Services Trade and the Choice of Online versus In-Person Delivery

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Abstract

Trade in services is unique from goods trade in that the trade cost associated with services exports depends on whether the service is delivered in-person (via travel of producer or consumer) or remotely (via the internet). Building on the trade-in-task framework of Grossman and Rossi-Hansberg (2008), this paper develops a task-based model of services trade that explains choice of delivering intermediate services tasks to customers in foreign markets either in-person or over the internet. To test the predictions of the empirical model, I isolate average trade costs for 24 U.S. services sectors, and consider the contribution of internet technology, travel costs, and the share of employees in each sector in occupations that can only be performed in-person to total trade costs. I find that U.S. services exporters with a higher concentration of in-person only employees face significantly higher trade costs than those with employees more concentrated in occupations that can be performed online. Additionally, higher internet use in the importing country significantly decrease trade costs, and sectors with more in-person only employees are more sensitive to changes in commercial flight prices.

Keywords: International trade model, services trade, trade costs, trade and technology

JEL Codes: F11, F14, D21, L23

1 Introduction

The COVID-19 pandemic represented a major disruption to how workers performed their jobs, as firms adopted technologies like videoconferencing software and cloud data storage to facilitate working from home. For services exporters in particular, limitations on international travel made online services delivery the only viable means to export. While services exporters in sectors like tourism saw large declines in export revenue, others sectors, like education, adapted by shifting their means of delivery online, as international students at U.S. universities joined classes online from their home countries. However, as travel restrictions eased, this shift to online exports has not proven permanent. For example, Morgan Stanley's expected that the

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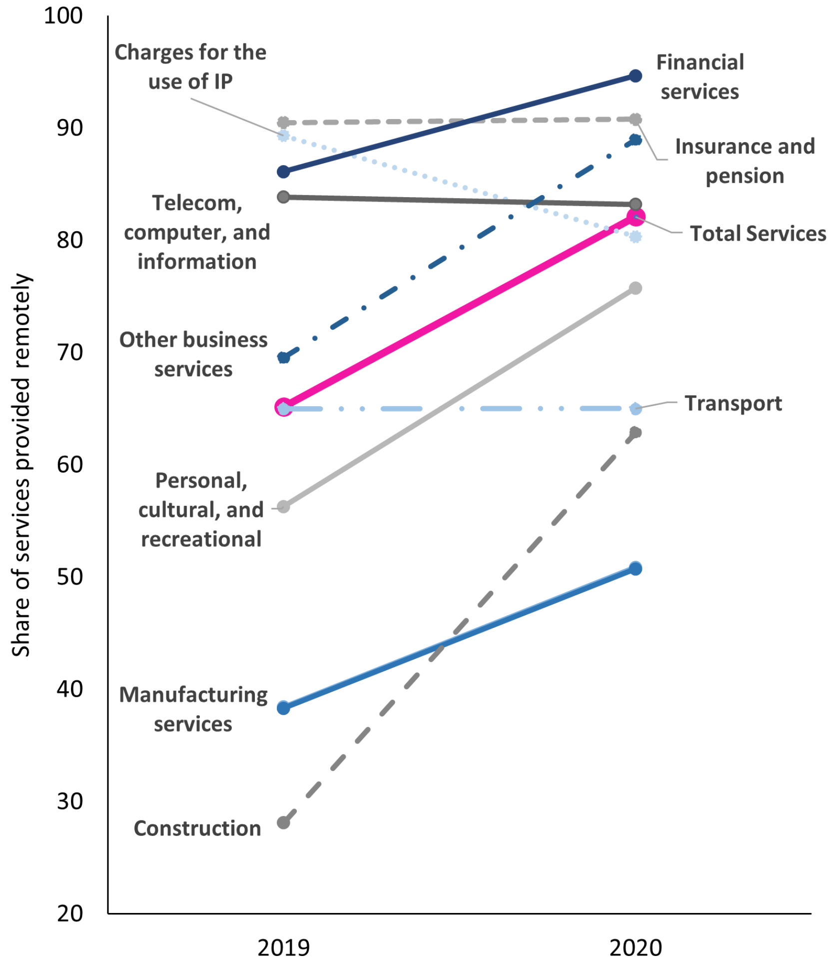
volume of business-related travel would recover to pre-pandemic levels in 2023, with only 18 percent of travel replaced by online meetings (Morgan Stanley, 2022).

Informed by COVID-19 pandemic trends, the primary goal of this paper is to better understand the tradeoffs exporting firms make when they choose how best to deliver services to international clients. I build a model of international trade in services that focuses on the delivery of intermediate services tasks, reflecting the idea that some components of final services products may be better suited to online trade than others. In equilibrium, exporting firms choose the optimal share of tasks to be delivered online, balancing the costs of travelling to a particular import market with the efficacy of delivering each task online in order to minimize overall trade costs associated with producing each final service product for export. The efficacy of delivering tasks online depends on both available technology in both markets and unobserved cultural preferences for in-person interactions between producers and consumers of services. The empirical tests of the model using U.S. export data confirm its predictions. Notably, U.S. services sectors with lower capacity for online trade (as measured by the share of workers employed in occupations that can only be completed in-person) have significantly higher trade costs.

The development of the internet dramatically shifted how services are traded globally, by introducing new channel for delivery of existing services that previously could only be traded through the travel of the producer or consumer of the service. It also expanded trade in services by facilitating the development of new online services products, such as cloud computing. Improvements in internet connectivity have significantly increased both the volume of services trade (Freund and Weinhold, 2002; Anderson et al., 2018; Herman and Oliver, 2023) and the diversity of services products exported (Gnangnon, 2020; Herman and Oliver, 2023). However, despite the growing importance of services trade in general (accounting for 22 percent of total trade in 2022) and evidence that the internet has facilitated growth in services exports overall, to date, theoretical models of international trade have not considered the implications of the services exporters shift of their products from in-person delivery to online delivery. This paper seeks to fill that gap in the literature.

The model presented in this paper combines the supply-side trade model of Eaton and Kortum (2002) with the task-based trade framework of Grossman and Rossi-Hansberg (2008), which they use to explain the offshoring decisions of firms. As defined by Grossman and Rossi-Hansberg (2012), tasks represent "the finest possible addition to the value added of a good or service done by a particular factor of production," and these tasks can be split across workers in different markets. This conception of trade, which focuses on the individual inputs required to produce final products, rather than the final product itself, is useful for understanding how services are traded following the development of the internet. There are two main features of services trade that point to the need for a task-based theoretical approach. These features are illustrated in figure 1, which presents data on the extent that UK services firms exported services remotely (via the internet or related means) before and after the COVID-19 pandemic (Scott, 2022). First, while all services exporters outside of travel services export some of their products remotely, no product is entirely online-traded, suggesting that services firms choose to export some components of their services via the internet, and others via travel. Second, comparing data from before and after the onset of the COVID-19 pandemic shows that many types of services exporters increased the share of exports delivered online. Particularly striking are the changes in construction services, where the share of services exported remotely doubled from 2019 to 2020, and personal and other business services, which both had almost a 20 percentage point increase in remote exports. This suggests that services firms can adapt how they deliver their services based on external conditions, such as restrictions to travel due to the pandemic.

Figure 1: Share of UK services exports delivered remotely, by services sector, 2019 versus 2020



Note: Travel services exporters were included in the survey but reported delivering no services remotely in both 2019 and 2020. Source: Scott (2022).

Better conceptualizing the choices that services providers make when delivering their services to customers in other markets is relevant for answering questions in a variety of international policy areas, including understanding the impact of services trade and immigration policy, COVID-19 related travel restrictions on services trade, and promotion of services-led growth strategies for developing markets. First, if services firms are flexible in how they provide services, higher barriers to internet-based trade, like data localization requirements, could shift firms towards exporting more services via travel, while changes to immigration policy, such as visa requirements for short term travel, could shift firms to exporting more services online. For example, Khachaturian and Oliver (2023) find suggestive evidence that when barriers to trade related to the movement of people across borders are high, services exporters may shift towards more online provision of services products. Second, this model can help in conceptualizing the services export response to the COVID-19 pandemic and related travel restrictions. As shown by Ando and Hayakawa (2022), trade in services directly related to or highly reliant on international transportation of goods and individuals were the most severely affected by the COVID-19 pandemic, while exporters of more online-traded services typically saw no significant negative relationship between COVID-19 cases and exports. Finally, this model can be useful for understanding the role of services trade in developing countries. Among developing markets, India in particular leveraged its high skilled, English-speaking labor force as internet technology expanded in the 1990s to build export capacity based on services trade (largely in products that are primarily traded online), rather than following a manufacturing-focused export strategy (Lamba and Subramanian, 2020). Recent work on services-led development has considered whether this path is viable for other markets, but Nayyar et al. (2021) has also cautioned that improvements in internet technology has only increased opportunities for services exports from high-skilled workers in developing markets by increasing access to remote jobs.

In the existing theoretical literature, trade models tailored specifically to trade in services are very limited and none consider differential trade costs based on the method of services delivery. Head et al. (2009) build an offshoring model of trade, where firms hire individual workers from the lowest cost supplier of a service after taking into account wages, productivity, and costs associated with adapting a service to a specific market, such as travel, training, and translation costs. Hanson and Xiang (2011) build a trade model for the motion picture industry, which they suggest could extend to other "copyright" services industries, such as TV, music, publishing, software and video games. For these sectors, fixed costs of production (creating the film) are high, while production costs per unit are small (creating additional copies of the film). Similarly, Eaton and Kortum (2018) also focus on the role of copyrighted material in trade in services, adding iceberg-like trade cost that captures a decline in productivity associated with technology diffusion. Previous work has also attempted to distinguish the types of services that are better traded online or in-person. Blinder (2006) divides service occupations into personal and impersonal categories, defining impersonal services as those that can be "delivered electronically over long distances with little or no degradation in quality". Services that fit into the personal category have a high degree of face-to-face contact (childcare), personal trust (therapy), or are location-specific (tourism). However, this characterization is limited in that it does not consider that most services rely on both online and in-person delivery. In contrast, my model allows for different tasks within a service sector to be more suited to online or in-person delivery, and is consistent with recent anecdotal evidence of how services exporters operate. In interviews with U.S. small and medium-sized legal and architecture services firms, Powell and Khachaturian (2023) find that the extent that firms provide services online or in-person depends on travel costs and the frequency and importance of communication with clients. Law firms, citing costs of travel and practices of hourly billing indicated that they primarily provide legal services to foreign clients via phone or email, while architecture firms indicated they more frequently required travel to closely communicate with clients on the status of projects.

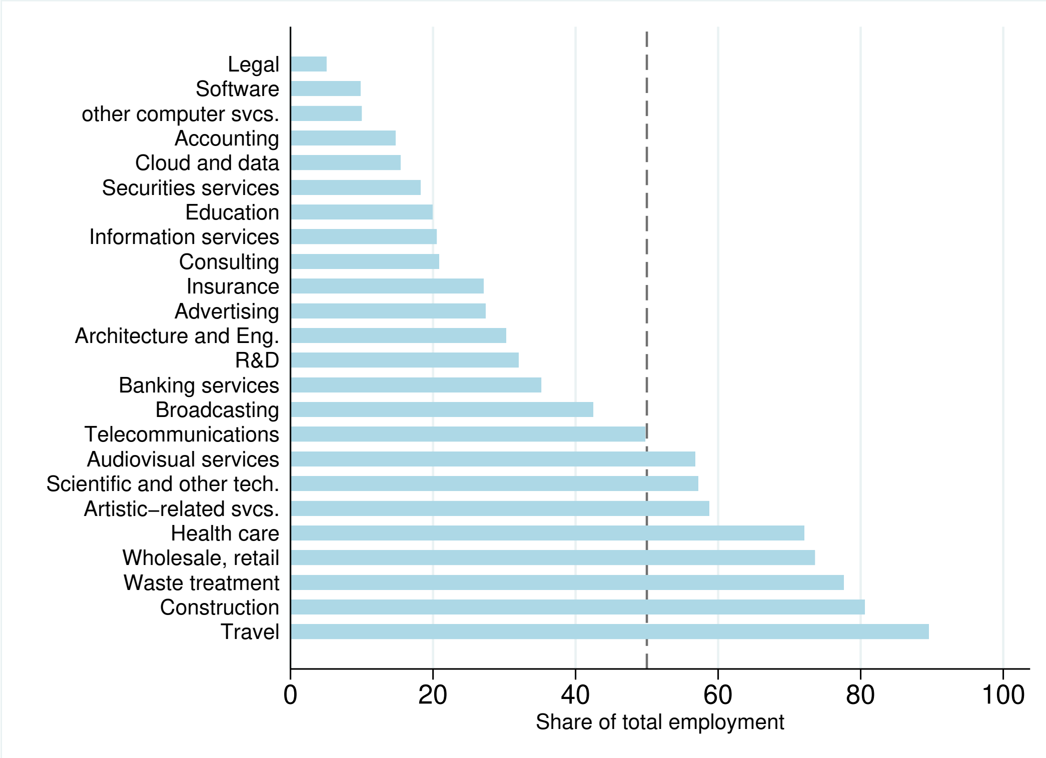
The model presented in this paper is a comparative static model that can be used to explore differences in the share of tasks that are exported online and via travel across different export markets, differences in labor allocation into in-person and online tasks across services sectors, and the role of changes in technology on both the share of tasks exported online and the overall magnitude of trade costs. For each service sector traded, the final service product export is divided into a series of tasks that require interaction between the service producer and final consumer. To export these final services products, the exporter faces a choice of whether to export each task via the internet or by travelling to the importing market.

