The Tradability of Services: Geographic Concentration and Trade Costs*

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Abstract

In this paper, we use a unique dataset on the distribution of output and demand across regions of the United States to estimate trade costs for 969 service and manufacturing industries. Our estimation method is a natural extension of the gravity model of trade and identifies trade costs in the absence of trade data. The estimated trade costs are higher on average for service industries, but there is considerable variation across industries within sectors. Using the trade cost estimates, we classify industries into tradable and non-tradable categories. We find that accounting for tradable service industries nearly doubles the international exposure of the US economy, tradable services value added is unevenly distributed across geographical regions, labor productivity and wages are higher on average for tradable industries, and potential welfare gains from trade liberalization in the service sector are sizable.

Keywords: Service sector, international trade, trade costs, monopolistic competition.

JEL Classification Numbers: F1.

1 Introduction

In this paper, we use a unique dataset on the distribution of producers and consumers across regions of the United States to estimate the share of economic activity exposed to international competition, a critical input for evaluating the impact of a broad range of domestic and external shocks.[1] To date, empirical studies have focused almost exclusively on the exposure of the manufacturing sector, implicitly assuming that services are not tradable. However, because service trade has grown over time and now accounts for about 20 percent of global international transactions (and 30 percent of US exports), the traditional assumption that goods are tradable and services are non-tradable is increasingly inadequate.[2] Our results suggest that accounting for tradable services nearly doubles the international trade exposure of the American economy.

An important impediment to incorporating service trade into economic models is the lack of information on the scope and characteristics of tradable service industries. Data on international trade in services is far less detailed and comprehensive than that for merchandise trade, so current empirical studies are limited to using bilateral trade data for only a small number of broad service categories (e.g., Anderson et al. (2014); Egger et al. (2012); Francois and Hoekman (2010)).[3] Instead, we use a novel dataset derived from the 2007 Economic Census to present a more comprehensive and detailed picture of service trade. Our empirical analysis demonstrates aggregated data mask important variation within service categories and may provide inaccurate measures of the exposure of regions to international trade.

1. A number of recent studies depend on estimates of the size of the tradable sector. For example, quantifying the labor market impact of offshoring (Liu and Trefler (2008) and Crino (2010)), the effect of local demand shocks on the labor market (Moretti (2010)), the"jobs multiplier" of fiscal stimulus spending (Wilson (2012)), and the link between real exchange rates and sectoral total factor productivity measures (Berka et al. (2014)). As described in Young (2014), assessing the impact of structural transformation on aggregate productivity will require similar estimates.

2. See Francois and Hoekman (2010) for a review of the growing literature on trade in services.

3. As described in Feenstra et al. (2010), the US Census Bureau publishes information on US imports and exports of goods for more than 10,000 product categories, whereas the Bureau of Economic Analysis publishes US services trade data for about 30 categories (up from 17 categories in 2005).

Our dataset collects region-level information on output, demand, and production costs for about one thousand manufacturing and service industries. However, it does not contain information on trade flows between regions. This prevents the implementation of standard estimation procedures, so-called gravity equations, which relate the volume of trade between regions to their economic size and the trade resistance between them. Instead, we develop a method that estimates the effect of trade costs from region-level information on industry output and demand. Our theoretical framework, which is a natural extension of the Anderson and Van Wincoop (2003) gravity model, formalizes the intuition of Jensen and Kletzer (2006) and Jensen (2011) that the disparity between local supply and local demand is an indicator of the extent of trade in an industry. In our model, as trade costs increase, consumers spend an increasing fraction of their income on output produced by local firms, such that regional demand and supply converge. Our estimation method relies on this insight and uses the structure of the theoretical model to infer measures of trade costs from the observed distribution of industry output and demand.

For the estimation, we focus on trade costs associated with distance between producers and consumers. Services can be delivered at a distance through a variety of modes: shipping (e.g., software publishing); movement of producers (e.g., consultants); or movement of consumers (e.g., amusement parks).[4] However, independent of the mode of delivery, service trade implies movement across space such that, as in manufacturing, distance between producers and consumers matters. In addition to trade costs, our theoretical framework features other factors that influence the extent of trade between regions, such as differences in production costs across regions, and differences in product differentiation and returns to scale across industries. Because we control for these differences in our estimation and because our estimates are derived from US data (where interregional policy barriers to trade tend to be low), our empirical measures of trade costs represent fundamental product or service characteristics

4. These methods of delivery are equivalent to the "modes" of service trade defined in the General Agreement on Trade in Services (GATS). In this paper, we define trade as modes 1 , 2, and 4 (shipping, and movement of consumers or producers, respectively) and think of mode 3 (local presence) as analogous to foreign direct investment.

associated with the cost of distance and, as a result, provide useful information on the potential scope for international trade in services.[5]

In our theoretical model, trade flows between regions depend on the “phi-ness” of trade; a function of the trade costs and price elasticity of demand parameters (e.g., Baldwin et al. (2003)). Conditional on trade costs, trade will be lower in high elasticity industries because demand is more sensitive to changes in price. Disentangling trade costs from elasticity of demand is therefore crucial to obtain accurate measures of the impact of distance on trade flows. An important measurement challenge we face is that measures of price elasticity are not readily available for service industries. Using the theoretical model as a guide, we construct measures of elasticity from data on profit margins collected by the Bureau of Economic Analysis. Our estimates take reasonable values. The average elasticity across all industries in our sample is 7.1. For manufacturing industries, the average is 8.1; a value in line with available estimates (e.g., Broda and Weinstein (2006)).

Our estimation method generates plausible values for trade costs. Consistent with the theoretical model, estimated trade costs are lower in industries characterized by large disparities in supply and demand within regions. We further validate our estimates by comparing them to other indices of tradability that have been used in the literature. As expected, our trade costs measures are negatively correlated with industry-level estimates of trade share and average distance shipped derived from the US Census Commodity Flow Survey (e.g., Head and Mayer (2010); and Holmes and Stevens (2012)). In contrast to our estimates, these measures are outcome variables that reflect variation in multiple fundamentals, only one of which is the impact of distance on trade costs. Our estimates are also negatively correlated with an indicator that captures the extent to which the average task in an industry can be offshored (e.g., Amiti and Wei (2005); Crino (2010); Grossman and Rossi-Hansberg (2008); and Jensen and Kletzer (2010)).

5. Similar to goods trade, culture, language, and other measures of “distance” are likely to affect international trade in services. Because we use US data in our estimation, the influence of these factors in our estimates is reduced.

Our empirical results challenge the conventional treatment of services as non-tradable. Our analysis confirms trade costs are higher on average in the service sector, but also reveals that many service industries have estimated trade costs comparable to manufacturing industries where we observe trade. We use our measures of trade costs to classify industries into tradable and non-tradable categories. As expected, a smaller share of service industries are tradable. However, because the service sector is relatively large (accounting for about 65 percent of value added in the United States, compared to about 20 percent for manufacturing), we find that about half of the value added in tradable industries comes from the service sector.

Our analysis highlights systematic variation in industry characteristics across tradable and non-tradable industries. On average, tradable industries have higher wages and labor productivity compared to non-tradable industries. These differences persist even when comparing industries within the same sector. We interpret these patterns as evidence of differences in factor-intensity across industries. Assuming wages and labor productivity reflect unmeasured differences in workers' ability and physical or intangible assets, respectively, our results suggest tradable industries are skill- and capital-intensive compared to non-tradable ones. These results are a first step to understanding how the location of services production might respond to changes in international economic policy for services.

The rest of the paper proceeds as follows. In the next section, we motivate the intuition for our empirical strategy by documenting geographical patterns of production for several industries. In section 3, we develop a theoretical model of trade between regions to obtain an analytical expression that relates trade costs to the share of excess supply, a measure of disparity between local production and demand. In section 4, we present descriptive statistics on the share of excess supply. In section 5, we discuss the empirical implementation of our model and obtain estimated trade costs for 969 service and manufacturing industries. In section 6, we use our estimates to characterize the international trade exposure of the US, examine the regional distribution of tradable services, compare the characteristics of tradable and non-tradable industries, and explore the potential welfare gains from trade liberalization in services. Section 7 concludes.

2 Geographic Concentration

To motivate our empirical approach, we present examples that illustrate the variation across industries in the geographic concentration of production. Figure 1 depicts the distribution of employment across US counties for two manufacturing industries, "Aircraft" and "Ready-mix concrete," and two service industries, "Software publishing" and "Tax preparation." The underlying data comes from the 2007 County Business Patterns (CBP) program.[6] Counties in white report zero employment in the industry, while counties in grey report positive employment.[7]

Figure 1 shows there are important differences across industries in the geographic distribution of employment across regions, even within sector. As seen in panel (a), aircraft production is concentrated in small number of counties; the four counties that contain Seattle, WA, Fort Worth, TX, and Wichita, KS account for almost half of aircraft manufacturing employment in the US.[8] In contrast to the geographic concentration of aircraft production, panel (c) shows employment in the Ready-mix concrete industry is distributed throughout the US. The right hand side of Figure 1 reveals similar patterns in the spatial distribution of production in the service sector. As seen in panel (b), employment in the software publishing industry is concentrated in a small number of counties. Together, the 3 counties that contain Seattle, WA and the Silicon Valley region account for almost a quarter of software employment

6. CBP is publicly available data, so we can provide a more detailed view of the distribution of employment. Census would not allow disclosure of microdata statistics at the county by industry level. See http://www.census.gov/econ/cbp/ for more information on the CBP program.

7. There are over 3,000 counties in the US, so the geographic area of individual counties tends to be small (particularly in the eastern US). We represent county borders in white to help distinguish between producing and non-producing regions; state borders are outlined in black.

