How Wide Is the Firm Border?

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Abstract

We examine the within- and across-firm shipment decisions of tens of thousands of goods-producing and distributing establishments. This allows us to quantify the normally unobservable forces that determine firm boundaries; which transactions are mediated by ownership control, as opposed to contracts or markets. We find firm boundaries to be an economically significant barrier to trade: having an additional vertically integrated establishment in a given destination zip code has the same effect on shipment volumes as a 40 percent reduction in distance. We then calibrate a multi-sector trade model to quantify the economy-wide implications of transacting across vs. within firm boundaries.

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1 Introduction

A vast literature initiated by Coase (1937) has sought to build an economic theory of the firm. A central question in this work regards what forces determine which transactions occur within firm boundaries as opposed to across them. The literature has put forward many possible explanations for why some transactions are better moderated by the firm. Among the more prominent classes of explanations include the transaction costs theories first developed by Williamson (1971, 1973, 1979) and Klein, Crawford, and Alchain (1978), the property rights theory in Grossman and Hart (1986) and Hart and Moore (1990), the ownership-as-incentive-instrument structure of Holmstrom and Milgrom (1991) and Holmstrom and Tirole (1991), the resource-based view of Wernerfelt (1984), the routines-based theory of Nelson and Winter (1982), and the knowledge-based explanation of Kogut and Zander (1992).[1]

The considerable empirical literature spurred by these theories has studied how such factors influence firm formation, size, and scope. The modal analysis in this literature identifies a likely (and hopefully exogenous) source of variation in the net gains to keeping a transaction inside the firm (e.g., greater capital specificity) and then relates this variation to observed outcomes in firm structure. The estimated object of interest is the sign of the comparative static (e.g., do increases in capital specificity increase the extent of vertical integration) and occasionally the magnitude of the relationship between the explanatory variable and firm structure outcomes.

What has not been attempted, however, is an estimate of actual magnitudes of the net benefits of internal transactions — the actual size of avoided transaction costs, or the benefit of retaining residual rights of control through ownership, or the advantage of internal incentives, and so on. This strikes us as an important missing piece. These benefits, after all, are the core empirical object in theories of the firm. Yet we do not know how big they actually are, or how they vary in magnitude with aspects of the market environment. There

[1] Gibbons (2005) discusses these various theories and distills the transaction cost, property rights, and incentive explanations into four formal theoretical structures.

are several reasons for this dearth of estimates of the magnitudes of “what makes a firm, a firm.” First, by their nature, the factors proposed by the theoretical literature tend to be shadow values. They are explicitly about non-market transactions and often about costs that aren’t paid, so they are inherently difficult to measure. More practically, even if one could imagine constructing a reasonable measure of these shadow values (using the payroll of a company’s procurement department as a measure of transaction costs, for example), this would require highly detailed data to construct. Further still, if such data exist, it would only be for specific firms in specific markets, and perhaps only for specific transactions. It would be difficult to extend any such measures to more general settings, at least without some model that empirically relates a transaction’s observables to its net benefit of keeping that transaction within the firm.

This paper proposes a method to measure the magnitude of the forces that shape firm boundaries. Our approach uses a firm-side analogue to the consumer concept of revealed preference to measure the shadow values of keeping transactions inside a firm. Specifically, we use firms’ revealed choices about what, where, and to whom to ship to measure the implied shadow values of in-house transactions.

We detail our approach below, but the basic logic is simple. An extensive empirical literature has established that transaction volumes decline in distance because of various costs ranging from physical transport costs to monitoring to coordination and beyond. If we observe, all else equal, that firms are systematically willing to send internal shipments further (or equivalently, to have a greater volume of internal than external transactions at any given distance), this implies that they perceive internal shipments as being less costly. And because we observe the overall relationship between shipment volumes and distance, which lets us characterize the magnitude of distance-based costs, we can obtain a cardinal measure of the “distance premium” of internal shipments — the perceived cost savings of keeping transactions within the firm. In other words, differences in the patterns of firms’ within- and across-firm shipments reveal the hurdle they perceive for transacting outside their borders. We do not need to see these costs directly the in the data. Firm behavior and the volume-distance relationship reveal to us what they are.

Besides allowing us to measure what to this point has not been quantified, our approach has other advantages. For one, our estimates are obtained based on behavior at the transaction level. This is the theoretically exact margin at which the firm's boundaries are determined. Additionally, we can apply our method to a wide swath of transactions, firms, and markets. We analyze millions of shipments (our transaction-level observation) from tens of thousands of establishments in the goods-producing and goods-distributing sectors in the U.S. This allows us to characterize how our estimated shadow values vary with observables about the product being transacted, the production function of the firm, and even the attributes of specific transactions.[2]

We find that the net benefits of keeping transactions in house are substantial. They are equivalent in magnitude to the costs associated with increasing the distance between separately owned counterparties by 40 percent. Moreover, the organizational and spatial structure of economic activity is significantly shaped by the forces that determine the boundaries of the firm. We characterize systematic patterns in the heterogeneity of firm boundary effects across different settings, finding that the net benefits of within-firm transactions are larger for more distant shipments, high value-to-weight products, more differentiated products, in industries that are more IT-capital intensive, and for establishments that produce goods rather than just convey them. We also address the potential bias created by the endogeneity of establishment ownership and location. Finally, we compute the aggregate welfare implications of the mitigation of costs conferred by common ownership.

These results extend and qualify the conclusions drawn from our earlier work (Atalay, Hortaçsu, and Syverson, 2014). In this earlier paper we documented that, for a large

[2]It is important to note that our "revealed preference" approach allows us to remain agnostic about the specific source(s) of the shadow benefits of keeping transactions in house, be they transaction cost savings, residual rights of control, advantages of incentive structures, some other factor, or any combination thereof. A firm's decisions tell us how large it perceives these benefits to be, not the specific mechanism(s) through which they arise. This cost does come with a benefit, though; we do not need to rely on untestable assumptions about the source for measurement.

fraction of firms that own establishments in vertically related industries, upstream establishments make almost all of their shipments to downstream establishments in other firms. We interpreted this empirical finding as signifying that for many firms that own production chains, the primary rationale for common ownership is to facilitate within-firm flows of intangible rather than physical inputs. However, this does not necessarily imply that the costs of making across-firm transactions (relative to internal transactions) are small. The relative frequencies of within-firm and across-firm transactions are a function of many characteristics (including firm identity, distance, and productivity) of the potential suppliers and customers with whom establishments can trade. The magnitude of firm boundary costs are identifiable only relative to other costs that make transactions across buyers and sellers more or less likely.

Besides the work mentioned above, our study relates to a recent literature examining how the forces that shape firm boundaries interact with firms' decisions about their location and scope. Fally and Hilberry (2015) construct a multi-industry, multi-country trade model with the goal of examining how declining transaction costs affect the within-country and international fragmentation of production chains. The main tradeoff in their model balances transaction costs against within-firm coordination costs. Tasks are integrated within the firm to save on the costs of transacting with suppliers or customers, but because of increasing marginal costs of coordinating tasks within the firm, not all tasks within a production chain are performed by the same firm. As transaction costs decline, product line fragmentation increases, and activity is spread out over a larger number of countries. Along similar lines, Forman and McElheran (2017) find that the diffusion of IT-enabled coordination tools between firms along supply chains is associated with a reduction in vertical integration of those chains, and Fort (2017) uses detailed data from manufacturers' purchases of contracted services to demonstrate that declining across-firm communication costs have fragmented production, especially for products whose specifications can be codified electronically. Antràs and Chor (2013) model a multi-stage production process where the value of the final good is a function of investments made at each stage. Each stage may either be integrated with the final producer or outsourced to a supplier. A key prediction of the model is that integration at later (resp. earlier) stages of production is more likely when investments along the chain are strategic complements (resp. strategic substitutes). They empirically test and find support for this prediction using aggregate data from the Census Related Party Database (this result is reaffirmed in firm-level data in Alfaro et al., 2015). In sum, this literature fits within the broader pattern of empirical work that has examined comparative statics regarding the how differences in proxies for transaction costs, property rights, and so on shape firm boundaries. Our complementary contribution is to measure the actual magnitude of the costs associated with transacting across firm boundaries and as such shape a firm's decision about where to draw its borders.

Our work also has ties to the vast literature that has used gravity models to infer the costs associated with transacting with faraway counterparties; see Anderson and van Wincoop (2004), Costinot and Rodríguez-Clare (2014), and Head and Mayer (2014) for syntheses of this literature.[3] As emphasized in these literature reviews, the gravity equation of trade — according to which the flows of goods or services across two regions is directly proportional to the size of these regions and inversely proportional to the distance between them — emerges as the prediction of a broad class of trade models. In this paper, we apply the particular model proposed by Eaton, Kortum, and Sotelo (2012) to generate our estimating equations. Their model is particularly useful in our context, as it accounts for the possibility of zero trade flows across pairs of regions, which are pervasive in our dataset. Our contribution in this paper is to leverage what is known from the gravity equation literature about distance-based trade impediments to obtain an estimate of across-firm transaction costs.

[3] McCallum (1995) provides one of the first attempts to infer the "width" of national borders from trade flows. A complementary literature uses deviations from the law of one price as a way to measure the costs of trading across regions. We owe the title of our paper to an exemplar of this literature, Engel and Rogers (1996).

2 The Gravity Equation

The framework we use to predict trade flows from establishments to destination zip codes borrows heavily from Eaton, Kortum, and Sotelo (2012). In particular, we adopt the model elements which yield a gravity equation that is both relatively simple to derive and allows for zero trade flows between pairs of regions. This latter element is important, as zero trade flows are common in our data. The model also aggregates up from the establishment level nicely. This is very useful, as while our data is extremely detailed, it does have one limitation in that we observe a shipment's destination zip code rather than its destination establishment within that zip code. We can use the model to directly derive an estimating equation that uses this more aggregate destination information.

We make two minor amendments to the Eaton, Kortum, and Sotelo (2012) model. First, we characterize the expected flows from specific sending establishments to destination regions (zip codes in the data as discussed above), as opposed to having both the origin and destination represent regions. Second, critically for our empirical question, we permit transaction costs to be lower when the sending and receiving establishment belong to the same firm.

Establishments operate in $1, ..., Z$ zip codes, with potentially multiple establishments located in each destination zip code z. Establishments ("plants") can both produce/send and use/receive commodities. Each produces a single, horizontally-differentiated traded commodity.[4] Denote the identity of a potential receiving establishment with its location z^e, and similarly refer to the sending establishment as i^e.[5]

[4] In the empirical application in Section 4, we construct market shares separately by commodity. We omit commodity-level superscripts throughout this section for notational simplicity. The analysis in this section can easily be extended to multiple traded commodities with constant expenditure on each commodity. This can be accommodated by a model in which a representative consumer in each zip code has Cobb-Douglas preferences over commodities; in Section 5, we discuss a multi-industry model along these lines.

[5] We do not attempt to directly model firms' decisions on where to locate their establishments, or which establishments to own, as in Antràs (2005), Keller and Yeaple (2013), or Ramondo and Rodríguez-Clare (2013). In an international setting, the aforementioned trade models emphasize that related-party vs. arms-length trade are substitutes. A richer, more complete model would analyze location and ownership choices in combination which establishments' sourcing decisions. Due to the complexity of modeling both sets of choices in our context, in which there are thousands of possible locations, we do not pursue this richer model.

Each sending establishment has access to a (random) number of linear production technologies, each which allows it to transform l units of labor into vl units of output. We assume that v is Pareto distributed with shape parameter θ and a lower cutoff $\bar{v}$ that can be set arbitrarily close to 0. We also assume that the (integer) number of establishment i^e's varieties with efficiency $V > \bar{v}$ (for $v > \bar{v}$) is the realization of a Poisson random variable with mean $T_{i^e} v^{-\theta}$. In this expression, T_{i^e} reflects the overall productivity of establishment i^e.

Call x_i the cost of a unit of labor inputs for establishments in zip code i. There are also iceberg-style transportation costs which vary not only in distance, but also based on ownership. Specifically, for establishment i^e to sell one unit of the commodity to plant z^e, it must produce $d_{zi^e} \geq 1$ units of output if plant z^e is owned by a different firm and $d_{zi^e}\delta_{zi^e} \geq 1$ units of output if the same firm owns it. Furthermore, forming a relationship with establishment z^e requires a fixed number of workers F_{z^e} to be hired in zip code z.

Given these assumptions, the unit cost of a variety with an idiosyncratic productivity draw v selling to plant z^e is

$$\psi_{z^e i^e}(v) = \frac{x_i}{v} d_{zi^e} \left(\delta_{zi^e}\right)^{\mathbf{1}^{SF}(z^e,i^e)},$$

where $\mathbf{1}^{\mathrm{SF}}$ is an indicator for a within-firm relationship between establishments i^e and z^e. Using properties of the Poisson distribution, the number of varieties that can be sold to establishment z^e at a cost less than or equal to ψ is the realization of a Poisson random variable with parameter $\Phi_{z^e}\psi^{\theta}$, with

$$\Phi_{z^e} \equiv \sum_{i=1}^{I} \sum_{i^e \in i} T_{i^e} \left(x_i d_{zi^e}\right)^{-\theta} \cdot \left(\left(\delta_{zi^e}\right)^{\mathbf{1}^{SF}(z^e,i^e)}\right)^{-\theta}.$$

Our last set of assumptions, again following the Eaton, Kortum, and Sotelo (2012) setup,

We do, however, further discuss the endogeneity of firms' ownership and location decisions in Section 4.3.

relate to establishments' entry and pricing decisions. We assume that i) upstream establishments compete monopolistically when serving each downstream establishment, ii) the downstream establishment z^e combines inputs form its suppliers according to a CES aggregator, iii) each upstream establishment takes as given the downstream establishment's intermediate input "ideal price index" P_{z^e} and total expenditures X_{z^e} on intermediate inputs, and iv) upstream establishments sell to z^e (referred to as entry) as long as profits are non-negative, with low-cost potential entrants making their decisions first.