The choice of means of export depends on two factors. First, like the shipping costs in analogous goods-trade models, tasks that are delivered by travelling to the partner market incur travel costs such as the cost of a commercial flight. The second factor is the efficacy of delivering a particular task in-person or online. In some cases, delivering a task online increases both the efficiency and quality (together, the efficacy) of completing the task. For example, an online check-depositing system may increase the efficiency of the workers processing checks, while also increasing the convenience of check-depositing for smartphone-using consumers who no longer have to travel to physical bank branches. In contrast, other tasks may be less efficient and of lower quality online than in-person. For example, an online course may both take longer for an instructor to prepare (less efficient) and have lower engagement from students (lower quality). Determinants of the efficacy of delivering a task online include the internet-related technology in the exporting and importing markets, quality and reliability of internet connections, and unobserved cultural preferences for in-person delivery. When new technology becomes available, exporting firms in a perfectly competitive market seek to shift some share of the delivery of their intermediate tasks online. Firms shift tasks online in order to increase the efficacy of providing these tasks to the final consumer, decrease overall trade costs, and incur positive profits in the short-run. The model solution finds a threshold task within each sector where the exporting firm is indifferent between trading that task via travel or via the internet.

To test the predictions of my model, I consider the relationship between services trade costs the share of tasks in a given service sector that can be traded over the internet across 24 U.S. services sectors. Between 2008 and 2021, almost 40 percent of U.S. workers on average in services sectors were employed in jobs that can only be accomplished in-person. While this composition has been fairly stable over time, there is considerable variation in the share of workers that are employed in in-person only jobs across service sectors, as shown in figure 2. Services like travel, construction, and health care are limited in their capacity for online trade, as more than half of their workforce on average is employed in jobs that can only be accomplished in-person. In contrast, professional services like legal and accounting services, and ICT services like software and cloud computing have high potential for trade via online services, with less than 20 percent of U.S. workers in these sectors employed in in-person only jobs.

Using this data as a proxy for the total share of labor in each sector that performs in-person tasks, my

Figure 2: Average share of occupations that are in-person only, by U.S. service sector, 2008–2021



Source: Author's calculations using data from O*NET, 2022 and BLS, 2022

empirical model is a two-stage process that considers the contribution of differences in labor allocation into in-person and online tasks across services products and available technology in different import markets to total trade costs for U.S. services exporters. In the first stage, I use a gravity-style specification to isolate bilateral trade costs from other determinants of trade. In the second stage, I decompose these trade costs to quantify the impact of in-person only occupation share, travel costs, and available technology. In my preferred second-stage specification, I find that a one percent increase in the share of labor in a sector that performs only in-person activities significantly increases total trade costs by 7 percentage points. This finding is driven largely by services sectors in professional and building-related services, as well as by services sectors that have majority in-person only occupations. I also find that technology in the importing market, as measured by the share of internet users in that market, significantly decreases trade costs by 0.9 percentage point for every one percent increase in internet users. Finally, the costs of travel, as measured by flight prices to the importing market, matter more for services sectors that are less online-tradable.

The empirical test of my model is most closely related to Ariu and Mion (2017), which uses firm level data from Belgium to assess the relationship between task complexity and trade at the extensive margin. Ariu and Mion (2017) find that the probability of exporting services increases for firms where employees perform a higher share of cognitive tasks (considered by the authors to be more online-tradable), while the probability of exporting decreased in firms with higher shares of face-to-face communication tasks. It is also related to a larger literature that considers the trade enhancing role of the internet, both in general (Herman and Oliver, 2023), and for services specifically (Freund and Weinhold, 2004; Blum and Goldfarb, 2006; Anderson et al., 2018).

The remainder of this paper is divided into six sections. Section 2 builds the theoretical model of services trade, and considers the dynamics of the model related to changes in travel costs, internet technology available and the share of employment in tasks that can only be delivered in-person. Section 3 converts the theoretical model into an empirical specification, and section 4 covers the data used. Section 5 presents results of the regression, including first stage results and aggregate and sector-specific service results. Section 6 concludes.

2 Services Trade with Differentiated Costs

As noted above, the theoretical model developed here adapts the supply side model of Eaton and Kortum (2002) to incorporate trade costs that vary at the task, rather than sector level. To present the model clearly, this section builds to the full model with internet technology and international trade. First, I describe the setup and choice of online and in-person task delivery for firms that are only serving their domestic market. Next, I introduce exports into the model and explore the resulting differences in the threshold task. Third, I integrate the findings of the task-based model into a larger Eaton-Kortum trade model. The final section illustrates the impact of a technology improvement on total trade costs and the share of tasks delivered online.

2.1 Domestic Trade

To begin, assume firms in each service sector only produce final service s for the domestic market. These perfectly competitive firms produce a final service s through a series of tasks n, indexed over a 0–1 interval ($n \in (0,1)$). I assume that labor is the only input into the production process. Following Grossman and Rossi-Hansberg (2008), the final product in each sector is created with a fixed intensity of each task, such that producing s always uses the same amount of labor for each task. While the 0–1 interval contains all possible services tasks, different sectors that produce service products do not necessarily perform the same range of tasks and can use different tasks at different levels of intensity. This means that each service product s has a unique labor allocation function $l^s(n) \geq 0 \; \forall \; n \in (0,1)$ that define the number of worker that perform each task in that sector. I assume constant returns to scale, such that the total quantity of labor required for each final service s is given by the total labor inputs employed across all tasks:

$$s = \int_0^1 l^s(n)dn. \tag{1}$$

The marginal cost for producing each s is defined in equation 2, which represents a modified version of marginal production costs in the Eaton and Kortum (2002) model:

$$MC^s = \frac{w}{\varphi^s}\int_0^1 l^s(n)dn. \tag{2}$$

Here, w represents the per-task wage rate (assumed to be constant across all tasks, for simplicity). The wage rate is discounted by the parameter φ^s, which captures the efficiency of producing final service s, and is drawn from a Fréchet distribution. Larger values of φ^s represent a more efficient labor force, which leads to lower marginal costs. φ^s varies across different final service products, but is constant across all types of workers that produce s. Since this is a perfectly competitive market, prices are equal to marginal costs, such that the price for domestic firms producing service s for consumers in the domestic market is given by:

$$p^s = \frac{w_n}{\varphi^s}\int_0^1 l^s(n)dn. \tag{3}$$

To introduce differential costs for online and in-person delivery of final service s, I assume that in order to deliver final product s, each worker interacts directly with the final consumer. Once the internet becomes a viable tool for communicating with customers, the firm faces a choice of whether each worker interacts with the consumer in-person or online. If workers performing task n interact with the consumer in person, it takes $l^s(n)$ units of labor in that task to produce the final product. However, if the workers performing task n interact with the consumer online, it takes $l^s(n)c(n)$ units of labor to produce the final product s. Let $0 < c(n) \leq \infty$ represent a non-decreasing continuously differentiable function of n, which is determined by technology available to firms and consumers, the reliability of internet connections between producers and consumers, and unobserved differences in consumer preferences for in-person versus online interactions.

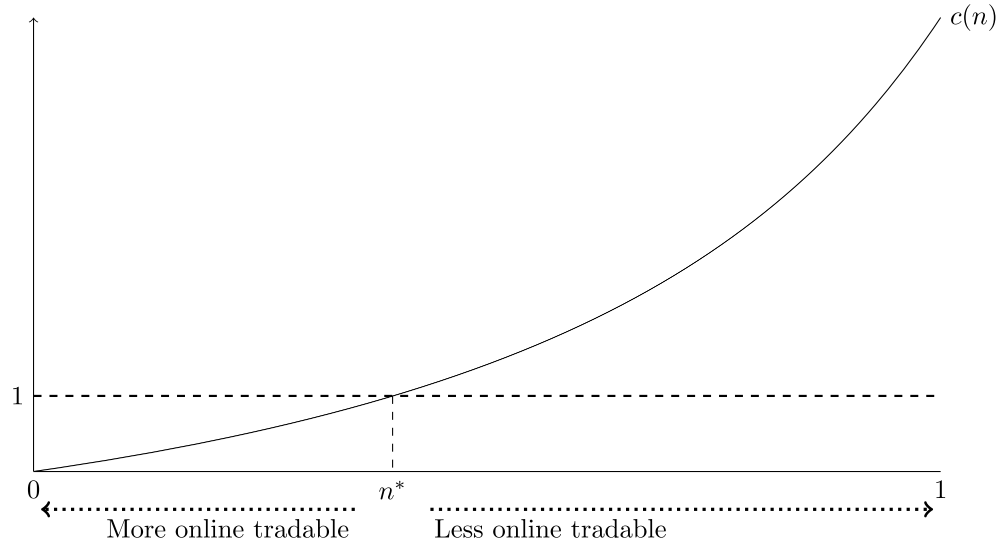
In the model, $c(n)$ represents the efficacy associated with delivering the online version of a task relative to the in-person version. Where $c(n) \leq 1$, substituting from in-person to online provision of a task represents an improvement in the efficiency and quality of task s for the same amount of labor input (i.e. online check-depositing). For $c(n) = 1$ task n can be performed online with the same level of efficacy as in person. For values of $c(n) > 1$ the task can still be delivered online, but the same amount of labor produces less of the task online than the online version of the task (i.e. online education). As the value of $c(n) \to \infty$, the task, such as a medical procedure, cannot be performed online at all. The function $c(n)$ is constant for all types of services products s produced in the domestic market, but the composition of each product s depends on the sector specific labor allocation across tasks $l^s(n)$

For each final service product s, the value of $c(n)$ orders tasks within the 0–1 index by efficacy of trading that task online, where 0 is the most internet tradeable task, and 1 is the least internet tradeable task. For a given set of firms and consumers, the functional form of $c(n)$ is driven by overall market conditions, including available technology (such as availability of online conferencing software, or the prevalence of smartphones among consumers), quality and reliability of internet connections, and unobserved differences in the importance of face-to-face communication for effectively delivering each task, (such as the cultural importance of trust). Let n^* represent the task in this index where $c(n) = 1$, and the firm is indifferent between online and in-person provision (hereafter the threshold task). When the internet becomes available to firms and consumers, in the short-run, firms producing product s will choose the cost-minimizing allocation of online and in-person tasks, as shown below in equation . If $0 < c(n) < 1$ for all tasks, delivery of s will shift entirely online. Similarly, if $c(n) > 1$ for all tasks, there will be no shift of any tasks to online provision.

$$p^s = \frac{w_n}{\varphi_i^s}\left[\int_0^{n^*} l^s(n)c(n)dn + \int_{n^*}^1 l^s(n)dn\right]. \tag{4}$$

Figure 1 plots an example of the function $c(n)$ in order to show the choice of online vs in-person task delivery graphically. The ordered tasks in sector s are on the x-axis, while the y-axis plots the value of $c(n)$ for each task. The threshold task n^* appears on the graph where $c(n) = 1$.

Figure 3: Choice of online vs in-person tasks, domestic market only



2.2 International Trade

Next, I consider the case where firms in exporting market i of service sector s also export services to foreign market j. For simplicity, I assume any outsourcing decisions are exogenous and N includes only the tasks that each exporter has already decided to produce in their home market rather than outsource. This assumption allows me to focus on the choice of delivery of a service, rather than the location of the producer of the service, but still could allow for offshoring to be reflected in other components of the larger trade model, such as the choice to import final services products rather than producing them in the domestic market.

Opening to foreign markets introduces two changes to the domestic trade model presented above. First, the efficacy function, $c_{ij}(n)$ is defined at the bilateral level, such that each pair of importers and exporters have a unique function defining the efficacy of trading each task online or in-person. There are several reasons $c_{ij}(n)$ could vary across different country partners. For example, different importing markets may have different technology available to them (for example, access to a 4G mobile phone connection vs a 2G connection), or different cultural preferences for in-person delivery of tasks. The unique $c_{ij}(n)$ function for each importer-exporter pair also implies that each pair of countries has a unique threshold task n^*_{ij}, where the firm is indifferent between in-person and online provision of that task. Second, $f_{ij} \geq 1$ is a new term that accounts for the costs associated with travelling from importer i to export market j to deliver a task in-person. Each worker that delivers a task in-person from i to j incurs cost f_{ij} to deliver the task, such that the cost of delivering each task in-person is f_{ij} multiplied by the number of workers that perform that task $l^s(n)$. The travel costs f_{ij} represent, for example, the cost of an airline ticket, and are constant across all types of tasks, but vary based on trade partner.

