The Task Composition of Offshoring by U.S. Multinationals *

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Abstract

Recent advances in communications technology allow for greater fragmentation of production across borders. However, we do not observe U.S. multinationals offshoring all activities that are technologically feasible to perform abroad. This paper uses task-level routineness data paired with firm-level offshoring data to explain why this is the case. I first sketch a model in which less routine tasks are more costly to offshore because when unexpected problems arise, managers at the headquarters firm must intervene to fix them, and such intervention is costly. I test this prediction using firm level data on U.S. multinationals to identify which intermediate inputs these firms offshore to their foreign affiliates. Controlling for parent firm and country fixed effects as well as a measure of the feasibility of offshoring, I find that U.S. producers are more likely to import an intermediate input from a foreign affiliate the more intensively that input uses routine tasks. More complex and nonroutine activities are more likely to be performed at the multinational's headquarters in the U.S.

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1 Introduction

In recent years, improvements in information technology have allowed for increased fragmentation of production tasks across borders in both manufacturing and information and business services. This trend has been the topic of policy discussions and theoretical models (Blinder 2006; Grossman and Rossi-Hansberg 2008; Antras, Garicano and Rossi-Hansberg 2006; Leamer and Storper 2001). However, very little little empirical work has been done on this topic, due primarily to the lack of data on task offshoring. The current paper gets around this lack of off-the-shelf data on task trade by matching data on the task content of occupations with confidential firm-level data on offshoring from the Bureau of Economic analysis, making it the first to empirically measure the task content of offshoring using U.S. firm-level data.

What determines which activities get offshored? A few papers have attempted to estimate which jobs are most likely to be performed abroad. However, due to a lack of data on service offshoring, these have primarily relied on subjective indices (Blinder 2009) or extrapolations based on U.S. production patterns (Jensen and Kletzer 2007). Alan Blinder has argued that the key component for offshorabilty is whether an activity is performed personally or impersonally. In other words, jobs such as child care and nursing which require the producer and consumer to be in the same location will not be offshored. Jobs such as accounting and computer programming which do not require proximity will be offshored. However, this dichotomy leaves out many important features of how multinational firms actually operate. For example, Jensen and Kletzer (2007) emphasize tradabilty (imports and exports) rather than offshorability (trade in only one direction) and present evidence to suggest that the U.S. does not offshore all tradeable services, and rather exports more tradable services than it imports. In addition to neglecting the fact that a significant number of tradable activities are not offshored, Blinder's narrow focus on communication intensity also leaves out a key dimension of the firm's offshoring decision: how routine the task is. A number of economists have demonstrated theoretically that routine tasks can be fragmented geographically more easily than nonroutine tasks (Grossman and Rossi-Hansberg 2008; Antras, Garicano and Rossi-Hansberg 2006; Leamer and Storper 2001). However, the lack of widely available firm-level data on task offshoring has, up until now, prevented empirical tests of these predictions.

I use confidential, firm-level data on the operations of U.S. multinational companies in both manufacturing and service industries, paired with data on the specific activities performed in these industries, to identify which activities multinational companies perform in the U.S. and which activities they perform at their foreign affiliates. I exploit the fact that each U.S. multinational parent firm has multiple affiliates operating in different countries and industries. By controlling for the identity of the parent firm and the country of location, I can identify which tasks are more likely to be performed at the U.S. headquarters and which tasks are more likely to be offshored. This identification strategy sets this paper apart from previous attempts to capture the content of offshoring. Offshoring decisions are made by firms, and thus an identification of the determinants of offshoring requires the use of firm level data. Multinational firms engage in complex decision making processes that rely on a wide range of firm specific factors such as financing, strategy, ownership structure, etc. Many of these factors may be correlated with the routineness or offshorability of the firm's activities. Thus it is also crucial to control for firm level fixed effects. The results show that more complex, nonroutine activities stay in the U.S. and more routine, manual tasks are more likely to be offshored. The results hold up when industry fixed effects are included, as well. I also control for the importance of interacting with customers to address the issue of tradeability emphasized by Blinder and find that the importance of routineness for offshoring still holds.

The empirical specification follows from a theoretical model of trade in tasks. Grossman and Rossi-Hansberg (2008) develop a model in which trade consists of a series of value-added tasks that can be performed in any location, rather than as physical shipments of goods. In their model, the extent of offshoring is determined by an exogenous cost parameter, which varies by task. My framework is similar, but I explicitly model the source of task-specific trade costs. This paper is also in the spirit of Antras, Garicano, and Rossi-Hansberg (2006) who model the optimal structure of international production teams in a world where problems arise and certain individuals are more skilled than others at solving these problems. During the production process, problematic situations may arise. These problematic situations are more easily resolved within the management center of the firm than at a foreign affiliate. Thus we would expect that firms are more likely to offshore intermediate inputs that are less likely to give rise to problematic situations. In other words, the more routine an intermediate input is, the more offshoring relative to domestic production should take place. In my model, firms also differ in their productivity levels, such that more productive firms are more likely to engage in offshoring.

The use of the routine versus nonroutine dichotomy is motivated by Autor, Levy and Murnane (2003) who use this distinction to measure how certain activities respond to skill biased technical change. Anecdotal evidence suggests that this dichotomy is also relevant for firm-level offshoring decisions. In "The World is Flat", Thomas Friedman includes an interview with Vivek Kulkarni, who tells a very similar story from the perspective of an Indian firm that handles those tasks offshored by U.S. investment firms. Kulkarni says, "We will do the lower-end work and they will do the things that require critical judgment and experience" (Friedman 2005). A Stanford Graduate School of Business case study about an offshoring company in India, ExlService, distinguishes between "commoditized" services, which western firms are eager to offshore, and more complex processes, an area in which it is much more difficult for Indian firms to attract business (Spitzer 2006). In addition, several recent papers include theoretical models in which U.S. firms offshore only the most routine tasks (Antras, Garicano and Rossi-Hansberg 2006 and 2008), however, they do not test these predictions empirically. In spite of this case study evidence and theoretical support, to my knowledge this is the first paper that empirically estimates the relationship between the routineness of tasks and offshoring at the firm level.