This setup provides three results on the margins of trade. First, conditional on entry, sales of different entrants are independent of the cost parameters x_i, d_{zi^e}, and δ_{zi^e}. These parameters affect only the extensive margin of trade, not the intensive margin. Second, the probability that a given variety produced by establishment i^e is among the lowest-cost varieties that are able to profitably enter is given by:

$$\begin{aligned} \pi_{z^e i^e} &= \frac{\Phi_{z^e i^e}}{\Phi_{z^e}}, \text{ with} \\ \Phi_{z^e i^e} &\equiv T_{i^e} \left(x_i d_{zi^e} \left(\delta_{zi^e}\right)^{\mathbf{1}^{SF}(z^e, i^e)} \right)^{-\theta}. \end{aligned} \tag{1}$$

Third, and related to the first two results, the fraction of z^e's expenditures purchased from upstream establishment i^e equals

$$\mathbb{E}\left[\frac{X_{z^e i^e}}{X_{z^e}}\right] = \frac{\Phi_{z^e i^e}}{\Phi_{z^e}}. \tag{2}$$

In Appendix A, we aggregate Equation 2 up to the sending establishment by destination zip code pair in order to match the aggregation level of our data, as discussed above:

$$\begin{aligned} \pi_{zi^e} &\equiv \frac{\Phi_{zi^e}}{\Phi_z} = \frac{T_{i^e} \left(x_i d_{zi^e}\right)^{-\theta} \left(1 - s_{zi^e} + s_{zi^e} \delta_{zi^e}^{-\theta}\right)}{\sum_{i'=1}^{N} \sum_{i'^e \in i'} T_{i^{e\prime}} \left(x_{i'} d_{zi'^e}\right)^{-\theta} \left(1 - s_{zi'^e} + s_{zi'^e} \delta_{zi'^e}^{-\theta}\right)} \\ &\approx \mathbb{E}\left[\frac{X_{zi^e}}{X_z}\right], \end{aligned} \tag{3}$$

where $s_{zi^e} \equiv \sum_{z^e \in z} \frac{X_{z^e}}{X_z} \mathbf{1}^{SF}(z^e, i^e)$ is the expenditure-weighted share of downstream establishments in the destination zip code owned by the same firm of the sending establishment i^e. The $\left(1 - s_{zi^e} + s_{zi^e}\delta_{zi^e}^{-\theta}\right)$ term reflects a weighted average of the trade-facilitating effects of common ownership: a fraction s_{zi^e} of the establishments in the destination share ownership with the sender and have lower trade costs by a factor of $\delta_{zi^e}^{-\theta}$. For the remaining $1-s_{zi^e}$ establishments in the destination, there is no analogous reduction in trade costs. Finally, throughout this paper, use $\frac{X_{zi^e}}{X_z}$ to refer to the market share of establishment i^e in zip code z. In our empirical analysis, later on, this market share will be specific to the commodity that i^e produces.

Consider a first-order Taylor approximation around the point at which sending establishment i^e has no same-firm establishments in the downstream zip code:[6]

$$1 + s_{zi^e}\left(\delta_{zi^e}^{-\theta} - 1\right) \approx \exp\left\{s_{zi^e}\left(\delta_{zi^e}^{-\theta} - 1\right)\right\}.$$

Using this approximation, we can rewrite Equation 3 as

$$\mathbb{E}\left[\frac{X_{zi^e}}{X_z}\right] = \pi_{zi^e} \approx \frac{\exp\left\{\log T_{i^e} - \theta \log x_i - \theta \log d_{zi^e} + s_{zi^e}\left(\exp\left[-\theta \log \delta_{zi^e}\right] - 1\right)\right\}}{\sum_{i'=1}^{N}\sum_{i'^e \in i'} \exp\left\{\log T_{i'^e} - \theta \log x_{i'} - \theta \log d_{zi'^e} + s_{zi'^e}\left(\exp\left[-\theta \log \delta_{zi'^e}\right] - 1\right)\right\}}. \tag{4}$$

We parameterize that the relationship between distance and same-firm-ownership on trade flows is

$$\begin{aligned} -\theta \log d_{zi^e} + s_{zi^e}\left(\exp\left[-\theta \log \delta_{zi^e}\right] - 1\right) \quad = \quad & \alpha_0 + \alpha_1 \cdot \log \text{mileage}_{z \leftarrow i} \\ & + \alpha_2 \cdot s_{zi^e} + \alpha_3 \cdot s_{zi^e} \cdot \log \text{mileage}_{z \leftarrow i} + \log \varepsilon_{z,i^e} \end{aligned} \tag{5}$$

In this equation, the ε_{z,i^e} reflect the random unobservable component of trade costs from establishment i^e to destination z, costs which are unrelated to mileage and common

[6]With this approximation, the relationship between the same-firm ratio, s_{zi^e}, and the expected market share is log-linear. Since in our sample the average value for s_{zi^e} equals 0.0009, the approximation error is inconsequential.

ownership. The ε_{z,i^e} are constructed as in Eaton, Kortum, and Sotelo (2012), as the ratio of Gamma distributed random variables (see their footnote 21), and are independent across $i^e - z$ pairs.[7] With randomly distributed ε_{z,i^e}, there are two sources of randomness: First, establishments' technologies have stochastic productivity. Second, the iceberg trade costs for each sending establishment-destination pair are randomly distributed. In combination with our assumption on the distribution of ε_{z,i^e}, plugging Equation 5 into Equation 4 yields a relatively simple expression for the expected market share as a function of a) sending-establishment specific terms, b) pair-specific observable variables, and c) a summation of destination-specific terms:

$$\mathbb{E}\left[\frac{X_{zi^e}}{X_z}|\Lambda\right] = \frac{\exp\left\{\alpha_{i^e} + \alpha_1 \cdot \log \text{mileage}_{z\leftarrow i} + \alpha_2 \cdot s_{zi^e} + \alpha_3 \cdot s_{zi^e} \cdot \log \text{mileage}_{z\leftarrow i}\right\}}{\sum_{i'=1}^{N} \sum_{i'^e \in i'} \exp\left\{\alpha_{i'^e} + \alpha_1 \cdot \log \text{mileage}_{z\leftarrow i'} + \alpha_2 \cdot s_{zi'^e} + \alpha_3 \cdot s_{zi'^e} \cdot \log \text{mileage}_{z\leftarrow i'}\right\}}. \tag{6}$$

Here, conditioning on Λ indicates that there is some random component of trade flows, due to the ε terms, and that our expression for the expected trade flows is a function of the observed distance and ownership variables. And, $\alpha_{i^e} \equiv \alpha_0 + \log T_{i^e} - \theta \log x_i$ collects all of the relevant sending establishment specific unobservable terms.

There are two possible approaches to estimate the parameters involved in the expression for the expected market share. The first, advocated by Anderson and van Wincoop (2003),

[7] First, define

$$\Lambda_{zi^e} \equiv \frac{\exp\left\{\alpha_{i^e} + \alpha_1 \cdot \log \text{mileage}_{z\leftarrow i} + \alpha_2 \cdot s_{zi^e} + \alpha_3 \cdot s_{zi^e} \cdot \log \text{mileage}_{z\leftarrow i}\right\}}{\sum_{i'=1}^{N} \sum_{i'^e \in i'} \exp\left\{\alpha_{i'^e} + \alpha_1 \cdot \log \text{mileage}_{z\leftarrow i'} + \alpha_2 \cdot s_{zi'^e} + \alpha_3 \cdot s_{zi'^e} \cdot \log \text{mileage}_{z\leftarrow i'}\right\}}$$

as the observable component of trade costs. To compute ε_{z,i^e}, consider a set of random variables ϑ_{zi^e} drawn (independently across $i^e - z$ pairs) from a Gamma distribution with scale parameter $\frac{\Lambda_{zi^e}}{\eta^2}$ and shape parameter $\frac{\eta^2}{\Lambda_{zi^e}}$, for some $\eta > 0$. The idiosyncratic components of trade costs are defined as $\varepsilon_{z,i^e} \equiv \frac{\vartheta_{zi^e}}{\vartheta_{ii^e}}$. Based on the properties of the Gamma distribution, with this parameterization the expression for the expected trade flows (conditional on the observable trade cost variables) retains a convenient multinomial logit form.

is to incorporate both destination and sending establishment fixed effects:

$$\mathbb{E}\left[\frac{X_{zi^e}}{X_z}|\Lambda\right] \approx \exp\left\{\alpha_1 \cdot \log \text{mileage}_{z\leftarrow i} + \alpha_2 \cdot s_{zi^e} + \alpha_3 \cdot s_{zi^e} \cdot \log \text{mileage}_{z\leftarrow i} + \alpha_{i^e} + \alpha_z\right\}. \tag{7}$$

The destination fixed effects in Equation 7 capture the terms in the denominator in Equation 6. This theoretically-motivated specification produces consistent estimates of the same-firm share, distance, and interaction terms.

One drawback of this approach is that with tens of thousands of sending establishments and tens of thousands of destination zip codes, it is computationally taxing. As an alternative approach, in most of our specifications we follow the earlier literature on gravity equation estimation and regress $\frac{X_{zi^e}}{X_z}$ against sending establishment fixed effects, distance terms, and destination-specific multilateral resistance terms (as discussed in Baier and Bergstrand, 2009). These multilateral resistance terms involve subtracting off a first-order Taylor approximation of the terms in the denominator of the right-hand-side of Equation 6. Namely, for each pair-specific explanatory variable, g_{zi^e}, our regressions include $g_{zi^e} - \overline{g}_{z\cdot} - \overline{g}_{\cdot i^e} + \overline{g}$ as the covariate; $\overline{g}_{z\cdot}$, $\overline{g}_{\cdot i^e}$, and $\overline{g}$ respectively denote the average value of the of the covariate g_{zi^e} for a given establishment i^e, for a given destination zip code z, or across all sending establishment-destination zip code pairs. In essence, the multilateral resistance terms apply the mechanics of linear models with two-way fixed effects to the gravity relationship.

An appropriate estimator for either specification is the multinomial pseudo maximum likelihood estimator, which can be implemented via a Poisson regression; see Head and Mayer (2014; Section 5.2) or Sotelo (2017).

3 Data Sources and Definitions

Our analysis employs two large-scale data sets maintained by the U.S. Census: the Longitudinal Business Database (LBD) and the Commodity Flow Survey (CFS). We supplement these data with two sets of industry-level definitions from past work: our definitions of vertically-related industry pairs (from Atalay, Hortaçsu, and Syverson, 2014) and Rauch (1999)'s product differentiation classification.

Our benchmark sample is drawn from the establishments surveyed in the 2007 Commodity Flow Survey. Like its predecessors, the 2007 CFS contains a sample of establishments operating in the economy's goods-producing and goods-distributing sectors: mining; manufacturing; wholesale; electronic shopping and mail-order houses; and newspaper, book, and music publishers. Once per quarter, each surveyed establishment is asked to report up to 40 randomly selected shipments that it made on a given week in that quarter. Relevant for our purposes, the data include each shipment's origin and destination zip code, weight, and dollar value. The sample contains approximately 4.3 million shipments made by roughly 58,000 establishments. Because we are interested in characterizing the shipment patterns of establishments that could make same-firm shipments, we only keep establishments from multi-unit firms. This reduces the sample size to approximately 35,000 establishments.[8] We also limit our analysis to domestic shipments. While the CFS includes shipments for export, the data only reports the zip code of the shipment's port of departure from the U.S. and its destination country; we do not see the specific destination within the foreign country or anything about ownership of the receiving establishment. Thus we cannot construct either of the key variables for our analysis for exports.

While the CFS is a shipment-level dataset, we sum up across shipments within a surveyed establishment-destination zip code pair to obtain each observation in our analysis dataset.[9] We create the sample as follows. We first segment the 2007 CFS by 6-digit North American Industry Classification System (NAICS) industry of the shipping plant. For each industry, we collect all destination zip codes that receive at least one shipment from industry establishments. We then create the Cartesian product of all shipping plants and all destination zip

[8]Census disclosure rules prohibit us from providing exact sample size counts throughout this paper.

[9]Note that the CFS allows us to observe the destination zip code of the shipment, not the identity of the particular recipient establishment. This is why our level of observation is demarcated by a (shipping) establishment on one side but a zip code on the other. It means we must infer internal shipments as a function of the prevalence of downstream establishments owned by the shipping establishment's firm rather than being able to observe these internal shipments directly.

codes for that industry. Our sample consists of the aggregation of these Cartesian products across all 6-digit industries. Our benchmark sample has 190 million sending establishment-destination zip code observations.

The main variables of interest in next section's empirical specification are the market share and distance measures. The market share for a shipping plant i^e in destination z is the total value of shipments from i^e to z divided by the total shipments sent to z by all plants in i^e's 6-digit NAICS industry to z. Our main analysis relates this market share to measures of the distance, be they literal or figurative, between i^e and the establishments located in zip code z. The physical, great circle distance between two zip codes is straightforward to compute using information on the zip codes' longitudes and latitudes. A key figurative distance measure s_{zi^e} is the fraction of downstream establishments in zip code z owned by the same firm that owns establishment i^e; below, we call this variable the "same-firm ownership fraction." To compute this fraction, we restrict attention to the establishments in zip code z that could conceivably use the product establishment i^e is shipping. For example, if i^e is a cement manufacturer, we would not want to include dairy producers, auto wholesalers, or gas stations when computing s_{zi^e}. To discern which establishments are downstream of i^e and could in turn conceivably use i^e's output, we apply the algorithm introduced in our earlier paper (Atalay, Hortaçsu, and Syverson, 2014). Namely, we find industry pairs I, J for which at least one percent of the output of industry I is purchased by establishments n industry J. Then, when computing s_{zi^e} for each establishment $i^e \in I$ we sum only over the plants in zip code z that belong to a downstream industry J.

Table 1 presents summary statistics for our sample of establishment-destination zip code pairs. Panel A indicates, first, that the total value shipped (summing across all potential sending establishments i^e) is highly skewed. While the median 6-digit product-destination zip code shipment total is around \$1.6 million, the mean is around \$14 million. Second, the average market share, $\frac{X_{zi^e}}{X_z}$, equals 0.004. Only 0.7 percent of sending establishments have any shipments to z. In short, zero trade flows are exceedingly common in our sample of i^e-z

pairs.

