classification: F14, F16, J31, F20

*This version: January 2013. Please share your comments! **Acknowledgements**: I would like to thank Irwin Collier, Avraham Ebenstein, and Holger Goerg for their helpful comments on earlier versions of this article. I am especially grateful to Alessandro Maravalle and Boris Vormann for comments that significantly improved the quality of this work.

†Graduate School of North American Studies (GSNAS), Free University Berlin, Lansstrasse 5, 14195 Berlin, Germany. Email: Pueschel@gsnas.fu-berlin.de

1 Introduction

Before the mid-1990s, the supply of intermediate inputs from abroad primarily concerned the trade in goods. However, during that same time period, service-providing tasks started to become increasingly offshored. The offshoring of service occupations, that were previously considered as non-tradable, has led researchers to question whether service offshoring affects labor markets in a qualitatively and quantitatively different manner from the offshoring of manufacturing activities (e.g., National Academy of Public Administration 2006; Molnar et al. 2007; Bhagwati and Blinder 2009). Alan S. Blinder (2006) has even predicted that the resulting changes in occupational compositions could turn out to be comparable to the industrial revolution.

Traditionally, the fortunes of workers were seen as tied to their skill levels. According to the Heckscher-Ohlin trade model the interplay of country factor endowments and industry factor intensity shapes the distributional consequences of trade. Recent empirical insights indicate that these predictions need to be refined. With the advent of service offshoring it became clear that there might be no systematic relationship between the offshoring susceptibility of different occupations and the educational attainments of the workers performing the occupations. Moreover, even if two occupations are classified as susceptible to offshoring, several scholars emphasize that the offshoring costs across them may be heterogeneous and may change over time (Blinder 2007; Moncarz et al. 2008). As a consequence, the distributional effects of globalization are more complex and harder to identify than traditionally assumed. As Paul R. Krugman concludes, "[p]utting numbers on these effects [...] will require a much better understanding of the increasingly fine-grained nature of international specialization and trade." (Krugman 2008, p. 135) In other words, one of the main tasks for trade and labor economists is to quantify the impact of offshoring on the labor market at a finer level of aggregation.

I estimate the effect of service offshoring on the real wages of workers in the United States by controlling for skills and tasks. Skills are measured by the educational attainment of the workers and tasks by the offshoring susceptibility of different occupations. The present analysis differs from similar studies for the United States in the following respects: First, in contrast to most studies, I focus on service industries rather than manufacturing industries. Second, I use wage data at the individual rather than at the firm or industry level. Third, I focus on the interplay between traditional proxy measures of skills and the task content of occupations in determining wages. Fourth, I estimate the impact of offshoring across industries. In so doing, I take the effects of labor mobility across industries into account and analyze a situation that is more in concordance with a general-equilibrium setting.

Two similar analyses by Baumgarten et al. (2010) and Ebenstein et al. (2011) confirm that the wage effects of offshoring become significant if one accounts for the cross-industry movements of workers. My work differs from Ebenstein et al. (2011) because it focuses on offshoring rather than total trade or foreign direct investment. Furthermore, I analyze a set of potential offshoring susceptibility determinants different from those analyzed by both Ebenstein et al. (2011) and Baumgarten et al. (2010). Finally, I focus on service industries in the United States rather than on manufacturing industries in Germany, as Baumgarten et al. (2010) do.[1]

Because I examine the period from 2006 to 2009, this analysis also contributes to the literature by using more recent data than most other analyses. As Feenstra (2010, p. 104) has emphasized, although offshoring has further increased during the last decade - for example, because of further declines in data transmission costs - trade economists have not empirically assessed the impact of offshoring on U.S. wages during this period.[2]

Methodologically, I longitudinally match the Outgoing Rotation Group (ORG) samples from the Current Population Survey (CPS) to obtain a panel data set for U.S. workers' real wages. Then, I combine these matched CPS ORG data for 2006–2009 with input-output tables from the Bureau of Economic Analysis (BEA).

The results indicate that, depending on the offshoring susceptibility of the respective occupation, service offshoring can influence wages in different directions. The real wages of medium- and high-skilled workers employed in the least offshorable occupations have increased, whereas, within these skill groups, the occupations that are most susceptible to offshoring have experienced real wage declines with increasing service offshoring.

The remainder of this paper is structured as follows. Section 2 offers a short review of the relevant theoretical and empirical literature. Section 3 presents the data (3.1) and describes the empirical specification (3.2). Section 4 presents the results and section 5 summarizes and discusses the findings.

2 Literature review - trade in tasks

Researchers in labor economics and international economics have recently started to devote substantial attention to the so-called task approach. The main insight of this approach is that the task content of occupations offers information that is relevant for a systematic analysis of the labor market. In particular, this body of literature distinguishes between the workers' educational attainments and the tasks that they perform in their occupations. This distinction becomes crucial when we acknowledge that workers with a certain educational level can

[1] Ebenstein et al. (2011) have also focused on manufacturing industries. Regarding the task content, Ebenstein et al. (2011) have only taken the routine content of an occupation into account, even though many recent contributions have shown that - unlike for a occupation's automatization potential - routineness is only one of many task characteristics that influence an occupation's offshoring susceptibility. Baumgarten et al. (2010) have established two binary classifications. One is based on the routine content of occupations and the other one on the degree to which occupations involve interactive tasks.

[2] Ebenstein et al.'s (2011) analysis also suggests that the impact of material offshoring has increased over time. They find the strongest impact of offshoring on wages during the latest sub-period of their sample. However, this period only lasts from 1997 to 2002. Crinò (2010) has analyzed the period from 1997 to 2006, but focuses on the impact of service offshoring on employment in the United States.

perform a variety of different tasks, such that there is no one-to-one relationship between skills and tasks and that international trade and technological change affect the demand for tasks (see, e.g., Autor et al., 2003). Supporting these ideas, Acemoglu and Autor (2011) provide evidence that the worker's occupational affiliation has gained in importance as a determinant of wages in comparison with the educational attainments of the workers or their industry affiliations since the 1990s.

In the context of international trade, winners and losers were traditionally identified by their respective skill categories.[3] The focus on skills was justified by the assumption that interplay of factor abundance and factor intensities shapes the pattern and, hence, the wage effects of trade. In the framework of the trade-in-tasks literature, it became clear that the pattern of offshoring is also determined by task-specific offshoring costs. These costs do not show a clear relationship with the educational attainment of the workers performing the tasks and, hence, with its traditional comparative advantage (see, e.g., Garner 2004; Blinder 2006; Jensen and Kletzer 2005, 2008).

Grossman and Rossi-Hansberg (2008) incorporate such heterogeneous trade costs across tasks into a perfect competition trade model. Products are produced using a continuum of tasks, which are either performed by low-skilled workers (L-tasks) or high-skilled workers (H-tasks) and which can be performed either in the home country or abroad. Offshoring may be beneficial because of factor cost differences, but it also entails costs. These costs are assumed to differ across tasks within one group of skills. By introducing such a richer structure of offshoring costs, relative factor endowment differences across countries and trade cost differences across tasks determine the pattern of trade. Feenstra sees this approach as "clearly a new aspect of trade, or of the costs of doing trade" (Feenstra 2010, pp. 102-103).

