European Economic Review 66 (2014) 63–83

Contents lists available at ScienceDirect

European Economic Review

journal homepage: www.elsevier.com/locate/eer

Revisiting the employment impact of offshoring

Greg C. Wright *

Department of Economics, University of Essex, Wivenhoe Park, Colchester CO4 3SQ, United Kingdom

ARTICLE INFO

Article history:
Received 19 January 2013
Accepted 12 November 2013
Available online 28 November 2013

JEL classification:
F23
F16
F11

Keywords:
Tasks offshoring
Offshoring and employment

ABSTRACT

The productivity gains due to offshoring may, in part, accrue to workers. This paper estimates the magnitude of these gains and compares it to the magnitude of employment loss due to worker displacement. A model based on the production task framework from Grossman and Rossi-Hansberg (2008) is used to demonstrate that the effect of offshoring depends on the intensity of use of these tasks and, ultimately, impacts domestic employment through three channels: a direct displacement effect, which negatively impacts employment; an output effect generated by the productivity gains from offshoring, which reorganizes and increases aggregate production in the economy and impacts domestic employment positively; and a substitution effect among factors and tasks, which has an ambiguous effect. Using the model's structure as a roadmap and applying it to detailed U.S. manufacturing sector data over 2001–2007, results from GMM 3SLS regressions provide overall support for the structure and predictions of the tasks model of offshoring. In particular, the economic magnitude of the productivity gains is found to have been important.

1. Introduction

Recent trade theory has demonstrated that firms' offshoring activities may generate gains for low-skill domestic workers by increasing the productivity of firms that use these workers intensively. However, the theory also highlights the more intuitive, and commonly emphasized fact, that some of these workers are likely to be displaced in the process and will have to “re-tool” in order to adjust to the changing demand for skills by firms. The seminal paper in this recent literature is Grossman and Rossi-Hansberg (GRH, 2008), who focus on the wage effects of offshoring and show that the equilibrium wage of low-skill domestic workers may go up or down due to offshoring, depending on the relative sizes of the productivity gains, the extent of displacement of workers and, also, depending on the size of the country in world markets.

The ambiguity present in equilibrium in the GRH (2008) model suggests that an empirical approach that is carefully motivated by the theory may help shed light on the economic magnitudes of these channels. This is the primary subject of this paper, and continues a line of recent research that attempts to disentangle the labor market effects of offshoring. Importantly, some previous work has estimated the employment impact of offshoring while explicitly conditioning on the channels through which the productivity gains of offshoring may operate, thereby producing estimates that are downward biased, as I discuss further below. Thus, a key contribution of the paper is to relax these empirical constraints.

As a first step, I explore the implications of the GRH (2008) framework in a two-factor, two-sector model. Here I focus on the impact of offshoring on both the employment and the wage of low-skill domestic workers, decomposing the demand for labor into three channels: a direct displacement effect, which negatively impacts employment; an output effect generated

* Tel.: +44 79 00305999.
E-mail address: gcwright@essex.ac.uk

0014-2921/$ - see front matter
http://dx.doi.org/10.1016/j.euroecorev.2013.11.008

by the productivity gains from offshoring, which reorganizes and increases aggregate production in the economy and impacts domestic employment positively; and a substitution effect among factors and tasks, which has an ambiguous effect. In bringing the theory to data I focus solely on the employment impact of offshoring, conditional on factor prices.[1] I argue that the channels through which offshoring impacts employment are simultaneously determined and endogenous to offshoring activity and, as a result, I estimate their magnitudes via a GMM 3SLS specification using data on U.S. offshoring activities and workers over the period 2001–2007. The results suggest that, conditional on changes in factor prices, both the displacement of U.S. workers and the employment gains have non-trivial economic magnitudes, such that *on net* the effect on workers has been negligible.

The theory also predicts that certain types of production activities, or tasks, are more easily moved offshore. As a result, firms that use these tasks relatively intensively should offshore more workers and reap larger productivity gains. In order to characterize production activities according to their "offshorability" I draw from a recent literature—mainly Blinder (2009) and Levy and Murnane (2006a,b)—that discusses the features that determine the relative ease with which production tasks can be performed at a distance. I find that these determinants are important in predicting which jobs will be moved offshore and, as a result, which firms will reap the productivity gains.

This paper sits within a recent literature that approaches the question of trade in intermediates from the standpoint of production tasks. The theoretical literature on trade in tasks, which owes much to previous work on trade in intermediates,[2] has recently been energized by GRH (2008), and has spawned several general equilibrium model extensions. Empirical tests which focus on production tasks in the context of offshoring include Jensen and Kletzer (forthcoming), Ottaviano et al. (2013), Becker et al. (2013), Blinder (2009), Harrison and McMillan (2008), Ehrl (2013) and Ebenstein et al. (2010).

Harrison and McMillan (2008) is quite closely related to this paper. In that paper, the authors adopt several empirical specifications and data on U.S. multinationals and their affiliates in order to explore the effect of affiliate employment (their measure of offshoring) on U.S. domestic employment.[3] However, the regression specifications they adopt condition on either output prices or output, whereas the approach in this paper is to allow for potential effects of offshoring via these channels. As we will see, conditioning on these channels leads to an estimate reflecting only the direct displacement of workers due to offshoring, which likely leads to an overestimate of the negative employment effect.

Other papers have also attempted to estimate the employment impact of offshoring while disentangling the channels through which offshoring may operate. Also similar to this paper are Becker et al. (2013), who estimate the net employment effect of vertical FDI while accounting for changing market shares across firms; Hummels et al. (forthcoming), who estimate the effects of offshoring while allowing for productivity effects to mitigate employment and wage declines; and Moser et al. (2009) who find that offshoring is associated with higher levels of employment, productivity and larger market shares among German firms. Other relevant research includes Desai et al. (2009) who find that offshoring by U.S. multinationals leads to increased employment and wages at home; Debaere et al. (forthcoming) who find that offshoring to low-income destinations reduces home employment while offshoring to high-income countries has no domestic employment effect; and Kramarz (2008) who finds a domestic employment loss due to offshoring. With respect to the pure productivity effects of offshoring, Gorg et al. (2007) find positive productivity effects for current exporters, and no productivity effects for non-exporters. In general, the findings from these studies are mixed, with most estimating rather small effects of offshoring on domestic employment, whether positive or negative.

Finally, other empirical work which utilizes production tasks in alternative (non-trade) frameworks include Peri and Sparber (2009), who draw conclusions regarding the impact of immigrants on native workers using the same O*NET dataset used here; Autor et al. (2003) who use a precursor to the O*NET in order to characterize the effects of computer adoption on wages; Autor and Dorn (2013) who tie the task-content of different labor markets to subsequent patterns of wage and employment polarization; and Spitz-Oener (2006) who uses firm-level data from Germany and finds that production tasks are becoming more complex over time, particularly in industries which rapidly adopted computers. The wide range of studies exploring the determinants of changes in the nature of work in industrialized countries illustrates that there are a variety of forces at play in the economy which alter the distribution of workplace tasks. This suggests that a clear and testable theoretical roadmap is needed and for this reason the next section derives a structural specification to then bring to the data.

The paper is organized as follows. Section 2 presents a model of labor demand under offshoring based on GRH (2008). Section 3 describes the data and variables to be used. Section 4 implements an empirical approach in order to explore the impact of offshoring on relative task use and employment. Section 5 concludes.

[1] There is, of course, a large literature that is focused on the wage impact of offshoring. The empirical methods and data required to estimate the wage impact are very different than what are required for estimation of the employment effects, and so the wage impact is not explored here. See Feenstra and Hanson (1999) for the effect of offshoring on wages across industries. I therefore set aside estimation of the substitution effect, which arises due to changes in factor prices, and focus on estimates of the other two channels that the model highlights, conditional on factor prices. This is discussed further below.

[2] Many of the results emphasized in the task-based theory exist in similar forms throughout the literature. For example, see Jones and Kierzkowski (1990) and Feenstra and Hanson (1999).

[3] The main results are a negative impact on U.S. workers due to offshoring to low-income countries and a small, positive impact due to offshoring to high-income countries.

2. A model of labor demand under offshoring

This section describes a two-sector model of offshoring based on the "production task" framework introduced in GRH (2008). In order to produce output, low-skill (e.g., assembly line) and high-skill (e.g., managerial) workers perform a range of tasks and it is initially assumed that the tasks performed by low-skill workers can be moved offshore, but not those performed by high-skill workers. However, it is often noted that both low- and high-skill tasks may be vulnerable to offshoring (see Blinder, 2009), and the model that follows can be easily extended to allow for offshoring of high-skill tasks.

The model is defined by the following assumptions. First, low-skill workers perform tasks whose output is combined to produce an intermediate composite good l, while high-skill worker task output is combined to produce the intermediate composite h. Finally, these composite goods are assembled to produce final output, Y. In addition, we assume there are two sectors, denoted by $z=\{1,2\}$, that differ in their production technology—specifically, sector 1 is relatively more intensive in the use of low-skill work and relatively less intensive in high-skill work than sector 2. In other words, $l_1/h_1 > l_2/h_2$. The composites l_z and h_z are combined in the following Cobb–Douglas production function:

$$Y_z = A_z l_z^{\theta_{zl}} h_z^{1-\theta_{zl}} \tag{1}$$

where A_z is a technological parameter and the cost-share of the low-skill factor is given by $\theta_{zl} \in [0,1]$, where $\theta_{1l} > \theta_{2l}$ due to the assumption on factor intensities. Demand for output is also assumed to be Cobb–Douglas and is defined further below.

Workers face a perfectly competitive labor market and are endowed with one unit of labor that is expended performing a range of workplace tasks that are combined to produce the low-skill and high-skill composites. Again, for now the high-skill tasks can never be moved offshore (it is simply too costly to do so) and so the focus is on the low-skill tasks. The range of tasks performed is normalized to a 0–1 continuum, $i \in [0,1]$, and both intermediate composites combine tasks through a constant elasticity of substitution (CES) technology, which for the production composite is given by

$$l_z = \left[\int_0^1 l_z(i)^{(\sigma-1)/\sigma}\, di \right]^{\sigma/(\sigma-1)} \tag{2}$$

where $l_z(i)$ is the input of task i in industry z and $\sigma > 0$ is the elasticity of substitution between tasks. Furthermore, low-skill tasks are defined so that when a task is performed at home for final industry z, a unit of task output is produced using $a_{zl}(\cdot)$ units of low-skill labor. The dependence of the unit labor requirement on the relative price of low- and high-skill labor, noted by the "dot", will be set aside in the notation for now. Note that the more low-skill labor intensive industry, 1, will require relatively more low-skill labor to produce a unit of output—i.e., $a_{1l} > a_{2l}$.

Offshoring takes the form of performing low-skill tasks abroad, however the firm incurs additional costs to do so. Specifically, these costs can be separated into a component that is common to all tasks in all industries, β, and an additional component that is specific to the task being offshored, given by $t(i)$, but which also is common across industries. The task continuum is ordered by decreasing vulnerability to (or increasing cost of) offshoring, such that $t'(i) > 0$. Combining this with the unit labor requirement for task production, the unit cost of performing a task abroad is $\beta t(i) a_{zl}$ so that $1/\beta t(i) a_{zl}$ is the marginal productivity of offshore workers. Again, note that this varies across tasks and industries. In order for offshoring to be costly it is assumed that $\beta t(i) \geq 1$.