Panels B and C split i^e-z pairs by the presence or absence of shipments from i^e to z. The two takeaways from these panels are that a) establishments tend to ship to zip codes that contain some potential counterparties with which they share ownership, but b) same-firm shares are still low, even in zip codes that receive at least one shipment. For the mean i^e-z pair, 12.9 establishments in z belong to industries downstream of sender i^e. But of these 12.9, only 0.01 establishments on average share ownership with the sender. Shipments are more likely to be sent to zip codes in which at least one of the potential recipients belongs to the same firm as the sender. For destination zip codes that receive at least one shipment from i^e, 0.51 percent of the potential recipients share ownership with the sender, compared to 0.09 percent when no shipment is sent.

Panel D offers a summary of shipment distances. Establishments under common ownership tend to be closer to one another. For i^e-z pairs with a potential recipient in z owned by the firm that also owns i^e, the 10th percentile distance is 184 miles, and the 25th and 50th percentile distances are 411 and 804 miles, respectively. In contrast, for pairs in which no such common ownership links exist, the 10th, 25th, and 50th percentile distances are uniformly larger: 264, 501, and 866 miles. Also, not surprisingly (and consistent with gravity models of the type we leverage in this paper), shipments become less likely as the distance to a potential recipient increase. The median distance between sending establishments and potential destinations that receive at least one shipment is 254 miles, while it is 870 miles for pairs with no shipments.

To sum up, we can draw the following three conclusions from Table 1. First, for any particular destination zip code, it is rare for there to be an establishment sharing ownership with the sender. Second, pairs of establishments that are owned by the same firm and belong to vertically-related industries tend to be located closer to one another than the typical upstream-downstream pair. Finally, a potential destination zip code that contains an establishment sharing ownership with the sending firm tends to receive more shipments. So,

Table 1: Summary Statistics

	Percentile						
	10	25	50	75	90	Mean	SD
Panel A: Entire Sample							
Total shipment value to z ($ millions)	0.1	0.3	1.6	7.6	27.5	14.5	94.1
Market share, $\frac{X_{zi^e}}{X_z}$	0	0	0	0	0	0.004	0.061
Panel B: If there is a shipment from i^e to z							
Number of total downstream ests. at z	0	2.0	7.5	18.5	42.5	17.26	30.49
Number of same-firm downstream ests. at z	0	0	0	0	0	0.041	0.250
Number of same-firm establishments at z	0	0	0	0	0	0.113	0.622
Same-firm ownership fraction	0	0	0	0	0	0.0051	0.0455
Panel C: If there is no shipment from i^e to z							
Number of total downstream ests. at z	0	1.0	5.0	13.5	31.0	12.90	24.86
Number of same-firm downstream ests. at z	0	0	0	0	0	0.009	0.110
Number of same-firm establishments at z	0	0	0	0	0	0.026	0.240
Same-firm ownership fraction	0	0	0	0	0	0.0009	0.0166
Panel D: Log Mileage...							
if the same-firm ownership fraction =0	5.58	6.22	6.77	7.29	7.65	6.66	0.87
if the same-firm ownership fraction >0	5.22	6.02	6.69	7.26	7.64	6.54	1.04
if there is no shipment from i^e to z	5.60	6.22	6.77	7.29	7.65	6.67	0.85
if there is a shipment from i^e to z	2.78	4.10	5.54	6.53	7.16	5.23	1.65

Notes: The sample consists of pairs of sending establishments and destination zip codes, i^e-z, for which at least one shipment by an establishment in the same industry as i^e was sent to zip code z. The market share equals the ratio of the shipments sent by i^e to zip code z, relative to the total amount sent by all establishments in the same industry as i^e to zip code z. The total number of i^e-z pairs in the sample is 189.6 million. Of these, for 1.4 million there is at least one shipment from i^e to z (and 188.2 million with no shipments). Of the 189.6 million i^e-z pairs, the same-firm ownership fraction is greater than 0 for 1.4 million pairs (and zero for the remaining 188.1 million pairs).

our data on domestic shipments indicate both that firms choose to locate their establishments close to one another, and that distance and common ownership shape shipment frequencies.

4 Results

4.1 Benchmark Specification

Table 2 reports our baseline regression results relating distance and ownership to the share of a zip code's purchases of a given product purchased from a sending establishment i^e. The columns differ according to how we model the relationship between distance and the market share (either logarithmically or more flexibly, with a sequence of categorical variables) and which multilateral resistance term we include (whether the averages that are being subtracted off of the distance and ownership measures are weighted by the trade flows or are unweighted).[10] Through the tradeoffs between distance and ownership, firms reveal in their shipment patterns the costs they perceive in transacting outside their borders. Given that transaction costs generally increase in distance, if establishments are systematically more likely to ship a greater distance to same-firm establishments than other-firm establishments (or equivalently, ship a greater volume internally than externally at any given distance), this indicates they see a differential cost in transacting within rather than between firms.

Consistent with a large body of evidence drawing on international trade flows (Disdier and Head, 2008), we find that the elasticity of bilateral trade flows with respect to distance is slightly less than 1. Newer to the literature and the focus of our study is the estimate embodied in the same-firm ownership share coefficient. We find values of approximately 2.5 to 3. Interpreting the magnitude of these coefficients requires a short calculation. Our same-firm ownership metric is the fraction of establishments in downstream zip code z that are owned by i^e's firm. Thus the addition of a same-firm establishment in the destination

[10]When computing $g_{zi^e} - \overline{g}_z - \overline{g}_{\cdot i^e} + \overline{g}$ in columns (2) and (5), $\overline{g}_{z\cdot}$, $\overline{g}_{\cdot i^e}$, and $\overline{g}$ are simple, unweighted averages. In columns (3) and (6), we also compute averages but instead weight observations by the observed flows from the sending establishment multiplied by the observed flows to the destination zip code.

Table 2: Relationship between distance, common ownership, and market shares

Dependent Variable: $\frac{X_{zi^e}}{X_z}$	(1)	(2)	(3)	(4)	(5)	(6)
Same-firm ownership fraction	2.596	2.828	2.941	2.664	2.884	2.939
	(0.047)	(0.049)	(0.047)	(0.038)	(0.038)	(0.039)
Log mileage	-0.923	-0.962	-0.944			
	(0.004)	(0.003)	(0.005)			
Distance$\leq$50 miles				3.732	3.893	3.993
				(0.015)	(0.015)	(0.016)
Distance$\in (50, 100]$ miles				2.653	2.824	2.884
				(0.015)	(0.015)	(0.016)
Distance$\in (100, 200]$ miles				1.755	1.901	1.927
				(0.013)	(0.013)	(0.014)
Distance$\in (200, 500]$ miles				0.711	0.804	0.790
				(0.008)	(0.009)	(0.010)
Distance$\geq$1000 miles				-0.491	-0.590	-0.345
				(0.010)	(0.013)	(0.021)
Multilateral Resistance	None	Unweighted	Weighted	None	Unweighted	Weighted

Notes: All regressions include sending-establishment fixed effects. The sample includes 189.6 million i^e-z pairs drawing on the shipments made by 35,000 establishments. In columns (4)-(6), the omitted distance category contains zip code pairs which are between 500 and 1000 miles apart.

zip code, equivalent to an increase in the same-firm ownership fraction by 0.315, is related to the same increase in the probability of i^e shipping to that zip code as would a 60 percent reduction in the distance between i^e and that zip code.[11] The implied "distance premium" of ownership increases somewhat as we first include (column 2) and then use a weighted version of (column 3) a multilateral resistance control. The final three columns replace log mileage with a flexible set of indicators for various distance categories to capture any non-linearities in distance effects. The same-firm ownership coefficients change little.

In Table 3, we explore how the relative importance of common ownership varies by distance, the measure of common ownership, and the inclusion of destination fixed effects. The first column includes an interaction of the same-firm ownership fraction with logged distance, allowing the relationship between ownership and the probability of shipping to a location to vary with distance. To help with interpretation, we demean the distance variable when including interaction term in our specification. The interaction has a positive coefficient, implying that the link between same-firm presence and the market shares is stronger for more distant destinations. An additional same-firm downstream establishment in the destination (again, equivalent to an increase in the same-firm ownership fraction by 0.315) in destinations at the 10th, 50th, and 90th percentile distances has roughly equivalent the same impact on trade flows as a reduction in shipping distance by 57 percent, 69 percent, and 80 percent, respectively. (The main effect of distance is somewhat larger in magnitude in this specification.)

Columns 2 and 3 use different measures of same-firm presence in the destination zip code. Column 2 has a binary indicator equal to one if the shipping establishment's firm owns *any* downstream plants in the destination zip code, regardless of the number, while column 3 uses the count of same-firm downstream plants. In both cases, the implied quantitative

[11] For the average i^e-z pair, there are 12.9 potential recipients (establishments in industries which are downstream of i^e) in the destination zip code. The average (across i^e-z pairs) of the inverse of one plus the number of potential recipients equals 0.315. Thus an extra same-firm establishment is associated with the same change in probability as a reduction in the distance from i^e to z by a factor of $\exp\left(\frac{0.315 \cdot 2.828}{-0.962}\right) \approx 0.40$, a 60 percent reduction.

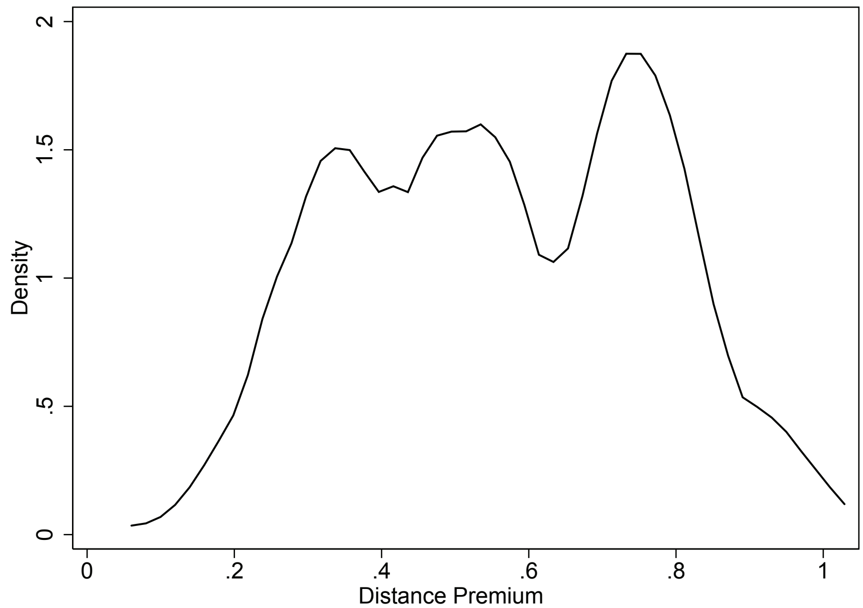
Table 3: Relationship between distance, common ownership, and market shares: interactions and sensitivity analysis

Dependent Variable: $\frac{X_{zi^e}}{X_z}$	(1)	(2)	(3)	(4)	(5)
Same-firm ownership fraction	3.432			2.641	3.090
	(0.040)			(0.026)	(0.026)
Log mileage	-0.964	-0.958	-0.964	-0.961	-0.962
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
Interaction between log mileage	0.291				0.218
and same-firm ownership fraction	(0.023)				(0.015)
Indicator: Number of downstream		1.328			
same-firm establishments > 0		(0.022)			
Number of downstream			0.193		
same-firm establishments			(0.025)		
Destination Zip Code Fixed Effects	No	No	No	Yes	Yes
Multilateral Resistance	Unweighted	Unweighted	Unweighted	None	None

Notes: All regressions include sending-establishment fixed effects. The sample includes 189.6 million i^e-z pairs, drawing on the shipments made by 35,000 establishments.

relationship between common ownership and trade flows is similar to that obtained using our model-based metric of the same-firm ownership fraction. For instance, column 2 suggests the average effect of having some same-firm downstream plants in the destination could provide a distance premium of 75 percent. Column 3 implies that, compared to a zip code with no same-firm presence, the inclusion of one same-firm downstream establishment in the destination zip code has approximately the same relationship with trade flows as a 20 percent ($\approx$1-exp$\left(\frac{0.193}{-0.964}\right)$) reduction of distance between origin and destination, a smaller effect. Finally, in columns 4 and 5, we apply destination zip code fixed effects, obviating the use of the multilateral resistance terms used in our specifications above. The coefficient estimates are reassuringly similar to that in the benchmark specification.

Figure 1: Distance premium, by 6-digit industry



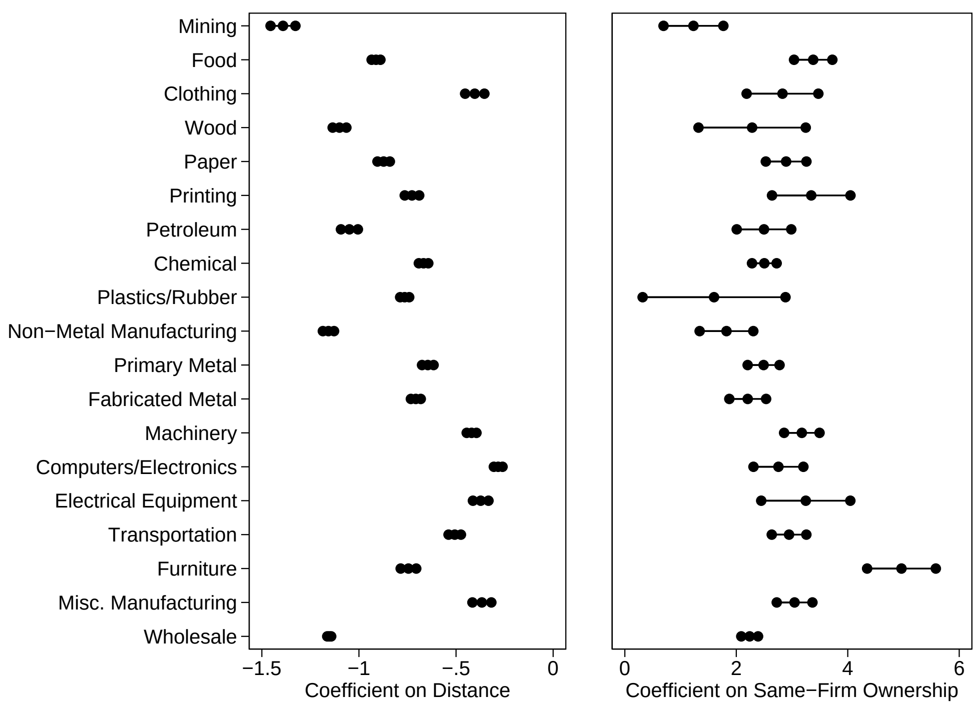
Notes: For each 6-digit NAICS industry, we regress, as in column (2) of Table 2, the market share of establishment i^e in zip code z against the same-firm ownership fraction and the logarithm of the mileage between i^e and z. We compute the distance premium as 1-exp$\left[0.315 \cdot \alpha_2 \cdot (\alpha_1)^{-1}\right]$, and plot the kernel density plot of these distance premia. The bottom five and top five percentiles of this distribution are not plotted, in accordance with Census disclosure prevention rules.

