Task Trade, Wages, and Transportation Costs*

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Abstract

This work investigates how falling trade costs affect wages and how these effects differ for workers in highly offshorable jobs. To address these issues empirically, I create new measures of transportation costs for imports which provide exogenous, industry level variation in trade costs. I adopt the insight from earlier literature on task based labor markets: that the specific tasks performed at various jobs make some occupations easier to offshore than others. I develop measures offshorability, which I use to test the prediction that falling transport costs decrease the relative wage of highly offshorable occupations by exposing them to foreign competition. I find that established measures of offshorability based on the face-to-face content of jobs produce counterintuitive results. I create a new measure of offshorability which also incorporates the routine content of occupations. Using this index leads to more sensible estimates, suggesting that declining transportation costs from 1989-2003 reduced the relative wages of offshorable workers by about 5 percent. My results indicate that commonly used measures of offshorability that focus on face-to-face job requirements alone miss an important dimension of offshorability. An advantage of my approach is that by focusing on transport costs, I address endogeneity issues that plague earlier work on the effect of trade on wages.

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1 Introduction

In a controversial 2009 paper titled "How Many U.S. Jobs Might be Offshorable," Alan Blinder estimated that nearly 30 percent of all U.S. workers were at risk of having their jobs sent abroad. The fierceness with which Blinder's assertions have been debated illustrates that offshoring is an issue worthy of further study. Data from the Bureau of Economic Analysis suggests that in 1989 the ratio of domestic to foreign employment at U.S. Multinational Companies was 35 percent; by 2003, this measure of offshoring had risen to 45 percent. Meanwhile, the imports as a percent of GDP rose from 8.8 percent to 11.6 percent. Over the same period manufacturing employment declined by 19% even as employment grew in other sectors of the economy. These trends make it unsurprising that there is interest in how much offshoring the U.S. might experience in the future. Rather than think about the number of jobs which might be sent abroad, this paper is focused on determining the wage impact of increased opportunities for offshoring and trade.

Blinder's estimates come from developing an index of offshorability based on how important face-to-face interactions with co-workers, clients, and equipment are to an occupation. This offshorability concept has gained prominence in the literature, although there has been little empirical evidence about its accuracy. I address this by looking for differential wage responses to falling trade costs across workers in positions with different levels of offshorability. To do this I develop a set of industry level transportation cost measures from import data which provide exogenous variation in the cost of trade. I then classify workers based on two measures of offshorability; one based solely on the concept of the face-to-face content of their occupation and a second which also accounts for routine content. I find that using only face-to-face content to measure offshorability leads to results which are counterintuitive. When I instead focus on the measure including routine content, I find that falling wage costs reduce the relative wage of highly offshorable workers, consistent with increased competition from abroad. From 1989-2003, falling trade costs across industries led to a roughly 5 percent decline in relative wages for workers classified as highly offshorable by my preferred measure. The Blinder and Krueger estimate of the number of offshorable jobs relies heavily on their classification of all manufacturing jobs as offshorable. The current paper takes a more nuanced approach and analyzes the relationship between offshorability measures and wages among manufacturing workers.[1] This is an important area of focus because of the precipitous decline in manufacturing employment over the period in question.

The approach in this paper draws heavily from recent literature focused on offshoring through trade in tasks. In this framework the labor input which goes into producing a particular good can be broken down into the labor tasks which an employee undertakes.[2] This is related to the familiar idea that a good embodies its factors of production, labor and capital, which resulted in a number of studies on the factor content of trade. Grossman and Rossi-Hansberg (2008) develop a formal model of trading tasks which emphasizes that some parts of that production process can be profitably performed offshore while others cannot. They speculate that the jobs which could be most easily offshored are those which are highly routine, making it easy to remotely control quality.[3] Blinder and Krueger (2009) and Blinder (2009) suggest that the physical presence requirements of certain jobs are the deciding factor in making a job offshorable, a concept I will refer to as face-to-face content. I use these insights on task trade to develop indexes of offshorability and determine the impact of recent declines in transportation costs on wages paid to workers across the offshorability spectrum.

The offshorability measures focus on the routine and face-to-face content of occupations as important determinants of offshorability.[4] The idea that face-to-face content is important in determining the ease of offshoring has become standard in the literature, but another strand has focused instead on the routine content. My work is one of the first to combine these two concepts into a single measure of offshorability and then examine that measure empirically. A very straightforward model, which can be thought of as a short-run equilibrium model, shows that as the costs of trade decline, the wages of workers focused on relatively more offshorable tasks will fall relative to workers focused on less offshorable tasks, due to increased competition from abroad.[5] To test this prediction, I combine data on the task content of occupations with micro-level data on workers' wages and characteristics. I use a set of industry level transportation cost

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[1] This paper also looks at non-manufacturing sectors for which there is trade data, such as agriculture and mining.

[2] For example, in creating and selling a piece of wooden furniture a number of steps must be undertaken, from milling to assembling to packaging to marketing.

[3] This view of "routineness" largely follows from Autor, Levy, and Murnane (2003) which was one of the first papers to develop a comprehensive model of a task based labor market.

[4] These measures are based on work by Acemoglu and Autor (2011).

[5] This would be the basic prediction of a number of models on task trade where frictions exist which prevent workers from moving freely between jobs.

indexes developed in Landefeld (2011) to measure the cost of trade. These transport cost measures vary across industries over time and provide industry level variation, which allows me to identify how changing trade costs impact the wage premium for highly offshorable jobs. The decline in transportation costs from 1990 and 2003 represented increased opportunities for offshoring, which exposes workers to higher levels of competition. The wage response varies across industries due to differential declines in transport costs, but also across occupations due to different levels of offshorability. Because trade costs in the service sector are not easily measured, I focus on the manufacturing and agricultural sectors. The use of these transport costs rather than import flows is another advancement of the current work, providing exogenous variation in offshoring opportunities.

To perform this analysis I bring together data from a number of disparate sources in order to create a dataset containing information on individual workers, the tasks those workers perform, and the transportation costs which are relevant to their industry. I pair micro-level data from the Current Population Survey (CPS) with occupation level task data from the Occupational Information Network (O*NET). I use the resultant dataset to estimate the premium (or penalty) associated with highly offshorable occupations according to two measures of offshorability.[6] This penalty/premium represents the relative wage of highly offshorable workers. I find that when offshorability is measured using a combination of routine and face-to-face tasks, the wage premium associated with highly offshorable jobs is negative, with highly Offshorable jobs paying on average nearly 6 percent less than the less Offshorable jobs. Furthermore, I find that a decrease in transportation costs leads to a significant decline in the offshorable wage premium. If I measure offshorability using only the concept of face-to-face tasks, I find that highly offshorable occupations pay more than 10 percent higher wages, more in line with the Blinder and Krueger study. I also find that this premium rises sharply as transportation costs decline. This is counterintuitive and difficult to reconcile with models of trade and wages.

In the next section I discuss the relevant literature that serves as a starting point for my work. I discuss my own task-based theoretical framework in section 3. In Section 4, I discuss the

[6] It turns out that for my preferred measure of offshorability the wage premium turns out to be negative, and is thus a wage penalty. This result is not unexpected.

construction of a time series of useable data on worker wages, tasks, and transport costs. I present my results in Section 5 and conclude in section 6.

2 Relevant Literature

Acemoglu and Autor (2010), AA,presents a comprehensive overview of the task framework, summarizes the current literature on task-based labor markets, and develops a very general, flexible, and tractable model of labor tasks. A major contribution of their work is to create a model of labor tasks of which the “canonical” model, in which workers are paid according to their skills, is a special case. Their model encompasses the endogenous assignment of skills to tasks, which leads to employment shifting between tasks as offshoring opportunities expand. This then leads to heterogenous effects on wages across the income distribution; similar to my own prediction that the wage response to a change in transportation costs varies according to the offshorability of an occupation. A secondary goal of their work is to bring together the many disparate pieces of data on tasks and develop a standard for how survey data on labor tasks is interpreted. They develop a standard set of line items from the O*NET data which are useful in thinking about the task content of occupations. This is an important contribution, because the O*NET content model comprises six separate “domains,” each of which contains dozens of questions about occupation and workplace characteristics. This makes it difficult to determine which portions of the data contain the most information content. I use their definitions to form measures of the relative offshorability of occupations. One measure of offshorability is defined directly by AA and includes variables which embody how frequently a person has to interact with a person or machine in a fixed location as a measure of offshorability. The idea here is that the more important your physical location, the less likely it is that your job will be offshored. The second offshorability measure I construct uses their measures of how easily it is to codify your job, or how routine it is. This gives some information on how easy it might be to remotely supervise a worker. I use these variables in conjunction with the AA offshorability measure to form an alternative measure of offshorability. I test my model using both measures and find evidence that in the manufacturing sector, my measure may be preferable to the AA measure.

The AA view of offshoring is similar to Blinder and Krueger (2009) which develops a measure of offshorability and determines that it is possible to offshore about 25 percent of the current domestic labor force.[7] Their work relies mainly on data from the Princeton Data Improvement Initiative but also draws on some of the same O*NET data used here. They classify jobs as more offshorable based on responses to questions about how easy it would be to perform their work at a remote location. The authors also discuss routine content as related to, but separatefrom, offshorability, though the exact distinction is unclear. Perhaps it is only that the AA sense of offshorability only determines whether or not a job is able to be offshored. The routine content measure on the other hand has more to say about how efficiently or profitable it might be to offshore that job. They find that the jobs they classify as more offshorable pay marginally higher wages than jobs which are not offshorable. This is consistent with my own findings using only AA measures of offshorability, but is at odds with my findings when I include routine task content in my measure of offshorability. This is also at odds with the occupation based analysis in Blinder (2009), which finds that offshorable jobs carry a negative wage premium (or a wage penalty). I follow a similar methodology but estimate separate offshorability premiums by industry and year. I document how these premiums change over time and how they are affected by changes in the cost of trade. When I use the same concept of offshorability, I mirror the finding that offshorable jobs pay more. However, when I also consider the routine content of occupations in defining offshorability, I find that the offshorability premium is in fact negative.[8]

In the trade literature, theoretical work by Grossman and Rossi-Hansberg (2008) demonstrates the impacts of task offshoring on wages and employment in a very clear and elegant setting and can be considered the basis of most of the subsequent research on task trade. In their model, workers are either low or high skill and performs a continuum of low or high skill tasks for firms. Firms are engaged in production of either a low skill intensive final good or a high skill intensive final good. Because of heterogeneity in offshoring costs, firms choose to hire some portion of the tasks from abroad and some at home. Changes in the cost of offshoring shift which tasks are performed domestically and result in a change in the wages of domestic workers.The possibility of offshoring tasks in the model results in three competing effects on wages: a productivity effect, a relative price effect, and a labor supply effect. The last two put

[7] In many ways Blinder and Krueger (2009) is a formalization of Blinder (2009), which develops a similar definition of offshorability.