Grossman and Rossi-Hansberg (2008) analyze the impact of a decrease in offshoring costs on wages in different specific trading environments and decompose the overall wage effect into three effects: a productivity effect, a labor-supply effect, and a relative-price effect. The productivity effect refers to the fact that offshoring is similar to technological change. This effect leads to a real wage gain for the factor that performs the offshored tasks. In contrast, the labor-supply effect leads to a real wage decline for the factor performing the offshored tasks by increasing the labor supply of this factor. As the price of the final product using the offshored intermediate inputs declines, this relative-price effect leads to negative wage effects for the factor performing the offshored tasks (Stolper-Samuelson effect). Overall, the effect of increased offshoring depends

[3] The human capital literature provides different views on the appropriate characterization of labor market skills. The international trade literature employs proxy measures for the so-called general human capital and largely distinguishes solely between skilled and unskilled workers by employing information about non-production and production workers (e.g., Feenstra and Hanson 1996, 1999) or years of schooling (e.g., Liu and Trefler 2008). In particular, it is the development of wage polarization since the mid-1990s that has illustrated the limitations of such binary skill classifications. Only recently, trade economists have also begun to employ skill distinctions that go beyond the skilled-v.-unskilled dichotomy (e.g., Geishecker and Goerg 2008).

on the relative strength of the negative and positive effects. In the Grossman and Rossi-Hansberg (2008) framework the law of one price holds for each skill group. In other words, workers with the same skill level receive the same wage - notwithstanding the tasks they are performing. If the law of one price was violated, no worker would perform tasks paying lower wages. Consequently, the wage effect of offshoring is the same across all tasks within each skill group.

Especially in the short run, this assumption of perfect labor mobility across occupations is unlikely to hold. There likely are frictions to switching between occupations and the matching process to reallocate resources is time consuming, due to for example necessary retraining. As emphasized by the OECD (2007a, p.126) the requirements for the lost occupations are not necessarily the same as those for the newly created ones. This idea is supported by recent empirical evidence suggesting that human capital is partly occupation specific (see Kambourov and Manoskii 2009). If we consider the evidence that certain occupations (tasks) are more susceptible to offshoring, and thus more likely to be relocated abroad, offshoring is likely to affect real wages for occupations differently - according to their offshorability. In order to investigate this, I estimate whether - in addition to the respective skill level - the wage effects of service offshoring depend on the character of the tasks performed.

First empirical contributions have been testing a similar hypothesis and thereby went beyond the traditional skill distinction in identifying the distributional impact of trade. Such a task-based approach seems especially appropriate for analyzing service offshoring (see Feenstra 2010, p. 42). However, most of the previous empirical contributions have focused on material offshoring because of data limitations on service trade in general and on "trade in tasks" (Grossman and Rossi-Hansberg 2008) in particular.[4] An exception that focuses on the U.S. labor market effects of service offshoring is the study by Crinò (2010). He estimates the impact of service offshoring on employment for 58 service occupations in the United States over the period from 1997 to 2002. His results indicate that service offshoring positively impacted high-skilled workers' employment, whereas employment of low- and medium-skilled workers was negatively affected. Furthermore, employment in tradable occupations was negatively affected by service offshoring, whereas employment in occupations classified as non-tradable increased across all skill levels. Overall, this evidence indicates that it is important to control for the task content of occupations in addition to the traditional proxy measures for skill levels, i.e., the educational attainment of the workers performing the tasks. In contrast to the present analysis, Crinò employs industry-level employment data. As a result, he cannot control for unobservable individual characteristics of the workers. Furthermore, he calculates an industry-level offshoring proxy measure so that his analysis is based on the assumption of no labor mobility across industries.

Liu and Trefler (2008) perform a study that examines the wage effects of international outsourcing of services by U.S. companies to unaffiliated firms in

[4] For an analysis of the reasons for the lack of detailed data on services trade, see Jensen (2011).

China and India and of international outsourcing of services into the United States. Similar to Crinò (2010), they link wage data at the occupational-industry level to international outsourcing proxy measures at the industry level from 1996 to 2006.[5] They distinguish between occupations that are exposed to offshoring and those that are not by mapping occupations to actual services trade. Their findings suggest that service outsourcing has only had very small wage effects, which leads them to conclude that the extensive attention that service offshoring has attracted is "much ado about nothing" (Liu and Trefler 2008, p. 35). Arguably, this conclusion is owed to measuring techniques.

As Ebenstein et al. (2009, 2011) have recently suggested that the partial equilibrium nature of previous analyses could explain why the impact of offshoring on wages within an industry was found to be relatively low. Even if theoretical contributions have already emphasized that offshoring takes place at the level of tasks across industries (see, e.g., Feenstra and Hanson 1996), empirical researchers have mostly calculated offshoring proxies at the industry level because trade data is collected at the firm or industry rather than at the task level. Ebenstein et al. (2009) propose a weighting scheme to circumvent this challenge and to calculate an occupation-specific measure of material offshoring. Their results show that the decision to measure offshoring at the occupational or the industry level leads to significantly different wage effects (more details on these different approaches are discussed in 3.1.2).

In this analysis, I combine these insights gained in previous contributions to improve our understanding of the interplay of tasks and skills in determining the wage effects of service offshoring. I estimate the impact of service offshoring on the real wages of U.S. workers by including information on the educational attainments of the workers and the offshoring susceptibility of the occupations into a Mincerian wage regression.

3 Empirical specification

In this section, I provide details on the empirical specification. Section 3.1 describes the data. I start by outlining the longitudinal matching of the Outgoing Rotation Group (ORG) samples of the CPS to obtain a panel data set for yearly data about the real hourly wages of U.S. workers from 2006 to 2009. The subsequent sections deal with the challenges in constructing measures for two of the main regressors (i.e., the offshoring intensity proxy measure and the offshoring susceptibility measure), before I present the estimation equation (3.2).

[5] However, this approach ignores an important aspect of service offshoring. According to the BEA's "Detailed statistics for cross-border trade," services trade within multinational companies accounted for almost one-third of the overall imports in other private services to the United States in 2008.

3.1 Data

3.1.1 Individual-level wage data

In line with the seminal work by Feenstra and Hanson (1996), most empirical contributions that explore the impact of offshoring on wages have employed data at the firm or industry level rather than at the individual level.[6] Data at the individual level offer the advantage of being able to control not only for observable individual characteristics that could affect wages, such as the educational attainment of workers, but also for unobservable, time-invariant individual characteristics, such as ability. Furthermore, individual-level data makes it possible to employ the educational attainment of the workers as a proxy measure for skill levels.[7] In contrast, studies employing firm- or industry-level data only possess information about which skills are, on average, required in a certain occupation. In other words, skill level and occupation are perfectly collinear. By allowing for individual skill level variation within each occupation, I am able to analyze the interplay between skills and tasks in shaping the wage effects of service offshoring.

The Current Population Survey (CPS) offers information about employment and wages at the individual level of U.S. workers. This survey collects information on hours, earnings, employment, unemployment, and union affiliation based on monthly household surveys, which are conducted by the Bureau of the Census for the Bureau of Labor Statistics with approximately 50,000 to 60,000 households (see Feenberg and Roth 2007). Each household is surveyed for four months and, after an interview break of eight months, again surveyed for four months. Information on workers' weekly hours and earnings are only collected at the fourth and eighth interviews. The surveys from these interviews are the so-called *Outgoing Rotation Groups* (ORGs) (see the NBER website).

Even if the CPS has a longitudinal dimension, most studies either use samples from separate months or treat the data as repeated cross-sectional data. In the present analysis, I exploit the information from the longitudinal dimension and build on Madrian and Lefgren (2000), who have developed an algorithm to match two consecutive March surveys of the CPS. I have adapted this matching algorithm to longitudinally match the CPS ORG samples in two steps. In a first step, individuals are matched based on a household identifier, a household number, and an individual line number within a household. If all three variables are identical in two consecutive ORGs, this mechanism results in a so-called "naïve" match. In a second step, this naïve match is validated if there are no

[6] Feenstra and Hanson (1996) have provided a theoretical framework that accounts for this increasing importance of material offshoring. They have also provided empirical evidence that the contribution of material offshoring to the increase in U.S. wage inequality during the 1980s was qualitatively and quantitatively akin to skill-biased technological change (Feenstra and Hanson 1996, 1999).

[7] More specifically, I define skill groups according to the International Standard Classification of Education (ISCED) of the UNESCO (2011). Low-skilled workers have a lower secondary education or less, medium-skilled workers have a degree between upper secondary and first-stage tertiary education, and high-skilled workers possess at least second-stage tertiary education.

inappropriate changes in an individual's sex, age, and race (see appendix A for further details). As a result, the unbalanced panel covers 95,527 individuals and two years over the period from 2006 to 2009. Due to missing data the total number of observations is 146,359.