For any particular task, home and foreign labor are assumed to be perfect substitutes such that each task will be performed by the lowest cost worker. This implies the existence of a single marginal task, I, between the home and foreign production locations in each industry. Letting w denote the wage paid to low-skill workers and q the wage paid to high-skill workers, and noting that the unit price of any low-skill task, denoted $p_{zl}(i)$, is assumed to be equal to its unit cost, we can write

$$p_{zl}(i) = \begin{cases} w^* \beta t(i) a_{zl}, & 0 \leq i < I \\ w a_{zl}, & I \leq i < 1 \end{cases}$$

where * will denote the foreign country throughout.[4] The marginal offshored task is therefore defined by the following equilibrium condition:

$$w = w^* \beta t(I) \tag{3}$$

which simply states that the cost of performing the marginal task at home must equal the cost of performing the task abroad. Fig. 1 depicts this equilibrium: as β falls the marginal task shifts rightward, increasing the range of tasks performed offshore. The empirical sections will focus on reductions in β as the driving force behind increases in the extent of offshoring across industries.

[4] Note that it has been assumed that the home firm can bring its production technology with it to the foreign country, so that $a_{zl} = a_l^*(z)$.

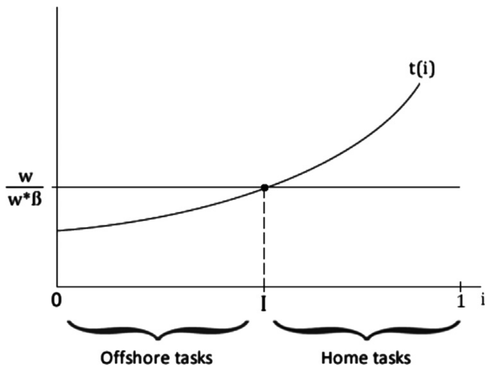

Fig. 1. Offshoring equilibrium.

2.1. The demand for production tasks

Combining (1) with (2) we can now solve for the demand for low-skill task i in industry z, which is given by

$$l_z(i) = \frac{1}{A_z}\left[\frac{p_{zl}(i)}{P_{zl}}\right]^{-\sigma} Y_z\left[\left(\frac{\theta_{zl}}{1-\theta_{zl}}\right)\frac{P_{zh}}{P_{zl}}\right]^{1-\theta_{zl}}$$

where $P_{zh} = qa_{zh}$ is the exact price index for the high-skill composite and P_{zl} is the low-skill counterpart, equal to

$$P_{zl} = a_{zl}\left\{\int_0^I [\beta t(i)w^*]^{1-\sigma}\, di + (1-I)w^{1-\sigma}\right\}^{1/(1-\sigma)}$$

Using (3) we can rewrite this price index as

$$P_{zl} = wa_{zl}\Omega(I)$$

where

$$\Omega(I) \equiv \left\{\int_0^I \left[\frac{t(i)}{t(I)}\right]^{1-\sigma} di + (1-I)\right\}^{1/(1-\sigma)} \tag{4}$$

reflects the distribution of low-skill tasks across the domestic and foreign locations. This is the source of the "productivity effect" in GRH (2008): as β falls and the set of tasks being performed abroad grows the firm saves on the marginal tasks but, in addition, saves on the infra-marginal tasks offshored previously, a source of cost-savings that could potentially lead to a significant decline in the price of the low-skill composite.[5]

Finally, the total labor needed to perform low-skill task i is given by $D_{zl}(i) = a_{zl}l_z(i)$, so that for a given industry z total domestic demand for low-skill labor is

$$D_{zl} = \int_I^1 D_{zl}(i)\, di = B_z\left\{a_{zl}(1-I)Y_z\left[\left(\frac{P_{zh}}{P_{zl}}\right)^{1-\theta_{zl}}\left(\frac{P_{zl}}{w}\right)^{\sigma}\right]\right\} \tag{5}$$

where $B_z = (1/A_z)(\theta_{zl}/(1-\theta_{zl}))^{1-\theta_{zl}}$. Eq. (5) will be the starting point for the empirics. Specifically, Eq. (5) illustrates that there are three competing forces affecting the demand for low-skill labor: a "displacement effect" ($a_{zl}(1-I)$), an "output effect" (Y_z) and a "substitution effect" ($[(P_{zh}/P_{zl})^{1-\theta_{zl}}(P_{zl}/w)^{\sigma}]$). I next discuss each of these in more detail, with a particular emphasis on the nature of the output effect.

2.2. Displacement effect

The first testable proposition is the following:

Proposition 1. *A marginal decline in offshoring costs leads to a direct decline in the demand for low-skill tasks.*

Proof. From (3) and the fact that $t'(I) > 0$:

$$\frac{dI}{d\beta} = -\frac{t(I)}{t'(I)\beta} < 0 \tag{6}$$

[5] From (4), one can show that $d\Omega/dI = -\{\Omega(I)^{\sigma}t(I)^{\sigma-2}t'(I)[\int_0^I t(i)^{1-\sigma}\, di]\} < 0$ and combining this with the fact that $dI/d\beta < 0$ (discussed further below), we have that $d\Omega/d\beta = (d\Omega/dI)dI/d\beta > 0$ so that Ω falls as offshoring costs decline. This is the productivity effect of offshoring.

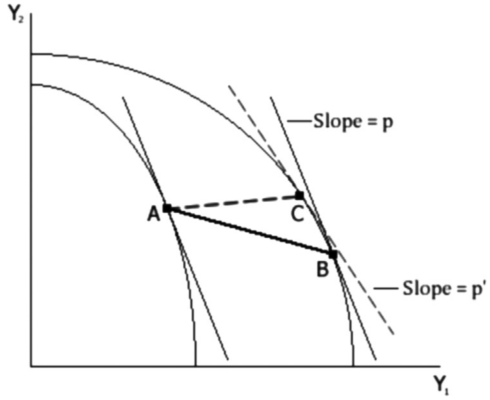

Fig. 2. Output effect in small and large country cases.

so that falling offshoring costs lead firms to move tasks overseas. From this it follows that the first term in (5), $a_{zl}(1-I)$, represents a direct displacement of employment at home—i.e., it takes less domestic labor to produce a unit of output as the result of offshoring—an effect that is relatively larger in industry 1, due to the fact that $a_{1l} > a_{2l}$. □

2.3. Output effect

In this section I focus on the intuition for the output effect of offshoring while leaving the formal derivations to Appendix A. The main point to be made is that offshoring will also affect the relative demand for low-skill tasks across industries by altering the distribution of output. This output effect—represented by Y_z in Eq. (5)—arises due to the productivity gains that firms enjoy due to the offshoring of low-skill tasks. In the simplest case, it is straightforward to show that when the country is small in world markets the output effect manifests as a Rybczynski effect, which shifts labor and production toward low-skill-labor-intensive industries at the expense of other industries, which contract. In contrast, in the large country case the productivity gains operate via two channels: the first is the Rybczynski effect but, in addition, the output price now falls in *all* industries, which leads to an expansion of each industry's global market share and, potentially, leads to a net increase in total output in all industries. In other words, despite the reallocation of output and labor away from some industries and toward others, it is possible that all industries expand. Again, Appendix A formally derives these results while Fig. 2 illustrates them graphically for the two-country, two-industry case.

Due to the reallocation of labor demand, low-skill workers are likely to see both increased employment and increased wages, where the extent to which the productivity gains accrue as employment versus wage gains hinges on the relative size of domestic industries in world markets (see Appendix A).[6] Regardless of the form that the gains to workers take, it is important to make clear that the gains *accrue to the workers whose tasks are being moved offshore*, which is the counter-intuitive result originally pointed out by GRH (2008).

It is also worth pointing out that, though the model presented here is a full-employment model and, as a result, displaced workers are necessarily re-absorbed, the model's usefulness is in highlighting the mechanism through which productivity gains due to offshoring may affect the demand for labor—namely, via the output effect. To the extent that search frictions generate unemployment, an outside sector absorbs dislocated workers, or other mechanisms arise outside the model, these factors will of course mitigate the output effect described here. In fact, the regression results will suggest that re-absorption is incomplete, suggesting that a subset of these factors may be operating.

The second testable proposition is the following:

Proposition 2. *For country labor endowments of finite size, a marginal decline in offshoring costs leads to increases in output and low-skill employment that are relatively larger in industries that are relatively intensive in the use of offshorable tasks. Furthermore, the magnitude of inter-industry reallocation is increasing in the relative size of the country whose firms are sending tasks abroad.*

Proof. The proof is relegated to Appendix A.

2.4. Substitution effect

Finally, falling offshoring costs will affect low-skill labor demand through the two relative price terms in (5), which will collectively be referred to as the "substitution effect" of offshoring and which reflect, first, the substitution between the

[6] Note that the model presented here assumes perfect competition in output and labor markets, so productivity gains accrue entirely to workers. In a model with monopolistic competition and wage bargaining the distribution of productivity gains could be split between the owners of firms and workers, however the mechanisms described here would operate in an identical fashion. See Sethupathy (forthcoming) for this type of setup.

high-skill factor and the low-skill factor—given by the term $(P_{zh}/P_{zl})^{1-\theta_{zl}}$ and to be referred to as factor substitution—and, second, within the low-skill factor between domestic tasks and foreign tasks—given by $(P_{zl}/w)^{\sigma}$ and to be referred to as task substitution. Writing the factor substitution term as $(qa_{zh}/wa_{zl}\Omega(I))^{1-\theta_{zl}}$ and noting from the previous section that under offshoring $\hat{q}=0$ and $\hat{w}+\widehat{\Omega(I)}<0$, it follows that the factor substitution term is increasing in the extent of offshoring. Next, conditional on factor substitution, the task substitution term will be declining since $(d(P_{zl}/w)^{\sigma})/d\beta=(a_{zl}\Omega(I))^{\sigma}(\sigma/\Omega(I))$ $d\Omega(I)/d\beta>0$. So task substitution leads to a decline in the average price of low-skill workers that is more rapid than the fall in the Home wage, which implies substitution away from Home tasks and toward Foreign tasks. Therefore, taking the task and factor substitution effects together, the net impact on the employment of low-skill workers from the substitution effect depends on whether substitution toward the low-skill factor outweighs substitution toward foreign tasks—i.e., it depends on the relative magnitudes of the factor and task substitution terms.[7]

2.5. *The demand for high-skill tasks*

Since the empirics will separately examine the impact on low- and high-skill employment of increased ease of offshoring low-skill tasks, I simply note here the form of the labor demand function for high-skill tasks. Note that it will still be assumed that only low-skill tasks can be moved offshore. Following the derivation in Section 2.1, the demand for high-skill tasks under offshoring of low-skill tasks is given by

$$D_h(z)=C_z\left\{a_{zh}Y_z\left[\left(\frac{P_{zl}}{P_{zh}}\right)^{\theta_{zl}}\left(\frac{P_{zh}}{q}\right)^{\sigma}\right]\right\} \tag{7}$$

where $C_z=(1/A_z)((1-\theta_{zl})/\theta_{zl})^{\theta_{zl}}$. Note that the components of the demand function are analogous to (5), however there is no direct employment effect for high-skill labor. For the output and substitution effects the comparative statics described above carry over.

