# Firm-Product Linkages and the Evolution of Product Scope*

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What are the factors that shape the evolution of a firm's product mix? New products added by firms often share similarities with their existing products or those of nearby firms. This paper provides a methodology for estimating the role of various measures of "distance" in firms' product choice decisions. We model additions of new products by firms using a dynamic model in which firms must pay a one-time startup cost for adding new products to their production line. We allow this cost to be reduced if the firm already produces similar products, or shares some characteristics with other firms already producing the product. We consider three measurable characteristics along which firms may be considered "close" to a particular product: input similarity, physical distance to existing locations of production, and upstream-downstream connectedness. The set of potential product combinations is prohibitively large for standard estimation methods. Instead, we apply the method of moment inequalities developed by Pakes et al. (forthcoming) and Morales et al (2014). Results are heterogeneous across sectors, though physical distance seems to be of greatest importance. The third measure (upstream-downstream connectedness) seems to matter little after controlling for the other two. Counterfactuals in which we negate the benefits from certain proximity channels show that even in sectors where input similarity is important, physical proximity has a greater impact on the number of profitable products available to a firm.

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# 1 Introduction

How does a firm's product mix evolve? Consider the example of ITC Ltd., a large conglomerate with over $8 billion in revenue. This company started in 1910, producing tobacco, and entered the packing and printing business in 1925 as a form of backward integration. It began producing paperboard in 1979. In 1990 it began the exportation of agricultural commodities, which it describes as a leveraging of their agri-sourcing competency (ostensibly based on their existing ability to source wood and tobacco). They started producing notebooks in 2002, and later expanded to books, pens, pencils, and other stationary over the course of 2007-2009. They entered the food business with ready-to-eat meals in 2001, which their company website describes as "successfully blending multiple internal competencies."[1] They then progressed into confectionary and wheat flour (2002), biscuits (2003), and instant noodles (2010).

The nature of what a country's firms produce is not merely a subject of idle curiosity. There is theoretical literature that suggests that a country's products can matter for welfare. For instance, there can be learning, or spillovers across products (Matsuyama [1992], Harrison and Rodriguez-Clare [2010]). On the empirical side, Bernard, Jensen, and Schott (2006) find that the capital intensity of an industry's products can affect employment growth and the probability of plant death in the presence of international trade. Furthermore, Hidalgo et al. (2007) find the pairwise export correlations predict the development of future comparative advantage, which implies that countries whose exports are correlated with many products are more likely to develop comparative advantage in a broader range of products. These authors all suggest that both the type and diversity of the products produced by a country can have welfare effects for that country. Thus, a better understanding of the sequence in which products are added by firms can in turn give us a better understanding of the development path of a country, in terms of both product scope and welfare.

The question of what factors shape the evolution of a firm's product mix also relates to the active recent literature on multi-product firms in an international context. The existing literature offers two leading explanations for what might drive the sequence in which firms add products. Bernard, Redding, and Schott (2010) models the adding and dropping of products as the result of stochastic shocks to demand and firm-product productivity. Eckel and Neary (2010) employ a model in which firms have a core competency (lowest production cost) product, and firms add products in order of how similar they are to the core product. But the former model fails to account for the high frequency at which certain pairs of products are produced together, and the latter model is agnostic about what characteristics cause a product to be "near" or "far" from a firm's core competency.

Our paper develops a methodology that allows us to estimate the costs that firms face in transitioning to new products, and calculate how those costs vary based on certain measures of "distance" between firms and products. We consider three such measures within this paper: 1) Overlapping inputs, 2) Physical proximity of the factory to other locations where the product is produced, 3) upstream/downstream connectedness via input-output linkages.

[1] http://www.itcportal.com/about-itc/profile/history-and-evolution.aspx (retrieved 9/16/2014)

Determining the topology of the product landscape is a non-trivial undertaking. Modelling a decision as complex as product choice would be difficult in a discrete-choice setting. The size of the choice set is very large, and the problem would be computationally infeasible even if firms' information sets were known. We circumvent these difficulties by using a novel econometric technique called moment inequalities, developed by Pakes, Porter, Ho, and Ishii (forthcoming) [henceforth, PPHI]. The method relies on a "revealed preferences" assumption. Rather than trying to explicitly model firms' choices, we observe their actions and assume they are at least weakly more profitable (on average) than their other possible choices. [2] This allows us to derive an inequality condition where on one side are the expected profits for engaging in the chosen action, and on the other are profits from a potential counterfactual choice. Each of these profit terms is a function of parameters defined in a theoretical model, and these inequalities allow us to find upper and lower bounds on the parameters (i.e. the highest and lowest values of the parameters that are consistent with the inequalities derived from the firm choices).

The theoretical and empirical framework for our analysis closely follows Morales, Sheu, and Zahler (2014) [henceforth, MSZ], a structural gravity model with a dynamic component to capture how firms' costs of entry into a new market might depend on their prior entry choices. MSZ studies firm entry into country markets, which are distanced from the firm in physical space. We adapt their model to study firm entry into product markets, where each new product has a distance from the firm within a "characteristic space." This model is able to capture the dynamic component of firm choice, incorporating the connections that potential new markets have to firms' existing abilities. In the model, firms choose whether to add new products, and which products to add, out of a universe of possible products. Each firm-product pair has a stream of projected revenue that it can offer the firm, but entry is deterred by startup costs the firm must incur to begin production of a particular product. These startup costs depend on whether the firm is "close" to the new product, along the three dimensions enumerated earlier.

The data we use come from India's Annual Survey of Industries, a factory-level dataset that includes inputs, outputs, and physical location, among many other characteristics. The data are an unbalanced panel with yearly observations, chosen because it allows us to observe adding of products by firms in an emerging markets setting.

Our results are bounds on the costs of transitioning into new products. We estimate these costs separately by sector, and results are heterogeneous across sectors. In general, the physical proximity measure seemed to perform the best out of the three, across all sectors. Counterfactual exercises in which we calculate the number of profitable products that would be available to firms if we nullified the effects from one of the distance measures support this. Removing the cost benefits received from physical proximity has the greatest impact on the number of potentially profitable products firms' have available.

[2] The full assumptions we make on firm behavior are made explicit in Section 4.3 of the paper. For the time being, it's worth noting that the assumptions we need are consistent with, but substantially weaker than, perfect rationality.

The paper will proceed as follows. Section 2 discusses the dataset. Section 3 offers some preliminary evidence from our data. Section 4 describes the model. Section 5 outlines the procedure by which the model is estimated. Section 6 provides the results. Section 7 performs some supplementary analyses, such as simulation of product entry by firms and counterfactuals. Section 8 concludes.

# 2 Data

The primary dataset we use is the panel portion of the *Annual Survey of Industries* (ASI) from India. This is an unbalanced panel spanning the years 1999-2008. The data are a representative sample of all factories with 20 or more employees without power, and 10 or more employees if the factories have power.

The standard panel dataset for the ASI includes (among other items), land, buildings, physical plant, workers (male, female, child, managerial, and contractors), wages, material inputs and their costs, fuel and electricity usage, and outputs and their associated revenues.

The data also have an associated cross-sectional version, which lacks unique identifiers for factories. We merged the cross-section with the panel in order to observe plant location at the district level, as well as the number of plants per firm.

In selecting firms for inclusion in our study, we dropped all factories that[3]:

1. Do not appear in at least two consecutive years, or
2. Did not fill out one of the blocks of the survey required for our analysis (inputs, outputs, employment, expenses), or
3. Provided only aggregate output data, or
4. Classified all outputs as "miscellaneous."

Table 1 presents some summary statistics for the data. As we can see, almost all factories in the data belong to single-factory firms. Thus, in this paper, we will use the terms *factory* and *firm* synonymously. The large proportion of single-factory firms is a useful feature of our data, because it implies our estimates will be informative for understanding firm strategy, as opposed to being based on incomplete information about products being transferred from one factory to another within the same firm. As a note, single-factory firms tend to be smaller than multi-factory firms, and within our data they represent a less than proportional share of output, but they nevertheless represent a non-trivial portion of the economic output counted by our dataset (84% of all revenues).

We can also see that products were added in 37% of the firm-years in the data. Having such a large number of observations in which products are added will be helpful for our estimation procedure, which relies on analyzing firm behavior, such as adding products.

[3] We also performed a robustness check in which we excluded all factories that were part of a collection of factories belonging to the same owner. This did not have any qualitative impact on our results.

Other observations from the table are that the firms in the dataset use a rich set of inputs, which will be helpful in analyzing how their input mix affects product choice. The average revenue per product line is included in the table to give readers a perspective on the magnitude of our coefficients when we provide our estimates later in the paper.

**Table 1 - Summary Statistics**

| | Mean (Std. Dev) | Observations (firm-years) |
|---|---|---|
| Number of products | 2.16 (1.85) | 192345 |
| % that added products* | 0.37 | 179972 |
| Number of products added** | 1.54 (1.00) | 66464 |
| Revenue per product line*** | 443378.1 (3605142) | 192345 |
| % Single-factory firms | 0.94 | 209857 |
| % of revenue from single-factory firms | 0.84 | 192586 |
| Number of inputs (indigenous) | 4.81 (3.15) | 191085 |
| Number of inputs (imported) | 10.75 (3.28) | 197166 |

* Among single-factory firms it is 36%
** Conditional on adding a product
*** Expressed in 1982 rupees

# 3 Preliminary Evidence

Here we will present some reduced form evidence to show that the cluster correlations we are looking for exist within our dataset, and will try to convince the readers that the explanations offered by the standard models do not adequately explain these clusters.

Table 2 displays the conditional probabilities that a firm whose primary product (defined as the product generating the most revenue for that firm) is in the row sector in period t will start producing a product

in the column sector in period t+1.[4] The colors in the table merely highlight the relative magnitude of the matrix elements and are not meant to convey any additional information beyond what is already contained within the elements of the table.