2 Related Literature

A number of different theoretical frameworks have been used to study offshoring. Feenstra and Hanson (1996) divide the production of final goods into a continuum of intermediate inputs and identify which activities along that continuum will be offshored based on the relative costs of production across countries. Antras, Garicano and Rossi-Hansberg (2006) look at the formation of global teams of high and low skilled workers. Grossman and Rossi-Hansberg (2008) develop a model in which trade consists of a series of value-added tasks that can be performed in any location, rather than as physical shipments of intermediate goods. For this paper, I use a model that draws on elements of both Grossman and Rossi-Hansberg (2008) and Antras, Garicano and Rossi-Hansberg (2006), but that also incorporates variations in firm-level productivity. Heterogeneous firms decide whether to perform each task at their U.S. headquarters or at a foreign affiliate. This decision depends on the productivity of the firm as well as the level of routinesss of the task.

The empirical measure of routine versus nonroutine tasks is motivated by Autor, Levy and Murnane (2003). They use the Department of Labor's Dictionary of Occupational Titles (DOT) to classify the extent to which industries and occupations are comprised of routine versus nonroutine tasks. Routine tasks are those that can be accomplished by following a set of specific, well-defined rules. Nonroutine tasks require more complicated activities like creative problem solving and decision making. Autor, Levy and Murnane emphasize that these tasks are sufficiently complex that they can not be completely specified in computer code and executed by machines. I follow this routine/nonroutine categorization in estimating the location of intermediate production activities, generalizing the Autor, Levy and Murnane framework to classify any activities that are too complex to be fully specified in a contract ex ante as nonroutine. Instead of the DOT, I use its successor, the Department of Labor's Occupational Information Network (O*NET). Blinder (2007) and Jensen and Kletzer (2007) use O*NET to develop subjective rankings of the offshorability of service occupations. The matching of task level data to firm level trade data used in this paper was first done by Oldenski (2009).

I also draw on adaptive models of the firm, following Costinot, Oldenski and Rauch (2009) to put structure on the task-specific trade costs. Costinot, Oldenski and Rauch cite earlier theoretical work by Simon (1951), Williamson (1975), Tadelis (2002), and Gibbons (2005). These models focus on the make versus buy decision, that is whether a firm will own its suppliers or source arms length, but the intuition is similar for the decision to produce in the U.S. or abroad. Rather than focusing on the ex ante costs of production, these models emphasize costs associated with the contracting of inputs that are incurred ex poste. During the production process, problematic situations may arise, the nature of which can not be fully specified ex ante. These problematic situations have been shown to be more easily resolved within the firm than between a headquarters firm and its arms-length suppliers. The current paper uses similar intuition, but for movement across international boundaries rather than across ownership boundaries. Thus we would expect that firms are more likely to offshore those intermediate inputs that are less likely to give rise to problematic situations that can't be fully specified ex ante. In other words, the more routine an intermediate input is, the more offshoring relative to domestic production should take place.

3 Theoretical Framework

3.1 Basic Setup

For this paper, I use a model that draws on elements of Antras, Garicano and Rossi-Hansberg (2006), Grossman and Rossi-Hansberg (2008), and Costinot, Oldenski and Rauch (2011) but also incorporates firm-level heterogeneity. Firms decide whether to perform each task at their U.S. headquarters or at a foreign affiliate. This decision depends on the productivity of the firm as well as the level of routinesss of the task.

Ideally, I would like to compare four options that are available to the firm: (1) sourcing domestically within the firm, (2) sourcing domestically outside of the firm, (3) sourcing internationally within the firm (i.e. producing at a foreign affiliate), and (4) sourcing internationally at arms length. However I only have access to firm-level data for production within the firm (options (1) and (3)). Thus, this analysis necessarily assumes that the firm has already decided to source internally and asks, conditional on that decision, whether production will be done in the U.S. headquarters or at a foreign affiliate.

The production process can be divided into two stages: the production of intermediate tasks and the production of final goods and services. To produce intermediates, parent firm p (or one of its affiliates) uses labor (L), to produce tasks (i) according to a constant returns to scale production function:

$$Y_{pc}(i) = \frac{L_{pc}(i)}{a_{pc}(i)} \tag{1}$$

where $L_{pc}(i)$ is the amount of labor allocated to task i in country c at affiliates of parent firm p and a_{pc} is the amount of labor necessary for a firm owned by parent p to perform task i once in country c. Following Melitz (2003) firms are heterogeneous in their productivity levels such that more productive firms have lower unit costs, $a_{pc}(i)$.

Final goods and services are produced at the U.S. multinational headquarters. Parent firms use intermediate task inputs to produce goods and services (j) according to:

$$Y_{pj} = F_j[Y_{pc}(1), ..., Y_{pc}(I)] \tag{2}$$

Grossman and Rossi-Hansberg (2008) introduce an offshoring cost $t(i)$ that captures the unspecified costs of performing each task abroad. I put structure on this cost by reframing it as a function of the routineness of each task. When each task is attempted, it is either completed successfully (the routine outcome) or else a problematic situation arises that must be dealt with (nonroutine outcome). Tasks differ in their probabilities $\mu(i)$ of being completed routinely. Without loss of generality, tasks are indexed such that higher numbered tasks are less routine. Note that the probability of being in the routine state, $\mu(i)$, is inversely related to the cost of offshoring, $t(i)$.