3. Data and variables

3.1. *Measuring the extent of offshoring*

The independent variable of interest will be β, a measure of the non-task-specific costs of offshoring encompassing a wide range of barriers, including the current state of communications technologies, infrastructure developments in potential offshoring hubs, government policies (e.g., tariffs or non-tariff policy barriers), transport costs, and many other factors. As a first step in constructing a measure of these costs, I start with a direct measure of the extent of offshoring by U.S. firms over the period 2001–2007—specifically, a measure of the offshoring of inputs into production. The inverse of this measure is clearly directly proportional to β. I use the narrow measure from Feenstra and Hanson (1999),[8] in which changes in offshoring are reflected in changes in the imports of intermediate material inputs into the production of final goods, and I alter the original measure by ensuring that the economy-wide import shares used to proxy for industry import shares only reflect economy-wide imports of *intermediate inputs* as a share of total consumption of *intermediates*, rather than *total* imports relative to *total* consumption, as in Feenstra and Hanson (1999) (see Appendix C for a detailed explanation of this measure). Formally, the measure is

$$Off_{zt}=\frac{\sum_k\left[(\text{intermediates purchased by } z \text{ from } k\,)\left(\dfrac{\text{imports of intermediates in } k}{\text{domestic consumption of intermediates in } k}\right)_t\right]}{\sum_k(\text{intermediates purchased by } z} \text{ from } k\,) \tag{8}$$

where industries z and k are restricted to the same 3-digit North American Industry Classification System (NAICS) category and the U.S. input–output tables for 2002 are used to capture the purchased value of intermediate k by industry z.[9] The import and domestic consumption values vary annually. The final measure covers 464 final industries and Fig. 3 illustrates the consistent upward trend in the extent of offshoring according to this measure across the major manufacturing sub-sectors.

A concern will be the potential for this measure to be correlated with technological shocks that are also correlated with the dependent variables (employment measures) in the regressions. I therefore discuss the instrumental variables strategy after presenting the estimating equations.

---

7 Note that when $\sigma=0$, as in GRH (2008), there is no task substitution and therefore no ambiguity as to the impact due to the substitution effect.

8 A variety of measures of offshoring have been used in the literature. This particular measure has been criticized for possibly being too broad a measure, potentially capturing more than just the displacement of domestic value added by foreign intermediate inputs. In other words, it may capture new intermediate inputs into the production process as well. However, Feenstra (1994) shows that the effect of new varieties on average costs is equivalent to a reduction in the cost of existing varieties. While importing new intermediate varieties does not constitute offshoring, per se, it likely is the result of similar global phenomena and will be unavoidably integrated into the analysis here.

9 The input–output structure of industries changes very little over this period such that the 2002 values nearly identical to previous and later input–output values.

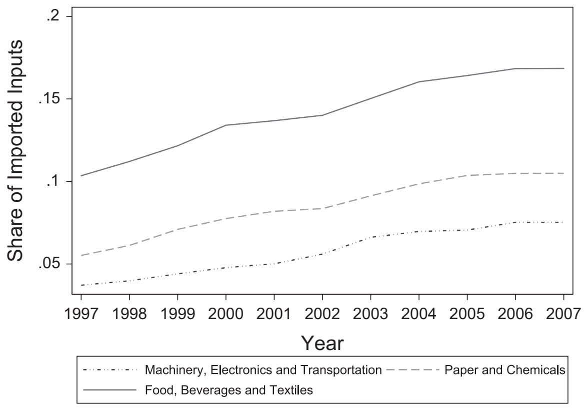

Fig. 3. Extent of offshoring across major manufacturing sub-sectors (share of inputs that are imported).

3.2. Industry output, employment, wages, and controls

Most variables used come from the Annual Survey of Manufactures and Economic Censuses, 2001–2007, and are classified by six-digit NAICS. Specifically, industry shipments are used as a measure of output, the low- and high-skill wage bills are used to construct the relative wage bill, and industry capital expenditures are used as a control. See Appendix B for more details about the construction of the dataset.

4. Estimating the employment impact of offshoring

Before introducing cross-industry heterogeneity in the use of offshorable production tasks—which the model suggests will determine the relative magnitudes of the displacement and output effects summarized in Propositions 1 and 2—this section will first estimate the average magnitudes of the direct displacement and output effects of offshoring across all industries, conditional on the substitution effect. Note that I do not estimate the substitution effect itself due to the fact that estimating wage effects in a cross-industry context is problematic. The reason is that, absent significant labor market frictions, a general equilibrium model would suggest that workers will reallocate in response to industry-specific shocks (such as offshoring) in order to equalize industry wages. As a result, in light of the empirical approach that I take in this paper, we would expect much of the wage effect of offshoring to be absorbed in the year fixed effects that will be included in each of the specifications.[10]

4.1. Estimating equations

First, taking logs, the labor demand function in (5) can be rewritten as

$$\ln D_{zl} = \ln\left[\frac{1}{A_z}\left(\frac{\theta_{zl}}{1-\theta_{zl}}\right)^{1-\theta_{zl}}\right] + \ln a_{zl}(1-I) + \ln Y_z + (1-\theta_{zl})\ln\left(\frac{qa_{zh}}{wa_{zl}}\right) + F_z(I) \tag{9}$$

where the substitution terms are now separated into a component that is directly observable, given by the relative wage bill qa_{zh}/wa_{zl}, and a component that cannot be directly observed, indicated by $F_z(I) \equiv \ln[a_{zl}^{\sigma}(\Omega(I)^{\sigma}/\Omega(I)^{1-\theta_{zl}})]$. Focusing on this term, note that since $\Omega(I)$ is a function of the marginal task, I, the ratio of $\Omega(I)$ terms simply reflect variation in employment due to offshoring. Furthermore, as with the direct displacement term (the second term) in (9) $F_z(I)$ also depends on an industry-specific scaling factor, a_{zl}^{σ}. The term $F_z(I)$ will therefore simply be combined with the direct displacement term, resulting in a more general form of the direct displacement effect that now includes the fact that substitution across factors and tasks that is unaccounted for by changes in the observed relative wage bill in the Home country can also directly influence employment levels. For clarity, we can formally define this term to be $G_z(I) \equiv a_{zl}^{1+\sigma}(1-I)(\Omega(I)^{\sigma}/\Omega(I)^{1-\theta_{zl}})$ and can rearrange (9):

$$\ln D_{zl} = \ln\left[\frac{1}{A_z}\left(\frac{\theta_{zl}}{1-\theta_{zl}}\right)^{1-\theta_{zl}}\right] + \ln G_z(I) + \ln Y_z + (1-\theta_{zl})\ln\left(\frac{qa_{zh}}{wa_{zl}}\right) \tag{10}$$

Note that this more inclusive form of the direct employment term could now be either increasing or decreasing in offshoring costs, depending on the relative magnitudes of σ and $1-\theta_{zl}$ (i.e., the sign of $dG_z(I)/dI$ is ambiguous).[11] This suggests that,

[10] There are certainly ways to estimate the wage effects of offshoring in an industry context, for instance as in Feenstra and Hanson (1999), but these approaches are somewhat complex and would be more suited to a separate paper.

[11] The intuition here is that offshoring may not only lead firms to shift their production intensity toward overseas tasks (task substitution), but may also provide the incentive for firms to alter their production technology in favor of low-skill intensive production methods more generally (factor substitution), in order to exploit offshoring possibilities. This could raise the overall demand for low-skill labor, even at Home. For this to lead to a net gain

conditional on variation in output or the relative wage bill, the sign of the direct employment effect under offshoring is ultimately an empirical issue.

Eq. (10) will provide the structural basis for the specifications below. First, note that the initial term varies across industries, as indexed by z, but not within industries. With respect to the second term, $\ln G_z(I)$, recall from (6) that there is a direct, inverse relationship between the location of the marginal task, I, and the level of offshoring costs, given by β in the model and reflected in the offshoring measure described in Section 3.1. Since this term is a function of I, while also varying across industries z, the estimation will proceed by first running a regression based directly on (10) that includes the offshoring measure as a proxy for $\ln G(I)$, conditional on industry heterogeneity in the intensity of use of offshorable tasks, where industry heterogeneity is explored in the following section.[12] The regression will also include industry output (Y_z), relative wage bills (qa_{zh}/wa_{zl}) and other control variables.

It is a variant of this regression that is often run in the literature and, as discussed, it only estimates the direct (negative) employment effect of offshoring. Here we estimate this effect, before moving on to estimation of the output effect and a comparison of the two. In anticipation of the instrumental variables strategy, the estimation is in first-differences:

$$\Delta \ln D_{zt} = c + \delta_t + \lambda_1 \Delta Off_{zt} + \lambda_2 \Delta \ln Y_{zt} + \lambda_3 \Delta \ln W_{zt} + \lambda_x \Delta \ln X_{zt} + \varepsilon_{zt} \tag{11}$$

where the additional control variables $Comp_{zt}$, Inv_{zt}, EXP_{zt}, and IMP_{zt} are subsumed in X_{zt} and δ_t is a year fixed effect. The offshoring variable is described in Section 3.1 and is here multiplied by 100 for ease of interpretation. For example, if the share of imported intermediates in total intermediate purchases increases from 0.17 to 0.18, this will now be calculated as a one percentage point change in offshoring. The variable Y represents industry output, $Comp$ is a measure drawn from the O*NET database that reflects the intensity of use of computers by individuals in an industry-year, Inv is total investment in capital goods, EXP is the value of industry exports, and IMP is the import share of final goods (non-intermediates). The regression is run across 464 NAICS industries over 2001–2007.

The inclusion of controls for computer use and capital investment is intended to control for variation in productivity due to skill-biased technical change, while the import share of final goods is included in order to control for trade-related determinants of industry output that are not captured by offshoring—in particular, the reduction in output resulting from loss of domestic market share in final goods. Furthermore, to the extent that there are time-invariant, industry-specific features that determine the level of employment, these will be eliminated via the first-difference specification, while sector-wide shocks in a period will be absorbed by the year fixed effects.

4.2. Instrumental variable strategy

The offshoring measure clearly directly reflects falling offshoring costs. However, it is also likely correlated with domestic industry-level demand shocks that also affect the distribution and employment level in tasks performed domestically, i.e., the dependent variable in the regression specifications.[13] Of greatest concern are technological shocks that impact the relative demand for domestic production tasks while simultaneously reducing the costs of offshoring. Some of these technological shocks will be controlled for explicitly in the regressions, but others are likely to be absorbed in the error term. In addition, there is likely to be endogeneity due to anticipation of trade barrier reductions by firms and policymakers. With respect to the latter, there is a large literature demonstrating that industry-specific trade policy, and hence the level of trade (and, most relevant here, offshoring), is endogenous to various fixed and time-varying features, including recent employment trends in the industry—this is the so-called "endogenous protection" literature.[14]

I therefore adopt a strategy that is motivated by a similar approach taken by Bloom et al. (2011). First, I focus narrowly on imports of intermediates from China, thereby constructing the measure (8) using only imports of these goods (and I now denote the offshoring measure as Off_{zt}^{CH}), and then I instrument for these flows using a "shift-share" strategy to be described. The focus on China exploits the country's entry into the WTO in 2001, an event whose timing was largely driven by exogenous policy decisions by the Chinese government. Furthermore, China accounted for 60% of the growth in U.S. intermediate imports over the period and so can explain the bulk of variation we are interested in.

In general, this event is well-suited to isolating plausibly exogenous variation in U.S. imports for the following reasons. First, the potential for technology shocks to be simultaneously correlated with U.S. industry trends and with the level of offshoring should be greatly mitigated by the fact that the timing and pattern of liberalization over the period was largely driven by internal politics within the Chinese government.[15] In particular, the motivations of the relevant policymakers were likely unrelated to aggregate technological trends that were impacting U.S. manufacturing industries, which should mitigate bias due to omitted variables. However, there is still the possibility of bias due to anticipation effects. Specifically, U.

