Information Inputs and International Trade: Evidence from U.S. State Level Data on Business Air Travel*

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Abstract
This paper provides theory and evidence examining the role of information as an input into trade in complex manufactures. In the model, consumers have unique valuations for quality-differentiated products, and firms can customize products to appeal to foreign buyers. Information enters as an input to relationship-specific product adaptation, becoming an endogenous fixed cost of trade. Differences in goods' information intensity, communication costs and in foreign markets' potential determine the optimal level of information transmitted within a trade relationship. Using U.S. state-level data on international business air travel and on manufacturing exports, I investigate and confirm the model's predictions that the demand for information (transferred via business travel) is directly related to the volume and composition of exports. The econometric identification relies only on cross-state variation in travel and trade flows, and controls for time-varying destination country effects in order to eliminate the incidence of spurious correlation. The results are robust to simultaneity between travel and trade, and to the inclusion of ethnic networks, inbound FDI and international leisure travel. I also estimate the dependence of information demand on industry level exports in order to identify the information intensity of trade at sector level, and find that exports of complex manufactures and goods requiring strategic inputs are most dependent on face-to-face meetings.

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Keywords: state exports; air transport; travel; information; face-to-face; product adaptation; fixed cost.

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1. Introduction

International trade has become increasingly dependent on the transmission of complex information. As trade involves a larger share of differentiated goods (Rauch, 1999) and as production networks spread across the globe (Hummels et al., 2001), communication between trade partners is an essential element of successful long-term partnerships. However, information is not always directly observable, and often times existing measures do not distinguish between its uses for production or personal consumption purposes. Both measurement problems are overcome when information is transmitted in person across national borders, because in this case communication flows leave a 'paper trail' in the form of business-class airline tickets.

This paper combines U.S. state level data on air passenger traffic with data on manufacturing exports in order to examine the role of face-to-face meetings in international trade. In doing so, it investigates whether trade in complex manufactures is mediated by face-to-face interactions between buyers and sellers, and then estimates which manufacturing industries are most dependent on this mode of communication as an effective way to increase foreign sales.

The need to extend our knowledge about the role of personal interactions in international trade has been increasingly recognized by trade economists in various areas of research such as economic geography (Grossman, 1998; Leamer and Storper, 2001), services trade (Head et al., 2008) and outsourcing (Grossman and Helpman, 2002; Grossman and Rossi-Hansberg, 2008). Understanding whether the transfer of goods and services across national borders is accompanied by the delivery of information from one person to the other has direct consequences for the geography of trade. Moreover, this direction of research also has important implications for policies that restrict international travel, such as visa programs or aviation market regulations that limit competition and keep travel costs high.

Anecdotal evidence suggests that producers initiate face-to-face meetings in order to establish international partnerships and learn the particular requirements of foreign buyers so that exported products could better match foreign demands. Egan and Mody (1992) provide ample evidence in that respect from field interviews with U.S. importers. They report:

> "US firms are reducing their number of suppliers in favor of closer partnerships with a few of their best suppliers. Under these closer arrangements, buyers visit plants frequently, engineers spend time at each other's facilities, and buyer's management invests time in building relationships with supplier's management." (p. 329) "[collaborative relationships] are often an essential source of information about developed country markets and production technology as well as product quality and delivery standards." (p. 321) "In exchange for larger, more regular orders from buyers, suppliers collaborate with buyers' product designers. Collaboration in design and manufacturing at early stages of product development cuts costs and improves quality." (p. 326)

A preview of the data I will describe later in more detail seems to support the intuition that knowledge about foreign markets gathered from personal meetings becomes a direct input in export production. Figure 1 identifies a positive correlation between manufacturing exports (normalized by foreign market size) and outbound business-class air traffic across destination countries for selected U.S. states. Figure 2 takes a different cut at the data and plots for several importing countries the distribution of trade and business air travel flows across U.S. source regions. The graphs suggest that the gains from information transfers get materialized in larger import demands. Yet, the correlations may also be spurious if they are born out of differences across locations such as income or development level. For example, some states invest more in transportation infrastructure relative to others, boosting both air travel and trade. Similarly, richer countries import more goods, of higher quality, and also provide attractive travel destinations.

To examine the role of information transmission in international trade, I propose a model of trade with endogenous quality choice[1] that combines the following features. Consumers across

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[1] Quality represents a simple yet versatile approach to capture trade gains from information transmission. It encompasses a wealth of scenarios for why products are traded within established business relationships rather than

markets have unique valuations for quality-differentiated products, and firms can customize their products to appeal to foreign buyers. The overall value attached to a traded product is determined by two distinct quality components: a 'mean' product quality component that is producer specific and identical across all destination markets, and a 'relationship-specific' quality component that is tailored to the particular characteristics of a foreign buyer. Information is modeled as an input in the production of relationship-specific quality, becoming a choice variable in the firm's profit maximization problem and an endogenous fixed cost of trade. Finally, the technology that transforms information into valuable product attributes is allowed to vary across goods, generating differences in their trade's dependence on face-to-face meetings. From this theoretical set-up, I derive the optimal demand for information inputs and show that it is effectively driven by the volume of exports and their composition in terms of information intensive goods.

To test the model's prediction that information conveyed via face-to-face conversations enters as an input to trade, I construct an international air travel dataset from the Passenger Origin Destination Survey provided by the U.S. Department of Transportation. This unique data source contains rich ticket level information on airfare, number of passengers, class type, and the entire flight itinerary detailed at airport level (e.g. origin of journey, connections and actual final destination). For the estimation, I aggregate the airline ticket level data by class type and by direction of travel in order to obtain bilateral measures for total air traffic and average fares that match the U.S. state level exports data provided by the U.S. Census. The constructed sample of bilateral travel and trade flows covers the period 1998-2003, a time interval that is ideal for doing empirical work because of the significant variation in air travel expenses. The richness of the data on the geographical dimension is of great value for testing this paper's predictions

between anonymous parties. Examples include: access to custom-made inputs, reduced production costs due to better coordination, increased efficiency as a result of trust and cooperation, lower advertising costs, etc.

because it allows me to exploit only the within U.S. cross state variation in exports and air travel, and control for time-varying destination market effects in order to remove sources of spurious correlation generated by country differences in income, infrastructure or development level.

In the empirical part, I estimate information input demands and determine the responsiveness of air travel to variations in the scale and the composition of U.S. manufacturing exports. I find that a 10% increase in the volume of exports raises the demand for business air travel by 2%. Conditional on the total value of exports, a 10% increase in the average share of differentiated goods raises the demand for international business travel by an additional 1.2-1.9%. These results are robust to the potential endogeneity of export flows, and to the inclusion of ethnic networks, inbound FDI or international tourism services. Further, I estimate the dependence of business air travel demand on industry level exports in order to identify the information intensity of trade at sector level. I find that the estimates are highly correlated with R&D expenditure shares and Nunn's (2007) contract intensities, suggesting that exports of complex manufactures and goods facing contractual difficulties are most dependent on face-to-face interactions.

This paper contributes to the literature on trade costs by adding to an insufficiently explored area of research on information barriers to trade. A number of empirical studies pioneered by Rauch (1999) have used various information measures in a gravity equation framework to estimate the effects of information frictions on the volume of trade.[2] However, in spite of the general consensus that information facilitates international trade, there is less said about the mechanisms that generate this outcome. This study tries to fill this gap by providing theory and evidence for an information-driven product adaptation mechanism.

[2] The information measures previously used by the literature are distance and common language/colonial ties (Rauch, 1999), ethnic networks (Rauch and Trindade, 2002; Herander and Saavedra, 2005), internet penetration (Freund and Weinhold, 2004), telecommunication costs (Fink et al., 2005; Tang, 2006), product standards (Moenius, 2004) and business travel (Poole, 2009).

By measuring information flows using air passenger data, this paper is closely related to the work of Poole (2009), who examines the dependence of U.S. exports on incoming business air traffic. Using a different dataset that has richer information on passenger characteristics, Poole (2009) finds that business air travel to the U.S. by non-residents and higher-skilled travelers has a positive impact on the extensive and intensive margins of U.S. exports. This paper reinforces Poole's (2009) main finding of a direct relation between U.S. trade and air travel flows, and extends this direction of research in three respects. First, it explicitly models why information matters for international trade and then takes the proposed hypothesis to a test. Second, the empirical exercises use an identification strategy that exploits the sub-national geographic dimension of the data in order to control for any time-varying differences across destination countries that might spuriously link exports and air travel flows. As a result, this study brings stronger empirical evidence that the volume and composition of manufacturing exports are positively related to information flows. These results are robust across specifications and estimation methods. Third, this paper provides estimates for the information intensity of exports at sector level and finds that the results align well with external measures of product complexity.

The findings of this paper also add to the literature on distance puzzle and economic agglomerations. Familiarity and personal contacts have been cited as having potentially important implications for the sensitivity of trade flows to distance (Grossman, 1998; Leamer and Storper, 2001; Head et. al, 2008). However, this insight has received little empirical attention, in large part because of data availability.[3]

[3] Hillberry and Hummels (2008) provide striking evidence for the geographic localization of manufacturing shipments and show that these patterns are driven by the co-location of final and intermediate goods producers. While transportation costs are invoked as the main driving force behind such industrial clusters, information transmission could provide an additional explanation.

The remainder of the paper proceeds as follows. Section 2 provides theory and generates predictions about the optimal demand for information measured as face-to-face communication. Section 3 describes the state level data on exports and business-class air travel, and discusses the econometric strategy. Section 4 analyzes the estimation results and provides robustness checks. Section 5 estimates information intensities of exports at sector level. Section 6 concludes.

2. Theoretical Model

This section outlines a simple partial equilibrium monopolistic competition framework. Information transmission is modeled as an input to product quality, which is assumed to be specific to a buyer-seller relationship (e.g., product adaptation). The set-up follows the recent endogenous quality literature.[4] However, it assumes that vertical product differentiation is realized using information inputs, which are fixed rather than variable costs.[5] Using this set-up, I derive an information input demand equation that takes into account differences in information costs across destination markets as well as differences in information intensities across sectors.