3.1.2 Offshoring proxy

This section provides details on the construction of the proxy measure for the service offshoring intensity and presents first evidence on U.S. service offshoring patterns across occupations.

Because of data limitations, it is not possible to directly measure the volume of offshoring.[8] However, a proxy measure can be calculated to measure offshoring indirectly. Given that offshoring refers to the international "unbundling" (Baldwin 2006) of the production process, intermediate services are likely to be imported back to the home country to be further integrated into the production process of the final good or service. As a result, I follow Feenstra and Hanson (1996) and expect offshoring to lead to imports of intermediate inputs.[9]

Unfortunately, even for trade in intermediates, there are severe data limitations. For the United States, official services trade data only measure overall trade (i.e., trade in intermediate services and trade in final services combined).[10] However, I can employ industry-level information from input-output tables and thereby calculate an offshoring proxy measure for the United States for different offshored service industries.

First, following Amiti and Wei (2005, 2009), the National Academy of Public Administration (2006 p. 57ff.), and the OECD (2007b pp. 51-52), I multiply the value of the intermediate purchases of a service industry s with the ratio of the total imports to the total domestic supply of that service industry to obtain an estimate of the imported intermediates of the respective service industry (see appendix B for further details).[11] Furthermore, to control for the different sizes of the respective service industries, I normalize this value with the value of gross production in the respective industry. The share of offshoring in gross production in service industry s at time t is calculated based on the following equation:

[8] Offshoring refers to the act of performing parts of the production process in a foreign country rather than in the home country, such that both foreign direct investments (FDIs) and international outsourcing constitute offshoring (e.g., van Welsum and Vickery 2005; Feenstra 2010, pp. 5-6).

[9] Feenstra and Hanson (1996) have proposed to use trade in intermediate inputs as a proxy measure for material offshoring. This approach has been extended to service offshoring by Amiti and Wei (2005, 2009).

[10] For detailed reports on the challenge of measuring the phenomenon of offshoring by employing information from official data sets in the United States, see the reports by the U.S. Government Accountability Office (2004) and by the National Academy of Public Administration (2006, pp. 49-50). Jensen (2011) discusses the reasons for the general lack of detail in services trade statistics.

[11] This approach assumes that the import ratio is identical for intermediate and final products. OECD researchers have shown that this assumption leads to a downward aggregation bias (Hatzichronoglou 2005, p. 13).

$$OFF_{st} = \frac{SP_{st}\left[\frac{SI_{st}}{TSO_{st}+SI_{st}-SE_{st}}\right]}{TSO_{st}}. \tag{1}$$

$TSO\ldots$ Total Service Output
$SI\ldots$ Service Imports
$SE\ldots$ Service Exports
$SP\ldots$ Service Purchases
$s = 1,\ldots,S$ Service Industry
$t = 1,\ldots,T$ Time
$c = 1,\ldots,C$ Country

The standard approach in the literature on offshoring and its labor market effects has been to regress wage and/or employment changes within an industry on changes in such industry-level offshoring intensities, i.e. OFF_{st}. In contrast, Ebenstein et al. (2009) propose to calculate an occupation-specific measure of offshoring across industries. The underlying idea is that offshoring takes place at the level of tasks and across different industries. For instance, computer programmers are employed in several industries, ranging from the mining sector to the accommodation and food service sector.[12] If such programmers are increasingly offshored this is likely to affect those workers performing similar tasks across all industries. As a result, offshoring affects labor demand for a certain occupation across all industries rather than changing labor demand for all occupations within an industry. This notion implies worker mobility across industries. In other words, in flexible labor markets, such as the United States, workers may switch industries in response to international competition, whereas switching occupations is likely to be more difficult and may involve higher losses of occupation-specific human capital.[13] Baumgarten et al. (2010) see the strategy of allowing for potential worker mobility across industries as being more in concordance with a general-equilibrium setting than the standard approach. When comparing the estimation results of both strategies, Ebenstein et al. (2011) find no wage effects when employing an industry-level offshoring proxy measure but large and significant effects on occupation-specific wages for routine workers.[14] These findings are supported by Baumgarten et al. (2010), who build on Ebenstein et al. (2009) and also employ an occupation-level material offshoring proxy measure in their analysis of offshoring on the wages of German workers. Both works suggest that the partial equilibrium nature of previous analyses is the reason why offshoring was often found to have only a low impact on wages.

I adapt the approach by Ebenstein et al. (2011) to service offshoring and compute a measure of U.S. service offshoring intensity at the occupational level.

[12]See the occupational employment statistics of the BLS for further information.

[13]For a recent empirical paper supporting the idea that human capital is occupation-specific, see Kambourov and Manovskii (2009).

[14]Ebenstein et al.'s (2011) employ an occupation-level measure of foreign affiliate employment and find that for the period from 1997 to 2002 a one-percent increase in affiliate employment in low-income countries decreases U.S. real wages by 0.11 percent.

More specifically, I re-weight the offshoring proxy measure at the industry level (i.e., OFF_{st}) with the number of workers in a certain occupation o within a service industry s relative to the number of workers employed in occupation o across all service industries:[15]

$$OFF_{ot} = OFF_{st} \times \sum_{s=1}^{S} \frac{N_{ost}}{N_{ot}}. \tag{2}$$

$o = 1, \ldots, O$ Occupation
$N \ldots$ Number of workers

3.1.3 Offshoring susceptibility

In order to assess whether the real wage effects of U.S. service offshoring do not only depend on traditional skill proxy measures but also on the offshoring susceptibility of occupations and on the interplay of skills and tasks, I have to obtain a measure of offshoring susceptibility. I employ the classification provided in Moncarz et al. (2008) for the following two reasons.[16] First, the ranking is continuous, whereas most other contributions only establish a dichotomy between offshorable and non-offshorable tasks. Such a dichotomy would not be useful in the present analysis because - in addition to the differences in wage effects across potentially offshorable and entirely non-offshorable occupations - I am also interested in whether wage effects differ within the group of offshorable occupations according to the degree of offshoring susceptibility. Second, among the plethora of different contributions that have tried to identify the characteristics of tasks that influence the susceptibility to offshoring (e.g., Bardhan and Kroll 2003; Garner 2004; Jensen and Kletzer 2005; van Welsum and Vickery 2005; Blinder 2006), the ranking by Moncarz et al. (2008) is, to my knowledge, the most comprehensive ranking.

Moncarz et al. (2008) build their classification on the works of twenty economists from the Bureau of Labor Statistics (BLS) Employment Projections Program who have ranked all 515 service occupations in the Standard Occupational Classification System (SOC) according to their offshorability.[17] First, they identified 355 service occupations as entirely non-tradable. Examples of such services include occupations that require face-to-face contact with customers (e.g., barbers) or need to be performed in a fixed location (e.g., security guards). For all other service occupations, the BLS economists evaluated the compliance of the task content of the occupation with the following four criteria and assigned an offshoring susceptibility score between four and sixteen to each of the service occupations.[18]

[15] For more details on this weighting procedure, see appendix B.

[16] Furthermore, this index performs best in terms of explained variance of actual offshoring flows. More details are available upon request from the author.

[17] The 2000 SOC system distinguishes between 840 detailed occupations. Service providing occupations comprise the major groups 11, 13, 15 to 29, 31 to 39, 41, 43, 49, and 53. For further information, see the Bureau of Labor Statistics webpage.

[18] One has to be careful in using the term "offshoring susceptibility." The actual pattern

1. To what degree can the inputs and outputs of the occupation be transmitted electronically, or otherwise be easily and cheaply transported?

2. To what degree do the duties of this occupation require interaction with other types of workers?

3. To what degree is knowledge of social and cultural idiosyncrasies, or other local knowledge, of the target market needed to carry out the tasks of this occupation?