8. In CBP data, some counties' employment is suppressed for disclosure avoidance reasons. In these cases, an employment size class is assigned to the county. For the employment share information reported in this section, we take the mid-point of the size class as the county's employment.

in the US. In contrast, panel (d) shows that employment in the tax preparation industry, which includes firms like H & R Block, is ubiquitously distributed throughout the US.

Relative to aircraft, ready-mix concrete is characterized by higher transport-cost-to-value ratios, while tax preparation is more intensive in face-to-face meetings with clients than software publishing. These differences suggest firms in the concrete and tax preparation industries face higher trade costs compared to firms in the aircraft and software industries. When trade costs are high, interregional sales are low and local production more closely matches local demand. The impact of differences in trade costs across industries is apparent in Figure 1. Consistent with high trade costs, concrete production and tax preparation services are widespread. Conversely, the spatial concentration of employment in the aircraft and software industries is far greater than local demand would support, which suggests trade costs are low in those industries. In the next section, we formalize this intuition by developing a model of interregional trade that relates differences in trade costs across industries to differences in the geographic concentration of industry output unexplained by the concentration of demand and other factors.[9]

3 Theoretical Framework

In this section, we extend the Anderson and Van Wincoop (2003) model of trade to include multiple industries and increasing returns in production. In our theoretical framework, products are distinguished by their kind and by their place of production, such that regions can produce a differentiated variety in each of the $s = 1, 2, \ldots, S$ industries. We assume

9. It is important to note that our model estimates trade costs in final output, not inputs, so we consider an industry that uses tradable inputs to produce non-tradable outputs as non-tradable. In particular, suppose that the production of final output requires the combination of non-tradable labor and tradable headquarters services. In headquarter intensive industries characterized by high final-output trade costs, multi-plant firms and interregional investment may emerge (e.g., Gervais (2015)). This is particularly relevant in retail and services industries (e.g., Walmart or Starbucks). Because in many of these industries, provision of final output is local, our model will infer high trade costs independent of the firm's organizational structure and headquarters intensity. In other words, we do not consider local presence (GATS mode 3) as trade, instead we think of it as akin to FDI. While headquarters services are clearly traded, because headquarters establishments (NAICS 551114) do not typically report revenue, we exclude them from our analysis.

production entails both fixed and marginal production costs. The cost function allows us to define (unobservable) prices as a function of (observable) region characteristics. We use our extension of the gravity model to derive an analytical expression that relates region-level production costs and bilateral trade costs to the industry's share of excess supply, an index of the disparity between the distributions of output and demand across regions. In the following sections of the paper, we use this result to develop a novel estimation strategy that identifies trade costs in the absence of trade data.[10]

3.1 Demand

We begin by characterizing the behavior of consumers. The economy consists of J regions each inhabited by a mass of identical consumers. Preferences of the representative consumer in any region $i \in J$ are defined over the consumption of differentiated varieties of goods and services in each industry

$$U_i = \prod_{s=1}^{S} Q_{is}^{\alpha_s}, \text{ with } Q_{is} = \left(\sum_{j=1}^{J} q_{ijs}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}}, \sum_{s=1}^{S} \alpha_s = 1, \text{ and } \alpha_s > 0, \tag{1}$$

where q_{ijs} is the quantity of region-j, industry-s variety consumed in region i, and $\sigma_s > 1$ is the price elasticity of demand in industry s.

The representative consumer maximizes her utility subject to her budget constraint. The consumer's problem can be solved in two steps. First, because the outer tier of preferences are Cobb-Douglas, the optimal expenditure on each industry is given by $E_{is} = \alpha_s E_i$, where E_i is region i's total expenditure. Second, within each industry s, the consumption of varieties is chosen to minimize the cost of the aggregate bundle Q_{is}. Region i's optimal expenditure on

10. In contrast, a series of recent papers use the standard gravity model and bilateral trade data to estimate trade costs for service sectors (e.g., Anderson et al. (2014); Egger et al. (2012); van der Marel and Shepherd (2013); and Gervais (2014)). These studies face the limitation that only highly aggregated bilateral trade data is available.

an industry s variety produced in region j is

$$r_{ijs} = E_{is} \left(\frac{p_{ijs}}{P_{is}} \right)^{1-\sigma_s}, \quad \text{with} \quad P_{is} = \left(\sum_{j=1}^{J} p_{ijs}^{1-\sigma_s} \right)^{\frac{1}{1-\sigma_s}} \tag{2}$$

where p_{ijs} is the price of a unit of differentiated output and P_{is} is the price of a unit of the aggregate bundle Q_{is}, so that $E_{is} = P_{is} Q_{is}$.

3.2 Supply

We now characterize the supply side of the economy. Production entails both fixed and marginal production costs and requires only one input, labor. The total cost function for each region-industry is given by

$$C_{js} = w_j \left(F_s + \frac{1}{z_{js}} \sum_i \tau_{ijs} q_{ijs} \right). \tag{3}$$

Production costs vary across regions and industries because of changes in wage rates and labor requirements. The wage rate w_j is region-specific, reflecting differences across regions in labor costs, whereas labor efficiency z_{js} is region-industry specific, reflecting productivity differences across industries within regions. Output can be traded across regions at some cost. As is customary, we assume these costs take the iceberg form such that when $\tau_{ijs} \geq 1$ units of product s is shipped from region j to region i, only one unit arrives. There are no intra-regional trade costs, i.e., $\tau_{jjs} = 1 \, \forall \, j, s$. The presence of fixed production costs, F_s, implies that each region will produce a unique variety.

We assume there is monopolistic competition in final output markets and that regions are segmented markets. In that case, profit maximization implies the following pricing rule

$$p_{ijs} = \left(\frac{\sigma_s}{\sigma_s - 1} \right) \frac{w_j \tau_{ijs}}{z_{js}}. \tag{4}$$

Equation (4) makes clear that prices are increasing in wages and bilateral trade costs, and decreasing in technical efficiency. The constant elasticity of substitution across varieties implies a constant markup, $\sigma_s/(\sigma_s - 1)$, above marginal costs. This markup depends only on the price elasticity of demand and varies across industries, but not across regions within-industries. When industry output is highly differentiated, the price elasticity of demand is low and markups are high. The variation across industries in profit margins will play a key role in our measurement strategy. Because of fixed production costs, average price may be lower than average cost if the region does not sell enough units.[11] Profit maximizing regions produce if and only if it makes positive profits in that industry, such that our model is consistent with non-producing regions.

3.3 Interregional Trade

We now combine the supply- and demand-side of the economy to characterize trade flows between regions. Substituting the pricing rule (4) into the optimal expenditure (2), we can express interregional sales from region j to i in industry s as

$$r_{ijs} = \left[\frac{(w_j \, \tau_{ijs}/z_{js})^{1-\sigma_s}}{\sum_{l \in J_S} (w_l \, \tau_{ils}/z_{ls})^{1-\sigma_s}} \right] E_{is}, \quad \forall\, j \in J_s, \tag{5}$$

where J_s denotes the set of regions producing output in industry s. Equation (5) is a typical gravity equation. It shows that interregional sales are increasing in destination-region total expenditure (E_{is}) and decreasing in producer-region production costs (w_j/z_{js}), and the trade costs between regions (τ_{ijs}). The term in square brackets shows that region expenditures is allocated across varieties according to their contributions to the price index.

In our data, we do not have information on interregional sales, r_{ijs}. Therefore, we cannot use gravity equation (5) to estimate trade costs, τ_{ijs}. Instead, we derive information on the extent of interregional trade from the excess supply (ES), defined as the region-industry level

11. From equations (3) and (4), the minimum quantity such that regions make positive profits is given by $q_{js}^{min} \equiv \sum_i \tau_{ijs} q_{ijs} = (\sigma_s - 1) F_s z_{js}$.

difference between local supply and local demand. The ES is, in essence, a region-industry level measure of current account. For example, when supply in a region-industry is greater than demand, the ES is positive and the region is a net exporter. In the model, revenue in each region-industry is obtained by taking the sum across all destinations of interregional sales, defined in (5). Because there are no fixed trade costs, regions will sell their output in all regions such that

$$ES_{js} \equiv R_{js} - E_{js} = \begin{cases} \sum_i \dfrac{\left(w_j\, \tau_{ijs}/z_{js}\right)^{1-\sigma_s} E_{is}}{\sum_{l \in J_S} \left(w_l\, \tau_{ils}/z_{ls}\right)^{1-\sigma_s}} - E_{js}, & \text{if } j \in J_s, \\ -E_{js}, & \text{otherwise.} \end{cases} \tag{6}$$

Equation (6) shows that, all else equal, low-cost regions that face low barriers to trade will generate greater revenue and have larger excess supply. It also makes clear the variation we exploit to identify the trade cost parameters. On the one hand, when trade costs are null (i.e., $\tau_{ijs} = 1$), firms face the same aggregate demand independent of their location such that production is distributed across regions in proportion to production costs only (i.e., $ES_{js} \neq 0$). On the other hand, production will equal consumption in each region when trade costs are prohibitive (i.e., $ES_{js} = 0$).

Equation (6) makes clear that because the ES is a function of the region-level expenditures, it is positively correlated with industry size. To obtain measures that are comparable across industries, we define the share of excess supply (SES) for each industry s as follows

$$SES_s = \frac{\sum_j \left|ES_{js}\right|}{2R_s}, \tag{7}$$

where $R_s = \sum_j R_{js}$ denotes total revenue in the industry. We use the absolute value because, by construction, the sum across regions of E_{js} is equal to zero. The SES_s ranges between 0 and 1. A high SES_s signals that some regions produce a significantly higher share of the industry's output, and others significantly lower, than is consumed in the region. For example, when $SES_s = 0$ production equals consumption in all regions, and when $SES_s = 1$

production is located in a subset of regions disjoint from the set of regions where consumption takes place. Because there is intra-industry trade in our model, the SES_s provides a lower bound estimate for the share of interregional sales in the industry.