As can be seen from the table, firms have a tendency to add products to their basket from within their own sector. However, there are also a sizeable number of firms that add products from other sectors. It is worth noting that the zeros in the table are "rounded zeros." That is, those elements in the table are very small, but not identically zero. We can deduce from this that path of a firm through the product space is potentially very complicated, and it would be difficult to feasibly model this decision and the choice set in a discrete-choice framework, thus necessitating the use of moment inequalities.

**Table 2**

| | | Conditional probability of adding product in a sector | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Main sector in previous year** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** |
| **1** | **Animal, vegetable, forestry** | 0.9 | 0.02 | 0.06 | 0 | 0 | 0.01 | 0.01 | 0 | 0 |
| **2** | **Ores, minerals, gas electricity** | 0.01 | 0.81 | 0.06 | 0.01 | 0 | 0 | 0.06 | 0 | 0.05 |
| **3** | **Chemicals** | 0.06 | 0.05 | 0.8 | 0.03 | 0.01 | 0.01 | 0.03 | 0 | 0.02 |
| **4** | **Rubber, plastic, leather** | 0.01 | 0 | 0.04 | 0.69 | 0.02 | 0.08 | 0.1 | 0.03 | 0.02 |
| **5** | **Wood, cork, paper** | 0.01 | 0 | 0.02 | 0.03 | 0.84 | 0.01 | 0.05 | 0 | 0.03 |
| **6** | **Textiles** | 0.02 | 0 | 0.01 | 0.04 | 0.01 | 0.92 | 0.01 | 0 | 0 |
| **7** | **Metals and machinery** | 0 | 0.02 | 0.02 | 0.04 | 0.01 | 0.01 | 0.83 | 0.05 | 0.03 |
| **8** | **Railways, ships, other transport** | 0 | 0 | 0 | 0.07 | 0.01 | 0 | 0.48 | 0.42 | 0.02 |
| **9** | **Other manuf. articles and services** | 0 | 0.07 | 0.02 | 0.04 | 0.03 | 0.02 | 0.19 | 0.01 | 0.62 |

The pattern observed in Table 2 persists even if we move to a greater level of disaggregation and observe a single sector. Firms continue to add products predominantly along the diagonal, indicating a tendency towards new products that are similar to ones they already produce.

Table 3 shows a similar conditional probability matrix for three-digit product categories within sector 77 (electrical machinery). As we indicated, firms tend to add new products along the diagonal. However, there are also substantial product additions in "close" categories. For instance, those firms manufacturing domestic and office equipment (777) are likely to add electrical machinery (771). Those firms making switchgear and control panels (773) add measuring and controlling instruments (775).

**Table 3 – Electrical and Electronic Machinery or Equipment**

| | Conditional probability of adding product in a sector | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Main sector in previous year** | **771** | **772** | **773** | **774** | **775** | **776** | **777** | **778** | **779** |

[4] Rows in the table do not add to 1 due to the presence of some firms adding multiple products in the same period.

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **771** | **Electrical Machinery** | 0.20 | 0.03 | 0.01 | 0.02 | 0.03 | 0.01 | 0.04 | 0.03 | 0.03 |
| **772** | **Motors, generators, transformers** | 0.04 | 0.22 | 0.05 | 0.02 | 0.05 | 0.01 | 0.00 | 0.03 | 0.05 |
| **773** | **Switchgear, control panels** | 0.02 | 0.06 | 0.27 | 0.05 | 0.09 | 0.00 | 0.00 | 0.02 | 0.07 |
| **774** | **Lamps, filaments, electrodes** | 0.01 | 0.01 | 0.03 | 0.37 | 0.02 | 0.00 | 0.01 | 0.01 | 0.05 |
| **775** | **Measuring/controlling instruments** | 0.02 | 0.06 | 0.08 | 0.02 | 0.24 | 0.01 | 0.00 | 0.01 | 0.07 |
| **776** | **Batteries and cells** | 0.03 | 0.04 | 0.00 | 0.03 | 0.03 | 0.51 | 0.00 | 0.00 | 0.02 |
| **777** | **Domestic and office equipment** | 0.10 | 0.02 | 0.02 | 0.04 | 0.00 | 0.00 | 0.17 | 0.04 | 0.04 |
| **778** | **Electromagnetic equipment** | 0.03 | 0.03 | 0.04 | 0.04 | 0.02 | 0.00 | 0.00 | 0.25 | 0.06 |
| **779** | **Electrical equipment, n.e.c.** | 0.02 | 0.05 | 0.07 | 0.08 | 0.07 | 0.00 | 0.02 | 0.02 | 0.12 |

# 4 Theoretical Framework

This section outlines the theoretical framework we use for our estimation. In a study of the connections between products, one might imagine that product linkages can exist on both the supply and demand sides of the market. For this exercise, we exclude the possibility of demand-side linkages, and focus only on supply-side features of products.[5]

The model we use is a modification of the model found in MSZ, but adapted to model the entry of firms into product markets rather than into locational markets. While the use of this type of model to study this type of problem may be unprecedented, the basic intuition underlying it applies to our situation as well as it applies to the problem of international trade. In their model, exporters select destination markets, favoring larger markets, and disfavoring markets that are further away. In our adaptation, the process is the same, except the destination markets are product lines rather than physical locations, and the "distance" between the firm and the destination is a startup cost for that product line, rather than the trade costs associated with physical distance.

## 4.1 Demand

Demand is modeled in the style of Dixit and Stiglitz (1977). There is a representative consumer with CES utility over varieties $i$ in a given product category $j$. The consumer has separable utilities over product categories, with the utility in any period $t$ from category $j$ given by:

$$Q_{jt} = \left[ \int_{i \in A_{jt}} q_{ijt}^{\frac{\eta_j - 1}{\eta_j}} \, di \right]^{\frac{\eta_j}{\eta_j - 1}} \qquad \eta_j > 1 \tag{1}$$

Where $A_{jt}$ is the set of available varieties, $\eta_j$ is the elasticity of substitution for products of type $j$, and $q_{ijt}$ is the consumption of variety $i$ in time $t$.

The demand for varieties that emerge out of this utility function is:

[5] We admit this is a strong assumption. However, it is made primarily due to data constraints, as opposed to prior beliefs by the authors regarding the drivers of firm product choice. We are not currently aware of a dataset that allows us to observe demand side linkages and connect them to our current list of firms and products. Existing data that we are aware of uses different product classifications than those found in the ASI, and we have not found a concordance to match the two. It may be possible to relax this assumption in future versions of the paper.

$$q_{ijt} = \frac{p_{ijt}^{-\eta_j}}{P_{jt}^{1-\eta_j}} C_{jt} \tag{2}$$

Where $P_{jt}$ is a price index given by:

$$P_{jt} = \left[ \int_{i \in A_{jt}} p_{ijt}^{1-\eta_j} di \right]^{\frac{1}{1-\eta_j}} \tag{3}$$

In the above index, $p_{ijt}$ is the price of a given variety and $C_{jt}$ is the total consumption of all products of type $j$.

## 4.2 Supply

Firms in the model must choose whether they will produce a variety in a given product category $j$. Firms that choose to produce will face three types of costs:

1. Marginal costs: $mc_{fjt}$
2. Fixed costs: $fc_J$
3. Product startup costs: $sc_{fjt}(b_{t-1})$

We will explain each of these elements in turn.

### 4.2.1 Marginal Costs

Similar to Goldberg, Khandelwal, Pavcnik, and Topalova (2010), we give firms a Cobb-Douglas production function:

$$q_{ijt} = \left(\beta_{ft}^{mc}\right)^{-1} L_{fjt}^{\beta_L^{mc}} IC_{fjt}^{\beta_{IC}^{mc}} \tag{4}$$

Where $L_{fjt}$ is the labor assigned by firm *f* to product *j* in period *t*, and $IC_{fjt}$ is the basket of intermediate inputs used in product *j*, and $\beta_L^{mc} + \beta_{IC}^{mc} = 1$.

This yields a log-linear form for marginal costs, as follows:

$$\ln\left(mc_{fjt}\right) = \beta_{ft}^{mc} + \beta_L^{mc} \ln\left(PL_j\right) + \beta_{IC}^{mc} \ln\left(PIC_{fjt}\right) + \epsilon_{fjt}^{mc} \tag{5}$$

Where $PL_j$ and $PIC_{fjt}$ are the price of labor and the price of the intermediate input basket respectively, and $\epsilon_{fjt}^{mc}$ is an error term. Please see the appendix, section 1, for details on the calculation of each of these terms.

### 4.2.2 Fixed Costs

Fixed costs reflect costs the firm incurs every year it produces product *j*, regardless of the quantity produced. We set fixed costs to be static for every product, but allow them to vary across industries.[6] We denote the industry for product *j* as $J$, where by industry we mean the 1-digit product classification associated with product *j*.

$$fc_{fjt} = \mu_j^{fc} + \epsilon_{fjt}^{fc} \tag{6}$$

### 4.2.3 Product Startup Costs

These are analogous to the sunk costs in MSZ, and are paid by firms that are producing *j* in a given period, but did not produce it in the previous period. They reflect the initial costs of setting up a new production line, and can be diminished if a product is "closer" to a firm along a certain distance measure. For instance, if a new product shares inputs with one or more of the firm's existing products, this diminishes or eliminates the search cost for the firm to find a supplier of these inputs, and potentially eliminates a learning cost associated with discerning how to use those inputs effectively.

The startup costs in period $t$ are defined to be a function of the firm's "basket" in the previous period, which we denote as $b_{t-1}$. The basket is the collection of characteristics of the firm in any given period. It is, most notably, the whole range of products produced by the firm in that period, but can also include less tangible characteristics (such as proximity of the firm to production locations of other products). By defining the startup costs as being a function of $b_{t-1}$ (as opposed to $b_t$), we are restricting the costs the firm has to pay to begin production of a new product to be determined by characteristics of the firm *prior* to making the decision to produce.