4. To what degree can the work of the occupation be routinized or handled by following a script?

(Moncarz et al., 2008, p. 75)

To render the interpretation of the wage effect estimations easier, I normalize this score to lie between zero and one for each of the 515 service-providing occupations. A value of one indicates the highest susceptibility to offshoring, and zero indicates that the respective occupation is classified as non-tradable. Figure 1 shows the resulting ordinal classification for eight exemplary service occupations. Among the highest-ranked occupations in terms of offshoring susceptibility are computer programmers (SOC code 15-1021) and bookkeeping, accounting, and auditing clerks (SOC code 43-3031). Database administrators (SOC code 15-1061) and loan officers and counselors (SOC code 13-2070) are among the middle-ranked occupations. Urban and regional planners (SOC code 19-3051) and marketing managers (SOC code 11-2021) are assigned to the lowest offshorability group. Couriers and messengers (SOC code 43-5021) and computer support specialists (SOC code 15-1041) are classified as non-tradable.

Note that this classification is based on the task content of the respective occupation and that it does not consider the educational attainment of the workers performing the tasks. In the following, I analyze the relationship between the task characteristics of occupations and the skill levels of workers in some more detail to improve our understanding about the relationship between tasks and skills.

Table 1 shows that there are statistically significant differences between the underlying distributions of the offshoring susceptibility score across educational groups. In particular, I can reject the null hypothesis of the Wilcoxon rank-sum test that the offshoring susceptibility distributions across educational groups are equal ($z = -27.904$ and $z = -103.661$, $p = 0.000$). For instance, high-skilled workers, on average, are employed in occupations that are classified as more offshorable than those of low- or medium-skilled workers (i.e., $\mu = 0.264$ as compared to $\mu = 0.037$ or $\mu = 0.176$).[19] However, these averages hide significant heterogeneity within each skill group. Figure 2 shows that also low-skilled workers are employed in occupations that are very easy to offshore.[20]

---

of offshoring depends on potential costs as well as on potential benefits, which are not taken into account in this ranking. Furthermore, actual offshoring costs also depend on the interactions between the task content and country characteristics (see also Pueschel 2012). The classification by Moncarz et al. (2008) ranks tasks according to their offshoring requirements.

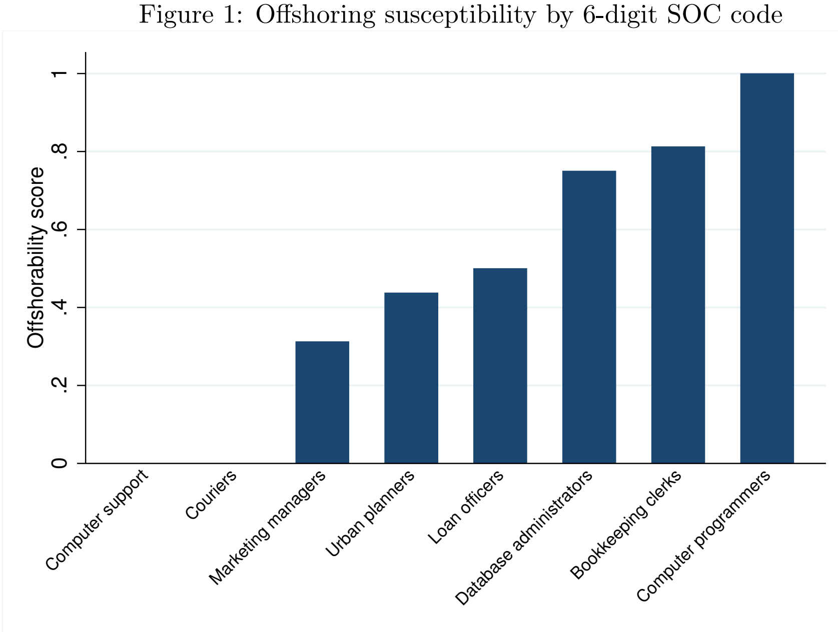
[19]Note that in the present sample there are few service workers with low educational attainment (i.e., only 3,680 observations out of a total of 146,359 observations).

[20]For illustrative purposes, the density distribution plot in figure 2 is based only on those observations that have an offshorability score higher than zero (i.e., 88,714 observations).

Table 1: Comparison of offshoring susceptibility distributions across skill groups

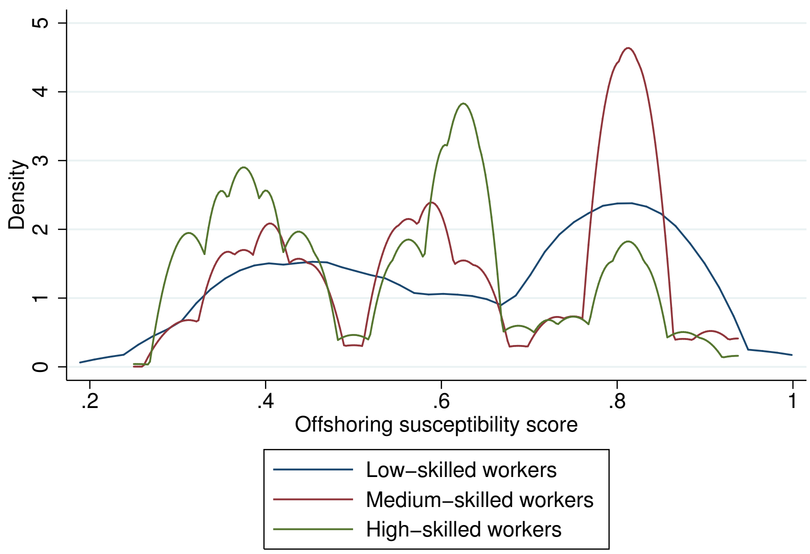
	All	Low-skilled	Medium-skilled	High-skilled
Offshorability				
Mean	0.211	0.037	0.176	0.264
Median [21]	0	0	0	0
Standard deviation	0.318	0.163	0.316	0.317
Wilcoxon rank-sum test	$H_0 : F_{low-skilled} = F_{medium-skilled}$ $z = -27.904$ $p = 0.000$		$H_0 : F_{medium-skilled} = F_{high-skilled}$ $z = -103.661$ $p = 0.000$	
Observations	146,359	3,680	78,267	64,412

Figure 1: Offshoring susceptibility by 6-digit SOC code



[21] 39.39 percent of all observations are zero-value observations.

Figure 2: Distribution of offshoring susceptibility by skill



Note: Only observations with offshorability > 0.

3.2 Model

After having constructed these three main variables, I can now estimate the effect of U.S. service offshoring on real wages. With respect to the empirical specification, I build on Baumgarten et al. (2010) and estimate the following Mincer log wage equation:

$$\begin{aligned} w_{iot} = \alpha + \sum_{e-1} \beta_e EDU_{eit} \\ + \sum_e \gamma_e EDU_{eit} \times TASK_o + \sum_e \delta_e EDU_{eit} \times OFF_{ot} \\ + \sum_e \theta_e EDU_{eit} \times TASK_o \times OFF_{ot} \\ + \kappa_o + \mu_t + \iota_i + \varepsilon_{iot}, \quad (3) \end{aligned}$$

$i = 1, \ldots, I \;\; Worker$
$o = 1, \ldots, O \;\; Occupation$
$t = 1, \ldots, T \;\; Time$

where w_{iot} is the log hourly wage of worker i in occupation o at time t. $\sum_{e-1} EDU_{eit}$ denotes a set of educational control variables that contain educational dummies for high and medium educational attainment of workers; low education is the omitted category. I control for the task content by including the measure $TASK_o$, which indicates the normalized offshoring susceptibility score for the respective occupation. By interacting this task content measure with the educational dummies, I allow for heterogeneous wage effects of the task content across different skill groups, $\sum_{e-1} EDU_{eit} \times TASK_o$. OFF_{ot} is a measure that indicates the U.S. service offshoring intensity for occupation o at time t. This proxy measure is interacted with the three educational dummies to account for the differential wage effects of offshoring across skill groups, $\sum_e EDU_{eit} \times OFF_{ot}$. I also include triple interaction terms to account for the differential effects of offshoring within each educational group according to the task content, $\sum_e EDU_{eit} \times TASK_o \times OFF_{ot}$.