For each task input, parent firms in the United States can choose between producing that task domestically or offshoring. Firms compare the cost of producing intermediate tasks in the U.S. ($c = 1$) against the cost of offshoring ($c = 2, ...C$). Location choices affect the cost of production in both the routine and the nonroutine state. The higher cost of offshoring less routine activities manifests itself as an increase in the unit labor requirement, as firms must expend effort to deal with the problematic state. Following Antras, Garicano, and Rossi-Hansberg (2006), when a problem arises that production workers are not able to solve, they must turn to managers for solutions. In Antras, Garicano, and Rossi-Hansberg, this is because production workers do not possess the required problem solving skills. In my case, it is because the headquarters, who developed the original concept and design for production, was not able to pass along instructions for dealing with every possible problematic situation that might arise during production due to the nonroutine nature of the task (rather than any characteristic of the workers). Dealing with these problematic situations thus requires additional units of headquarters labor, denoted $\beta_p(i)$. Headquarters workers are the only ones who know how to resolve idiosyncratic problems because they are the originators of the product concept and production design. If the production worker is in a different country than the firm's headquarters, then there is an additional fixed communication cost, δ, associated with communicating solutions to complex problems across borders. Let $a_{pc}(i) > 0$ denote the amount of labor necessary for firm p to perform task i once in country c and let w_c denote the wage in country c. The cost of producing a task in a given country, $w_c a_{pc}(i)$ is

$$w_{us} a_{p,us}(i) = w_{us}\alpha_{p,us}(i) + (1-\mu(i))w_{us}\beta_{p,us}(i) \tag{3}$$

if the task is performed in the U.S. and

$$w_c a_{pc}(i) = w_c \alpha_{pc}(i) + (1-\mu(i))(w_{us}\beta_{p,us}(i) + \delta(i)) \tag{4}$$

if the task is offshored, where $\alpha_{pc} > 0$ is the unit labor requirement if no problems arise, $\beta_{pc,us} > 0$ is an additional unit labor requirement capturing the amount of headquarters labor necessary to deal with the problematic state, should it occur, and $\delta(i)$ is the cost of communicating the problem and its solution across borders.

Two main predictions result from this cost structures.
(1) If this routine versus nonroutine motive for determining the location of task "production holds, then we would expect that for any country $c = 2, ..., C$, cost savings result from offshoring ex ante, $w_{us}\alpha_{p,us}(i) > w_c\alpha_{pc}(i)$, but if the problematic situation obtains, then productivity is higher under domestic production ex post, $w_{us}\beta_{p,us}(i) < w_{us}\beta_{p,us}(i) + \delta(i)$.
(2) The cost savings that result from keeping problematic activities in house are greater for more productive firms. Under a fixed communications cost, $\delta(i)$, the relative difference in the

cost of offshoring the most routine ($\mu = 1$) versus the least routine ($\mu = 0$) task compared to producing them at the headquarters is greater for more productive firms.

The source of production differences across firms has been kept in the background of this paper, and is assumed to follow Melitz (2003). Thus we would also expect more productive firms to have higher levels of offshoring overall, as their lower marginal costs and higher profits make them better able to overcome the fixed costs associated with opening a foreign affiliate. However, in the empirical analysis, firm-level productivity will be subsumed by a firm-level fixed effect and is not the main focus of analysis.

The basic trade-off associated with the decision to locate production at home or abroad is that domestic production is more costly ex ante, but less costly ex post. It has been shown in previous research that this tradeoff exists for the decision to produce inside or outside the firm (see Costinot, Oldenski and Rauch 2009). The same result should hold for the geographic location of production inside the firm. Traditional studies of adaptive theories of the firm define the boundaries of the firm based on ownership regardless of location. The intuition is the same for moving across the boundary of the multinational parent to produce at an affiliate branch.

3.2 Testable implications

For each intermediate task input, profit maximization requires that the firm produces that task where $w_c a_{pc}$ is lowest. Tasks can be indexed such that $i = 1$ is the most routine and $i = I$ is the least routine. By equations (3) and (4), then for any firm p, there exists $i^* \in 0, ..., I$ such that task i is offshored if and only if $i \leq i^*$.

Ideally I would like to test the relationship between routineness and offshoring using task-level data. However, data on multinational operations are collected at the level of industries and firms, not tasks. Instead, I define an industry-level measure that captures the intensity with which each task is used in a given industry.

Definition 1 *An industry j is less routine than another industry j' in country c if, for every pair of tasks $I \geq i \geq i' \geq 1$, task intensities satisfy $b_c^j(i)/b_c^j(i') \geq b_c^{j'}(i)/b_c^{j'}(i')$.*

Where $b_c^j(i)$ is the share of task i relative to total task inputs required for the production of output in industry j. In other words, an industry j is less routine than another industry j' if j is relatively more intensive in the less routine tasks. I will be using this industry level definition of task intensity to test the relationship between routineness and offshoring.[1]

[1]Note that this assumes that the ranking of sectors in terms of routineness does not vary across countries.

4 Empirical Specification

As mentioned in the theoretical motivation, I would ideally like to use data on how multinationals divide tasks across locations. But trade and FDI data are collected at the industry and firm level, rather than at the task level. Thus I rely on firm level data augmented with industry level task intensity measures to examine the relationship between routine task intensity and offshoring. Several additional characteristics of the data on multinational activities aid in the empirical identification strategy. First, a single U.S. multinational parent firm often has affiliates operating in a number of different countries and industries. I use this variation in location of activities within the firm to identify which activities are offshored, controlling for both parent firm and destination country fixed effects. Second, while a single multinational parent generally operates in several different industries, individual affiliates of that parent tend to be much more narrowly focused by industry. Therefore I can exploit the variation in the focus of production activities across affiliates of one parent.