[8] One important difference is that Blinder and Krueger (2009) and Blinder (2009) both assume that all manufacturing workers are offshorable, something I do not do in my analysis.

downward pressure on low skill wages through the familiar Stolper-Samuelson effect and increased competition. The productivity effect is more surprising, in that it works to the benefit of low skill labor by making the domestic low skill intensive industry more productive, thus putting upward pressure on wages. If such a productivity effect exists, it will serve to attenuate my findings. This suggests that it is possible for task trade to occur to the benefit of all factors in the economy, a truly surprising result. Following from Autor, Levy, and Murnane (2003), Grossman and Rossi-Hansberg suggest that the set of tasks which are offshored correspond to those tasks which are most routine.

Ottaviano, Peri, and Wright (2010) uses a modified version of the Grossman and Rossi-Hansberg model to empirically test some of the main predictions. The authors use data from the Census and the American Community Survey to analyze whether an increase in offshoring activity results in a decrease in domestic employment. They find that rising offshoring by American multinationals has zero net effect on the domestic labor market, suggesting that Grossman and Rossi Hansberg's productivity effect is finely balanced by the other two channels. The authors also incorporate data from O*NET to show that increases in offshoring push native workers away from routine intensive occupations into communication/interactive intensive occupations. Rather than reducing domestic employment, they find that offshoring causes domestic workers to shift they types provide and in fact, industries engaging in offshoring fared better in terms of employment than those that did not.However, their work has nothing to say about wages for domestic workers, which is the focus of my paper. Ottaviano, Peri, and Wright use a regression based index of offshoring costs constructed from industry level offshoring measures, that is, the number of offshore employees by industry. I also focus on industry level variation in offshoring, but I address the endogeneity issue by focusing on how changing transport costs across industries affect the opportunities for offshoring. Because of data limitations, their offshoring measures only incorporate offshoring by U.S. multinationals, whereas my data includes companies which are not multinationals. This difference in definitions means that I am more generally focused on trade in tasks. For example, my measures capture offshoring embodied by imports of intermediate inputs.

A second recent paper using microdata to analyze the potential labor market impacts of trade in tasks is Ebenstein, Harrison, McMillan, and Phillips (2010). Ebenstein, et al uses wage information from the Current Population Survey to analyze the impact of task trade on wages. They link workers to import penetration rates, offshoring activity, and export shares both through their industry and through novel occupation level measures of these variables. In addition, they use information from the Dictionary of Occupational Titles (DOT) to control for the routine content of occupations. Among a number of other interesting results, the authors find that offshoring to low income countries results in a decline in wages, and offshoring to high income locales results in an increase in wages. What is most relevant to the current paper, is that they find these gains and losses are concentrated in occupations classified as highly routine. In a similar fashion, my own results show that wage declines associated with declining transport costs are focused in the more offshorable occupations.

Two other papers which use individual micro-data to estimate wage premiums are Autor and Handel (2009) and Peri and Sparber (2009). Neither paper is about offshoring, but both use similar data on tasks in an attempt to estimate the wage premiums paid to those tasks. Autor and Handel use a survey created as part of the Princeton Data Improvement Initiative (PDII) which collected individual level data on the task content of occupations. They motivate their work with a model of workers with heterogenous skills endogenously sorting into occupations with different task requirements. They then use the PDII data to test the model, and find that the endogenous assignment of skills to tasks appears important. They do this by estimating the wage premiums to various tasks via linear regression and find that these wage premiums covary in a way consistent with their Roy style model of assignment. They also compare individual level PDII task measures with the occupation level O*NET task measures. They find that the O*NET occupation level measures mask significant intra-occupation variation in the tasks required of individuals on the job. This makes the individual level measures preferable, but they find that the O*NET measures contain significant information on actual tasks performed due to their correlation with the PDII measures.

Peri and Sparber (2009) estimate the impact of immigrant labor supply on the wages of native workers. They develop a simple model of native workers supplying tasks in the production of a final product and competing with immigrant workers, who are imperfect substitutes. The main finding of their paper is that immigration of low skilled foreign workers to the U.S. has a negative, but very small, impact on the wages of low skilled workers. The wage effects are dampened because native workers specialize in tasks which are communication intensive and thus do not compete directly with immigrants,who specialize in manual tasks.

A final strand of the literature which I would be remiss in omitting, is the literature on trade and the rising wage inequality experienced in the U.S.over the past three decades. Autor, Katz, and Kearney (2006) refers to this as the "polarization" of the labor market, where there is a hollowing out of the middle portion of the wage distribution. Autor, Levy, and Murnane (2003) provide a sturdy empirical basis for this assertion in a paper showing that the computerization of routine tasks can explain a significant portion of rising wage inequality. [9] The recognition of this polarization and the inability of standard models to explain it, is in large part motivation for Acemoglu and Autor's (2010) work generalizing what they refer to as the "canonical model." The standard model of labor markets was unable to match many of the relevant features of widening inequality in the U.S., something that the task framework has been successful in doing both theoretically and empirically. Firpo, Fortin, and Lemieux (2010) make a similar point, showing that wage dispersion can largely be attributed to changing compensation for routine tasks. They are unable to attribute this directly to offshoring (or computerization), but they argue fairly convincingly that those are the two most plausible causes. It is interesting to see long recognized features of the overall wage distribution mirrored in the wage premiums for different types of tasks, a result consistent with almost all models of tasks in the labor market. Although this work does not directly address this issue, the framework I develop here does have the potential to answer questions about the changing wage distribution.

3 A Task Based Model of Labor Markets and Trade

I use a simple model of labor markets in which workers choose between two occupations and supply labor to firms in the production of a final good. The two occupations are inherently different in that one is more offshorable than the other. The model predicts that as the cost of offshoring falls, via transport costs, the wage of the easy to offshore occupation declines more than the wage of the difficult to offshore occupation. This is a very intuitive result:As transportation costs fall, there is downward wage pressure on all workers, but those workers whos jobs are most likely to be offshored see a bigger decline in wages. The empirical section is

[9] This is one of the first papers to recognize that tasks are one channel through which technology (and analogously, trade) can impact the wage distribution.

concerned with testing this hypothesis using two measures of offshorability drawn from the recent literature. [MENTION THE TWO MEASURES HERE]

3.1 The Firm's Problem

Firms combine labor inputs from workers in two distinct occupations to form a final good according to a CES technology. First, I will consider the case in which offshoring is impossible and firms buy labor inputs from only domestic workers. They then solve the problem:

$$\max_{L_1,L_2}\left(\beta L_1^{\frac{\sigma-1}{\sigma}}+(1-\beta)L_2^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}-w_1L_1-w_2L_2 \tag{1}$$

L_1 and L_2 are output from workers engaged in the two occupations. Perfect competition in the labor market yields familiar factor demands for each occupation.

$$L_1=\left(\frac{\beta}{w_1}\right)^{\sigma}\frac{Y}{\beta^{\sigma}w_1^{1-\sigma}+(1-\beta)^{\sigma}w_2^{1-\sigma}} \tag{2}$$

and

$$L_2=\left(\frac{1-\beta}{w_2}\right)^{\sigma}\frac{Y}{\beta^{\sigma}w_1^{1-\sigma}+(1-\beta)^{\sigma}w_2^{1-\sigma}} \tag{3}$$

Because I am interested in looking at wage premiums, the relative factor demand is of particular interest.

$$\frac{L_1}{L_2}=\left(\frac{\beta}{1-\beta}\right)^{\sigma}\left(\frac{w_2}{w_1}\right)^{\sigma} \tag{4}$$

The demand for L_1 relative to L_2 depends both on its relative importance in the production process and the relative wage.

3.2 Worker's Problem

Workers are endowed with one unit of labor and choose between providing L_1 or L_2 to firms in order to maximize their own income. There are two types of workers who differ by their efficiency in providing L_1 and L_2. Type 1 workers have efficiencies $\rho_{1,1}$ and $\rho_{1,2}$, meaning that if they use their unit of labor for L_1 they will provide the firm with $\rho_{1,1}$ units of L_1. Type 2 workers have efficiencies $\rho_{2,1}$ and $\rho_{2,2}$. I assume that $\rho_{1,1} > \rho_{2,1}$ and $\rho_{1,2} < \rho_{2,2}$ so that each worker has an absolute advantage in one occupation. Workers are then paid the wage for whichever occupation they choose, times their efficiency in that occupation. There are N_1 and N_2 workers of type 1 and type 2, respectively. One way to think about the two occupations is that they embody two different types of tasks which affects the ease with which they can be offshored. There are three possible cases which can be observed in equilibrium:

1. All workers choose to enter occupation 1, which occurse when $w_1\rho_{1,1} > w_2\rho_{1,2}$ and $w_1\rho_{2,1} > w_2\rho_{2,2}$.
2. All workers choose to enter occupation 2, which occurs when $w_1\rho_{1,1} < w_2\rho_{1,2}$ and $w_1\rho_{2,1} < w_2\rho_{2,2}$.
3. Type 1 workers sort into occupation 1 and type 2 workers sort into occupation 2, which occurs when $w_1\rho_{1,1} > w_2\rho_{1,2}$ and $w_1\rho_{2,1} < w_2\rho_{2,2}$.

Because I am interested in the wage premium between the two occupations, only case 3 is of interest here and I will focus on that scenario. Here the supply of L_1 and L_2 are determined by the sorting and are equal to $N_1\rho_{1,1}$ and $N_2\rho_{2,2}$ respectively. Therefore the relative factor supply is

$$\frac{L_1}{L_2} = N_1\rho_{1,1}/N_2\rho_{2,2} \tag{5}$$

After showing the equilibrium I will define the conditions which much exist in order to see workers positively sort into separate occupations according to their types.