The error term is decomposed into occupational fixed effects κ_o, time-specific effects μ_t, and individual fixed effects ι_i. Time-specific effects capture general macroeconomic trends and individual fixed effects control for time-invariant observable and unobservable individual characteristics. The remaining error term ε_{iot} is assumed to be normally distributed.[22]

4 Econometric estimation results

This section examines the estimation results of the fixed-effects model (FEM) regression of equation (3).[23] Column (1) in table 2 presents the baseline results without any interaction terms. Column (2) includes the interaction terms between the offshoring proxy measure and educational groups as well as between the task content and educational groups. This column also includes the triple interaction terms between the offshoring proxy measure, the task content and the education dummies.

The significant coefficients on the medium- and high-skilled dummies in column (1) suggest that, ceteris paribus, - in comparison to low-skilled workers, which constitute the baseline category - real wages are 6.22 percent higher for the group of people who have between six to ten years of education and 14.6 percent higher for those people who have more than ten years of education.[24]

The task content has no statistically significant wage effect at any of the conventional levels across all three skill levels (see column (1)). However, this average hides significant differences across educational groups. The coefficients on the interaction terms in column (2) suggest that within the groups of medium- and high-skilled workers, wages differ according to the offshoring susceptibility of the occupation. Within each of these skill groups, workers who are employed in those occupations that are the most susceptible to offshoring earn more than

[22] Because the task content measure is a time-invariant variable at the occupational level, the occupation dummies and task content measures are perfectly collinear. As a consequence, I omit the occupation dummies in the estimation.

[23] Unobserved individual heterogeneity is likely to be correlated with some of the regressors, such as, for example, educational attainment of the workers. In line with this theoretical argument, the Hausman specification test rejects the null hypothesis of zero correlation between individual effects and the error terms ($\chi^2(14)$,$p = 0.000$). Such zero correlation would be required for the estimates of a random-effects model to provide consistent estimates (see also Cameron and Trivedi 2010, p. 267).

[24] This convexity of wages in educational attainment is in line with other findings in the literature (e.g., Lemieux 2006).

those workers with a similar skill level who are employed in the least offshoring susceptible occupations.

The positive coefficient on the offshoring proxy measure in column (1) suggests that service offshoring has a statistically significant and positive effect on real wages. However, the coefficients on the interaction terms between the offshoring proxy measure and the educational dummies in column (2) (i.e., $\sum_e \delta_e EDU_{eit} \times OFF_{ot}$) indicate that this overall positive effect of offshoring hides significant differences across educational groups. More specifically, the interaction effects in column (2) indicate that only medium- and high-skilled workers benefit from service offshoring, whereas the effect for low-skilled workers is not statistically significant at any of the conventional levels.[25]

Thus far, we have only analyzed the effect of an increase in the offshoring intensity for those workers who are employed in the least offshorable occupations (i.e., $TASK_0 = 0$). Let us now consider whether the effects of offshoring change for the group of workers employed in the most offshorable occupations (i.e., $TASK_0 = 1$). The coefficients on the triple interaction terms (i.e., $\sum_e \theta_e EDU_{eit} \times TASK_o \times OFF_{ot}$) provide an answer to this question. The marginal effects of offshoring on wages for each educational group are given by:

$$\frac{\delta w_{iot}}{\delta OFF_{ot}} = \delta_e + \theta_e \times TASK_o. \tag{4}$$

The negative triple interaction terms in column (2) outweigh the positive effect of the skill-interacted offshoring proxy measure (i.e., $\sum_e \delta_e EDU_{eit} \times OFF_{ot}$). This finding indicates that for the medium- and high-skilled workers in the most offshorable occupations, an increase in service offshoring leads, ceteris paribus, to a decline in real wages. Figure 3 illustrates how the marginal effect of service offshoring on real wages of medium- and high-skilled workers changes over the range of the occupational offshoring susceptibility.[26]

Notwithstanding the statistical significance of the effects, we are mainly interested in economic significance. Therefore, based on the results of the preferred specification in column (2), I calculate the cumulated effect of service offshoring over the period from 2006 to 2009. I do so separately for low-, medium-, and high-skilled workers and further distinguish between workers in the least offshorable occupations (i.e., $TASK_o = 0$) and workers in the most offshorable occupations (i.e., $TASK_o = 1$). Table 3 shows the results. In the following discussion of these results, I focus on those cases in which the two coefficients of interest (i.e., δ_e and θ_e) are jointly statistically significant, i.e., for medium- and high-skilled workers.

Medium-skilled workers in the least offshorable occupations experienced a four dollar cents (0.28 percent) increase in real hourly wages because of the cu-

[25]The fact that I cannot identify any wage effect for low-skilled workers with sufficient precision could be due to the low number of observations within the low-skilled category (see also table 1).

[26]I wish to thank Thomas Brambor, William Roberts Clark, and Matt Golder, who provide an excellent documentation on the graphical representation of interaction effects on their website.

Table 2: Panel regression, FEM

Dependent variable: *Log hourly wage*	(1)	(2)
D: Medium-skilled	0.0622**	0.0519*
	(0.0198)	(0.0212)
D: High-skilled	0.146***	0.138***
	(0.0220)	(0.0240)
Task content	0.0125	
	(0.0128)	
interacted with		
*D: Low-skilled		-0.0753
		(0.0770)
*D: Medium-skilled		0.0741***
		(0.0125)
*D: High-skilled		0.0524**
		(0.0178)
Offshoring proxy	2.877***	
	(0.588)	
interacted with		
*D: Low-skilled		5.106
		(12.12)
*D: Medium-skilled		12.61***
		(1.734)
*D: High-skilled		11.07***
		(1.848)
Offshoring proxy *Task content		
interacted with		
*D: Low-skilled		-1.784
		(16.73)
*D: Medium-skilled		-17.44***
		(2.474)
*D: High-skilled		-12.68***
		(2.823)
Constant	2.714***	2.706***
	(0.0200)	(0.0214)
Fixed effects	Year, individual	Year, individual
Observations	146,359	143,359
adj. R-squared	0.717	0.717

Columns (1), (2) and (3): Robust standard errors in parentheses;
* significant at 10%; ** significant at 5%; *** significant at 1%

mulated increase in service offshoring over the period from 2006 to 2009, while workers with the same skills who were employed in the most offshorable occupations realized an eight dollar cents (0.51 percent) decline in real wages. If we assume 2,087 yearly work hours,[27] the gross yearly income (in constant 2009 prices) for medium-skilled workers in the least offshorable occupations increased by 93.81 dollars. For medium-skilled workers in the most offshorable occupations, gross yearly income (in constant 2000 prices) declined by 169.33 dollars.

A similar pattern emerges for the group of high-skilled workers. The hourly wages of high-skilled workers employed in the least offshorable occupations increased by 11 dollar cents (0.4 percent), whereas the hourly wages of workers with the same skill level who were employed in the most offshorable occupations declined by seven dollar cents (0.28 percent). If we again assume 2,087 yearly work hours, this assumption implies that the gross yearly income of high-skilled workers in the least offshorable occupations (in constant 2009 prices) increased by 267.50 dollars. The gross yearly income of high-skilled workers in the most offshorable occupations (in constant 2009 prices) declined by 166.96 dollars.[28]

One implicit assumption in the FEM estimation of equation (3) is that the regressors are exogenous, i.e., $E\left(x_i \varepsilon_i\right) \neq 0$. If this assumption was violated, the coefficients in table 2 would be inconsistent and biased estimates of the true parameter values. The exogeneity assumption could be violated in particular for the case of the offshoring intensity proxy measure, OFF_{ot}, because of reverse causality. In other words, if wages of a certain occupation increase, firms could decide to increasingly offshore those occupations.