The introduction of travel costs f_{ij} shifts the firm-level cost-minimization problem described in the previous section. As in the domestic market case, without travel costs, the labor required to produce task n for consumers in market j in-person, $l^s(n)$ is equivalent to the labor required to produce task n online for market j, $c_{ij}(n)l^s(n)$. However, introducing travel costs means that the labor required to produce task n in-person is weighted by travel costs f_{ij}. For each task n, a cost-minimizing firm chooses the less costly and most efficient of the two options. f_{ij} is fixed for all tasks, but $c_{ij}(n)$ is increasing (or at least non-decreasing) as tasks become more internet tradeable. Thus, for a given importer market j the threshold task n^*_j is given where:

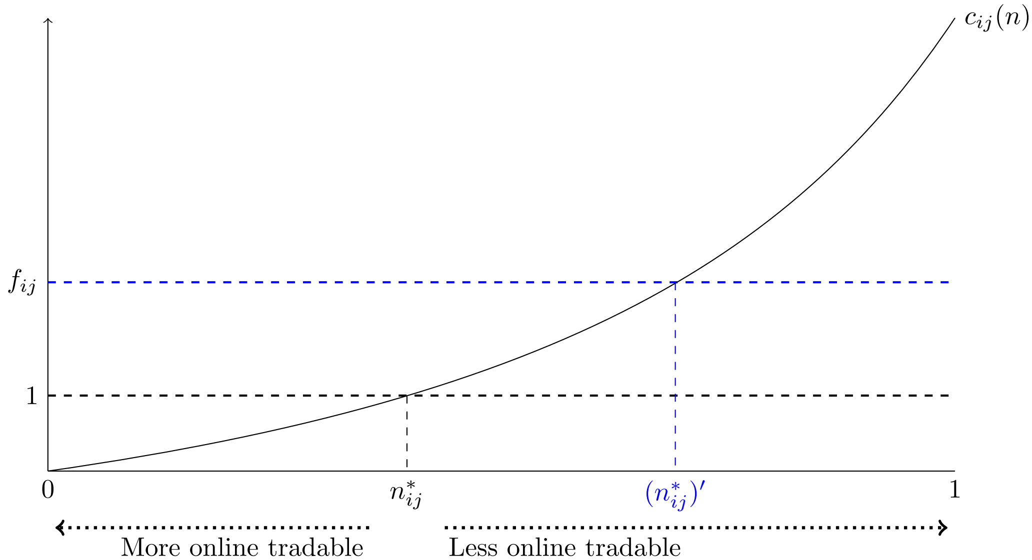
$$c_{ij}(n^*_{ij}) = f_{ij}. \tag{5}$$

As shown in figure 4, which represents the choice of online and in-person tasks for import market j, the dotted line delineating the location of the threshold task in figure 1 shifts upward from $c_{ij}(n) = 1$ to $c_{ij}(n) = f_{ij}$ In contrast to firms in sector s only serving the domestic market, the introduction of travel costs in the services export case leads to three different categories of tasks exported:

- $c_{ij}(n) \leq 1$: Tasks that are always traded online, regardless of travel costs.
- $1 < c_{ij}(n) \leq f_{ij}$: Tasks that will be performed in-person for the domestic market but online in the foreign market, because the loss of efficacy associated with online trade are smaller than travel costs.
- $c_{ij}(n) > f_{ij}$: Tasks that are traded in person, because travel costs are smaller than the inefficiencies and quality differences associated with online trade.

Next, this determination of the new threshold task for exports can be used to construct a measure of trade costs for final service s. Typically, in models of international trade, trade costs are measured relative to trade costs in the exporter's domestic market. In particular, in the Eaton and Kortum (2002) model, when labor is the only input to the final production, the price of exporting product s from country i to country j is given by:

Figure 4: Choice of online vs in-person tasks, exports to country j



$$p_{ij}^s = \frac{w_i}{\varphi_i^s} T_{ij}^s. \tag{6}$$

The first term of equation 6 covers production costs that are constant for each unit of s produced in exported in i, regardless of whether the final service is exported or produced for the domestic market. w_i represents the per-task wage rate in the exporting market, divided by the service-specific productivity parameter φ_i^s. Together, these parameters help define the comparative advantage of exporter i in producing final service s relative to the rest of the world, as either lower wages or higher productivity in the sector lead to a lower overall price of the final service s. The second term, T_{ij}^s comprises costs that are unique to the specific exporter-importer pair of countries. $T_{ij}^s \geq 1$, known as an "iceberg" trade cost, measures the additional costs associated with delivery of product s to country j, *relative* to the costs of delivering that same product in the domestic market of exporter i. In this paper's model, T_{ij}^s depends on the relative costs of travel f, the $c(n)$ function, and the allocation of labor into online and in-person tasks. Thus, trade costs are given by:

$$T_{ij}^s = \frac{\left[\int_0^{n_{ij}^*} l^s(n) c_{ij}(n) dn + f_{ij} \int_{n_{ij}^*}^1 l^s(n) dn\right]}{\left[\int_0^{n_{ii}^*} l^s(n) c_{ii}(n) dn + \int_{n_{ii}^*}^1 l^s(n) dn\right]}, \tag{7}$$

and price of exporting service s from country i to country j is:

$$p_{ij}^s = \frac{w_{in}}{\varphi_i^s} \frac{\left[\int_0^{n_{ij}^*} l^s(n) c_{ij}(n) dn + f_{ij} \int_{n_{ij}^*}^1 l^s(n) dn\right]}{\left[\int_0^{n_{ii}^*} l^s(n) c_{ii}(n) dn + \int_{n_{ii}^*}^1 l^s(n) dn\right]}. \tag{8}$$

The main distinction between equation 8 and the standard Eaton and Kortum (2002) model is that the labor required to produce the final services s appears as part of the trade cost term, rather than as part of the production cost term. This difference reflects the impact of differences in the share of services tasks that are traded online on the total labor required to produce a final service s. In particular, the $c_{ij}(n)$ term increases the efficacy of delivering a particular task n such that less labor is required to produce the same final product s, but only if that task is delivered online.

Aside from defining the sub-components of T_{ij}^s, the remainder of this trade model is idendentical to the Eaton and Kortum (2002) model. For each services product s, international export patterns are determined by importer-exporter specific prices for each service. In particular, the goal of importer j is to find the lowest price for each product s from all of its potential trade partners (if country j is the lowest price producer, they will source domestically). Thus, when some tasks are shifted online, if firms in country i decrease prices in response to the efficiency gains associated with online service delivery, importing from country i becomes more likely, increasing overall export of final product s from country i to country j. The full version of the trade model for each final service s is given by:

$$x_{ij}^s = \frac{(\frac{T_{ij}^s}{p_j})^{-\theta} Q_i x_j}{\sum_{m=1}^{M} (\frac{T_{im}^s}{p_m})^{-\theta} x_m}. \tag{9}$$

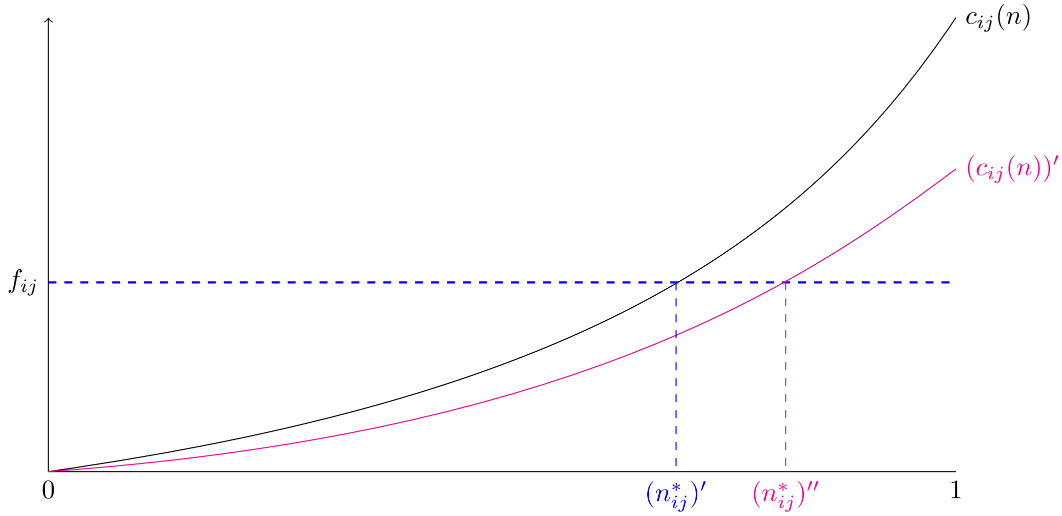
Where T_{ij}^s is defined by equation 7. In equation 9, x_{ij}^s represents total exports of final service s from country i to country j. p_j^s represents the price level in importer j. Both T_{ij}^s and $\frac{1}{p_j^s}$ are raised to $-\theta$, a parameter in the model that reflects the importance of comparative advantage in the world trade system. Q_i^s and the denominator together represent the world market for service s through the eyes of exporter i (i.e. exporter multilateral resistance). Finally, x_j^s represents total spending in importer j on service s. Together, importer multilateral resistance, which captures importer-specific factors that determine trade patterns, is represented by the $(\frac{1}{p_j^s})^-\theta$ and x_j^s terms.

2.3 Predicted Impacts of changes to $c_{ij}(n)$ and f_{ij}

Changes to the efficacy of trading tasks over the internet, $c_{ij}(n)$, and changes to travel costs for in-person traded tasks, f_{ij}, both change overall trade costs and shift the threshold task n^*. This section will briefly explain the dynamics of each of these model changes. First, an improvement in internet technology (such as the development of videoconferencing software) shifts the $c_{ij}(n)$ curve downward. As shown in figure 3, this downward shift has two impacts on the method of delivery for each task. First, the downward shift in $c_{ij}(n)$ improves the efficacy of services delivered online, as the online interaction with the consumer becomes more similar to a face-to-face interaction, reducing the value of C_{ij}^s and lowering overall trade costs T_{ij}^s of delivering final product s. A second order impact is at the extensive margin, where the threshold task n_{ij}^* also shifts outward to $(n_{ij}^*)''$, increasing the number of tasks that are traded via the internet. For large changes in technology, both the first order cost savings and second order change in the threshold task can decrease overall trade costs T_{ij}^s, which in turn, increases the total value of exports from country i to country

j. However, at the margin, shifting the threshold from travel to online provision represents a negligible improvement in costs for delivering that task, and thus is unlikely to have a substantial impact on overall trade (by the envelope theorem). Finally, since this model assumes that all tasks needed to produce final service s are completed in the home market, the downward shift has no effect on the required labor input per unit of s in the home market $l^s(n)$ performing each task.

Figure 5: Choice of online vs in-person tasks, following a technology improvement in importer j



Similarly, an improvement in travel costs f_{ij} relative to the domestic market decreases the value of f_{ij} resulting in a first order improvement in the costs of delivering services in-person, and a resulting decrease in total trade costs T^s_{ij}, and increase in total exports. This cost improvement also shifts the value of n^*_{ij} inward, so that the equality $c_{ij}(n^*_{ij}) = f_{ij}$ continues to hold, resulting in a higher share of in-person services delivery. As in the previous case, this shift will have a negligible impact on total trade costs at the margin.

2.4 Comparisons across services products

In addition to understanding how changes to travel costs and the efficacy of trading tasks online affect total trade costs, it is also interesting to consider differences in the labor allocation function $l^s(n)$ across different final services products s. Without defining a specific functional form of the labor function for different products, under certain conditions, the model shows that larger shares of workers performing in-person tasks results in larger overall trade costs. In particular, assume that two services products have labor $l^s(n)$ functions that differ only in that a proportional number of workers in the the second service product shift from online-tradeable tasks to in-person tradeable tasks. Given that $c_{ij}(n) < f_{ij}$ holds for each task performed online, proportionally increasing the number of workers that perform tasks above the n^*_{ij} threshold (which is common to all products) and decreasing to the number of workers that perform tasks online leads to an increase in total trade costs. See appendix A1 for a more detailed explanation of conditions for comparing differences in $l^s(n)$ across different services products.

3 Empirical Tests

In order to validate the predictions of the model, the remainder of this paper builds an empirical specification that includes proxies for f_{ij}, $c_{ij}(n)$, and $\int_{n^*_{ij}}^{1} l^s(n)dn$. The primary challenge with validating the model is that there is not data available on the threshold task n^*, where firms are indifferent, from a cost perspective, from providing a specific task to a customer via the internet or in-person. This means that the empirical test of the model cannot be used to assess the impact of differences in travel costs or internet technology on the threshold task. However, there are several predictions of the model that can be assessed empirically, including:

1. Higher costs of travel f_{ij} increase overall trade costs T^s_{ijt},
2. Better internet technology (a downward shift in $c_{ij}(n)$) decreases overall trade costs T^s_{ijt}, and
3. A higher number of workers performing in-person only tasks $\int_{n^*_j}^{1} l^s(n)dn$, increase overall trade costs T^s_{ijt}.

My primary focus in the empirical test of the model is the third prediction. In particular, holding technology and travel costs fixed, do U.S. services exporters in sectors with higher levels of employees with jobs that require in-person tasks have higher export trade costs? The empirical specification comprises of two regression stages. In the first regression, I isolate trade costs T^s_{ijt} by country, year, and sector. In the second stage regression, I decompose trade costs with measures of the share of workers in each sector that perform in-person tasks, and controls for travel costs and internet technology. First, to isolate trade cost from other determinants of trade, such as market size, I rely on a modified version of the gravity model in equation 9. Due to the detailed data available on U.S. service exports by sector and the tasks completed by U.S. workers by occupation, my empirical test focuses on 24 U.S. services export categories for 71 U.S. export partners from 2008 to 2021. Focusing on U.S. data allows for a better exploration of heterogeneity across individual service sectors, but presents a challenge for the empirical gravity model, since no variation in the exporter i means that exporter-year fixed effects (used to control for exporter multilateral resistance) cannot be included at all, and importer-year fixed effects typically used to control for importer multilateral resistance terms are colinear with all other determinants of trade. In order to correct for this issue somewhat, following Herman (2022), I include a control for total services output of the importing country, to separate the impact of importer market size from other time-varying determinants of importer multilateral resistance terms, such as technology available in the importing market.