Together, equations (6) and (7) provide a theoretical expression for the SES and play a central role in the empirical analysis below. Equation (6) shows that the SES depends on the distributions of supply, demand, production costs, and trade costs across regions.[12] As explained in detail in the following sections, it is possible to use information on revenue, expenditure, wages, and labor productivity to infer measures of trade costs from these equations, i.e., without bilateral trade data. We note that while our model accounts for a large number of factors that affect the extent of trade between regions, it remains tractable and provides a flexible framework to evaluate the impact of trade costs on interregional trade.

4 Share of Excess Supply

In this section, we provide information on the SES_s defined in equation (7); the key statistics of the data we use to estimate industry-level measures of trade costs. We begin with a discussion of the dataset we use for our empirical analysis. We then explain how we measure the two components of the SES, region-industry revenue and expenditure. Finally, we present descriptive statistics for SES_s, defined in (7).

For the empirical analysis, we use data from the US Census Bureau's 2007 Economic Census. The Economic Census collects information on revenue, payroll, employment, location and principal industry for almost all establishments located in the US. We use this information to construct a region-industry level dataset. We define an industry as a six-digit North American Industrial Classification System (NAICS) category, the most disaggregated level available. We partition the US into regions using the Bureau of Economic Analysis' Economic Areas

12. Fixed production costs do not appear directly in those equations, but the effect of changes in fixed production costs are captured indirectly through variation in the number of regions that produce output (i.e., differences in J_s across industries). All else equal, high fixed costs industries will be characterized by a smaller number of producing regions.

(EA) as our unit of geography. As described in Johnson and Kort (2004), EA group together cities and adjacent counties based on commuting patterns and other indicators of interaction. In contrast with other available measures of geography, such as state, county, or zip code, EAs are consistent with the notion of a "geographic market." The 183 EAs are mutually exclusive and exhaustive of the land area of the United States. The Data Appendix at the end of the paper provides more details on the Economic Census and the construction of our sample.

Following our model, we measure region-industry revenue, R_{js}, using information on total sales in industry s reported by producers located in region j. As described in the Data Appendix at the end of the paper, we adjust our measures of revenue to account for international transactions. To construct region-industry expenditure, E_{is}, we use information from the Bureau of Economic Analysis' 2007 Input-Output Use table to identify how demand for industry s's output is distributed across consuming industries, investment, government, and final demand. We combine the input-output information with data on the location of demand from the Economic Census and the American Community Survey (for final demand and industries not in scope for the Economic Census). As explained in the Data Appendix, we adjust the demand measures to account for imports using information from Bureau of Economic Analysis' supplemental import matrix.

Using our industry-region measures of expenditure and revenue, we compute SES_s as defined in equation (7) for each of the 969 service and manufacturing industries in our sample. Table 1 lists the most and least concentrated manufacturing and service industries as measured by SES_s. Recall that a high SES indicates that production is concentrated in some regions beyond what can be explained by the concentration of demand in those regions. The results reported in Table 1 show there is considerable variation in the measured SES_s across industries. The highest SES_s measure is 0.94 for Sheer Hosiery Mills and the lowest SES_s measure is 0.06 for Offices of Dentists.

[TABLE 1: HERE]

As reported in Table 1, there is substantial variation in measured SES_s within the manufacturing sector. Manufacturing industries characterized by high transport-cost-to-value ratios, such as ready-mix concrete and quick printing, have low estimated SES_s measures. Conversely, manufacturing industries with lower transport-cost-to-value ratios such as Tobacco, Sugar, and Batteries all have high SES_s measures. Consistent with the model, these results suggest the SES_s reflects variation in trade costs across industries. Table 1 also show considerable variation in estimated SES_s across service industries. Geophysical Surveying and Mapping Services, Electronic Auctions, and Credit Card Issuing, all have SES_s measures of about 0.80, while Office Supply Stores, Supermarkets, Restaurants and Dentists all have SES_s measures below 0.10. While measures of SES_s for service industries are not quite as high as in manufacturing, there is still a considerable amount of services consumed outside the region where they are produced. For instance, by definition of the SES_s, (at least) 80 percent of revenue in the electronic auction industry is generated from interregional sales.

To provide a more comprehensive description of the SES_s measures, we presents the mean and standard deviation across all industries and by broad industry groups in Table 2. The simple average of SES_s across all industries implies that (at least) 45 percent of revenue in the average industry is associated with transactions in which the buyer and the seller are located in different geographical regions. The standard deviation across industries is large at 0.21 and indicates substantial variation in measured SES_s. The results also show that manufacturing industries are the most concentrated on average, with an SES_s of 0.59, retail industries are the least concentrated, with an SES_s of 0.21. Within services, the broad industry groups Transportation, Information, and Finance and Insurance group all have relatively high average SES_s of about 0.45.

[TABLE 2: HERE]

The results reported in Table 2 reveal considerable variation in estimated SES_s across industries within broad groups. For instance, the mean and standard deviation across

Information industries are 0.45 and 0.17, respectively. By comparison, the mean and standard deviation across all industries in the sample are 0.45 and 0.21, respectively. This implies there is as much variation across industries within the Information group as across all industries in the sample. Therefore, classifying all industries within a broad group as either tradable or non-tradable is equivalent to assuming that all industries in our sample are either tradable or non-tradable.

5 Estimating Trade Costs

In this section, we use our theoretical model and data to obtain industry-level estimates of trade costs from our measures of SES_s. We first describe the empirical implementation of the model. We then discuss measurement issues we face and how we address them. Finally, we present the estimation results and compare our estimates with alternative measures of tradability that have been used in the literature. In section 6, we use our estimates of trade costs to evaluate the scope for trade in services.

5.1 Empirical Approach

Taking the sum across regions of interregional sales defined in equation (5), we can express region-industry revenue as

$$R_{js} = \sum_{i=1}^{J} \frac{\lambda_{js}\phi_{ijs}E_{is}}{\sum_{l \in J_s} \lambda_{ls}\phi_{ils}} \quad \text{with} \quad \lambda_{js} = \left(\frac{w_j}{z_{js}}\right)^{1-\sigma_s}, \text{ and } \phi_{ijs} = \tau_{ijs}^{1-\sigma_s}. \tag{8}$$

This equation shows that region-industry revenue depends (only) on the distributions of industry expenditure across regions, and two sets of parameters.[13] The first parameter, λ_{js}, is a function of production costs. The second parameter, ϕ_{ijs}, is known as the "phi-ness" of trade

13. We do not have information on international trade in services at the region-industry level. Therefore, as in Hottman et al. (2014), we ignore foreign varieties in the construction of the region-industry multilateral resistance terms (i.e., the price indices). However, as explained in the Appendix, we correct our region-industry measures of supply and demand to account for international trade.

and captures the impact of trade costs on revenue (e.g. Baldwin et al. (2003)). Substituting (8) into the share of excess supply (7) yields

$$SES(\boldsymbol{\lambda}_s, \boldsymbol{\phi}_s, \boldsymbol{E}_s, R_s) = \frac{\sum_j \left| R_{js}(\boldsymbol{\lambda}_s, \boldsymbol{\phi}_s, \boldsymbol{E}_s) - E_{js} \right|}{2R_s}, \tag{9}$$

where $\boldsymbol{\lambda}_s$, $\boldsymbol{\phi}_s$, and $\boldsymbol{E}_s$ denote $J \times 1$ vectors. Using our data, we can construct measures of revenue, expenditure, and obtain controls for the vector of λ_{js}. Therefore, for any given vector of trade costs, $\boldsymbol{\phi}_s$, we can use equation (9) to obtain a "simulated" SES.

In our data, we have only 183 observations for each industry (one per region). Therefore, we cannot identify the bilateral trade cost parameters, ϕ_{ijs}, without making additional assumptions. Trade in services implies movement across space of either the output (e.g., software publishing), producers (e.g., consultants), or consumers (e.g., amusement parks), so that, as in manufacturing, geography is an important determinant of trade costs. Therefore, we follow the gravity equation literature and assume bilateral trade costs are proportional to distance between regions. We assume that trade costs are related to distance as follows

$$\phi_{ijs} = \begin{cases} (1 + t_s d_{ij})^{1-\sigma_s} & \text{if } i \neq j, \\ 1, & \text{otherwise.} \end{cases} \tag{10}$$

where d_{ij} is a measure of distance between the largest counties of each EA. Using the $J \times J$ matrix of bilateral distance $\boldsymbol{D}$ and information on measures of elasticity, we can construct the vector $\boldsymbol{\phi}_s(t_s, \sigma_s, \boldsymbol{D})$ using equation (10) for any given value of the trade cost parameter t_s.[14]

Because policy restrictions to trade between regions within the US are relatively small, we ignore border effects and focus on distance between producers and consumers as the main impediment to trade between regions. We interpret our estimates as technological properties of the good or service that makes it more or less sensitive to distance between consumer and

14. The parameters t_s is a constant which transforms units of distance into ad valorem trade barriers. While our estimates are not invariant to the units in which distance is measured, they are comparable across industries.

producer. For instance, industries where most of the services can be digitized and sent over the internet (e.g., software publishing) will not be affected by distance whereas industries that require face-to-face interaction will (e.g., barbershops). By definition, our trade cost estimates provide information on the likelihood of international trade in each industry. If distance matters, international trade is less likely, even if policy barriers are trivial.

Combining (9) and (10) implies the SES_s depends on data and one parameter, t_s. Our estimation strategy is to calibrate our model by choosing the value of t_s which minimizes the difference between the simulated and the measured SES. In other words, we define

$$\widehat{t_s} \equiv \underset{t_s}{\operatorname{argmin}}\, \mu(t_s) = \left(SES(t_s|\boldsymbol{\lambda}_s, \sigma_s, \boldsymbol{D}, \boldsymbol{E}_s, R_s) - SES_s\right)^2, \tag{11}$$

where SES_s denotes the share of excess supply measured from the data. In the estimation, we take the distribution of demand and expenditure across regions as exogenous and simply ask which value of the trade cost parameter is consistent with these observed distributions.