(*footnote continued*)
for low-skill labor at Home requires factor substitution to significantly exceed task substitution, which may be unrealistic. In that case, the direct employment effect would lead to a decline in the demand for low-skill labor as before.

[12] In this section we are, in effect, assuming that the unit labor requirement to perform each task is constant across industries and equal to the average value in the economy.

[13] A Durbin–Wu–Hausman test for endogeneity of the offshoring and output measures indeed indicate that both are endogenous to employment.

[14] The seminal paper in the empirical literature on endogenous protection is Trefler (1993).

[15] For discussion of the background to Chinese WTO entry and some (conjectural) analysis of the internal deliberations within the Chinese government, see Lardy (2001).

S. firms may have adjusted their production technology and level of output and employment after the decision to enter the WTO had been announced by the Chinese, but prior to actual entry. Furthermore, these adjustments may have been largest among firms anticipating the largest growth in import competition. Additionally, U.S. trade policy may have been developed strategically over this period in order to mitigate the impact of future import competition.

Some initial evidence suggests that the latter effect may not have been important. Following WTO entry, growth in U.S. imports of Chinese goods in an industry was strongly predicted by the comparative advantage that China held in that industry prior to entry (see Bloom et al., 2011), a fact further supported by evidence from Amiti and Freund (2010) who show that three-quarters of the growth in Chinese imports over the 1997–2005 period was due to expansion of existing products. For the purposes here, this suggests that U.S. trade policies that were implemented in anticipation of WTO entry, in order to affect the industrial impact of Chinese imports, may have been inconsequential. In light of this, the IV strategy described below attempts to exploit the pre-entry pattern of comparative advantage held by China.

However, there remains the possibility that U.S. firms adjusted their labor and output levels in anticipation of Chinese WTO entry. To explore this possibility, I run an OLS regression in which the growth in employment and, separately, output across industries over the pre-period, 1997–2000, is the independent variable and the dependent variable is the growth in import penetration across industries post-WTO entry, 2001–2007. Table 5 reports these results. There is a negative but insignificant correlation between both employment and output growth in the pre-period and subsequent offshoring, suggesting that domestic anticipation of China WTO accession was not an important determinant of subsequent changes in the extent of offshoring. Nevertheless, as a matter of caution I include the pre-period industry output growth in the regressions.

As noted, I instrument for ΔOff_{zt}^{CH} by exploiting the fact that China's export growth was relatively larger in industries in which it had a comparative advantage prior to the period.[16] I capture this by interacting the level of U.S. offshoring to China in 1997 with the annual change in total (over all industries) offshoring ΔOff_{t}^{CH}. In other words, I instrument for ΔOff_{zt}^{CH} with $Off_{z,1997}^{CH} * \Delta Off_{t}^{CH}$. This approach provides significant power in the first stage, with an *F*-Statistic of 14.

Finally, an additional potential pitfall in running regressions based on (11) is that an explicit assumption of the model is that industry output is affected by offshoring and, as a result, the instrument for offshoring cannot satisfy the exclusion restriction since *Y* contains offshoring itself. As a solution to this problem I instrument for industry output by dropping the import share of final goods from (11) and instrumenting for *Y* using variation in tariffs on final goods in each industry-year.[17] Again, import competition is likely a source of variation in manufacturing output over this period, though to ensure the variation is exogenous tariffs are used rather than import shares.

4.3. Results

Column (3) in the top half of Table 1 indicates that a one percentage point increase in the extent of offshoring is associated with a 0.29% direct decline in low-skill worker hours. Given that the average annual decline in production worker employment in the manufacturing sector during this period was 1.49%,[18] this estimate indicates that the direct effect due to offshoring can explain approximately 19% of this decline. (See Fig. 4 for the change in the share of employment in value added across major manufacturing sectors over the period).[19]

Next, in order to estimate the magnitude of the output effect I run the following regression:

$$\Delta \ln Y_{zt} = c + \delta_t + \gamma_1 \Delta Off_{z,t-1} + \gamma_x \Delta X_{z,t-1} + \gamma_2 \Delta \ln W_{zt} + \gamma_3 \Delta \ln IMP_{zt} + \varepsilon_{zt} \tag{12}$$

where the control variables (*Comp*,*Inv*,*EXP*) are again in logs and are subsumed in *X*. The (first-difference of the) offshoring measure and the variables *Comp*, *EXP* and *Inv* are lagged one period under the assumption that their impact on output may take time to manifest, while the relative wage and import penetration measures are assumed to be contemporaneous.

Since the error term in (12) is almost certainly correlated with the error term in (11) (i.e., $cov(\varepsilon_{zt}, \varepsilon_{zt}) \neq 0$), efficiency can be improved by running both regressions jointly as seemingly unrelated regressions (SUR).[20] In addition, since offshoring will be instrumented for using the measures discussed in Section 4.2, the regressions will ultimately be run jointly via three-stage least squares (3SLS), which combines SUR with 2SLS. In short, the 3SLS estimator is motivated by the fact that the SUR estimator requires a cross-equation covariance matrix, and in the context of endogenous regressors one can be calculated using the results from 2SLS regression on the individual equations. Finally, the method also adjusts the weighting matrix for potential heteroskedasticity of the errors by estimating the coefficients within a GMM framework, an approach outlined in Wooldridge (2010).

---

[16] This is very similar to the shift-share instrumental variables approach commonly used in the immigration literature and initiated by Card (2001).

[17] Specifically, I exploit variation in Most Favored Nation (MFN), regional, and Information Technology Agreement (ITA) tariff rates. These data are all publicly available, but much of the raw MFN and regional data come from a dataset compiled independently over time by Raymond Robertson of Macalester College and Chang Hong of Clark University.

[18] In 2001 there were 11 million production workers. Employment of production workers declined by 1.2 million over this period.

[19] All of the regression specifications are robust to excluding outliers as well as observations with relatively large leverage. Formally, I repeat all of the regressions while excluding observations whose "Cook's D" value is above the 95th percentile, and find the results are largely unchanged.

[20] The results with respect to the direct employment effect discussed at the beginning of this section are also the outcome of the SUR strategy described here.

Table 1
The average direct employment and output effects of offshoring on low-skill workers.

Explanatory variables:	(**1**)	(**2**)	(**3**)
Direct employment effect (dependent variable: Δ Log **production worker employment**)			
Δ(100 × **extent of offshoring**)	**−0.31****	**−0.31****	**−0.29****
	(**0.13**)	(**0.12**)	(**0.15**)
Δ Log of industry output	0.12***	0.14***	0.20***
	(0.03)	(0.04)	(0.04)
Δ Log of relative factor prices		0.15***	0.19***
		(0.05)	(0.06)
Δ Log of computer use			2.74***
			(0.82)
Δ Log of capital investment			0.04**
			(0.02)
Δ Log of exports			−0.01
			(0.03)
Partial *F*-stat, predicted offsh	21	22	14
Partial *F*-stat, tariffs	60	52	34
Observations	1174	1174	1174
Output effect (dependent variable: Δ Log **industry output**)			
Δ (100 × **lagged extent of offshoring**)	**0.82***	**0.86***	**1.01****
	(**0.48**)	(**0.48**)	(**0.43**)
Δ Log of relative factor prices		−0.24	−0.30
		(0.20)	(0.25)
Δ Lagged log of capital investment			0.04*
			(0.02)
Δ Log of computer use			2.56**
			(1.10)
Δ Lagged log of exports			0.07*
			(0.04)
Δ Log of final good imports			0.09***
			(0.03)
Partial *F*-stat, predicted offsh	35	31	21
Observations	1174	1174	1174

Note: The method of estimation is GMM 3SLS. Asymptotic standard errors are reported in parentheses. Regressions cover 7 years: 2001–2007. The offshoring measure is based on the Feenstra and Hanson (1999) definition and is constructed as described in Section 3. All regressions include year fixed effects and controls for pre-period output trends. The Hansen's *J* statistic associated with the joint estimation of the effects is 1.04, and does not allow us to reject the null that the instruments are valid.

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

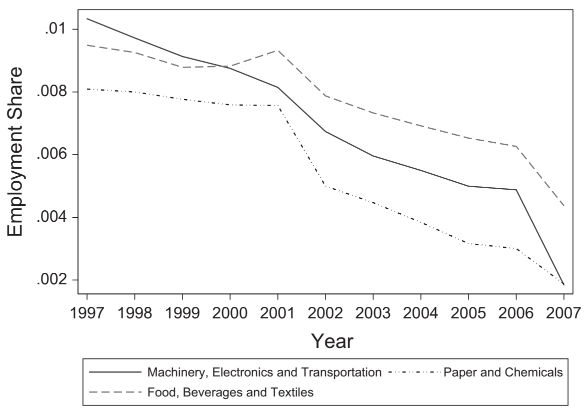

Fig. 4. Share of employment in value added, 1997–2007.

By taking the product of the coefficient on the offshoring measure from this regression and the coefficient on industry output in (11), we can obtain the average magnitude of the employment impact due to the output effect. This can then be combined with the estimate of the direct effect from (11) to obtain an estimate of the aggregate, average employment impact due to offshoring. Note that this two stage process is directly motivated by the prediction of the model that offshoring impacts employment in part *through* the output effect.

The results are presented in Column (3) in the bottom half of Table 1. Increases in the extent of offshoring on average led to a statistically significant increase in industry output, suggesting an output effect does in fact operate, in an average sense, with the U.S. manufacturing sector. This provides evidence that economy-wide output also increases due to offshoring, which is an implication of Proposition 1. The magnitude of this effect is such that a one percentage point increase in the extent of offshoring led to a 1.01% increase in industry output. Combining this with the coefficient on output from the top half of Table 1 we find that this reduces the negative impact of the direct employment effect by 69%, which supports the notion that it is important to account for this channel when estimating the employment impact of offshoring. On the other hand, it also demonstrates that the productivity gains due to offshoring are not, on average, great enough to offset the employment losses. Combining the direct employment and output effects, *on average* offshoring can explain approximately 6% of the average annual decline in production worker employment over this period.[21] This implies that offshoring is responsible for a net loss of 69,000 production worker jobs, a relatively minor impact during a period in which 1.2 million production worker jobs were lost.[22]

4.4. Defining offshorable tasks

The next objective is to test the model's prediction (Proposition 1) that the intensity of use of offshorable labor across industries determines the magnitude of the productivity-enhancing cost savings due to offshoring, and through that the magnitude of the output effect. First however, we require an industry-level measure of the intensity of use of offshorable labor, which can then be used to characterize industries. First, note that from (1) the cost-share of the portion of the workforce that can feasibly be moved offshore is given by θ_{zl}. Furthermore, some subset of the tasks performed by these workers, those between 0 and I, are already being performed offshore and, as a result, the cost share of the offshorable tasks performed at Home is given by $\theta_{zl}(1-I)$. However, the Cobb–Douglas distinction in the model between the type of labor that can and cannot be moved offshore was used largely for tractability and likely does not accurately reflect an industry's production structure. As a result, rather than use the cost share of Home low-skill labor as a measure of offshorable labor intensity, I instead set the cost share values equal to 1. This essentially removes the strict assumption that only production tasks can be moved offshore.