Several arguments support the conclusions that I have drawn from the FEM estimation.[29] First, by matching individual-level wage data with offshoring intensity proxy measures at the occupational level I reduce the likelihood of reverse causality in comparison to traditional analyses of the wage effects of offshoring that largely employ information on wages and offshoring intensities at the same level of aggregation. In other words, it is unlikely that the variation in individual wages causes changes in the occupation-level offshoring intensity measure.[30] Third, I statistically test the assumption that the offshoring intensity measure is exogenous by estimating equation (3) additionally with an instrumental variable general method of moments (GMM) approach. Based on the results of

[27] According to the Bureau of Labor Statistics, wage and salary workers worked, on average, 5.27 hours per day in 2011 (see table 5 of the American Time Use Survey).

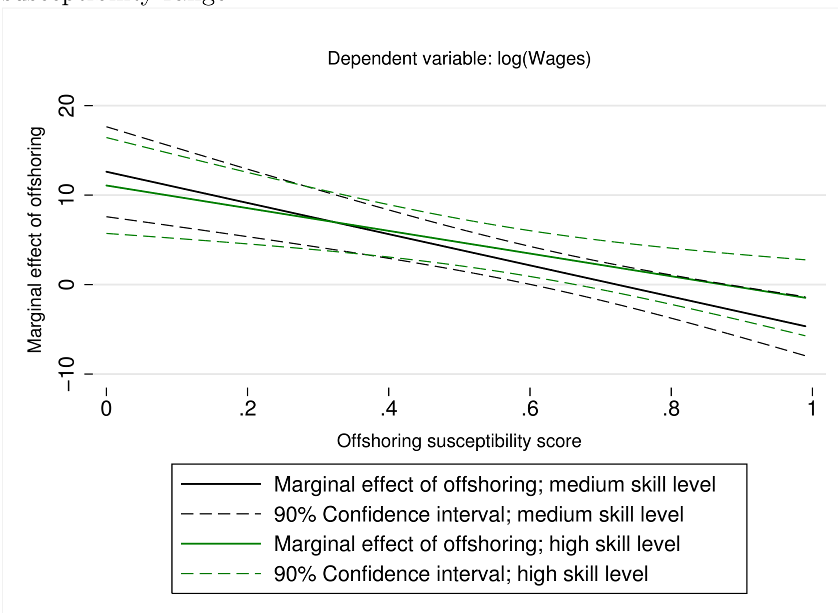
[28] Baumgarten et al. (2010) find negative effects of material offshoring on the real wages of low- and medium-skilled workers in Germany from 1991 to 2006. Unlike the present analysis, their findings suggest that only the magnitude (and not the sign) of the effects of offshoring depends on the task content of the respective occupation. A possible explanation could be that in a more flexible labor market such as the United States, wages can adjust more easily, whereas in less flexible labor markets (in terms of prices) such as Germany, adjustment takes place primarily via the quantity.

[29] Furthermore, I have estimated equation (3) with a full set of occupation-specific time trends, $TREND_{ot}$, that control for technological change at the occupational level. The coefficients were robust to this additional control, which, however, was not statistically significant at any of the conventional levels.

[30] This argument is elaborated in a more formal manner in appendix C.

the C-test, I fail to reject the exogeneity of the offshoring intensity measure within reasonable confidence bounds. These findings indicate that the FEM is a consistent estimator of the true value of the parameter.

Figure 3: Marginal effect of service offshoring on real wages across the offshoring susceptibility range



Source: Author's calculation and illustration; based on column (2) of table 2

Table 3: Economic significance calculations

	Low skilled		Medium skill		High skill	
Average hourly wage 2006 in Dollar	10.54475		15.67739		27.66987	
Joint significance of offshoring	F=0.27 p=0.7649		**F=27.12** **p=0.0000**		**F=19.31** **p=0.0000**	
Cumulated effect of offshoring 2006-2009	*in Dollar*	*in percent*	*in Dollar*	*in percent*	*in Dollar*	*in percent*
$TASK_o = 0$	0.0007	0.007	**0.04495**	**0.287**	**0.1124**	**0.405**
$TASK_o = 1$	-0.0188	-0.178	**-0.081**	**-0.518**	**-0.079**	**-0.2881**

5 Conclusion

The offshoring of service occupations, which were previously deemed to be shielded from international competition, has spawned controversial debates in academic and political circles. Perhaps the most contested question pertains to the implications of service offshoring for wages. The present analysis highlights features of the data that have traditionally been overlooked because of the aggregate level of analysis. It indicates that the wage effects of service offshoring depend on the interplay of the worker's educational attainment and the occupational task content.

By employing wage information from individual-level data and matching these data with occupation-specific information on offshoring intensities and susceptibilities, I have analyzed how service offshoring affects the real wages of U.S. workers. The results suggest that, in addition to the skill level of workers, task characteristics play an important role in determining the effect of service offshoring on wages. Depending on the offshoring susceptibility of the respective occupation, service offshoring can have qualitatively different impacts on wages. Medium- and high-skilled workers employed in those service occupations that are the least susceptible to offshoring experience real wage increases, whereas medium- and high-skilled workers in those occupations that are the most offshorable experience real wage declines. These interaction effects are robust to the control for unobservable individual heterogeneity. Such new empirical evidence broadens our understanding of the determinants of residual wage inequality within the groups of medium- and high-skilled U.S. workers.

Put differently, occupations which, according to their task content, are the most susceptible to offshoring, also experience real wage declines with increased service offshoring. This finding bears important implications for the future of the labor market. Even if the present level of service offshoring is still low, offshoring, especially of those occupations that - in terms of their task content - are most susceptible to offshoring, can be expected to increase. According to the index by Moncarz et al. (2008), these services are characterized by complexity, personal interaction, and context-dependency. This finding contradicts existing education policies and their insistence on standardized testing, because tasks that will be demanded in the future require an individual's capacity to react promptly and flexibly in complex situations. In a similar vein, Alan S. Blinder criticizes that the U.S. school system "will not build the creative, flexible, people-oriented workforce we will need in the future by drilling kids incessantly with rote preparation for standardized tests in the vain hope that they will perform as well as memory chips." (Blinder 2006, p. 7)

References

[1] Acemoglu, A., & Autor, D. H. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In O. Ashenfelter & D. Card

(Eds.), Handbook of Labor Economics (Vol. 4B, pp. 1043-1171). Amsterdam: Elsevier.

[2] Amiti, M., & Wei, S.-J. (2005). Service Offshoring, Productivity, and Employment: Evidence from the United States. IMF Working Paper, 05(238).

[3] Amiti, M., & Wei, S.-J. (2009). Does Service Offshoring Lead to Job Losses? Evidence from the United States. In M. Reinsdorf & M. J. Slaughter (Eds.), International Trade in Services and Intangibles in the Era of Globalization (pp. 227-243). Chicago: University of Chicago Press.

[4] Autor, D., Levy, F., & Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Investigation. Quarterly Journal of Economics, 118(4), 1279-1333.

[5] Baldwin, R. (2006). Globalisation: The Great Unbundling(s). Mimeo, Graduate Institute of International Studies Geneva.

[6] Bardhan, A. D., & Kroll, C. A. (2003). The New Wave of Outsourcing. Fisher Center for Real Estate and Urban Economics, University of California Berkeley , Working Paper (No. 1103).

[7] Baum, C. F., Schaffer, M. E., & Stillman, S. (2007). Enhanced Routines for Instrumental Variables/Generalized Method of Moments Estimation and Testing. The Stata Journal, 7(4), 465-506.

[8] Baumgarten, D., Geishecker, I., & Goerg, H. (2010). Offshoring, Tasks, and the Skill-Wage Pattern. CEPR Discussion Paper Series (No.7756).

[9] Bhagwati, J., & Blinder, A. (Eds.). (2009). Offshoring of American Jobs: What Response from U.S. Economic Policy? Cambridge MA, London: MIT Press.

[10] Blinder, A. S. (2006). Offshoring: The Next Industrial Revolution? Foreign Affairs, 85(2), 112-128.

[11] Blinder, A. S. (2007). How Many U.S. Jobs might be Offshorable? Princeton University Center for Economic Policy Studies, Working Paper (No. 142).