4.2 Interactions with Industry Characteristics

We build on our benchmark analysis by exploring whether there are systematic variations in the associations among distance, ownership, and transactions. We first re-run our baseline regression (given in the specification of the second column of Table 2) separately for each of the 6-digit NAICS industries in our sample. Using α_1 and α_2 to denote the coefficient estimates on the ownership and distance terms respectively, we compute the distance premium associated with an extra same-firm establishment in the destination zip code as "$1 - \exp\left[0.315 \cdot \alpha_2 \cdot (\alpha_1)^{-1}\right]$". We then plot the distribution of these distance premia in Figure 1. This figure indicates that there is substantial heterogeneity across industries in how distance and ownership are related to shipment flows.

In the remainder of this subsection, we explore the industry characteristics underlying

Figure 2: Coefficient estimates and confidence intervals, by 2/3-digit industry



Notes: The left panel gives the coefficient estimate (and corresponding ±1.96 standard error confidence interval) of the logarithm of mileage on the sending establishment's market share. The right panel gives the coefficient estimate and corresponding confidence intervals of the same-firm ownership share variable. These coefficients and confidence intervals result from a specification analogous to column (2) of Table 2, run separately for each 2 or 3-digit NAICS industry.

this heterogeneity. In Figure 2, we plot the coefficient estimates and confidence intervals of the relationships between distance and our market share variable (left panel) and the relationships between the same-firm ownership share and the sending establishment's market share (right panel) for the 19 broadly-defined industries that comprise our sample.[12]

Unsurprisingly, industries with the strongest relationship between trade flows and distance produce bulky (and thus costly to ship) products: mining, non-metal manufacturing, and wood. In addition, trade flows are more responsive to distance in the wholesale sector than in manufacturing. Industries with the largest estimates of α_2 (the coefficient on the same-firm ownership share) include furniture, printing, and electrical equipment. Conversely, for the mining, non-metal manufacturing, wood, and wholesale industries, the coefficient estimates of α_2 are relatively small. In combination, these estimates suggest that trade flows respond more heavily to distance for certain perhaps-heavy-to-ship products and respond more to common ownership in other industries.

Returning to our entire sample of 190 million observations, we interact the key explanatory variables in our specifications (both those allowing the same-firm-ownership relationship to vary with distance and those not) with several measures of industry attributes. The results are shown in Table 4. In Panel A, we group industries by the average value-to-weight ratio of shipments made by industry establishments in our CFS sample. Industries with above median value-to-weight shipments exhibit a weaker relationship between distance and trade flows, consistent with our results above. On the other hand, the relationship between trade flows and firm ownership is stronger for these high value-to-weight commodities. Specifically, the distance premium for above-median value-to-weight commodities is 77 percent ($=1 - \exp[\frac{(2.460+1.038)\cdot 0.315}{(-1.075+0.330)}]$). It is 51 percent for below-median value-to-weight commodities.

Panel B probes the determinants of trade flows separately for goods distributors (mainly wholesalers, but also some mail-order retail catalogues) and goods producers (manufacturers

[12] For the most part, these industries are defined at the 3-digit level. However, to maintain sufficiently large samples sizes to conform with Census disclosure avoidance rules, we combine some 3-digit industries: Food is the combination of NAICS codes 311 and 312; Clothing is the combination of NAICS codes 313, 314, 315, and 316. And, finally, Wholesale is the combination of NAICS codes 421-429.

Table 4: Relationship between distance, common ownership, and market shares: interactions with other shipment characteristics

Panel A: Value-to-weight	(1)	(2)	**Panel B: Producers vs. Distributors**	(3)	(4)
Log mileage	-1.075	-1.078	Log mileage	-0.811	-0.813
	(0.004)	(0.004)		(0.004)	(0.004)
Same-firm ownership fraction	2.460	0.750	Same-firm ownership fraction	3.135	2.265
	(0.066)	(0.163)		(0.060)	(0.214)
Interaction between distance		0.411	Interaction between distance		0.179
and same-firm ownership fraction		(0.029)	and same-firm ownership fraction		(0.036)
Interaction between distance	0.330	0.332	Interaction between distance	-0.351	-0.352
and value-to-weight indicator	(0.007)	(0.007)	and indicator for distributors	(0.006)	(0.007)
Interaction btw. same-firm fraction	1.038	2.648	Interaction btw. same-firm ownership	-0.851	-1.605
and value-to-weight indicator	(0.097)	(0.292)	fraction and indicator for distributors	(0.097)	(0.255)
Same-firm ownership fraction×		-0.391	Same-firm ownership fraction×		0.258
distance×value-to-weight indicator		(0.050)	distance×distributor indicator		(0.045)
In-sample average: $(1 + \text{plants.} \in z)^{-1}$	0.315	0.315	In-sample average: $(1 + \text{plants.} \in z)^{-1}$	0.315	0.315
Number of i^e-z pairs (millions)	190	190	Number of i^e-z pairs (millions)	190	190
Number of establishments (thousands)	35	35	Number of establishments (thousands)	35	35

Notes: The dependent variable equals $\frac{X_{zi^e}}{X_z}$ in each regression. In Panels A and B, our indicators describe whether the industry of the sending establishment had above-median value-to-weight shipments (in Panel A), or is in the wholesale sector (in Panel B). In all specifications throughout Panels A through F we calculate the unweighted multilateral resistance terms.

Table 4 (Continued): Relationship between distance, common ownership, and market shares: interactions with other shipment characteristics

Panel C: Product Differentiation	(5)	(6)	(7)	(8)	**Panel D: IT Intensity**	(9)	(10)
Log mileage	-0.974	-0.977	-0.939	-0.941	Log mileage	-0.869	-0.871
	(0.009)	(0.009)	(0.009)	(0.009)		(0.005)	(0.005)
Same-firm ownership fraction	2.584	0.890	2.552	0.946	Same-firm ownership fraction	2.731	0.783
	(0.101)	(0.390)	(0.105)	(0.368)		(0.093)	(0.284)
Interaction between distance		0.343		0.324	Interaction between distance		0.388
and ownership fraction		(0.067)		(0.063)	and same-firm ownership fraction		(0.047)
Interaction between distance	0.262	0.263	0.224	0.225	Interaction between distance and	0.246	0.248
and differentiated goods indicator	(0.011)	(0.011)	(0.011)	(0.011)	indicator for IT-intensity indicator	(0.009)	(0.009)
Interaction btw. same-firm fraction	0.304	0.243	0.381	0.250	Interaction btw. same-firm ownership	0.314	1.258
and differentiated goods indicator	(0.126)	(0.442)	(0.129)	(0.425)	fraction and IT-intensity indicator	(0.125)	(0.398)
Same-firm fraction$\times$distance		-0.009		0.006	Same-firm ownership fraction$\times$		-0.200
$\times$differentiated goods indicator		(0.075)		(0.072)	distance$\times$ IT-intensity indicator		(0.065)
Interaction between distance	0.012	0.010	0.012	0.012			
and traded-on-exchange indicator	(0.026)	(0.027)	(0.021)	(0.022)			
Interaction btw. same-firm fraction	0.102	-0.249	0.134	0.060			
and traded-on-exchanges indicator	(0.294)	(0.779)	(0.263)	(0.697)			
Same-firm fraction$\times$distance		0.102		0.040			
$\times$traded-on-exchange indicator		(0.143)		(0.127)			
Rauch's Classification	Cons.	Cons.	Liberal	Liberal			
In-sample average: $(1 + \text{plants.} \in z)^{-1}$	0.343	0.343	0.343	0.343	In-sample average: $(1 + \text{plants.} \in z)^{-1}$	0.339	0.339
Number of i^e-z pairs (millions)	49	49	49	49	Number of i^e-z pairs (millions)	56	56
Number of establishments (thousands)	16	16	16	16	Number of establishments (thousands)	18	18

Notes: The dependent variable equals $\frac{X_{zi^e}}{X_z}$ in each regression. In Panel C, "Cons." refers to Rauch's conservative classification, which assigns more commodities to be classified as reference-priced or differentiated. Rauch's liberal classification assigns a larger fraction of commodities as sold on an organized exchange. In Panel C, the omitted category includes reference-priced goods. In Panel D, our indicator variable describes whether the industry of the sending establishment had above-median ratios of information-technology investment purchases to the total value of shipments.

Table 4 (Continued): Relationship between distance, common ownership, and market shares: interactions with other shipment characteristics

Panel E: E-Commerce Intensity	(11)	(12)	**Panel F: Capital Intensity**	(13)	(14)
Log mileage	-0.864	-0.866	Log mileage	-0.707	-0.708
	(0.008)	(0.008)		(0.007)	(0.007)
Same-firm ownership fraction	2.576	1.113	Same-firm ownership fraction	3.103	1.822
	(0.097)	(0.309)		(0.103)	(0.285)
Interaction between distance		0.295	Interaction between distance		0.251
and ownership fraction		(0.053)	and same-firm ownership fraction		(0.046)
Interaction between distance	0.161	0.161	Interaction between distance	-0.106	-0.107
and E-commerce indicator	(0.009)	(0.009)	and capital intensity indicator	(0.009)	(0.009)
Interaction btw. same-firm fraction	0.441	0.462	Interaction btw. same-firm fraction	-0.381	-0.842
and E-commerce indicator	(0.123)	(0.400)	and capital intensity indicator	(0.132)	(0.397)
Same-firm ownership fraction$\times$distance		-0.020	Same-firm ownership fraction$\times$		0.090
$\times$E-commerce indicator		(0.067)	distance$\times$capital intensity indicator		(0.065)
In-sample average: $(1 + \text{plants.} \in z)^{-1}$	0.339	0.339	In-sample average: $(1 + \text{plants.} \in z)^{-1}$	0.339	0.339
Number of i^e-z pairs (millions)	56	56	Number of i^e-z pairs (millions)	56	56
Number of establishments (thousands)	18	18	Number of establishments (thousands)	18	18

Notes: The dependent variable equals $\frac{X_{zi^e}}{X_z}$ in each regression. In Panel E, our indicator variable describes whether the industry of the sending establishment had above-median ratios of E-commerce sales to the total value of shipments. In Panel F, our indicator variable describes whether the industry of the sending establishment had above-median capital intensity.

and mining establishments). Bernard et al. (2010) and Ahn, Khandelwal, and Wei (2011), among others, demonstrate that wholesalers have different exporting patterns compared to manufacturers and play a special role in facilitating international trade. Complementary to this work, we find that the domestic shipments of wholesalers/mail-order retailers and manufacturers/mining establishments differ as well. First, the shipments of distributors are more sensitive to distance, consistent with Hillberry and Hummels's (2003) characterization of manufacturers and wholesalers belonging to a hub-and-spoke arrangement.[13] Moreover, the relationship between shipment intensity and common ownership is weaker for distributors (see the "Interaction btw. same-firm ownership fraction and indicator for distributors" term). Comparing the two effects, the distance premium for distributors for median-distance $i^e - z$ pairs is 46 percent for distributors and 70 percent for establishments in other industries. In the remaining panels of Table 4, our industry-level variables are measured only for the manufacturing sector, meaning we will be examining the interactions of observable characteristics within the subset of establishments with the latter 70 percent distance premium.

In Panel C, we apply Rauch's (1999) classification to check whether common ownership plays a larger role in facilitating physical input flows for goods more likely to involve relationship-specific investments. Rauch classifies manufactured products into three classes, in ascending order of relationship specificity: products that are traded on an organized exchange; those that are not traded in an organized market, but are reference priced in trade publications; and those which are neither exchange traded nor reference priced. We find that for the most differentiated products—those in the last of the three categories—the slope of the relationship between market shares and the same-firm ownership fraction is significantly larger than it is for reference-priced commodities or exchange-traded commodities. The distance premium for these differentiated products is 75 percent, while it is 59 percent for reference-priced products, and 61 percent for exchange-traded products.[14] While there is lit-

[13] According to Hillberry and Hummels, in this hub-and-spoke configuration "[g]oods are manufactured in the hub and dispersed, sometimes at great distances, to a number of wholesaling spokes spread throughout the country. The wholesaling spokes then distribute, over very short distances, to retailers." (p. 1090)

[14] In computing these premia, note that within the Panel C subsample an additional same-firm establish-

tle difference in the distance premium between reference-priced and exchange-traded goods, the larger value for differentiated products is consistent with Monteverde and Teece (1982), Masten (1984), and Masten, Meehan, and Snyder (1989, 1991), who posit that the potential for costly hold up between an input supplier and input customer will tend to be larger for products that are complex or specific to the customer-supplier relationship.

In Panels D and E we consider industries' use of new technologies. In Panel D, we group industries based on the ratio of their investment in information technology to their total value of shipments. The results in column (9) of Table 4 indicate a distance premium for industries with above-median IT intensities of 81 percent, compared to 66 percent for below-median industries. In Panel E, we group industries based on the fraction of their sales conducted through the internet. Industries with above-median e-commerce shares have a distance premium of 77 percent, as opposed to a 64 percent distance premium for low e-commerce industries. These results complement recent work by Fort (2017) and Forman and McElheran (2017), which tie the arrival of new information technologies to a decline in production fragmentation. In our setup, this would correspond to a decline in the average same-firm ownership fraction, with larger declines occurring in more IT intensive industries. Here, we find that the relationship between the volume of shipments and common ownership is stronger for IT intensive industries for a given configuration of establishments across firms and locations.

Finally, in the international setting, Antràs (2003, 2005) demonstrates that intra-firm shipments are more prevalent in industries with a higher capital intensity, and in countries with higher capital-labor ratios. Motivated by these results, Panel F compares the relationships between shipment intensity, common ownership, and distance by the capital intensity (dollar value of capital stock per employee) of an industry. The distance premia for above-median and below-median capital intensity industries are respectively 68 percent and 77 percent. It is unclear that capital intensity has much bearing on the relative importance

ment in the destination zip code increases the same-firm ownership fraction by 0.343, as opposed to 0.315 in the benchmark sample in Panels A and B.

between distance and firm ownership on domestic trade flows.