To construct a proxy for the marginal task, I, I draw from recent theory and discussion in the literature on the offshorability of tasks or occupations. Though there are a variety of features that play a role in a task's offshorability, I focus on two that have been the most emphasized: (i) the extent to which a task can be described in rules-based form, or its routineness (see Levy and Murnane, 2006a,b), and (ii) the extent to which a task involves interacting with other people (see Blinder, 2007, Blinder, 2009). Next, I use data from the U.S. Department of Labor-affiliated O*NET database, from which measures of the routineness and "interaction-intensity" of U.S. occupations are selected. I take the average of these two measures as a reflection of an occupation's "offshorability", given by $i=[(1-Routine)+Interactivity]/2$.[23] As indicated, this effectively maps out the task index, $i\in(0,1)$, from the model—i.e., the measure ranks occupations according to the offshorability of the tasks which comprise them. This offshorability measure is then assigned to individuals (via their occupations) in the American Community Survey (ACS) for 2000, the earliest ACS survey.[24]

In order to construct an industry-level proxy for I that is also motivated by the structure of the model, note that the model states that the total amount of labor that is allocated to any production task in industry z is given by $D_{zl}(i)$. Combining the values of i from above with the employment in each occupation from the ACS, a straightforward proxy for I is given by *the* (*Home*) *employment-weighted average value of i in industry z*. In the context of the model, this measure is given by

$$A_{zt}(I)=\frac{\int_I^1 D_{zlt}(i)i\,di}{\int_I^1 D_{zlt}(i)\,di}$$

and is depicted graphically in Fig. 5. This measure captures the extent to which the tasks performed at Home are concentrated among the most routine and non-interactive tasks at time t. As offshoring costs decline and the most routine and non-interactive tasks are moved offshore, the marginal task shifts rightward, as does $A_{zt}(I)$. Thus, lower values of $A_{zt}(I)$ reflect a greater intensity of offshorable tasks in an industry. Formally, it is easy to show that

$$\frac{dA_{zt}(I)}{dI}=\frac{D_{zl}(i)}{\int_I^1 D_{zl}(i)\,di}(A_{zt}(I)-I)>0 \tag{13}$$

[21] I obtain this number by dividing the average annual net effect of offshoring on production worker employment (-0.09) by the observed average annual decline in production worker employment (1.49).

[22] I repeated these regressions using equation-by-equation 2SLS regressions and obtained somewhat different results. In particular, the direct effect is estimated to be positive, but not significant, though the output effect estimate is quite similar to that estimated via GMM 3SLS. These results would therefore place more weight on the productivity gains due to offshoring, however for the reasons discussed above the GMM 3SLS specifications are preferred.

[23] Since offshorability is decreasing in Interactivity but increasing in Routine, and since both measures are normalized to be between 0 and 1, I take the value $1-Routine$ so that in the final measure the most offshorable tasks are associated with *low* values of i, as in the model.

[24] More details regarding the task data and the measure constructed here can be found in Appendix D.

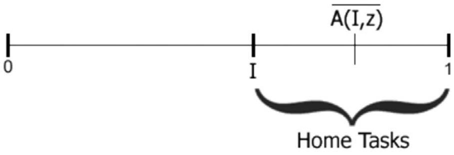

Fig. 5. A measure of industry heterogeneity in offshorable tasks.

so that $A_{zt}(I)$ is increasing monotonically in I and is therefore a suitable first-order proxy for I. Table 7 lists the most and least offshorable industries according to this metric.

As a preliminary test of the relevance of the measure, it is straightforward to ask whether it is able to predict the extent of future offshoring in an industry. In other words, if relatively low values of $A_z(I)$ reflect a greater intensity of use of offshorable tasks at time t, those industries that are more intensive in these tasks should subsequently offshore more. To test this, I fit the following regression, where the independent variable is the value of $A_z(I)$ in industry z in 2001 and the dependent variable is the change in offshoring across industries over the period in z:

$$\Delta Off_{z,2001-2007} = -\underset{(0.93)}{2.08} - \underset{(0.13)}{0.58} \cdot A_z(I)_{2001} \quad (n = , R^2 = 0.03) \tag{14}$$

The coefficient is negative and significant, suggesting that this measure is a strong predictor of offshoring activity over the period. Noting that the mean value of $A_{zt}(I)$ is 0.46 with standard deviation of 0.08, the estimates suggest that a 0.16 point, or two standard deviation, difference in labor offshorability across industries in 2001 was associated with a 9.3 percentage point difference in subsequent offshoring growth over this 7-year period.

4.5. The role of offshorable labor

I now turn to the prediction of Proposition 1 of a differential response to falling offshoring costs according to the intensity with which offshorable labor is used in production. Throughout this section I consider the intensity with which offshorable labor is used in industry z to be reflected by the value of $A_{zt}(I)$, as described above. Proposition 1 can be straightforwardly tested by once again jointly estimating the following regressions:

$$\begin{aligned}\Delta \ln D_{zt} &= c + \delta_t + \lambda_1 \Delta Off_{zt} + \lambda_2 A_{zt}(I) + \lambda_3[\Delta Off_{zt} \cdot A_{zt}(I)] \\ &\quad + \lambda_4 \Delta \ln Y_{zt} + \lambda_5 \Delta \ln W_{zt} + \lambda_x \Delta \ln X_{zt} + \varepsilon_{zt}\end{aligned} \tag{15}$$

and

$$\begin{aligned}\Delta \ln Y_{zt} &= c + \delta_t + \gamma_1 \Delta Off_{z,t-1} + \gamma_2 A_{zt}(I) + \gamma_3[\Delta Off_{z,t-1} \cdot A_{zt}(I)] \\ &\quad + \gamma_x \Delta X_{z,t-1} + \gamma_4 \Delta \ln W_{zt} + \gamma_5 \Delta \ln IMP_{zt} + \varepsilon_{zt}\end{aligned} \tag{16}$$

where now the offshoring variable is interacted with the proxy for the relative intensity of use of offshorable labor so that the second term in (10) is now allowed to vary across industries as indicated in the model.

The top half of Table 2, Column (3) shows the results for regression (15). Recalling that when $A_{zt}(I)$ is small, the domestic intensity of offshorable tasks is large, we see that the direct employment effect is clearly increasing in the use of offshorable labor, which again suggests that the ordering of industries by $A_{zt}(I)$ is meaningful.[25] Recalling that the offshoring variable reflects the predicted share of imported intermediates in total purchased intermediates, this result indicates that the low-skill labor content of imported intermediates is greater, on the margin, for industries intensive in offshorable labor. This result supports the model's prediction of a heterogeneous direct employment effect across industries due to offshoring.

The bottom half of Table 2, Column (3) illustrates that the magnitude of the output effect also depends on the intensity of use of offshorable labor, as suggested in Proposition 1. The results provide evidence that output gains due to offshoring are the result of the productivity-enhancing cost savings that come from moving production tasks offshore. Multiplying γ_3 by λ_4, we can calculate that the marginal increase in employment *via the output effect* for a one standard deviation increase (0.08 decline in the value of $A_{zt}(I)$) in the intensity of use of offshorable labor across industries is equal to 5.60%. So the employment gains due to the output effect are increasing in the use of offshorable labor.[26]

4.6. The impact of offshoring on high-skill labor

Offshoring, as defined in the model, involves tasks that are performed primarily by relatively low-skill workers, an assumption that is supported by the rank correlation between industries that offshore most and their low-skill labor shares,

[25] Ebenstein et al. (2010) also find a larger negative effect of offshoring on low-skill employment for workers who perform more routine work.

[26] Note that the fact that $|\gamma_1 * \lambda_4| < |\lambda_1|$ indicates that for the average industry over this period, in terms of offshorable labor content, a marginal increase in offshoring led to a net employment loss, which simply reiterates the result found in Section 4.1 above.

Table 2
The marginal direct employment and output effects of offshoring and the task content of industries (low-skill workers).

Explanatory variables:	(**1**)	(**2**)	(**3**)
Direct employment effect (dependent variable: Δ Log **production worker employment**)			
$A_z(I)$	−0.63***	−0.60***	−0.59
	(0.20)	(0.20)	(0.44)
Δ (100 × Extent of offshoring)	−19.94***	−19.21***	−16.86*
	(6.82)	(6.64)	(9.75)
Δ (100 × **Extent of offshoring**) · $\boldsymbol{A_z(I)}$	**46.23***	**44.45***	**39.14**
	(**16.01**)	(**15.61**)	(**23.01**)
Δ Log of industry output		0.73**	1.01
		(0.33)	(0.79)
Δ Log of relative factor prices		0.23***	0.28**
		(0.09)	(0.11)
Δ Log of computer use			0.93
			(1.40)
Δ Log of capital investment			−0.05
			(0.08)
Partial *F*-stat, predicted offsh	1590	1058	762
Partial *F*-stat, tariffs	–	31	42
Observations	962	962	962
Output effect (dependent variable: Δ Log **industry output**)			
$A_z(I)$	−0.30**	−0.30**	−0.14
	(0.12)	(0.13)	(0.17)
Δ (100 × Lagged extent of offshoring)	0.61	0.62	0.84**
	(0.42)	(0.41)	(0.40)
Δ (100 × **Lagged extent of offshoring**) · $\boldsymbol{A_z(I)}$	**−0.67***	**−0.68***	**−0.70****
	(**0.37**)	(**0.37**)	(**0.35**)
Δ Log of relative factor prices		−0.02	1.00
		(0.07)	(1.09)
Δ Lagged Log of capital investment			0.06***
			(0.02)
Δ Log of computer use			0.01
			(0.07)
Partial *F*-stat, predicted offsh	31	20	17
Observations	962	962	962

Note: The method of estimation is GMM 3SLS. Asymptotic standard errors are reported in parentheses. All regressions include year fixed effects and controls for pre-period output trends. The Hansen's *J* statistic associated with the joint estimation of the effects is 0.30, and does not allow us to reject the null that the instruments are valid.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

as depicted in Table 6. However, according to (7) the demand for high-skill labor will also be indirectly affected by reductions in offshoring costs, specifically via the output and substitution effects, *though not* via the direct employment effect since non-production tasks are assumed to be too costly to offshore. To obtain an estimate of the effect of variation in output due to offshoring on the demand for high-skill labor, I again run regression (11) with high-skill labor demand as the dependent variable. Then, the coefficient on the output term from this regression can be combined with the output effect estimate using (12), again estimated jointly using GMM 3SLS, to get an estimate of the impact of offshoring on non-production employment. Note that the model predicts that the coefficient on the offshoring variable from regression (11) should be zero, since there should be no direct impact of offshoring on high-skill labor. From the top half of Table 3 Column (3) we can see that this coefficient is negative, but not significant.

The bottom half of Table 3 Column (3) indicates that the output effect is measured to be of nearly identical magnitude as when jointly measured with the direct effect on low-skill labor in Table 1. Combining this output effect coefficient with the coefficient on output from the top half of the table indicates that a one-percentage point increase in the extent of offshoring increased employment of high-skill workers by 0.25%, or a cumulative 0.75% over the period. On aggregate, employment of high-skill workers fell by 17.5% over the period, so offshoring clearly served to somewhat offset this decline. Finally, for completeness, Table 4 displays the results from running regressions (15) and (16) for the case of high-skill labor. Unsurprisingly, the offshorable labor content of an industry does not predict employment declines due to offshoring (via the direct effect) though, consistent with the above results, the magnitude of the output effect is estimated to be greater the more offshorable are the tasks in an industry (bottom half of Table 4).

Since, on average, high-skill workers perform less-routine, more-interactive tasks more intensively than low-skill workers, these results suggest there is rising relative demand for these tasks due to offshoring, a result found elsewhere in the literature.

Table 3
The average direct employment and output effects of offshoring on high-skill workers.