2.1. Model Set-up

There are N foreign markets indexed by j that import differentiated goods from sectors k, produced in one country of origin (the U.S.) by firms located in sub-national regions s (states). I assume homogeneity of buyers within a market and of sellers within a location and industry.[6]

Demand side. Buyers in country j derive utility from all available products according to a two-tier utility that is Cobb-Douglas over sectors and asymmetric CES within sectors:

[4] See for example Verhoogen (2008), Kugler and Verhoogen (2008), Baldwin and Harrigan (2008).

[5] Johnson (2008) and Hallak and Sivadashan (2008) also relate quality production to fixed costs, however the fixed inputs do not vary by destination market. Arkolakis (2008) proposes a model with endogenous bilateral marketing costs, however such investments increase the number of foreign buyers reached, rather than the sales per consumer.

[6] The homogeneity of buyers and sellers in a location ensures identical trade partnerships within a bilateral market pair, simplifying the aggregation of information and trade flows across exporters, for conformity with the data.

$$U_j = \prod_k \left(X_{jk}\right)^{\mu_{jk}}, \quad \text{where} \quad X_{jk} = \left(\sum_{\Omega_{jk}} q_{sjk}^{\frac{1}{\sigma}} x_{sjk}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \quad \sigma > 1, \quad \sum_{\mathrm{k}} \mu_{\mathrm{jk}} = 1 \tag{1}$$

where q_{sjk} is the value attached by consumers in market j to a variety of good k produced in the US region s (quality shifter), x_{sjk} is the quantity consumed of that variety, σ is the elasticity of substitution between all the varieties, μ_{jk} is the exogenous expenditure share of good k in market j, and finally Ω_{jk} represents the variety set available in market j.[7]

I assume that the preference weights q_{sjk} are separable into two quality components: one that is producer-specific and identical across all destination markets, denoted λ_{sk}, and one that is specific to a bilateral trading pair, denoted λ_{sjk}. That is:

$$q_{sjk} = \lambda_{sk}\lambda_{sjk}, \qquad \lambda_{sk}, \lambda_{sjk} \geq 1 \tag{2}$$

Most research on vertical differentiation examines the producer-specific quality component, linking it to technological factors (Flam and Helpman, 1987), endowments (Schott, 2004), input quality (Verhoogen, 2008) or productivity (Baldwin and Harrigan, 2008). In contrast, this paper pays close attention to the relationship-specific preference parameter, assumes it to be a deterministic component of the import demand[8] and interprets it as the per-unit product value added obtained when trading within a familiar buyer-seller link.

The solution to the utility maximization problem faced by the representative buyer of country j delivers the usual Dixit-Stiglitz demand. Substituting for the preference weights using equation (2), after some rearranging, the import demand function becomes:

$$x_{sjk} = \lambda_{sjk}\left(\tau_{sjk}\frac{p_{sk}}{\lambda_{sk}^{1/\sigma}}\right)^{-\sigma}\frac{\mu_{jk}Y_j}{P_{jk}}, \quad \text{with} \quad P_{jk} = \sum_{\Omega_{jk}} q_{sjk}\left(\tau_{sjk}p_{sk}\right)^{1-\sigma} \tag{3}$$

where τ_{sjk} represents the "iceberg" trade cost, p_{sk} is the f.o.b. product price, P_{jk} is the CES consumer price index and Y_j is total income of country j.

[7] Since a product is identified by a location-industry pair *(s,k)*, the key difference between this utility and the standard asymmetric CES function is that here product quality can have different rankings across markets *j*.

[8] Assuming a deterministic demand shifter distinguishes the set-up from models of demand uncertainty (Nguyen, 2008).

Supply side. Following Verhoogen (2008), I assume that the production technology for each good k is separable into the production of the physical output and quality. Further, I separate the production of quality into the production of 'mean' quality λ_{sk} (e.g. standard product performance), and the production of relationship-specific quality λ_{sjk}. I think of the relationship-specific quality component as any favorable attribute that individualizes a shipment, by making it specific to a foreign buyer. These attributes could characterize the physical product (e.g. custom-made inputs, products compatible with market-specific standards, packaging in the format and language of the destination country) or the delivery service (e.g. improved coordination, better customer service, reduced likelihood of recalls due to a more careful inspection of shipments).

Production of the physical output requires only labor, which is homogenous and mobile across sectors within the same region. Labor is also the only factor used in the production of 'mean' quality. In region s and sector k one product of quality λ_{sk} is obtained using β_{sk} units of labor. Note that this specification encompasses factors and technology differences across production locations. Firms are assumed to produce only for export. To enter foreign markets they must pay a fixed bilateral entry cost F_{sjk}. Since the technology for physical output involves fixed and variable costs, in equilibrium firms choose to horizontally differentiate their products.

Production of the 'relationship-specific' quality requires information inputs, fixed in nature, gathered from personal meetings with foreign buyers. Face-to-face communication is viewed as a form of capital generated from the interaction of trade partners, which has the ability to create product value-added that is unique to a trade partnership. I assume that the technology to transform information capital into bilateral product quality takes the form:

$$\lambda_{sjk} = \left(i_{sjk}\right)^{\theta_k} , \qquad \theta_k \in [0,1) \tag{4}$$

where i_{sjk} represents the amount of information transmitted within a buyer-seller link, and θ_k is an exogenous parameter that captures the importance of face-to-face communication for trade in sector k. A large value of θ_k implies high returns to relationship investments because it provides high scope for quality improvements. Restricting θ_k to be less than one ensures a well-behaved optimization problem.

Total cost. Combining the assumptions on the production technologies, a firm located in US region s exporting a variety of good k to foreign market j faces the total cost (TC):

$$\mathrm{TC}_{\mathrm{sjk}} = \left(\beta_{sk} w_s\right) x_{\mathrm{sjk}} + \mathrm{i}_{\mathrm{sjk}} \mathrm{c}_{\mathrm{sj}} + \mathrm{F}_{\mathrm{sjk}} \tag{5}$$

where β_{sk} represents the unit labor requirement, w_s is the wage rate in the source region, c_{sj} is the bilateral unit cost of communication, and F_{sjk} is the per-period market entry cost.

A couple of points are in place here. First, the total information cost, $i_{sjk}c_{sj}$, measures the investment a firm is willing to make in order to increase buyers' valuation for its products, as captured by λ_{sjk}. The fixed cost assumption implies that once the communication efforts are chosen, the knowledge from such investments is costlessly incorporated in each product sold. Second, the production of relationship-specific quality does not require per-unit costs. This is a simplification that keeps the model centered on the fixed cost nature of information inputs.[9] Finally, even with identical countries, the total cost of export varies across destination markets because of the two-part fixed cost (c_{sj}, F_{sjk}) and of the variable trade cost (τ_{sjk}).

2.2. Firm's optimization problem

In every period, an exporter has to decide the amount of communication effort spent with a foreign buyer, and the price level charged for its market-adapted products. Since there is no uncertainty in this model, the optimal choices of information transmission and product price are made in the same period so as to maximize profits.

[9] The model can be extended by adding per-unit factor requirements in the production of relationship-specific quality. This is left for future work as it is not essential for this paper's questions. Also, the econometrics accounts for source fixed effects that control for any differences in endowments or technology.

Combining the import demand equation given by equation (3) with the relationship-specific quality technology from equation (4) and the cost structure given by equation (5), one obtains the expressions for export revenues and profits at firm level. The profit maximization problem delivers the standard monopoly pricing rule, as a constant mark-up over the marginal cost $p_{sk} = \frac{\sigma}{\sigma - 1}\beta_{sk} w_s$. The optimal export price is independent of communication efforts. The fact that the information transferred within a buyer-seller link does not affect the price of a product (only the quantity demanded) follows from assuming information to be a fixed rather than per-unit input, as well as from expressing the demand shifter q_{sjk} in quantity equivalent units.[10]

The first order condition with respect to information delivers the expression for the optimal level of information transfer. After substituting for the pricing decision, this becomes:

$$i^*_{sjk} = \left[\frac{\theta_k}{\sigma c_{sj}}\widetilde{R}_{sjk}\right]^{1/1-\theta_k} \quad , \qquad \widetilde{\mathrm{R}}_{\mathrm{sjk}} \equiv \frac{p_{sk} x_{sjk}}{\lambda_{sjk}} = \left(\tau_{sjk}\frac{p_{sk}}{\lambda_{sk}^{1/1-\sigma}}\right)^{1-\sigma}\frac{\mu_{jk} Y_j}{P_{jk}} \tag{6}$$

where $\widetilde{R}_{sjk}$ denotes the export revenues *net* of the relationship-specific quality term.[11] However, since the actual export revenues recorded in the data embed the value that foreign buyers attach to product adaptation, a useful way to rewrite equation (6) is in terms of observables, as follows:

$$i^*_{sjk}(\lambda_{sjk}) = \frac{\theta_k}{\sigma c_{sj}} R_{sjk} \quad , \qquad R_{sjk} \equiv p_{sk} x_{sjk} = \lambda_{sjk}\widetilde{R}_{sjk} \tag{7}$$

where R_{sjk} represents the actual (observable) export revenue.

Proposition 1 *The optimal amount of information transmitted between a US producer and a foreign buyer is positively related to the size of the destination market ($\mu_{jk}Y_j$) and the information intensity of a sector (θ_k), and is negatively related to the communication costs (c_{sj}), the elasticity of substitution between varieties (σ) and the "iceberg" trade cost (τ_{sjk}).*

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[10] The choice of units for q_{sjk} is a harmless normalization for this study, since the model's predictions and empirical exercises are only going to involve export revenues.

[11] Given the assumption that $\lambda_{sjk} \geq 1$, in equilibrium the following condition: $\widetilde{\mathrm{R}}_{\mathrm{sjk}} \geq \sigma \mathrm{c}_{\mathrm{sj}}/\theta_k$ must hold for any $\theta_k > 0$.

The proof follows directly from equation (6).

The intuition behind Proposition 1 goes as follows. Specific information on foreign markets is costly to obtain, however its fixed cost nature allows exporters to apply the acquired expertise costlessly to each additional unit that is adapted for that particular market, and earn more profits from higher sales per buyer. As a result, markets with large potential, either because of size (large Y_j), geographical proximity (low τ_{sjk}) or reduced competition (low σ), provide scope for product adaptation. In fact, the market potential of a destination acts as an income shifter in the demand for information inputs, affecting the amount of information transfer at any level of communication cost c_{sj}.