The primary specification is:

$$V_{pci} = \alpha + \beta T_i + \gamma_p + \gamma_c + \varepsilon_{pci} \tag{5}$$

Where V_{pci} is a measure of vertical offshoring, defined as shipments from foreign affiliates of U.S. multinational to the U.S. as a share of total sales by the multinational parent. More specifically, V_{pci} includes shipments from affiliates of parent p that are operating in industry i and located in country c as a share of total sales by the parent firm. T_i captures the intensity with which industry i uses certain routine or nonroutine tasks. γ_p is a parent firm fixed effect and γ_c is a country fixed effect.

To accurately capture vertical offshoring, I would like to have data on the volume of each input that is imported relative to the volume that is produced in the multinational headquarters. However, absent this data, weighting by parent firm sales provides a measure of vertical offshoring relative to total production by the headquarters firm.

Equation (5) does not include industry fixed effects because task intensity is a time-invariant industry level characteristic. However, prediction (2) of Section 2.2 suggests that the results relating the routineness of tasks to offshoring should be strongest for the most productive firms. Testing this prediction does allow for the inclusion of industry fixed effects. I test it using the following specification:

This assumption allows me to conduct empirical tests using data on the task intensity of industries from the U.S. (rather than the country in which the offshoring occurs).

$$V_{pci} = \alpha + \beta T_i * S_p + \gamma_p + \gamma_c + \gamma_i + \varepsilon_{pci} \quad (6)$$

Where $T_i * S_p$ is the interaction of the task intensity measure (T_i) with total firm sales (S_p). Note that S_p captures total global firm sales, that is sales by the U.S. parent or any of its foreign affiliates, and is a measure of overall global firm size. V_{pci} is the shipments from affiliate to parent as a share of sales by the U.S. parent only and does not include sales by foreign affiliates which are conceptually distinct in that they fall under the category of horizontal rather than vertical motives for multinational production. Previous literature has shown that total firm sales are highly correlated with productivity and has used sales as a proxy when firm-level productivity data were not available.[2] This specification also allows for the inclusion of industry-level fixed effects, to rule out the possibility that some industry characteristic other than task intensity is driving the results.

5 Data

The Bureau of Economic Analysis collects firm-level data on U.S. multinational company operations in both goods-producing and service-producing industries in its benchmark surveys of U.S. direct investment abroad. I use these data to define a measure of vertical offshoring. This variable consists of the total shipments by a foreign affiliate back to the U.S. as a share of the U.S. parent firm's total sales. The data do not distinguish between sales back to the U.S. parent of intermediates and final goods. However, the basic decision to locate production at the U.S. headquarters or at a foreign affiliate should apply to both intermediate inputs as well as final goods and services that are simply distributed by the parent firm.

The information on manufacturing firms contained in this dataset has been used in previous studies, however the data on service trade and investment are not frequently exploited.[3] My primary specification uses data from 2004, however for robustness checks I also use data from 1994 and 1999, two other years in which benchmark surveys were conducted. The BEA surveys cover 54 manufacturing industries and 33 service industries, classified according to BEA versions of 3-digit Standard Industrial Classification (SIC) codes.

Data from other sources are used for robustness checks. I use an index of regulation and enforcement from the World Bank's Doing Business Database to proxy for the level of insti-

[2] See, for example, Bernard and Jensen (1999), Melitz (2003), Antras and Helpman (2004), Helpman, Melitz and Yeaple (2004), Bernard et al. (2006), or Breinlich and Criscoulo (2009)

[3] See for example Hanson, Mataloni, and Slaughter 2005 or Desai, Foley and Hines 2001

tutional quality. The great circle distance between capital cities proxies for transport costs. GDP is used to capture market size. Data on firm-level sales by industry from Compustat are used to construct a measure of productivity dispersion for each industry in the sample. Data on the relative endowment of skilled to unskilled labor by country are from Hall and Jones (1999). Relative wages in manufacturing and services are constructed using data from Freeman and Oostendorp (2000). Data on corporate tax rates are from the University of Michigan World Tax Database. I use data on the educational level of industries from the the U.S. Census. The linguistic distance between countries based on language trees from Fearon (2003) is used to capture the effect of language.

6 Construction of Task Intensities

Autor, Levy and Murnane (2003) use the Department of Labor's Dictionary of Occupational Titles (DOT) and divide the set of all possible job tasks that workers perform into two basic categories: routine and nonroutine. Routine tasks are those that can be accomplished by following a set of specific, well-defined rules. Nonroutine tasks require more complicated activities like creative problem solving and decision making. I follow this routine/nonroutine distinction, but use the DOT's successor, the Department of Labor's Occupational Information Network (O*NET), which includes data on the importance of 277 worker and job characteristics in about 800 occupations. The worker and job characteristics are divided into seven broad categories: abilities, interests, knowledge, skills, work activities, work context, and work values. I focus on work activities, which are conceptually closest to the notion of tasks used in the theoretical literature on offshoring. Of these, I select the activities most directly related to the routine versus nonroutine dichotomy, using the importance of creativity and problem solving to capture nonroutine tasks. To match the relevant task measures to the industry-level trade and investment data, I aggregate the raw O*NET scores up to the industry level, weight them by share in total task composition of each industry and merge them with trade data to get an index of the intensity of each task in each industry. Industries can then be defined by a vector of tasks, each weighted by its importance in that industry.