Explanatory variables:	(**1**)	(**2**)	(**3**)
Direct employment effect (dependent variable: Δ Log **non-production worker employment**)			
Δ(**100 × Extent of offshoring**)	**−0.99**	**−0.88**	**−0.46**
	(**0.13**)	(**1.79**)	(**0.95**)
Δ Log of industry output	0.29***	0.27***	0.24***
	(0.05)	(0.05)	(0.09)
Δ Log of relative factor prices		−0.96***	−1.03***
		(0.23)	(0.25)
Δ Log of computer use			4.17**
			(1.96)
Δ Log of capital investment			−0.04
			(0.08)
Δ Log of exports			0.09
			(0.10)
Partial *F*-stat, predicted offsh	19	21	14
Partial *F*-stat, tariffs	61	54	36
Observations	1174	1174	1174
Output effect (dependent variable: Δ Log **industry output**)			
Δ (100 × **Lagged extent of offshoring**)	**0.88***	**0.91***	**1.06****
	(**0.50**)	(**0.49**)	(**0.44**)
Δ Log of relative factor prices		−0.22	−0.27
		(0.24)	(0.28)
Δ Lagged log of capital investment			0.04
			(0.03)
Δ Log of computer use			2.65***
			(0.97)
Δ Lagged log of exports			0.07*
			(0.04)
Δ Log of final good imports			0.08***
			(0.03)
Partial *F*-stat, predicted offsh	35	31	21
Observations	1174	1174	1174

Note: The method of estimation is GMM 3SLS. Asymptotic standard errors are reported in parentheses. Regressions cover 7 years: 2001–2007. The offshoring measure is based on the Feenstra and Hanson (1999) definition and is constructed as described in Section 3. All regressions include year fixed effects and controls for pre-period output trends. The Hansen's *J* statistic associated with the joint estimation of the effects is 0.48, and does not allow us to reject the null that the instruments are valid.

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

4.7. The aggregate employment impact of offshoring

Combining the results from the previous sections, an estimate of the average impact on aggregate employment—i.e., including both production and high-skill workers—can be made. Noting that the average share of low-skill workers in employment within the manufacturing sector averages 0.71 over the period and applying the estimated contribution of offshoring to the decline in low-skill worker employment and the rise in high-skill worker employment, the aggregate effect of offshoring is estimated to have led to a cumulative increase in aggregate employment of 2.6% over the period 2001–2007, a relatively minor effect.

5. Conclusions

In order to evaluate the aggregate impact of offshoring on employment, assumptions are needed about the mechanisms at work. This suggests that a structural model may be useful in order to provide a roadmap for empirical specifications. This paper has provided such a roadmap based on the tasks model of offshoring and has used the predictions and structure to evaluate the impact of offshoring over the recent period within the manufacturing sector. The empirical estimates rely on the construction of a plausibly exogenous measure of offshoring, derived using variation in U.S. offshoring to China during its recent rapid trade liberalization. The results suggest that offshoring directly displaces workers while simultaneously generating cost-savings that lead to increased hiring. Both these effects are larger for industries that use "offshorable" tasks more intensively, a prediction of the model. The balance of these effects is such that, on net, offshoring has generated an overall loss of production (low-skill) jobs in the manufacturing sector that is equal to about 6% of all production jobs lost over this period. In contrast, offshoring has generated an almost 1% increase in the employment of non-production workers. Combining the estimates for both low- and high-skill worker types, offshoring to China resulted in an overall increase in employment of all workers of 2.6% over the period following China's accession to the WTO.

Table 4
The marginal direct employment and output effects of offshoring and the task content of industries (high-skill workers).

Explanatory variables:	(1)	(2)	(3)
Direct employment effect (dependent variable: Δ Log **production worker employment**)			
$A_z(I)$	−0.16	−0.60	0.57
	(0.10)	(0.89)	(0.86)
Δ (100 × Extent of offshoring)	6.57	29.75	28.59
	(7.80)	(21.39)	(19.87)
Δ (100 × **Extent of offshoring**) · $\boldsymbol{A_z(I)}$	−**15.58**	−**69.95**	−**67.25**
	(**17.54**)	(**50.07**)	(**46.50**)
Δ Log of industry output		−1.07	−1.02
		(1.73)	(1.65)
Δ Log of relative factor prices		−1.18***	−1.17***
		(0.45)	(0.43)
Δ Log of computer use			0.69
			(3.80)
Δ Log of capital investment			0.02
			(0.16)
Partial *F*-stat, predicted offsh	1590	1058	762
Partial *F*-stat, tariffs	–	31	42
Observations	962	962	962
Output effect (dependent variable: Δ Log **industry output**)			
$A_z(I)$	−0.30***	−0.08	−0.05
	(0.10)	(0.20)	(0.19)
Δ (100 × Lagged extent of offshoring)	0.39	0.82	0.82**
	(0.30)	(0.39)	(0.39)
Δ (100 × **Lagged extent of offshoring**) · $\mathbf{i_l(I)}$	−**0.81****	−**0.86****	−**0.84****
	(**0.37**)	(**0.39**)	(**0.40**)
Δ Log of relative factor prices		−0.04	0.05
		(0.08)	(0.08)
Δ Lagged log of capital investment			0.07***
			(0.02)
Δ Log of computer use			1.19
			(1.06)
First stage *F*-stat, predicted offsh	31	20	17
Observations	962	962	962

Note: The method of estimation is GMM 3SLS. Asymptotic standard errors are reported in parentheses. All regressions include year fixed effects and controls for pre-period output trends. The Hansen's *J* statistic associated with the joint estimation of the effects is 0.00, and does not allow us to reject the null that the instruments are valid.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Acknowledgements

I would like to thank Emek Basker, Robert Feenstra, Rowena Gray, Hilary Hoynes, Kohei Kawamura, Giovanni Peri, Gianmarco Ottaviano, Katheryn Russ, Anson Soderbery, and Deborah Swenson along with three anonymous referees for invaluable comments.

Appendix A. The output effect and proof of Proposition 2

First assume that the Home country trades final output with a Foreign country and that together they constitute the world economy. Full employment and immobility of factors across countries are assumed throughout. Home and Foreign preferences for industry output are given by the following Cobb–Douglas utility function:

$$U = Y_1^{\alpha} Y_2^{1-\alpha}$$

In addition, each of the industries is taken to be uniformly less productive in Foreign relative to Home, so that there is a Hicks-neutral productivity disadvantage $A^* > 1$ abroad. In an integrated world economy this leads to "adjusted factor price equalization" such that

$$w\Omega(I) = w^* A^* \quad \text{and} \quad q = q^* A^* \tag{17}$$

It follows that the ratio of effective factor prices $w\Omega(I)/q$ and w^*/q^* are equal across countries and therefore so are the unit labor requirements, $a_{zl} = a_l^*(z)$ and $a_{zh} = a_h^*(z)$.

The equilibrium conditions in Home are reflected in the zero-profit conditions and full employment conditions, the former given by

$$\begin{aligned} p_1 &= a_{1l} w\Omega(I) + a_{1h} q \\ p_2 &= a_{2h} w\Omega(I) + a_{2h} q \end{aligned} \tag{18}$$

and the latter given by

$$\begin{aligned} L/(1-I) &= a_{1l} Y_1 + a_{2l} Y_2 \\ H &= a_{1h} Y_1 + a_{2h} Y_2 \end{aligned} \tag{19}$$

In the small country case output prices are fixed and therefore, from the zero-profit conditions, so are factor prices. To see the impact on output in each industry due to offshoring we can therefore focus on the full-employment conditions. First note that offshoring increases the range of tasks performed abroad and therefore, if we consider the left-hand side of the first condition in (19) as reflecting the Home *effective* low-skill labor endowment, increased offshoring can be seen to increase this endowment. What, then, is the corresponding effect of offshoring on industry output? Total differentiation of the labor market clearing conditions in (19) lead to the result that an increase in the range of tasks performed abroad causes the low-skill labor intensive industry, 1, to expand while industry 2 will contract.[27] This is the well-known Rybczynski effect, and it is depicted in Fig. 2 where an increase in the effective endowment of low-skill labor at constant prices leads to the redistribution of output from point A to point B.

The intuition behind this result can be stated as follows. Since the productivity gains from offshoring are larger for the more low-skill labor intensive industry, 1, its output increases relative to 2 (in fact, industry 2 contracts), raising the demand for low-skill labor. The wage for domestic low-skill workers therefore rises and, in the small country case, it does so until the productivity gains are fully appropriated by workers in the form of higher wages. We can see this by exploiting condition (17) and noting that the Home country takes the Foreign wage as fixed. Letting "hats" denote log changes it follows that $\widehat{w} = -\widehat{\Omega(I)}$ and $\widehat{q} = 0$, so that in equilibrium there is an increase in the Home low-skill wage which completely offsets the productivity gain $(-\widehat{\Omega(I)})$, while there is no change in the high-skill wage. Furthermore, labor and output have shifted toward industry 1.

We are also interested in the case when the Home country is large, since we will be testing the model using U.S. data.[28] Now, the output expansion in industry 1 will cause a decline in its output price which, from (19) must lead to a decline in unit costs. The result is that now the productivity gains only partially accrue to low-skill workers in the form of a wage increase. Instead, the Rybczynski effect is mitigated and wages rise only enough to equate the new price with unit costs. This can be seen in Fig. 2: the output expansion in industry 1 now causes a decline in the output price of industry 1 relative to industry 2, where p and p' represent the industry price ratio before and after adjustment. In fact, it is clear that if this relative price adjustment is large enough then both industries may experience a net output expansion, as depicted in the movement from A to C.

Denoting $w\Omega(I)$ as the *effective* low-skill wage,[29] we can demonstrate this result by first noting that the effective factor endowments in Home can be written as $L/\Omega(I)$ and H and in Foreign by L^*/A^* and H^*/A^*. With adjusted factor price equalization total factor payments can therefore be written as

$$q\left(H + \frac{H^*}{A^*}\right) = E[\alpha\theta_{1h} + (1-\alpha)\theta_{2h}] \tag{20}$$

$$\omega\left(\frac{L}{\Omega(I)} + \frac{L^*}{A^*}\right) = E[\alpha\theta_{1l} + (1-\alpha)\theta_{2l}] \tag{21}$$

where $\omega = w\Omega(I)$ and E is total world expenditure, which is normalized to 1. Taking natural logs and differentiating (20) and (21), we have

$$\widehat{q} = \frac{\alpha\, d\theta_{1h} + (1-\alpha)\, d\theta_{2h}}{\alpha\theta_{1h} + (1-\alpha)\theta_{2h}}$$

and

$$\widehat{\omega} = \widehat{\Omega}\left[\frac{L/\Omega)I)}{\dfrac{L}{\Omega(I)} + \dfrac{L^*}{A^*}}\right] + \frac{\alpha\, d\theta_{1l} + (1-\alpha)\, d\theta_{2l}}{\alpha\theta_{1l} + (1-\alpha)\theta_{2l}}$$

However, the Cobb–Douglas production technology implies that the cost shares are constant, therefore both $d\theta_{zl} = 0$ and $d\theta_{zh} = 0$. So, in the large country case the cost of high-skill workers remains unchanged ($\widehat{q} = 0$), just as in the small country

[27] See Feenstra (2004) for details of this well-known result.

[28] In fact, the "large-country" case is a misnomer to some extent, since significant global market power is often held by firms in countries of all sizes. In any extent, it will clearly be relevant to many U.S. industries.