In addition to U.S. export data, I also include domestic U.S. trade in each services product (total output less exports), following the recommendations of Heid et al. (2021). This allows me to estimate the trade costs for each importer-sector-year relative to the costs of providing the service in the domestic market, which is consistent with the theoretical specification of the model. I estimate the equation using the multiplicative Poisson Pseudo Maximum Likelihood (PPML) estimator, which corrects for heteroskedasticity of the data and allows for the inclusion of zero trade flows (Santos Silva and Tenreyro, 2006).[1] For each importer j in time t, U.S. exports in sector s is given by:

$$USExports^s_{jt} = exp(\beta^s_1 FTA_{jt} + \beta^s_2 log(ServicesOutput)_{jt} + \delta^s[International_j \times year_t] + \upsilon^s[International_j \times importer_j]) + \epsilon_{jt} \quad (10)$$

.

In equation 10, the primary terms of interest for calculating trade costs T_{jt} are $\delta[International_j \times year_t]$ and $\upsilon[International_j \times importer_j]$. The $International_j$ interaction component present in both of these terms is a binary variable that equals 0 for domestic trade flows (services produced in the United States for U.S. consumers) and 1 for international trade flows. $\delta[International_j \times year_t]$ is a set of year dummy variables that explain differences in trade patterns in a given year, relative to domestic U.S. production of service s. The year term controls for global shocks to U.S. exports, such as the global financial crisis in 2008/2009 or the COVID-19 pandemic in 2020/2021. Second, $\upsilon[International_j \times importer_j]$ is a set of dummy variables that control for importer-specific characteristics that determine trade patterns with the United States, including cultural determinants like common language, as well as the internet technology and travel cost determinants of interest. These dummies are again measured relative to the costs associated with producing that service for the domestic U.S. market, through the international interaction term. The $log(GDP)_{jt}$ control separates market size from the υ dummies. Finally, I include a control for the presence of a free trade agreement between the United States and its export partners, $\beta_1 FTA_{jt}$, to separate their impact from other time-varying trade costs the υ dummies. Equation 10 is estimated separately for each service sector in the data.

After estimating equation 10, I calculate annual, product-specific trade costs for each importer using the ad-valorum tariff equivalent calculation described in Yotov et al. (2016), which is adapted to the Eaton and Kortum (2002) supply-side model.[2] Trade costs are given as the sum of the importer-sector specific υ and the year-product specific δ for each importer:

$$\hat{T^s_{jt}} = exp\left(\frac{\delta^s_t + \upsilon^s_j}{-\theta}\right). \quad (11)$$

Here, for the parameter θ, which captures the importance of comparative advantage in the world economy in the Eaton and Kortum (2002) model, I use the value of 4, taken from Simonovska and Waugh (2014). The resulting trade costs are measured relative to the U.S. domestic market in each year (the denominator of equation 7, $\left[\int_0^{n^*_{ii}} l^s(n)c_{ii}(n)dn + \int_{n^*_{ii}}^1 l^s(n)dn\right] = 1$ for each sector and year).

The goal of the second stage of the analysis is to decompose the components of T^s_{jt} as in equation 7, in

[1] The estimations are conducted using the ppml package in STATA.

[2] Specifically, the elasticity of substitution $1 - \sigma$ in Yotov et al. (2016) is replaced with the comparative advantage term $-\theta$, and the excludes the term that coverts $\hat{T}$ into a tariff rate-equivalent percentage.

order to estimate the impact of differences the share of total employment in each sector that is comprised of in-person labor $\int_{n_j^*}^1 l^s(n)dn$, travel costs f_{jt}, and the level of technology available in the import market (an observable component of C_{jt}^s). First, to measure the share of total employment that is comprised of in-person labor, I use the classification presented in Dingel and Neiman (2020) to categorize U.S. occupations as online-tradable or in-person only, then use the employment-weighted share of in-person occupations across U.S. services sectors as my measure of total labor working in in-person only tasks. Next, to approximate f_{jt}, I create an index of flight costs, which varies across countries and sectors, which is calculated relative to intra-U.S. flight costs. Finally, approximating C_{jt}^s is less straightforward, given that there are both observable (available technology and internet reliability) and unobservable (cultural preferences for in-person vs online interactions) components of the term. Additionally, the functional form of C_{jt}^s does not cleanly separate the technology costs from the labor engaged in online tasks. As such, the second-stage regression focuses on controlling for the level of internet-related technology available in importer j, to capture at least some components of C_{jt}^s. In particular, I include variables measuring the internet-related patent stock and the share of the population that are internet users in the importing market, as well as the number of direct fiber optic undersea cable connections between the United States and its import partners.

The second-stage regression is given by equation 12, which is represented linearly below, but will be estimated both linearly and non-linearly via a PPML estimator. This reflects the possibility that the relationship between the variables of interest are multiplicative rather than additive.[3]

$$\begin{aligned}\hat{T_{jt}^s} = \alpha + \gamma_1 inperson_t^s + \gamma_2 TravelCosts_{jt} + \gamma_3 PatentStock_{jt} + \gamma_4 InternetUsers_{jt} + \\ \gamma_5 CableConnection_{jt} + \gamma_6 TradeRestictions_j + \psi BilateralDeterminants_j + \\ dyear_t + e_{ijt}.\end{aligned} \tag{12}$$

In addition to the variables described above, the specification also includes a control for services trade restrictions in the importing market ($\gamma_6 TradeRestictions_j$) and vector of bilateral, non-time varying determinants of trade, $\psi BilateralDeterminants_j$, including log distance, contiguity, common language and colonial relationship. Additionally, the model includes year trends, to control for heterogeneity in trade costs across years.

4 Data

In order to test the model presented above empirically, I rely on several data sources, described in detail below. I focus on U.S. services exports because of the level of detail available on trade in services by service type and the availability of data on the tasks performed by U.S. workers over time and across occupations.

[3]As noted in Anderson and van Wincoop (2004), the log-linear decomposition of trade costs common in gravity literature is an arbitrary choice.

However, this focus may also limit the generalizability of the findings of this empirical tests to other high-income countries, as the share of tasks that can be traded online may be considerably different in developing markets.

First, to estimate bilateral trade costs $\hat{T^s_{ijt}}$, I start with U.S. services export data from U.S. Bureau of Economic Analysis (BEA) international trade in services data (BEA, 2022). The data is available at a disaggregated services sector level for 71 U.S. trade partners, and includes coverage of both developed and developing country markets.[4] Together, these countries account for 90 to 93 percent of total U.S. service exports across years the sample. This data is classified in a way that is largely consistent with the IMF Extended Balance of Payments System (EBoPs) for recording services trade transactions.[5] I exclude transportation services from the final sample, because transportation services are tied to the movement of goods across borders, rather than the movement of producers or consumers of the service.

The BEA services data has several types of missing values. First, some entries are "true" missing variables (coded as n.a.) where data are not available. Other entries are suppressed values (coded as (D)) where data is available, but suppressed in order to avoid disclosing data on the operations of specific companies. Both of these types of missing values are dropped from the final sample. Cases where there is zero trade in a particular service category are recorded as 0 in the data, but transactions between 0 and $500,000 are coded as (*), and represent about 9 percent of the total sample. Rather than dropping these data points, I replace (*) values with the midpoint value of $250,000. Finally, negative trade values in the data are replaced with zeros.[6]

To combine this trade data with sector-specific variables, such as U.S. domestic output and employment by sector, the trade data was concorded to U.S North American Industry Classification System (NAICS), building on classifications used by Khachaturian and Oliver (2023), Borchert et al. (2021), and USITC (2020). A list of trade codes and corresponding NAICS sectors is presented in table 1. In most cases, the services sectors present in the export data concord to a three or four-digit NAICS category.[7] The major exception is the retail and wholesale sector, which encompasses a large group of NAICS industries, but only accounts for a single trade flow in the trade data.[8] The final trade data includes 24 non-transportation services sectors.[9] Following the recommendations of Heid et al. (2021) for calculating trade costs, I also include domestic trade flows for the United States, so that I can measure export transportation costs relative to the domestic market.[10] Relying on the NAICS to exports correspondence in table 1, I calculate total domestic trade by

[4]However, data for the African continent is particularly limited, including only observations for Morocco and Nigeria.

[5]For more information on the construction of BEA services trade data, see `https://www.bea.gov/international/concepts_methods.htm`

[6]Negative values in services occasionally occur in insurance, when bilateral claims are larger than premiums in a given year, or are related to large merchanting transactions (Fortainier et al., 2017).

[7]I use the 2017 edition of the NAICS industry codes, but at this level of aggregation, codes are consistent with the 2012 and 2007 editions of the NAICS

[8]This reflects the business models of retail and wholesale services trade, which are primarily traded internationally via the establishment of affiliates in a foreign market.

[9]Heritage and recreational services also fall under non-transportation services sectors, but were excluded due to missing data.

[10]Data on total output comes from BEA data on gross output by industry (BEA, 2022b).

service sector as the difference between gross output by sector and total exports by sector.

In addition to the main trade data sample, in my first stage regression (equation 10), I also incorporate a variable indicating the presence of a preferential trade agreement, using the Dynamic Gravity Dataset (Gurevich and Herman, 2018). This variable captures U.S. trade agreements that entered into force during the period, and include the CAFTA-DR expansions to the Dominican Republic and Costa Rica, the U.S.-Peru, U.S.-Oman, KORUS, U.S.-Colombia, U.S.-Panama, and USMCA agreements. All of the U.S. trade agreements signed over the period include provisions dedicated to services trade, and use a "negative list" approach, which means that provisions in the agreements apply to all services sectors unless there is a specific exclusion noted in the agreement (USITC, 2021). The final control in the first stage regression is total services output of each importer, which is calculated as the total GDP of each importer multiplied by that importer's value-added share of services output, both taken from the World Bank World Development indicators (World Bank, 2023).

For the second stage regression, I next gather data on the shares of employment in online and in-person tradable occupations, technology, and travel costs. Measuring the share of services that are traded over the internet is a key challenge for understanding the dynamics of service trade: aside from recent surveys conducted by the UK Office of National Statistics (referenced in the introduction) and the U.S. Bureau of Economic Analysis (Mann and Cheung, 2019), there is little data on the share of services that are traded online. There have been several attempts to proxy for the share of services that are online traded. van der Marel and Ferracane (2021) calculate "data intensity" of different services sectors as either the usage of software in that sector or inputs of data processing services from input-output tables. Similarly, Calvino et al. (2018) classify goods and services sectors by their use of digital technology using the share of information and communication technology (ICT) investment, purchases of intermediate ICT goods and services, robot stock, ICT specialists employed and turnover from online sales. An alternative approach, employed by Dingel and Neiman (2020) is to consider the potential for online operations by looking at the employment composition of different sectors. Using data on the activities of workers by occupation, Dingel and Neiman (2020) classify occupations as non-telework capable based on whether workers in those occupations report frequently completing tasks that require physical presence, like repairing machinery. Given the close parallels to my model setup, this paper uses the Dingel and Neiman (2020) approach to calculate the share of workers in each U.S. services sector that could deliver their components of final services produces online versus in-person.

First, to proxy for the share of labor in a given sector that is engaged in in-person versus online activities, I use on the Occupational Information Network (O*NET) database, which compiles survey data on work activities and tasks of U.S. workers by occupation (O*NET, 2022). The O*NET database has been used by many of the empirical tests of the Grossman and Rossi-Handsberg models, as it provides detailed descriptions of the types of tasks performed by different occupations (see, for example Crinò (2010), Wright (2014), and Oldenski (2012)). These data are available at the occupation level and updated annually. In particular, this

Table 1: Correspondence between NAICS codes and BEA services trade categories

NAICS	NAICS Industry Description	BEA Trade Category Description
23	Construction	Construction
42,44,45	Wholesale Trade; Retail Trade	Trade-related services
5112	Software Publishers	Computer software, including end-user licenses and customization; Licenses to reproduce and/or distribute computer software
512	Motion Picture and Sound Recording Industries	Audiovisual originals; Rights to use audiovisual products
515	Broadcasting (except Internet)	Broadcasting and recording of live events
517	Telecommunications	Telecommunications services
5182	Data processing, hosting, and related services	Cloud computing and data storage services
5191	Other Information services	Information services
522	Credit Intermediation and Related Activities	Credit card and other credit-related services; Financial advisory and custody services; Financial management services
523	Securities, Commodity Contracts, and other financial investments and related activities	Brokerage and market-making services; Securities lending, electronic funds transfer; Underwriting and private placement services
524	Insurance Carriers and Related Activities	Insurance services
5411	Legal Services	Legal services
5412	Accounting, Tax Preparation, Bookkeeping, and Payroll Services	Accounting, auditing, bookkeeping, and tax consulting services
5413	Architectural, Engineering, and Related Services	Architectural services; Engineering services
5415	Computer systems design and related services	Other computer services
5416	Management, Scientific, and Technical Consulting Services	Business and management consulting and public relations services
5417	Scientific Research and Development Services	Research and development services; Licenses for the use of outcomes of research and development
5418	Advertising, Public Relations, and Related Services	Advertising and related services
5419	Other Professional, Scientific, and Technical Services	Scientific and other technical services
562	Waste Management and Remediation Services	Waste treatment and de-pollution services
611	Educational Services	Education related travel; Education services
62	Health care and social assistance	Health related travel; Health services;
711	Performing Arts, Spectator Sports, and Related Industries	Artistic-related services
72	Accommodation and food services	Business travel; Other personal travel

paper focuses on the work activities and work context datasets in O*NET, which cover broad tasks completed by workers in a particular occupation (i.e. Environmental Engineers) and the frequency (context) and importance (activities) of these tasks. For example, the O*NET work context survey provides information on how frequently workers in a specific occupation use electronic mail, while the work activities survey provides information on the importance analyzing data in the occupation. Using these surveys, I classify occupations as online-tradeable, based on the classification used by Dingel and Neiman (2020) to estimate the share of U.S. workers that could work from home during the COVID-19 pandemic. In particular, Dingel and Neiman (2020) classify occupations with any of the characteristics presented in table 2 as not able to be done from home (hereafter "in-person only").