The importance of the information intensity parameter θ_k becomes transparent in equation (6). When θ_k is equal to zero, the optimal level of information transmitted within a buyer-seller link becomes zero as well. This particular case corresponds to the benchmark monopolistic competition model with quality differentiation and identical CES preferences, and provides a natural alternative hypothesis for the information-driven quality differentiation model.[12]

2.3. Aggregate information demands

Testing the information demand equation (7) requires firm-level data on export revenues and volumes of information transfers (e.g. time spent for international business meetings), observed by foreign destination market. In the absence of such micro level data, the prediction regarding optimal information demands needs to be aggregated across firms and sectors in order to match the aggregation level in the available data, i.e., US origin region x destination country pair.

[12] The intuition for this finding goes as follows: with identical quality rankings across world markets (i.e., $\theta_k = 0$), interacting with foreign buyers brings no additional information about the specific characteristics a product must satisfy, having no effect on export revenues. As a result, profit maximizing exporters optimally decide not to engage in face-to-face interactions. This implies that business meetings are an optimal input to international trade only if there are significant gains from trading with a familiar partner.

Let n_{sjk} denote the exogenous number of exporters from region s that ship varieties of good k to destination market j. Since firms are symmetric in this model, adding the information demand equation (7) across all the exporters within a sector k, gives the following expression for the volume of information transmission (I_{sjk}) at sector level:

$$\mathrm{I}_{sjk} \equiv n_{sjk} i_{sjk} = \frac{\theta_k}{\sigma c_{sj}} X_{sjk} \tag{8}$$

where $\mathrm{X}_{sjk} \equiv n_{sjk} R_{sjk}$ denotes industry level exports.

Next, I aggregate the sector level information demands across industries for a given origin region x destination country pair. Factoring out bilateral exports X_{sj}, I decompose the total effect of trade on aggregate information I_{sj} into a scale and a composition effect:

$$\mathrm{I}_{sj} \equiv \sum_k I_{sjk} = \left(\frac{X_{sj}}{\sigma c_{sj}}\right)\left(\sum_k \theta_k z_{sjk}\right), \qquad \mathrm{X}_{sj} \equiv \sum_{\mathrm{k}} \mathrm{X}_{\mathrm{sjk}}, \qquad z_{sjk} \equiv \frac{X_{sjk}}{X_{sj}} \tag{9}$$

This expression can now be easily mapped into available data, and thus provides the basic structure for the econometric regression model. Equation (9) identifies the main factors that determine the aggregate demand for information transmission: the bilateral communication cost c_{sj}, the volume of international trade between the two trading partners X_{sj}, and the composition of exports in terms of information intensive products $\sum \theta_k z_{sjk}$. To understand the driving forces behind the export composition index, the summation term can be rewritten as follows:

$$\sum_k \theta_k z_{sjk} = \mathrm{K} * Cov\left(\theta_k, z_{sjk}\right) + \bar{\theta} \tag{10}$$

where K is the total number of sectors and $\bar{\theta}$ is the average information intensity of all sectors. The main source of variation in the export composition term is given by the proportion of trade that takes place in industries that are dependent on face-to-face meetings, i.e., the covariance between θ_k and sector k's share in bilateral exports, z_{sjk}. This implies that the information transfers must be larger between partners that trade a higher fraction of differentiated goods.

3. Empirics

The expression for the aggregate information input demand delivers a simple estimation model that is well suited for testing the core idea of the paper that information (transferred via business travel) is a valuable input into market-specific export production. Under the model's hypothesis, the volume and composition of exports should predict the demand for business-class international air travel. Two empirical challenges remain: one, identifying the true effect of exports on the demand for business air travel given the likelihood of spurious correlation; and two, distinguishing the proposed quality differentiation mechanism from other possible channels that might be at work. The data and model specification are essential for tackling these issues.

3.1. Data sources and variable construction

This paper employs US state level data on manufacturing exports and outbound business air travel over the period 1998-2003. The export data is taken from the Origin of Movement (OM) series provided by the Census Bureau, which classifies exports by the state where the export journey begins. For manufactured goods this represents "the closest approximation to state of production origin".[13] The export data is reported at three-digit NAICS disaggregation level (21 manufacturing sectors) and for each sector I compute the fraction of goods that are differentiated using Rauch "liberal" classification. I consider this share as a measure for the importance of information in a sector (i.e., proxy for θ_k), and use it to construct the export composition index.

The international air travel data comes from the DB1B Passenger Origin-Destination Survey provided by the US Department of Transportation. The DB1B database is a quarterly 10% sample of domestic and international airline tickets, where at least one flight segment is serviced

[13] See www.wisertrade.org for reference. Also, Cassey (2006) provides a good description of the data and examines its shortcomings in capturing production locations.

by a U.S. carrier. Each sampled ticket contains information on the number of passengers included on the ticket, the airfare, distance traveled, full flight itinerary at airport detail, and a set of characteristics specific to each flight segment, among which is the class type. The air travel quantity and airfare variables are obtained by aggregating the ticket-level information on the number of travelers and dollar value, for all the tickets issued on any route between a U.S. state and a foreign destination.[14] I distinguish the airline tickets by direction of travel (inbound vs. outbound) and class type (economy vs. business class[15]), and restrict attention only to outbound business-class flight tickets in order to avoid differences across countries in terms of U.S. visa issues or other travel restrictions. The details on data construction are relegated to the Appendix.

One limitation of the DB1B airline ticket dataset is the sample coverage. The air carriers that report ticket level information to the US Department of Transportation are domestic and foreign carriers that have been granted antitrust immunity.[16] Because the original dataset omits the passengers that depart the US on *direct* flights operated by unimmunized foreign carriers, the constructed bilateral air travel flows are measured with error. The likelihood of under-representing air traffic is not uniform across bilateral pairs, being greater for dense aviation routes involving large US gateways. However, the mis-measurement in the air travel variable is presumably directly related to origin and destination characteristics (e.g. population size, income), and to international aviation market regulations (common across the U.S. states), which will all be controlled for in the empirical exercises by fixed effects.[17] Nevertheless, I will directly address this sampling limitation in one of the robustness exercises.

[14] Airfares are computed as passenger-weighted averages of individual ticket prices.

[15] Since the ticket class is reported for each flight segment of an itinerary, I define as business class any ticket that has a distance-weighted average share of business/first class segments greater than one half.

[16] Even though unimmunized foreign carriers do not report travel information to the Department of Transportation, tickets sold by these airlines show up in the data provided they contain at least one segment operated by a U.S. carrier.

[17] For a subset of city-pair international aviation routes, I compare the total air travel flows reported in the DB1B dataset with those constructed from a representative sample of air passenger traffic, the T100 Market dataset,

In the original datasets, both travel and trade flows are observed at US state level. Since states are geopolitical units that are delimited independently of the more dynamic aviation network, I cluster the contiguous US states into 17 regions based on their proximity to the nearest large hub or gateway airport, using a classification provided by the Federal Aviation Administration (FAA). Table A1 in the Appendix provides the allocation of states to regions. The export and air passenger flows are first aggregated at regional level by destination country, and then merged into a single dataset. Table A2 summarizes the changes in sample coverage due to merging and then screening the data for missing values. Even though a significant number of bilateral pairs are dropped while creating the sample used for estimation, those pairs correspond to very small trade flows. In fact, the resulting dataset accounts for 99% of the total U.S. manufacturing exports. When looking across origin regions, the largest export share that is dropped is 11%, with an average truncation share of no more than 0.5%. Overall, these numbers suggest that the restricted sample is representative of the volume and pattern of U.S. exports.

The final sample used in the empirics is an unbalanced panel of bilateral trade and air passenger flows covering 93 foreign destinations over the period 1998-2003.[18] Panel A of Table 1 reports the summary statistics of all variables. Besides air travel and exports data, the empirics employ several state level control variables that are available from the following sources. Data on foreign-born population by state by origin of birth is provided in the Decennial US Census for year 2000. State level population, gross state product (GSP) and employment in foreign affiliates by country of ultimate beneficiary owner are taken from the Bureau of Economic Analysis.

The geographical detail of the data is essential for the empirical exercises as it allows me to exploit the within US cross-regional variation in air travel and export flows in order to identify

provided by the Department of Transportation. I find evidence that the mis-measurement in the DB1B sample is significantly reduced after controlling for origin and destination fixed effects. Results are available upon request.

[18] The list of countries is available in the Appendix Table A3.

the main predictions of the theory. If information is an input to international trade, then one should observe a direct relationship between export patterns and the demand for international business-class air travel across US regions for a given destination country and time period. So, before moving to the more formal discussion on the estimation strategy, it is helpful to examine the source of variation in the state level export data and understand the extent to which U.S. regions differ in the intensity and composition of manufacturing exports.

Panel B of Table 1 reports the variance decomposition of the regional manufacturing exports into source, destination and time specific sources. Most of the variation in exports is coming from differences across destination countries, which is not at all surprising given that everything that causes variation in U.S. exports to, say, China versus Costa Rica, or to Germany versus Ghana, including size, development level, comparative advantage, trade barriers, etc., is captured in the destination country effect. Note however that the residual variation, which includes the relationship-specific quality component modeled in the theory, is comparable in size to the variation in regional exports arising from, for example, comparing New York and California to Rhode Island and North Dakota; in other words, it is comparable to the variation in manufacturing exports caused by differences in size, factor endowments, average productivity, etc. Nevertheless, it is the econometric exercises described in the next section that are going to reveal if the bilateral variation in the residual exports is systematically related to the volume of information transfer.