3.3 No Trade Equilibrium

Under autarky, firms source all of their L_1 and L_2 domestically from the two types of workers. In this case the equilibrium relative wage can be found by setting relative supply equal to relative demand to obtain market clearing.

$$\frac{w_1}{w_2} = \left(\frac{\beta}{1-\beta}\right)\left(\frac{N_2\phi_2}{N_1\rho_1}\right)^{\frac{1}{\sigma}} \tag{6}$$

The log wage premium paid to type 1 workers is then

$$\ln(w_1) - \ln(w_2) = \ln\left(\frac{\beta}{1-\beta}\right) + \frac{1}{\sigma}\left[\ln\left(N_2\rho_{2,2}\right) - \ln\left(N_1\rho_{1,1}\right)\right] \tag{7}$$

The premium depends only on the number of workers and their efficiencies as well as other parameters of the model. In order for this equilibrium to be reached it must be the case that $\frac{\rho_{1,2}}{\rho_{1,1}} < \left(\frac{\beta}{1-\beta}\right)\left(\frac{N_2\rho_{2,2}}{N_1\rho_{1,1}}\right)^{\frac{1}{\sigma}} < \frac{\rho_{2,2}}{\rho_{2,1}}$.

3.3 Trade Equilibrium

I introduce offshoring to the model by allowing firms to purchase labor inputs either domestically or from abroad. If an input j=1,2 is purchased from abroad, employers must pay the worker's wages w^* and an additional offshoring cost of ω_j. In addition, there is an iceberg transportation cost τ, meaning that in order to receive 1 unit of L_j from abroad a firm must purchase $1+\tau$ units of the input. This offshoring cost varies by the occupation being offshored and is meant to capture the idea that some occupations are more easily offshored than others. ω_j might be high because occupation j requires a lot of face-to-face interaction with customers which is difficult to provide with a foreign worker. For example, a worker might be required to meet clients face-to-face on a regular basis and introduce them to new features of a product. On the other hand ω_j might be quite low because occupation j is very routine in nature, making it easy to remotely control quality. Assembly line workers who manufacture parts to given tolerances can have their work checked quite easily once the product is shipped to the U.S. In any case, I assume that $\omega_1 < \omega_2$, meaning that occupation 1 is more Offshorable than occupation 2. Taking all this into consideration, the price of a unit of L_j from abroad is $(1+\tau)(w^* + \omega_j)$. I assume that there is an infinite supply of foreign labor available to sell labor to domestic firms. This means that if an occupation can be profitably offshored, domestic workers in that occupation will earn the same wage as foreign workers.

As in the autarky equilibrium, the discrete nature of the problem leads to a number of cases in which all domestic workers work in one task or another. These cases are not interesting because there is no domestic wage premium to analyze. Another possibility is that both occupations are offshored, which will lead to the wage premium being exogenously determined by the offshoring costs. Since neither of these have interesting empirical implications, I focus only on the case where only L_1 is purchased from foreign workers and domestic workers still find it profitable to sort into the occupations in which they have absolute advantage. The relative supplies and demands are analogous to the no-task trade case and the new market clearing condition for the wage premium is:

$$\frac{(1+\tau)(w^* + \omega_1)}{w_2} = \left(\frac{N_2\rho_{2,2}}{N_1\rho_{1,1} + L_1^*}\right)^{\frac{1}{\sigma}} \left(\frac{\beta}{1-\beta}\right) \tag{8}$$

Here L_1^* is the number of units of L_1 purchased from foreign workers. Note that $(1+\tau)(w^* + \omega_1)$ is simply the wage rate for L_1, which I will refer to as w_1. This can again be expressed in logs as

$$\begin{aligned} \ln(\mathrm{w}_1) - \ln(\mathrm{w}_2) \\ = \ln\left(\frac{\beta}{1-\beta}\right) + \frac{1}{\sigma}\ln\left(\mathrm{N}_2\rho_{2,2}\right) - \frac{1}{\sigma}\ln\left(\mathrm{N}_1\rho_{1,1} + \mathrm{L}_1^*\right) \end{aligned} \tag{9}$$

The wage premium now depends not only on model parameters but also on the amount of L_1^*, which is decreasing in τ. This means that as τ rises, the wage premium of the easy to offshore task relative to the difficult to offshore task also rises. That is,

$$\frac{\delta \ln\left(\frac{w_1}{w_2}\right)}{\delta\tau} \geq 0 \tag{10}$$

It is this prediction which I test in Section 5, but before doing so I need to construct a dataset to measure wages and the offshorability of various occupations, something I address in Section 4.

4 Data

A significant contribution of this paper is in bringing together data from disparate sources to form a long, usable panel of data on tasks, wages, and trade costs in order to test the model's main prediction. Data on individual wages and worker characteristics comes from the Current Population Survey's Merged Outgoing Rotation Groups, occupation level data on tasks comes from the Occupational Information Network (O*NET), and price indexes for industry level trade costs are created using product level Census Trade data. While others have used matched wage-task data in the past, bringing these transport cost measures together with the matched wage/task data is wholly new to this paper. I will discuss each of these data sources in turn, as well as how they are used in the subsequent analysis.

4.1 Worker Micro-data

Micro-data on wages comes from the Current Population Survey's Merged Outgoing Rotation Groups (CPS-MORG) sample available from the NBER. Households are covered by the CPS for a total of 16 months, They are a part of the sample for 4 months, idle for 6, and then back in the sample for another 4 months. Households are only asked for detailed wage and income information in the months in which they are exiting the survey frame (that is, months 4 and 16). This makes the MORG survey invaluable to economists who wish to use micro-data on wages. I use data on manufacturing workers in their 8th month of the CPS MORG from 1989 to 2003. The CPS MORG records both the 3 digit industry and the 3 digit census occupation code, the CIC and COC respectively, of each worker. These occupations are far more aggregated than the Standard Occupational Classification (SOC) which is used by O*NET.

In addition to the wage, occupation, and industry variables, the data contains information on age, gender, race, and education. I deflate usual hourly wages by the consumer price index to form a real measure of wages. I also censor workers whose wages have been topcoded, workers who are not full-time, and workers with missing wage or industry information.[10] Finally, because this work focuses on the impact of transportation costs, I must restrict the sample to the sectors for which trade data is readily available. This leaves me with a total of 234,279 workers over the sample. A breakdown of workers by year displays a sharp downward trend in manufacturing employment over this period, which mirrors the overall decline in manufacturing employment shown by the BLS Establishment Survey. The model and estimation used here are not designed to address the issue of unemployment or falling employment, but it is a question that merits more analysis in the context of task trade. This employment effect is the focus of Ottaviano, Peri, and Wright (2010) and Harrison and McMillan (2010), both of which find small or non-existent employment effects. This paper focuses on how offshoring affects wages, rather than employment, something which has been less well studied in the context of task trade.

4.2 Task Measures

Measures on offshorability are created from data on occupational tasks from O*NET. O*NET is a database created by the Department of Labor which provides raw data on the tasks, requirements, and environments of over 800 detailed occupations. The primary purpose of O*NET is to help job seekers determine which types of occupations might best suit the particular set of skills, education, and experience. As such, it contains a set of rich information about what types of tasks are performed by workers. The O*NET content model breaks down each occupation into 277 separate variables on what workers do in a given occupation. While the richness of O*NET's task measures makes it a valuable source of data on tasks performed, it makes it difficult to filter the enormous amount of information to extract those variables which are useful. In addition, the academic work reviewed in Section 2 has not come to absolute agreement on what factors are most important in determining the offshorability of a job. The first major view is that it is the face-to-face content of a job which determines its offshorability. The second major view is that it is the routine content of the job which is important. In many ways, this can be seen as a debate between feasibility and profitability. A requirement for constant face-to-face interaction between workers and customers makes a job infeasible to offshore. A job with varied and difficult to quantify day-to-day requirements is unprofitable to offshore because

[10] This is justified by the fact that the model really is considering full-time workers at the lower end of the skill distribution. Very few of these workers have their wages topcoded, and those who are can be considered outliers.

of the difficulty in monitoring and supervising employees. I will analyze both of these concepts in order to define highly offshorable jobs.

The AA measure of offshorability chooses to focus on those tasks which make a job inherently difficult to offshore, namely the need for a worker to be in a specific physical location or physically close to co-workers/customers in order to perform their job (the face-to-face aspect). The authors choose seven variables from O*NET's abilities, "work content," and "work activities" datasets. The variables used in each are presented in the first column of Table 1. The questions specifically ask how frequently a worker is required to engage in tasks of the type in the table and their answers are scaled from 0 to 5 on what is called the "importance" scale. Generally a 0 indicates that workers never engage in that type of task and a 5 indicates they engage in that type of task daily. I use the reciprocal of the sum of the responses to these questions to form the raw AA offshorability index. This process leaves me with a raw AA offshorability score for each SOC occupation. Because SOC occupations are significantly more detailed than the Census classifications that the worker microdata uses, I use a concordance provided by the department of labor to match and aggregate across the two systems. Once each worker in the microdata is assigned an AA offshorability score. A higher score on this index means an occupation is more easily offshored. I normalize the index to have a mean of 0 and a standard deviation of 1 over all workers and years in the sample. Therefore a positive score denotes a worker who is more offshorable than the mean worker according to the AA index, while a negative score denotes a worker is less offshorable.

The reasoning behind the AA offshorability measure is fairly obvious. It would be difficult to offshore a job if the worker holding that job is required to be located in a specific plant or interact face-to-face with other specific workers on a regular basis. This is largely the reasoning behind the Blinder and Krueger (2009) measure of offshorability as well. This is certainly a sensible criteria, but in thinking about manufacturing offshoring it may be misleading. In fact, in AA (2010) the authors discuss the similarity between mechanizing a process and offshoring it; namely that the ability to clearly codify what a job requires makes it easy to assign it either to a machine or a remote worker. In addition, the face-to-face aspect of offshorability may take on less importance in manufacturing, where the possibility of moving equipment and other employees offshore exists. Therefore, it seems sensible to pay attention not only to what makes a job feasible to offshore, but what makes it profitable to offshore, that is, its routine content. AA (2010) extracts 6 variables which embody the routine task content of occupations, which I list in the second column of Table 1. These all have to do with the frequency of performing tasks which are easily codified and thus potentially easy to supervise remotely. Summing across "importance" scores for these variables results in a measure of routine content, which when multiplied by the AA offshorability measure and normalized to have a mean of 0 and a standard deviation of 1 gives a new index of offshorability. This Ratio Index can be seen as measuring the proportion of time a worker spends on tasks that are easy to offshore to time spent on tasks that are difficult to offshore.