Table 2: Job Characteristics that determine in-person only occupations

From the context survey:	**From the activities survey:** "very important" activities
• Use electronic mail less than once per month; • Deal with physically aggressive people at least once a week; • Work outdoors, exposed to weather, daily; • Work outdoors, under cover, daily; • Exposed to minor burns, cuts, bites, or stings at least once a week; • Spend majority of time walking and running; • Spend majority of time wearing common protective safety equipment such as safety shoes, glasses, gloves, hearing protection, hard hats, or life jackets; • Spend majority of time wearing specialized protective or safety equipment such as breathing apparatus, safety harness, full protection, suits, or radiation protection.	• Inspecting equipment, structures, or materials; • Performing general physical activities; • Repairing and maintaining electronic equipment. • Handling and moving objects; • Controlling machines and processes; • Performing for or working directly with the public; • Repairing and maintaining mechanical equipment; • Operating vehicles, mechanized devices, or equipment (except computers);

Source: Dingel and Neiman (2020). For the activities survey, "very important" activities received a score of 4 out of 5 or higher.

While Dingel and Neiman (2020) focus on the 24.2 data release of O*NET (published in February 2020), I extend their classification to a wider range of data, applying it to releases 13.0-26.0 of the data (published between 2007 and 2022) to get a count of occupations that are in-person only over time. I assume a one-year lag in the data, such that data released in 2022 reflect conditions in 2021.

To calculate the total employment of in-person only occupations per service sector, I merge this data with the U.S. Bureau of Labor Statistics (BLS) occupational employment and wage statistics survey, which provides data on industry employment by occupation by year at the NAICS three and four digit industry level (BLS, 2022). Both of the datasets classify occupations via 6-digit standard occupational classification

(SOC) codes. However, the O*NET data typically does not include "all other" SOC occupations (such as SOC code 15-1299: "Computer Occupations, All Other"). In those cases, I classify occupations as in-person only if nearby codes are classified as in-person only.[11] This merged data allows me to calculate the total number of employees in each in-person only and online-tradable occupation over time for each of the NAICS sectors and aggregations in table 1. From this data, I calculate the employment weighted share of employment that is in-person only.

Table 3 shows the distribution of employment in occupations that can only be completed in-person across the service sectors in my sample. The variation in average in-person only employment in each sector follows expected patterns: travel, construction, and waste treatment services have the largest share of in-person occupations, while professional services such as legal and accounting services, and computer and software services have the smallest share. Within sectors, there is not a consistent trend of employment in in-person only occupations over time. Some sectors, such as artistic-related, audiovisual and securities services became considerably less reliant on in-person only labor between 2008 and 2021, while other sectors, such as telecommunications, advertising and architecture and engineering services have become more in-person labor intensive over time.

Next, I use prices of commercial flights originating in the United States to proxy for travel costs f_{jt}. Data on the price of commercial flights from the United States to its export partners comes from GSA contract prices for federal workers (GSA, 2022).[12] Price data is available beginning in 2008 at the city-pair level (for example, the negotiated price of a flight from New York City to Paris), and represents nominal one-way fares for each pair of cities in the data in a given year.

In order to get average fare prices across countries (United States to France), I constructed population-weighted prices based on the origin and destination prices for the cities. Data on population by city come from SimpleMaps, which covers roughly 42,000 cities for the year 2022 (Simplemaps, 2022). When population data was unavailable for smaller cities, I dropped those cities from the sample of airports in that country. Countries with a single flight destination in the data (such as Lisbon in Portugal), were not population weighted. Although this data does not capture variation in the populations of cities over time, proved the relative sizes of the cities are consistent over time, this should still provide reasonable weights. After calculating population-weighted flight prices, I divide the population-weighted average price by country by the population-weighted average flight price for the United States. This transformation means that the travel costs in each year are expressed relative to domestic travel. So, instead of using the information that the population-weighted average single flight from the U.S. to France costs $550 in 2016, instead the data instead shows that traveling to internationally to France in 2016 is 1.73 times more expensive than travelling within the United States in 2016.[13]

[11] For example, codes near 15-1299 include 15-1251: "Computer Programmers" and 15-1252: "Software Developers," are both online-tradeable, so 15-1299 is also coded as online-tradable.

[12] These data are available on the GSA website for the 10 most recent years, and additional data is available from GSA upon request

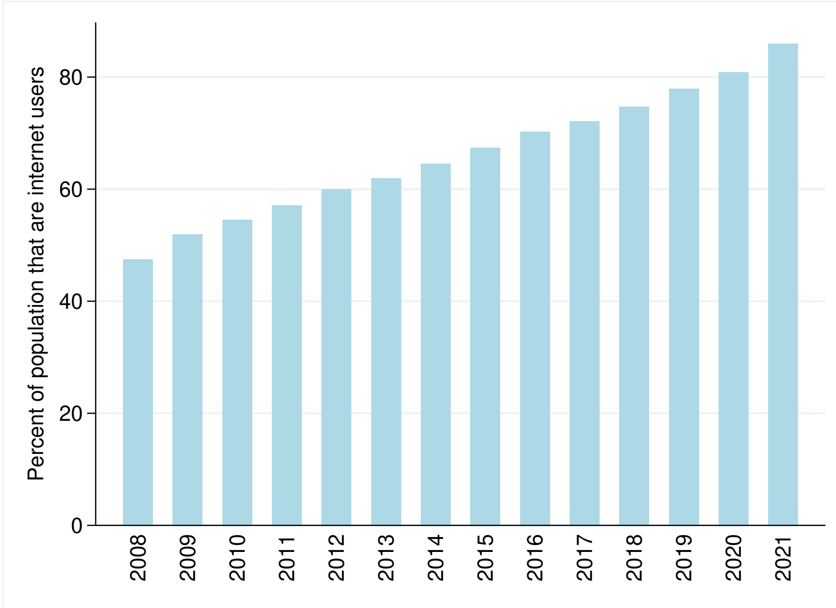
[13] This transformation also accounts for the lower-than-market rates negotiated by GSA contractors, assuming that discounts on fares for government travel are applied uniformly across destinations.

Table 3: Share of employment in in-person only occupations, by U.S. services sector, 2008–2021

	Average	Std. Deviation	2008 share	2021 share
Legal	5.1	1.1	3.4	5.8
Software	9.8	3.9	6.2	12.8
other computer services	10.0	4.2	6.2	12.4
Accounting	14.7	5.4	7	10.6
Cloud and data	15.4	5	9.9	19.4
Securities services	18.3	12.4	38.8	7.9
Education	19.9	1.6	21.3	19.7
Information	20.5	5.4	14.3	21.6
Consulting	20.8	1.8	17.6	23.3
Insurance	27.1	10.0	21.9	20.2
Advertising	27.4	9.4	18.8	41.7
Architecture and eng.	30.3	6	24	40.5
R&D	32.0	5.4	26.1	39.6
Banking services	35.2	6.6	30.9	32.7
Broadcasting	42.5	5.6	41.0	49.9
Telecommunications	49.8	5.3	39.0	55.9
Audiovisual	56.8	5.4	67.2	51.2
Scientific and other tech.	57.2	7.3	44.5	68.7
Artistic-related svcs.	58.7	5.3	65.2	48.4
Healthcare	72.1	1.4	74.8	73.4
Wholesale, retail	73.6	2.5	71.9	70.3
Waste treatment	77.6	2.1	76.2	81
Construction	80.6	1.8	83	81.5
Travel	89.6	3.1	94.9	91.3
Average	39.4	25.7	37.7	40.8

Finally, I use three measures of internet technology to account for differences in available technology across different importing markets. First I use data on internet-related patents published in that market in each year of my sample to create a measure of internet-patent stocks. Data on internet-related patents comes from the World Intellectual Property Organization (WIPO) Statistics Database (WIPO, 2022). In particular, I use WIPO data on the number of patent publications by technology in each market and year. I classify 5 of the available WIPO technology fields as "internet-related" patents: audio-visual technology, telecommunications, digital communication, computer technology, and IT methods for management. The average number of internet-related patents per year in my sample was 7,064, but the distribution of patents is skewed, with only China, Japan, South Korea, and the United States publishing more than 5,000 patents per year on average. The overall number of internet-related patents published per year did increase over the sample, from 7.2 million in 2008 to 15.8 million in 2021, though the number of publications do seem to vary based on overall economic conditions, declining after the global financial crisis and in 2020. Since the knowledge gained from patents more closely resembles a stock rather than a flow (i.e. knowledge builds on itself over time), I convert these data from flows of patents in each year to the stock of patents in every year. For each importer, I approximate the stock of patents in 2008 (the first year of my sample) as:

Figure 6: Average percent of the population that is internet users, 2008-2021



Source: World Bank (2023)

$$PatentStock_{j,2008} = \frac{Patents_{j,2008}(1 + g_{j,2000-21})}{(\delta + g_{2000-21})}, \tag{13}$$

where $g_{j,2000-21}$ is the average growth rate of internet-related patents between 2000 and 2021, and δ is the depreciation rate of the technology developed in the internet-related patents. I set δ to 10 percent. Each subsequent year of internet-related patent stock is calculated as the new patents published plus the depreciated patents stock from the previous year: $PatentStock_{j,t+1} = PatentStock_{j,t}(1-\delta)+Patents_{j,t+1}$.[14]

To measure consumer adoption of the internet, I use the data on "Individuals using the internet (percent)" from the International Telecommunication Union (ITU) World Telecommunication/ICT Indicators Database (ITU, 2023) (available via the World Bank World Development Indicators Database). This measure of internet access is broad, and counts all individuals who have reported using the internet in the past 3 months from any device, including computers, video game consoles, and mobile phones. As shown in figure 6, the average share of internet users has steadily increased over the entire sample.

Finally, measures of direct fiber optic undersea cable connections come from TeleGeography's Submarine Cable Map (TeleGeography, 2021), which includes information on the landing points of undersea cables and their "ready for service" date, which allows for a time-varying measure of the connections between the United States and its export partners. Undersea cables improve the quality of internet connections by allowing for faster transfer of data between markets and additional cables can improve the reliability of connections by introducing redundancy in the system in cases where one cable is damaged. In 2021, the countries with the

[14]For some smaller import markets, there is only a single year in 2000–2021 with reported patent publications. In these cases, patent stock is 0 before that observation, then depreciates at a rate of 10 percent per year in all subsequent years.

most direct undersea fiber optic cable connections to the United States were Japan (10 cables), Colombia, and Brazil (8 cables each). Given that the data does not include overland fiber optic cable connections, this measure likely underestimates the reliability of internet connections between the United States, Mexico and Canada. However, the contiguity control in the second stage regression implicitly also accounts for the overland fiber optic connections between these three markets.

In addition to the main internet-related controls of interest, additional controls for the the second stage regression includes standard gravity covariates (distance, common language, colonial relationship and contiguity) taken from Gurevich and Herman (2018) and a control for services trade restrictions in the importing market, taken from the World Bank/WTO Services Trade Restrictions Index (STRI) (Organisation for Economic Cooperation and Development (OECD), 2021). This index covers 34 service sectors and 129 economies, and ranges from 0 (completely open market) to 100 (completely closed to trade in a specific services sector).[15] The STRI was collected via surveys between 2016 and 2021, and thus is limited in that it only represents only a cross-section of the restrictions faced by services exporters in the sample, rather than tracking restrictions over time.

The final sample includes 24 industries and 71 trade partners for the years 2008 to 2021, as summarized in table 4.