I combine data on the task requirements of occupations from O*NET with data on the operations of multinational firms from the BEA to create an index of task intensity in each industry. The importance score of each task, i in each industry, j is

$$M_{ij} = \sum_{o} \gamma_{jo} \ell_{io} \tag{7}$$

where i indexes tasks, o indexes occupations, and j indexes industries. Thus γ_{jo} is the share of occupation o used in the production of industry j, and ℓ_{io} is an index of the importance of task i for occupation o.[4] Summing over occupations in a given industry results in an index of the un-scaled importance score for each each task in that industry. Each raw score is then divided by the sum of scores for each task in each industry, resulting in an input intensity measure for each task, i, in each industry, j:

$$I_{ij} = \frac{M_{ij}}{\sum_i M_{ij}} \tag{8}$$

Occupations are matched to industries using the Bureau of Labor Statistics Occupational Employment Statistics. These intensities are then matched to the BEA data on multinational firms. BEA collects data at the level of the firm and then reports the primary industry classification of each firm.

I took two different approaches to distilling the O*NET data into a simple measure of each task characteristic. The first approach is similar to Autor, Levy and Murnane (2003) and consists of identifying an individual task measure that most closely proxies each desired characteristic. To capture the level of task complexity (which corresponds to Autor, Levy and Murnane's "non-routine cognitive" category), I use the O*NET measures of "creative thinking" and "making decisions and solving problems." I use the O*NET measures "handling objects" and "operating machines (other than vehicles)" to proxy routine manual activities.

The second approach uses principal components analysis to distill a large number of tasks down to their core elements. I create one measure of nonroutine intensity using the primary component among creativity, problem solving, giving consultation or advice, developing objectives, communicating internally, and working with computers. The routine manual component is drawn from the tasks handling objects, operating machines and general physical activities. All empirical results are robust to the use of individual task proxies or principal component measures. Table 1 shows these task intensity scores for a selection of industries

[4] ℓ_{io} corresponds to the 0-100 score O*NET reports to measure the importance of each task in each occupation. These scores are constructed from surveys of individuals in those occupations and are normalized to a 0-100 scale by analysts at the Department of Labor. Due to the subjective nature of the surveys, one unit of importance for given task can not be directly compared to one unit of another task. This is a limitation of the data and motivates the use of relative intensity scores rather than the raw scores reported by O*NET.

included in the sample.

Table 2 shows correlations between the task measures and other relevant variables. All three measures of nonroutine task intensity are positively correlated with each other and negatively correlated with the measures of routine task intensity. Nonroutine tasks are positively correlated with the average worker education level by industry, while routine tasks are negatively correlated with this measure of skill-intensity. Similarly, the need to communicate with customers is positively associated with nonroutine task intensity and negatively associated with routine task intensity. Observations for less routine tasks are positively correlated with institutions and wages, while more routine tasks are associated with countries that have low wages and weaker institutions, however the magnitudes are small in these unconditional correlations.

7 Results

Table 3 presents the results of the specification using 2004 data and controlling for both country and parent firm fixed effects. The dependant variable is vertical offshoring by parent firms whose primary industry is either manufacturing or services. Column 1 shows that there is a negative and significant relationship between the importance of communicating with customers in an industry and the extent of offshoring done by firms in that industry. The communication variable captures the technical feasibility of offshoring, such that we would expect that tasks requiring more communication would be more costly to offshore. This is a simple yet intuitive result. If certain activities require interaction between producers and consumers, then they are more likely to be performed near those consumers rather than offshored. Column 2 shows the impact of the principal component measure of nonroutine task intensity. Columns 3 and 4 show the impact of the individual task proxies for nonroutineness: problem solving and creativity. All three sets of results suggest that the more nonroutine an industry is, the lower is the share of value-added by foreign affiliates, or in other words, the less likely it is to be offshored. Columns 5 through 7 present the results using three different measures of routineness. Consistent with the first three specifications, more routine task-intensive intermediates are more likely to be performed by foreign affiliates. These results support the adaptive theory of offshoring outlined in Section 2. More routine task intensive industries are less likely to give rise to unpredictable and problematic situations and are therefore less costly to offshore relative to nonroutine task intensive industries.

Table 4 controls for communication intensity in the routineness regressions. Even when controlling for this measure of the feasibility of offshoring, nonroutine tasks are still significantly associated with less offshoring while routine tasks are significantly more likely to be offshored. In all specifications, the role of routine task intensity is greater than the role of communication intensity in terms of coefficient magnitude and/or significance.

Because the nonroutine task intensity of an industry is correlated with skill intensity, I also run the regressions controlling for the average education level of workers in each industry. These results are presented in Table 5. The coefficient on skill is positive and significant for most specifications, suggesting that, all else equal, an increase in the skill-intensity of an industry is associated with a larger share of offshoring in total firm sales. This is perhaps surprising from a comparative advantage perspective, since we would expect the U.S. to offshore more low skilled activities. However, keep in mind that these regressions also control for the task composition of industries as well as country fixed effects. Also, because data are not available to compare the task intensity of offshored intermediates to that of inputs produced at home, the left hand side of the regression captures the share of offshoring in total production. If the per unit value of high-skill intensive inputs is higher than that of low-skill intensive inputs, then this could explain the larger share for those high-skilled inputs. These results also suggest that routine task intensity, rather than skill intensity, may be a better measure of U.S. comparative advantage.