5.2 Measurement

Before we present the estimation results, we discuss two additional measurement issues we face. Estimating equation (11) requires data on revenue, expenditure, and production costs for each region-industry, as well as information on the elasticity of substitution for each industry. We use the same measures of revenue, R, and expenditure, E, as in section 3 above, so we only discuss the construction of the elasticity of demand, σ_s, and the production cost parameters, λ_{js}. Additional details on the construction of these variables are provided in the Data Appendix.

5.2.1 Elasticity of Demand

Industry-level measures of the elasticity of demand are not readily available for the service sector, so we need to construct our own. We use a relationship identified in the theoretical model to construct σ_s for each industry. From the pricing rule (2) and the optimal demand (4), it follows that

$$\widehat{\sigma}_s = \frac{R_s}{G_s}, \tag{12}$$

where $G_s \equiv (1/\sigma_s)\left(\sum_i \sum_{j \in J_s} r_{ijs} - F_s\right)$ denotes gross operating surplus in the industry. Equation (12) shows that the price elasticity of demand is equal to the inverse of an industry-level measure of gross profit margins.

We estimate the elasticity of demand using equation (12) and information on value added and gross operating surplus from the Bureau of Economic Analysis' Gross-Domestic-Product-by-Industry data. Our estimates take reasonable values. The average elasticity for manufacturing industries is 8.1. Using trade data, Broda and Weinstein (2006) obtain averages across manufacturing industries of 4.0 or 17.3 depending on the period and level of aggregation. An advantage of our approach and data set is that we can obtain estimates for the elasticity of demand using the same methodology and data for manufacturing and service industries. The average elasticity for services is 6.2. The lower elasticity indicates services are less differentiated on average compared to manufacturing goods.

5.2.2 Production Costs

To construct the region-industry measures of production costs, λ_{js}, we need information on wages and technical efficiency. We measure the wage rate by dividing total payroll by total employment in each region. The data does not contain information on physical output and, for many industries, the only input on which we have information is labor. As a result, we cannot compute measures of technical efficiency such as physical total factor productivity or quantity produced per worker, or even value added per worker. Therefore, we measure region-industry's technical efficiency using labor productivity defined as sales per worker. Our estimate of λ_{js} is defined as follows

$$\widehat{\lambda}_{js} = \frac{\text{Sales}_{js}/\ \text{Workers}_{js}}{\text{Payroll}_j/\ \text{Workers}_j}. \tag{13}$$

The Data Appendix at the end of the paper provides more information on the construction of this measure.

As shown in the Data Appendix, the ratio of output per worker to wages for region j industry s in our theoretical model is given by

$$\widehat{\lambda}_{js} \equiv \frac{r_{js}/l_{js}}{w_j} = \left(\frac{\sigma_s}{\sigma_s - 1}\right)\left[1 - \frac{1}{1 + \left(\frac{\sigma_s - 1}{\sigma_s}\right)^{\sigma_s}\left(\frac{w_j A_{js}}{F_s}\right)\lambda_{js}}\right], \tag{14}$$

where $A_{js} = \sum_i E_{is} P_{is}^{\sigma_s - 1} \tau_{ins}^{1-\sigma_s}$ is the region-industry market access term. This expression makes clear that our proxy is positively correlated to the model parameter λ_{js}. As in Foster et al. (2008), equation (14) shows that our revenue-based cost measure $\widehat{\lambda}_{js}$ is positively correlated with region-industry technical efficiency, but also reflects differences in demand (A_{js}). In addition, in our model differences in fixed production costs and elasticity of demand across industries lead to variation in estimated production costs. Because we implement our estimation procedure separately for each industry, these differences will not drive any of the results.

5.3 Results

In this section, we present the calibration results for our model. For each industry, we find the value for the trade cost parameter t_s consistent with our measure SES_s. Because the relationship between the excess supply and trade costs is non-linear, we use numerical methods to search over values of $t_s > 0$. For each guess $\tilde{t}_s$, we use our data on expenditure ($\boldsymbol{E_s}$) and distance ($\boldsymbol{D}$), and our measures of price elasticity of demand ($\widehat{\sigma}$) and production costs ($\widehat{\lambda}_{js}$) to construct the simulated $SES(\tilde{t}_s)$ defined in (9). As shown in equation (11), we define our estimated trade costs, $\widehat{t}_s$, as the parameter that minimizes the distance between the simulated and actual SES.

We report the estimation results in Table 3. Overall, our model performs well.[15] As indicated in the table, the objective function $\mu\left(\widehat{t}_s\right)$, defined as the square of the difference between actual and simulated share of excess supply, is close to zero on average. As seen in the table, the manufacturing sector has the lowest average estimated trade costs while retail trade has the highest. The empirical results also show there is considerable variation within sectors in the estimated trade costs. In all cases, the standard deviation in estimated trade costs across industries within broad industry groups is large relative to the average.

[TABLE 3: HERE]

Figure 2 provides a detailed view of the within industry group dispersion in estimated trade costs. Each panel plots our estimates, $\widehat{t}_s$, against the share of excess supply for one of twelve groups. Each dot represents a six-digits NAICS industry. Panel (a) shows manufacturing industries have relatively low trade costs compared to services industries represented in the other panels. Comparing across panels reveals the substantial variation in estimated trade costs across industries within each sector and the considerable overlap between the estimated trade costs of manufacturing and service industries. As expected, there is a negative correlation between estimated trade costs and SES_s. Across all industries, the correlation is equal to -0.61. Figure 2 makes clear the negative correlation between estimated trade costs and SES is very robust. It holds within each major industry group and is not due to the influence of a few individual industries.[16]

[FIGURE 2: HERE]

15. For 60 industries, our estimates of trade costs do not conform with our priors. These industries typically have an SES above 0.5 and an estimated trade cost above 5. Rather than exclude these outliers from the analysis, we impute a value for $\widehat{t}_s$ to these industries using the simple empirical relationship between SES_s, σ_s, and $\widehat{t}_s$ observed in other industries. Most outliers are in the manufacturing sector (54 of 60), so our imputation reduces the average trade cost in manufacturing (which works against finding tradable services in our analysis below). Our results are robust to excluding these industries, which together account for only about 1.6 percent of value added.

16. We note that we restricted $t_s \in [0, 25]$ for the estimation. While many industries in the Real estate broad industry group attain that upper bound, this restriction has no impact on the empirical analysis we present below.

5.4 Validation

To further confirm our trade cost measures capture useful variation in trade costs across industries, we compute correlations between our estimates and several measures that are used as proxies for international trade intensity. Our first measure is an industry-level estimate of trade share derived from Bureau of Economic Analysis' input-output tables. Our second measure uses information from the Commodity Flow Survey (CFS) to estimate the average distance shipped for each industry (e.g., Head and Mayer (2010); Holmes and Stevens (2012); and Yilmazkuday (2012)). Our third measure is an indicator derived from occupation characteristics that captures the extent to which the average task in an industry can be offshored (e.g., Amiti and Wei (2005); Crino (2010); Grossman and Rossi-Hansberg (2008); and Jensen and Kletzer (2010)). Additional information on these measures is available in the Data Appendix.

We report the correlations between the trade indices and our estimated trade costs in Table 4. In all cases, the correlation is negative as expected; Industries with higher estimated trade costs are observed to have lower trade barriers. At the same time, the magnitude of the estimated correlations imply there are important differences between those measures. Our estimates have several advantages over the other indices. First, the BEA trade share and the CFS average distance shipped measures have similar limitations to using SES_s as a proxy for trade costs. Each is an outcome variable that reflects variation in multiple fundamentals, one of which is the impact of distance on trade costs. Second, because the CFS collects information on output shipments, the vast majority of service industries are out of scope. Therefore, the CFS index cannot be used to construct measures of trade costs for service industries. Third, the occupation-based measure captures the extent to which tasks can be traded or not, not the impact of distance on interregional sales.[17] For these reasons,

17. In addition, tradability indices that use occupation characteristics to determine tradability often focus on whether the worker in the occupation needs to be physically present with co-workers to do their job. This results in many production jobs (and as a result many manufacturing industries) being classified as "non-tradable."

we believe our estimated trade costs have advantages over these other measures to address questions related to the exposure of the economy to international shocks.

[TABLE 4 HERE]

6 Tradable Services

In this section, we explore the empirical implications of our trade cost estimates. First, we compute the share of service production in the US that could be traded internationally and examine the geographic distribution of trade exposure. We then compare average wages and labor productivity in tradable and non-tradable industries. Last, we use the model to quantify the potential welfare gains from trade liberalization in the service sector.

6.1 Value Added

To identify how much economic activity is in tradable service industries, we classify industries as "tradable" or "non-tradable" based on a threshold trade cost. Because we have priors on the tradability of output in the manufacturing sector, we use our trade cost estimates for manufacturing industries to define this threshold. For each $y \in [0, 100]$, we find the threshold trade cost t_y that results in y percent of manufacturing sector value added being classified as tradable.[18] We use our thresholds (t_y) to group services industries into tradable and non-tradable categories (i.e., $\widehat{t}_s > t_y$).

Table 5 presents the distribution of value added across broad industry groups and tradability assuming that 75 percent of manufacturing value added is in tradable industries (i.e., using t_{75} as our threshold). While the average service industry has higher trade costs

18. To determine these thresholds, we proceed as follow. First, we order manufacturing industries from lowest to highest estimated trade costs and compute the share of manufacturing employment for each industry. Let $a = 1, 2, ..., A$ denote the rank of manufacturing industries with 1 indicating the lowest trade costs industry and A the highest and b_a industry a's share of manufacturing employment. Second, for each $k \leq A$, we sum employment shares across industries to obtain $B_k = \sum_{a=1}^{k} b_a$. Third, we define t_y as the trade cost of industry k, where k is the lowest value such that $B_k \geq y$.

than the average manufacturing industry, because the service sector is larger than the manufacturing sector, there is significant value added in tradable service industries. We find that about 20 percent of aggregate value added is produced in industries classified as tradable and that the service sector accounts for almost half of tradable value added. These results imply that accounting for services almost doubles the estimated size of the tradable sector in the US and calls into question the common assumption that services are not tradable.