[29] This is the wage paid to all low-skill workers from the perspective of the firm, and clearly combines both the cost of Home and Foreign low-skill labor. The domestic low-skill wage is simply w.

case, while the change in the Home component of the low-skill wage is equal to

$$\hat{w} = \widehat{\Omega(I)}\left[\frac{L/\Omega(I)}{\dfrac{L}{\Omega(I)}+\dfrac{L^*}{A^*}}-1\right] \tag{22}$$

Defining the term in brackets as T, it is clear that $-1 \le T \le 0$, and since offshoring leads to a fall in $\Omega(I)$ the Home low-skill wage is non-decreasing in offshoring costs. The key point to be taken from (22) is that whereas in the small country case the rise in the Home low-skill wage perfectly offset the productivity gain from offshoring, now the rise in the wage is only equal to a fraction T of the productivity gain. Note that in the limit when the size of the Foreign low-skill labor endowment in (22) goes to zero there is no change in the Home low-skill wage. In this case the productivity gain associated with reductions in offshoring costs manifests entirely via a uniform increase in output in both industries. There is no reallocation across industries (no Rybczynski effect) and therefore no effect on wages. Conversely, when the size of the Home country low-skill endowment goes to zero we are back in the small-country case in which productivity gains manifest fully through an increase in the low-skill wage. Thus, we have the result stated in Proposition 2.

Appendix B. Construction of industry variables

Construction of the industry-level variables largely follows the methodology outlined in Sitchinava (2008). Data on employment, shipments, materials, and investment are obtained from the Census' Annual Survey of Manufactures for 2001–2007. One issue is that while for 1997–2001 the ASM data follow a six-digit NAICS classification, across 2002–2007 some NAICS industries are aggregated to a higher level. As a result, I impute the more disaggregate industry values using industry shares from 2001. This only occurs for a small minority of industries and so only removes a small amount of relevant variation. For the case of the capital investment variable this can, in fact, be done using the more disaggregate categories of structures and equipment and then recombining these. Also, some industries in the ASM data have missing information due to the disclosure reasons. While some of this data can be directly imputed from more aggregate industry information, in a few cases the method of imputing values described above was used.

Appendix C. Construction of the offshoring measure

This appendix draws from Feenstra and Jensen (2009) to which this author contributed. More specifically, I include here a comparison of the original Feenstra and Hanson (1999) offshoring measure with the one used in this paper, a comparison that is included in Feenstra and Jensen (2009). The goal is to update the offshoring measure described in Feenstra and Hanson (1999) which is defined for any industry z purchasing inputs k as

$$\frac{\sum_k\left[(\text{purchases by industry } z \text{ from } k)\left(\dfrac{\text{imports into } k}{\text{domestic consumption of } k}\right)\right]}{\sum_k(\text{purchases by } z \text{ from } k)} \tag{23}$$

The primary shortcoming of this measure is the use of good k's share of imports in total domestic consumption, in the numerator, which is computed for the entire U.S. economy. As it is stated, (23) essentially assumes that the economy-wide import share for good k is the same as the industry z import share for good k, which is the "import comparability" assumption.

Given this limitation of (23), there are still some improvements that can be considered. Specifically, I recalculate the measure of offshoring in (23) while focusing more carefully on only imported intermediate inputs. Specifically, the inputs k that are used in (23) are defined by the classifications used in input–output tables off the United States, which are classified according to 6-digit NAICS. For each NAICS industry, there will be multiple 10-digit Harmonized System (HS) imported products. Let us denote by $i \in U_k$ the set of 10-digit HS products within each 6-digit NAICS good i. Some of these imported products can be final goods rather than intermediate inputs. Imports of such final goods are often not what we have in mind with materials offshoring. To correct this problem we can restrict attention to HS goods with corresponding "end-use codes" that are indeed intermediate inputs. The end-use codes are used by the Bureau of Economic Analysis to allocate goods to their final use, within the National Income and Product Accounts. Accordingly, U.S. imports and exports by Harmonized System are also allocated to end-use codes. As described by the Census Bureau, Guide to Foreign Trade Statistics:

"The 1-digit level end-use categories provide data for the following broad aggregates: (0) Foods, feeds, and beverages; (1) Industrial supplies and materials; (2) Capital goods, except automotives; (3) Automotive vehicles, parts and engines; (4) Consumer goods (nonfood), except auto; and (5) Other merchandise…The HTSUSA and Schedule B classifications are summarized into six principal "end-use" categories and further subdivided into about 140 broad commodity groupings. These categories are used in developing seasonally adjusted and constant dollar totals. The concept of end-use demand was developed for balance of payments purposes by the Bureau of Economic Analysis."

Based on the numbering system defined in the above quotation, food and other items begin with the digit "0", which include both final goods and intermediate inputs; raw materials and intermediate goods begin with "1"; investment goods begin with the digit "2"; automotive goods begin with "3", which include both final goods (finished autos) and intermediate inputs (parts); final consumer goods (nonfood) begin with the digit "4"; and "5" is a miscellaneous category. Table 5 lists the

Table 5
Correlation between offshoring and pre-period employment and output trends.

Dependent variable: **Δ offshoring, 2001–2007**	
Employment	
Δ Employment, 1997–2000	−10.19
	(10.78)
Output	
Δ Output, 1997–2000	−13.58
	(8.46)
Number of observations	3059

Note: This table presents OLS regressions of the extent of offshoring on pre-period trends in employment in output across U.S. manufacturing industries.

Table 6
Characterizing "offshorable" labor-intensive industries rankings are by NAICS Industries in 2000.

	Ranked by $(\mathbf{1-A_z(I)})$	**Extent of offshoring** $(\mathbf{1/\beta})$
1	YARNS	**0.22**
2	WOOD KITCHEN CABINETS AND COUNTERTOPS	**0.37**
3	AUTOMOBILES AND LIGHT DUTY MOTOR VEHICLES	**0.42**
4	MACHINE TOOLS (METAL CUTTING TYPES)	**0.21**
5	MEN'S AND BOYS' TROUSERS, SLACKS, AND JEANS	**0.33**
6	POULTRY, PREPARED OR PRESERVED	**0.09**
7	MEN'S AND BOYS' UNDERWEAR AND NIGHTWEAR	**0.18**
8	TEXTILE MACHINERY	**0.19**
9	FROZEN FRUITS, JUICES AND VEGETABLES	**0.11**
10	GLASS CONTAINERS	**0.15**
.		
.		
457	PHARMACEUTICAL PREPARATIONS	**0.08**
458	AUDIO AND VIDEO EQUIPMENT	**0.14**
459	OTHER COMMUNICATIONS EQUIPMENT	**0.22**
460	MILITARY ARMORED VEHICLE, TANKS, AND TANK COMPONENTS	**0.14**
461	ELECTROMEDICAL AND ELECTROTHERAPEUTIC APPARATUS	**0.16**
462	SEARCH, DETECTION, NAVIGATION, …INSTRUMENTS	**0.08**
463	GUIDED MISSILES AND SPACE VEHICLES	**0.01**
464	TOTALIZING FLUID METERS AND COUNTING DEVICES	**0.05**

Note: The extent of offshoring measure is the Feenstra–Hanson (1999) measure described in Section 3. The construction of $A_z(I)$ is described in Section 4.4.

precise 5-digit end-use codes that are included within final goods (i.e. consumption and investment), while all other end-use codes are treated here as intermediate inputs or raw materials.

Using this end-use classification, I consider a restricted set of HS codes within each NAICS industry k: $\overline{U_k} \equiv$ {HS goods i within industry k that are also intermediate inputs}. Then the revised measure of materials offshoring is given by (8).

Note that the import share used in the numerator of (8) restricts the set of goods used in both the numerator and the denominator, so we cannot tell how it compares with the import share used in (23). Specifically, the denominator of this import share is constructed as: total domestic consumption $i \in \overline{U_k} =$ domestic shipments for $i \in \overline{U_k}$ + sum over imports $i \in \overline{U_k}$ −sum over exports $i \in \overline{U_k}$.

The import and export terms in this expression do not need any explanation: they are simply the sum over HS imports or exports within the NAICS industry k that are also intermediate inputs (as defined by their end-use classification). But the domestic shipments term does require an explanation. Rather than use the total domestic shipments of industry k, I instead apportioned those domestic shipments into various HS products i, by assuming that the share of domestic shipments for each HS product i within industry k equals the share of U.S. exports in that HS product and industry. I then sum domestic shipments over just those HS products that are also intermediate inputs (as defined by their end-use classification).

I construct the offshoring measure (8) for all years between 2001 and 2007 within the manufacturing sector. I begin with measures of intermediates purchases by U.S. industries, which are obtained from the Economic Census for benchmark years (1997, 2002, 2007). The values are by 6-digit NAICS.

Each observation in the Economic Census benchmark dataset contains a purchasing industry, a corresponding intermediate industry which provides inputs, and a total value of purchases (inputs). To obtain purchases for all years for an industry from a particular intermediate industry, I simply interpolate the benchmark values linearly throughout the period 1997–2007.

The next step is to construct the import share of intermediates in domestic consumption of intermediates. This industry share will be merged with the input-providing industries from the purchases data described above. First, we merge data on imports and exports from Feenstra et al., 2002 with yearly data on total industry shipments, obtained from the Annual Survey of Manufactures.

Table 7
End-use final goods.

The following include both final and intermediate goods:
00020 Cane and beet sugar
00100 Meat products & poultry
00110 Dairy products & poultry
00120 Fruits & preparations including juices
00130 Vegetables & preparations
00140 Nuts & preparations
00150 Food oils & oilseeds
00160 Bakery products & confectionery
00170 Tea, spices, & preparations
00180 Agricultural foods, n.e.c.
00190 Wine & related products
01000 Fish and shellfish
01010 Whiskey and other alcoholic beverages
01020 Other nonagricultural foods & food additives
15200 Fabricated metal products
16110 Blank audio and visual tapes and other media

The following are final goods only:
40000 Apparel, & household goods–cotton
40010 Apparel, & household goods–wool
40020 Apparel, & household goods–other textiles
40030 Non-textile apparel & household goods
40040 Footwear of leather, rubber & other materials
40050 Sporting & camping apparel, footwear & gear
40100 Medicinal, dental, & pharmaceutical preparations includ. vitamins
40110 Books, magazines, & other printed matter
40120 Toiletries & cosmetics
40140 Consumer nondurables, n.e.c.
41000 Furniture, household items & baskets
41010 Glassware, porcelain, & chinaware
41020 Cookware, cutlery, house & garden ware & tools
41030 Household and kitchen appliances
41040 Rugs & other textile floor coverings
41050 Other household goods
41100 Motorcycles & parts
41110 Pleasure boats & motors
41120 Toys, shooting & sporting goods, including bicycles
41130 Photographic & optical equipment
41140 Musical instruments & other recreational equipment
41200 Television receivers, video receivers, & other video equipment
41210 Radios, phonographs, tape decks, & other stereo equipment & parts
41220 Records, tapes, & disks
413 Coins, gems, jewelry, & collectibles
42000 Unmanufactured goods
421 Unmanufactured diamonds

Investment (***final goods***):
20000 Generators, transformers, and accessories
20005 Electrical equipment and parts n.e.c.
21000 Oil-drilling, mining, and construction machinery
21100 Industrial engines, pumps, compressors, and generators
21110 Food- and tobacco-processing machinery
21120 Machine tools & metal-working machinery, molding and rolling
21130 Textile, sewing and leather working machinery
21140 Woodworking, glass-working & plastic- and rubber-molding mach.
21150 Pulp & paper machinery, bookbinding, printing & packaging mach.
21160 Measuring, testing, and control instruments
21170 Materials-handling equipment
21180 Other industrial machinery
21190 Photo- & service-industry machinery and trade tools
21200 Agricultural machinery and equipment
21400 Telecommunications equipment
21500 Other business machines
21600 Scientific, hospital, and medical equipment and parts
22000 Civilian aircraft, complete[a]
22010 Civilian aircraft, parts
22020 Civilian aircraft, engines
22100 Railway & other commercial transportation equipment
22200 Vessels (except military & pleasure craft) & misc. vehicles
22300 Spacecraft, engines & parts, except military

Automotive Vehicles, Parts, and Engines (***final and intermediate goods***):[b]
30000 Passenger Cars, New and Used
30100 Complete and Assembled

Raw Materials (***not final goods nor intermediate inputs***:[a]
14200 Bauxite and Aluminum
14220 Copper
14240 Nickel
14250 Tin
14260 Zinc
14270 Nonmonetary Gold
14280 Other Precious Metals
14290 Misc. Non-ferrous Metals
10 Crude, Fuel Oil, Other Petroleum products, Coal, Gas, Nuclear Fuel, Electric Energy

[a] These classifications are always excluded from the offshoring calculation.
[b] This broad category includes both final and intermediate goods. Those listed here are final goods and are excluded from the offshoring calculation.