Further, I examine whether US states differ in their specialization in manufacturing exports. This is essential for understanding if there are any differences in the composition of exports shipped to the same destination market but that are produced across different US regions. To get a sense of how specialized US states are, I compute the following measure: $\frac{X^k_{state}}{X^k} \Big/ \frac{GDP_{state}}{GDP}$, as the state's export share in total industry exports normalized by the state's size share in U.S. GDP. This measure captures the degree of industrial concentration of exports across US states. If in each sector exports are distributed across states in proportion to the states' size, implying an industrial concentration index equal to one, then this suggests the absence of any specialization patterns across the US states. Panel C of Table 1 reports the summary statistics of the normalized state level export shares across all industries. The magnitude of the standard deviation relative to the mean indicates that there are significant differences in the specialization of US states in manufacturing exports, revealing one main source of variation in the export composition index.[19]

3.2. Estimation strategy

Model specification. Taking logs of the aggregate information demand given by equation (9), and adding time subscripts corresponding to the panel dataset, I obtain the regression equation:

$$\ln I_{sjt} = \beta_1 \ln c_{sjt} + \beta_2 \ln X_{sjt} + \beta_3 \ln\left(\sum_k \theta_k z_{sjkt}\right) + \lambda_t + \varepsilon_{sjt} \tag{11}$$

In the empirics I_{sjt} is measured by the number of business-class air passengers traveling from origin region s to destination country j, c_{sjt} is measured by the average business class airfare, X_{sjt} is measured by the total manufacturing exports, and the export composition term $\sum_k \theta_k z_{sjkt}$ is proxied by the average share of differentiated manufactures in total exports.

The theory predicts that controlling for information costs, the volume and composition of exports should have a positive and significant effect on the demand for business-class air travel. That is, $\beta_2 > 0$ and $\beta_3 > 0$. In the alternative case, when international trade is not mediated by face-to-face interactions (i.e., $\theta_k = 0$), the volume and composition of exports should not be related in any systematic way to business-class air travel flows, which implies that $\beta_2 = \beta_3 = 0$.

[19] I have computed the coefficient of variation (CoV) for the concentration index separately for each 3-digit NAICS industry in the data, and the range of sector level CoV values is between 0.72 and 2.37 (with the mean at 1.32).

One challenge in performing this hypothesis test is to ensure that the estimated coefficients from equation (11) capture the true relation between air passenger traffic and international trade, and not some spurious correlation generated by macroeconomic differences across destination countries. For example, population and per-capita income are frequently used as determinants of air passenger traffic in empirical industrial organization studies[20], and the gravity models provide ample evidence that these same variables also determine the volume of international trade. The list of macro level factors that are related to travel and trade flows is likely more extensive, including geography, quality of infrastructure, level of development or patterns of industrial specialization. To eliminate any sources of endogeneity or spurious correlation coming from cross-country differences, I add to the baseline model country–year fixed effects. Note that since the export locations are regions within the same country, the fixed effects also control for any time varying factors that are specific to the U.S. - country j bilateral relationship. Examples include exchange rates, bilateral trade and travel agreements, historical and cultural proximity. To account for similar systematic differences across source locations, I also add to the regression region fixed effects and the regional income level, the latter controlling for origin-specific trends.

While extensive in terms of coverage, the structure of origin and destination–time pair fixed effects does not eliminate all potential sources of spurious correlation. In particular, it does not control for omitted variables that have state i by destination j variation such as ethnic networks. Rauch and Trindade (2002) provide evidence that ethnic networks facilitate the exchange of goods across national borders, with larger effects for trade in differentiated goods. It is reasonable to think that ethnic networks have a significant contribution to the volume of international air travel services demanded for consumption purposes. To eliminate this source of

[20] See for example Brueckner (2003) and Whalen (2007) among others.

spurious correlation (e.g. large Korean immigrant population established in California), I also account for the size of foreign-born population in US region *s* that originates from country *j*.

Adding the described control variables to equation (11), the baseline estimation model becomes:

$$\begin{aligned}\ln(BTrav)_{sjt} = \beta_1 \ln(fare)_{sjt} + \beta_2 \ln X_{sjt} + \beta_3 \ln\left(\sum_k \theta_k z_{sjkt}\right) + \beta_4 \ln\left(PCGDP\right)_{st} + \\ + \ln(ForeignPop)_{sj} + \alpha_s + \alpha_{jt} + \varepsilon_{sjt}\end{aligned} \quad (12)$$

where α_s stands for region dummies and α_{jt} denotes the destination country-time fixed effects.

Given the geographic detail of the data, the model identification relies on two sources of variation: one coming from the spatial distribution of U.S. manufacturing firms that export to a given destination country *j* at time *t* (i.e., variation in *export volumes* across origin regions *s* for a given *(j,t)* pair), and the other coming from differences in the specialization pattern of US states in terms of complex, information-intensive manufactures (i.e., variation in *export composition* across origin regions *s* for a give *(j,t)* pair).

Estimation methods. Applying ordinary least squares to the baseline model requires that the explanatory variables are independent of the error term. However, the regression equation (12) is essentially a demand model and therefore airfares are endogenous to the size of the air passenger traffic. To address this problem, I use two-stage least squares (TSLS) and instrument for airfares using the interaction between average ticket distance and oil prices, as a proxy for fuel costs.

One might be concerned that the export variables are also correlated with the residual from the business air travel demand. Countries that experience income or productivity shocks engage in more international trade and demand more sophisticated goods, which implicitly necessitates better information linkages with world markets. However, since these shocks are destination country specific, such sources of endogeneity are already accounted for by the regression's time-varying structure of fixed effects. Further, some U.S. states face a more rapid growth and carry larger investments in transportation infrastructure, others have a more attractive taxation system that provides location incentives for economic activities, and finally some states have better access to foreign markets (e.g. inland versus coast states). All these state level characteristics generate more international trade and travel. However, if they are not destination specific, it is again the case that origin region dummies and income levels account for such effects. As a result, any potential factors that make the volume and composition of exports still be endogenous to travel flows must be induced by omitted channels that have source s by destination country j variation. In this sense, any transportation cost shocks that are bilateral specific but not correlated with the level of airfares might presumably affect both travel and trade flows.

It is also possible that shocks to the air passenger flows in a given international market have feedback effects on the export revenues of information intensive industries, directly affecting the volume and composition of trade. For example, consider the degree of airline competition or the quality of travel services offered on an aviation route (e.g. flight frequency, connectivity). Both these factors affect the demand for business air travel and indirectly influence the location of information intensive sectors, inducing an upward bias in the estimated export coefficients.

While the endogeneity generated by omitted variables or reverse causality is probably not of first order magnitude, I nevertheless correct for the potential bias induced by the trade estimates using as excluded instruments one-year lags in the volume and composition of exports.[21] The validity of the instruments depends on whether lagged trade variables are independent of contemporaneous business air travel flows. This condition is likely to hold if exporters fly to foreign countries and set up trade relationships previous to any shipments taking place, or else if technical support engineers fly to destination markets for on-site training and customer service within the trading year. In either case, current business air traffic cannot affect past trade flows.

[21] The choice of instruments is much restricted by the structure of fixed effects. The ideal instruments must affect *directional* volume and composition of U.S. regional exports, but be uncorrelated with bilateral business air travel.

4. Results and Robustness

4.1. Baseline results

Table 2 reports the estimates of the baseline regression model given by equation (12). The first column reports the OLS results, while columns 2 and 3 instrument for airfares using the interaction between the average ticket distance and the oil price. In all three specifications the volume and composition of regional manufacturing exports have positive and significant coefficients, confirming the theoretical prediction that the strength of information linkages across trade partners depends on the volume and sophistication of exported products. The results from the basic specification reported in column 2 suggest that a one percent increase in total exports raises the demand for business air travel by 0.24 percent. Moreover, an increase in the export composition index, as measured by the average share of traded differentiated goods, raises the demand for business air travel by an additional 0.17 percent. This second result brings empirical confirmation to Leamer and Storper's (2001) insight that complex manufactures must be more dependent on face-to-face interactions.

Accounting for the strength of ethnic networks, as captured by the size of the foreign born population originating from country *j* and living in US region *s*, reduces the effects of the volume and composition of exports as shown by the results reported in the third column of Table 2. The decrease in the export estimates is expected given the existing evidence of a positive relation between ethnic networks and trade (Rauch and Trindade, 2002). Nevertheless, both of the coefficients of interest remain positive and highly significant.

The baseline regression model fits the data quite well and the reported first stage statistics indicate that the excluded instrument is significant (high F-statistic) and correlated with airfares (high partial R-squared). Overall, the estimation results reported in Table 2 are consistent with the theoretical predictions, giving support to the information-driven quality hypothesis. That is, exporters that face large foreign demands and that produce complex manufactures invest more in establishing close relationships and good information networks with their foreign partners.

For reasons already discussed in the empirical methodology section, the trade variables could be endogenous in the baseline regression model, in which case the estimated coefficients are biased. To address this problem, I instrument for the volume and composition of exports using their lagged values. The two state least squares (TSLS) results are reported in Table 3. Panel 1 estimates are obtained using as excluded instruments one year lags for the two export variables. Panel 2 adds the two-year lags to the set of excluded instruments, making it possible to apply the test of overidentifying restrictions. Both specifications also instrument for airfares.

The coefficients of interest for the scale and composition of exports maintain their predicted positive and significant effect on the demand for business air travel even when correcting for the endogeneity between trade and air travel. Comparing the TSLS coefficients from Panel 1 with the previous results obtained when instrumenting only for airfares (reported in column 3 of Table 2), one can notice that the TSLS estimates for the volume and composition of exports increase in magnitude. This direction of change might seem contrary to the prior expectations of an upward bias in the trade estimates. However, it is likely that the TSLS export estimates capture two counteracting effects – one predicted by the theoretical framework and developed in the discussion on endogeneity (which induces an upward bias), and one coming from sampling error and attenuation bias (which induces a downward bias). To expand on the latter effect, recall from the data section that a fraction of bilateral air passenger traffic is omitted from the original sample. This fraction is presumably proportional to the density and profitability of the international aviation route. If trade is an indicator for market profitability, then the use of instrumental variables would correct the induced downward bias in the estimates.[22] Furthermore, note also that the export composition index is imperfectly measuring the information intensity of exports, partly because of the sparse industrial disaggregation in the export data and partly because of the proxy used to capture a sector's dependence on face-to-face communication.

Comparing the behavior of the other variables under the TSLS specifications, the estimates of airfares and foreign-born population do not change very much. The coefficient for per-capita income increases in magnitude and sometimes becomes significant, but remains in reasonable bounds and keeps its expected sign. The instruments also perform well, as seen from the first stage statistics reported at the bottom of Table 3. The partial R-squared values suggest that the excluded instruments are relevant (i.e., correlated with the endogenous variables), the F statistics show that they are significantly different from zero, and the test for overidentifying restrictions indicates that the (extended set of) excluded instruments are valid (i.e., independent of the error).