Table 4: Summary Statistics

	Observations	Mean	Std. Deviation	Min	Max
U.S. exports, billions $	21,912	9.2	0.1	0.0	4.8
Importer GDP, billions	21,456	1,110.2	2,711.5	6.3	23,315.1
In-person share, percent	21,912	39.4	25.7	3.4	94.9
Flight Price Index	21,912	2.7	1.3	0.7	8.4
Internet Patent stock	20,575	49,996.69	18,8299.9	0	1,709,667
Internet users (percent of population)	20,856	66.1	23.9	4.4	100
Undersea Internet Cables	21,912	1.5	2.8	0	21
Service trade restrictions	17,616	43.6	9.4	12.5	100
Distance (population weighted km)	21,912	8,347.5	3,465.4	1,918.3	15417.7
	Observations	0	1		
Free Trade Agreement	21,912	16,464	5,5448		
Common Language	21,912	8,544	13,368		
Colonial Relationship	21,912	19,944	1,968		
Contiguity	21,912	21,240	672		

5 First Stage Results

First stage regression results are presented table A1. Across the sectors in the sample, importer services output is a positive and significant predictor of trade for every sector, with a one percent increase in importer

[15] Unlike goods trade, trade policy related to services is set at the country, rather than EU-level (Benz and Gonzales, 2019).

GDP increasing trade between 29.6 and 64.4 percent across sectors.[16] In contrast, the presence of a free trade agreement between members does not have a consistent relationship across U.S. service sectors. For seven of the 25 sectors, membership in an FTA significantly increase exports, with the largest positive effects in cloud computing and other data storage services exports. In contrast, eight of the 25 sectors show a negative and significant impact of FTA membership on trade (the remaining nine sectors show no significant relationship). There are several potential explanations for this results. First, for services that are predominantly traded via travel, changes to visa policy may be more important than trade liberalization under a FTA, and only one U.S. trade agreement that entered into force in the sample period contained provisions related to visas for business travellers (USMCA).[17] Second, while several U.S. trade agreements entered into force or were expanded over the sample period, major U.S. services trading partners such as the UK, EU, Japan, and India are not part of any trade agreements with the United States.

Estimates of bilateral trade costs $\hat{T_{jt}}$, calculated from the first stage regression (equation 10) and equation 11 are summarized in table A2. Overall, the average trade cost relative to domestic U.S. trade takes a value of 8.7, which corresponds to an 770 percent ad valorum tariff equivalent for U.S. exports.[18] While this average estimated trade cost is large, it does fall within the range of other recent estimates of trade costs for U.S. services trade. For example, trade costs for services estimated in Gervais and Jensen (2019) range from 1.9 to 12.7. As shown in figure 7, on average, trade costs declined steadily over the first 10 years of the sample, then increased in the COVID-19 period in 2020 and 2021. This increase in trade costs may reflect the impact of travel restrictions related to COVID-19, which severely restricted the in-person delivery channel for services exports.[19]

At the sector level, many of the service sectors with low capacity for online trade including construction, wholesale and retail, healthcare, and waste treatment services have the highest trade costs on average, as shown in figure 8. However, this pattern does not hold across all services. For example, travel services, which is the least online tradable sector, has the smallest average trade costs while cloud computing and data storage services have relatively large estimated trade costs, despite being highly-online tradable.

Finally, average estimated trade costs by import partner, shown in figure 9 shows less variation in trade costs across import partner compared to across sectors. By construction, the smallest estimated trade costs are U.S. trade in the domestic market (taking a value of one). The next smallest trade costs represent close countries (Canada, Mexico), English speaking countries (UK and Australia) and markets that are historically open to services trade (Singapore, Hong Kong).

[16] Calculated as $(exp(\beta_1^s) - 1) * 100$.

[17] U.S.-Chile and U.S.-Singapore FTAs also include visa-related provisions, but entered into force in 2004, before the start of the sample period.

[18] ad valorum tariff equivalents are calculated as $(\hat{T_{jt}} - 1) * 100$.

[19] Robustness checks excluding 2020 and 2021 were consistent with the main findings of this paper.

Figure 7: Average estimated $\hat{T}^s_{jt}$ value, by year

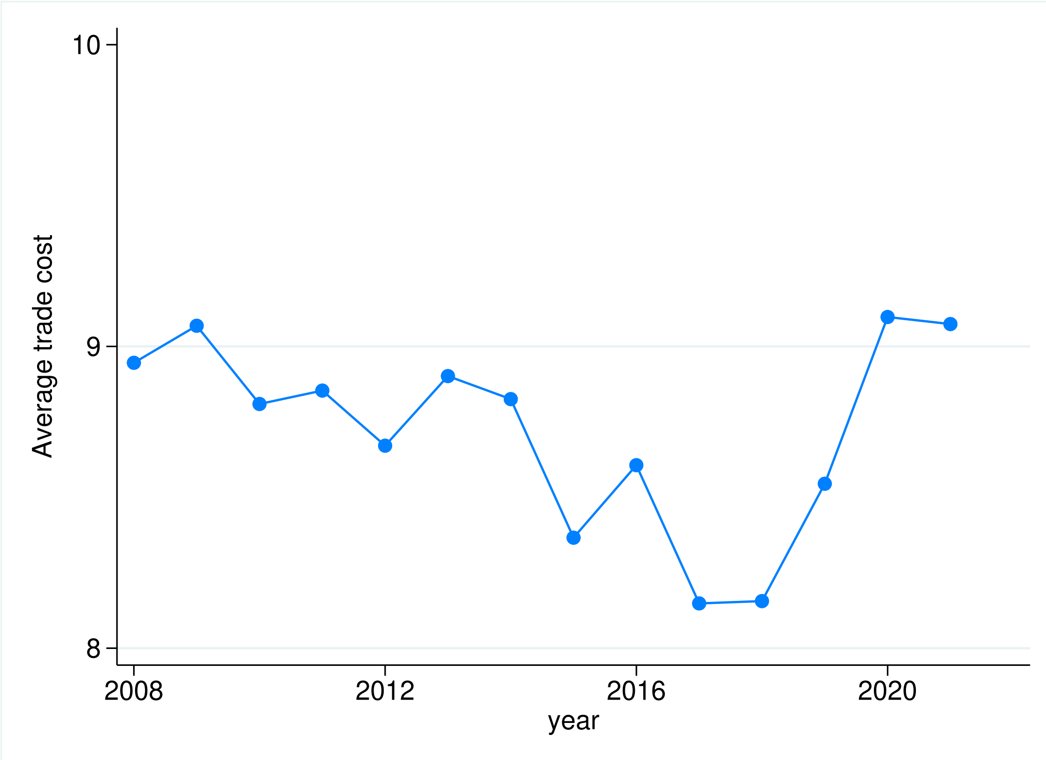


Figure 8: Average estimated $\hat{T}^s_{jt}$ value, by service sector

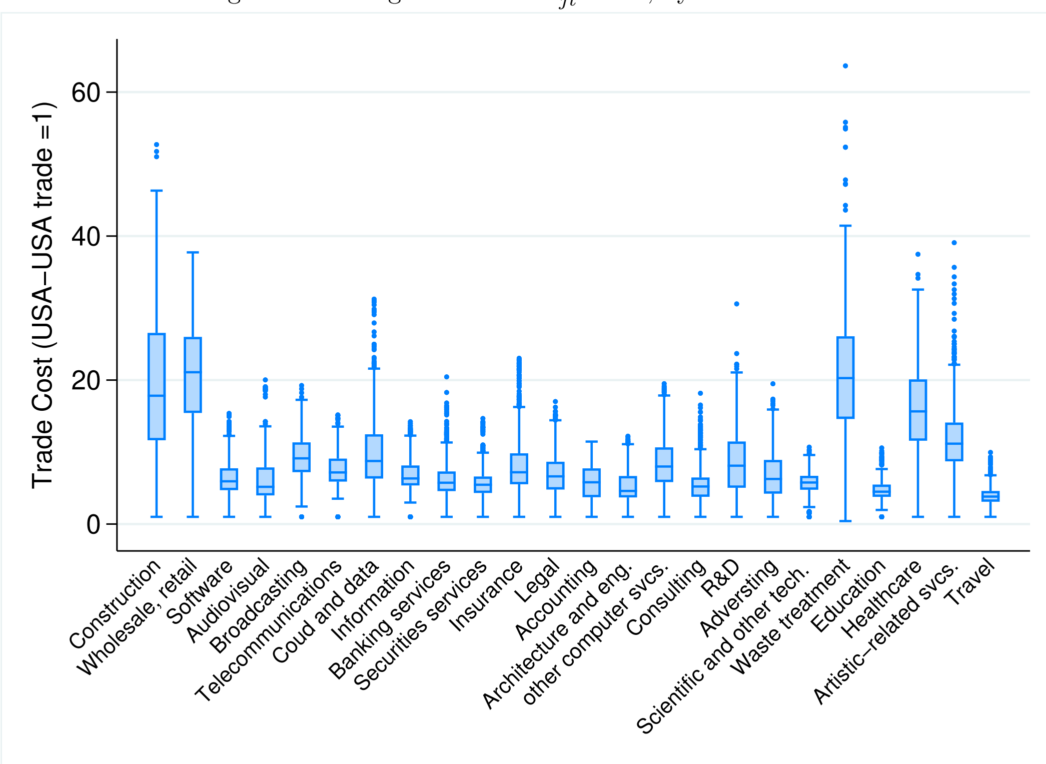
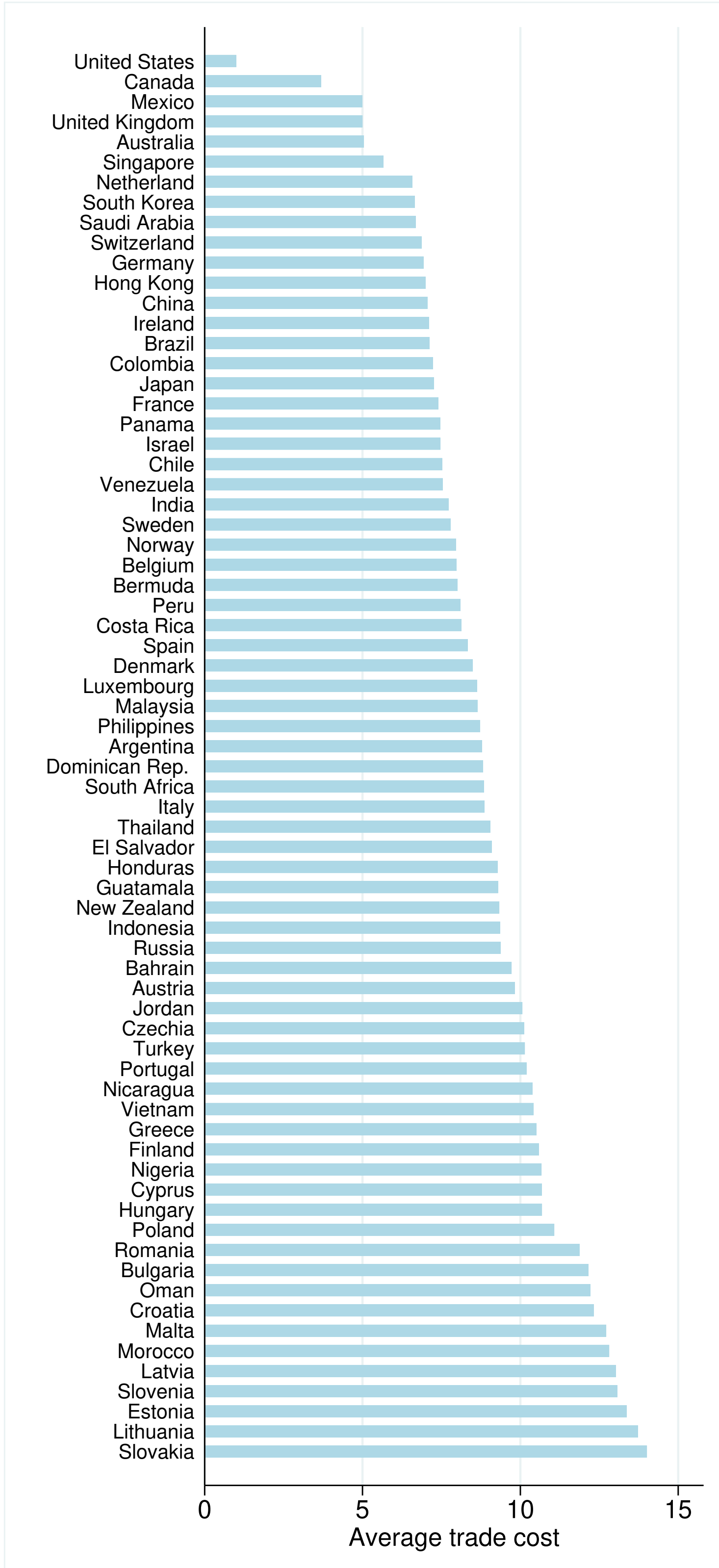


Figure 9: Average estimated $\hat{T^s_{jt}}$ value, by import partner



6 Second Stage Results

Table 5 presents the main findings of the second stage regressions, sequentially adding additional controls and fixed effects across each column in order to better understand the source of variation in the data. Column (1) in table 5 includes year fixed effects and non-time varying characteristics of importers (services trade restrictions, distance, contiguity, colonial relationship and common language). Column (1) shows a positive and significant impact of in-person share of labor on total trade costs, such that a one percent increase in the share of labor in a sector and year that perform in-person only jobs is associated with an 11 percentage point increase in total trade costs. This supports the predictions of the theoretical model described in section 2.5, where services exporters with larger shares of labor performing in-person tasks are expected to have higher overall trade costs. In addition to this main finding, the results in column (1) also support the general predictions of the model regarding the direction of different types of trade costs. Higher flight prices (relative to United States domestic travel) significantly increase trade costs, while the stock of internet related patents, and number of underseas fiber optic cable connections significantly decrease trade costs. Services trade restrictions (STRI) and distance have no significant relationship to trade costs, while contiguous importers (Mexico and Canada), importers with a colonial relationship with the United States, and those that share a common language all have significantly smaller trade costs.