The preferred specifications presented in Tables 3 through 5 control for country fixed effects. However, these country dummies hide potentially interesting information about individual country characteristics that may impact the offshoring decision. Table 6 presents the results of a specification that replaces the country fixed effects with several country characteristics. Consistent with standard gravity results, distance decreases the offshoring share and GDP of the country where the affiliate is located increases it. Linguistic distance ($langdist$) is also a deterrent to offshoring. The variable $dispersion$ measures the standard deviation of sales of firms within each industry. Consistent with Melitz (2003), an increase in this proxy for heterogeneity of productivity among firms in an industry increases trade. The variable $lnwcwu$ is the log of the average manufacturing wage in the country in which the the affiliate is located relative to the average U.S. manufacturing wage. The negative coefficients on this measure suggest that U.S. firms offshore more intermediate production to countries with lower wages. Institutional quality, as measured by the World Bank's Doing Business database, increases the offshoring share. Low corporate tax rates have no significant impact on the offshoring decision, as defined in this study. It is possible that tax rates determine where affiliates are located in the first place, however this study considers the shares of shipments from existing affiliates by industry, which does not vary with corporate tax rates. The relationship between task intensity and offshoring still holds in this specification, such that more routine tasks are more likely to be offshored relative to less routine tasks.

In addition to their statistical significance, the results are also economically significant in magnitude. The results from Table 3 suggest that a 1 point decrease in the scaled problem solving intensity of an industry leads to a 228% increase in the share of offshoring in total production. The standard deviation of the problem solving scores is 0.21. So, for example, moving from the 25th to the 75th percentile in terms of problem solving intensity results in a 60% decrease in the expected offshoring share. Also, the average service industry has a problem solving intensity score that is 0.21 points higher than the average manufacturing industry. This would suggest that there should be about 48% more offshoring in manufacturing relative to service industries due to this task dimension.

8 Results using industry fixed effects

Because the measures of task intensity are non-time varying industry level characteristics, it is not possible to control for industry fixed effects in specifications using these measures. However, prediction 2 of Section 3 provides an opportunity to estimate the relationship of tasks and offshoring in a framework that does permit the inclusion of industry fixed effects. Prediction 2 suggests that the impact of task routineness on production location decisions will be greater for more productive firms. Thus we would expect that the interaction between firm size, which has been shown to be a good proxy for firm productivity,[5] and routine task intensity, should be positive and significant. Table 7 presents the results including fixed effects at the industry, country and firm level. Columns 2 through 4 show that the interactions between total firm sales and the nonroutine task intensity are negative and significant. The coefficients on interactions between routine tasks and total firm sales are positive and significant. These results suggest that the task content of firm activities is a significant predictor of the geographic location of production within the firm, even when industry fixed effects are controlled for. In addition, the relationship between the routineness of tasks and offshoring is stronger for larger, more productive firms. The same result holds for the importance of communicating with customers.

Table 8 shows the impact of routine task intensity interacted with total firm sales while

[5]See for example Bernard and Jensen (1999), Melitz (2003), Antras and Helpman (2004), Helpman, Melitz and Yeaple (2004), Bernard et al. (2006), or Breinlich and Criscoulo (2009)

controlling for communication intensity interacted with sales. The results for routineness still hold. However, when the routineness interactions are included, communication intensity interacted with firm sales is either not significant or else significantly positive. This implies that, controlling for routineness, larger firms are more likely than smaller ones to offshore tasks that involve communicating with consumers.

Table 9 includes both the task intensity measures (without industry fixed effects) and the interactions between task intensity and total firm sales. Again, the results suggest that nonroutine tasks are less likely to be offshored to foreign affiliates, and this effect is greater for larger, more productive firms. More routine tasks are more likely to be offshored, especially in the case of firms with higher volumes of sales. Tasks requiring communication with customers are less likely to be offshored, however, there is some evidence that larger firms are more likely to overcome this communication hurdle than are smaller firms.

9 Robustness Checks

Several robustness checks are included in Table 10. To save space, only the specifications using the principal components measure of nonroutine task intensity are reported, however results are similar for specifications using the other task measures. The results presented in Tables 3-9 use data on offshoring from 2004 only. To test the sensitivity of the results to the use of this year, I also run the regressions using data from 1994 and 1999. Column 1 of Table 10 pools these years and also controls for year specific fixed effects. As in the previous results, more routine tasks are more likely to be offshored, even when controlling for the skill intensity of the industry and the importance of communicating with customers. To see if the relationship between tasks and offshoring has changed over time, I also run the model using only 1994 and only 1999 offshoring data. These results are presented in Columns 2 and 3 of Table 10. The numbers of observations for these two years are much smaller than for 2004, showing that the number of affiliates shipping products back to the U.S. increased between 1994 and 2004. The basic relationship between tasks and offshoring holds for all years. However, the magnitude and significance of the effect of task intensity is increasing with time.

It is possible that manufacturing and service industries exhibit different relationships between task intensities and offshoring. Column 4 of Table 10 presents the results of the model using only affiliates whose primary activity is a service industry. Column 5 presents the results using only manufacturing affiliates. The main results still hold, however, the coefficient on nonroutine task intensity is larger in magnitude for the sample of services producers relative to the sample of manufacturers, suggesting that the task composition of an industry matters more for the offshoring of services than for the offshoring of manufactures.