The startup costs are modeled as follows:

$$\begin{aligned} sc_{fjb_{t-1}t} &= \mu_j^{sc} - e_j^{sc}(b_{t-1}) + \epsilon_{fjt}^{sc} \\ e_j^{SC}(b_{t-1}) &= \zeta_1^{SC}\phi_j^1(b_{t-1}) + \zeta_2^{SC}\phi_j^2(b_{t-1}) + \zeta_3^{SC}\phi_j^3(b_{t-1}) \end{aligned} \tag{7}$$

In the above equations, the $\phi_j$ are proximity measures, ranging from 0 to 1, where 1 indicates a destination product *j* is considered "close" to a firm along a certain measure of distance. We have three such distance measures we are considering in this paper, which we will explain in turn.

[6] Previous versions of our estimation included more parameters, including labor, capital, or labor intensity. However, these were found not to have a significant effect. In MSZ, they include many of the terms from the startup costs in the fixed cost equation as well. However, they are able to do this because there exists static versions of the startup costs in their framework. Specifically, they can look at the "distance" between Chile and another country (which is static), as opposed to the distance between a firm and another country (which is dynamic). However, in our framework, all of the distance measures are inherently dynamic. There are no static country-level versions to incorporate. Thus, in order to stay true to the nature of their model, in which the dynamics only appear in the startup costs, we avoid including the distance terms in our fixed cost.

#### 4.2.3.1 Distance Measure 1: Similarity of Input Cost Shares

This distance measure corresponds to the variable $\phi_j^1(b_{t-1})$ in the equation for product startup costs. We use Kugler and Verhoogen's (2012) modified Gollop and Monahan (1991) measure of horizontal differentiation. We use it to capture whether a firm *f*, seeking to produce product *j* uses similar inputs to other firms already producing *j*. The index ranges from 0 to 1, where 0 represents completely identical inputs (measured in terms of cost share), and 1 represents completely dissimilar inputs. The index is calculated as follows, for any two firms *f* and *f'*:

$$\sigma_{ff'} = \left( \sum_m \frac{|w_{fm} - w_{f'm}|}{2} \right)^{\frac{1}{2}} \tag{8}$$

Where $w_{hm}$ is the cost share of input *m* into firm *h*.

Having calculated $\sigma_{ff'}$ for every pair of firms, we define the distance from a firm to a product to be the minimum of the distances to the firms already producing the desired product. After computing this distance index, we convert this distance to a proximity, $\phi^1$, which in this case merely requires reversing the distance. More precisely:

$$\phi_{fj}^1(b_{t-1}) = \left| \left( \min_{f' \in \mathcal{F}_{j,t-1}} \sigma_{ff'} \right) - 1 \right| \tag{9}$$

Where $\mathcal{F}_{j,t-1}$ is the set of all firms already producing *j* in *t-1*.[7] If $F_{j,t-1}$ is the empty set, then we say $\phi^1$ is undefined. The |. | is the absolute value operator.

By including this measure in our estimation, we hope to capture some of the costs that firms must incur in order to add new inputs to their production lines. These could include costs such as finding suppliers, learning about new inputs, purchasing machines to process these inputs, training employees to use the new inputs, etc.

#### 4.2.3.2 Distance Measure 2: Physical Distance

Our second distance measure gives the physical distance between a selected firm *f* and the nearest firm already producing its destination product *j*. We do not have the exact location of firms in the data, but we do know a firm's district, out of 619 districts in India that were indexed by the Ministry of Statistics and Programme Implementation (MOSPI). See Appendix section 2 for a discussion of how districts were mapped to firms, as well as further details on the distance calculation.

[7] It is worth noting that although we only use 44,022 firms to find observations for the moments (see the Data section of the paper for a discussion of this), we use all available firms in the dataset (over 100,000) to compute the modified Gollop and Monahan distance measure. This was to avoid the possibility that a firm producing *j* and having very similar inputs to a firm *f* would be excluded from the calculation because it did not satisfy the criteria needed in order to be used for the moment inequality estimation.

#### 4.2.3.3 Distance Measure 3: Upstream/Downstream Connectedness

Our third type of distance measures how connected products are via upstream or downstream linkages, as determined by our input-output table. This is distinct from Measure 1 (input similarity). For two products, $i$ and $j$, Measure 1 tells us whether $i$ and $j$ share similar inputs, whereas Measure 3 tells us whether $i$ is used as an input in $j$ (or vice versa). The formula we use to represent this is as follows:

$$\phi_{fj}^{3}(b_{t-1}) = \max_{i \in b_{t-1}} \left( \max\{w_{ij}, w_{ji}\} \right) \tag{10}$$

where $w_{ij}$ is the cost share of input $i$ into product $j$.

Because this is a measure of distance, we want it to be symmetric. Thus, we view the use of $i$ in $j$ and the use of $j$ in $i$ equivalently. $\max\{w_{ij}, w_{ji}\}$ gives us the defined proximity between two products, and after computing this for every product pair, the proximity of the firm to the given product $j$ is simply the distance of the closest product to $j$ found within the firm's basket in the previous period, $b_{t-1}$.

This measure of proximity varies between 0 and 1, with $\phi^3 = 0$ if none of the firm's products use product $j$ as an input, nor are used in the production of $j$. On the other hand, $\phi^3 = 1$ if the firm possesses at least one product whose *only* input is product $j$ (or alternatively, if any of the firm's products are the only input *in* product *j*).

## 4.3 Firms' Optimal Behavior

The above theoretical framework yields the following profit function for firms:

$$\begin{aligned} \pi_{ft}(b_t|b_{t-1}) &= \sum_{j \in b_t} \pi_{fjt}(b_{t-1}) \\ \pi_{fjt}(b_{t-1}) &= v_{fjt} - fc_{fjt} - \mathbb{I}\{j \notin b_{t-1}\} sc_{fjt}(b_{t-1}) \end{aligned} \tag{11}$$

Intuitively, a firm's total profit is equal to the sum of the profits from its individual product lines. $\mathbb{I}\{.\}$ is an indicator function, and $v_{fjt}$ is the gross value of producing *j* to firm *f* in period *t*, as calculated from the demand function. The marginal costs are incorporated into the calculation of $v_{fjt}$, thus they do not appear separately in the profit function. We will explain the estimation of $v_{fjt}$ in the section on the first stage estimation, to follow shortly.

As in MSZ, firms in this model solve a two-stage problem to determine which product lines to enter. The first stage is static, in which the firm looks at the universe of all products, and calculates the expected

gross profits from entering into each of those products[8]. The second stage is dynamic, in which the firm chooses which products to produce, factoring in the fixed costs and startup costs.

There are a number of assumptions that need to be made about firm behavior in order to estimate this model. We borrow these assumptions from MSZ, and modify them only to fit the notation found in this paper.

**Assumption 1:** *Let us denote by* $b_1^T = \{b_1, b_2, \dots, b_T\}$ *the observed sequence of baskets chosen by any given firm* f *between periods 1 and T. Given a sequence of information sets for firm* f *at different time periods,* $\{\mathcal{I}_{ft}, \mathcal{I}_{ft+1}, \dots\}$*, a sequence of choice sets from which firm* f *picks its preferred basket,* $\{\mathcal{B}_{ft}, \mathcal{B}_{ft+1}, \dots\}$*, and a particular conditional expectation function* $\mathbb{E}[.]$ *capturing its subjective expectations, we assume:*

$$b_t = \underset{o_t \in \mathcal{B}_{ft}}{\operatorname{argmax}} \mathbb{E}\left[\Pi_{ft}(o_t|b_{t-1}) \middle| \mathcal{I}_{ft}\right] \ \forall t = 1, 2, \dots, T$$

*Where*

$$\Pi_{ft}(o_t|b_{t-1}) = \pi_{ft}(o_t|b_{t-1}) + \delta\pi_{ft+1}(o_{t+1}|o_t) + \omega_{fo_{t+1}t+2} \tag{12}$$

*The term* $\omega_{fo_{t+1}t+2}$ *is any arbitrary function that satisfies:*

$$\left(\omega_{fo_{t+1}t+2} \perp o_t\right)|o_{t+1} \tag{13}$$

*And the basket* $o_{t+1}$ *is defined as the optimal basket that would be chosen at period* $t+1$ *if the basket* $o_t$ *was chosen at period* $t$*:*

$$o_{t+1} = \underset{o_{t+1} \in \mathcal{B}_{ft+1}}{\operatorname{argmax}} \mathbb{E}\left[\Pi_{ft+1}(o_{t+1}|o_t) \middle| \mathcal{I}_{ft+1}\right] \tag{14}$$

Assumption 1 imposes that the basket actually chosen by the firm must be the one that maximizes its value function ($\Pi_{ft}$) in expectation, where the expectations of the firm are based on $\mathcal{I}_{ft}$, the information set of the firm in the period in which it is making the decision. It also imposes that the firm takes into account the effect of its decisions on future profits at least one period ahead. Note, this is still consistent with firms that are perfectly forward looking (for instance, if $\omega_{fo_{t+1}t+2}$ is the discounted stream of all future profits).

Equation (13) imposes that the basket choice in period $t$ does not affect firm profits beyond period $t+1$, *except* through its effect on the basket choice the firm makes at $t+1$. This is because the startup costs the firm must pay in period $t$ only depend on the basket in period $t-1$, and not in any prior periods. Furthermore, the firm internalizes that its choice in period $t+1$ is going to be the result of an analogous optimization problem to the one it solved in period $t$ (see equation (14)).

[8] We define "gross" here to mean profits before subtracting fixed costs and startup costs. Gross profits *do* take into account marginal costs.

Assumption 1 does not impose any constraints on the expectation functions of the firms, the firms' information sets, nor on the choice sets[9], all of which may differ by firm, and the latter two of which may differ by period.