In summary, the sign and significance of the variables of interest – the scale and composition of exports – give support to the hypothesis that face-to-face communication is a valuable input to trade in complex manufactures. The estimated effects remain significant even after accounting for ethnic networks and for the endogeneity induced by reverse causality or omitted variables.

4.2. Robustness

I perform two sets of robustness exercises. The first set extends the analysis of spurious correlation between travel and trade, and thus augments the baseline regression with additional covariates. The second set addresses the measurement issue in the business travel variable and examines the stability of the model's predictions across different subsamples.

[22] More formally, assume that: $BTravel_{sj} = (1- v_{sj})\ BTravel^{*}_{sj}$, where * indicates the true value, and v is the share of business travel omitted from the data. Then, the regression model becomes: $\ln (BTravel)_{sj} = \ln (1- v_{sj}) + XB + \varepsilon_{sj}$. If the omitted air carriers are more likely to operate from airports located in large export areas that specialize in information intensive goods, then v_{sj} is positively correlated with the volume and composition of exports inducing a downward bias.

The use of instrumental variables in lagged values purges any sources of endogeneity that are contemporaneous to the demand for business air travel. However, the positive effect of the scale and composition of exports on the demand for business travel could still be inconsistent if there are omitted channels that: (1) have bilateral variation, (2) are persistent over time,[23] and (3) are correlated with both travel and trade. I could think of two channels that satisfy these conditions: horizontal FDI inflows and international leisure travel. In the first case, suppose that affiliates of foreign owned multinationals locate next to US exporters and that the demand for business air travel comes exclusively from foreign affiliate executives. Since horizontal FDI plants produce mainly for the domestic market, the correlation between business air travel and exports could simply be an artifact of the co-location across U.S. regions of exports and inbound FDI. Similarly, for the second case, suppose that a fraction of the observed business-class air traffic comes from personal consumption of luxury travel services. Many US trade partners also provide attractive tourism destinations. If in addition high-income consumers predominantly live in export oriented industrial regions, then the estimated relation between exports and business air travel could also be the result of omitted leisure travel.

To ensure the robustness of previous findings, I augment the baseline regression model with two additional control variables: the size of inbound multinational networks, as measured by total employment in foreign owned affiliates across US regions, and the volume of international tourism services, as measured by the economy-class air travel. I estimate the augmented model using instrumental variables in all three endogenous variables and the same set of excluded instruments (i.e., ticket distance interacted with oil price; one-year lagged exports and one-year lagged export composition).[24] Table 4 reports the TSLS estimates. The results from column 1

[23] Persistency makes the regression error ε_{sjt} follow an AR process, invalidating the use of lags as instruments.
[24] The robustness checks go through even if I instrument only for airfares. Results are available upon request.

indicate that even when accounting for bilateral inbound FDI, the effects of the volume and composition of exports on the demand for business class air travel remain positive and significant. Although the magnitudes of the coefficients are changed in a significant way, this is likely due to the severely reduced sample size (imposed by the availability of bilateral state level data on FDI employment).[25] Further, the results reported in column 2 show that the main predictions of the paper hold also when accounting for patterns in international leisure travel.[26]

The next set of robustness checks examine whether the significant effects of the volume and composition of exports on the demand for business air travel could be driven by non-random measurement error in the dependent variable or by a subsample of destination countries.

In the data section, I describe the under-representation problem in the constructed business air travel flows that is induced by the absence of unimmunized foreign air carriers in the original DB1B dataset. If the fraction of bilateral air traffic that is omitted during the data sampling process is not captured by the control variables or by the regression fixed effects, then this could lead to biased estimates. However, if this share of omitted air traffic does not differ by ticket class type (say because the ratio of business to economy class passengers is roughly the same across all air carriers in a market), then the ratio of business to economy class travel should completely remove any bilateral-specific mis-measurement in the data. So, I re-estimate the baseline model using as dependent variable the relative demand for business air travel and report the TSLS results in column 1 of Table 5. Even though the coefficients change their interpretation, as they measure the effect of a variable on the demand for business class air travel *relative to* economy class travel, the results confirm once more the previous findings that the scale and composition of exports have a significant and positive impact on business travel.

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[25] The countries with publicly available data are: Australia, Canada, France, Germany, Japan, Netherlands, United Kingdom and Switzerland. Canada is omitted from the empirics because of proximity to the US.
[26] Economy travel and foreign-born population cannot be included in the same regression due to multicollinearity.

The remaining three columns of Table 5 examine the stability of the coefficients of interest on various sub-samples, continuing to instrument for all three endogenous variables. The coefficients in column 2 are obtained after eliminating all the bilateral pairs involving Canada or Mexico, since the proximity of the NAFTA countries to the US might distort business-class air travel flows.[27] However, there is little change in the coefficients of interest. Columns 2 and 3 report the results obtained on a subsample of high and low income countries respectively. Countries with per-capita GDP above the sample median are classified as having high income, while the rest of the sampled countries are considered low income. The significant estimates obtained in both subsamples indicate that results are not driven by a subset of US trade partners.

In conclusion, the robustness exercises confirm previous findings that the volume and composition of exports have a significant effect on the demand for international business air travel, giving support to the hypothesis of information transmission as an input to trade.

5. Information intensities of manufacturing sectors

In this section, I investigate which manufacturing sectors are more dependent on the transmission of information via face-to-face communication.[28] To do that, I exploit the disaggregation level in the US export data (21 manufacturing sectors) and estimate the dependence of business air travel flows on industry level exports. Had I observed industry level expenditures on international business travel by destination market, the empirical strategy would have required estimating the baseline regression model separately for each sector. Absent such disaggregated data, one way to circumvent this problem is to jointly estimate the sector level

[27] For example, the substitution patterns across ticket class types might look different for travel to Canada or Mexico as compared to further away destinations. Also, the NAFTA trade and aviation markets are presumably more integrated, leading to significantly larger export and travel flows.

[28] The exclusive focus on manufacturing sectors is imposed by the unavailability of state level service exports data, and by the inaccuracy of agricultural exports data (due to the freight consolidation of such goods across the U.S.).

elasticities in a specification that takes as dependent variable the aggregate volume of business travel. To do that, I employ the baseline regression model given by equation (12) and allow the sector level export shares to take different slope coefficients. This leads to the following estimating equation:

$$\begin{aligned}\ln(BTrav)_{sjt} &= \beta_0 + \beta_1 \ln(fare)_{sjt} + \beta_2 \ln X_{sjt} + \sum_k \delta_k \ln\left(\theta_k z_{sjkt}\right) + \beta_4 \ln PCGDP_{st} + \\ &+ \beta_3 \ln(ForeignPop)_{sj} + \alpha_s + \alpha_{jt} + \varepsilon_{sjt}\end{aligned} \tag{13}$$

The coefficient δ_k captures the information intensity of exports in a manufacturing sector k. Their identification relies on the observed patterns of specialization across US state exports. More precisely, the sector slope coefficients are identified from variation across US regions in the share that sector k has in total manufacturing exports shipped to a given destination j. It is useful to note that including all sector export shares in the same regression reduces the potential for spurious correlation induced by the co-location of sectors with different information intensities.

Table 6 reports the results using instrumental variables in airfares and total manufacturing exports. An overall look at the positive and significant sector level coefficients confirms the intuition that complex manufactures are the goods that primarily rely on the transmission of information via personal meetings. The most information intensive sectors are Machinery (333), Computer and Electronic Products (334), Miscellaneous Manufactures (339), and Fabricated Metal Products (332). The estimation reported in Table 6 does not instrument for the sector level export shares. However, the TSLS estimates obtained from using one-year lags as instruments for export shares are very close to the reported results, with a correlation coefficient of 0.94.[29]

As robustness check, I compare the obtained estimates for the information intensities of US exports with external measures of product complexity, such as R&D expenditure shares (reported by NSF), the contract intensity index computed by Nunn (2007), and the elasticity of

[29] In unreported results, I estimate alternative versions of equation (13), e.g., using sector export levels rather than shares; ignoring the sectors with no exports. However, the correlations among all these sets of estimates are high.

substitution estimated by Broda and Weinstein (2006). All the indicators are adjusted at the 3-digit NAICS disaggregation level.[30] Table 7 reports the correlation coefficients between the information intensity estimates and the selected indicators. All the coefficients have the expected sign, though they are not always statistically significant. The information intensity estimates get the best match with the R&D intensity of manufacturing sectors, but they also align well with Nunn's (2007) contract intensities. This finding suggests that exports of complex manufactures and goods requiring strategic inputs of unverifiable quality are most dependent on face-to-face communication. This gives further support to the product adaptation hypothesis and confirms the insight that face-to-face interactions are essential for transferring tacit knowledge.[31]

6. Conclusions

This paper provides theory and evidence examining the role of information as an input to trade in complex manufactures. When buyers have unique valuations for quality-differentiated goods, exporters need to customize their products to appeal to foreign consumers. A necessary input in the production of relationship-specific quality is knowledge about buyers' requirements, gathered from personal interactions. Information, measured as face-to-face communication, is modeled as an input to product quality and as an endogenous fixed cost of export, becoming a choice variable for the profit-maximizing exporters. Solving for the information input demand equation, the theory reveals a direct relation between the amount of information transmission and the volume and composition of traded manufactures. These theoretical predictions are strongly supported by the US state level data on business air passenger travel and manufacturing exports

[30] The R&D expenditure shares, reported annually at 3-digit NAICS level, are employed as averages over the interval 1998-2003. The contract intensities are available at 6 digit NAICS level and simply averaged to the 3 digit level. The substitution elasticities are first converted from SITC to NAICS codes, and then averaged up.

[31] This assumption is frequently encountered in regional economics (Gaspar and Glaeser, 1998) and information spillovers literatures (Jaffe et al., 1993; Audresch and Stephen, 1996).

over the period 1998-2003. Furthermore, using the developed econometric set-up, I estimate the information intensity of trade at sector level and find that the results align with external measures of product complexity such as R&D expenditure shares or contract intensities (Nunn, 2007).