[TABLE 5 HERE]

The results in Table 3 and Table 5 highlight the advantage of using detailed, industry level data to estimate trade costs for the service sector. Currently available international trade data for the service sector is highly aggregated, nearly as aggregated as the 11 service industry categories reported in Table 3. So, any estimate of trade costs derived from international trade data would aggregate a range of industries with different trade costs. If we compare the average trade cost for the sectors reported in Table 3 to the 75 percent threshold, $t_{75} = 1.45$, no service sector would be classified as tradable, biasing downward the estimate of the trade exposure of the US economy. These results suggest that highly aggregated data hides important variation in the tradability of service activities.

The results in Table 5 are based on the hypothesis that 75 percent of manufacturing employment is in tradable industries. To evaluate the sensitivity of this result to changes in the threshold, we compute t_y for each $y \in \{5, 10, ..., 95\}$ and reclassify industries according to each threshold. Figure 3 shows the share of total value added in industries classified as tradable separately for manufacturing and services. By construction, the share of tradable manufacturing sector value added is a 45 degree line. Two important findings emerge from Figure 3. First, the share of value added in tradable industries is evenly distributed across manufacturing and services for tradability thresholds, $t_y < 0.8$. Second, for $t_y > 0.8$ the value added in tradable services is larger than in manufacturing. Therefore, the finding that accounting for services doubles the estimated size of the tradable sector is robust to our choice of threshold and, for reasonable assumptions regarding the tradability of manufacturing industries, services account for a larger share of tradable industry value-added.

[FIGURE 3 HERE]

6.2 Geographic Distribution of Trade Exposure

The results in the previous section suggest that the trade exposure of the US economy is significantly higher due to tradable services. However, because of geographical concentration in production of tradable services (e.g., securities and commodities trading, motion pictures, computer systems design and support industries, or casinos), it may be the case that not all regions are affected equally. In this section, we present information on the geographical distribution of tradable service industries to explore how services trade liberalization may impact regions differently.

[FIGURE 4 HERE]

Figure 4 reports the share of value added in tradable service industries for each EAs. As seen in the figure, every EA produces some tradable services, but the relative importance of these industries vary significantly across regions. EAs in black, (e.g., Austin, Las Vegas, New York, San Francisco, and Washington) all have more than 15 percent of region value added in tradable service industries, while EAs in dark grey (e.g., Boston, Chicago, Denver, and Los Angeles) all have more than 10 percent of region value added in tradable service industries. Most of these regions have relatively small manufacturing sectors, so tradable services represent a significant increase in these regions' trade exposure. In contrast, many other EAs have less than 5 percent of region value added in tradable services.

Figure 4 shows that the uneven concentration of production of tradable service industries implies the international trade exposure of regions varies significantly and highlights an advantage of using disaggregated data to estimate trade costs. For example, this distinction could also be important when comparing the trade exposure of different countries.

6.3 Characteristics of Tradable Industries

We use our estimated trade costs to compare tradable and non-tradable industry characteristics. In our model, production requires only one input, labor. In the data, variation in average wages across industries may reflect changes in the skill composition of the labor force. At the same time, measures of labor productivity will capture variation in unmeasured input across industries (e.g., capital intensity, possibly either physical or knowledge). We compare the characteristics of tradable and non-tradable industries using OLS regressions of the form

$$lnY_s = \beta_0 + \beta_t \, \mathrm{ID}_{75} + \mu_s \tag{15}$$

where Y_s denotes, in turn, log co-worker average wage and log labor productivity and ID_{75} is an indicator variable equal to 1 if the industry is classified as tradable (i.e. if $\widehat{t_s} < t_{75}$), and 0 otherwise. We report the results in panel A of Table 6. The estimation results shows there are important differences between tradable and non-tradable industries. On average, workers in tradable industries are about 30 percent more productive and receive 30 percent higher wages compared to workers in non-tradable industries.

[TABLE 6]

The estimated differences between tradable and non-tradable industry characteristics could be driven by the sectoral composition of each group. For instance, we know from previous results that a larger share of manufacturing industries are classified as tradable. To account for this possibility, we replace the constant β_0 in equation (15) with a set broad industry group dummies. We present the results in panel B of Table 6. The point estimates are smaller but the systematic differences between tradable and non-tradable remain even within broad industry groups. Tradable industries have 16 percent higher labor productivity compared to non-tradable industries in the same group, and 24 percent higher average wages. In panel C, we re-estimate the regressions restricting the sample to services industries only.

The results show that workers' wages and productivity in tradable services industries are almost 30 percent higher than in non-tradable industries

Overall, the results reported in Table 6 suggest there are significant differences between tradable and non-tradable industries even within the same sector. We interpret the average wage differences as suggestive evidence that tradable industries use more skill-intensive technologies compared to non-tradable industries, and the labor productivity differences as suggestive evidence that tradable industries are more intensive in other inputs like physical capital or intellectual property capital. These results suggest that simplifying assumptions regarding the tradability of sectors or groups of industries based on highly aggregated data hide important variation in tradability, average wages, and labor productivity that may mask differential factor demands.

6.4 Potential Gains from Trade

Last, we consider the potential welfare gains from trade liberalization in the service sector. For simplicity, we assume that changes in trade costs have no general equilibrium impact on wages, and focus on the first order impact on prices.[19] From equations (2) and (4), the price index is:

$$P_{is} = \left[\sum_{j \in J_s} \left(\frac{w_j \tau_{ijs}}{z_{ijs}} \right)^{1-\sigma_s} \right]^{\frac{1}{1-\sigma_s}} \tag{16}$$

Therefore, a symmetric change in trade costs of the form $\tau^1_{ijs} = \delta \tau^0_{ijs}$ for some $\delta > 0$, leads to an equivalent change in the price index, $P^1_{is} = \delta P^0_{is}$. From equation (1), log welfare is defined as the weighted sum of the log price indices, where the weights are given by the share of expenditure in each industry. Then, if Ω_y represents the set of industries that are tradable

19. This would be the case if we included a homogenous good produced under constant returns to scale and traded at no cost in our model. Changes in wages across regions would then reflect variation in worker productivity in the homogenous good industry and variation in trade costs in the differentiated sector would have no impact on equilibrium wages.

(i.e. $t_s < t_y$), a symmetric change in trade costs leads to the following change in welfare

$$\%\Delta W = ln\ \delta \cdot \sum_{s \in \Omega_y} \alpha_s. \tag{17}$$

The model shows that the gains from trade are equal to the product of the percentage change in trade costs and the share of demand affected by the change in trade costs.

Table 7 presents the distribution of welfare gains associated with a symmetric liberalization assuming the threshold for tradability is τ_{75}. As expected, given the share of value added in tradable service industries, the potential welfare gains in the service sector are of a similar magnitude to welfare gains in the manufacturing sector. This simple exercise shows that, for similar reductions in trade barriers, gains from liberalization in services trade are of the same order of magnitude as the gains in manufacturing. However, existing evidence suggests that policy restrictions in the service sector are significantly higher than in manufacturing. (e.g. Hufbauer et al. (2010)). Therefore, welfare gains from trade liberalization in the service sector could potentially be much larger than those in manufacturing.

[TABLE 7 HERE]

7 Conclusion

Because of data limitations, current empirical studies of international trade in services are limited to a small number of relatively aggregated service categories. In this paper, we develop an estimation methodology that exploits information on the spatial distribution of producers and consumers across US regions to obtain measures of trade costs for almost one thousand manufacturing and service industries. Overall, our empirical results suggest that aggregating industries into broad sectors and characterizing these sectors as either tradable or non-tradable hides important differences across industries within sectors in trade costs and industry characteristics.

Estimated trade costs are higher on average in the service sector than in manufacturing, but many service industries have estimated trade costs comparable to manufacturing industries. Using our measures, we classify industries into tradable and non-tradable categories and find that accounting for tradable services almost doubles the international trade exposure of the US economy. This suggests that potential welfare gains from trade liberalization in the service sector are large. We also find that tradable industries have higher average wages and labor productivity, differences that persist even when we compare industries within the same sector. We interpret these differences as evidence of differential factor demands in tradable and non-tradable industries.

Our results have caveats. First, we abstract from non-homotheticity. It is well-known that services share of expenditure is increasing in income per capita. While variation across regions of the US may not be as large as across countries, and final demand is only a fraction of total demand in each industry, it is possible that non-homotheticity plays a role in explaining production patterns. Second, our model does not include firm heterogeneity and selection into exporting, both of which feature prominently in recent trade literature (e.g., Melitz (2003) and Bernard et al. (2003)).[20] Third, our theoretical framework ignores the location decision of firms, which prevents us from doing counterfactual analysis. These are important topics for future research.

However, because our approach is easy to implement and requires only information on the geographic distribution of production, it is potentially widely applicable. For instance, Europe, where data is increasingly collected on a consistent basis across national borders, could provide a rich empirical context to apply this framework. Comparing our estimates, derived from US data where interregional barriers to trade are relatively low, with estimates from European data could provide useful insight into trade barriers to services within Europe. Our procedure is flexible and could be used to estimate the impact of national borders and policy

20. There is a growing literature using firm-level micro data to analyze service firms that trade with findings similar to studies of manufacturing firms (e.g. Bernard and Jensen (1999)). See for example Jensen (2011) for the US, Breinlich and Criscuolo (2011) for the UK, Ariu et al. (2012) for Belgium, Guillaume et al. (2011) for the EU, and Kelle et al. (2013) for Germany.

impediments on trade in services in other contexts as well. More generally, distinguishing between tradable and non-tradable activities at a detailed industry level is likely to improve empirical estimates of the impact of a broad range of economic shocks, from the gains to trade liberalization to the labor market effects of offshoring to accurately appraising the empirical impact of fiscal policy or other domestic shocks.