Assumption 1 implies the following:

**Corollary 1:**[10] *If Assumption 1 holds, and* $b_t' \in \mathcal{B}_{ft}$*, then:*

$$\mathbb{E}\left[\pi_{ft}(b_t|b_{t-1}) + \delta\pi_{ft+1}(o_{t+1}|b_t)\middle|\mathcal{I}_{ft}\right] \geq \mathbb{E}\left[\pi_{ft}(b_t'|b_{t-1}) + \delta\pi_{ft+1}(o_{t+1}|b_t')\middle|\mathcal{I}_{ft}\right] \quad (15)$$

*Where*

$$o_{t+1} = \underset{o_{t+1}\in\mathcal{B}_{ft+1}}{\operatorname{argmax}} \mathbb{E}\left[\Pi_{ft+1}(o_{t+1}|o_t)\middle|\mathcal{I}_{ft+1}\right]$$

This corollary is used to derive observations for the moment inequalities, based on Assumption 1. It states that the observed basket choice by the firm must be at least weakly more profitable (in expectation) than any other basket that was in the firm's choice set.

Assumption 1 and its associated corollary allow us to apply an analogue of Euler's perturbation method with one-period deviations to the analysis of single-agent dynamic discrete choice problems, like the one we are analyzing.[11] This lets us obtain our estimates without the need to compute the fixed point for the value function, which would be infeasible in a problem of this size.

Each of the $\pi$ functions expressed in equation (15) is a function of the parameters we are seeking to estimate. The estimation method then consists of solving a linear programming problem to find the values of those parameters that are consistent with a set of inequalities of a form analogous to equation (15). As one might surmise, inequalities with fewer terms lead to less ambiguity about the acceptable values of the parameters.[12] It is thus desirable to generate simpler inequalities when possible. This end is aided by the use of one-period deviations. Equation (13) allows us to ignore the terms of the profit function beyond period $t+1$ whenever we use a one-period deviation in period $t$ to generate an

[9] In finding observations for the estimation of the moment inequalities, we do assume a certain minimum size for the choice sets in order to generate our perturbations. The types of one-period deviations we consider are: 1) Beginning production of a product one period earlier than was actually chosen; 2) Delaying production of a product for one period; 3) Choosing production of some alternate product in lieu of a product the firm actually chose; 4) Choosing production of a product in lieu of non-production; and 5) Choosing non-production of a product in lieu of production. Thus, we require the choice set to include the firms' actual choices, as well as a small space of perturbations around those choices. This is nowhere near the size of the space of all possible firm choices, although our framework does not exclude the possibility that firms are using that space.

[10] This corollary to Assumption 1 is equivalent to "Proposition 1" in MSZ, and is proved in the appendix of their paper.

[11] See Pakes, Porter, Ho, and Ishii (2011) for further details.

[12] As an example of this, consider the following two sets of inequalities:

$$\begin{Bmatrix} 2 \leq x \leq 4 \\ 1 \leq y \leq 2 \end{Bmatrix} \quad \begin{Bmatrix} 3 \leq x+y \leq 6 \\ 1 \leq y \leq 2 \end{Bmatrix}$$

The first set generates a smaller range of acceptable values for $x$: $[2,4]$ vs $[1,5]$. Because $x$ appears with $y$ in the second set's inequality, any ambiguity in the true value of $y$ propagates into $x$.

inequality. Since (13) guarantees the profit beyond $t+1$ is the same in both the actual and counterfactual scenarios, the profit terms past $t+1$ simply cancel out, leading to inequalities of the sort found in equation (15).

Our procedure also requires some assumptions about the firms' choice sets and information sets. The constraints that we impose on the choice sets are laid out in Assumption 2:

**Assumption 2:** *Let us denote by $\mathcal{B}_{ft}$ the choice set of $f$ at t, and by $b_t$ its optimal basket. Then:*

$$\left(b_t, \{\overline{b}_{jt}; \forall j\}, \{\overline{b}_{jj't}; \forall j, j'\}\right) \in \mathcal{B}_{ft}$$

*where $\overline{b}_{jt}$ is the basket that results from modifying the value corresponding to $j$ in $b_t$, and $\overline{b}_{jj't}$ is the basket that results from exchanging elements $j$ and $j'$ in $b_t$*

This assumption requires the choice set of any given firm to include, at the very least, the actual observed choice of the firm ($b_t$), and a small number of perturbations around it. Requiring $\overline{b}_{jt}$ to be in the choice set means that a firm could have chosen to produce either one more, or one less product than it actually chose to produce. Requiring $\overline{b}_{jj't}$ to be in the choice set means the firm could have produced some other product, instead of one of the products it actually chose to produce.

Note that Assumption 2 is consistent with a firm's choice set including the whole universe of possible product combinations, but it does not require the choice set to be so large. Rather, it only imposes certain minimum requirements on the choice set.

We further have Assumption 3, imposing the minimum necessary contents of the firms' information sets:

**Assumption 3:** *Let us denote by $\mathcal{I}_{ft}$ the information set of $f$ at $t$. Then,*

$$Z_{ft} \in \mathcal{I}_{ft}$$

*where $Z_{ft} = \{Z_{fjt}; \forall j \in \mathcal{B}_{ft}\}$, and $Z_{fjt}$ includes $b_{t-1}$, $\mu_j^{fc}$, $\mu_j^{sc}$, and all of the covariates determining $r_{fjt}$ and $e_j^{sc}$.*

So at the time in which the firm must choose its basket for the current period, Assumption 3 requires the firm to know its basket in the previous period ($b_{t-1}$), the determinants of the expected gross revenue it would receive ($r_{fjt}$),[13] and the determinants of the fixed and startup costs ($\mu_j^{fc}$, $\mu_j^{sc}$, $e_j^{sc}$) that it would face if it were to produce any given product under consideration (less any $\epsilon$ error terms included in the equations for those costs).

[13] We have not introduced this term yet, but we will be discussing it shortly, at the beginning of section 5.

# 5 Estimation

Estimation proceeds in two stages, mirroring the two-stage optimization problem of the firm. In the first stage, we compute the expected gross profits for each firm of entering each product market. In the second stage, we employ moment inequalities using the firms' observed choices to estimate the parameters of interest ($\mu$ and $\zeta$). This two-stage estimation allows us to generate moment inequalities that are linear in the parameters of interest[14], thus avoiding the added computational difficulty of estimating with non-linear moments.

## 5.1 First Stage

We use the first stage to find point estimates for the parameter vector $\beta$ found in equation (5). The subsequent estimates of the $\mu$ and $\zeta$ parameters in the model[15] will depend on this $\beta$. A difficulty arises because (5) is an equation for marginal costs, which are typically unobserved. However, from the Dixit-Stiglitz demand system in our model, we can calculate the gross revenue a firm could expect from producing *j* in period *t*:

$$r_{fjt} = \left(\frac{\eta_j}{\eta_j - 1}\frac{mc_{fjt}(\beta)}{P_{jt}}\right)^{1-\eta_j} C_{jt} \tag{16}$$

This equation is log-linear, so we can take the log of (16), collect all the observable variables into a vector that we shall call $z_{fjt}$, and estimate the $\beta$'s with the following regression:

$$\ln(r_{fjt}) = \beta z_{fjt} + (1-\eta_j)\epsilon_{fjt}^{mc} \tag{17}$$

Where $z_{fjt}$ includes all observable variables in equation (5), $\eta_j$ is taken as given, and $\epsilon_{fjt}^{mc}$ is assumed to be independent of all variables included in $z_{fjt}$. We use a power function of the market size (total sales of product *j*) to proxy for the $P_{jt}^{\eta_j - 1}C_{jt}$ in equation (16), and include firm-year fixed effects.

We then take the predicted values from this regression and convert them to levels—$\exp(\hat{\beta} z_{fjt})$—to get preliminary predictions for the revenue. However, as pointed out by Santos Silva and Tenreyro (2006), estimating log-linear models with OLS can be biased due to Jensen's Inequality. As an ad hoc way of addressing this potential bias, we take the observed revenues and regress them on the predictions, with no constant:

$$r_{fjt} = \alpha \exp(\hat{\beta} z_{fjt}) + \epsilon_{fjt}^{r} \tag{18}$$

The predicted $\hat{\alpha}$ from this regression is then used to generate our final predictions for the revenue, as follows:

$$\hat{v}_{fjt} = v_{fjt}(\hat{\beta}) = \frac{1}{\eta_j}\hat{r}_{fjt} = \frac{1}{\eta_j}\hat{\alpha}\exp(\hat{\beta} z_{fjt}) \tag{19}$$

[14] As will be shown, the moments are linear in all parameters except $\beta$, in which they are log-linear.
[15] See equations (6) and (7) for $\mu$ and $\zeta$.

Because the elasticities of substitution $\eta_j$ are not identified in this framework, we use the values calculated by Broda, Greenfeld, and Weinstein (2006)[16]. Denote the error in our estimate of $\hat{v}_{fjt}$ as $\epsilon^{v}_{fjt}$.

As a robustness check for our predictions, we also performed the first stage regression in levels (as opposed to performing it in logs, and converting to levels). This was done by running a nonlinear least squares regression based on the orthogonality condition $\mathbb{E}\left[r_{ijt} - \exp\left(\beta z_{fjt}\right)\right] = 0$. This NLS regression would not be subject to the same Jensen's Inequality bias as a standard log-linear OLS. We then did a within-sample comparison of the predicted revenues from the NLS and found they performed substantially worse than the two-step OLS. As a result, the values we report for the remainder of the paper will be those coinciding with the two-step OLS described in this section.

## 5.2 Second Stage

Using the predicted values of potential revenue from the first stage regression, $\hat{v}_{fjt}$, we estimate the second stage using the system of moment inequalities laid out in PPHI. The estimation is founded upon a "revealed preferences" assumption. That is, whatever profits a firm receives from its actions must be at least as large as the profits it could have earned from some counterfactual course of action in its original choice set. (This notion is formalized in Corollary 1).