10 Conclusion

Much of the political debate over services trade rests on the assumption that an increase in offshoring will put a large number of jobs at risk in the U.S., particularly those that can be considered "good" jobs. This paper shows that when offshoring by U.S. service firms occurs, it is the more routine activities that are the most likely to go overseas while the more nonroutine activities remain at U.S. headquarters. Certain analysts perpetuate fears of massive U.S. job loss resulting from the increasing tradability of services, suggesting that the majority of jobs that can be performed remotely will be offshored. For example, Alan Blinder claims that we should focus on "the types of jobs that can be delivered electronically with ease" because "the majority of these jobs are at risk" (Blinder 2005). However, the data suggest that the offshoring decisions of multinational firms are much more complicated than that. Simply because certain activities can be performed at a distance and other countries have lower wages than the U.S., that does not imply that it will be more profitable for firms to import all of those activities. In addition, because more nonroutine jobs are correlated with higher wages and greater educational levels, the results of this paper suggests that the increased specialization that occurs with service offshoring results in higher skilled, higher paying jobs being performed in the U.S. and relatively more low skilled, low paying jobs moving abroad.

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Table 1: Top ten most routine and nonroutine services, ranked by raw creativity scores

	Most nonroutine industries	
1	Computer related services	83.06
2	Engineering & architecture	74.98
3	Computer processing & data prep	72.84
4	Other finance	72.76
5	Telephone and telegraph	71.48
6	Research, development & testing	71.45
7	Information retrieval	71.01
8	Communications	70.47
9	Advertising	70.44
10	Mgmt consulting & pub relations	70.19

	Most routine industries	
1	Meat products	32.74
2	Leather and leather products	45.18
3	Glass products	47.54
4	Bakery products	47.73
5	Apparel and textile products	48.32
6	Textile mill products	48.65
7	Grain mill products	48.97
8	Heating equip, plumbing, etc	49.37
9	Preserved fruits & vegetables	49.73
10	Plastics products	49.90

Table 2: correlations

	skill	comm	nonrtne	prob	creative	routine	object	machine	gdp	inst	wages
skill	1										
communicate	0.281	1									
nonrtne	0.8741	0.4514	1								
prob solve	0.7555	0.3242	0.9252	1							
creative	0.7632	0.3582	0.8803	0.7566	1						
routine	-0.8154	-0.675	-0.9386	-0.8313	-0.7742	1					
object	-0.8092	-0.6608	-0.9344	-0.8292	-0.7571	0.9966	1				
machine	-0.7911	-0.732	-0.917	-0.798	-0.7681	0.9917	0.9853	1			
gdp	-0.0191	-0.025	-0.0145	-0.0163	0.0139	0.0246	0.0304	0.0256	1		
institutions	-0.0611	-0.0849	-0.0935	-0.0803	-0.0889	0.0991	0.0932	0.0987	-0.239	1	
wages	0.0361	0.0783	0.0711	0.0584	0.0732	-0.0747	-0.0704	-0.0759	0.3292	-0.6696	1

Table 3: Share of shipments from affiliates to parents in total parent sales, 2004. Robust standard errors are in parentheses

Model :	1	2	3	4	5	6	7
N:	13296	13296	13296	13296	13296	13296	13296
communicate	-0.899***						
	(0.088)						
nonroutine		-0.330***					
		(0.025)					
prob solve			-2.277***				
			(0.244)				
creative				-1.813***			
				(0.154)			
routine					0.390***		
					(0.029)		
object						0.553***	
						(0.042)	
machine							0.627***
							(0.046)
							(0.04)
Firm FE	yes	yes	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	yes	yes	yes	yes
R-sq	0.152	0.132	0.133	0.119	0.152	0.153	0.152

*,** and *** indicate significance at the 10, 5 and 1 percent levels, respectively

Table 4: Share of shipments from affiliates to parents in total parent sales, 2004. Robust standard errors are in parentheses

Model :	1	2	3	4	5	6
N:	13296	13296	13296	13296	13296	13296
communicate	-0.408***	-0.668***	-0.593***	-0.135	-0.165	-0.018
	(0.103)	(0.096)	(0.095)	(0.126)	(0.124)	(0.136)
nonroutine	-0.268****					
	(0.030)					
prob solve		-1.483***				
		(0.270)				
creative			-1.425***			
			(0.166)			
routine				0.357***		
				(0.042)		
object					0.498***	
					(0.059)	
machine						0.634***
						(0.072)
Firm FE	yes	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	yes	yes	yes
R-sq	0.125	0.146	0.116	0.141	0.143	0.135

*,** and *** indicate significance at the 10, 5 and 1 percent levels, respectively

Table 5: Share of shipments from affiliates to parents in total parent sales, 2004. Robust standard errors are in parentheses

Model :	1	2	3	4	5	6
N:	13296	13296	13296	13296	13296	13296
skill	1.009***	-0.042	0.395**	1.090***	0.937***	1.304***
	(0.190)	(0.150)	(0.160)	(0.201)	(0.193)	(0.208)
communicate	-0.368***	-0.664***	-0.636***	0.153	0.047	0.483***
	(0.104)	(0.099)	(0.096)	(0.137)	(0.131)	(0.155)
nonroutine	-0.438****					
	(0.044)					
prob solve		-1.441***				
		(0.311)				
creative			-1.717***			
			(0.204)			
routine				0.628***		
				(0.065)		
object					0.812***	
					(0.088)	
machine						1.196***
						(0.115)
Firm FE	yes	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	yes	yes	yes
R-sq	0.130	0.145	0.115	0.155	0.157	0.148

*,** and *** indicate significance at the 10, 5 and 1 percent levels, respectively

Table 6: Share of shipments from affiliates to parents in total parent sales, 2004. Standard errors clustered by country are in parentheses