4.3 Quasi-exogenous Changes in Common Ownership

Up to this point, we have refrained from lending a causal interpretation to our regression estimates. Location and ownership choices could well be endogenous to expected shipment destinations.[15] Recognizing this, we seek to identify the causal effect of ownership on shipment patterns by using instances where firms acquire establishments for reasons other than the favorability or lack thereof of those establishments' locations viz-a-viz their expected shipments. Namely, we look at cases where new within-firm vertical links are created when a subset of establishments experiences an ownership change that is incidental to a large multi-establishment acquisition by its new parent firm. The logic of this approach is that when two multi-industry firms merge, or when a multi-industry firm purchases multiple establishments from another firm, it is unlikely that those establishments in the merging firms' secondary and tertiary lines of business triggered the acquisition. As a result, the locations of these peripheral establishments relative to other establishments in the acquiring firm are plausibly exogenous. The identifying assumption is that the acquiring firm's motivation for the merger was to acquire the establishments in the acquired firm's primary lines of business, not so that it could own a peripheral establishment.[16]

To give an example, consider an establishment that produces hardwood flooring and is initially owned by a firm whose primary business segments are in products other than hardwood flooring. If this firm is then acquired by another whose primary segments are also not involved in the supply of flooring, then it is likely that its acquisition of the flooring establishment is incidental to the broader merger. That establishment was essentially "along

[15] Firms might also spatially cluster their establishments for other reasons. For instance, Giroud (2013) and Klanins and Lafontaine (2013) demonstrate that proximity allows a firm's headquarters to monitor and acquire information from the firm's other establishments, thereby increasing those establishments' productivity and, in turn, profitability.

[16] Hastings and Gilbert (2005) and Hortaçsu and Syverson (2007) use a related strategy of exploiting within-firm, cross-market variation following a multiple-market merger to identify the effect of firm boundaries. In these earlier papers, the dependent variable of interest was the downstream market price rather than the propensity to ship to a given location, as is the focus here.

for the ride" in the merger. The acquiring firm now has an additional establishment to ship to or from whose distance to other establishments in the firm was unlikely to be endogenously determined.

We implement this strategy as follows. From the set of establishments that were part of a merger or acquisition between 2002 and 2007, we define our subset of "incidental merger" establishments by identifying establishments which satisfy the following criteria: a) both the acquired firm and the acquiring firm contain at least three segments, where a segment is defined by 4-digit NAICS code, and b) the establishment's sector is in neither of the pre-merger firms' top S segments. Among the 35,000 establishments in our benchmark sample, 2400 satisfy criteria (a) and (b) when S equals 1 (i.e., 2400 establishments were acquired and did not belong to either the acquiring or the acquired firm's top segment), and 1100 satisfy criteria (a) and (b) for S equal to 3.[17]

After identifying the incidental mergers in the sample, we construct an instrumental variable for our same-firm ownership fraction. For each $i^e - z$ pair, for an establishment i^e that changes ownership because of an incidental merger, we count the number of establishments in z (belonging to an industry which is downstream of i^e) which were part of a different firm from i^e before the merger, and part of the same firm as i^e after the merger. Our instrument takes this count and then divides by the number of total plants in z which are downstream of i^e.[18] For establishments i^e which did not change ownership due to an incidental merger, our instrument is equal to zero.

Because of our large sample size and nonlinear gravity specification, we implement the estimation using a two-stage control-function based estimator. In the first stage, we use a linear regression to regress our endogenous same-firm ownership fraction on the instrumental variable along with log mileage and sending-establishment fixed effects.[19] The residual

[17]Additional details on the construction of our incidental merger sample are provided in Appendix B.

[18]With S equal to 1, there are 14,400 sending establishment-destination zip code pairs for which our instrumental variable is greater than zero. With S equal to 2, the number of observations for which our instrument is greater than zero decreases to 8900. With S equal to 3, this same figure falls to 5300.

[19]Our estimation falls within the class of panel count data models with multiplicative fixed effects (in our context, one for each establishment in our sample) and endogenous explanatory variables. Since the

Table 5: Relationship between distance, common ownership, and market shares: control function estimates

Dependent Variable: $\frac{X_{zi^e}}{X_z}$	(1)	(2)	(3)	(4)
	Control	Function	Estimates	Baseline
Log Mileage	-0.963	-0.963	-0.963	-0.962
	(0.003)	(0.003)	(0.003)	(0.003)
Same-firm ownership	1.785	1.815	1.607	2.828
fraction	(0.322)	(0.371)	(0.582)	(0.049)
Residual from	1.050	1.016	1.223	–
first the Stage	(0.325)	(0.374)	(0.584)	–
First Stage:				
Fraction of establishments in	1.015	1.027	1.028	–
z in an incidental merger	(0.001)	(0.001)	(0.001)	–
Number of segments	1	2	3	–

Notes: All regressions include sending-establishment fixed effects. The first-stage regressions also include log mileage as a covariate. The sample includes 189.6 million i^e-z pairs, drawing on the shipments made by 35,000 establishments. In the final row, "Number of segments" refers to the S we used when identifying which establishments were part of an incidental merger. In all specifications, we calculate the unweighted multilateral resistance terms. The last column reports our baseline results (column 2 from Table 2) without attempting to address potential endogeneity in the same-firm ownership fraction variable.

from this regression is then included as an additional covariate in a second-stage regression, which is a fixed effect Poisson model as before. In Appendix D, we discuss the underlying assumptions needed for consistent estimates and report the results from our Monte Carlo study on our approach.

The first three columns of Table 5 presents the output of this exercise. Here, the coefficient estimate of the same-firm ownership fraction is approximately one-third smaller than the estimates in Table 2. (On the other hand, the estimates related to the importance of distance are as before). Now, increasing the same-firm ownership fraction in the destination zip code by 0.315 (corresponding to adding a single common ownership establishment there) has the same impact on trade flows as decreasing the distance between origin and destination by 40

endogenous common ownership share variable is restricted to lie between zero and one, we would ideally apply a maximum likelihood estimation procedure. However, this is computationally infeasible given our large sample size, necessitating using ordinary least squares for the first stage.

percent.

4.4 Sensitivity Analysis

In Appendix C, we perform four exercises to explore the sensitivity of the results in this section. We first verify that our main results are robust to our choice of cutoff when defining which pairs of industries are vertically related to one another. We then argue that the distance premium of common ownership is the same for establishments belonging to small versus large firms. Third, for the set of establishments which are surveyed in both the 2002 and 2007 Commodity Flow Survey, we demonstrate that our assessed distance premium is robust to the inclusion of past shipment behavior in our estimating equations. And finally, as an alternative to the control function approach we apply a GMM procedure — due to Woolridge (1997) and Windmeijer (2000) — to estimate the relationship between trade flows, common ownership, and distance. Here, both the coefficient estimates and the standard errors are somewhat larger than those in Table 5.

5 Aggregate Effects

In this section, we apply our estimates on the prevalence of intra-firm shipments and the relationships among shipment intensity, common ownership, and distance to quantify the aggregate importance of common ownership. To perform these counterfactual exercises, we employ the models of Caliendo and Parro (2015) and Caliendo et al. (2016). An extended and aggregated version of the model we have laid out in Section 2, these models incorporate input-output linkages across sectors, multiple primary inputs, and (in the case of Caliendo et al., 2016) labor mobility across regions.

To summarize the Caliendo et al. (2016) model, each region has an initial stock of land and structures. In Caliendo et al. (2016), each region is one of 50 U.S. States. In our analysis here, closer to the geographic definition used in the earlier parts of this paper, an individual region represents a either a single MSA (Metropolitan Statistical Area) or a state's non-metropolitan portion.[20] Consumers within each region work and consume a bundle of consumption goods produced by different industries. Their preferences are described by a Cobb-Douglas utility function over the goods and services consumed of each industry's commodity. Within each region-industry pair, a continuum of intermediate input producers combine (via a Cobb-Douglas production function) land and structures, labor, and material inputs to make output. Establishments compete as a function of their own idiosyncratic productivity and the average productivity of the establishments in their region-industry to sell to the final good producer, who resides within each destination market; the intermediate-good-supplying establishment that is able to deliver the good at the lowest price serves the destination. This aspect of the model corresponds to the partial equilibrium model discussed in Section 2. Also within each industry and region, final goods producers make a region-industry-specific bundle by combining the goods that they have purchased from intermediate input suppliers. In Appendix E, we delineate the maximization problems faced by consumers, intermediate input producers, and final goods producers. We spell out the market clearing conditions, define the model's equilibrium, and discuss the model's solution. Much of the material in that appendix can be found, in much greater detail, in Caliendo and Parro (2015) and Caliendo et al. (2016).[21]

[20] There are two reasons why we apply a geographic classification based on MSAs rather than zip codes. First, some of the required regional data on employees' compensation or total gross output do not exist at the finer level. Second, in computing the counterfactual equilibrium, we must repeatedly solve a system of (linear) equations of dimension equal to the $Z \cdot J$, the number of regions multiplied by the number of industries. This would be computationally challenging, to say the least, with the finer zip-code-based geographic classification.

[21] There is one meaningful way in which the Caliendo et al. model—and, consequently, the model used in this section—does not nest the Eaton, Kortum, and Sotelo (2012)-based model introduced in Section 2: In this section, we revert to the more conventional representation of establishments as points on a continuum. As a result, when computing counterfactual responses to changes in trade costs, the entire response will occur through the intensive margin: A decline in trade costs will not result in pairs of regions to go from having zero to positive trade flows. For the goal of this section—computing the welfare effects of counterfactual changes in trade costs—the representation of firms as points on a continuum is a reasonable approximation.

In one of their counterfactual exercises, using a single-sector model, Eaton, Kortum, and Sotelo examine the change in international trade flows which would result from a uniform 10 percent reduction in cross-border trade costs. They report that ... "World exports rise by 43 percent due to lower trade costs, in line with results in Eaton, Kortum, and Kramarz (2011)... nearly all of this increased trade occurs within pairs of countries that were already trading, 99.9984 percent." (p. 365) On the other hand, when examining

We focus here on the model's calibration. Beyond the aforementioned data on same-firm ownership shares, distance measures, and shipment rates, this exercise requires data parameterizing consumers' preferences for different final consumption goods, industries' production functions, regions' initial labor and capital endowments, and the dispersion in establishments' fundamental productivity. For these parameters we follow, as much as possible, the calibration procedure outlined in Caliendo et al. (2016). We adopt an industry classification scheme with 19 tradable and 10 non-tradable industries.[22] For this set of industry definitions and for our more coarsely defined regions, we re-compute trade flows and same-firm ownership shares from the 2007 Commodity Flow Survey. Data from the 2007 BEA Input-Output Table identify parameters related to sectoral production functions and the representative consumer's final preferences: We set γ^{jk}—which is the Cobb-Douglas share parameter that describes the importance of industry k's commodity as an input for production in sector j—equal to the share of industry j's expenditures that are spent on purchases of commodity k, and we let γ^j (the share of capital and labor in production) equal the residual share of industry j's expenditures. The preference parameter for industry j's output, ξ^j, is proportional to the industry's final consumption expenditures. The initial labor endowment, L_i, equals MSA i's total employment as a share of aggregate employment. (These employment figures are taken from the BEA Regional Accounts. The total labor endowment, L, is nor-

trade across MSAs (instead of countries) separately by industry (instead of aggregating across industries), the extensive margin will likely play a larger role than in Eaton, Kortum, and Sotelo's experiment.

In addition, one can rationalize the difference in formulations—a continuum of establishments in this section as opposed to a countable number in Section 2—as in Gaubert and Itskhoki (2016). Gaubert and Itskhoki propose a model in which each industry has a small number of firms (since they are interested in the extent to which individual firms can explain countries' comparative advantage), but with a continuum of industries. In this section, in line with Caliendo and Parro (2015) and Caliendo et al. (2016), we apply a coarser industry definition compared to what we use in Section 2. So, one may think of the sectors in this section as a collection of more finely defined industries which formed the basis of our Section 2 model.

[22] The tradable industries are Food, Beverages, and Tobacco; Textiles; Apparel and Leather; Paper Products; Printing; Petroleum and Coal Products; Chemical Products; Rubber and Plastic Products; Wood Products; Nonmetallic Mineral Products; Primary Metals; Fabricated Metal Products; Machinery; Computer and Electronic Products; Electrical Equipment; Transportation Equipment; Furniture; Miscellaneous Manufacturing; and Wholesaling. The non-tradable industries are Farms, Forestry, and Fishing; Mining and Utilities; Construction; Retail; Transportation Services; Finance, Insurance, and Real Estate; Information, and Professional, Business, and Other Services; Health and Education; Arts, Amusement, Accommodation, and Food Services; and Government.

malized to 1.) We compute the share of land and structures in value added for MSA i, β_i, following the procedure of Caliendo et al. (2016).[23] Our estimates of θ^j, which parameterize the dispersion of establishments' idiosyncratic productivity, are taken from Caliendo and Parro (2015).[24]

For the initial and counterfactual trade costs, τ^j_{zi} and $\tilde{\tau}^j_{zi}$ respectively, we set

$$\begin{aligned} \tau^j_{zi} &= \frac{\alpha_1}{\theta^j} \cdot \log \text{mileage}_{z \leftarrow i} + \frac{\alpha_2}{\theta^j} s^j_{zi} \text{ , and} \\ \tilde{\tau}^j_{zi} &= \frac{\alpha_1}{\theta^j} \cdot \log \text{mileage}_{z \leftarrow i} + \kappa \frac{\alpha_2}{\theta^j} s^j_{zi}, \end{aligned}$$

where $\alpha_1 = 0.95$ and $\alpha_2 = -1.80$ equal the values given in the second column of Table 5.

Table 6 presents the results from our counterfactual exercises for $\kappa \in \{0, 1, 2, 3, 4, 5\}$. These exercises correspond to the elimination of common ownership ($\kappa = 0$), the status quo ($\kappa = 1$), or a 2-, 3-, 4-, or 5-fold increase in the share of same-firm establishments in destination zip codes.

