

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 in both goods and services. However, this fragmentation is difficult to observe in the existing trade data. To get around this lack of data, several recent papers have used the task content of occupations as a proxy for offshorability. Up until this point, that relationship between tasks and offshorability has been based on intuition, rather than empirical evidence. In this paper, I use confidential data from firm-level surveys to offer the first empirical evidence on the link between tasks and offshoring. The results show that US multinationals are significantly more likely to perform a stage of production at a foreign affiliate the more intensively that input uses routine tasks, and the less intensively it uses communication tasks.

Keywords: Multinational Firms, Offshoring, International Trade, Tasks

JEL Codes: F10, F21, L21

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1 Introduction

In recent years, improvements in information technology have allowed firms to increasingly fragment production tasks across borders in both manufacturing and information and business services. Firms no longer just ship goods between countries. They can now also locate intangible production tasks, such as research, design, management, and IT support across a number of different countries. This trend has been the topic of much policy discussion. A number of theoretical models have also emerged to explain how and why firms fragment tasks across borders.¹ However, very little empirical work has been done on this topic, due primarily to the lack of data on task offshoring and the difficulty of measuring intangible tasks.

The U.S. Department of Labor collects data on which tasks are used in the performance of about 800 different occupations. However, no data exist on which tasks are *actually offshored*. To get around this lack of data on offshored tasks, a number of papers have considered which tasks are likely to be *offshorable*, that is, more easily performed abroad due to characteristics such as the lack of a need for face-to-face contact or processes that are relatively routine and thus easily translated into instructions for the offshore producers.² However, up until this point, the justification for using task measures to proxy for offshorability has been based on intuitive arguments and theoretical models rather than empirical evidence.

I get 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 this paper the first to empirically measure the task content of offshoring using U.S. firm-level data. I show that U.S. firms are more likely to offshore more routine tasks, while less routine tasks are more likely to be performed in their U.S. headquarters. The data on offshoring by multinationals are only available at the firm and industry level, so I construct an index of the intensity with which each industry uses routine and nonroutine tasks. 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 show that goods and services that are intensive in nonroutine tasks are more likely to be produced at the U.S. headquarters and those that are intensive in routine tasks are more likely to be offshored by U.S. firms.

¹See, for example, Baldwin and Robert-Nicoud (2010); Grossman and Rossi-Hansberg (2008); Antras, Garicano and Rossi-Hansberg (2006); Markusen (2006); Leamer and Storper (2001)

²See, for example, Blinder (2009), Blinder and Kruegar (forthcoming), or Firpo, Fortin, and Lemieux (2011)

This is an important contribution for three reasons: (1) It offers the first empirical evidence in support of theoretical models of trade in tasks such as those developed by Grossman and Rossi-Hansberg (2008) and Antras, Garicano and Rossi-Hansberg (2006). (2) It builds a foundation for the literature that uses tasks to proxy for offshorability by demonstrating empirically that there is a direct link between the task content of an industry and the likelihood that production in that industry will be offshored by US multinational firms, thus providing much needed empirical support to this body of work. (3) The results have important broader implications for the effects of offshoring on wages, employment, and inequality in the countries that are both initiating and receiving the offshoring.

The identification strategy used in this paper also sets it 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. I also control for the importance of interacting with customers to address the issue of tradeability emphasized by Blinder (2006), as well as the skill intensity of each industry, and find that the importance of routineness for offshoring still holds. The results are economically significant, suggesting that moving from the 25th to the 75th percentile in terms of the intensity with which a firm's industry uses nonroutine tasks results in a 60% decrease in the expected offshoring share.

2 Related Literature

A few papers have attempted to estimate which occupations or industries are most likely to be produced abroad. However, those that include offshoring of business processes, IT, call centers, or other services suffer from a lack of available data, and thus rely on intuitive or subjective measures (Blinder 2009, Firpo, Fortin, and Lemieux 2011). For example, Alan Blinder has argued that the key component for offshorability 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 tradability (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 (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.