Table 2 presents the most and least offshorable occupations according to the AA Index;the higher the score the more offshorable a job. Under this metric, economists are one of the most offshorable of all occupations, as are mathemeticians, statisticians, and aerospace engineers. These types of occupations are generally not what come immediately to mind when people think about offshoring, but it is difficult to argue that these are jobs which are easy to perform with little face-to-face interaction with either specific people or machinery. On the other hand, the least offshorable occupations are dominated by repair workers and mechanics who need to interact with a piece of machinery in a specific location.

Table 3 provides a similar accounting based on the Ratio Index and once again the most offshorable occupations are generally those in which an individual can work alone or with little equipment. However, occupations which have come to be seen as more offshorable in recent years, like accountants, have crept up closer to the top of the list as well. The least offshorable occupations based on these criteria are what could be considered service occupations, which interact heavily with other individuals in a very non-routine way, like clergy. Because criteria of working with the public only make up about one half of the total AA index, these workers are not necessarily considered non-offshorable based on those criteria alone. Introducing the routine content measures, on which clergy have a very low score, serves to balance out this bias in the measure. The lists in Tables 2 and 3 suggest that something may be missing from the AA index which the routine content measure can help correct.

Another consideration is whether or not the AA and Ratio Indexes display any systematic differences. One way to investigate this is to look at the occupations for which the AA index significantly overstates (or understates) offshorability relative to the Ratio Index. This is presented in Table 4, which lists the occupations having the largest difference in the AA and Ratio rankings of offshorability. According to the AA index "Grinding, abrading, buffing, & polishing machine operators" are only the 314th most offshorable occupation, presumably because they are not able to work at all unless they are in front of very specific equipment. On the other hand, they are the 99th most offshorable occupation according to the Ratio Index because the actual tasks they perform in front of those specialized machines is quite routine. This pattern generally holds when the AA index understates offshorability relative to the Ratio Index. Once again, these jobs become very offshorable if the equipment these workers require is moved offshore as well. The occupations for which the AA index overstates offshorability are those which have a large face-to-face component but are also highly non-routine. While it is encouraging that these results largely line up with intuition, the existence of 398 detailed occupations about which I know little means that inspection of the scores and rankings can only do so much. These tables certainly provide some motivation for preferring the Ratio Index, but it is important to not put too much weight on a few selected anecdotes. Looking at the extremes, while interesting, is not a fair way to judge the index as a whole and tells little about how the AA measure performs in general. For now it is enough to just present some facts about the indexes and understand what dimension of offshorability each is trying to capture. In Section 5 I will provide further evidence that it is misleading to ignore the routine content of occupations in thinking about offshorability.

4.3 Transportation Costs

Identification of the labor market impact of offshoring tasks comes from industry level variation in transportation costs. Many papers on trade and labor markets have focused on the fact that rising import volumes are an important source of competition for domestic workers, potentially putting downward pressure on wages. However, for the most part these studies of trade and wages have failed to adequately account for the endogeneity of imports and wages. I overcome this difficulty by focusing on transportation costs, which exhibit exogenous variation due to idiosyncratic cost shocks across industries. Following the model developed in Section 3, I bring this same insight to the area of task trade by showing that some workers are more severely affected by this phenomenon, namely those workers performing tasks which are easily offshorable.

My identification strategy focuses on quality adjusted, industry level transportation costs which I create in Landefeld (2011). These transportation costs are largely driven by cost side factors, such as oil prices or technological changes. The fact that different industries realize these cost shocks in different ways leads to industry level variation in transportation costs over time. Because this variation is being driven by cost shocks on the side of shippers rather than manufacturers, these are uncorrelated with wages of domestic workers, something which cannot be said of import volumes or import penetration rates. I use this to identify the impact of falling trade costs on the relative wage of highly offshorable workers.

The methodological details of the transport cost measures I use can be found in Landefeld (2011), but it is useful to briefly discuss the indexes here. The underlying data for these price indexes comprises highly disaggregated Census trade data on imports to the U.S. for the years 1989-2003.[11] In that work I develop a set of industry level hedonic price indexes, which control for changing quality with simple regression techniques, allowing me to measure the "pure" price change in industry level transportation costs over time. These indexes control for changing quality of these transportation services, which might cause spurious increases or declines in the index. For example, if a shipper moves from shipping a good via ocean transport to air transport, a simple average will register a price increase, whereas the hedonic price index will recognize the quality difference between ocean and air transport and register a price decline. In addition to means of transportation, I am able to control for the composition of goods and source countries and various other dimensions via the hedonic methods.[12] After applying this methodology to the trade data I am left with transport cost indexes for 75 manufacturing and agricultural industries. On average these indexes fall by about 25 percent over the course of the sample, but there is significant variation in these rates of decline. This cross industry variation is what enables me to identify the impact of falling transport costs on relative wages. Matching them to the task and

[11] This data is available online from Peter Schott in an easy to use format at: http://www.som.yale.edu/faculty/pks4/sub_international.htm.

[12] Conventional or matched model price indexes are also able to control for a number of these quality dimensions, but Landefeld (2011) has shown that the hedonic price indexes appear to capture the true price changes better and also display a higher correlation with import flows. Results using these conventional price indexes are qualitatively similar.[GET RID OF THIS FOOTNOTE]

wage data based on a worker's industry of employment provides me with a dataset on individual workers, the corresponding offshorability of their occupation, and the transportation costs they are exposed to in their industry.

5 Empirical Evidence

Using the datasets which I have compiled and created in section 4, I am able to test the main prediction of the model: that the wage premium paid to relatively more offshorable jobs will fall as transportation costs fall due to increased competition from abroad as the cost of trade declines.

5.1 Wages and Transport Costs

Before directly testing this prediction it is valuable to determine whether there is any link between transportation costs and wages. Following the literature on trade and wages, any individual worker might see his/her wages increase or decrease due to an increase in trade, depending on whether the imported good is a substitute or complement for his/her output. A large body of academic literature exists attempting to determine the extent to which trade has led to a stagnation of real wages in the U.S. This paper takes that insight to the task dimension; workers whose tasks are highly offshorable should see a decline in their wages as task trade becomes easier, while workers performing less offshorable tasks should see a smaller decline or even an increase. In addition, I focus on the trade costs rather than actual trade volumes or import penetration rates, in contrast to most of the existing literature.

Simple linear regressions can help to illustrate the general relationship between wages and transportation costs. I run a simple regression of transport costs on log wages in the following form:

$$\ln(w_{ist}) = \alpha_0 + \alpha_1\tau_{st} + \alpha_2 X_{it} + \alpha_3 S + \alpha_4 T_t + \epsilon_{it} \qquad (11)$$

Here the log wage of individual i in sector s year t depends on individual characteristics X_{it}, a sector specific fixed effect S, and the transportation costs $\tau_{st}$for that sector. There is also a linear time trend. The worker characteristics include age, age squared, race, gender, and education. The sample runs from 1989-2003 and comprises nearly 170,000 workers. Results are presented in

Table 5 column (i). The demographic coefficients all have the expected sign and are highly significant. The transport cost measure is also large and positive with a point estimate of 0.186. This suggests that if transportation costs for a given sector double from their 1989 level, workers in that sector will experience an 18.6 percent increase in their wages. As trade becomes more costly, wages rise on average. The expected sign here was indeterminate, so it is interesting in itself that the average impact of trade costs is positive.

Allowing the impact of transportation costs to vary based on the offshorability of the worker should reveal that transportation costs have a stronger positive relationship with wages when the worker is more easily offshored. To investigate this I split the sample based on two measures of offshorability in order to see whether the more offshorable workers are more strongly affected by changes in transport costs. The first offshorability measure is the AA index which assigns a score based mainly on the face-to-face or location specific content of an occupation according to section 4.2. The second combines this measure with the measure of routine content, my Ratio Index. I classify occupations as highly offshorable if they have scores for the indexes above the mean for all workers over all years. The expectation is that highly offshorable occupations should see a larger decline in their wages due to falling transport costs (or equivalently an increase in wages with an increase in transport costs). Columns (ii-a) and (ii-b) use the AA measure to run the same regression separately by low and high offshorability workers, respectively. The sample split based on the AA measure actually exhibits the opposite behavior, with the point estimate falling from 0.303 to 0.127 when looking at the highly offshorable occupations; this difference is significant at the 1 percent level. This could suggest that the offshorability measure is incomplete in some way or improperly specified.[13] Columns (iii-a)-(iii-b) split the sample based on the ratio of routine and face-to-face task requirements. In this case the highly offshorable jobs exhibit a stronger relationship with transport costs than the less offshorable jobs, with the point estimate rising to 0.245 from 0.161, again a statistically significant difference. I suspect this measure performs better than the AA measure alone because it incorporates not only a measure of what makes a job difficult to offshore, but also a measure of what makes offshoring viable.

[13] This result does not qualitatively change when the exact cutoff value for determining whether or not a job is classified as highly offshorable is changed.

Again, this has astraightforward interpretation: workers performing offshorable tasks face increased competition from abroad as the cost of trading tasks falls, directly putting downward pressure on their wages. This preliminary result is related to the main prediction of the model, but is not necessarily a direct test. In the next section I will look more carefully at how the data supports the model.