[12] Brambor, T., Clark, W. R., & Golder, M. (2006). Understanding Interaction Models: Improving Empirical Analyses. Political Analysis, 14, 63-82.

[13] Cameron, A. C., & Trivedi, P. K. (2010). Microeconometrics Using Stata (second ed.). College Station: Stata Press.

[14] Crinò, R. (2010). Service Offshoring and White-Collar Employment. Review of Economic Studies, 77(2), 595-632.

[15] Ebenstein, A. Y., Harrison, A. E., McMillan, M. S., & Phillips, S. (2009). Estimating the Impact of Trade and Offshoring on American Workers Using the Current Population Surveys. NBER Working Paper (No. W15107).

[16] Ebenstein, A. Y., Harrison, A. E., McMillan, M. S., & Phillips, S. (2011). Estimating the Impact of Trade and Offshoring on American Workers Using the Current Population Surveys. World Bank Policy Research Working Paper (No. 5750).

[17] Feenberg, D., & Roth, J. (2007). CPS Labor Extracts 1979 - 2006. Cambridge, MA: NBER.

[18] Feenstra, R. C. (2010). Offshoring in the Global Economy – Microeconomic Structure and Macroeconomic Implications. Cambridge MA, London: The MIT Press.

[19] Feenstra, R. C., & Hanson, G. H. (1996). Globalization, Outsourcing and Wage Inequality. American Economic Review, 86(2), 240-245.

[20] Feenstra, R. C., & Hanson, G. H. (1999). The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States, 1979-1990. Quarterly Journal of Economics, 114(3), 907-940.

[21] Garner, A. C. (2004). Offshoring in the Service Sector: Economic Impact and Policy Issues. Federal Reserve Bank of Kansas City - Economic Review 2004(3), 5-37.

[22] Geishecker, I., & Goerg, H. (2008). Winners and Losers: A Micro-Level Analysis of International Outsourcing and Wages. Canadian Journal of Economics, 41(1), 243-270.

[23] Grossman, G. M., & Rossi-Hansberg, E. (2008). Trading Tasks: A Simple Theory of Offshoring. American Economic Review, 98(5), 1978-1997.

[24] Hansen, L. P. (1982). Large Sample Properties of Generalized Method of Moments Estimators. Econometrica, 50(4), 1029-1054.

[25] Hatzichronoglou, T. (2005). The Impact of Offshoring on Employment: Measurement Issues and Implications. Paris, Washington, DC: OECD.

[26] Hayashi, F. (2000). Econometrics. Princeton: Princeton University Press.

[27] Jensen, B. J., & Kletzer, L. (2005). Tradable Services: Understanding the Scope and Impact of Services Offshoring. In L. Brainard & S. M. Collins (Eds.), Brookings Trade Forum: Offshoring White-Collar Work – The Issues and the Implications (pp. 73-133). Washington, DC: Brookings Institution Press.

[28] Jensen, B. J., & Kletzer, L. (2008). Measuring Tradable Services and the Task Content of Offshorable Services Jobs. In K. Abraham, M. Harper & J. Spletzer (Eds.), Labor in the New Economy (pp. 309-335). Chicago: University of Chicago Press.

[29] Jensen, J. B. (2011). Global Trade in Services - Fear, Facts and Offshoring. Washington, DC: Peterson Institute for International Economics.

[30] Kambourov, G., & Manovskii, I. (2009). Occupational Mobility and Wage Inequality. Review of Economic Studies, 76, 731-759.

[31] Krugman, P. R. (2008). Trade and Wages, Reconsidered. Brookings Paper on Economic Activity (Spring), 103-154.

[32] Lemieux, T. (2006). The Mincer Equation Thirty Years after Schooling, Experience and Earnings. In S. Grossbard-Shechtman (Ed.), Jacob Mincer, A Pioneer of Modern Labor Economics (pp. 127-148). New York: Springer.

[33] Liu, R., & Trefler, D. (2008). Much Ado About Nothing: American Jobs and the Rise of Service Outsourcing to China and India. NBER Working Paper (No. 14061).

[34] Madrian, B. C., & Lefgren, L. J. (2000). An Approach to Longitudinally Matching Current Population Survey (CPS) Respondents. Journal of Economic and Social Measurement, 26(2000), 31-62.

[35] Molnar, M., Pain, N., & Taglioni, D. (2007). The Internationalisation of Production, International Outsourcing and Employment in the OECD. OECD Department of Economics Working Paper (No. 21).

[36] Moncarz, R. J., Wolf, M. G., & Wright, B. (2008). Service-providing Occupations, Offshoring, and the Labor Market. BLS Monthly Labor Review, 71-86.

[37] National Academy of Public Administration (2006). Offshoring: How big is it? - Report for the U.S. Congress and the Bureau of Economic Analysis.

[38] OECD (2007a). OECD Employment Outlook. Paris, Washington, DC: OECD.

[39] OECD (2007b). Offshoring and Employment: Trends and Impacts. Paris, Washington, DC: OECD.

[40] Pueschel, J. (2012). Task Dependence of U.S. Service Offshoring Patterns. School of Business and Economics, Free University Berlin, Discussion Paper Economics (2012/15).

[41] Schmitt, J. (2003). Creating a Consistent Hourly Wage Series from the Current Population Survey's Outgoing Rotation Group, 1979-2002. CEPR Working Paper.

[42] U.S. Government Accountability Office (2004). International Trade - Current Government Data Provide Limited Insight into Offshoring of Services. Washington, DC: United States Government Accountability Office.

[43] UNESCO (2011). Revision of the International Standard Classification of Education (ISCED). Paris: United Nations Educational, Scientific and Cultural Organization (UNESCO).

[44] van Welsum, V., & Vickery, G. (2005). Potential Off-Shoring of ICT-Intensive Occupations. In OECD (Ed.), Enhancing the Performance of the Services Sector (pp. 187-213). Paris, Washington, DC: OECD.

[45] Wooldridge, J. M. (2002). Econometric Analysis of Cross-Section and Panel Data (first ed.). Cambridge MA, London: MIT Press.

Appendix A: Individual-level wage data

I use the Center for Economic Policy Research (CEPR) version of the CPS ORG samples for the years 2006 to 2009, which are available at the CEPR website.[31] As a measure of hourly real wages, I employ the wage variable recommended by the CEPR. This variable does not include overtime, tips, and commissions. The top-coded wages are computed by assuming a log-normal distribution for weekly earnings (see Schmitt 2003). The economists at the CEPR have converted the nominal hourly wage calculated by the National Bureau of Economic Analysis (NBER) to a real wage by using the Consumer Price Index for 2009. The sample is restricted to the wages of workers who were at least 16 years old and employed at the time of the survey.

Because workers are surveyed more than once, I can build on Madrian and Lefgren (2000), who have developed an algorithm to match two consecutive March surveys of the CPS. This approach can be adapted to merge the CPS' Outgoing Rotation Group files. After creating two data extracts, one for time t and one for t+1 by renaming certain variables, I use information from three formal identifying variables (i.e., the household identifier [HHID], the household number [HHNUM], and the individual line number [LINENO]) to obtain a "naïve" match of the records. The maximum share of observations that could be matched in the CPS ORG samples is approximately 50 percent (see the potential match rate in table A.1). In the present analysis, the fraction of individuals that are naïvely matched is around 33 percent for each year pair. This actual matching rate is lower than the theoretical one because of non-response, mortality, migration, and recording errors. For the same reasons, however, some false positive matches are also included. Thus, in a second step, I evaluate the validity of these naïve matches by comparing the information on sex, age, and race across the matches and drop those matches that cannot be true based on these three criteria (the so-called S|R|A criterion in Madrian and Lefgren

[31] Details on how the CPS raw data from the Census Bureau has been processed by the CEPR can also be found on this website.

[2000]). Approximately 18 percent of all naïve matches are dropped in this second step such that the final matching rate is around 27 percent for each year pair (see table A.1).