Next, column (2) of table 5 replaces the time-invariant trade controls with importer fixed effects. In this specification, the a higher share of in-person only employment still significantly increases trade costs (though only at the 90 percent level), with about the same magnitude of effect. However, flight prices, patent stock and fiber optic cable connections are no longer significant, suggesting the main variation in these predictors of trade costs is at the importer, rather than importer-time level. In contrast to column (1), the internet users variable is significant in column (2), with a 1 percent increase in the share of internet users in an importing market leading to a 0.92 percentage point decrease in total trade costs. Column (3) adds a term interacting the share of in-person only labor and flight prices to the specification in column (2), to make the empirical specification more in line with equation 7. This interaction shows that the impact of flight prices on trade costs is significantly higher for services sectors with higher shares of in-person labor, suggesting that for these products, flight prices are a larger contributor to total costs than for more online-traded services sectors.

Finally, column (4) introduces sector fixed effects into the regression. The inclusion of sector fixed effects changes the sign of the in-person labor share variable, but maintains the same signs and significance on the interaction of flight prices and the internet users variables. As shown above, the change in sign and significance of the in-person only labor share variable may reflect the sources of variation in the data. While there is considerable variation in the in-person share of labor across sectors, within sector variation is more limited. This result also highlights the limitations of the data available, as we do not observe the share of online-tradable tasks that are actually traded online.

Table 6 reproduces table 5 using a PPML estimator rather than a linear estimator in the second stage.

Table 5: Second Stage Results, linear estimator

	(1)	(2)	(3)	(4)
Dependent variable: $\hat{T}$				
In-person only labor share	0.107**	0.0996*	0.0677*	-0.0403*
(percent)	[0.0496]	[0.0487]	[0.0340]	[0.0210]
Flight price index	0.593***	0.00529	-0.473	-0.515*
	[0.107]	[0.0230]	[0.291]	[0.292]
In-person x Flight price			0.0126*	0.0137*
			[0.00701]	[0.00699]
Log(Patent stock)	-0.350***	-0.00166	-0.00182	-0.00273
	[0.0550]	[0.0125]	[0.0128]	[0.0133]
Underseas fiber optic cables	-0.203***	0.0829	0.0839	0.0866
	[0.0404]	[0.0515]	[0.0519]	[0.0520]
Internet users	-0.0163	-0.00918**	-0.00945**	-0.00947**
(percent of population)	[0.0125]	[0.00380]	[0.00391]	[0.00395]
Services Trade Restrictions	-0.0222			
	[0.0316]			
Log(Distance)	-0.261			
	[0.420]			
Contiguity	-1.760***			
	[0.613]			
Colonial relationship	-0.831***			
	[0.273]			
Common language	-1.873***			
	[0.350]			
Constant	11.85***	-3.081	-1.844	-0.0599
	[3.846]	[1.880]	[1.295]	[0.880]
Observations	15,288	17,573	17,573	17,573
Year FE	x	x	x	x
Importer FE		x	x	x
Sector FE				x
Adj. R-squared	0.297	0.305	0.308	0.706

Results estimated via OLS. Robust standard errors, clustered at the services product level in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Year, importer and sector fixed effects omitted for brevity.

This reflects the idea that trade costs may be multiplicative instead of linear. In terms of significance, the results in table 6 are largely consistent with the linear results (thought it is interesting to note that in column 4 the negative impact of the share of labor that can only be done in-person is not significant). However, the magnitude of the effects are considerably smaller in the PPML version of the second stage, with a 1 percent increase in the in-person share of total employment increasing trade cost by only 1 percentage point in column (3).[20] This result is consistent with the findings of Santos Silva and Tenreyro (2006), who attribute the larger coefficients in their OLS results to heteroskedacticity in the ordinary least squares method.

Table 6: Second Stage Results, PPML estimator

Dependent variable: $\hat{T}$	(1)	(2)	(3)	(4)
In-person only labor share	0.0122***	0.0111**	0.00994**	-0.00211
(percent)	[0.00468]	[0.00456]	[0.00426]	[0.00177]
Flight price index	0.0515***	0.00360	-0.0156	-0.0195
	[0.0138]	[0.00257]	[0.0177]	[0.0168]
In-person x Flight price			0.000421	0.000519*
			[0.000340]	[0.000308]
Log(Patent stock)	-0.0419***	0.000959	0.000953	0.000932
	[0.00612]	[0.000846]	[0.000867]	[0.000946]
Underseas fiber optic cables	-0.0463***	0.00616	0.00617	0.00671
	[0.00677]	[0.00499]	[0.00497]	[0.00508]
Internet users	-0.00281*	-0.000939**	-0.000947**	-0.000963**
(percent of population)	[0.00148]	[0.000414]	[0.000417]	[0.000426]
Services Trade Restrictions	-0.00339			
	[0.00406]			
Log(Distance)	0.00218			
	[0.0666]			
Contiguity	-0.334***			
	[0.0952]			
Colonial relationship	-0.0918**			
	[0.0422]			
Common language	-0.199***			
	[0.0290]			
Constant	2.351***	-0.470**	-0.418**	-0.224
	[0.607]	[0.221]	[0.210]	[0.154]
Observations	15,288	17,573	17,573	17,573
Year FE	x	x	x	x
Importer FE		x	x	x
Sector FE				x
Pseudo R-squared	0.311	0.311	0.311	0.741

Results estimated via PPML. Robust standard errors, clustered at the sector level in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Year, importer and sector fixed effects omitted for brevity.

Next, to account for potential non-linearity in the impact of the share in-person only labor on total trade

[20]Calculated as $(exp(\gamma_{inperson}) - 1) * 100$

costs, results in table 7 separate the in-person labor share variable into 4 categories: 0-25 percent in-person labor, 25-50 percent in-person labor, 50-75 percent in-person labor, and 75-100 percent labor. Table 7 reproduces columns (1) and (2) of table 5 using this new categorical variable (0-25 percent in person is the omitted category). Column (1) shows no significant difference in trade costs between exporters with 0-25 percent in-person only labor and 25-50 percent in person labor in a given sector and year. However, sectors with 50-75 percent in-person labor have significantly higher trade costs than those in the 0-25 percent category, amounting to 433 percentage point higher trade costs. Finally, sectors in the 75-100 percent category have 831 percentage point higher trade than those in the 0-25 percent category. Taken together, these results suggest non-linearities in the effect of in-person only labor share on total trade costs, such that sectors with less than 50 percent in-person only labor do not have significantly different trade costs, but trade costs increase considerably after passing that 50 percent mark.

Finally, table 8 separates the U.S. services products into five sub-categories of services, in order to determine whether there are differences in the impact of the in-person only labor share across similar types of services. The five sub-categories include professional services (legal, accounting, education, health care, consulting, advertising, R&D, scientific and other technical), financial services (insurance, banking, securities services), electronic services (software, cloud and data, other computer, information, broadcasting, telecommunications, audiovisual), building-related services (construction, architecture and engineering) and hospitality services (travel, waste treatment, wholesale and retail, artistic-related). Table 8 reproduces column (3) of table 5. In contrast to the aggregate findings, these sector level results show that only professional and building- related services see a significant increase in trade costs associated with higher in-person only labor shares. The magnitude of these effects are also higher than in the main sample, with higher shares of in-person only labor significantly increasing total trade costs by 16.7 percentage points for building-related services and by 14.3 percentage points for professional services. For building-related services, exporters are also significantly more sensitive to flight prices as the share of in-person only labor increases. Additionally, while the in-person labor share does not significantly increase trade costs overall for electronic services, the interaction with flight prices is positive and significant, suggesting that the less online tradable services in this category are more sensitive to changes in travel costs.

Taken together, these results show that while services products overall see significant increases to trade costs when the share of employment in in-person only occupations increase, the effect is likely driven by specific types of services, and largely due to differences in costs for majority in-person versus majority online-capable occupations.

Table 7: Second Stage Results with categorical in-person employment share variable

	(1)	(2)
Dependent variable: $\hat{T}$		
25-50 percent in-person	0.573	0.538
	[0.597]	[0.599]
50-75 percent in-person	4.330*	4.230*
	[2.165]	[2.145]
75-100 percent in-person	8.310*	7.711
	[4.674]	[4.673]
Flight price index	0.598***	0.00575
	[0.103]	[0.0222]
Log(Patent stock)	-0.355***	-0.00501
	[0.0547]	[0.0115]
Underseas fiber optic cables	-0.206***	0.0835
	[0.0413]	[0.0519]
Internet users	-0.0178	-0.00910**
(percent of population)	[0.0119]	[0.00375]
Services Trade Restrictions	-0.0308	
	[0.0265]	
Log(Distance)	-0.244	
	[0.420]	
Contiguity	-1.763**	
	[0.651]	
Colonial relationship	-0.835***	
	[0.271]	
Common language	-1.884***	
	[0.356]	
Constant	14.54***	-1.093
	[3.283]	[0.897]
Observations	15,288	17,573
Year FE	x	x
Importer FE		x
Adjusted R-squared	0.318	0.324

Results estimated via OLS. Robust standard errors, clustered at the sector level in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Year and importer fixed effects omitted for brevity.

Table 8: Second Stage Results by sector aggregates

Dependent variable: $\hat{T}$	(1) Professional	(2) Financial	(3) Electronic	(4) Building-related	(5) Hospitality
In-person only labor share	0.119**	0.00456	-0.0211	0.167***	-0.277
(percent)	[0.0384]	[0.0162]	[0.0242]	[0.00155]	[0.104]
Flight price index	-0.260	-0.0952	-0.289	-2.775	-1.115
	[0.384]	[0.246]	[0.172]	[1.339]	[3.252]
In-person x Flight price	0.00944	0.00361	0.0131**	0.0492***	0.0142
	[0.00989]	[0.00992]	[0.00467]	[0.000573]	[0.0456]
Log(Patent stock)	0.00729	-0.00436	-0.0483	0.0768	0.00510
	[0.0173]	[0.0117]	[0.0247]	[0.0943]	[0.0202]
Underseas fiber optic cables	0.150**	0.0506	0.197	-0.310	0.0368
	[0.0507]	[0.0440]	[0.122]	[0.332]	[0.163]
Internet users	-0.0123**	-0.000196	-0.0150	-0.0201	0.00209
(percent of population)	[0.00523]	[0.00198]	[0.0114]	[0.0169]	[0.0101]
Constant	1.683	-0.321	-0.736	-5.932	20.43
	[1.575]	[0.425]	[1.849]	[5.246]	[9.780]
Observations	6,349	2,259	4,504	1,477	2,244
Year FE	x	x	x	x	x
Importer FE	x	x	x	x	x
Adjusted R-squared	0.453	0.748	0.537	0.772	0.272

Results in this table estimated via OLS. Robust standard errors, clustered at the sector level in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Year, importer, and sector fixed effects omitted for brevity.

7 Conclusion

This paper builds a model of trade in services that is distinct from existing models because it accounts for the different costs associated with exporting final services to the end consumer, depending on whether components of that final service are delivered in-person via travel or online. Using a task-based framework where each intermediate task within a final service can be delivered online or in-person, a firm seeking to minimize costs will choose the least costly option for delivering each task, taking into account the cost of travelling to deliver that task and the efficacy of delivery of that task online. In equilibrium, for each export destination, a firm chooses the threshold task where it is indifferent between delivering that task online or in-person.

The empirical test of the model focuses on the relationship between the share of U.S. service employees that can only be completed in-person and total trade costs for 24 U.S. services export sectors. Overall, as predicted by the model, increases in the share of in-person only employment significantly increases trade costs, with a one percent increase in the in-person employment share of a services sector increases total trade costs by about 10 percentage points. This result is more pronounced when comparing majority in-person services sectors to those with majority online-tradeable employment, and for professional and building-related services. In addition to these main findings, the empirical test also confirms the predictions of the model that higher travel costs are associated with higher overall trade costs and better internet technology in the importing market are associated with lower overall trade costs.

There are several potential policy implications of the model and empirical findings of this paper. First, this model can be used to examine changes in immigration policy, particularly those related to changes to visa policy for business travellers, including obtaining a visa and the length of time travellers can stay in a country visa-free, COVID-19 related travel restrictions, and changes to UK citizens movement in the EU following Brexit. Additionally, while this paper considers changes to technology broadly, it could also be used to look at the impact of a specific change in technology on trade costs, such as the widespread adoption of videoconferencing software, or technology-related policy, such as the impact of limitations on free movement of data across international borders, which could limit trade in otherwise online-tradable tasks.