An increase trade costs due to the elimination of common ownership, the $\kappa = 0$ case, leads to a modest 0.2 percent decrease in real wages and a 0.1 percent drop in gross output. Given the small same-firm ownership fraction present in the data (a reduction from 0.05 percent to 0), these aggregate effects are nontrivial. There are two reasons behind this multiplier effect. First, common ownership tends to be prevalent for destination-origin pairs which are close to one another—pairs over which many shipments already occur. Second, increases in trade costs propagate (via input output linkages) throughout all industries, not only the manufacturing and wholesale industries which experience the initial decrease in productivity. Moreover, it is likely these values are lower bound estimates of the trade volume effect of

[23] That is, we begin by computing $1 - \tilde{\beta}_i$ as the share of total compensation in MSA i that is paid to labor. Since the non-labor compensation equals not only payments to land and structures, but also equipment rentals, we calculate the share of land and structures as $\beta_i = \frac{\tilde{\beta} - 0.17}{0.83}$, where the value 0.17 reflects payments to equipment.

[24] The two tradable-good industries for Caliendo and Parro (2015) did not estimate θ^j are Furniture and Wholesaling. For these and for the non-tradeable good industries we set θ^j=5.

eliminating common ownership, because our counterfactual calculation imposes the marginal trade effects from our estimates onto inframarginal ownership links. It is likely that the most trade-enhancing links in the economy have effects on shipment volumes considerably larger than that implied by the magnitude of our esitmates.

In the subsequent rows, we compute the welfare and gross output changes which would occur if common ownership shares in destination MSAs were progressively larger. When the same-firm ownership share is five times its current value ($\kappa = 5$), the most trade-enhancing case, welfare increases by 1.2 percent and gross output by 5.6 percent relative to the initial allocation. Comparing across the $\kappa \in \{2, 3, 4, 5\}$ cases indicates the marginal welfare gains due to the reduction in transaction costs from increasing common ownership grow non-linearly. (At the same time the marginal/inframarginal differential noted in the $\kappa = 0$ discussion above implies the estimates for the cases with greater common ownership are upper bounds.) In columns 3 and 4, corresponding of Caliendo and Parro (2015), we consider an alternate specification in which labor is immobile across regions and the share of structures and land in production equals 0. Here, counterfactual changes in welfare and gross trade flows are somewhat smaller.

To sum up, our counterfactual exercises imply that increasing levels of vertical integration would lead to both higher trade flows and higher welfare. Together with the results given in the previous subsection, Table 6 indicates that the shadow benefit of conducting transactions within the firm are sizable not only at the individual transaction level, but also represent a sizable catalyst to trade at the aggregate level.

We want to emphasize that this exercise is only meant to assess the aggregate implications of across-establishment trade costs, one of the several channels through which firm ownership patterns affect consumer welfare. We argue in our earlier work that the private benefits of vertical integration are not primarily motivated by easing the flows of physical inputs along production chains. Thus it is likely that the figures in Table 6 understate the welfare effects of vertical integration. On the other hand, in our application of Caliendo et al. (2016)'s

Table 6: Counterfactual effects of changing the same-firm ownership fraction

Same-firm ownership fraction	Welfare	Gross Output	Welfare	Gross Output
0×	-0.2	-0.1.	-0.2	-0.1
1×	0.0	0.0	0.0	0.0
2×	0.2	0.1	0.2	0.1
3×	0.5	0.3	0.5	0.3
4×	0.8	1.3	0.8	1.2
5×	1.2	5.6	1.2	5.2
Is labor mobile?	Yes	Yes	No	No

Notes: Each row describes the counterfactual welfare and trade response, stated as percentage changes, of uniformly increasing the same-firm ownership fraction by a different factor. Welfare, as given in the first and third column, equals the change in real wages, $d\log\left(\frac{w_i}{P_i}\right)$, averaged across all regions i.

perfect-competition-based framework, we did not attempt to assess the affect of changing ownership patterns on markups or product availability. It is certainly possible that, through market foreclosure and other anti-competitive practices, increased vertical integration may lead to lower trade flows and consumer welfare compared to what we report in Table 6. Thus the counterfactual exercises in this section are only a first step, albeit an important one, towards measuring the aggregate effects of alternate ownership patterns.

6 Conclusion

Establishments are substantially more likely to ship to destinations that are i) close by and ii) contain downstream establishments which share ownership with the sender. In this paper, we have used data on shipments made by tens of thousands of establishments throughout the manufacturing and wholesale sectors of the U.S. to characterize the relationships between transaction volume, distance, and common ownership. We find that, all else equal, firms send internal shipments further (or equivalently, have a greater propensity to make internal shipments any given distance). The magnitude of this differential willingness to ship implies that the shadow benefit of internal transactions is substantial: an extra same-firm downstream establishment in the destination zip code has roughly the same effect on transaction volumes as a 40 percent reduction in distance. Moreover, a simple multi-sector general equilibrium trade model suggests that there is a notable reduction in trade costs from even the relatively modest amount of common ownership in the economy. Aggregate welfare would be approximately 0.2 percent lower in a counterfactual environment without the trade-enhancing effect of common ownership.

Quantifying the magnitude and aggregate effects of other benefits associated with common ownership—beyond the elusion of transaction costs—is an exciting topic for future research. In an earlier paper (Atalay et al., 2014), we argued that the primary motivation for common ownership of production chains is to share intangible inputs across establishments, with the mitigation of transaction costs as a secondary concern. However, due to data limitations, we could only provide circumstantial evidence in favor of the intangible input hypothesis.[25] Now, thanks to new survey being collected and linked to Census micro data (Bloom et al., 2014, and Buffington et al., 2017), it is possible to directly quantify the extent to which profitability-increasing management practices respond to changes in firm boundaries, and thus should also be possible to evaluate aggregate productivity in counterfactual environments in which firms' sharing of intangible managerial inputs is muted.

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[25] We wrote: "It is difficult to directly test our 'intangible input' explanation for vertical ownership structures because such inputs are by definition hard to measure. Ideally, we would have information on the application of managerial or other intangible inputs (like managers' time-use patterns across the different business units of the firm) across firm structures. Such data do not exist for the breadth of industries which we are looking at here, however." (p. 1141)

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A Calculations Related to Section 2

The goal of this appendix is to relate Equations 2 and 3. Begin with π_{zi^e}, the fraction of shipments to zip code z which come from establishment i^e. As a reminder, to emphasize, these calculations refer to share of sales of a given product in zip code z that come from different sending establishments. As in Section 2, we omit commodity or industry superscripts.

$$\begin{aligned}
\pi_{zi^e} &= \frac{\Phi_{zi^e}}{\Phi_z} \\
&= \frac{T_i(x_i d_{zi^e})^{-\theta}\left(1 - s_{zi^e} + s_{zi^e}(\delta_{zi^e})^{-\theta}\right)}{\sum_{i'=1}^{Z}\sum_{i'^e \in i} T_{i'}(x_{i'} d_{zi'^e})^{-\theta}(1 - s_{zi'^e} + s_{zi'^e}(\delta_{zi'^e})^{-\theta}))} \\
&= \frac{\sum_{z^e \in z}\frac{X_{z^e}}{X_z} T_i(x_i d_{zi^e}(\delta_{zi^e})^{\mathbf{1}^{SF}(z^e,i^e)})^{-\theta})}{\sum_{i'=1}^{Z}\sum_{i'^e \in i'}\sum_{z^e \in z}\frac{X_{z^e}}{X_z} T_{i'}(x_{i'} d_{zi'^e}(\delta_{zi'^e})^{\mathbf{1}^{SF}(z^e,i'^e)})^{-\theta}}.
\end{aligned}$$

Above, the second line follows from the definitions of Φ_z and Φ_{zi^e}, while the second equality follows from the definition of s_{zi^e} (which again is the share of establishments in the destination zip code that share ownership with the sender). Next, we apply the definition of $\Phi_{z^e i^e}$ and Φ_{z^e} :

$$\begin{aligned}
\pi_{zi^e} &= \frac{\sum_{z^e \in z}\frac{X_{z^e}}{X_z}\Phi_{z^e i^e}}{\sum_{z^e \in z}\frac{X_{z^e}}{X_z}\Phi_{z^e}} \\
&= \sum_{z^e \in z}\frac{X_{z^e}}{X_z}\frac{\Phi_{z^e i^e}}{\Phi_{z^e}}\frac{\left[\sum_{z^e \in z}\frac{X_{z^e}}{X_z}\Phi_{z^e i^e}\right]}{\left[\sum_{z^e \in z}\frac{X_{z^e}}{X_z}\Phi_{z^e}\right]\left[\sum_{z^e \in z}\frac{X_{z^e}}{X_z}\frac{\Phi_{z^e i^e}}{\Phi_{z^e}}\right]} \\
&\approx \sum_{z^e \in z}\frac{X_{z^e}}{X_z}\frac{\Phi_{z^e i^e}}{\Phi_{z^e}}.
\end{aligned}$$

Above, the approximation results from the fraction $\frac{\left[\sum_{z^e \in z}\frac{X_{z^e}}{X_z}\Phi_{z^e i^e}\right]}{\left[\sum_{z^e \in z}\frac{X_{z^e}}{X_z}\Phi_{z^e}\right]\left[\sum_{z^e \in z}\frac{X_{z^e}}{X_z}\frac{\Phi_{z^e i^e}}{\Phi_{z^e}}\right]}$ being close, but not equal, to 1. The Φ_{z^e, i^e} term roughly gives the "expected" trade flows from establishment code i^e to establishment z^e . This expectation varies non-linearly with a) the distance between establishment i^e and establishment z^e, and with b) the distance interacted with an indicator for a within-firm relationship. The approximation comes about because the average (over all plants, z^e, that are located in zip code z) of the expectation is not equal to the expectation of the average of the distance, or the distance by same-firm indicator variables. In the original Eaton, Kortum, and Sotelo formulation, the only variables that shape i-to-z expected trade flows are the same for all destination zip code establishments (as there is no same-firm indicator which could vary across establishments within a destination zip code). As a result, in Eaton, Kortum, and Sotelo (2012) there is no need for an approximation. In our context, the approximation error should be small.

Moving forward, we apply the definition of $\pi_{z^e i^e}$, and then use Equation 1 to substitute out the $\pi_{z^e i^e}$ terms:

$$
\begin{aligned}
\pi_{zi^e} &\approx \sum_{z^e \in z} \frac{X_{z^e}}{X_z} \pi_{z^e i^e} \\
&= \sum_{z^e \in z} \frac{X_{z^e}}{X_z} \mathbb{E}\left[\frac{X_{z^e i^e}}{X_{z^e}}\right] \\
&= \sum_{z^e \in z} \mathbb{E}\left[\frac{X_{z^e i^e}}{X_z}\right] \\
&= \mathbb{E}\left[\frac{X_{zi^e}}{X_z}\right].
\end{aligned}
$$

The final expression is equivalent to Equation 3.

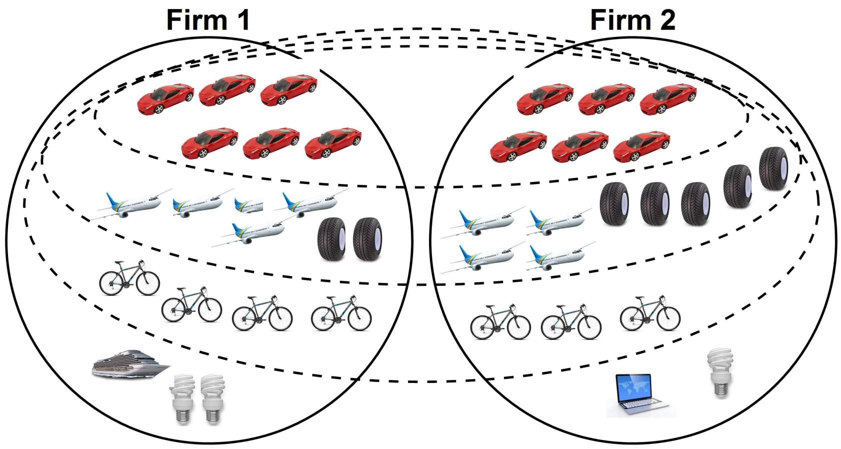
B Identifying Incidental Mergers

This section aims to explain both the data and sample generation in more detail. We use the Longitudinal Business Database from the Census Bureau to identify mergers, and incidental mergers, that occurred between 2002 and 2007. A merger in year t is identified when a plant which has its firm identifier switch from year t to year t+1, which has the firm identifier from year *t+1* to year *t+2*, which switches to a firm identifier that was already present in the market as of year t.

We then compute the total number of plants which change ownership between the acquiring-acquired firm pair in each merger year. From this set of establishments which participated in a merger, we classify acquired establishments which change hands as part of an incidental merger using the following procedure. First, among plants in multi-establishment transactions, we exclude (from our set of incidental merger establishments) plants whose acquiring firm or acquired firm had fewer than three business segments (a segment referring to a set of establishments belonging to a 4-digit NAICS industry). We rank these business segments by payroll for each firm. From the establishments retained from the previous step our sample of incidental merger establishments are those which are not in either the acquiring or acquired firm's top S segments.

Figure 3 illustrates these criteria for a hypothetical merger between two firms. Within this figure, there are two firms, where each firm has multiple establishments across multiple business segments. Each symbol represents a separate establishment in one of seven possible segments: Automotive Transportation, Airplane Manufacturing, Bicycle Manufacturing, Ship Manufacturing, Tire Manufacturing, Electric Lighting Manufacturing, and Computer Manufacturing. Before the merger, the three segments for Firm 1 are Automotive Transportation, Airplane Manufacturing, and Bicycle Manufacturing. For Firm 2, the top segments are Automotive Manufacturing, Tires, and Airplane Manufacturing. Since both firms have multiple establishments in more than three segments, a merger of the two firms would satisfy the first two criteria of the previous paragraph. Depending on the chosen value of S, the number of plants classified as "incidental" to the merger would vary. With S=1, all establishments outside of Automotive Manufacturing would be classified as incidental merger plants. For S=3, Shipbuilding, Electric Lighting, and Computer manufacturers would be classified as incidental to the merger.