Table A.1: CPS matching rates

Year	Potential Match	Naïve Match	Valid Match	Final Match
2006-2007	49.78	32.73	82.10	26.87
2007-2008	50.10	33.36	82.76	27.61
2008-2009	49.46	33.16	82.89	27.49

Note: "Valid match" indicates the percentage of naïve matches that are valid according to the S|R|A criterion in Madrian and Lefgren (2000).

One issue arises from matching the CPS ORG data with the offshoring susceptibility information from Moncarz et al. (2008). Both occupational classifications are based on the 2000 SOC codes. However, some of the occupations in the CPS ORG extracts are coded at a more aggregate level than they are in Moncarz et al. (i.e., at the five-digit rather than the six-digit level). In those cases, I employ information about the six-digit SOC occupations that each of those five-digit SOC occupations consists of (see the BLS' website on the SOC codes). Then, I assign the average offshoring susceptibility score of all six-digit SOC occupations to the respective five-digit occupation.

Appendix B: Offshoring intensity measure

The BEA provides public access to input-output tables (see The Use of Commodities by Industries before Redefinitions (1997 to 2009)), which classify service industries according to input-output codes. The industry-specific occupational employment and wage estimates of the BLS, which provide the necessary information for the weighting procedure according to Ebenstein et al. (2011), are classified according to the North American Industry Classification System (NAICS). Input-output codes can be converted to categories of the North American Industry Classification System (NAICS) according to the list provided in the BEA input-output tables. The results are displayed in table A.2.

Table A.2: Concordance between input-output codes and NAICS codes

Input-output codes	2002 NAICS codes
521C1, 523, 525	522000, 523000, 525000
524	524000
513	517000
5415, 514	541500
55	551100
5411	541100
5412OP	541900

Ebenstein et al. (2011) have not computed their offshoring measure as described in equation (1). Instead they have employed foreign affiliate employment as a proxy measure for offshoring. In affiliate trade data there is no distinction between those industries that produce certain products and those that purchase these products - as is the case in input-output data. If we want to compute an offshoring proxy measure at the occupational level based on the information regarding imported intermediate inputs, we must decide whether to weight the industry-level offshoring intensity measure with the respective ratio calculated based on information about employment in the producing industry p or the industry of use u.[32] The idea behind constructing an offshoring proxy measure at the occupational level is to obtain "a measure of the effective exposure of an occupation to offshoring" (Ebenstein et al. 2009, p. 29). When we take into consideration the occupational distribution within the industries that produce the intermediates ($p = 1, ..., P$), this offers insights about which types of occupations are "embodied" in the offshored products. This is why I have decided to use the employment of a specific occupation o within the producing industry p as a weight.

Table A.3: Correlation coefficients

	log (Real wage)	Education	Offshorability
Education	0.5097	1	
Offshorability	0.2097	0.2043	1
log(Offshoring)	0.4097	0.3208	0.5519

[32]In another study, Baumgarten et al. (2010) have computed an occupational-level offshoring measure and circumvented this problem by restricting their analysis to narrow offshoring such that $u = p$. I prefer to apply a broad offshoring definition because it better reflects public concerns regarding the labor market effects of offshoring.

Table A.4: Summary statistics

Variable	Observations	Mean	Standard Deviation	Min	Max
Hourly real wage	250,375	21.22619	15.98083	1.743494	344.4235
D: Low-skilled	8,852	1	0	-	-
D: Medium-skilled	163,184				
D: High-skilled	138,788				
Offshoring susceptibility	310,824	0.1565522	0.2722418	0	1
Offshoring intensity	183610	0.0032616	0.0051085	0	0.0451897

Appendix C: Exogeneity of the offshoring variable

By matching individual-level wage data with offshoring intensity proxy measures at the occupational level I reduce the size of the potential endogeneity bias as compared to analyses that employ information on wages and offshoring intensities at the same level of aggregation. More formally, we can illustrate this argument by analyzing the following equation, which is a simplified version of equation (3) and an adapted version of the example of Baumgarten et al. (2010, pp. 45-46):

$$w_{iot} = \alpha + \mu OFF_{ot} + \varepsilon_{iot}. \tag{5}$$

If, in addition, we have reverse causality and the offshoring intensity depends on the level of wages, this implies that:

$$OFF_{ot} = \sigma + \nu w_{iot} + \varsigma, \tag{6}$$

with $\nu \neq 0$ holds.

This violates the assumption that each regressor is uncorrelated with the error terms and hence the OLS estimator is biased and inconsistent (Wooldridge 2002, pp. 53-58). The potential endogeneity bias of the OLS estimator can then be written as:

$$bias = \frac{Cov\,(OFF, \varepsilon)}{Var\,(OFF)}. \tag{7}$$

Substituting for $Cov\,(OFF, \varepsilon)$ by using the reduced form of equation (6), we obtain:

$$bias = \frac{\nu}{(1-\nu\mu)} \frac{Var\,(\varepsilon)}{Var\,(OFF)},$$

with $\nu\mu \neq 1$.

Because $\frac{\delta bias}{\delta \nu} > 0$, we can see that, ceteris paribus, the size of the bias increases in ν.

Let us now compare ν for the case that we employ wage and offshoring data at the same level of aggregation and for the case of the combination of individual-level with occupational level data. In the first case, we obtain that:

$$\nu_{same} = \frac{Cov\left(OFF_{ot}, w_{ot}\right)}{Var\left(w_{ot}\right)}.$$

And for the case of the present analysis:

$$\nu_{diff} = \frac{Cov\left(OFF_{ot}, w_{iot}\right)}{Var\left(w_{iot}\right)}.$$

Because $Var\left(w_{iot}\right) > Var\left(w_{ot}\right)$ and $Cov\left(OFF_{ot}, w_{ot}\right) = Cov\left(OFF_{ot}, w_{iot}\right)$, we know that $\nu_{same} > \nu_{diff}$.

The GMM estimations and tests are performed by employing the user-written Stata command *xtivreg2* developed by Baum et al. (2007).[33] One challenge in performing such an exogeneity test is the necessity to find valid instruments for offshoring intensity, i.e. variables that are correlated with a firm's decision to offshore but are uncorrelated with changes in wages. I employ lagged values of the offshoring intensity and the offshoring susceptibility measure of an occupation as instrumental variables for the offshoring intensity proxy measure. In a second step, I perform different diagnostic tests to assess the need for performing a GMM estimation rather than a FEM estimation. The results are shown in table A.5 and will be discussed in the following paragraphs.

The results of the first stage regression show that the coefficients on all of the instruments are statistically significant. The first-stage F-test indicates that the instruments are jointly significantly different from zero. In addition to being relevant, which means that the instruments are correlated with the potentially endogenous regressor, instrumental variables must also be valid. In other words, the instruments need to be uncorrelated with the error terms of the second stage estimation. Validity can be tested only if the equation is overidentified, which is the case in the present analysis. Based on the Hansen J statistic, we fail to reject orthogonality of the instruments to the error process.[34] This result supports the instruments' validity.

After having tested for the instruments' relevance and validity, I can now test whether the offshoring intensity measure can be treated as exogenous. Based on the results of the C-test, I cannot reject the exogeneity of the offshoring intensity measure within reasonable confidence bounds.[35]

---

[33]The GMM allows for efficient estimation even in the presence of arbitrary heteroscedasticity (see Hansen 1982; Wooldridge 2002, p. 213ff.).

[34]Under the null hypothesis that all instruments are valid, the J statistic has a chi-squared distribution with two degrees of freedom (Wooldridge 2002, pp. 228-229).

[35]Under the null hypothesis that the regressor can be treated as exogenous, the endogeneity test statistic has a chi-squared distribution with one degree of freedom (Hayashi 2000, pp. 233-234).

Table A.5: Diagnostic tests for GMM estimation

First-stage F-test

F=293.16
p=0.000000

Overidentification test of all instruments:
Hansen J statistic (for excluded instruments)

Chi^2=0.769
p=0.6809

Exogeneity test of regressors:
C-test (of endogeneity)

Chi^2=1.188
p=0.2757

Observations: 47,712