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TABLE 1

MOST AND LEAST CONCENTRATED MANUFACTURING AND SERVICES INDUSTRIES

NAICS	Sector	Industry description	SES
Panel A: Most concentrated industries			
315111	Manufacturing	Sheer Hosiery Mills	0.94
312210	Manufacturing	Tobacco Stemming and Redrying	0.93
311311	Manufacturing	Sugarcane Mills	0.92
335912	Manufacturing	Primary Battery Manufacturing	0.91
325182	Manufacturing	Carbon Black Manufacturing	0.91
541360	Services	Geophysical Surveying and Mapping Services	0.82
483211	Services	Inland Water Freight Transportation	0.82
454112	Services	Electronic Auctions	0.82
487990	Services	Scenic and Sightseeing Transportation, Other	0.80
522210	Services	Credit Card Issuing	0.78
Panel B: Least concentrated industries			
322211	Manufacturing	Corrugated and Solid Fiber Box Manufacturing	0.22
327390	Manufacturing	Other Concrete Product Manufacturing	0.22
332710	Manufacturing	Machine Shops	0.22
323114	Manufacturing	Quick Printing	0.19
327320	Manufacturing	Ready-Mix Concrete Manufacturing	0.15
453210	Services	Office Supplies and Stationery Stores	0.07
445110	Services	Supermarkets and Other Grocery Stores	0.07
443112	Services	Radio, Television, and Other Electronics Stores	0.07
722110	Services	Full-Service Restaurants	0.06
621210	Services	Offices of Dentists	0.06

Notes: This table presents the six-digit NAICS code, sector, description and measured share of excess supply (SES_s defined in equation (7)) for the top 5 most concentrated and least concentrated manufacturing and services industries. The SES ranges from 0 (production equal consumption in all regions) to 1 (production is located in a subset of regions disjoint from the set of regions where consumption takes place).

TABLE 2

Summary data of share of excess supply

NAICS	Sector description	Share of excess supply		Number of
		Mean	S.D.	Industries
31-33	Manufacturing	0.59	0.16	463
42	Wholesale trade	0.39	0.13	71
44-45	Retail trade	0.21	0.14	72
48-49	Transportation	0.45	0.19	48
51	Information	0.43	0.17	30
52	Finance and insurance	0.44	0.19	33
53	Real Estate and leasing	0.29	0.15	24
54	Professional services	0.32	0.14	47
56	Administrative services	0.28	0.12	43
61-62	Education and health care	0.23	0.12	53
71-72	Recreation and Food Service	0.35	0.18	40
81	Other personal services	0.25	0.11	45
	Overall	0.45	0.21	969

Notes: For each broad industry group, the table presents the mean and standard deviation across six-digits NAICS industries for the share of excess supply (the measure of disparity between local output and expenditure defined in equation (7)), and the number of six-digits NAICS industry.

TABLE 3

Summary statistics for estimated trade costs

NAICS	Description	$\widehat{t}_s$	$\mu\left(\widehat{t}_s\right)$
31-33	Manufacturing	0.769	0.010
		(1.533)	(0.020)
42	Wholesale trade	3.041	0.002
		(2.516)	(0.006)
44-45	Retail trade	6.020	0.001
		(2.836)	(0.005)
48-49	Transportation	3.224	0.002
		(3.087)	(0.006)
51	Information	7.774	0.005
		(10.200)	(0.009)
52	Finance and insurance	5.669	0.003
		(6.881)	(0.010)
53	Real Estate and leasing	22.050	0.049
		(7.982)	(0.032)
54	Professional services	4.887	0.001
		(3.392)	(0.006)
56	Administrative services	4.657	0.000
		(2.309)	(0.000)
61-62	Education and health care	3.058	0.000
		(2.224)	(0.000)
71-72	Recreation and food services	3.727	0.000
		(2.360)	(0.002)
81	Other Personal Services	4.830	0.000
		(2.488)	(0.001)
	Overall	3.166	0.006
		(4.881)	(0.017)

Notes: This table presents results from estimating trade costs separately for each of the 969 six-digits NAICS industries in our sample. For each broad industry group, the table presents the mean and standard deviation across industries for the estimated trade costs and objective function, defined as the square of the difference between the actual and simulated share of excess supply.

TABLE 4

Estimated trade costs and indicators of tradability

	Correlation with trade costs
Trade share	-0.31
Average distance shipped	-0.24
Occupation index	-0.13

Notes: This table presents correlations between the estimated trade costs and indicators of tradability. See Appendix for variable definitions and construction. The sample contains the 969 industries included in our sample except for "Average distance shipped" which is available only for 545 (predominantly manufacturing) industries covered in the US Census Bureau's Commodity Flow Survey.

TABLE 5

Distribution of value added across industry-group and tradability

NAICS	Sector description	Total	Non-tradable	Tradable
31-33	Manufacturing	17.3	4.6	12.7
42	Wholesale trade	8.1	5.5	2.6
44-45	Retail trade	8.2	8.1	0.1
48-49	Transportation	3.5	2.7	0.9
51	Information	6.6	5.0	1.6
52	Finance and insurance	9.4	7.4	2.0
53	Real estate and leasing	17.2	17.2	0.0
54	Professional services	9.1	7.9	1.2
56	Administrative services	4.0	3.9	0.1
61-62	Education and health care	9.0	8.5	0.5
71-72	Recreation and food Services	4.9	4.4	0.6
81	Other personal services	2.7	2.4	0.3
	Total	100.0	77.6	22.4

Notes: This table presents the distribution of value added across broad industry group and tradability. We classify an industry as tradable if the estimated trade costs for that industry is lower than t_{75}, where t_{75} is the trade costs threshold such that 75 percent of manufacturing employment is classified in tradable industries.

TABLE 6

Tradable vs. non-tradable industry characteristics

	Wage	Productivity
Panel A: Across industries		
Tradable indicator	0.28	0.32
	(0.03)	(0.04)
R^2	0.10	0.06
Observations	969	969
Panel B: Across industries within broad group		
Tradable indicator	0.16	0.24
	(0.03)	(0.04)
R^2	0.38	0.46
Observations	969	969
Panel C: Across industries within broad group, service sector only		
Tradable indicator	0.28	0.26
	(0.05)	(0.06)
R^2	0.44	0.65
Observations	506	506

Notes: This table presents results from OLS regressions of industry-level measures of average wages and labor productivity on a variable indicator equal to 1 if the industry is tradable and 0 otherwise. We classify an industry as tradable if the estimated trade costs for that industry is lower than t_{75}, where t_{75} is the trade costs threshold such that 75 percent of manufacturing employment is classified in tradable industries.

TABLE 7

DISTRIBUTION OF GAINS FROM TRADE ACROSS INDUSTRY-GROUP

NAICS	Sector description	Share
31-33	Manufacturing	0.565
42	Wholesale trade	0.116
44-45	Retail trade	0.005
48-49	Transportation	0.039
51	Information	0.070
52	Finance and insurance	0.089
53	Real Estate and leasing	0.001
54	Professional services	0.051
56	Administrative services	0.004
61-62	Education and health care	0.024
71-72	Recreation and Food Service	0.025
81	Other personal services	0.012

Notes: This table presents the distribution of gains from trade across broad industry group associated with a symmetric liberalization.