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. 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 determinants of offshoring, generalizing the Autor, Levy and Murnane framework to classify any tasks that are too complex to be fully communicated to production teams in another country as nonroutine. Anecdotal evidence suggests that this routine versus nonroutine 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 spite of this case study evidence, to my knowledge the current paper is the first to empirically estimate the relationship between the routineness of tasks and offshoring at the firm level.

3 Empirical Specification

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.³

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 to estimate the following equation:

$$V_{pci} = \alpha + \beta T_i + \gamma_p + \gamma_c + \varepsilon_{pci} \quad (1)$$

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, which captures firm-level productivity, and γ_c is a country fixed effect, which captures wages, distance from the U.S., and other country-level characteristics.

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

³Note that this assumes that the ranking of sectors in terms of routineness does not vary across countries. 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).

headquarters. However, absent this data, scaling by parent firm sales provides a measure of vertical offshoring relative to total production by the headquarters firm.

4 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. 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 institutional 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.

5 Construction of Task Intensities

I follow the construction of task intensity measures used by Oldenski (2012). This method draws upon Autor, Levy and Murnane (2003) who 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 use raw data on routine and nonroutine tasks from 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.

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

$$M_{ij} = \sum_o \gamma_{jo} \ell_{io} \quad (2)$$

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 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 :

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.

$$I_{ij} = \frac{M_{ij}}{\sum_i M_{ij}} \quad (3)$$

Occupations are matched to industries using the Bureau of Labor Statistics Occupational Employment Statistics, which gives the share of workers performing each occupation within each industry. 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.

One may be concerned about potential bias created by using the actual shares of occupations employed in U.S. industries to construct the task measures, as this excludes the occupations that have already been offshored. To address this issue, I construct the measure using occupational employment shares from 1999 for γ_{jo} . This year is at the very beginning of the boom in service task offshoring, and thus represents employment shares in the U.S. before service task offshoring really took off and before 2004, which is the year of the offshoring data in the primary specification. Thus constructing the task intensity measure using data from 1999 removes some of the potential bias. In addition, any endogeneity between the task composition of the work performed in the U.S. and firm-level offshoring decisions would bias me against finding a positive relationship between routine task intensity and offshoring. Consider a firm that had already offshored its most routine tasks prior to the time period used in this paper. This firm will show up as performing a high share of nonroutine tasks in the US and as doing a large amount of offshoring, making the results appear to show a relationship between more nonroutine tasks and greater offshoring. Thus the evidence that I present in Section 7 showing that more routine tasks are associated with greater offshoring shares is even stronger in the face of this potential bias.

I took two different approaches to distilling the O*NET data into a simple measure of each task characteristic. The first approach identifies the individual task measures that most closely proxy 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 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.

6 Results

Table 3 presents the results of the specification using 2004 data and controlling for both country and parent firm fixed effects, as given by equation (1). The dependant variable is the offshoring share of 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 theories of offshoring advanced by Grossman and Rossi-Hansberg (2008) and Antras, Garicano and Rossi-Hansberg (2006). 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. As discussed in Section 5, any potential endogeneity between the task composition of the work performed in the U.S. and firm-level offshoring decisions would bias me against finding a positive relationship between routine task intensity and offshoring and suggests that the results presented in Table 3 may understate the relationship between task routineness and offshoring.

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. These results suggest that industrial organization motives for keeping nonroutine tasks in a firms headquarters exert an influence independent of the technological feasibility of trading certain tasks.

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. When these fixed effects are included, the results are estimated off of variation in the types of industries that a given firm chooses to produce in each country, conditional on

having an affiliate in that country in the first place. However, the destination country is also a choice variable for the firm, so removing the country fixed effects allows us to think about the routineness of tasks in general, not only within a specific country. The country dummies in tables 3-5 also hide potentially interesting information about individual country characteristics that may impact the offshoring decision, such as wages, GDP, language, distance, and institutions.

Table 6 presents the results of a specification that does not use country fixed effects but that does include 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 *lnwcu* 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.