This estimation method does not allow us to obtain point estimates on the variables of interest; however it does allow us to establish upper and lower bounds on those variables, by determining which values of the variables are consistent with the observed firm behavior, or in the absence of any such values, what values minimize the deviation from the moment inequalities.

The estimation proceeds in several phases. In the first phase, we select observations from the data that will help us identify particular coefficients in $\theta$, the set of variables to be estimated. In the second phase, we aggregate those observations into moments, which take the form of a set of linear inequalities. Estimation of the identified set then becomes equivalent to solving a linear programming problem using these moment inequalities as constraints.

### 5.2.1 Selecting Observations for Moments

As explained in section 4.3, we search for one-period deviations to derive inequalities based on the theoretical model described in the paper. Each of these inequalities becomes one "observation." We then aggregate these observations into moments by averaging them, and it is these final aggregated moments that are used for the estimation of the parameter vector.

[16] We use the values they calculate for the country India. Note that Broda, Greenfeld, and Weinstein provide their elasticities for 3-digit harmonized system codes, whereas our data are 5-digit ASICC codes. We accounted for this by building a concordance from 3-digit ASICC codes to 3-digit Harmonized System codes. In cases where there was an imperfect matching (such as when several different HS codes corresponding to one ASICC code) we averaged the associated elasticities. There were a few cases in which certain elasticities were "substantially" different from other elasticities within their HS category (that is, differing by half an order of magnitude or more). In these cases, we matched 5-digit ASICC codes to 3-digit HS codes, to ensure that these particular values were not misapplied to the wrong products within the data.

Equation (15) in Corollary 1 gives the expression for a single such observation. We can rewrite this equation as $\mathbb{E}[\pi_{fdt}|\mathcal{I}_{ft}] \geq 0$, where the $d$ denotes a deviation at period $t$ from $b_t$ to $b_t'$. Using Assumption 3, we can express this conditional inequality as an unconditional moment inequality:

$$\mathbb{M}_k = \mathbb{E}[g_k(Z_{ft})\pi_{fdt}] \geq 0 \tag{20}$$

where $g_k(.)$ is a positive-valued weighting function, and $Z_{ft}$ is the set of values we require to be in the firm's information set in Assumption 3. $k$ is an index for the particular moment inequality we are considering, $k = 1, \dots, K$.

Selecting observations for the moments is therefore equivalent to choosing the weight functions $g_k$ to isolate one-period deviations that can be used to identify the parameters of interest. These $g_k$ are allowed to depend on any information present in the firm's information set in period $t$.

The process of observation selection involves searching for patterns of firm behavior that would be informative for identifying one of the variables in our model. All of the variables we are estimating in the second stage relate to costs the firm has to pay (or an abatement of those costs). Thus, we will identify a variable by finding cases where the firm paid the costs associated with a variable, and then compare them to counterfactuals in the firm's choice set in which it could have avoided payment of the cost (in all or in part).

Consider the following example for the distance term, $\zeta_1^{SC}$, which appears in equation (7). This term represents the abatement of startup costs the firm receives for sharing common inputs with its destination product. The following table represents a hypothetical firm's choice of whether to produce a particular product *j* in periods 1 and 2. The "actual" row represents the observed production decision of the firm. The "counterfactual" row represents a possible alternative decision that was in the firm's choice set in period 2. (Because we are doing one-period deviations, period 2 is the only period in which the counterfactual behavior deviates from the actual behavior of the firm). A "1" in the table below signifies production of the given product, while a 0 signifies non-production.

| | t = | 1 | 2 | 3 |
|---|---|---|---|---|
| Actual | j | 0 | 1 | 0 |
| | j' | 0 | 0 | 0 |
| Counterfactual | j | 0 | 0 | 0 |
| | j' | 0 | 1 | 0 |

In the table above, the actual, observed behavior of the firm is production of product *j* in period 2, and non-production of *j'* in periods 1, 2, and 3. We consider the counterfactual where, in period 2, the firm chooses to produce *j'* instead of *j*.[17] In this example, the firm produces neither *j* nor *j'* in period 3.

[17] Note there are many other potential counterfactuals that could be considered in this setting, each of which would give rise to different inequalities. We focus on this one merely to give an example of the method.

By Corollary 1, the expected profits the firm receives from its actual behavior must be at least weakly greater than the profits from the counterfactual. This allows us to write the following inequality:

$$\begin{aligned}&\mathbb{E}\left[\nu_{fj2} - \mu_0^{fc} - \epsilon_j^{fc} - \mu_0^{sc} + \zeta_1^{SC}\phi_{jb_1}^1 + \zeta_2^{SC}\phi_{jb_1}^2 + \zeta_3^{SC}\phi_{jb_1}^3 - \epsilon_{fj2}^{sc}\middle|\mathcal{I}_{f2}\right] \\ &\geq \mathbb{E}\left[\nu_{fj'2} - \mu_0^{fc} - \epsilon_{j'}^{fc} - \mu_0^{sc} + \zeta_1^{SC}\phi_{j'b_1}^1 + \zeta_2^{SC}\phi_{j'b_1}^2 + \zeta_3^{SC}\phi_{j'b_1}^3 - \epsilon_{fj'2}^{sc}\middle|\mathcal{I}_{f2}\right]\end{aligned} \tag{21}$$

Which reduces to:

$$\begin{aligned}\mathbb{E}\Big[\left(\nu_{fj2} - \nu_{fj'2}\right) + \zeta_1^{SC}\left(\phi_{jb_1}^1 - \phi_{j'b_1}^1\right) + \zeta_2^{SC}\left(\phi_{jb_1}^2 - \phi_{j'b_1}^2\right) + \zeta_3^{SC}\left(\phi_{jb_1}^3 - \phi_{j'b_1}^3\right) \\ - \left(\epsilon_j^{fc} - \epsilon_{j'}^{fc}\right) - \left(\epsilon_{fj2}^{sc} - \epsilon_{fj'2}^{sc}\right)\Big|\mathcal{I}_{f2}\Big] \geq 0\end{aligned} \tag{22}$$

Thus, the $\pi_{fdt}$ found in equation (20) is merely the left-hand side of equation (22). The above equation shows what a typical observation would look like for this particular pattern of firm behavior. If we needed to form the lower bound of $\zeta_1^{SC}$, we would select those observations for which $\left(\phi_{jb_1}^1 - \phi_{j'b_1}^1\right) \geq 0$. That is, those observations for which the proximity to the actual product chosen (along dimension 1) is greater than the proximity to the counterfactual product. To see why this is, consider the simplified scenario in which all the differenced terms in equation (22) are zero, except for $\left(\phi_{jb_1}^1 - \phi_{j'b_1}^1\right)$ and $\left(\nu_{fj2} - \nu_{fj'2}\right)$. Also, ignore the conditional expectation operator. We will discuss it momentarily. Then, equation (22) becomes:

$$\left(\nu_{fj2} - \nu_{fj'2}\right) + \zeta_1^{SC}\left(\phi_{jb_1}^1 - \phi_{j'b_1}^1\right) \geq 0 \tag{23}$$

Looking at it this way, it becomes clear why having $\left(\phi_{jb_1}^1 - \phi_{j'b_1}^1\right) \geq 0$ is desirable for establishing a lower bound for $\zeta_1^{SC}$, since it allows us to write (23) as:

$$\zeta_1^{SC} \geq \frac{\left(\nu_{fj'2} - \nu_{fj2}\right)}{\left(\phi_{jb_1}^1 - \phi_{j'b_1}^1\right)} \tag{24}$$

which is clearly a lower bound on $\zeta_1^{SC}$. However, if it had been that $\left(\phi_{jb_1}^1 - \phi_{j'b_1}^1\right) \leq 0$, we would have had to reverse the direction of the inequality when dividing by that term, and equation (24) would have represented an upper bound instead.

Of course, when we actually write the moments, we write them not in terms of ex-post realized values of the gross revenue terms, but rather in terms of the ex-ante expected values of those terms, conditional on the information the firm had available in the period in which it was making its decision. This is because our assumptions do not require the firms' decisions to be ex-post optimal, but only ex-ante optimal. Thus, the $\nu_{fjt}$ terms in equations (23) and (24) represented expected gross profits.

We were able to express the lower bound for $\zeta_1^{SC}$ in a very simple form by assuming that many of the other terms from equation (22) simply equated to zero. In practice, however, that will almost never be the case. What this means is that the bounds for $\zeta_1^{SC}$ will depend on the bounds for many of the other

variables in the model, and vice versa. This is not necessarily a crippling obstacle for our estimation, since in the moment inequalities method, all of the bounds are simultaneously determined. However, what this does mean for our estimation is that wider bounds for one variable will translate into wider bounds for the other variables that depend on it.

The pattern of firm behavior we used as a demonstration above is useful for finding a bound on $\zeta_1^{SC}$, but is less informative about other terms within the firms' profit functions. For instance, both $\mu_0^{SC}$ and $\mu_0^{FC}$ cancel out in equation (21). This is useful for estimating $\zeta_1^{SC}$, since it allows us to attain simpler bounds on that coefficient and thus estimate it with less ambiguity. However, this means that particular pattern of behavior is useless for estimating $\mu_0^{SC}$ and $\mu_0^{FC}$. We instead use different patterns for isolating these other variables.

Choosing such patterns for use in the moment inequalities framework is a bit of an art form, the goal being to generate observations in such a way as to get unneeded terms to cancel out in order to best isolate the coefficient of interest. Due to the similarity of our model to MSZ, many of the patterns we use mirror the ones found in their paper.