Figure 1: Geographical distribution of industry employment

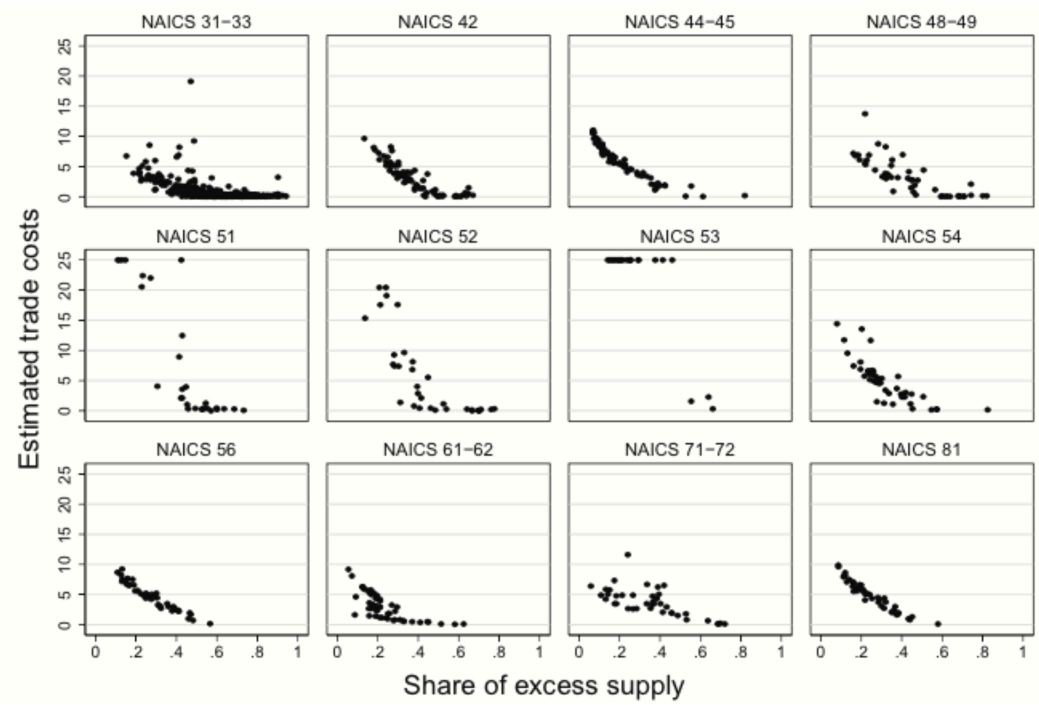

Figure 2: Share of excess supply and estimated trade costs

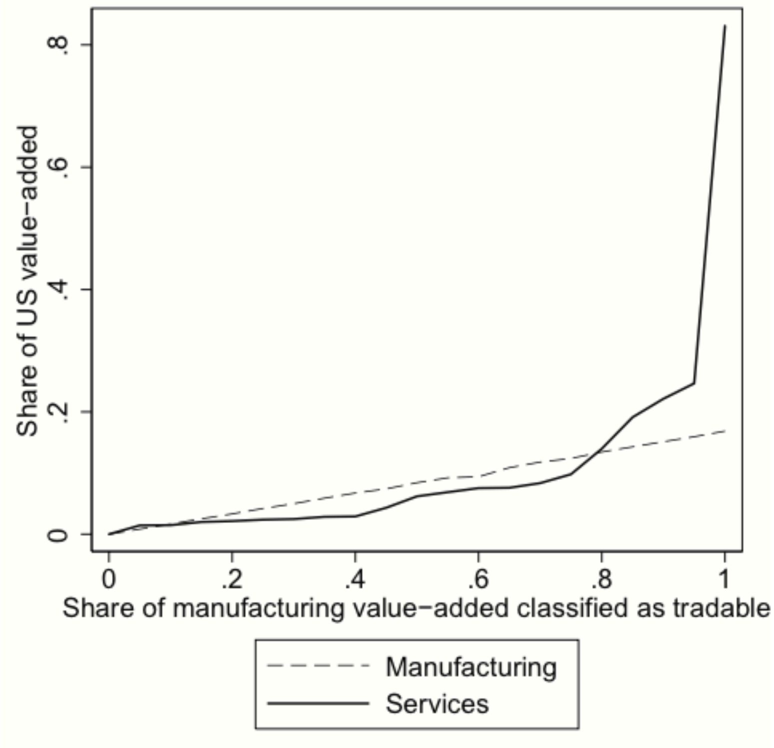

Figure 3: Sectors' share of US value-added in tradable industries

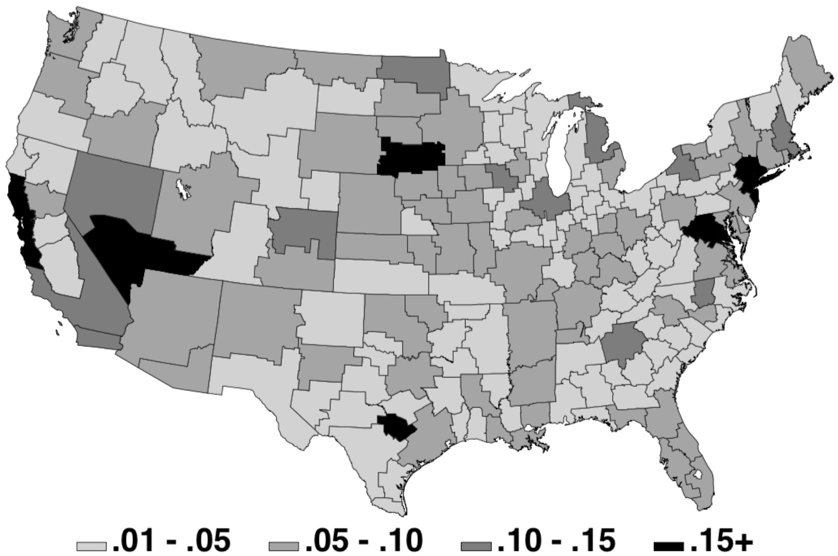

Figure 4: Tradable service industries' share of regional value added

A Data Appendix – For Online Publication

In this appendix, we provide additional details on the data, sample and measurement.

A.1 Economic Census

The Economic Census (EC) is conducted by the US Census Bureau, and firms are required by law to complete the questionnaires they receive. Respondents are asked to provide a range of operational and performance data. The Economic Census is primarily conducted on an establishment basis – a single physical location at which business is conducted, or services or industrial operations are performed. An establishment is not necessarily identical with a firm (or enterprise), which may consist of one or more establishments. A company operating at more than one location is required to file a separate report for each location or establishment. Companies engaged in distinctly different lines of activity at one location are requested to submit separate reports, if the business records permit such a separation, and if the activities are substantial in size. When these conditions are not met, activities at the same location are generally grouped together as a single establishment and the entire establishment is classified on the basis of its primary activity. Business establishments in the EC are grouped into industries based on the similarity of their production processes and classified according to the North American Industry Classification System (NAICS).

The EC covers the vast majority of the private economy but does not provide information on self-employed individuals, employees of private households, railroads, agricultural production, or most government activities. Specifically, the following NAICS codes are not covered in the economic census: 11 Agriculture, Forestry, Fishing and Hunting; 482 Rail Transportation; 491 Postal Service; 525 Funds, Trusts, and Other Financial Vehicles; 6111 Elementary and Secondary Schools; 6112 Junior Colleges; 6113 Colleges, Universities, and Professional Schools; 8131 Religious Organizations; 81393 Labor Unions and Similar Labor Organizations; 81394 Political Organizations; 814 Private Households; 92 Public Administration. In addition, the economic census does not generally include government-owned establishments, even when their primary activity would be classified in industries covered by the economic census.[21]

We make use of the detailed, county-level geographical information on the EC records, industrial classification information, revenue, and employment data to construct region-industry measures of supply and demand. Establishments are assigned to regions that are the Economic Areas (EA) defined by the Bureau of Economic Analysis (BEA) as described in Johnson and Kort (2004). Industries are defined at the six-digit NAICS level.

Revenue

For each region-industry, we measure total revenue (supply) by taking the sum of revenue over all plants in an industry s in a region j so that $R_{js} = \sum_{k=1}^{N_j} r_{jsk}$ where r_{jk} is the revenue of the k^{th} plant in region j. In the estimation, we use the region's share of industry supply as the measure of revenue.

The data do not contain information on region-level exports for all industries that can be used to adjust supply to account for international trade. Instead, we assume that exports are distributed across regions according to production. In other words, a region that produces 10 percent of output in an industry is assumed to also account for 10 percent of US exports in that industry. To examine the implications of this assumption, we produced the revenue share for each region-industry in the manufacturing sector, where direct export information is available, adjusting for direct exports and compared this to the region-industry measure constructed using the proportional adjustment. The correlation between direct export adjustment and the proportional adjustment of industry revenue is 0.98 in the manufacturing sector. This suggests that the measurement error associated with assuming international trade is distributed proportionally with output is generally small.

21. See http://www.census.gov/econ/census/help/naics_other_classification_systems/codes_not_covered.html for more information.

Expenditure

For each region-industry, we measure total expenditure (demand) using information on the industrial composition of the region from the EC and the 2007 American Community Survey for industries out of scope for the EC and information on each industry's use of all inputs from the BEA's Detailed Input-Output Use table for 2007. Specifically, our measure of industry s's demand in region i is defined as:

$$E_{si} = \left(\sum_t s_{st}^{IO} \cdot s_{it}^{D} \right) R_s$$

where s_{st}^{IO} represents the share of industry s output demanded by each industry t, for all $t = 1, ..., T$ (T includes all industries in the private sector, investment, government, and final demand), s_{it}^{D} represents the share of industry demand measures by the share of employment or, in the case of final demand, share of total income from the 2007 American Community Survey in region i, and R_s is aggregate revenue in industry s.[22] Because we do not know the distribution of investment demand across industries, we use final demand to represent the geographical distribution of investment demand. The term in parentheses gives the adjusted share of demand for industry s in region i. Multiplying this term by total revenue in the industry gives expenditure in regions i. In the estimation, we use the region's share of total industry demand as the measure of expenditure.

A measurement issue we face is that some region-industry demand is served by imports, so region-industry demand would be overstated without adjusting for imports. The EC data do not have direct information on imports of intermediate products. Instead, we use information from BEA's supplemental Import Matrix to adjust demand for imported inputs. The Import Matrix provides estimates of imports by industry by commodity using the import comparability assumption.[23] We match the Import Matrix to the Input-Output table and

22. We use the location of employment instead of revenue because we include demand from sectors where revenue information are not reliable (Management of Companies and Enterprises (NAICS 55)) or industries outside the scope of the EC (e.g. federal, state, and local government, Postal Service, Education, Agriculture (NAICS 1)).

23. See Feenstra and Jensen (2012) for a discussion of the import comparability assumption.

adjust demand by imports.

Production costs

The revenue-based labor productivity for region j industry s equals its revenue in the industry per unit of labor employed

$$\theta_{js} \equiv \frac{r_{js}}{l_{js}}. \tag{18}$$

Regional revenue in an industry can be computed from equation (5) by taking the sum of bilateral sales across all destinations

$$r_{js} = \sum_i r_{ijs} = \left(\frac{\sigma_s}{\sigma_s - 1}\right)^{1-\sigma_s} \left(\frac{w_j}{z_{js}}\right)^{1-\sigma_s} A_{js}, \tag{19}$$

where $A_{js} = \sum_i E_{is} P_{is}^{\sigma_s - 1} \tau_{ins}^{1-\sigma_s}$ is the region-industry market access term, a measure of aggregate demand. From the total cost function (3), labor per region is

$$l_{js} = F_s + \frac{q_{js}}{z_{js}} \quad \text{with} \quad q_{js} = \sum_i \tau_{ijs} q_{ijs} = \left(\frac{\sigma_s}{\sigma_s - 1}\right)^{-\sigma_s} \left(\frac{w_j}{z_{js}}\right)^{-\sigma_s} A_{js}. \tag{20}$$

Substituting equations (19) and (20) into (18) yields

$$\theta_{js} = \left(\frac{\sigma_s}{\sigma_s - 1}\right) \left(1 - \frac{F_s}{l_{js}}\right) w_j \tag{21}$$

where we have used $q_{js} = (l_{js} - F_s) z_{js}$.