5.2 Testing the Model: Offshorability Premiums and Transport costs

In order to test the theory that premiums paid to more easily offshorable occupations rise with transportation costs, I first have to recover the offshorability wage premium from the datasets which I have compiled.[14] In order to do this I create an offshorability indicator equal to 1 if the Ratio Index, or alternatively the AA index, is positive and 0 if it is negative.[15] Therefore the indicator is switched on if a worker is in a job that is more easily offshorable than the mean job in the economy. I then regress this variable and a number of individual characteristics on the worker's real log wage as in equation (19).

$$\ln(w_{it}) = \alpha_0 + \sum_{s=1}^{75} \alpha_{s,1} 1_{i,s,t}(OFF > 0) + \sum_{s=1}^{75} \alpha_{s,2} R_i + \sum_{s=1}^{75} \alpha_{s,3} F_i + \alpha_4 X_{i,t} + S_t + \epsilon_{st} \tag{12}$$

The first term, $1_{i,s,t}(OFF > 0)$, is an indicator variable equal to 1 if a worker's offshorability index is higher than the mean worker in the sample. Therefore, $\alpha_{s,1}$ is the real log wage premium in sector s paid to the easy to offshore job. The summation is simply the offshorability indicator multiplied by a full set of industry dummies. S_t is the corresponding set of industry fixed effects. R_i and F_i are the levels of routine and face-to-face tasks which each worker performs, which correspond to the numerator and denominator of the Ratio measure, and are included to control for the fact that the total level of task performance may be correlated with the wage and is, by construction, correlated with the offshorability dummy. I also include specifications where I omit R_i and F_i as independent variables. While my model does not

[14] Note that it is not necessarily possible to determine the "return" to choosing an offshorable job. The returns to education literature has made it clear that identification under sorting is no mean feat, however, the model predicts movements in the equilibrium wage premium, something it is possible to recover in the reduced form.
[15] The appendix contains results where the exact cutoff values for the index are not the mean andthe results are qualitatively similar.

explicitly include direct task measures, a number of other theoretical works on task trade suggest their inclusion may be important. In some specifications I also allow α_4 to vary by industry so that the return to each demographic variable is dependent on industry. $X_{i,t}$ is a vector of worker characteristics from the CPS files comprising dummy variables for male, non-white, and high school graduate. In order to create a panel of offshorability premiums the regressions are run separately by year.[16] The end result is a panel of offshorability premiums from 1990-2003 for 75 agricultural and manufacturing industries. I estimate these panels twice, once using the AA based classification of offshorability and once using the Ratio based classification.

Results are presented in Chart 1, which plots the average coefficients for each year weighted by the number of workers in each industry for that year. These coefficients were estimated by allowing the returns to demographic characteristics to vary by industry. The chart shows that on average, the offshorability premium according to the AA measure rose substantially until 2001, when it began to decline. This is somewhat in conflict with anecdotal evidence about what has happened to wages over that period. The chart also shows that workers who had high scores on the AA index were paid a significant wage premium, about 10-15 percent over less offshorable jobs. This mirrors the result from Blinder and Krueger (2009), which uses the PDII anda similar concept of offshorability. The offshorability premium as measured by the Ratio Index was negative and more volatile over the period and has no discernible trend. The fact that the premium for offshorable jobs measured by the Ratio Index is negative indicates that offshorable jobs pay lower wages than non-offshorable jobs, something which may fit well with priors about offshoring. It is not surprising that this conflicts with the Blinder-Krueger findings, since I am using a significantly different concept of offshorability. Charts 2 and 3 present the average movement of the offshorability premiums and the average transportation costs as measured by the hedonic index. I would not expect to see much correlation between the series based on averages, but it is interesting that the AA offshorability premium in Chart 2 generally moves in the opposite direction from transportation costs, which fell dramatically over the sample. Chart 3 shows the Ratio offshorability premium and hedonic transportation costs. It is impossible to see any correlation in the aggregate here, but this is

[16] Since the CPS is not balanced across industries and occupations it is useful to have a larger sample size. To achieve this I pool three years at a time, so that the offshorability premiums for 1990 are estimated using data from 1989-1991.

unsurprising since there is so much variation across industries in both the behavior of wages and transportation costs.

Because of the substantial cross-industry variation in both the premiums and transport costs it is difficult to tell much from the behavior of the aggregates. In fact, it is exactly this cross-sectional variation in transportation costs which I use to sort out the impact of falling transportation costs on the wage premium for offshorable occupations. In order to analyze this relationship more systematically I treat the panel of industry level offshorability premiums as data and run regressions using transportation costs to explain movements in the premiums.

$$\mathrm{Prem}_{\mathrm{st}} = \beta_0 + \beta_1 \tau_{st} + \beta_2 T_t + \beta_3 S + \epsilon_{st} \tag{13}$$

Equation (20) includes a linear time trend and a full set of industry fixed effects. I run this regression using both the AA and Ratio offshorability premiums. β_1 is the main coefficient of interest, indicating how much the wage premium (which is in logs) responds to a change in transportation costs. The model predicts that β_1 will be positive, that more easily offshored jobs see larger wage decreases as transportation costs fall. The linear time trend helps to sort out any secular trend in the premium over the sample, leaving the idiosyncratic differences in transportation costs across industries to identify the impact. In Table 6 the offshorability premium is estimated using the AA measure of offshorability. The main explanatory variable is the hedonic transportation cost measures developed in Landefeld (2011). Columns (i)-(iv) vary based on the types of controls included when estimating the offshorability premiums.

Column (i) of Table 7 uses the most parsimonious specification of equation (19) in estimating the offshorability premiums. Only the premium itself is allowed to vary across industries and it does not control for the level of routine and face-to-face tasks. Surprisingly, the point estimate in (i) is negative and significant, suggesting a doubling in transportation costs from the baseline would lead to a 22.4 percent decline in the log wage premium for offshorable jobs. This is puzzling because an increase in transport costs ought to decrease competition for offshorable workers, having a positive effect on their wages. This pattern is constant regardless of how the wage premium is measured in the first stage. Specification (ii) allows for varying returns to demographic characteristics by industry and specification (iii) controls for the levels of face-to-face and routine tasks in an individual's occupation. Specification (iv) is the fully saturated model where all demographics and task levels are included and vary by industry. Across all these specifications there is no statistically significant difference between the point estimates.

Table 8 presents the same regressions but where the offshorability premium, or penalty in this case, is based on the Ratio measure of offshorability. Immediately it is obvious that all the coefficients on the transport costs are positive, which is the expected sign. The baseline specification suggests that a doubling of transport costs from the initial level would lead to a 16 percent increase in the wages of highly offshorable workers. The size of this effect does vary across specifications, but in all cases it suggests a large and statistically significant impact of changing transportation costs on the relative wage for offshorable workers. With transportation costs falling on average 22 percent over the sample period, the impact on the Ratio wage premium paid to offshorable jobs was substantial, reducing the premium by anywhere from 2-8 percent.

The results using the AA offshorability measure are difficult to reconcile with nearly any model of trade and labor markets, including the model motivating this paper. The Ratio measure performs much better, confirming the primary prediction of the model. These results suggest that it is imperative to augment the face-to-face concept of offshorability with a measure of routine content in considering task trade empirically. One reason the AA measure may perform so poorly in this context is that it was developed mainly to examine services offshoring. In both Blinder (2009) and Blinder and Krueger (2009) manufacturing workers were classified as offshorable a-priori and the face-to-face criteria was applied to individuals in service industries. My results suggest that within the manufacturing sector the effects of trade are highly heterogenous and that an offshorability measure like the Ratio Index is an appealing lens through which to view this heterogeneity. In any case, increased opportunities for offshoring, via declines in transport costs, appear to put downward pressure on wages and disproportionately affect workers who have a high ratio of routine to face-to-face content in their occupations.

5.2 Robustness Results

I perform a battery of robustness checks to ensure that the results in tables 7 and 8 are not highly sensitive to the specifications I've chosen. I perform robustness checks which change the offshorability cutoff level, control for lagged dependent variables, control for lagged transport costs, and instrument for transport costs. Remarkably, the general pattern of results is fairly stable across all these alternative specifications, although the point estimates vary. In particular, the fact that the Ratio measure performs better than the AA measure is preserved throughout.

One obvious criticism which might be leveled at my analysis is that the cutoff for highly offshorable workers which I have defined is arbitrary. In Tables 9 and 10, rather than using a mean cutoff, I define workers as offshorable if they have an offshorability score more than 1 standard deviation above the mean. In this case the AA measure performs much better than the baseline specifications, the point estimates all have the correct sign. However, except in the fully saturated specification, none of these are statistically significant. The Ratio measure, in Table 10,on the other hand, has the same pattern as before, though the results are strengthened. This makes sense since I am using a more restrictive definition of offshorability. Tables 11 and 12 use a higher offshorability cutoff, namely 1 standard deviation above the mean and the results are similar. Using the AA measure point estimates have the correct positive sign but are generally insignificant. With the Ratio measure the results are all significant, though weaker than the mean specification, again because here I use a broader definition of offshorability.

Tables 13 and 14 include a lag of the wage premium, and the pattern is unchanged.[17] Tables 15 and 16 include lags of transportation costs and the pattern is largely similar. However, the results in specifications (ii) and (iv) are significantly attenuated. In addition, the lag of transport costs is larger and more significant than the contemporaneous measure. This is difficult to interpret, but is not necessarily out of line with the model; for example if contracts are written one period in advance where there is uncertainty about future transportation costs, the previous period might be more important than the current period. The final two tables, 17 and 18, provide IV estimates of the impact of transport costs on the wage premium/penalty. There may be some concern that the transport costs are being driven in some cases by demand side factors which are passed

[17] These use the Arellano and Bond (1991) GMM estimator in order to obtain consistent estimates.

through to shipping prices. The hedonic indexes go to great lengths to ensure this isn’t the case by controlling for both the amount of each good being shipped and the unit values of these goods. However, there may still be some concerns about endogeneity which I address by using the transportation costs from other industries as instruments.[18] Doing so actually strengthens the baseline findings across the board for both the AA measure and the Ratio measure. To varying degrees, all of these alternative specifications confirm the original findings and suggest that the Ratio measure is preferable to the AA measure.

6 Conclusion

Much recent work on offshoring has focused on the idea of trading tasks, whereby certain types of jobs (or tasks within those jobs) are easier to offshore than others due to the nature of the tasks workers are performing. The primary goal of this paper is to develop and test a simple framework for the impact of trade on wages while drawing insights from this recent literature. I go further than many previous works by using microdata on workers to directly estimate the premiums associated with offshorable jobs and make a connection between these wage premiums and trade. Additionally, many studies on offshoring (or trade) and wages do not adequately account for the endogeneity of trade and wages, which I address by using plausibly exogenous cross sectional variation in transportation costs which I develop. I find that the standard concept of offshorability, based solely on the face-to-face content of a job is unsatisfactory when looking at the manufacturing sector. When I also account for the routine content of an occupation I find that the offshorability measure performs far better.