Table 4 shows explicitly which patterns were used to bound each coefficient. In selection of our patterns, we always conditioned on two periods: the period for which we are considering the counterfactual deviation, and one period prior. Those periods are indexed in the table by *t=0* and *t=-1* respectively. A "1" in the table represents production of the given product, while a "0" represents non-production. As explained earlier in the paper, firms are excluded if they are unobserved in any of the periods on which we are conditioning, or in the period following the counterfactual deviation.[18]

**Table 4**

| Coefficient | Bound | Product | Actual | | Counterfactual | | Description of Counterfactual |
|---|---|---|---|---|---|---|---|
| | | | t = -1 | t = 0 | t = -1 | t = 0 | |
| $\mu_0^{fc}$ | lower | j | 1 | 0 | 1 | 1 | Halt production of j |
| | upper | j | 1 | 1 | 1 | 0 | Produce j for one additional period |
| $\mu_0^{sc}$ | lower | j | 0 | 0 | 0 | 1 | Produce j |
| | upper | j | 0 | 1 | 0 | 0 | Do not produce j |
| $\zeta^{sc}$ (all) | lower | j | 0 | 1 | 0 | 0 | Produce j' instead of j |
| | | j' | 0 | 0 | 0 | 1 | |
| | upper | j | 0 | 1 | 0 | 0 | Same as lower bound |
| | | j' | 0 | 0 | 0 | 1 | |

As the reader might have guessed from the earlier discussion, although the patterns used for estimating the upper and lower bounds of the $\zeta^{SC}$ terms are identical, we can identify which bound we are

[18] We also perform a version of the estimation on large firms, since they are sampled with probability 1 in the ASI, thus eliminating ambiguity that may arise from firms entering and exiting the sample. The results are found in the appendix.

estimating by further conditioning on the sign of $(\phi_j - \phi_{j'})$ along the given proximity dimension under consideration.

There is one further complication to consider. As we have already stated, we can only condition our selection of observations on data in the firm's information set during the period in which the counterfactual deviation is occurring. This means we can condition on any number of periods into the past, but not on any periods that occur after the deviation, since those were not observable to the firm at the time. This means there are actually four patterns of firm behavior that we must consider when estimating the bounds on the $\zeta$'s[19]:

| | t = | 1 | 2 | 3 |
|---|---|---|---|---|
| Actual | j | 0 | 1 | 0 |
| | j' | 0 | 0 | 0 |
| Counterfactual | j | 0 | 0 | 0 |
| | j' | 0 | 1 | 0 |

| | | 1 | 2 | 3 |
|---|---|---|---|---|
| Actual | j | 0 | 1 | 1 |
| | j' | 0 | 0 | 0 |
| Counterfactual | j | 0 | 0 | 1 |
| | j' | 0 | 1 | 0 |

| | | 1 | 2 | 3 |
|---|---|---|---|---|
| Actual | j | 0 | 1 | 0 |
| | j' | 0 | 0 | 1 |
| Counterfactual | j | 0 | 0 | 0 |
| | j' | 0 | 1 | 1 |

| | | 1 | 2 | 3 |
|---|---|---|---|---|
| Actual | j | 0 | 1 | 1 |
| | j' | 0 | 0 | 1 |
| Counterfactual | j | 0 | 0 | 1 |
| | j' | 0 | 1 | 1 |

Each of the observations for those patterns would give rise to a separate type of inequality. For instance, in the second pattern above, the firm would have to pay the static portion of the startup cost, $\mu_0^{SC}$ twice in the counterfactual case, once for product *j'* in period 2, and then again for product *j* in period 3, whereas in the actual case, the firm only has to pay it once. This means that in addition to the other variables above, $\mu_0^{SC}$ will also appear in the bounds for the $\zeta$'s, since it cannot be differenced out in the second and third firm behavior possibilities above.[20]

Note that these potential effects on firm profits in period 3 are not meant to imply that we use two-period deviations in our estimation. In each of the examples given above, the only difference in firm behavior between the actual and counterfactual cases occurs in period 2. Rather, we are saying that because firm profits are at least partially dependent on the state of the firm in previous periods, actions taken in period 2 can cause profits in period 3 to be different in the actual vs counterfactual cases, even if the period 3 actions of the firm are identical in both of those scenarios.

### 5.2.2 Aggregating Observations into Moments

After selecting observations in the manner described in the previous section, it remains to aggregate those observations into moments to be used in the estimation.[21] The theoretical moment inequalities

[19] We are fleshing out this explanation for the bounding of the $\zeta$'s, but the principle we are describing (i.e. that we cannot condition on future periods) applies to the selection of observations for each of our coefficients.

[20] We do impose *one* restriction on the future in selecting our observations, and that is that the firm must actually be observed in all three periods of the search pattern. Because we need to know the firm behavior following the counterfactual period in order to fully compute the desired bound, if the firm does not appear in the dataset in the third period of our pattern, we drop that observation for being incomplete.

[21] A reader might wonder why we do this at all. If we have two observations, one saying $x > 4$ and another saying $x > 10$, why not just say $x > 10$ and be done with it? Econometrically, such a procedure would have undesirable

are of the form given in equation (20). Thus, the sample moment inequalities are obtained by averaging all of the observations associated with a particular moment inequality, as follows:

$$\mathbb{m}_k(\theta) = \frac{1}{D_k}\sum_{f=1}^{F}\sum_{t=1}^{T}\sum_{d=1}^{D_{it}} g_k(Z_{ft})\hat{\pi}_{fdt}(\theta, \hat{\beta}) \quad (25)$$

Thus, for each moment inequality, (indexed by $k$), we are summing over all firms (*F*), all periods (*T*), and all possible deviations consistent with the assumptions in our paper ($D_{it}$). $\hat{\pi}_{fdt}(\theta, \hat{\beta})$ is the predicted difference in profits between the actual and counterfactual firm actions, which depends on predicted values from the first stage regression (a function of $\hat{\beta}$) and the parameter vector being estimated in the second stage, $\theta$.[22] $D_k$ is the total number of observations used to compute the sample moment $\mathbb{m}_k$. Note that since the weighting function $g_k(Z_{ft})$ can be zero for some values of $Z_{ft}$, $\mathbb{m}_k$ is computed with only a subset of the possible deviations.

### 5.2.3 Estimating the Bounds

After aggregating the observations, the estimation procedure involves solving a simple linear programming problem with the sample moment inequalities as constraints, as well as some "common sense" restrictions we place on our estimation. These additional restrictions are 1) Since each of the parameters we estimate is a cost, we require the acceptable values to be weakly positive, and 2) the value of the abatement of the startup cost due to proximity cannot exceed the startup cost itself (i.e. $\zeta_1^{sc} + \zeta_2^{sc} + \zeta_3^{sc} \leq \mu_0^{sc}$).

More formally, let $\Theta$ be the parameter space for $\theta$, and let $\Theta_{\mathbb{m}}$ be the set of all values of $\theta$ that satisfy the moment inequalities (as well as our additional restrictions, listed above). Thus, $\Theta_{\mathbb{m}} = \{\theta \in \Theta: \mathbb{m}(\theta) \geq 0\}$, where $\mathbb{m}(\theta)$ represents the set of all *K* of the moment inequalities $\mathbb{m}_k(\theta)$.

Then, the maximum value along the first dimension of $\theta$ is given by:

$$\overline{\theta}_1 = \left\{\theta \in \Theta_{\mathbb{m}}: \theta_1 = \arg\max_{\tilde{\theta} \in \Theta_{\mathbb{m}}} \tilde{\theta}_1\right\} \quad (26)$$

The definitions for the minimum and maximum values along other dimensions of the parameter vector are analogous.

### 5.2.4 Properties of the Error Terms

One of the advantages of the PPHI moment inequalities framework is that it does not require us to assume a specific functional form for the error terms. There are, however, some restrictions that must

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properties (such as being vulnerable to measurement error), and might be compared to a linear regression performed on a single observation.

[22] Note that although we do not index it, $\theta = (\mu_0^{fc}, \mu_0^{sc}, \zeta_1^{sc}, \zeta_2^{sc}, \zeta_3^{sc})$ is allowed to vary across sectors (that is, across 1-digit ASICC categories).

be applied to ensure that our estimated set contains the true value of $\theta$. These restrictions are encompassed by the following assumption:

**Assumption 4:**[23] *The error terms are such that*

$$\mathbb{E}\left[g_k(Z_{ft})\left(\epsilon^{v}_{fdt} + \epsilon^{fc}_{fdt} + \epsilon^{sc}_{fdt}\right)\right] \leq 0 \tag{27}$$

Recall that $\epsilon^{v}_{fjt}$ is the approximation error of our gross profit prediction, $\hat{v}_{fjt}$ from the first stage regression, and $\epsilon^{fc}_{fjt}$ and $\epsilon^{sc}_{fjt}$ are the error terms from the fixed and sunk costs, equations (6) and (7), respectively. The $d$ subscript (as opposed to $j$) on these error terms found in equation (27) merely shows that Assumption 4 imposes restrictions on the differences in the $\epsilon$'s between the actual and counterfactual cases, and not on the $\epsilon_{fjt}$'s themselves.

However, following MSZ, we can impose conditions on the $\epsilon_{fjt}$'s that are sufficient for the satisfaction of Assumption 4: 1) The first stage estimation procedure yields a consistent prediction for the expected gross revenues, and 2) $\mathbb{E}\left[\epsilon^{fc}_{fjt},\ \epsilon^{sc}_{fjt}\middle|\mathcal{I}_{ft}\right] = 0$. The latter restriction imposes that the firm does not have information on the fixed or sunk costs that is unknown to the econometrician.

### 5.2.5 Confidence Intervals

Confidence intervals for our parameter estimates follow the procedure outlined in PPHI, with the adjustment made in Holmes (2011) to account for correlation between observations arising from the same firm. We refer the reader to the cited papers for details on how these are computed.