The results of this paper complement existing work on information barriers to trade and extend our understanding of the particular mechanisms through which face-to-face interactions facilitate international trade. They are relevant also for the new theories of outsourcing and services trade, which place an increasing role on information transmission and relationship-specific transactions (Grossman and Helpman, 2002). In this context, communication and coordination become crucial for global production networks. Finally, these findings also relate to recent evidence provided by Eaton et al. (2008), which reveals that firm-level export growth is generated from frequent transactions with the same foreign buyers rather than new partners.

Several implications emerge from this study. If information transferred via face-to-face contact is an important input to trade in complex manufactures, then presumably the geographic localization of international trade should be higher in such industries. Similarly, if intermediate goods are more likely to be tailored to the specific requirements of foreign buyers relative to final goods, then agglomeration forces should be stronger for trade in intermediates. All these suggest the potential to develop sharper links between information and the geography of trade.

Further, this study opens up important policy questions regarding the restrictions imposed on international air travel. In light of this paper's evidence of a direct relation between business air travel and international trade, it becomes even more important to understand the factors that inhibit air passenger traffic. How large is the effect of visa programs on the demand for business travel? How restrictive are the international aviation regulations and what is the impact of recent liberalization efforts? Such issues require close consideration and are left for future work.

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Appendix

Data Appendix

I construct air travel price and quantity variables at regional level by aggregating ticket level information on number of passengers and distance traveled between a US state and a foreign destination country. To reduce the measurement error in constructing the variables of interest, I follow the empirical industrial organization literature on the airline industry (Brueckner, 2003; Whalen, 2007) and impose a set of filters on the original DB1B dataset. First, I keep only the tickets that contain an international flight segment and that originate or terminate their journey in the US (i.e., I drop domestic flights and international flights transiting the US). Second, I keep only the tickets that have no more than eight coupons per itinerary (four coupons respectively for one-way trips) and the tickets that have a single directional trip break (the more circuitous tickets are difficult to be assigned to a given bilateral pair). Third, I drop all the tickets whose prices have been signaled by the Department of Transportation (DOT) as failing the 'dollar credibility'. To reduce measurement error, I also drop tickets with values below $100 and those with prices outside the range ¼, respectively 4 times the geometric average airfare for a US state x foreign country route. Finally, I use a concordance provided by the DOT between airport codes and geopolitical regions to obtain a dataset of international air travel tickets connecting US states with foreign countries.

Using the resulting dataset, I create several new ticket-level variables that are of interest for the purpose of this paper. First, I construct an indicator variable for the direction of air travel, to distinguish between tickets that originate in the US with the final destination abroad (outbound air traffic) and tickets that start in a foreign country and terminate the journey in the US (inbound air traffic). Then, I create an indicator variable for round trip tickets, defined as itineraries that originate and terminate in the *same city*. Finally, I create a variable that assigns a class type – business or economy – to the entire itinerary. I define as business class any ticket that has a distance-weighted fraction of business/first class flight segments greater than a half.[32]

Since states are geopolitical units that are presumably delimited independently of the more dynamic aviation network, I have grouped the US states in small regions using the following allocation criteria: states that share the access to a large international airport are grouped in the same region, and each region must include at least one large hub or major gateway airport (airport classification is taken from the Federal Aviation Administration (FAA)). After consolidating the contiguous states by taking into account the domestic aviation network, I end up with 17 regions. The allocation of states to regions is presented in Table A1.

The final step is to use ticket level information to construct aggregate measures for the total volume of air traffic and for the average airfare for the itinerary between a given US region and a foreign destination country. I compute the annual volume of air travel by summing the number of passengers traveling on each ticket, over all the tickets issued in a given year for a particular route. I do this calculation separately for inbound and outbound travel, and within each directional category I separate between business and economy class travelers. In the end, I obtain aggregate quantity variables measuring the number of business class air travelers that originate their journey in a given

[32] The formula applied for computing the business class dummy variable is:

$$b\_class = \sum_{s=1}^{S} \frac{\text{dist}_s}{\text{total distance}} \text{I}_s(1 = \text{business or first class})$$

where S denotes the total number of flight segments of a given ticket, $dist_s$ represents the flight distance corresponding to segment s, and *total distance* represents the trip length of that ticket. If b_class>0.5, that is if more than 50% of the distance flown is at business or first class, then the ticket is considered a business class ticket. This definition of business class tickets is more restrictive than computing the fraction of segments traveled at business class, which is what has been used in the IO literature (Brueckner (2003) among others).

US region and fly towards a foreign country as their final destination. I perform a similar computation to obtain the average airfare for the travel between a US region and a given foreign destination country. To collapse the ticket-level price information into a country aggregate, I use passenger-weighted averages of individual fares, distinguishing again between the direction and class type of tickets.[33] The resulting average airfares are then deflated using the US GDP deflator, in order to be expressed in constant US dollars. Finally, I compute the average air travel distance for itineraries between a given US regions - foreign country pair, again separating between the direction and class type of the itineraries.

Table Appendix

Table A1 – Allocation of US States to Regions

Region	FAA Region / States	Large Hub Airports
	Northwest – Mountain:	
1	WA, OR	Seattle, Portland
2	ID, MT, WY, UT, CO	Denver, Salt Lake City
	Western Pacific:	
3	CA, NV	LA, San Diego, San Francisco, Las Vegas
4	AZ, NM	Phoenix
	Southwest:	
5	TX, OK,	Houston, Dallas
	Southern:	
6	LA, AR, TN, MS, AL	New Orleans, LA; Memphis, TN
7	FL	Miami, Ft. Lauderdale, Orlando, Tampa
8	GA, SC, NC	Atlanta, Charlotte-NC
	Central:	
9	MO, NE, KS, IA	Kansas City, St. Louis
	Great Lakes:	
10	SD, ND, MN	Minneapolis/ St. Paul
11	WI, IL, IN	Chicago, Indianapolis
12	MI	Detroit
13	OH, KY	Cincinnati, Cleveland, Louisville KY
	Eastern:	
14	PA	Philadelphia, Pittsburg
15	WV, VA, MD, DC, DE	Washington, Baltimore
16	NJ, NY, CT	JFK, Newark, La Guardia
	New England:	
17	MA, RI, VT, NH, ME	Boston

Note: The Federal Aviation Administration (FAA) defines nine aviation regions within the US. Starting from these predefined regions, I split them further into smaller groups by taking into account the location of large airport hubs. Several states have been included in a different group than their original FAA regional allocation because of their proximity to large airport hubs located in other regions.

[33] To average together round trip and one-way airfares, I first divide in half all the round trip ticket values to obtain the price per direction of flight, and only then average out all the ticket prices within a country pair.

Table A2 – Sample Coverage for the Merged Exports and Air Travel Dataset

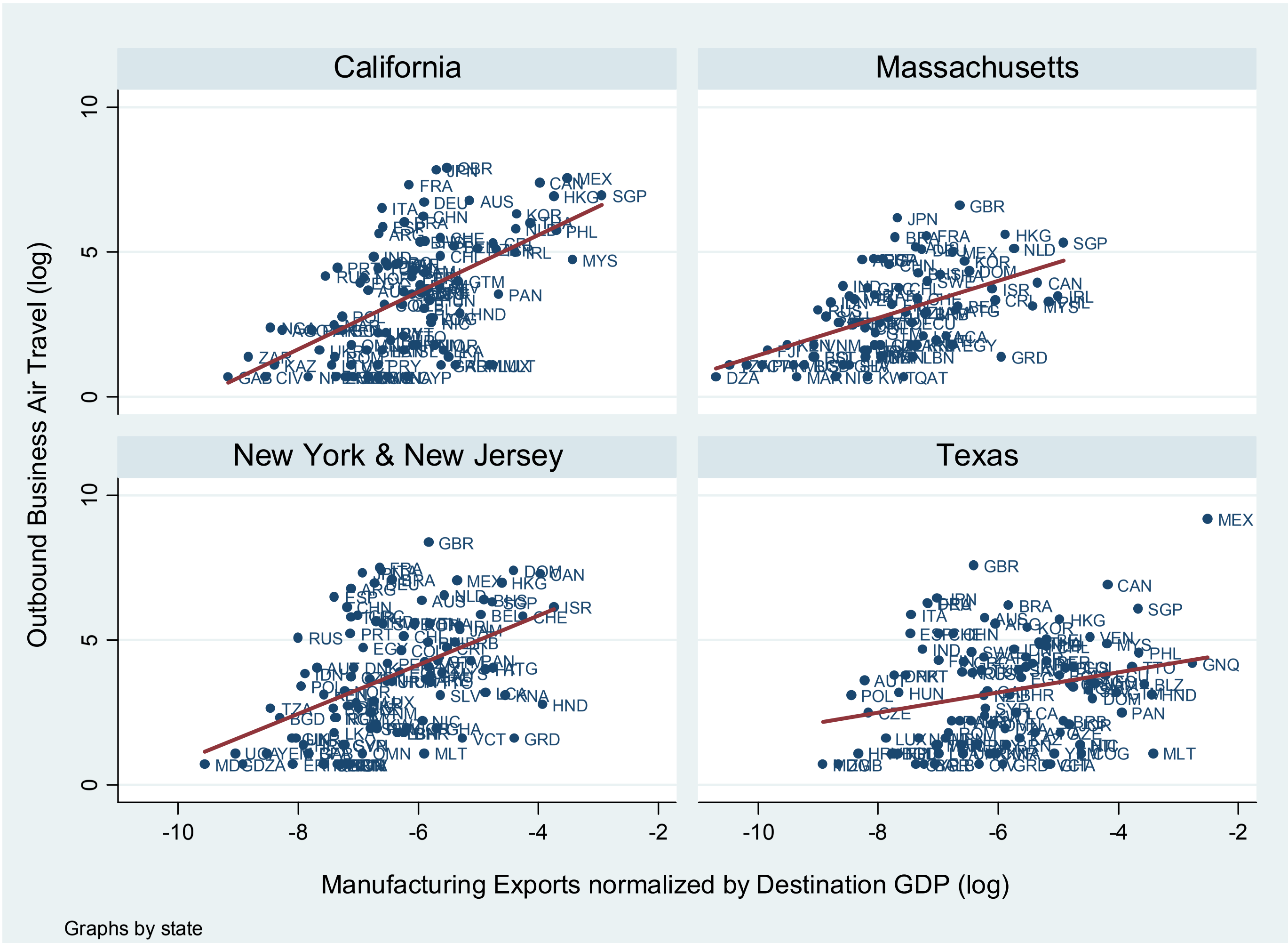
	US region – foreign destination country pairs with				
	Zero exports	**Positive exports**		**Positive exports and business travel**	
	Positive travel	**Zero travel**	**Economy travel only**	**Total**	**Estimation sample**
No. pairs	131	291	1,345	8,083	7,846
Average export share in total *US exports* (%)	--	0.012 (max = 0.04)	0.26 (max =0.42)	99.7 (min =99.5)	99.7 (min =99.5)
Average export share in total *regional exports (%)*	--	0.015 (max = 0.31)	0.63 (max =11.1)	99.6 (min =88.9)	99.6 (min =88.6)

Note: This table reports the summary from merging the export and air travel datasets, once each individual dataset was aggregated at US region by destination country level. The estimation sample represents the sample obtained after dropping the pairs with missing values. For each indicated subsample, I compute the proportion of manufacturing exports in total US manufacturing exports accounted for by the bilateral pairs included in that subsample. I redo the exercise at regional level to see for each source region and year the share of manufacturing exports covered by the selected bilateral pairs.