7 Robustness Checks

Several robustness checks are included in Table 7. 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 3-6 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 7 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 7. 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 7 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.

8 Conclusion

This paper addresses the fragmentation of tasks across borders within multinational firms, an issue that has received much attention in policy debates and the theoretical trade literature, but which is difficult to address empirically. Using detailed data on firm-level offshoring and occupational tasks, I show that U.S. multinationals are more likely to offshore more routine tasks, while less routine tasks are performed in their headquarters.

These results have important implications for the larger body of work on offshoring and tasks. Given the difficulty of acquiring data on offshoring of services, many previous papers

have used intuition about which types of tasks are more likely to be offshored to justify using task intensity measures as a proxy for offshorability. By offering empirical evidence that such a link between tasks and offshoring does indeed exist in the data, I provide a crucial step that was previously missing from the growing body of work on tasks and offshoring.

In addition, 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.

9 References

Antras, Pol, Luis Garicano, and Esteban Rossi-Hansberg, 2006, Offshoring in a Knowledge Economy. *Quarterly Journal of Economics* 121(1), pp. 31-77.

Antras, Pol, Luis Garicano, and Esteban Rossi-Hansberg, 2008, Organizing Offshoring: Middle Managers and Communication Costs, In Helpman, E., D. Marin, and T. Verdier, *The Organization of Firms in a Global Economy*, Harvard University Press.

Autor, D, F. Levy, and R. Murnane, 2003, The Skill Content of Recent Technological Change: an Empirical Exploration. *Quarterly Journal of Economics* 118(4)

Baldwin, Richard and Frédéric Robert-Nicoud, 2010, Trade-in-goods and trade-in-tasks: An Integrating Framework. Working Paper.

Blinder, A, 2009, How Many U.S. Jobs Might be Offshorable? *World Economics* 10(2), pp.41-78.

Blinder, Alan. 2006. "Offshoring: The Next Industrial Revolution?" *Foreign Affairs*

Blinder, Alan and Alan Krueger, 2012, Alternative Measures of Offshorability: A Survey Approach, forthcoming in a special issue of the *Journal of Labor Economics*.

Fearon, J., 2003, Ethnic and Cultural Diversity by Country. *Journal of Economic Growth*, 8(2), pp. 195-222

Firpo, Sergio, Nicole M. Fortin, and Thomas Lemieux, 2011, Occupational Tasks and Changes in the Wage Structure. Working Paper.

Freeman, Richard B. and Remco Oostendorp, 2000, Wages Around the World: Pay Across Occupations and Countries. NBER Working Paper No. W8058.

Friedman, Thomas, 2005, *The World is Flat: A Brief History of the Twenty-first Century*. Farrar, Straus Giroux.

Grossman, G. and E. Rossi-Hansberg, 2008. "Trading Tasks: A Simple Theory of Offshoring," *American Economic Review*, 98(5).

Hall, Robert E and Charles I. Jones, 1999, Why Do Some Countries Produce So Much More Output Per Worker Than Others? *Quarterly Journal of Economics*, 114(1), pp. 83-116.

Jensen, J. B. and L. Kletzer, 2007, Measuring Tradable Services and the Task Content of Offshorable Services Jobs. In K. Abraham, M. Harper and J. Spletzer, eds., *Labor in the New Economy*, University of Chicago Press, forthcoming.

Leamer, Edward and Michael Storper, 2001, "The Economic Geography of the Internet Age"

Journal of International Business Studies 32(4), pp. 641-665.

Markusen, James R., 2006, "Modeling the Offshoring of White-Collar Services: From Comparative Advantage to the New Theories of Trade and Foreign Direct Investment," in Lael Brainard and Susan M. Collins, eds., *Offshoring white-collar work*, Brookings Trade Forum, Washington, D.C.: Brookings Institution, chapter 1, pp. 1-34.

Melitz, M.J. 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica* 71, 1695-725.