Using q_{js}, defined in (20), in the definition of labor per firm, we get

$$l_{js} = F_s + \left(\frac{\sigma_s - 1}{\sigma_s}\right)^{\sigma_s} \frac{A_{js} z_{js}^{\sigma_s - 1}}{w_j^{\sigma_s}} \tag{22}$$

Substituting this result into equation (21), we get

$$\theta_{js} = \left(\frac{\sigma_s}{\sigma_s - 1}\right)\left[1 - \frac{1}{1 + \left(\frac{\sigma_s - 1}{\sigma_s}\right)^{\sigma_s} \frac{A_{js} z_{js}^{\sigma_s - 1}}{F_s w_j^{\sigma_s}}}\right] w_j \tag{23}$$

Our measure of λ is defined as the ratio of revenue-based labor productivity to wage (i.e., θ_{js}/w_j). Equation (23) shows that this measure is positively correlated with region-industry technical efficiency (z_{js}) but also captures variation in the elasticity of demand across industry as well as variation in fixed production costs across industry-region. Therefore, because of fixed production costs, revenue based measures of productivity are correlated with technical efficiency (e.g., Bernard et al. (2010) and Bernard et al. (2011)).

Summary Statistics

Table A1 reports descriptive statistics for the measures used in our estimation. Because we use shares of R and E in the estimation, we do not report the simple mean and standard deviation. Instead, we calculate the standard deviation across regions within an industry and present the mean and standard deviation across industries of the industry-level measures of standard deviation for R, E, and λ. Table A1 shows that there is significantly more concentration in supply than demand across regions. The mean standard deviation of R across regions within industries is 1.80, while the measure for E is 0.94. The higher level of variation in R suggests that identification of trade costs is coming primarily through R. This is reassuring as R is well measured.

[TABLE A1 HERE]

Value Added

The EC data contain sales, but not value added measures. We compute the share of value added in each industry using value added (GDP) information from BEA's IO Tables 2007. For BEA commodities for which there are multiple six-digit NAICS codes, we allocate value added based on the share of payroll in each six-digit NAICS industry within the commodity category. We use the share of payroll rather than sales because the BEA commodity codes are particularly aggregated in wholesale and retail trade, where payroll is likely to be more correlated with value added than sales.

Sample construction

There are about one thousand six-digit NAICS industry classifications.[24] We retain all industries from the EC while developing the supply and demand measures. However, we do not report analytical results for all industries. We exclude Mining (NAICS 21) and Utilities (NAICS 22) because many of the industries in these sectors have small numbers of producers and, as a result, do not meet the disclosure release protocols of the US Census Bureau. We exclude Construction (NAICS 23) because the unit of analysis is not consistent with the other EC data. We exclude Management of Companies (NAICS 55) because there is no reliable revenue data and we cannot produce the productivity estimates required for estimating trade costs. We lose an additional 21 industries across the Manufacturing (NAICS 30), Retail (NAICS 44-45), Transportation and Warehousing (NAICS 48-49), Information (NAICS 51), Finance and Insurance (NAICS 52), and Administrative Support and Waste Remediation (NAICS 56) sectors due to disclosure prevention protocols. Our final analytical sample includes 969 six-digit NAICS industries.

A.2 Measuring the elasticity of demand

Estimates of the elasticity of demand for services industries are not readily available, so we construct elasticity of demand measures for all industries. From our theoretical model, the price elasticity of demand is defined as $\widehat{\sigma}_s = R_s/G_s)$, where G_s denotes gross operating surplus (see equation (12). We use this results and BEA data on gross operating surplus and value added to estimate the price elasticity of demand for each of the roughly 70 industries

24. See http://www.census.gov/eos/www/naics/ for more information.

(approximately three-digit NAICS) for which information is available.[25] We divide value added GDP (our measure of R_s) by gross operating surplus (a proxy for G_s) for each industry for years 1998 - 2012. Gross operating surplus is a residual for most industries constructed by subtracting total intermediate inputs, compensation of employees, and taxes on production and imports less subsidies from total industry output. However, it includes consumption of fixed capital, proprietors' income, and corporate profits and therefore provides a reasonable approximation to G_s. We take the median across year for each industry to obtain a measure of central tendency robust to outliers.

Table A2 report the mean and standard deviation across industry for each broad industry group. The results for manufacturing are in line with estimates provided in the literature. For instance, Broda and Weinstein (2006) uses trade flows to estimate the price elasticity of demand and report means ranging from 4.0 to 17.3 depending on the time period and level of aggregation used in the estimation. An advantage of our approach is that we obtain estimates comparable across all sectors of the economy. Expect for "Education and health care", the mean and median estimated elasticity of demand is lower on average in services industries than in manufacturing industries. This indicates that consumers are less sensitive to variation in prices in services industry which, according to our model, indicates output is less differentiated in those industries.

[TABLE A2 HERE]

Our estimates vary at subsector-level. We experimented with the most disaggregated data available, input-output commodity level data (approximately six-digit NAICS). The estimates of σ derived from the more detailed commodity-level data had much higher variance than those at the 3-digit level. In particular, we obtain estimates smaller than 1 and some negative values. Because our model does not accommodate σs below 1, we could not estimate trade costs for these industries. However, the main empirical results (presented in section 6) are robust to using the more detailed σ estimates.

25. See www.bea.gov/industry/gdpbyind_data.htm for more information on these data.

A.3 Measures of Tradability

In this section, we describe the construction of measures of tradability to which we compare our trade costs measures.

Trade Share

We use data from BEA's Detailed Input-Output Use Table to construct a measure of trade exposure at the BEA commodity level. The measure of trade exposure we construct to compare to our estimates of trade costs is:

$$\text{Trade Exposure} = \frac{\text{IMP}}{\text{Absorbtion}} + \frac{\text{EXP}}{\text{Production}} \tag{24}$$

where Absorbtion = Output + IMP - EXP, IMP denotes imports, and EXP is exports. We note that BEA produces import estimates for approximately 100 service sector commodities (industries), even though the underlying data collection instrument contains only between 17 and 30 categories of services trade. In addition, as described above, these estimates are developed using the "import comparability" assumption. BEA uses estimation and imputation methods to allocate the services trade measured in their survey programs across the detailed commodity categories in the input-output tables. For the service sector, because of the allocation from around 20 service trade categories across 100 service industries, these estimates might differ substantially from actual trade. In addition, there are more service industries in our sample (approximately 400) than in the BEA input-output tables (approximately 100). This might also introduce noise in the correlations.

Distance Shipped

The Commodity Flow Survey (CFS) produces data on the movement of goods in the United States. It provides information on commodities shipped, their value, weight, and mode of transportation, as well as the origin and destination of shipments of commodities from manufacturing, mining, wholesale, and select retail and services establishments – namely, electronic shopping and mail-order houses, fuel dealers, and publishers (including newspaper, periodical, book, directory, and music publishers). Additionally, the survey covers auxiliary establishments (i.e., warehouses and managing offices) of multi-establishment companies. The survey does not cover establishments classified in transportation, construction, and most retail and services industries. Farms, fisheries, foreign establishments, and most government-owned establishments are also excluded.

We use confidential, respondent-level data from the CFS to construct weighted average distance shipped measures (using the same methodology as those published by the CFS program at the three-digit NAICS level) for each six-digit NAICS industry for which data are collected.

Occupation-Based index

For each of hundreds of occupations, the O*Net database contains detailed qualitative information on job tasks, work activities (interacting with computers, processing information), and work context (face-to-face discussions, work with others, work outdoors). We use this information to construct an index to compare to our estimated trade costs. To obtain comparable measures across all industries, we use the tradability index developed by Jensen and Kletzer (2010) and then weight each occupation's index by that occupation's share of total employment in an industry to obtain a 4-digit NAICS level industry measure of tradability

$$\text{O*NET TRADABILITY}_i = \sum_o \text{INDEX}_o \cdot s_{io}^{Emp}$$

where $INDEX_o$ is the occupation tradability index developed by Jensen and Kletzer (2010) and s_{io}^{Emp} is the share of industry i employment in occupation o. In comparison, Crino (2010) constructs tradability measures for "white-collars" occupations only.

TABLE A1

Summary statistics for region-industry variables

	Expenditure (E)	Revenue (R)	Costs (λ)
Mean	0.94	1.80	0.22
S.D.	0.14	0.90	0.51
	Correlations		
E	1.00		
R	0.54	1.00	
λ	0.04	0.12	1.00

Notes: This table presents the mean and standard deviation across industries of the standard deviation across regions for expenditure, revenue and our measure of λ. The table also presents the correlations between the region-industry measures. The sample contains 177,327 industry-regions across 969 industries.

TABLE A2

Estimates for the elasticity of demand

NAICS	Sector description	Mean	Median	S.D.
31-33	Manufacturing	8.14	7.52	2.87
42	Wholesale trade	5.17	5.17	–
44-45	Retail trade	6.31	6.31	–
48-49	Transportation	6.35	6.18	2.18
51	Information	3.02	3.12	0.18
52	Finance and insurance	5.91	4.31	3.41
53	Real estate and leasing	1.90	2.06	0.22
54	Professional services	5.60	5.24	1.92
56	Administrative services	5.98	6.16	0.34
61-62	Education and health care	12.17	9.46	5.57
71-72	Recreation and food Services	6.09	5.27	1.84
81	Other personal services	6.23	6.23	–
	All industries	7.14	6.31	3.20

Notes: This table presents the mean, median and standard deviation across industries within broad groups for the estimated elasticity of demand.