I use two measures of offshorability drawn from AA (2010) to classify jobs as offshorable, one (the AA measure) relying entirely on the face-to-face or location specific content of an occupation and the other (the Ratio measure) combining those characteristics with the routine content of the occupation. I use a very intuitive model which predicts that the relative wage paid to offshorable occupations falls significantly when the cost of offshoring falls, exposing those workers to more foreign competition. When I use the AA, face-to-face only, measure of offshorability I find that the relative wage of highly offshorable workers actually rises as transport costs fall. This is difficult to reconcile with the model presented here, but also

[18] This is very similar to the instruments used in Nevo (2000)

nearly any other model of trade and labor markets. However, when I also account for the routine content of an occupation in my Ratio measure, I find that there is a very strong positive relationship between transport costs and the relative wage of offshorable workers. In fact, declining transport costs from 1989-2003 served to reduce the relative wage of these workers by about 5 percent on average. These results are remarkably robust across a number of alternative specifications.

The fact that this paper does not include an analysis of service workers is regrettable, but unavoidable due to the use of transportation costs to measure the cost of offshoring. One extension to this paper might be in gathering information about the costs of services trade across industries, or even the volume of services trade, which could then be used in a similar framework. Future work which can incorporate the changing costs of service offshoring would be invaluable in determining the potential impact of offshoring on domestic labor markets. A second area for future work using this methodology would be to develop occupation level measures of transportation costs. In some ways these would capture the cost of offshoring various tasks, shedding more direct light on what types of tasks are offshorable.

The major contribution of this paper is to demonstrate empirically that workers in highly offshorable jobs are more vulnerable to wage pressure from offshoring. I also find that looking only at the face-to-face content of occupations is not adequate in determining the degree of offshorability and that incorporating a measure of routine content yields more sensible results, even though the former measure has become somewhat of a standard in the literature. A second contribution has been to address the endogeneity of trade and wages through the use of transportation costs rather than direct import measures. I demonstrate that falling transport costs from 1989-2003 were an important driver in holding down the wages of offshorable occupations. The novel use of data and transportation costs in this work makes it an important step in understanding the impact of offshoring on domestic wages. Few other papers have been able to present empirical evidence about what makes a job offshorable or demonstrate the impact that type of classification might have on workers in the presence of offshoring.

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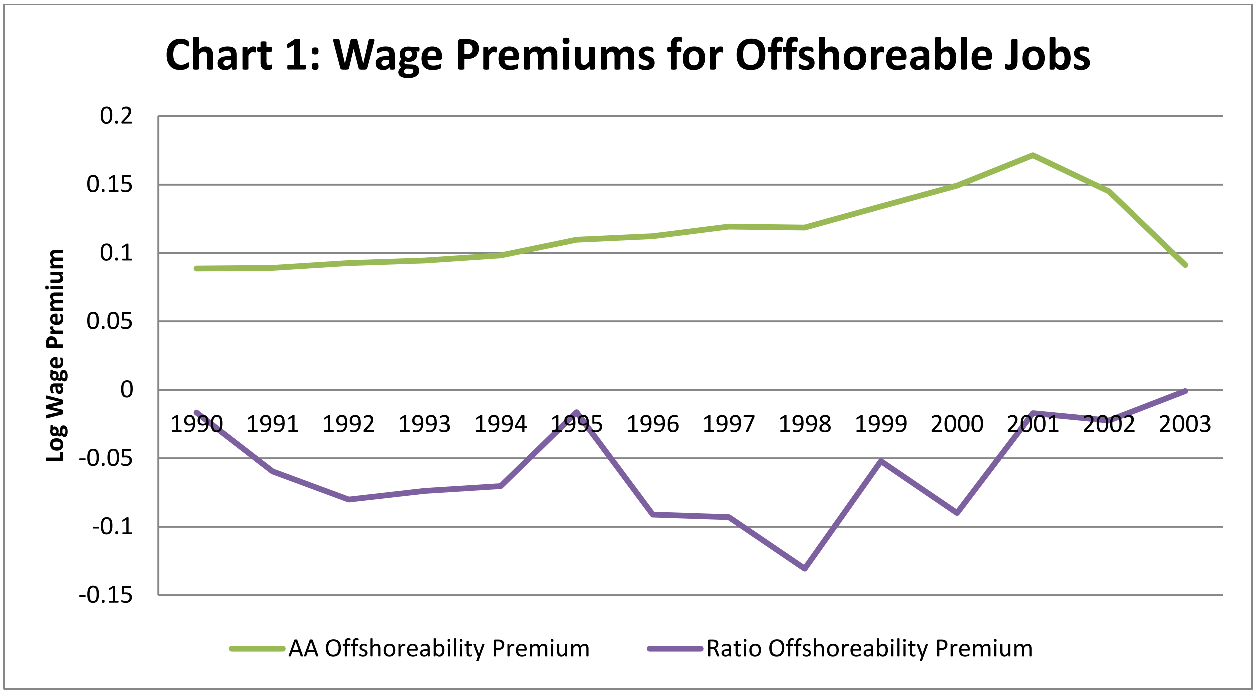
Chart 1: Wage Premiums for Offshoreable Jobs
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
Log Wage Premium
1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003
AA Offshoreability Premium
Ratio Offshoreability Premium

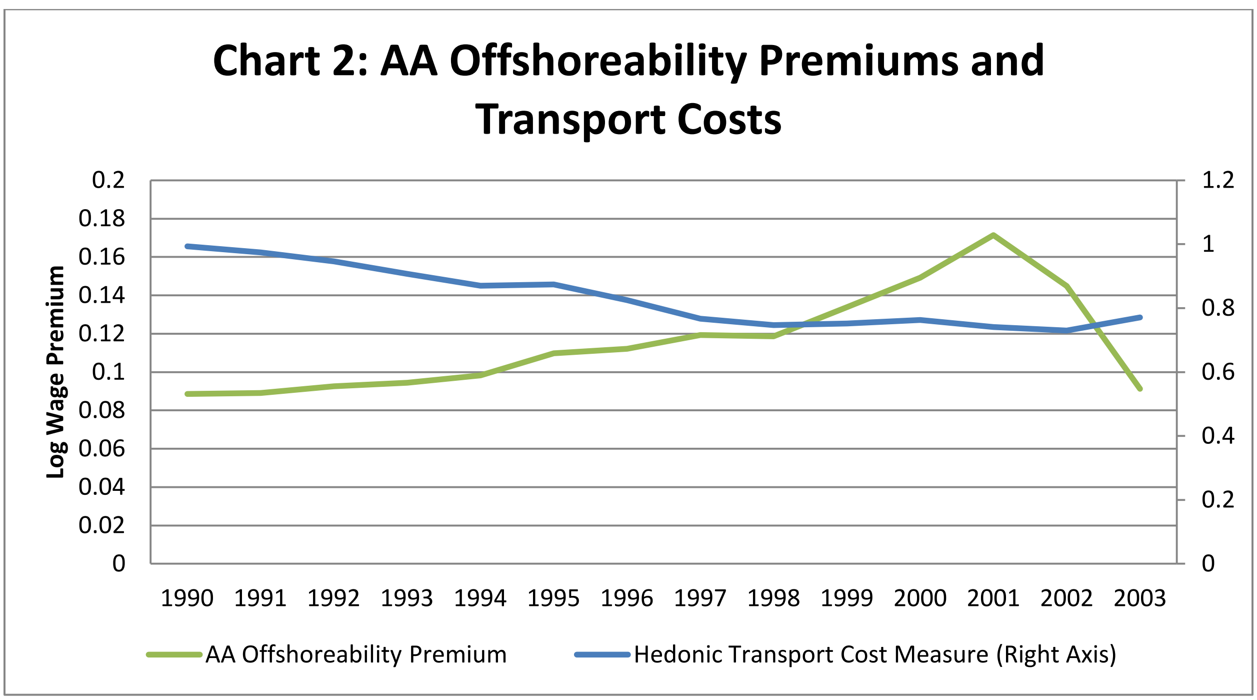
Chart 2: AA Offshoreability Premiums and Transport Costs
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
Log Wage Premium
1.2
1
0.8
0.6
0.4
0.2
0
1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003
AA Offshoreability Premium
Hedonic Transport Cost Measure (Right Axis)

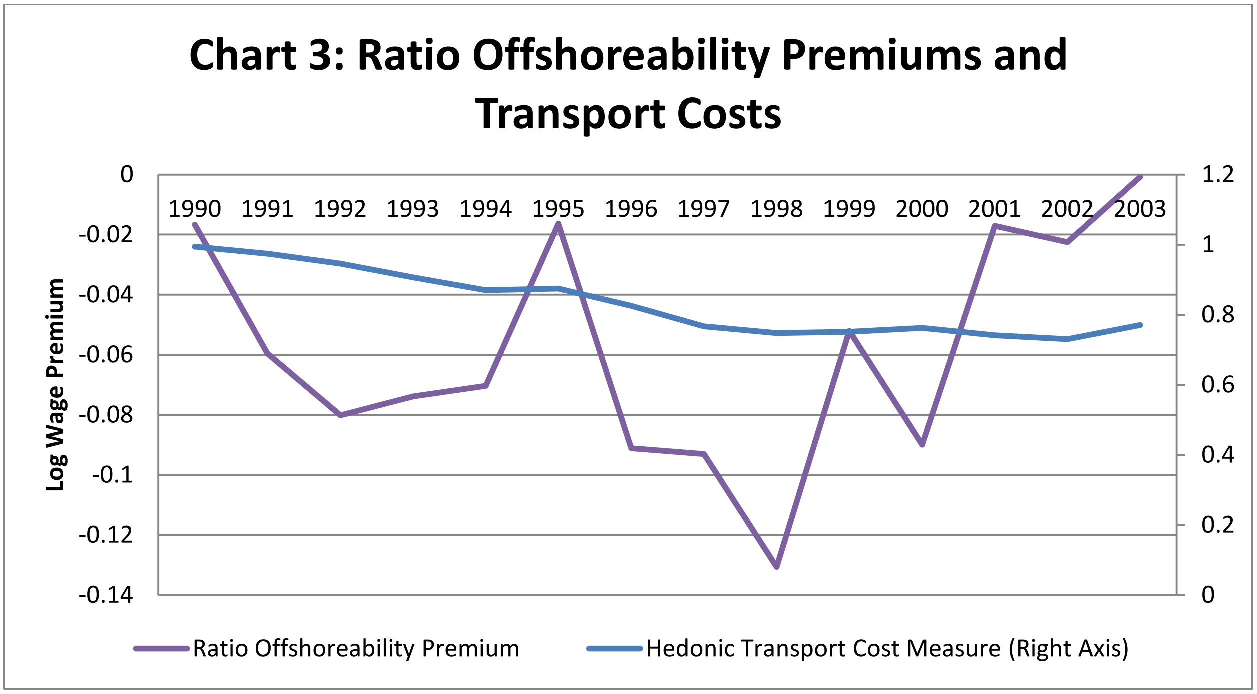
Chart 3: Ratio Offshoreability Premiums and Transport Costs
Log Wage Premium
0
-0.02
-0.04
-0.06
-0.08
-0.1
-0.12
-0.14
1.2
1
0.8
0.6
0.4
0.2
0
1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003
Ratio Offshoreability Premium
Hedonic Transport Cost Measure (Right Axis)