Oldenski, Lindsay, 2012(Forthcoming), *Export Versus FDI and the Communication of Complex Information*. *Journal of International Economics*.

Spitzer, Joshua, 2006, "ExlService: Business Process Outsourcing in India" Stanford Graduate School of Business Case Study.

Table 1: Ten least or most routine industries, ranked by raw creativity scores

Least routine 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

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

Robust standard errors are in parentheses

Table 4: Share of shipments from affiliates to parents in total parent sales, 2004

Model :	1	2	3	4	5	6
N:	13296	13296	13296	13296	13296	13296
communicate	-0.408*** (0.103)	-0.668*** (0.096)	-0.593*** (0.095)	-0.135 (0.126)	-0.165 (0.124)	-0.018 (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
 Robust standard errors are in parentheses

Table 5: Share of shipments from affiliates to parents in total parent sales, 2004

Model :	1	2	3	4	5	6
N:	13296	13296	13296	13296	13296	13296
skill	1.009*** (0.190)	-0.042 (0.150)	0.395** (0.160)	1.090*** (0.201)	0.937*** (0.193)	1.304*** (0.208)
communicate	-0.368*** (0.104)	-0.664*** (0.099)	-0.636*** (0.096)	0.153 (0.137)	0.047 (0.131)	0.483*** (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
Robust standard errors are in parentheses

Table 6: Share of shipments from affiliates to parents in total parent sales, 2004

Model :	1	2	3	4	5	6
N:	10556	10556	10556	10556	10556	10556
skill	0.964*** (0.216)	-0.090 (0.168)	0.210 (0.184)	1.053*** (0.227)	0.855*** (0.217)	1.280*** (0.235)
ln(distance)	-0.466*** (0.039)	-0.467*** (0.039)	-0.468*** (0.039)	-0.467*** (0.039)	-0.467*** (0.039)	-0.466*** (0.039)
ln(gdp)	0.177*** (0.022)	0.178*** (0.022)	0.178*** (0.022)	0.177*** (0.022)	0.178*** (0.022)	0.179*** (0.022)
lang dist	-0.372** (0.187)	-0.365* (0.188)	-0.365* (0.188)	-0.373** (0.187)	-0.373** (0.187)	-0.379** (0.187)
dispersion	0.215*** (0.042)	0.241*** (0.042)	0.178*** (0.043)	0.203*** (0.042)	0.203*** (0.042)	0.205*** (0.042)
lnwcu	-0.072** (0.034)	-0.071** (0.034)	-0.076** (0.034)	-0.073** (0.034)	-0.073** (0.034)	-0.074** (0.034)
institutions	0.008*** (0.001)	0.008*** (0.001)	0.008*** (0.001)	0.008*** (0.001)	0.008*** (0.001)	0.008*** (0.001)
tax benefit	-0.003 (0.005)	-0.003 (0.005)	-0.002 (0.005)	-0.003 (0.005)	-0.003 (0.005)	-0.003 (0.005)
skill endowment	0.044 (0.072)	0.049 (0.072)	0.051 (0.072)	0.043 (0.072)	0.043 (0.072)	0.042 (0.072)
communicate	-0.369*** (0.124)	-0.661*** (0.119)	-0.703*** (0.115)	0.132 (0.158)	-0.001 (0.151)	0.488*** (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

Standard errors clustered by country are in parentheses

Table 7: Robustness Checks

Model:	1	2	3	4	5
Sample:	1994-2004	1994	1999	services only	mfg only
N:	21180	3893	3991	4739	8182
skill	0.725*** (0.136)	0.645** (0.278)	0.897*** (0.331)	1.098*** (0.383)	0.442* (0.24)
communicate	-0.394*** (0.084)	-0.043 (0.225)	-0.174 (0.249)	0.427* (0.239)	-1.111*** (0.161)
nonroutine	-0.357*** (0.033)	-0.226*** (0.076)	-0.245*** (0.091)	-0.492*** (0.095)	-0.181*** (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
Robust standard errors are in parentheses