# 6 Results

The main results are presented here, in Table 5. Using the moment inequalities method in PPHI, we do not get point estimates for any of our coefficients. Rather, we get upper and lower bounds on the potential values that those coefficients can take. As an example, of how to interpret this, observe that the static portion of fixed costs, $\mu_0^{fc}$, takes a maximum value of \$29,910 per product in industry 1 (Animals, vegetables, and forestry), and a minimum value of \$31,120 per product in industry 8 (railways, ships, and other transportation equipment), indicating that fixed costs are much greater in industry 8, as one might expect.

The values on the $\zeta$ coefficients are telling for the importance of the different distance measures in each industry. To interpret the $\zeta$'s, remember that the proximity measures were all projected onto a 0 to 1 space, with a proximity of 0 representing products that are as far away as possible from the given firm along the chosen distance measure, and a proximity of 1 representing products that are "immediately adjacent" to the firm along the given dimension of distance. Therefore, products with a proximity of 1

[23] Note that Assumption 4 is analogous to Assumption 3 in PPHI. The additional requirement in PPHI's assumption is trivially satisfied in our model by the fact that weight function for firm *f*, $g_k(Z_{ft})$ does not depend on the choices of firms other than *f*.

to a firm along the first distance measure (input similarity) will receive the full benefit of the startup cost abatement for that measure. Products with a proximity of 0 will not receive any such abatement (though it is possible that such products are close to the firm along another measure, receiving startup cost abatement from that alternate source).

**Table 5 – Baseline Estimation**

| | **Lower** | **Upper** | **Lower** | **Upper** | **Lower** | **Upper** | **Lower** | **Upper** |
|---|---|---|---|---|---|---|---|---|
| Industry: | Animal, Vegetable, Forestry | | Ores, minerals, gas, electricity | | Chemicals | | Rubber, plastic, leather | |
| $\mu_0^{fc}$ | 4.04 | 29.91 | 27.82 | 171.17 | 22.93 | 170.60 | 8.37 | 35.94 |
| $\mu_0^{sc}$ | 5.70 | 109.21 | 26.41 | 598.02 | 56.45 | 670.82 | 28.35 | 164.29 |
| $\zeta_1^{sc}$ | 0.00 | 66.52 | 0.00 | 318.94 | 0.00 | 273.82 | 0.00 | 62.26 |
| $\zeta_2^{sc}$ | 0.00 | 109.21 | 0.00 | 598.02 | 0.00 | 670.82 | 0.00 | 164.29 |
| $\zeta_3^{sc}$ | 0.00 | 36.18 | 0.00 | 190.08 | 0.00 | 203.24 | 0.00 | 43.75 |

| Industry: | Wood, cork, paper | | Textiles | | Metals, Machinery | | Railways, ships, transport | |
|---|---|---|---|---|---|---|---|---|
| $\mu_0^{fc}$ | 4.88 | 25.14 | 6.68 | 41.58 | 12.15 | 58.38 | 31.12 | 154.14 |
| $\mu_0^{sc}$ | 9.49 | 99.01 | 6.46 | 191.79 | 36.51 | 260.71 | 104.23 | 700.00 |
| $\zeta_1^{sc}$ | 0.00 | 50.41 | 0.00 | 77.76 | 0.00 | 87.36 | 0.00 | 234.34 |
| $\zeta_2^{sc}$ | 0.00 | 99.01 | 0.00 | 191.79 | 0.00 | 260.71 | 0.00 | 700.00 |
| $\zeta_3^{sc}$ | 0.00 | 30.41 | 0.00 | 49.02 | 0.00 | 64.79 | 0.00 | 170.27 |

*Notes: Values expressed in thousands of 1982 dollars. An exchange rate of 9 rupees per dollar was used for the conversion from rupees.*

For example, consider animals, vegetables and forestry. The coefficient on $\zeta_1^{sc}$ has a maximum possible value of \$66,520. This means that if a potential destination product *j* had an inputs-similarity proximity of 1 to a firm in that industry (meaning, the cost share of the inputs for *j* exactly mirrored the existing cost shares of the firm in the period prior to introducing *j*), that firm would receive a maximum of \$66,520 reduction in the startup costs associated with beginning production of that product. If none of the firms products shared any inputs with product *j* (and *j* was similarly far from the firm along the other two dimensions of distance), then the firm would have to pay the full startup cost to begin production of *j*, which our estimates show to be between \$5700 and \$109,210.

Adding a product with a proximity of 0 to your firm would provide no abatement of the startup costs along the given distance measure. In our model, for proximities between 0 and 1, the benefit decreases linearly. So in animals, vegetables, and forestry, the maximum benefit of adding a product with a proximity of 0.5 along distance measure 1 would be \$66,520/2 = \$33,260.

It may appear from looking at the zeros in the table that it is possible that the distance measures do not matter at all. It should be noted, however, that the estimated set is *not* the Cartesian product of the upper and lower bounds presented in the table. Thus, just because the $\zeta$ parameters all have 0 as their

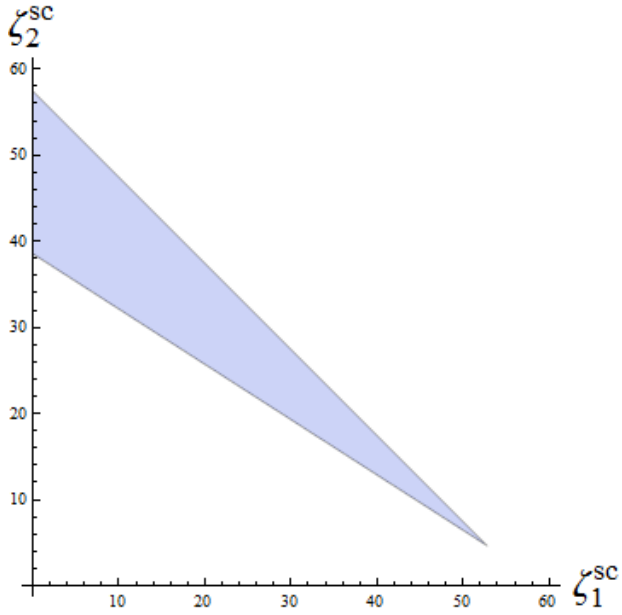
lower bound in the table, it does not follow that $(\zeta_1^{sc}, \zeta_2^{sc}, \zeta_3^{sc}) = (0,0,0)$ is a point within the estimated set. Each one of the distance parameters might individually be zero, given certain choices for the other coefficients, but that does not imply they are jointly zero.

This is not easy to intuit just from looking at the table. The estimated set is a five-dimensional manifold, whose true shape is computationally difficult to determine, and even more difficult to represent in a two-dimensional picture. However, we can show a cross-section of the set, to illustrate to the reader that the bounds are not jointly zero. One such cross-section is presented in Figure 1.

Figure 1 examines a cross-section of the estimated set for the Animals, Vegetables, and Forestry sector. We chose the median values of $\mu_0^{sc}$ and $\mu_0^{fc}$, and $\zeta_3^{sc} = 0$ to determine the location of the cross-section. We can observe from the picture that $\zeta_2^{sc}$ is bounded away 0 for all values of $\zeta_1^{sc}$, and $\zeta_1^{sc}$ is only 0 for particularly large values of $\zeta_2^{sc}$.

The readers are referred to the appendix if they wish to see the linear inequalities that define the entire estimated set. Using these inequalities, it is possible to create cross-sections such as these for any choice of the other parameters in the estimation.

**Figure 1 – Cross-Section of the Estimated Set for Animals, Vegetables, and Forestry**




*Notes: Values along the axes are thousands of 1982 dollars. Values of* $\mu_0^{fc} = \$16{,}975$, $\mu_0^{sc} = \$57{,}455$, *and* $\zeta_3^{sc} = 0$ *were used to determine the position of the cross-section in the dimensions not shown in the picture.*

By examining the $\zeta$'s, we can receive some indication of which distance measures matter in which industries. In every industry, the ranking of relative importance for the three distance measures seems

to be the same. Merely looking at the maximum values, physical distance ($\zeta_2$) seems to be the greatest contributor to product additions, followed by input similarity ($\zeta_1$). The upstream/downstream connectedness measure ($\zeta_3$) seems to fair the worst out of the three, consistently.

This is not to say that inputs and vertical connections are meaningless for product additions. Rather, that even at their maximum possible effectiveness, they tend to explain less of the variations in product additions than the physical distance component. On the other hand, there is a point in the estimated set for every industry in which the entire startup cost for new products in that industry can be abated by immediate physical proximity to the location of production.

Unfortunately, due to data limitations, it is not possible at this time for us to know precisely which portion of the production process is being helped by physical proximity. Many potential explanations come to mind, among them, knowledge sharing, access to natural resources, or local labor markets where workers have specialized skills. Distinguishing between these competing explanations is beyond the scope of the present paper, but we feel our results are a useful first pass, to indicate which areas of firm-product relatedness would be fruitful to investigate in the future.

Ninety-five percent single-sided confidence intervals for the baseline estimation and the restricted found in Table 6. While the estimated set specified by the confidence interval is obviously wider than that found in the estimation, the results are not dramatically different (with the exception of the chemical industry), ostensibly due to the large number of observations included in the estimation.