Table 1 - Variables in Task Indexes

AA Offshorability Measure	AA Routine content Measure
Face-to-face discussions	Importance of repeating same tasks
Assisting and caring for others	Importance of being exact or accurate
Performing for or working directly with the public	Structured v. Unstructured work
Inspecting equipment, structures or materials	Pace determined by speed of machines
Handling and moving objects	Controlling machines and processes
Repairing and maintaining mechanical equipment (1/2)	Time spent making repetitive motions
Repairing and maintaining electrical equipment (1/2)	

Table 2 : Occupations by Acemoglu-Autor Offshorability Index

5 Most Offshorable	**AA Score**
Mathematical scientists, n.e.c.	5.49
Aerospace Engineers	5.22
Economists	3.60
Statisticians	3.14
Proofreaders	3.12
5 Least Offshorable	
Elevator installers and repairers	-2.09
Telephone line installers and repairers	-1.96
Household appliance and power tool repairers	-1.96
Electrical power installers and repairers	-1.95
Heating, air conditioning, and refrigeration mechanics	-1.89

Table 3: Occupations by Ratio Offshorability Index

5 Most Offshorable	**Ratio Score**
Aerospace Engineers	4.36
Proofreaders	3.70
Classified-ad clerks	3.05
Bookkeepers, accounting, and auditing clerks	3.01
Actuaries	2.94
5 Least Offshorable	
Clergy	-3.14
Therapists, n.e.c.	-3.02
Physical therapists	-2.95
Recreation workers	-2.81
Household appliance and power tool repairers	-2.79

Table 4: Biggest Differences between AA Rank and Ratio Rank

Most Understated Offshorability	**AA Rank**	**Ratio Rank**
Grinding, abrading, buffing, & polishing machine operators	314	99
Mining machine operators	326	114
Rolling machine operators	334	135
Hoist and winch operators	305	106
Folding machine operators	261	68
Most Overstated Offshorability		
Demonstrators, promoters and models, sales	14	348
News vendors	63	357
Teachers aides	79	366
Counselors, educational and vocational	107	370
Dietitians	109	383

Table 5: Impact of Transport Costs on Individuals' Wages

	Dependent Variable: Log Wage				
	Full Sample	Continuous	Categorical	Low AA	High AA
Hedonic Transport Cost Measure	**0.186*** **	**0.175*** **	**0.381*** **	**0.303*** **	**0.127** **
	[0.0386]	[0.0415]	[0.0658]	[0.0535]	[0.0515]
AA Offshorability	--	**0.274*** **	**0.612*** **	--	--
		[0.0293]	[0.0551]		
Interaction: Offshorability*Transport	--	**-0.194*** **	**-0.405*** **	--	--
		[0.0303]	[0.0639]		
Non-white	**-0.136*** **	**-0.119*** **	**-0.106*** **	**-0.115*** **	**-0.0846*** **
	[0.00849]	[0.00860]	[0.00897]	[0.00866]	[0.0158]
No Diploma	**-0.318*** **	**-0.277*** **	**-0.256*** **	**-0.225*** **	**-0.404*** **
	[0.0119]	[0.00965]	[0.0105]	[0.00802]	[0.0216]
Female	**-0.267*** **	**-0.301*** **	**-0.302*** **	**-0.254*** **	**-0.345*** **
	[0.0134]	[0.0112]	[0.00814]	[0.00851]	[0.0123]
Age	**0.0555*** **	**0.0545*** **	**0.0531*** **	**0.0493*** **	**0.0595*** **
	[0.00181]	[0.00174]	[0.00165]	[0.00165]	[0.00261]
Age Squared	**-0.000558*** **	**-0.000547*** **	**-0.000533*** **	**-0.000492*** **	**-0.000603*** **
	[2.04e-05]	[1.91e-05]	[1.79e-05]	[1.66e-05]	[2.88e-05]
Linear Time Trend	**0.00760*** **	**0.00666*** **	**0.00763*** **	**0.00592*** **	**0.0106*** **
	[0.00117]	[0.00110]	[0.00121]	[0.00131]	[0.00137]
Observations	169654	169654	169654	104679	64975
R-Squared	0.203	0.243	0.265	0.199	0.219
Industries	75	75	75	75	75

Notes: Dependent variable is the industry specific log wage premium accruing to offshorable occupations. The "Offshorability Measure" classifies occupations as offhoreable according to the Acemoglu-Autor Scale. The "Routine-Offshorability Ratio" classifies occupations by multiplying this scale by a scale measuring routine content. Standard errors are reported in the parentheses and are clustered by industry All regressions include industry fixed effects and a linear time trend. *** indicates significance at 1 % level, ** at 5 %, and * at 10 % level.

Table 6: Impact of Transport Costs on Individuals' Wages

	Dependent Variable: Log Wage				
	Full Sample	Continuous	Categorical	Low Ratio	High Ratio
Hedonic Transport Cost Measure	**0.186*** **	**0.183*** **	**0.207*** **	**0.161*** **	**0.245*** **
	[0.0386]	[0.0375]	[0.0507]	[0.0434]	[0.0550]
Ratio Offshorability	--	0.0114	-0.0322	--	--
		[0.0252]	[0.0366]		
Interaction: Offshorability*Transport	--	-0.0411	-0.0352	--	--
		[0.0328]	[0.0433]		
Non-white	**-0.136*** **	**-0.135*** **	**-0.134*** **	**-0.157*** **	**-0.102*** **
	[0.00849]	[0.00831]	[0.00821]	[0.0119]	[0.00768]
No Diploma	**-0.318*** **	**-0.318*** **	**-0.316*** **	**-0.347*** **	**-0.267*** **
	[0.0119]	[0.0119]	[0.0120]	[0.0134]	[0.0150]
Female	**-0.267*** **	**-0.259*** **	**-0.258*** **	**-0.275*** **	**-0.231*** **
	[0.0134]	[0.0136]	[0.0131]	[0.0114]	[0.0182]
Age	**0.0555*** **	**0.0552*** **	**0.0551*** **	**0.0605*** **	**0.0484*** **
	[0.00181]	[0.00180]	[0.00181]	[0.00173]	[0.00243]
Age Squared	**-0.000558*** **	**-0.000556*** **	**-0.000555*** **	**-0.000605*** **	**-0.000493*** **
	[2.04e-05]	[2.02e-05]	[2.02e-05]	[1.99e-05]	[2.76e-05]
Linear Time Trend	**0.00760*** **	**0.00759*** **	**0.00765*** **	**0.00700*** **	**0.00884*** **
	[0.00117]	[0.00116]	[0.00117]	[0.00133]	[0.00147]
Observations	169654	169654	169654	96984	72670
R-Squared	0.203	0.205	0.206	0.215	0.169
Industries	75	75	75	75	75

Notes: Dependent variable is the industry specific log wage premium accruing to offshorable occupations. The "Offshorability Measure" classifies occupations as offhoreable according to the Acemoglu-Autor Scale. The "Routine-Offshorability Ratio" classifies occupations by multiplying this scale by a scale measuring routine content. Standard errors are reported in the parentheses and are clustered by industry All regressions include industry fixed effects and a linear time trend. *** indicates significance at 1 % level, ** at 5 %, and * at 10 % level.

Table 7: Impact of Transport Costs on Premium for Offshorable Occupations-AA Measure

	Dependent Variable: AA Offshorability Log Wage Premium			
	(i)	(ii)	(iii)	(iv
Hedonic Transport Cost Index	**-0.224*** **	**-0.173*** **	-0.15	**-0.164*** **
	[0.0748]	[0.0590]	[0.170]	[0.0599]
Linear Time Trend	-0.00156	-0.000508	0.0035	-0.00155
	[0.00181]	[0.00143]	[0.00553]	[0.00143]
First Stage Controls:				
Task Levels	No	No	Yes	Yes
All returns vary by industry	No	Yes	No	Yes
Observations	1,021	1,021	1,021	1,021
R-Squared	0.023	0.035	0.01	0.019
Industries	75	75	75	75

Notes: Dependent variable is the industry specific log wage premium accruing to offshorable occupations. Standard errors are reported in the parentheses and are clustered by industry All regressions include industry fixed effects and a linear time trend. *** indicates significance at 1 % level, ** at 5 %, and * at 10 % level.

Table 8: Impact of Transport Costs on Premium for Offshorable Occupations-Ratio Measure

	Dependent Variable: Ratio Offshorability Log Wage Premium			
	(i)	(ii)	(iii)	(iv
Hedonic Transport Cost Index	**0.161*** **	**0.101*** **	**0.386*** **	**0.127*** **
	[0.00947]	[0.00864]	[0.0219]	[0.0118]
Linear Time Trend	**0.00400*** **	**0.00427*** **	**0.00921*** **	**0.00319*** **
	[0.000210]	[0.000176]	[0.000505]	[0.000226]
First Stage Controls:				
Task Levels	No	No	Yes	Yes
All returns vary by industry	No	Yes	No	Yes
Observations	1,021	1,021	1,021	1,021
R-Squared	0.167	0.192	0.285	0.048
Industries	75	75	75	75

Notes: Dependent variable is the industry specific log wage premium accruing to offshorable occupations. Standard errors are reported in the parentheses and are clustered by industry All regressions include industry fixed effects and a linear time trend. *** indicates significance at 1 % level, ** at 5 %, and * at 10 % level.