Figure 3: Incidental Merger Example



Notes: Firms 1 and 2 have multiple segments, with each segment potentially containing multiple establishments. Each establishment is represented by an individual symbol (e.g., with a car representing an Automotive plant; a plane representing an Airplane Manufacturer). The three dashed circles, for $S \in \{1, 2, 3\}$, enclose the establishments which are excluded from the set of incidental merger establishments.

C Additional Robustness Checks

In this section, we discuss four robustness checks, aimed at examining the sensitivity of the Section 4 results to alternate sample construction and estimation methods, and to the inclusion of past shipment data in our regressions.

In our benchmark regression, we restrict our sample to establishments belonging to multi-unit firms. We apply this restriction because establishments belonging to single-unit firms mechanically cannot possibly sell to another establishment in their firm (as no such establishment exists). However, even in our restricted sample, a establishment belonging to a two-establishment firm will only have a positive same-firm ownership fraction in one destination zip code, with zeros elsewhere. To see whether most of our observations are drawn from relatively small firms like these, or if the relationship between trade flows and our same-firm ownership fraction varies with firm size (the number of establishments belonging to i^e's firm), we re-estimate the regression from column (2) of Table 2 only using observations from large firms. In columns (2) through (4) of Table 7, we progressively restrict the sample to

Table 7: Relationship between distance, common ownership, and market shares: sensitivity analysis

Dependent Variable: $\frac{X_{zi^e}}{X_z}$	(1)	(2)	(3)	(4)	(5)	(6)
Same-firm ownership fraction	2.828	2.811	2.813	2.832	2.038	1.909
	(0.049)	(0.049)	(0.052)	(0.055)	(0.039)	(0.033)
Log mileage	-0.962	-0.987	-1.003	-1.019	-0.963	-0.963
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Firm Size to be in Sample	Multi-Unit	⩾5 Ests.	⩾10 Ests.	⩾20 Ests.	Multi-Unit	
Cutoff for IO links (Percent)	1	1	1	1	2	3

Notes: The first column reiterates column (2) of Table 2. Relative to the first column, in columns (2) through (4), we vary the sample according to the size of the firm of the sending establishment. In columns (5) and (6), we vary the cutt-off share of (6-digit NAICS) industry I's revenues that must go to industry J for the I,J industry pair to be defined as vertically linked. The sample size in columns (1), (5), and (6) are 189.6 million $i^e - z$ pairs, representing the shipments of 35,000 establishments. In columns (2), (3), and (4), the sample sizes are 149 million, 125 million, and 103 million, respectively, representing the shipments made by 27,000, 23,000, and 18,000 establishments. In all specifications, we calculate the unweighted multilateral resistance terms.

sending establishments belonging to 5-establishment, 10-establishment, or 20-establishment firms. The estimated coefficients across the first four columns are similar to one another.

Second, in constructing the samples in any of our regression specifications, a key step is to define pairs of industries which are upstream/downstream of one another. This step is necessary to construct the same-firm ownership fraction,s_{zi^e}. Under a definition in which many pairs of industries are classified to be vertically linked, the number of downstream establishments for a sending establishment i^e will be relatively high. As a result, the same-firm ownership fraction (which computes the fraction of downstream establishments in the destination zip code that belong to the same firm asi^e) will tend to be relatively large.[26] In the final two columns of Table 7, we consider increasingly restrictive definitions. In these latter two columns, the estimated coefficient on the log mileage term is similar to the estimate of the benchmark specification. The coefficient estimates for the same-firm

[26]In this fraction, both the numerator and the denominator will be smaller. However, with a definition in which many pairs of industries that are classified as vertically integrated, the denominator decreases more than the numerator does.

Table 8: Relationship between distance, common ownership, and market shares: sensitivity analysis

Dependent Variable: $\frac{X_{zi^e}}{X_z}$	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline		Control Function Estimates			
Log Mileage	-0.911	-0.787	-0.912	-0.912	-0.787	-0.787
	(0.0060	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Same-firm ownership	2.970	2.396	1.293	1.575	1.243	1.348
fraction	(0.088)	(0.083)	(0.549)	(0.686)	(0.446)	(0.546)
$X_{zi^e} \cdot (X_z)^{-1}$		2.319			2.326	2.325
from five years prior		(0.017)			(0.017)	0.018)
Residual from			1.689	1.401	1.159	1.052
first the Stage			(0.555)	(0.691)	(0.452)	(0.552)
First Stage:						
Fraction of establishments in			1.029	1.036	1.029	1.036
z in an incidental merger			(0.002)	(0.002)	(0.001)	(0.002)
Number of segments			1	2	1	2

Notes: All regressions include sending-establishment fixed effects. The first-stage regressions in columns (3) through (6) also include log mileage as a covariate. The sample includes 43 million i^e-z pairs, drawing on the shipments made by 9,000 establishments who are included in both the 2002 and 2007 versions of the Commodity Flow Survey. In the final row, "Number of segments" refers to the S we used when identifying which establishments were part of an incidental merger. In all specifications, we calculate the unweighted multilateral resistance terms.

ownership fraction term is smaller by approximately one-third. However, since the number of downstream establishments (with the more restrictive definition of vertical linkages) is lower, the resulting distance premium in the specifications in the last two columns are 69 percent and 73 percent, somewhat larger than the 60 percent of the benchmark specification.

Third, establishments' shipment decisions are persistent. Establishments which ship to a location in a given year are, all else equal, substantially more likely to ship to that location in subsequent years. In our Section 4 analysis, we excluded past shipment information as a potential covariate, primarily because the set of establishments which are surveyed by the Census changes from one edition to the next, meaning that including past shipment information as an explanatory variable reduces the sample size considerably. In Table 8, we include $\frac{X_{zi^e}}{X_z}$ from the 2002 Commodity Flow Survey as an additional regressor, using as a sample the set of establishments who were surveyed in both the 2002 and 2007 versions of the Commodity Flow Survey. The first two columns conduct a Poisson regression, without attempting to account for the endogeneity of the same-firm ownership fraction. Across these first two columns, the distance premium of an additional same-firm establishment is similar, around 60 percent in both columns. In columns (3) through (6), we conduct our control function estimates. Here, too, the relative magnitudes on the coefficients on the log mileage and the same-firm ownership fraction variables are unaffected by the inclusion of previous shipment behavior.

Finally, as an alternative to the control function approach, Woolridge (1997) and Windmeijer (2000) derive the moment conditions for cases with a linear first stage and a fixed effect Poisson second stage. We apply these moment conditions and re-estimate the relationships between trade flows, distance, and common onwership. The estimates are given Table 9, with each column applying a different definition of incidental merger establishments. The coefficients on the same-firm ownership fraction are now larger than the benchmark Poisson regression estimates, though with substantially larger standard errors. It's because of the larger uncertainty surrounding the GMM estimates that we take the coefficient estimates from our two-stage control function approach to be our headline results.

D Control Function and GMM Approaches

We explore the control function and GMM approaches which we use in Section 4.3. In particular, we specify our GMM moments conditions and perform a Monte Carlo exercise to assess the performance of our control function and GMM estimators. For this appendix only, let π_{zi^e} be our dependent variable; d_{zi^e} an explanatory variable; s_{zi^e} an endogenous explanatory variable; i^e the index of a sending establishment, an z the index of a destination zip code. There are a large number of sending establishments, but a fixed sets of locations Z.

Table 9: Relationship between distance, common ownership, and market shares: GMM estimates

Dependent Variable: $\frac{X_{zi^e}}{X_z}$	(1)	(2)	(3)	(4)
	GMM Estimates			Baseline
Log Mileage	-0.972	-0.972	-0.972	-0.962
	(0.005)	(0.005)	(0.005)	(0.003)
Same-firm ownership	4.660	4.051	4.095	2.828
fraction	(0.942)	(1.429)	(2.039)	(0.049)
Residual from	–	–	–	–
first the Stage	–	–	–	–
First Stage:				
Fraction of establishments in	–	–	–	–
z in an incidental merger	–	–	–	–
Number of segments	1	2	3	–

Notes: All regressions include sending-establishment fixed effects. The first-stage regressions also include log mileage as a covariate. The sample includes 189.6 million i^e-z pairs, drawing on the shipments made by 35,000 establishments. In the final row, "Number of segments" refers to the S we used when identifying which establishments were part of an incidental merger. In all specifications, we calculate the unweighted multilateral resistance terms. The last column reports our baseline results (column 2 from Table 2) without attempting to address potential endogeneity in the same-firm ownership fraction variable.

Consider the following data generating process, a fixed effect Poisson model with endogenous regressor:

$$
\begin{aligned}
\pi_{zi^e} &\sim Poisson(\exp(s_{zi^e}\beta + d_{zi^e}\gamma + v_{i^e} + \epsilon_{zi^e})) \\
s_{zi^e} &= d_{zi^e}\alpha + x_{zi^e}\sigma + \eta_{i^e} + \xi_{zi^e} \\
\epsilon_{zi^e} &= \xi_{zi^e}\rho + \phi_{zi^e}
\end{aligned}
$$

In the final equation ϕ_{zi^e} is independent of ξ_{zi^e}. Also, $\mathbb{E}[\exp(\phi_{zi^e})] = 1$. We also assume that ϵ_{zi^e} is uncorrelated with $\epsilon_{z'i^e}$ for $z \neq z'$ and that $\mathbb{E}[\exp(\epsilon_{zi^e})] = 1$. Finally, let x_{zi^e} denote our instrument for s_{zi^e}. With endogeneity, $Cov(s_{zi^e},\, \epsilon_{zi^e}) \neq 0$, but $Cov(x_{zi^e},\, \epsilon_{zi^e}) = 0$.

Our GMM estimator is due to Woolridge (1997) and Windmeijer (2000). Our moment condition is:

$$
\mathbb{E}\left[\mathrm{x}_{\mathrm{zi}^{\mathrm{e}}}\left(\frac{\pi_{\mathrm{zi}^{\mathrm{e}}}}{\exp(\mathrm{s}_{\mathrm{zi}^{\mathrm{e}}}\beta + \mathrm{d}_{\mathrm{zi}^{\mathrm{e}}}\gamma)} - \frac{\frac{1}{\mathrm{Z}}\sum_{\mathrm{z}'}\pi_{\mathrm{z}'\mathrm{i}^{\mathrm{e}}}}{\frac{1}{\mathrm{Z}}\sum_{\mathrm{z}'}\exp(\mathrm{s}_{\mathrm{z}'\mathrm{i}^{\mathrm{e}}}\beta + \mathrm{d}_{\mathrm{z}'\mathrm{i}^{\mathrm{e}}}\gamma)}\right)\right] = 0. \tag{8}
$$

To understand where this moment condition comes from, note that

$$
\begin{aligned}
\frac{\pi_{zi^e}}{\exp(s_{zi^e}\beta + d_{zi^e}\gamma)} - \frac{\frac{1}{Z}\sum_{z'}\pi_{z'i^e}}{\frac{1}{Z}\sum_{z'}\exp(s_{z'i^e}\beta + d_{z'i^e}\gamma)} &= \frac{\exp(s_{zi^e}\beta + d_{zi^e}\gamma)\exp(v_{i^e})\exp\epsilon_{zi^e}}{\exp(s_{zi^e}\beta + d_{zi^e}\gamma)} \\
&\quad - \frac{\frac{1}{Z}\sum_{z'}\exp(s_{z'i^e}\beta + d_{z'i^e}\gamma)\exp(v_{i^e})\exp\epsilon_{z'i^e}}{\frac{1}{Z}\sum_{z'}\exp(s_{z'i^e}\beta + d_{z'i^e}\gamma)} \\
&= [\exp(v_{i^e})\exp\epsilon_{zi^e} - \exp(v_{i^e})]\,\frac{1}{Z}\sum_{z'}\exp\epsilon_{z'i^e} \\
&= \exp(v_{i^e})\cdot\left[\exp\epsilon_{zi^e} - \frac{1}{Z}\sum_{z'}\exp\epsilon_{z'i^e}\right].
\end{aligned}
$$

So long as we assume that v_{i^e} and ϵ_{zi^e} are independent of one another, and that both are independent with our instrument, then Equation 8 will be satisfied.

With the goal of examining the performance of the control function and GMM estimators that we use in Section 4.3 we perform a series of Monte Carlo simulations. In these

Table 10: Monte Carlo Results

	N=100		N=500		N=1000	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Panel A: Poisson Regression, No Instruments						
β	0.051	0.017	0.050	0.019	0.050	0.019
γ	0.028	0.031	0.025	0.040	0.030	0.041
Panel B: Control Function Estimation						
β	0.009	0.022	0.011	0.021	0.010	0.021
γ	0.040	0.031	0.037	0.039	0.042	0.040
First Stage						
σ	2.001	0.003	2.000	0.003	2.000	0.003
α	0.300	0.003	0.300	0.003	0.300	0.003
Panel C: GMM Estimation						
β	0.014	0.047	0.012	0.034	0.011	0.035
γ	0.037	0.039	0.037	0.041	0.041	0.041

Notes: True values: $\beta = 0.01$, $\gamma = 0.04$, $\alpha = 0.3$, $\sigma = 2$, and $\rho = 0.2$

simulations, we use the following parameter values: $\beta = 0.01$, $\gamma = 0.04$, $\alpha = 0.3$, $\sigma = 2$, $\rho = 0.2$. With these parameter values we simulate data 500 sending establishments and $Z = 200$ destinations, for a total of 100,000 observations.

Monte Carlo results for 100, 500, and 1000 simulations are reported in Table 10. In Panel A, we report the estimation results from a fixed effect Poisson model without addressing endogeneity. Panel B uses our two-step control function approach. In the first stage, we use linear ordinary least square with fixed effect to regress s_{zi^e} on d_{zi^e} and the instrument x_{zi^e}. We then predict $\hat{s_{zi^e}}$ and obtain a residual $\hat{\xi_{zi^e}}$. Adding this residual as a control in the second stage fixed effect Poisson model estimation, we are able to recover the true parameter values reasonably well. Similarly, Panel C indicates that our GMM estimator, based on Equation 8, allows us to recover the correct parameter values.

E Details of the Section 5 Model

In this section, we spell out the model that we use in Section 5 to quantify the aggregate effects of trade-inhibiting transaction costs. We first describe the maximization problems faced by each region's representative consumer, each region-industry's intermediate good producing firm, and each region-industry's final good producing firm. We then present the market-clearing conditions, and define the competitive equilibrium. Finally, we outline the algorithm with which one can compute the counterfactual equilibrium. To emphasize, these models were originally introduced in Caliendo and Parro (2015) and Caliendo et al. (2016).