Model :	1	2	3	4	5	6
N:	10556	10556	10556	10556	10556	10556
skill	0.964***	-0.090	0.210	1.053***	0.855***	1.280***
	(0.216)	(0.168)	(0.184)	(0.227)	(0.217)	(0.235)
ln(distance)	-0.466***	-0.467***	-0.468***	-0.467****	-0.467***	-0.466***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
ln(gdp)	0.177***	0.178***	0.178***	0.177***	0.178***	0.179***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
lang dist	-0.372**	-0.365*	-0.365*	-0.373**	-0.373**	-0.379**
	(0.187)	(0.188)	(0.188)	(0.187)	(0.187)	(0.187)
dispersion	0.215***	0.241***	0.178***	0.203***	0.203***	0.205***
	(0.042)	(0.042)	(0.043)	(0.042)	(0.042)	(0.042)
lnwcwu	-0.072**	-0.071**	-0.076**	-0.073**	-0.073**	-0.074**
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
institutions	0.008****	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
tax benefit	-0.003	-0.003	-0.002	-0.003	-0.003	-0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
skill endowment	0.044	0.049	0.051	0.043	0.043	0.042
	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)
communicate	-0.369***	-0.661***	-0.703***	0.132	-0.001	0.488***
	(0.124)	(0.119)	(0.115)	(0.158)	(0.151)	(0.179)
nonroutine	-0.443***					
	(0.050)					
prob solve		-1.510***				
		(0.346)				
creative			-1.384***			
			(0.236)			
routine				0.632***		
				(0.073)		
object					0.790***	
					(0.097)	
machine						1.218***
						(0.130)
Firm FE	yes	yes	yes	yes	yes	yes
Country FE	no	no	no	no	no	no
R-sq	0.092	0.098	0.090	0.114	0.116	0.110

*,** and *** indicate significance at the 10, 5 and 1 percent levels, respectively

Table 7: Industry fixed effects model, share of shipments from affiliates to parents in total parent sales for 2004. Robust standard errors are in parentheses

Model :	1	2	3	4	5	6	7
N:	13296	13296	13296	13296	13296	13296	13296
comm*sales	-0.270**						
	(0.126)						
nrtne*sales		-0.002***					
		(0.000)					
prob*sales			-1.426***				
			(0.499)				
crtv*sales				-1.259***			
				(0.276)			
rtne*sales					0.002***		
					(0.000)		
objct*sales						0.262***	
						(0.066)	
mchn*sales							0.253***
							(0.070)
Firm FE	yes	yes	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes
R-sq	0.166	0.144	0.254	0.266	0.139	0.073	0.076

*,** and *** indicate significance at the 10, 5 and 1 percent levels, respectively

Table 8: Industry fixed effects model, share of shipments from affiliates to parents in total parent sales for 2004. Robust standard errors are in parentheses

Model :	1	2	3	4	5	6
N:	13296	13296	13296	13296	13296	13296
comm*sales	0.346*	-0.050	0.079	0.563**	0.519**	0.626**
	(0.189)	(0.171)	(0.153)	(0.244)	(0.233)	(0.272)
nrtne*sales	-0.003***					
	(0.001)					
prob*sales		-1.294*				
		(0.675)				
crtv*sales			-1.356***			
			(0.334)			
rtne*sales				0.004***		
				(0.001)		
objct*sales					0.489***	
					(0.122)	
mchn*sales						0.560***
						(0.150)
Firm FE	yes	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
R-sq	0.095	0.257	0.266	0.064	0.032	0.028

*,** and *** indicate significance at the 10, 5 and 1 percent levels, respectively

Table 9: Share of shipments from affiliates to parents in total parent sales for 2004. Robust standard errors are in parentheses

Model :	1	2	3	4	5	6
N:	13296	13296	13296	13296	13296	13296
skill	0.893***	-0.013	0.331**	0.968***	0.844***	1.178***
	(0.191)	(0.150)	(0.160)	(0.202)	(0.193)	(0.208)
communicate	-0.616***	-0.615***	-0.779***	-0.212	-0.269*	0.002
	(0.131)	(0.121)	(0.120)	(0.170)	(0.163)	(0.191)
comm*sales	0.669***	0.000	0.378***	0.890***	0.818***	1.151***
	(0.170)	(0.148)	(0.142)	(0.220)	(0.212)	(0.243)
nonroutine	-0.246***					
	(0.050)					
nrtne*sales	-0.004***					
	(0.001)					
prob solve		-0.918**				
		(0.362)				
prob*sales		-1.654***				
		(0.577)				
creative			-0.673***			
			(0.238)			
crtv*sales			-2.412***			
			(0.284)			
routine				0.398***		
				(0.075)		
rtne*sales				0.005***		
				(0.001)		
object					0.512***	
					(0.100)	
objct*sales					0.675***	
					(0.110)	
machine						0.795***
						(0.130)
mchn*sales						0.899***
						(0.133)
Firm FE	yes	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	yes	yes	yes
Industry FE	no	no	no	no	no	no
R-sq	0.097	0.235	0.245	0.041	0.030	0.023

*,** and *** indicate significance at the 10, 5 and 1 percent levels, respectively

Table 10: Robustness Checks. Robust standard errors are in parentheses

Model:	1	2	3	4	5
Sample:	1994-2004	1994	1999	services only	mfg only
N:	21180	3893	3991	4739	8182
skill	0.725***	0.645**	0.897***	1.098***	0.442*
	(0.136)	(0.278)	(0.331)	(0.383)	(0.24)
communicate	-0.394***	-0.043	-0.174	0.427*	-1.111***
	(0.084)	(0.225)	(0.249)	(0.239)	(0.161)
nonroutine	-0.357***	-0.226***	-0.245***	-0.492***	-0.181***
	(0.033)	(0.076)	(0.091)	(0.095)	(0.066)
Firm FE	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	yes	yes
Year FE	yes	no	no	no	no
R-sq	0.139	0.097	0.123	0.093	0.153

*,** and *** indicate significance at the 10, 5 and 1 percent levels, respectively