Table 9: Impact of Transport Costs on Premium for Offshorable Occupations-AA Measure

	Dependent Variable: AA Offshorability Log Wage Premium			
	(i)	(ii)	(iii)	(iv
Hedonic Transport Cost Index	0.00773	0.0913	0.18	**0.253*** **
	[0.0831]	[0.0726]	[0.168]	[0.0743]
Linear Time Trend	**-0.00388***	-0.00173	**-0.00856***	**-0.00673*** **
	[0.00223]	[0.00191]	[0.00508]	[0.00191]
First Stage Controls:				
Task Levels	No	No	Yes	Yes
All returns vary by industry	No	Yes	No	Yes
Observations	1,021	1,021	1,021	1,021
R-Squared	0.016	0.018	0.039	0.163
Industries	75	75	75	75

Notes: Dependent variable is the industry specific log wage premium accruing to offshorable occupations. Standard errors are reported in the parentheses and are clustered by industry All regressions include industry fixed effects and a linear time trend. *** indicates significance at 1 % level, ** at 5 %, and * at 10 % level.

Table 10: Impact of Transport Costs on Premium for Offshorable Occupations-Ratio Measure

	Dependent Variable: Ratio Offshorability Log Wage Premium			
	(i)	(ii)	(iii)	(iv
Hedonic Transport Cost Index	**0.224*** **	**0.211*** **	**0.541*** **	**0.309*** **
	[0.0156]	[0.0149]	[0.0331]	[0.0284]
Linear Time Trend	**0.00384*** **	**0.00268*** **	**0.00602*** **	**0.00335*** **
	[0.000330]	[0.000316]	[0.000695]	[0.000533]
First Stage Controls:				
Task Levels	No	No	Yes	Yes
All returns vary by industry	No	Yes	No	Yes
Observations	1,021	1,021	1,021	1,021
R-Squared	0.086	0.096	0.4	0.08
Industries	75	75	75	75

Notes: Dependent variable is the industry specific log wage premium accruing to offshorable occupations. Standard errors are reported in the parentheses and are clustered by industry All regressions include industry fixed effects and a linear time trend. *** indicates significance at 1 % level, ** at 5 %, and * at 10 % level.

Table 11: Impact of Transport Costs on Premium for Offshorable Occupations-AA Measure

	Dependent Variable: AA Offshorability Log Wage Premium			
	(i)	(ii)	(iii)	(iv
Hedonic Transport Cost Index	0.154	0.186	0.218	**0.283****
	[0.123]	[0.125]	[0.148]	[0.130]
Linear Time Trend	-0.00258	-0.00266	-0.00407	-0.00224
	[0.00342]	[0.00309]	[0.00388]	[0.00316]
First Stage Controls:				
Task Levels				
All returns vary by industry				
Observations	1,021	1,021	1,021	1,021
R-Squared	0.034	0.055	0.053	0.084
Industries	75	75	75	75

Notes: Dependent variable is the industry specific log wage premium accruing to offshorable occupations. Standard errors are reported in the parentheses. All regressions include industry fixed effects and a linear time trend. *** indicates significance at 1 % level, ** at 5 %, and * at 10 % level.

Table 12: Impact of Transport Costs on Premium for Offshorable Occupations-Ratio Measure

	Dependent Variable: Ratio Offshorability Log Wage Premium			
	(i)	(ii)	(iii)	(iv
Hedonic Transport Cost Index	**0.173*****	**0.146*****	**0.147*****	**0.250*****
	[0.0129]	[0.0114]	[0.0147]	[0.0176]
Linear Time Trend	**-0.000776*****	**-0.000666*****	**-0.0102*****	**-0.00218*****
	[0.000276]	[0.000247]	[0.000274]	[0.000397]
First Stage Controls:				
Task Levels	No	No	Yes	Yes
All returns vary by industry	No	Yes	No	Yes
Observations	1,021	1,021	1,021	1,021
R-Squared	0.446	0.414	0.759	0.52
Industries	75	75	75	75

Notes: Dependent variable is the industry specific log wage premium accruing to offshorable occupations. Standard errors are reported in the parentheses. All regressions include industry fixed effects and a linear time trend. *** indicates significance at 1 % level, ** at 5 %, and * at 10 % level.

Table 13: Impact of Transport Costs with Lagged Dependent Variable-AA Measure

	Dependent Variable: AA Offshorability Wage Premium			
	(i)	(ii)	(iii)	(iv)
Hedonic Transport Cost Index	**-0.125***	**-0.146*****	**-0.507*****	**-0.236*****
	[0.0694]	[0.0466]	[0.203]	[0.0477]
Lagged Wage Premium	**0.238*****	**0.207*****	**0.216*****	**0.209*****
	[0.0305]	[0.0304]	[0.0547]	[0.0312]
Task Levels	No	No	Yes	Yes
All returns vary by industry	No	Yes	No	Yes
Observations	872	872	872	872
Industries	73	73	73	73

Notes: Dependent variable is the industry specific log wage premium accruing to offshoreable occupations. Standard errors are reported in the parentheses and are clustered by industry All regressions include industry fixed effects and a linear time trend. *** indicates significance at 1 % level, ** at 5 %, and * at 10 % level.

Table 14: Impact of Transport Costs with Lagged Dependent Variable-Ratio Measure

	Dependent Variable: Ratio Offshorability Wage Premium			
	(i)	(ii)	(iii)	(iv)
Hedonic Transport Cost Index	**0.207*****	**0.0973*****	**0.598*****	**0.0589*****
	[0.0163]	[0.0171]	[0.0304]	[0.0208]
Lagged Wage Premium	**0.0690****	**0.195*****	**-0.102*****	**0.272*****
	[0.0295]	[0.0282]	[0.0330]	[0.0246]
First Stage Controls:				
Task Levels	No	No	Yes	Yes
All returns vary by industry	No	Yes	No	Yes
Observations	872	872	872	872
Industries	73	73	73	73

Notes: Dependent variable is the industry specific log wage premium accruing to offshoreable occupations. Standard errors are reported in the parentheses and are clustered by industry All regressions include industry fixed effects and a linear time trend. *** indicates significance at 1 % level, ** at 5 %, and * at 10 % level.

Table 15: Impact of Transport Costs and Lagged Transport Costs-AA Measure

	Dependent Variable: AA Offshorability Wage Premium			
	(i)	(ii)	(iii)	(iv)
Hedonic Transport Cost Index	-0.111	**-0.160*** **	**-0.273*****	**-0.192*****
	[0.0810]	[0.0632]	[0.0958]	[0.0649]
Lagged Transport Cost Index	-0.146	0.0395	0.154	0.055
	[0.0902]	[0.0679]	[0.215]	[0.0652]
First Stage Controls:				
Task Levels	No	No	Yes	Yes
All returns vary by industry	No	Yes	No	Yes
Observations	946	946	946	946
R-Squared	0.014	0.013	0.011	0.013
Industries	74	74	74	74

Notes: Dependent variable is the industry specific log wage premium accruing to offshorable occupations. Standard errors are reported in the parentheses and are clustered by industry All regressions include industry fixed effects and a linear time trend. *** indicates significance at 1 % level, ** at 5 %, and * at 10 % level.

Table 16: Impact of Transport Costs and Lagged Transport Costs-RatioMeasure

	Dependent Variable: Ratio Offshorability Wage Premium			
	(i)	(ii)	(iii)	(iv)
Hedonic Transport Cost Index	**0.106*****	0.0156	**0.325*****	0.00366
	[0.0120]	[0.0145]	[0.0218]	[0.0168]
Lagged Transport Cost Index	**0.0521*****	**0.0801*****	0.0406	**0.0806*****
	[0.0156]	[0.0176]	[0.0278]	[0.0234]
First Stage Controls:				
Task Levels	No	No	Yes	Yes
All returns vary by industry	No	Yes	No	Yes
Observations	946	946	946	946
R-Squared	0.014	0.013	0.011	0.013
Industries	74	74	74	74

Notes: Dependent variable is the industry specific log wage premium accruing to offshorable occupations. Standard errors are reported in the parentheses and are clustered by industry All regressions include industry fixed effects and a linear time trend. *** indicates significance at 1 % level, ** at 5 %, and * at 10 % level.

Table 17: IV Estimates Impact of Transport Costs-AA Measure

	Dependent Variable: AA Offshorability Log Wage Premium			
	(i)	(ii)	(iii)	(iv)
Hedonic Transport Cost Index	**-0.357*** **	**-0.324*** **	-0.203	**-0.321*** **
	[0.124]	[0.0963]	[0.302]	[0.0953]
Linear Time Trend	-0.00415	**-0.00344***	0.00248	**-0.00460*** **
	[0.00255]	[0.00182]	[0.00797]	[0.00177]
First Stage Controls:				
Task Levels	No	No	Yes	Yes
All returns vary by industry	No	Yes	No	Yes
Observations	1,020	1,020	1,020	1,020
R-Squared	0.019	0.026	0.01	0.009
Industries	74	74	74	74

Notes: Dependent variable is the industry specific log wage premium accruing to offshorable occupations. Standard errors are reported in the parentheses and are clustered by industry All regressions include industry fixed effects and a linear time trend. *** indicates significance at 1 % level, ** at 5 %, and * at 10 % level.

Table 18: IV Estimates Impact of Transport Costs-Ratio Measure

	Dependent Variable: Ratio Offshorability Log Wage Premium			
	(i)	(ii)	(iii)	(iv)
Hedonic Transport Cost Index	**0.362*** **	**0.231*** **	**0.866*** **	**0.297*** **
	[0.0134]	[0.00848]	[0.0323]	[0.0111]
Linear Time Trend	**0.00790*** **	**0.00679*** **	**0.0185*** **	**0.00649*** **
	[0.000391]	[0.000250]	[0.000937]	[0.000326]
First Stage Controls:				
Task Levels	No	No	Yes	Yes
All returns vary by industry	No	Yes	No	Yes
Observations	1,020	1,020	1,020	1,020
R-Squared	-0.048	0.124	-0.101	-0.022
Industries	74	74	74	74

Notes: Dependent variable is the industry specific log wage premium accruing to offshorable occupations. Standard errors are reported in the parentheses and are clustered by industry All regressions include industry fixed effects and a linear time trend. *** indicates significance at 1 % level, ** at 5 %, and * at 10 % level.