Table A3 – List of Countries

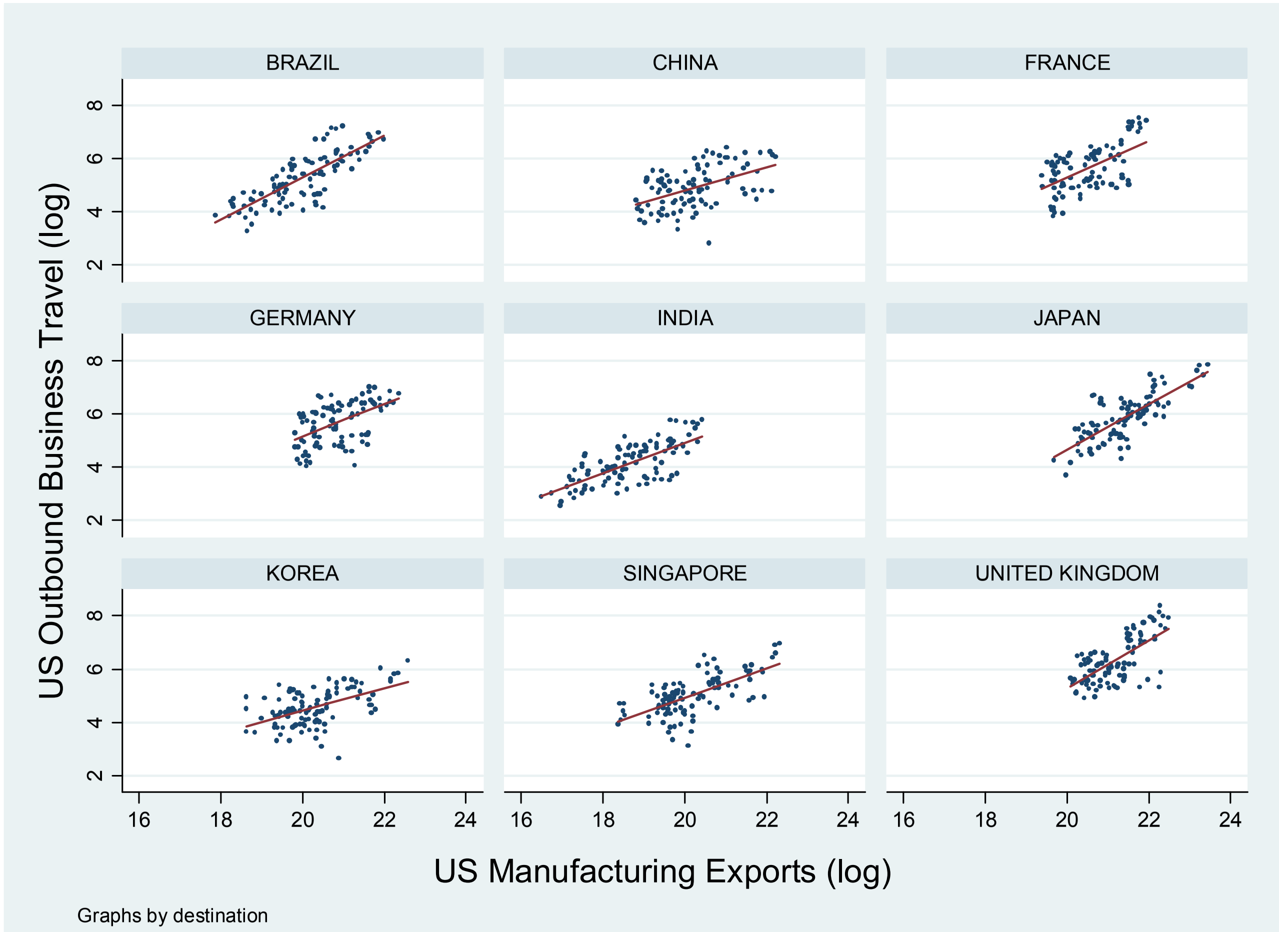
1 Argentina
2 Armenia
3 Australia
4 Austria
5 Bangladesh
6 Barbados
7 Belarus
8 Belgium
9 Belize
10 Bolivia
11 Bosnia and Herzegovina
12 Brazil
13 Cambodia
14 Canada
15 Chile
16 China
17 Colombia
18 Costa Rica
19 Czechoslovakia
20 Dominican Republic
21 Ecuador
22 Egypt
23 El Salvador
24 Ethiopia
25 France
26 Germany
27 Ghana
28 Greece
29 Guatemala
30 Guyana
31 Haiti
32 Honduras
33 Hong Kong
34 Hungary
35 India
36 Indonesia
37 Iran
38 Ireland
39 Israel
40 Italy
41 Jamaica
42 Japan
43 Jordan
44 Korea
45 Laos
46 Lebanon
47 Luxembourg
48 Malaysia
49 Melanesia
50 Mexico
51 Micronesia
52 Middle Africa
53 Netherlands
54 New Zealand
55 Nicaragua
56 Nigeria
57 Other Caribbean
58 Other Eastern Africa
59 Other Eastern Asia
60 Other Eastern Europe
61 Other Northern Africa
62 Other Northern America
63 Other Northern Europe
64 Other South America
65 Other South Central Asia
66 Other South Eastern Asia
67 Other Southern Africa
68 Other Southern Europe
69 Other Western Africa
70 Other Western Asia
71 Pakistan
72 Panama
73 Peru
74 Philippines
75 Poland
76 Polynesia
77 Portugal
78 Romania
79 Russia
80 South Africa
81 Spain
82 Sweden
83 Switzerland
84 Syria
85 Taiwan
86 Thailand
87 Trinidad and Tobago
88 Turkey
89 Ukraine
90 United Kingdom
91 Venezuela
92 Vietnam
93 Yugoslavia

Figure 1: US State Level Exports and International Business Air Travel (year 2000)



Source: Department of Transportation DB1B dataset for the constructed air travel flows; US Census for State Export data; World Bank for GDP data.

Figure 2: Sub-national Distribution of US Exports and Outbound Business Air Travel by Destination Country



Source: US Census for State Export data; Department of Transportation DB1B dataset for the constructed air travel flows

Note: A point in the graph represents a bilateral trading pair, formed by one US origin region (see the list in the Appendix) and one foreign destination country.

Table 1: Summary Statistics

Panel A - Variables in the Model			
	No. obs.	**Mean**	**Std. Dev.**
Travel variables:			
Business Travel (log)	7840	3.066	1.801
Economy Travel (log)	7835	5.712	1.742
Business/Econ. Travel (log)	7835	-2.644	1.092
Business Airfare (log)	7840	6.464	1.232
Economy Airfare (log)	7835	5.538	0.593
Trade variables:			
Total Exports (log) [1]	7840	17.911	2.227
Composition Exports (log) [2]	7840	-0.29	0.239
Region GDP (log)	7840	13.148	0.521
Region GDP/capita (log)	7840	-3.393	0.103
Destination GDP (log)	7614	25.006	1.859
Destination GDP/capita (log)	7614	8.263	1.442
Foreign-born population (log) [3]	7840	8.365	1.65
FDI employment (log) [4]	779	8.946	1.127
Instruments:			
Ticket Distance * Oil Price (log)	7840	12.652	0.659
Lag Total Exports (log)	6491	17.911	2.237
Lag Composition Exports (log)	6491	-0.289	0.241
2 yr. Lag Total Exports (log)	5156	17.931	2.228
2 yr. Lag Composition Exp. (log)	5156	-0.286	0.237

Panel B - ANOVA Regional Manufacturing Exports (log)			
	Partial SS	**D.f.**	**% explained**
Origin region	4917.05	16	0.121
Destination country	29744.41	92	0.733
Year	28.95	5	0.001
Residual	5875.81	7726	0.145

Panel C – Specialization across US States			
	No. obs.	**Mean**	**Std. Dev.**
State shares in sector exports (normalized)[5]	7871	0.823	1.207

Notes:
1. Total Exports includes only manufacturing exports.
2. Export composition is calculated as the weighted-average share of differentiated goods across sectors with positive manufacturing exports, using as weights export shares.
3. Data on foreign born population is available from the US Census only for year 2000.
4. Data on foreign affiliate employment by state, by ultimate beneficiary owner is available only for eight countries: Australia, Canada, France, Germany, Japan, Netherlands, Switzerland and UK.
5. State level export shares within 3-digit NAICS sectors are computed as follows: $\frac{X^k_{state}}{X^k} \Big/ \frac{GSP_{state}}{US\ GDP}$, where X denotes exports and k indexes the sector.