While this paper sheds light on the dynamics of services trade beyond what has previously been explored in the theoretical literature, it also highlights the data gaps that still exist for services trade. Most notably, while proxies for the share of services tasks that can be traded online and in-person can be constructed for U.S. export sectors, there is very little information on the actual share of U.S. services exports that are traded online and in-person. The theoretical model predicts that improvements in internet-related technology will both decrease trade costs via lower per-task costs for tasks that are already traded online and by shifting some tasks from in-person to online delivery. While my empirical analysis does largely confirm the first-order effects of the theoretical model, I am unable to observe the second-order shifts with the available data. Future research, particularly as more data about trade patterns and remote work during the COVID-19 pandemic becomes available could potentially shed more light on these second order effects.

Additionally, it is not clear how generalizable my results are to the rest of the world. For other high-income countries, the shares of workers in the U.S. market that are employed in occupations that can only be performed in-person could be a reasonable proxy for in-person occupations in other markets. For example, Dingel and Neiman (2020) show that EU countries and the United States have similar levels of telework-friendly occupations in aggregate (roughly 40 percent of all occupations, including manufacturing occupations). However, similar work focusing on developing markets have found considerably smaller aggregate levels of telework-friendly occupations (roughly 10 percent of occupations) (Gottlieb et al., 2021; Hasan et al., 2021) driven by factors such as differences in rural and urban internet access, education and income levels, and availability of IT equipment. These differences highlight the importance of future research to help determine the extent to which a developing country market can feasibly expand the share of tasks that are traded online in their services exports.

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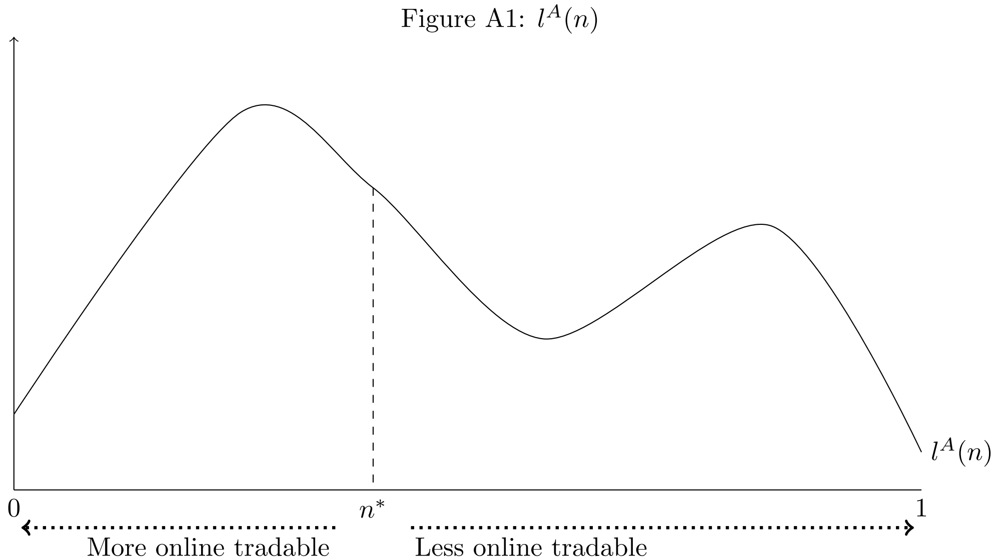
A Appendix

A.1 Changes in labor allocation in in-person and online tasks

This appendix provides additional detail on the conditions needed to assess the impact of differences in the labor allocation function $l^s(n)$ across services products without defining a specific functional form for $l^s(n)$. Rather than define a specific functional form for $l^s(n)$, which would require knowledge of both the distribution of labor across tasks and the rank order of tasks by internet-tradeabilty, I focus on the proportionality of changes in the total number of online traded and in-person only tasks.

First, let $l^A(n)$ represent the labor allocation function for services product A. An example functional form for $l^A(n)$ is plotted below in figure A1, with tasks ordered from the most to least internet-tradable along the x-axis. The n^* threshold task is determined by the $c(n)$ function and travel costs f, so it is exogenous to the labor allocation function.

Figure A1: $l^A(n)$

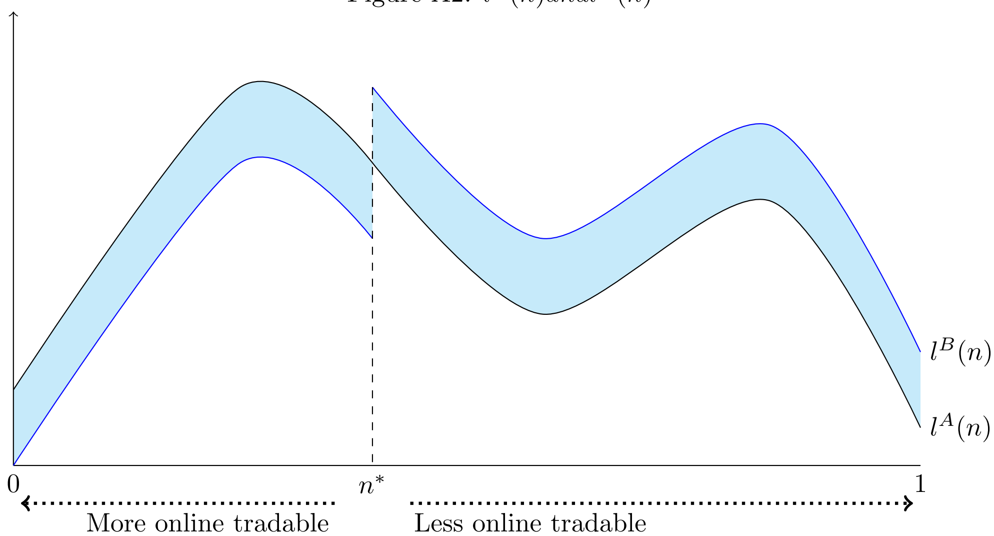


The implications of the functional form of $l(n)^A$ on total trade costs differ based on whether tasks fall above or below the n^* threshold. For tasks that are traded in-person and fall between n^* and 1, the specific allocation of labor into different tasks has no bearing on the value of in-person related trade costs. Instead, the total value of labor across all in-person tasks is multiplied by constant travel costs f_{ij}. In contrast, the functional form of $l(n)^A$ does affect the total value of online trade costs. Since $c(n)_{ij}$ is a non-decreasing function, the efficiency gains from trading tasks online will be larger for tasks closer to 0 than tasks near n^*. Thus, without defining a functional form for $l(n)^A$ the total value of the online task component of trade costs is ambiguous.

The importance of task order for online-traded tasks means that changes to the share of workers that perform in-person and online tasks only have clear predictions under certain conditions. Namely, consider the case where services product B has a labor allocation function $l(n)^B$, which only differs from $l(n)^B$ in two respects. For all online-traded tasks $(0 - n^*)$, the curve is shifted downward, while for all in-person tasks $(n^* - 1)$, the curve is shifted upward by the same amount. These changes are shown in figure A2.

shown in figure A2

Figure A2: $l^A(n) and l^B(n)$



The distribution of $l^B(n)$ relative to $l^A(n)$ shows a shift in labor from online tradable tasks to in-person tasks that is proportional across all tasks in the distribution. This proportional shift is useful because it removes ambiguity about the impact of changing the labor allocation function on trade costs.[21] First, for online traded tasks, since the same number of workers are removed from each tasks, the overall online traded component of trade costs in product B, $\int_0^{n^*} c(n)l^B(n)$, is smaller than for product A because there are fewer workers employed overall, not because the distribution of employees in online tradeable tasks has changed. Similarly, the value of the in-person costs for product B is larger than for product A, because $\int_{n^*}^1 l^B(n) > \int_{n^*}^1 l^A(n)$. Taken together, the decrease in online-related trade costs coupled with the increase in in-person trade costs means that trade costs for services product B are larger than for product A.

[21] The proportional shift is also a fairly restrictive assumption. However for a sufficiently large sample of products and distributions, random shocks to the number of workers completing each in-person and online task will become proportional over time by the law of large numbers.

A.2 Additional Regression Results

Table A1: First stage results

DV: exports, millions $	Construction (1)	Wholesale/retail (2)	Computer software (3)	Audiovisual (4)	Broadcasting (5)	Telecom (6)
FTA member	-1.753***	-0.733***	0.776***	0.896***	-1.218***	-0.211**
	[0.405]	[0.134]	[0.104]	[0.154]	[0.265]	[0.0916]
Importer Log(Svc. Output)	0.468***	0.497***	0.420***	0.389***	0.378***	0.444***
	[7.86e-09]	[2.82e-09]	[2.03e-07]	[1.20e-06]	[7.31e-08]	[5.03e-08]
Observations	855	874	889	875	859	889
Pseudo R-squared	0.979	0.987	0.990	0.994	0.796	0.999

DV: exports, millions $	Cloud and data (7)	Information (8)	Banking (9)	Securities (10)	Insurance (11)	Legal (12)
FTA member	1.947***	0.428***	0.159***	0.0509	-0.375***	-0.0345
	[0.155]	[0.0633]	[0.0549]	[0.0483]	[0.137]	[0.0571]
Importer Log(Svc. Output)	0.375***	0.407***	0.449***	0.435***	0.456***	0.419***
	[1.37e-07]	[1.70e-07]	[1.95e-07]	[2.19e-07]	[9.59e-08]	[1.01e-07]
Observations	889	889	889	889	889	888
Pseudo R-squared	0.500	0.957	0.994	0.985	0.968	0.997

DV: exports, millions $	Accounting (13)	Arch and eng (14)	Other computer (15)	Consulting (16)	R&D (17)	Advertising (18)
FTA member	-0.223*	-0.0991	0.0671	-0.0752	-0.174	0.0868
	[0.125]	[0.121]	[0.136]	[0.121]	[0.135]	[0.229]
Importer Log(Svc. Output)	0.316***	0.382***	0.426***	0.422***	0.442***	0.380***
	[[1.41e-06]	[1.66e-06]	[1.13e-07]	[1.51e-06]	[7.75e-07]	[1.95e-06]
Observations	888	889	875	889	889	877
Pseudo R-squared	0.917	0.945	0.979	0.929	0.994	0.896

DV: exports, millions $	Scientific (19)	Waste mgmt (20)	Education (21)	Health care (22)	Artistic (23)	Travel (24)
FTA member	-0.572*	-12.33***	-0.690***	-0.0593	0.880***	0.136**
	[0.300]	[0.324]	[0.144]	[0.262]	[0.160]	[0.0588]
Importer Log(Svc. Output)	0.259***	0.379***	0.417***	0.482***	0.396***	0.451***
	[1.71e-06]	[6.29e-10]	[1.68e-06]	[4.19e-09]	[1.30e-08]	[1.36e-06]
Observations	889	396	889	889	889	889
Pseudo R-squared	0.970	0.989	0.998	0.993	0.985	0.976

This table presents estimates derived from the gravity model of trade, estimated via PPML. Robust standard errors, clustered at the importer level in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Year and importer fixed effects, with USA-USA trade as the omitted category included in all regressions, but omitted for brevity.

Table A2: Summary of estimates of $\hat{T_{ijt}}$ derived from first stage regression

	Mean	St. Deviation	Min	25th percentile	Median	75th	Max	Obs
Construction	19.4	9.7	1	11.6	17.8	26.5	52.7	865
Wholesale, retail	20.7	7.0	1	15.4	21.1	26	37.7	884
Software	6.5	2.5	1	4.7	5.9	7.7	15.4	899
Audiovisual	6.2	3.3	1	4.0	5.2	7.9	20	885
Broadcasting	9.3	3.1	1	7.2	9.1	11.3	19.2	864
Telecommunications	7.5	2.3	1	5.9	7.2	9.1	15.2	899
Cloud and Data Storage	9.9	5.1	1	6.3	8.8	12.5	31.2	899
Information	6.9	2.4	1	5.4	6.3	8.1	14.2	899
Banking services	6.2	2.8	1	4.6	5.7	7.3	20.4	899
Securities services	5.7	2.2	1	4.3	5.5	6.6	14.7	899
Insurance	8.2	4.2	1	5.5	7.2	9.8	23.0	899
Legal	7.0	2.8	1	4.8	6.6	8.7	17.0	898
Accounting	5.9	2.5	1	3.7	5.8	7.7	11.5	898
Architecture and Eng.	5.2	2.2	1	3.7	4.6	6.7	12.2	899
other computer services	8.5	3.5	1	5.8	8.0	10.7	19.5	885
Consulting	5.5	2.6	1	3.8	5.2	6.5	18.2	889
Research and development	8.6	4.4	1	5.0	8.1	11.5	30.6	899
Advertisitng	6.8	3.3	1	4.2	6.3	8.9	19.5	887
Scientificand other technical	5.6	1.5	1	4.8	5.8	6.7	10.7	899
Waste treatment	19.7	11.7	1	14.6	20.3	26.1	63.6	399
Education	4.6	1.4	1	3.8	4.5	5.5	10.6	899
Healthcare	16	5.7	1	11.6	15.6	20.1	37.5	899
Artistic-related services	12	4.9	1	8.7	11.2	14.1	39.1	899
Travel	4.0	1.3	1	3.1	3.8	4.6	10.0	899
Total	8.7	6.2	1	4.8	6.8	10.5	63.6	20,950

Summary statistics based on first-stage regression results presented in table A1. Minimum trade cost estimates all refer to internal trade (USA-USA) by construction.