Now, in order to restrict the imports, exports, and shipments to intermediates only, I use the end-use categories which are matched to NAICS industries in the import/export datasets. I separate out investment goods and most automobile categories from the list because these include many things that we think of as vulnerable to offshoring, such as automobile parts, machinery and equipment, and therefore we ultimately would like to include these items. For personal consumption expenditure (PCE) goods a portion of the list is more subjective, with some categories split between intermediate and final goods. Here I simply remove all end-use categories which encompass some final goods, and since the categories which are problematic are primarily food items, which we do not generally associate with offshoring activities, this approach seems reasonable. In addition, I remove certain raw materials detailed in Table 5, such as petroleum products and various metals, whose value and import volumes are likely unrelated to offshoring activities.

Comparing the original and revised offshoring measures, to determine which industries show the greatest differences (averaged over years), the following results are obtained:

NAICS industry	Description	Difference in measures
339931	Dolls and Stuffed Toys	0.85
315991	Hats and Caps	0.35
331316	Aluminum Extruded Products	0.35

311320	Chocolate and Confectionary Products	0.29
339941	Pens and Mechanical Pencils	0.28
339992	Musical Instruments	0.25

The industries with the greatest difference are simply consumer items that are imported directly to retail outlets, so these imports are clearly final goods, and therefore omitted from the revised offshoring measure.

Appendix D. Industry task offshorability measure

The key dataset used is the O*NET dataset. The purpose of the dataset is to provide information on a range of occupations, and to this end 1100 occupations are surveyed with a corresponding measure provided for each of 277 occupation attributes which are arranged in a hierarchical structure according to the nature of the metric. Knowledge, Abilities, Skills, Tasks, Work Context and Activities are some examples of the higher-level classifications. Within these categories are more detailed metrics, including the ones I select as potentially characterizing features of task offshorability. Next, note that the O*NET data are assigned to occupations rather than tasks, per se. The O*NET attributes, however, are clearly reflections of the work activities that comprise the occupations and so will be interpreted as characterizing the tasks performed in a job.

The selected features are then combined with American Community Survey data obtained from the Integrated Public Use Microdata Series (King et al., 2009). Using data on individuals from 2000 to 2007, I attach the occupation attribute measures to each individual according to their occupation.[30] Finally, observations are aggregated to the industry level as described in Section 4.4: each observation is weighted by the "person weight" (number of individuals) and total hours worked. Note that since the same attribute measures are used for each period there is no within-occupation variation over time, and thus the results are driven by shifts in the employment intensity (hours worked) of occupations within industries.

Turning to the specific attributes selected, I first construct a measure of the intensity of human interaction inherent in a task. Blinder (2007) does just this using the O*NET data, and I follow his method. He begins by selecting five O*NET variables which reflect the extent to which an occupation requires face-to-face interaction. Because O*NET rates these attributes on two scales — "importance" and "level" — he arbitrarily combines these in a Cobb–Douglas combination, giving "importance" a two-thirds weight and "level" a one-third weight. Letting I_i represent the value for the "importance" of the ith attribute and l_i represent the value for the "level" of the ith attribute, the overall measure of occupation j's dependence on face-to-face interaction is $S_j = \sum_{i-1,5} I_{ij}^{2/3} l_{ij}^{1/3}$.

For the measure of the routineness of the occupation, I simply take the average of the occupation features that fall under the O*NET Work Context category "Routine versus Challenging Work". I then take the simple average of these two measures of routineness and human interaction to create an aggregate measure of an occupation's vulnerability to offshoring due to the features of the tasks which comprise it. Still, along the spectrum of this aggregate measure there are occupations that are not remotely offshorable due to other idiosyncratic features of the occupations which require that they are performed at home. For example, some occupations such as construction jobs, though they are routine and non-interactive, also require interaction with the physical environment and thus are not offshorable. As a remedy, I select all the occupations that Blinder (2007) classifies as "Highly non-offshorable" and give them an index of 1. As a result, the final aggregate index orders all tasks that are remotely offshorable by the average of their routineness and non-interactivity.

Appendix E. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.euroecorev.2013.11.008.

References

Amiti, M., Freund, C., 2010. The anatomy of China's export growth. In: Feenstra, Robert C., Wei, Shang-Jin (Eds.), China's Growing Role in World Trade, University of Chicago Press, Chicago, IL.

Autor, D., Dorn, D., 2013. The growth of low-skill service jobs and the polarization of the U.S. labor market. Am. Econ. Rev. 103 (5), 1553–1597.

Autor, D.H., Levy, F., Murnane, R.J., 2003. The skill content of recent technological change: an empirical exploration. Q. J. Econ. 118 (November (4)).

Becker, S.O., Ekholm, K., Muendler, M., 2013. Offshoring and the onshore composition of tasks and skills. J. Int. Econ. 90 (1), 91–106.

Blinder, A.S., 2009. How many U.S. jobs might be offshorable? World Econ. 10 (2), 41–78.

Blinder, A.S., Krueger, A.B., 2009. Alternative measures of offshorability: a survey approach. J. Labor Econ. 31 (2), 97–128.

Bloom, N., Draca, M., Van Reenen, J., 2011. Trade induced technological change? The impact of Chinese imports on innovation, IT and productivity. CEP Discussion Paper No. 1000.

Card, David, 2001. Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. J. Labor Econ. 19, 22–64.

[30] Because each O*NET variable is measured on a different scale, I rescale each variable to correspond to the distribution of the population in 2000. For example, a value of 0.34 indicates that 34% of the population in 2000 worked in an occupation which was equally or less intensive in the use of that variable. This new scale is then applied to occupations in all subsequent years.

Debaere, P., Lee, H., Lee, J. Does where you go matter? The impact of outward foreign direct investment on multinationals' employment at home. J. Dev. Econ., forthcoming.
Desai, M., Foley, F., Hines, J., 2009. Domestic effects of the foreign activities of U.S. multinationals. Am. Econ. J.: Econ. Policy 1, 181–203.
Ebenstein, A., Harrison, A., McMillan, M., Phillips, S., 2010. Estimating the impact of trade and offshoring on American workers using the current population surveys. NBER Working Paper No. 15107.
Ehrl, P., 2013. Task trade and the employment pattern: the offshoring and onshoring of Brazilian firms. EIIT Working Paper 557.
Feenstra, R.C., 1994. New product varieties and the measurement of international prices. Am. Econ. Rev. 84 (1), 157–177.
Feenstra, R.C., Hanson, G., 1999. The impact of outsourcing and high technology capital on wages: estimates for the United States 1979–1990. Q. J. Econ. 114 (3), 907–940.
Feenstra, R.C., Romalis, J., Schott, P.K., 2002. U.S. imports, exports and tariff data. The Center for International Data, UC Davis.
Feenstra, R.C., 2004. Advanced International Trade. Princeton University Press, Princeton, NJ.
Feenstra, R.C., Jensen, J.B., 2009. Evaluating estimates of materials offshoring from U.S. manufacturing. UC Davis Working Paper.
Gorg, H., Hanley, A., Strobl, E., 2007. Productivity effects of international outsourcing: evidence from plant-level data. Can. J. Econ. 41, 670–688.
Grossman, G., Rossi-Hansberg, E., 2008. Trading tasks: a simple theory of offshoring. Am. Econ. Rev. 98 (5), 1978–1998.
Harrison, A., McMillan, M., 2008. Offshoring jobs? Multinational and U.S. manufacturing employment. Rev. Econ. Stat. 93 (3), 857–875.
Hummels, D., Jorgenson, J., Munch, J., Xiang, C. The wage and employment effects of outsourcing: evidence from Danish matched worker-firm data. Am. Econ. Rev., forthcoming.
Jensen, J.B., Kletzer, L. Measuring tradable services and the task content of offshorable services jobs. In: Abraham, Katharine, Harper, Mike, Spletzer, James (Eds.), Labor in the New Economy. University of Chicago Press, Chicago, IL, forthcoming.
Jones, R.W., Kierzkowski, H., 1990. The role of services in production and international trade: a theoretical framework. In: Jones, Ronald W., Krueger, Anne O. (Eds.), The Political Economy of International Trade, Basil Blackwell, Oxford, UK.
King, M., Ruggles, S., Alexander, T., Leicach, D., Sobek, M., 2009. Integrated Public Use Microdata Series, Current Population Survey: Version 2.0. [Machine-readable database]. Minnesota Population Center [producer and distributor], Minneapolis, MN.
Kramarz, F., 2008. Offshoring, wages, and employment: evidence from data matching imports, firms and workers, mimeo, CREST-INSEE.
Lardy, Nicholas, 2001. Issues in China's WTO Accession. Testimony before the U.S.-China Security Review Commission, Brookings Institution, Washington, D.C.
Levy, F., Murnane, R.J., 2006a. How computerized work and globalization shape human skill demands. In: First International Conference on Globalization and Learning Conference Volume.
Levy, F., Murnane, R.J., 2006b. What sorts of rich-country jobs (and how many) are at risk to globalization. CESifo Forum, Pro and Contra, February.
Moser, C., Urban, D.M., Weder, B., 2009. Offshoring, firm performance and establishment-level employment: identifying productivity and downsizing effects. Centre for Economic Policy Research Working Paper.
Ottaviano, G.I.P., Peri, G., Wright, G.C., 2013. Immigration, offshoring and American jobs. Am. Econ. Rev. 103 (5).
Peri, G., Sparber, C., 2009. Task specialization, immigration and wages. Am. Econ. J.: Appl. Econ. 1 (3).
Sethupathy, G., 2013 Offshoring, wages and employment: theory and evidence. Eur. Econ. Rev., 62, 73–97.
Sitchinava, N., 2008. Trade, Technology, and Wage Inequality: Evidence from U.S. Manufacturing, 1989–2004 (Ph.D. dissertation). University of Oregon.
Spitz-Oener, A., 2006. Technical change, job tasks, and rising educational demands: looking outside the wage structure. J. Labor Econ. 24 (2).
Trefler, D., 1993. Trade liberalization and the theory of endogenous protection: an econometric study of U.S. import policy. J. Polit. Econ. 101 (1).
Wooldridge, J.M., 2010. Econometric Analysis of Cross-Section and Panel Data, 2nd ed. MIT Press, Cambridge, MA.