Each region is home to a representative consumer, who inelastically supplies labor and has Cobb-Douglas preferences over the goods produced by each industry:

$$U_i = \prod_{j=1}^{J} (c_i^j)^{\xi^j} \text{where } \sum_{j=1}^{J} \xi^j = 1.$$

These preference parameters are identical across regions. Using P_i^j to refer to the price of final good j in region i, and $I_i = \frac{r_i H_i + w_i L_i}{L_i}$ as the per capita income of households in region i, the indirect utility of households in region i equals

$$U_i = \frac{I_i}{P_i}; \text{ and where } P_i \equiv \prod_{j=1}^{J} \left(\frac{P_i^j}{\xi^j} \right)^{\xi^j}$$

equals the ideal price index in region i.

Within each region and industry, a continuum of intermediate-good-producing establishments produce using a combination of materials, structures and land, and labor. Individual establishments have idiosyncratic productivity levels, v_i^j, with the levels drawn from a Frechet distribution with parameter θ^j. The production function for the set of establishments in region i and industry j with productivity draw v_i^j is given by

$$q_i^j(v_i^j) \quad = \quad v_i^j \cdot \left[T_i^j \cdot h_i^j(v_i^j)^{\beta_i} \cdot l_i^j(v_i^j)^{1-\beta_i} \right]^{\gamma^j} \cdot \prod_{k=1}^{J} \left[M_i^{jk}(v_i^j) \right]^{\gamma^{jk}}.$$

In this equation, the input choices $h_i^j(\cdot)$, $l_i^j(\cdot)$, and $M_i^{jk}(\cdot)$ of establishments in region i are functions of their idiosyncratic productivity levels. Each establishment in region i rents structures at (constant) unit price r_i, hires labor at constant unit price w_i, and purchases material inputs at constant unit prices P_i^k (for $k \in 1, 2, ..., J$). Assuming production functions exhibit constant returns to scale (so that $\gamma^j + \sum_k \gamma^{jk}=1$), an establishment with idiosyncratic productivity equal to v_i^j produces at constant marginal cost

$$\frac{x_i^j}{v_i^j \left(T_i^j\right)^{\gamma^j}}; \text{ where } x_i^j \equiv \left[\left(\frac{r_i}{\beta_i \gamma^j}\right)^{\beta_i} \cdot \left(\frac{w_i}{(1-\beta_i)\gamma^j}\right)^{1-\beta_i} \right]^{\gamma^j} \cdot \prod_{k=1}^{J} \left[\frac{P_i^k}{\gamma^{jk}}\right]^{\gamma^{jk}}. \tag{9}$$

For each region and industry, there is a perfectly competitive industry of final goods producers, who combine the output of intermediate input producers purchased from the continua of establishments from different supplying regions, according to the following production function:

$$Q_i^j = \left[\int_{\mathbb{R}_+^Z} \left[\tilde{q}_i^j(v_i^j)\right]^{\frac{\varsigma_i^j - 1}{\varsigma_i^j}} \phi^j(v^j) dv^j \right]^{\frac{\varsigma_i^j}{\varsigma_i^j - 1}}.$$

Here, $\tilde{q}_i^j(v_i^j)$ equals the intermediate goods purchased from producers that have idiosyncratic productivity v_i^j, $\phi^j(v^j)$ denotes the joint density function of the idiosyncratic productivity levels of the producers from the Z possible origin regions, and ς_i^jequals the elasticity of substitution across intermediate good varieties. The purpose of introducing these final goods producers is to cleanly characterize the price of an industry's output in each region. This price equals the final good producers' marginal cost:

$$P_i^j = \left[\int_{\mathbb{R}_+^Z} \left[p_i^j(v_i^j)\right]^{1-\varsigma_i^j} \phi(v_i^j) dv^j \right]^{\frac{1}{1-\varsigma_i^j}}. \tag{10}$$

As in Section 2, each final good producer purchases from the intermediate good supplier that is able to supply the good at the lowest price. Because competition across intermediate good suppliers is perfectly competitive, the price paid by the intermediate good user equals the supplier's marginal cost multiplied by the cost of transporting the good from the supplier to the destination:

$$p_i^j(v^j) = \min_{i\in\{1,\ldots Z\}} \left\{ \frac{\omega_i^j \tau_{zi}^j}{v_i^j \left(T_i^j\right)^{\gamma^j}} \right\}.$$

The transportation cost, τ_{zi}^j, potentially varies by industry, and reflects both the distance from i to z and the share of good-j producing establishments in i which share ownership with downstream plants in destination z. In the case of non-tradable goods and services, $\tau_{zi}^j = \infty$.

Caliendo et al. show that, if the idiosyncratic productivity is drawn from a Frechet distribution, then Equation 10 is equivalent to

$$P_i^j = \left[\Gamma\left(\frac{\theta^j + 1 - \varsigma_i^j}{\theta^j}\right)\right]^{1-\varsigma_i^j} \cdot \left[\sum_{i=1}^{Z} \left[x_i^j \tau_{zi}^j\right]^{-\theta^j} \left(T_i^j\right)^{\theta^j \gamma^j}\right]^{-1/\theta^j}, \tag{11}$$

where the $\Gamma(\cdot)$ is the Gamma function.

To complete the description of this model, the market clearing conditions for labor, structures and land, and final goods are given by Equations 12-14, below:

$$L = \sum_{i=1}^{Z}\sum_{j=1}^{J} L_i^j = \sum_{i=1}^{Z}\sum_{j=1}^{J} \int_{\mathbb{R}_+} l_i^j(v)\, \phi_i^j(v) dv \tag{12}$$

$$H_i = \sum_{j=1}^{J} H_i^j = \sum_{j=1}^{J} \int_{\mathbb{R}_+} h_i^j(v)\, \phi_i^j(v) dv \text{ for } i \in 1, 2, ..., Z \tag{13}$$

$$Q_i^j = L_i \cdot c_i^j + \sum_{k=1}^{J} M_i^{jk} = L_i \cdot c_i^j + \sum_{k=1}^{J} \int_{\mathbb{R}_+} M_i^{jk}(v)\, \phi_i^j(v) dv \text{ for } i \in 1, 2, ..., Z \tag{14}$$

Use X_z^j denote total expenditures on commodity j in region z. In equilibrium, aggregate trade balance for each region, z is given by:[27]

[27] A simplification we make, here, is to impose balanced trade across regions. As Caliendo et al. (2016) document, in reality, within the United States trade imbalance is prevalent. Certain regions—such as Indiana and Wisconsin—run substantial trade surpluses, while others—including Florida and Georgia–have large trade deficits. To rationalize these trade imbalances, Caliendo et al. (2016) assume that, while some fraction of a state's land and structures are owned locally, the remainder are owned nationally. States with a deficit are able to finance their consumption because they own a relatively large share of the national portfolio of structures. To match the trade imbalances, then, Caliendo et al. define state total income (which will equal

$$\sum_{i=1}^{Z}\sum_{j=1}^{J}\pi_{zi}^{j}X_{z}^{j} \;=\; \sum_{i=1}^{Z}\sum_{j=1}^{J}\pi_{iz}^{j}X_{i}^{j} \text{ for } z \in 1,2,...,Z \;. \tag{15}$$

One of the key differences between Caliendo and Parro (2015) and Caliendo et al. (2016)—the two papers upon which we build—relates to the treatment of primary inputs. In Caliendo et al. (2016), consumers are allowed to costlessly migrate across regions. As a result, utility is equalized across regions: $U_i = \frac{I_i}{P_i} = U$ for all i. Differently, in Caliendo and Parro (2015) labor is completely immobile. There is some initial exogenously given allocation of labor across regions, which does not respond to changes in trade costs or technology. Also in Caliendo and Parro (2015), labor is the sole primary factor of production: $\beta_i = 0$. Below, we will apply these two alternate, diametrically opposed specifications for our counterfactual exercises.

Having specified the consumers' and producers' maximization problems and the market-clearing conditions, we now define a competitive equilibrium. This definition is taken almost directly from Caliendo et al. (2016): Given factor supplies, L and H_i, a *competitive equilibrium* for this economy is given by a set of factor prices in each region $\{r_i, w_i\}$; a set of labor allocations, structure and land allocations, final good expenditures, consumption of final goods per person, and final goods prices $\left\{L_i^j, H_i^j, X_i^j, c_i^j, P_i^j\right\}$ for each industry and region; a set of pairwise sectoral material use in every region M_i^{jk}; and pairwise regional intermediate expenditure shares in every sector, π_{zi}^j; such that i) the optimization conditions for consumers and intermediate and final goods producers hold; all markets clear (Equation 12-14); ii) aggregate trade is balanced (Equation 15); iii) and utility is equalized across regions. Condition iii) is omitted in the specification with immobile labor.

total final consumption expenditures) to be equal to the sum of the state's trade imbalances (as recorded in the Commodity Flow Survey) and the state's value added (as recorded by the BEA). With our finer definition of areas, this procedure unfortunately results in negative income for certain MSAs (principally those which send large volumes of refined petroleum to other areas, such as Lake Charles, Louisiana). So, instead, we assume that all structures and land are owned locally and, correspondingly and counterfactually, that trade across regions is balanced.

Next, we outline the algorithm presented in Caliendo and Parro (2015) and Caliendo et al. (2016) to compute the change in equilibrium trade flows and aggregate welfare in response to a change in trade costs. As in those earlier papers, we will use Y' to refer to the counterfactual value of an arbitrary variable Y, and $\widehat{Y} = \frac{Y'}{Y}$ to refer to the change in variable Y.

- Step 1: Guess an initial vector of costs for the primary input (labor and land/structures) bundle: Call $\omega_i = \left(\frac{r_i}{\beta_i}\right)^{\beta_i} \left(\frac{w_i}{1-\beta_i}\right)^{1-\beta_i}$ the primary input unit price and $\hat{\omega}= (\hat{\omega}_1, ...\hat{\omega}_Z)$ the vector of changes in the primary input prices.

- Step 2: Given this guess for the primary input bundles' cost changes, compute the changes in the costs of each industry-region's input cost bundles, and the final good prices in each industry-region using Equations 9 and 11:

$$
\begin{aligned}
\hat{x}_i^j &= \left(\hat{\omega}_i^j\right)^{\gamma^k} \prod_{k=1}^{J} \left[\hat{P}_i^k\right]^{\gamma^{jk}} \\
\hat{P}_i^j &= \left[\sum_{i=1}^{Z} \pi_{zi}^j \left[\hat{x}_i^j \widehat{\tau}_{zi}^j\right]^{-\theta^j}\right]^{-1/\theta^j}
\end{aligned}
$$

- Step 3: Given changes in the costs of industry-regions' input cost bundles and prices for industry-regions' final good, compute the changes in the trade shares.

  The changes in trade shares are given by

$$
\hat{\pi}_{zi}^j = \left(\frac{\hat{x}_i^j}{\hat{P}_z^j} \widehat{\tau}_{zi}^j\right)^{-\theta^j}.
$$

- Step 4: Labor mobility condition:

  In the specification with immobile labor, $\hat{L}_i = 1$ for all regions i. If, instead, we follow the Caliendo et al. (2016) algorithm, changes in the labor force of each region are given by:

$$\hat{L}_i = \frac{\left(\frac{\hat{\omega}_i}{\hat{P}_i \hat{U}}\right)^{1/\beta_i}}{\sum_z L_z \left(\frac{\hat{\omega}_z}{\hat{P}_z \hat{U}}\right)^{1/\beta_z}} L, \text{ where } \hat{U} = \sum_z \frac{L_z}{L} \left(\frac{\hat{\omega}_z}{\hat{P}_z}\right) \left(\hat{L}_z\right)^{1-\beta_i}.$$

- Step 5: Regional-market clearing in final goods:

$$(X')^j_z = \alpha^j \hat{\omega}_z \left(\hat{L}_z\right)^{1-\beta_z} I_z L_z + \sum_{k=1}^{J} \gamma^{kj} \sum_{i=1}^{Z} (\pi')^k_{iz} (X')^k_i .$$

This equation states that shipments of commodity j can either be consumed (the first summand on the right hand side) or used as a material input (the second summand).[28]

To update our initial guess of costs for the primary input bundle, we need one additional market clearing condition. Caliendo and Parro (2015) and Caliendo et al. (2016) use different market clearing conditions.

- Step 6: Trade balance (used in Caliendo and Parro, 2015):

$$\sum_{i=1}^{Z} \sum_{j=1}^{J} (\pi')^j_{zi} (X')^j_z = \sum_{i=1}^{Z} \sum_{j=1}^{J} (\pi')^j_{iz} (X')^j_i . \tag{16}$$

- Step 6′: Labor-market clearing (used in Caliendo et al., 2016):

$$\hat{\omega}_z \left(\hat{L}_z\right)^{1-\beta_z} (I_z L_z) = \sum_{j=1}^{J} \gamma^j \sum_{i=1}^{Z} (\pi')^j_{iz} (X')^j_i . \tag{17}$$

  This condition states that the payments to region z's structures/land and labor after the change in trade costs (given on the left-hand side) equal the value of the shipments sent to all other regions (given on the right-hand side).

  Since the trade shares (the πs), changes in each region's labor force (the Ls), and the shipments of different commodities from different regions (the Xs) are each functions of the $\hat{\omega}$ vector, failure of Equation 16 or 17 imply that our guess of $\hat{\omega}$ needs to be updated.

[28] Regarding the first summand, note that $\hat{\omega}_z \left(\hat{L}_z\right)^{1-\beta_z} I_z L_z$ equals $\hat{\omega}_z \left(\hat{L}_z\right)^{-\beta_z} I_z L'_z$. Also note that intermediate good producers cost-minimizing choices of land/structures and labor implies that $\hat{I}_z = \hat{\omega}_z \left(\frac{\hat{H}_z}{\hat{L}_z}\right)^{\beta_z}$. Since the stock of land/structures is fixed within each region, $\hat{\omega}_z \left(\hat{L}_z\right)^{1-\beta_z} I_z L_z$ equals $I'_z L'_z$.

The algorithm follows steps 2-6 until Equation 16 holds (when working through the case with immobile labor) or Equation 17 holds (when working through the case with mobile labor).