Table 2: Derived Demand for Business Travel (Baseline Specification)

A. Second Stage	*Dependent variable: Business Travel (log)*		
	(1) - OLS	**(2) - IV**	**(3) - IV**
Airfare (log)	-0.033**	-0.139**	-0.083**
	(0.010)	(0.014)	(0.012)
Total Exports (log)	0.238**	0.241**	0.170**
	(0.011)	(0.011)	(0.010)
Export Composition (log)	0.155**	0.166**	0.115**
	(0.042)	(0.043)	(0.040)
PCGDP origin region (log)	0.258	0.625	0.492
	(0.583)	(0.495)	(0.475)
Foreign-Born Pop. (log)			0.276**
			(0.013)
Country-year fixed effects	yes	yes	yes
Regional fixed effects	yes	yes	yes
Observations	7840	7836	7836
R-squared	0.605	0.596	0.637
B. First Stage		*Dependent variable: Airfares (log)*	
Distance*Oil Price (log)		2.730**	2.807**
		(0.053)	(0.054)
Total Exports (log)		0.214**	0.185**
		(0.011)	(0.010)
Export Composition (log)		0.051	0.026
		(0.044)	(0.043)
PCGDP origin region (log)		1.064*	1.028*
		(0.467)	(0.464)
Foreign-Born Pop. (log)			0.138**
			(0.012)
First stage statistics			
Partial R^2	n.a.	0.53	0.54
F statistics (instruments)	n.a.	2626.47	2671.6

** p<0.01, * p<0.05, + p<0.1

Notes:
1. The table contains estimates of the baseline model given by equation (12) in the text.
2. Robust standard errors in parentheses.

Table 3: Derived Demand for Business Travel (Instrumental Variables)

	Dependent variable: Business Travel (log)					
A. Second Stage		**Panel (1)**			**Panel (2)**	
Airfare		-0.076**			-0.083**	
		(0.013)			(0.014)	
Total Exports		0.206**			0.206**	
		(0.014)			(0.015)	
Export Composition		0.193**			0.219**	
		(0.065)			(0.071)	
PCGDP origin region		1.316*			0.834	
		(0.634)			(0.932)	
Foreign-Born Pop.		0.263**			0.269**	
		(0.014)			(0.016)	
Country-year fixed effects		yes			yes	
Regional fixed effects		yes			yes	
Hansen J statistic		n.a.			2.15	
Hansen J p-value		n.a.			0.34	
Observations		6487			5152	
R-squared		0.632			0.63	
B. First Stage	**(1a) Airfares**	**(1b) Exports**	**(1c) XComp**	**(2a) Airfares**	**(2b) Exports**	**(2c) XComp**
Distance*Oil Price	2.817**	-0.080**	0.021*	2.887**	-0.017	0.029**
	(0.058)	(0.035)	(0.008)	(0.064)	(0.037)	(0.009)
1-Year Lag Exports	0.197**	0.765**	-0.003	0.112**	0.508**	-0.009
	(0.011)	(0.014)	(0.003)	(0.018)	(0.031)	(0.006)
2-Year Lag Exports				0.115**	0.346**	0.010+
				(0.018)	(0.031)	(0.006)
1-Year Export Composit.	-0.014	-0.001	0.672**	-0.101	-0.122	0.516**
	(0.048)	(0.047)	(0.017)	(0.077)	(0.075)	(0.028)
2-Year Export Composit.				0.065	0.117+	0.249**
				(0.074)	(0.069)	(0.027)
First stage statistics						
Partial R^2, 1^{st} stage	0.55	0.61	0.47	0.57	0.68	0.52
Partial F, 1^{st} stage	791.71	1109.51	511.6	419.03	1084.35	366.1

** p<0.01, * p<0.05, + p<0.

Notes:
1. The table contains estimates of the baseline model given by equation (12) in the text.
2. All variables – dependent and explanatory – are used in the estimations in log form.
3. 'XComp' is the abbreviation for export composition.
4. The first stage regressions include also the PCGDP (origin region) and Foreign-Born Population variables, but for conciseness their estimates are omitted from the table.
5. Robust standard errors in parentheses.

Table 4: Robustness checks – Additional Covariates

Dependent variable:	*Business Travel (log)*	
	(1)	**(2)**
(Endogenous Var.)	*(airfare; exports; export composition)*	
Airfare (log)	-0.102+	-0.055**
	(0.059)	(0.012)
Total Exports (log)	0.092+	0.132**
	(0.053)	(0.012)
Export Composition (log)	0.439**	0.203**
	(0.115)	(0.060)
PCGDP origin region (log)	1.130	1.191*
	(1.307)	(0.565)
Foreign-Born Pop. (log)	0.400**	
	(0.066)	
Foreign Affil. Employment (log)	0.155**	
	(0.037)	
Economy Travel (log)		0.605**
		(0.016)
Country-year fixed effects	yes	yes
Region fixed effects	yes	yes
Observations	559	6483
R-squared	0.818	0.711
First stage partial F statistics		
Dep. var: Log Airfare	50.14	788.69
Dep. var: Log Exports	264.85	1160.61
Dep. var: Log Export Comp.	265.03	531.23

** $p<0.01$, * $p<0.05$, + $p<0.1$

Notes:

1. The table contains robustness checks for the baseline model given by equation (12).
2. All estimations use as excluded instruments: distance*oil price (log); lagged exports (log); lagged export composition (log).
3. The estimation using foreign affiliate employment data at sub-national level includes the following countries: France, Germany, Netherlands, United Kingdom, Japan and Australia. This limitation is imposed by data availability.
4. Robust standard errors in parentheses.

Table 5: Econometric robustness and Sensitivity Analysis

Dependent variable:	*Business/Economy (log)*	*Business Travel (log)*		
		No NAFTA	High Income	Low Income
	(1)	(2)	(3)	(4)
(Endogenous Var.)	*(airfare; exp.; exp. comp.)*	*(airfare; exports; export composition)*		
Airfare Business/Econ. (log)	-0.047**			
	(0.014)			
Airfare Business (log)		-0.076**	-0.051**	-0.111**
		(0.013)	(0.018)	(0.020)
Total Exports (log)	0.094**	0.221**	0.193**	0.210**
	(0.013)	(0.014)	(0.018)	(0.024)
Export Composition (log)	0.220**	0.198**	0.165*	0.233*
	(0.064)	(0.067)	(0.076)	(0.109)
PCGDP origin region (log)	1.148+	1.295*	0.273	2.699*
	(0.596)	(0.633)	(0.722)	(1.095)
Foreign-Born Pop. (log)	-0.201**	0.265**	0.226**	0.293**
	(0.013)	(0.015)	(0.017)	(0.022)
Country-year fixed effects	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes
Observations	6483	6317	3769	2718
R-squared	0.188	0.64	0.682	0.629
First stage partial F statistic				
Dep. var: Log Airfare	698.12	603.97	509.47	340.57
Dep. var: Log Exports	1147.35	680.93	822.75	344.3
Dep. var: Log Export Comp.	528.47	453.11	512.78	194.76

** p<0.01, * p<0.05, + p<0.1

Notes:

1. The table contains sensitivity analyses for the baseline model given by equation (12).
2. All estimations use as excluded instruments: distance*oil price (log); lagged exports (log); lagged export composition (log).
3. The countries with per-capita GDP above the sample median are defined as high income countries.
4. Robust standard errors in parentheses.

Table 6: Information Intensities across Manufacturing Sectors

		Export shares	
NAICS	**Description**	**Coefficient**	**St. Dev.**
311	Food And Kindred Products	**0.026****	(0.005)
312	Beverages And Tobacco Prod.	**-0.004***	(0.002)
313	Textiles And Fabrics	-0.004	(0.003)
314	Textile Mill Products	0.004	(0.003)
315	Apparel And Accessories	0.004	(0.003)
316	Leather And Allied Products	**0.010****	(0.003)
321	Wood Products	-0.005	(0.003)
322	Paper	**0.009***	(0.004)
323	Printed Matter and Related Prod.	**0.013****	(0.005)
324	Petroleum And Coal Products	0.002	(0.002)
325	Chemicals	**0.027****	(0.008)
326	Plastics And Rubber Products	**0.028****	(0.006)
327	Nonmetallic Mineral Products	**0.011***	(0.005)
331	Primary Metal Manufacturing	0.000	(0.004)
332	Fabricated Metal Products, Nesoi	**0.037****	(0.007)
333	Machinery, Except Electrical	**0.097****	(0.011)
334	Computer And Electronic Products	**0.062****	(0.012)
335	Electrical Equipm., Appliances, Compon.	**0.016***	(0.008)
336	Transportation Equipment	**0.016***	(0.007)
337	Furniture And Fixtures	**0.014****	(0.004)
339	Misc. Manufactured Commodities	**0.044****	(0.009)
TOT	Total manufacturing exports	**0.373****	(0.021)
Other regressors			
Log airfare		**-0.063****	**(0.012)**
Log GDP per Capita (origin region)		**1.368***	(0.617)
Log Foreign-born Pop.		**0.224****	(0.014)
Destination-Year FE		yes	
Instrumented variables		*airfares; exports*	
Observations		6487	
R-squared		0.661	

** p<0.01, * p<0.05, $^{+}$ p<0.1

Notes:
1. The table contains estimates for the regression model described by equation (13).
2. The excluded instruments are: distance*oil price (log) for airfare; one-year lagged exports (log) for total exports.
3. Robust standard errors in parentheses.

Table 7: Correlation coefficients between information intensity estimates and external measures of product complexity

Information Intensities:	Sector R&D intensity (NSF data)	Contract intensity (Nunn, 2007)	Elasticity of substit. (Broda and Weinstein)
All Manufacturing (21 sectors)		0.418+	0.006
Manufacturing with R&D data (15 sectors)	0.632*	0.457+	-0.086

** $p<0.01$, * $p<0.05$, + $p<0.1$

Notes:

1. The correlation coefficients are computed using the estimates of information intensity across 3-digit NAICS sectors, reported in Table 7.
2. R&D expenditure shares represent the percentage of R&D expenditures in net sales. The data is provided by the NSF and is reported at 3-digit NAICS level, by state and year. For each industry, I calculate the average R&D expenditure shares over states and years.
3. Contract intensity is constructed by Nunn (2007) and represents the proportion of differentiated intermediate inputs used in the production of a given final good. Nunn reports the values of contract intensity at 6-digit NAICS level. I use simple averages to conform the values to 3-digit NAICS level.
4. The elasticity of substitution is taken from Broda and Weinstein (2006). I use a concordance from 5 digit SITC rev3 to 3 digit NAICS categories and then use simple averages to collapse the original elasticities to the required level of aggregation.