**Table 6 – Confidence Intervals for Baseline Estimation**

| | **Lower** | **Upper** | **Lower** | **Upper** | **Lower** | **Upper** | **Lower** | **Upper** |
|---|---|---|---|---|---|---|---|---|
| Industry: | Animal, Vegetable, Forestry | | Ores, minerals, gas, electricity | | Chemicals | | Rubber, plastic, leather | |
| $\mu_0^{fc}$ | 4.04 | 35.53 | 27.82 | 207.50 | 22.93 | 221.16 | 8.37 | 42.00 |
| $\mu_0^{sc}$ | 5.70 | 120.79 | 26.41 | 679.02 | 56.45 | 1,983.00 | 28.35 | 176.84 |
| $\zeta_1^{sc}$ | 0.00 | 70.22 | 0.00 | 372.46 | 0.00 | 2,133.67 | 0.00 | 88.27 |
| $\zeta_2^{sc}$ | 0.00 | 146.51 | 0.00 | 841.23 | 0.00 | 1,887.56 | 0.00 | 196.97 |
| $\zeta_3^{sc}$ | 0.00 | 48.44 | 0.00 | 274.88 | 0.00 | 552.33 | 0.00 | 65.88 |
| Industry: | Wood, cork, paper | | Textiles | | Metals, Machinery | | Railways, ships, transport | |
| $\mu_0^{fc}$ | 4.88 | 32.49 | 6.68 | 49.68 | 12.15 | 68.60 | 31.12 | 184.60 |
| $\mu_0^{sc}$ | 9.49 | 123.59 | 6.46 | 213.73 | 36.51 | 281.51 | 104.23 | 872.74 |
| $\zeta_1^{sc}$ | 0.00 | 64.93 | 0.00 | 88.40 | 0.00 | 127.21 | 0.00 | 592.46 |
| $\zeta_2^{sc}$ | 0.00 | 149.72 | 0.00 | 244.77 | 0.00 | 311.22 | 0.00 | 885.64 |
| $\zeta_3^{sc}$ | 0.00 | 48.52 | 0.00 | 57.82 | 0.00 | 87.50 | 0.00 | 852.07 |

*Notes: Values expressed in thousands of 1982 dollars. An exchange rate of 9 rupees per dollar was used for the conversion from rupees. The left parameter in every column represents the single-sided 95% confidence interval on the lower bound, and the right parameter is the single-sided 95% confidence interval on the upper bound. Values account for correlation across observations, and were computed using 500 subsamples.*

# 7 Supplementary Analyses

To help us understand how the different channels affect firm behavior, we performed some calculations of potential firm product transitions using the model, and data from the estimation. Firms within this calculation determine profits in the way we have described in the theoretical model, with two notable exceptions: the degree to which firms are forward looking, and the calculation of the error terms.

In the model, we were not required to specify the degree to which firms are forward looking, because the moment inequality framework is consistent with a broad array of firm expectations and behaviors (see section 4.3). However, for the purposes of performing these calculations, this unbounded set of behaviors needs to be made finite and concrete. Our assumptions require that firms take into account the effects of their current choice on static profit at least one period ahead. We therefore take this minimum required capacity for looking forward as the baseline for our calculation.

Secondly, within the PPHI moment inequalities framework, there are also relatively relaxed assumptions on the error terms (see section 5.2.4). However, for the purposes of our simulation, we draw the error terms from normal distributions with mean 0, which is consistent with the assumptions of the model. For the error terms associated with firm-product profits ($\epsilon_{fjt}^{v}$, see section 5.1), the standard deviation for the distribution is taken to be the actual standard deviation of a given firm's profits within its industry and year. For the other error terms ($\epsilon_{fjt}^{fc}$ and $\epsilon_{fjt}^{sc}$, mentioned in 4.2.2 and 4.2.3, respectively), the standard deviation is taken to be $\frac{1}{4}$ of the parameter estimate for the associated cost being used in the simulation.

The expected gross profits for each firm in the calculation are exactly the gross profit estimates we computed during our first-stage regression for the estimation. However, in order to mitigate the effects of some large outliers in the data, we dropped the top ten percent of the predicted profits. Firm locations are also identical to the actual locations found within the data.

We set the base year for the calculation to be 2000, and examined which products would be considered profitable by firms. For the second stage costs, we used the median values of the estimates from our baseline specification (those reported in Table 5). We excluded the upstream/downstream distance measure from the calculation due to its poor performance in the estimation.

This calculation, in addition to showing us the strength or weakness of our estimates also allows us to run counterfactuals, such as examining the results if we shut off or enhance one or both of the potential distance channels, or seeing the effect of the density of the firm-product connections on the number of profitable products.

## 7.1 Number of Profitable Products

For our first exercise, we examine the impact of negating the effect of each distance measure. Due to the amount of data produced by a calculation of this manner, we will only report one column of the output, in order to give the reader the basic intuition of how to interpret our results. Other rows within the output matrices follow the same general pattern.

The results of this exercise are reported in Table 7. Numbers in the table represent a count of the total products that have positive expected profits for firms whose main product is in ASICC category 21 (Salts, Sulpher, Lime, Cement). Stated another way, it is the sum of all the profitable firm-product relationships for firms in category 21. For example, imagine there are only two firms in category 21, A and B. Firm A has 3 potentially profitable products in Ores, and Firm B has 6 potentially profitable products in Ores. In that case, the entry in the table for Ores would be 3+6 = 9. Thus, the table represents the number of possible expansion paths available to firms within that industry.

The first column of the table represents the result of these calculations for the baseline results. The second and third columns consider the counterfactual cases in which $\zeta_1^{sc} = 0$ and $\zeta_2^{sc} = 0$, respectively. Setting $\zeta_1^{sc} = 0$ effectively removes any benefit the firm might receive from sharing inputs with potential products. Similarly, $\zeta_2^{sc} = 0$ removes any benefits it would receive from having production of a potential product located nearby.

**Table 7 – Profitable Products Available to Firms in Salts, Sulpher, Lime, and Cement**

| | Baseline | $\zeta_1 = 0$ | $\zeta_2 = 0$ |
|---|---|---|---|
| Salts, sulpher, lime, cement | 1750 | 1744 | 1146 |
| Ores | 110 | 110 | 70 |
| Mineral fuels | 391 | 391 | 264 |
| Gas (fuel) | 108 | 108 | 80 |
| Electrical energy | 154 | 154 | 107 |

Of note from the table is that negating the effect of the shared inputs does not substantially affect the number of profitable products at all, whereas negating the effects of local production affects it significantly.

Readers might be tempted to believe that this is an indictment against the shared inputs measure of similarity. However, it is necessary to interpret results within the context of the population distributions for the distances. In particular, observe the distribution for the input similarity measure. Most products are stacked up at 1. Products with a measure of 1 for this distance share no inputs with the firms' existing products, and thus receive no benefit from the cost abatement provided by $\zeta_1^{sc}$. Thus, setting $\zeta_1^{sc} = 0$ does not affect the profitability for many products at all.

Alternatively, the distribution for the physical distances shows many products being produced in close proximity to the firm. These products will receive a substantial reduction in their startup costs from the physical proximity channel. Therefore, setting $\zeta_2^{sc} = 0$ makes a big difference for a large number of products.

Therefore, the lesson to be learned from this exercise is that when interpreting the estimates, it is not enough to look only at the magnitude of the coefficients, but to consider also how those cost measures are interacting with the set of products in the firms' potential choice sets, and along which dimensions those products are "distanced" from the firm.

## 7.2 Firms' Product Choices

The previous exercise looked at all the profitable products available to the firm. In this exercise, we try to predict which products firms will move into, by allowing them to choose one product to add each period. For this simulation, we use the data for 2001-2002, since the earlier years of the sample were a little more sparse.

We'll motivate this exercise by showing the actual matrix of firm-product additions. The entries in the matrix show the number of firms that added a product in the column sector, conditional on having their main product in the row sector in the previous year.

**Table 8 – Actual Product Additions (Base Metals and Machinery)**

| | | Count of firms adding products in given sector | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Main sector in previous year** | **71** | **72** | **73** | **74** | **75** | **76** | **77** | **78** | **79** |
| **71** | **Iron, steel, & articles** | 283 | 11 | 35 | 47 | 28 | 19 | 13 | 5 | 9 |
| **72** | **Copper, nickel, zinc, & articles** | 2 | 21 | 7 | 6 | 0 | 1 | 1 | 0 | 0 |
| **73** | **Aluminum, tin, etc., & articles** | 14 | 4 | 47 | 13 | 3 | 3 | 8 | 0 | 1 |
| **74** | **Misc. manuf. Articles** | 58 | 10 | 14 | 35 | 39 | 23 | 17 | 5 | 7 |
| **75** | **General purpose mach. (non-elec)** | 57 | 3 | 7 | 26 | 155 | 69 | 56 | 7 | 9 |
| **76** | **Industry-specific mach. (non-elec)** | 34 | 2 | 4 | 16 | 67 | 158 | 31 | 6 | 15 |
| **77** | **Electrical machinery** | 43 | 17 | 30 | 26 | 63 | 35 | 259 | 51 | 16 |
| **78** | **Electronics equipment** | 6 | 2 | 2 | 3 | 7 | 5 | 34 | 82 | 1 |
| **79** | **Special purpose machines** | 12 | 5 | 3 | 6 | 13 | 12 | 15 | 2 | 21 |

Next, we will show the results from our simulation.

**Table 9 – Simulated Product Additions (Base Metals and Machinery)**

| | | Count of firms adding products in given sector | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Main sector in previous year** | **71** | **72** | **73** | **74** | **75** | **76** | **77** | **78** | **79** |
| **71** | **Iron, steel, & articles** | 87 | 1 | 14 | 61 | 237 | 156 | 274 | 36 | 26 |
| **72** | **Copper, nickel, zinc, & articles** | 9 | 0 | 3 | 4 | 19 | 12 | 23 | 4 | 2 |
| **73** | **Aluminum, tin, etc., & articles** | 18 | 0 | 3 | 19 | 39 | 24 | 61 | 3 | 7 |
| **74** | **Misc. manuf. Articles** | 34 | 1 | 7 | 16 | 73 | 65 | 125 | 17 | 14 |
| **75** | **General purpose mach. (non-elec)** | 51 | 0 | 5 | 39 | 143 | 83 | 163 | 19 | 18 |
| **76** | **Industry-specific mach. (non-elec)** | 37 | 1 | 17 | 25 | 89 | 73 | 117 | 19 | 7 |
| **77** | **Electrical machinery** | 82 | 4 | 11 | 44 | 199 | 124 | 279 | 38 | 19 |
| **78** | **Electronics equipment** | 19 | 0 | 4 | 16 | 42 | 34 | 67 | 7 | 5 |
| **79** | **Special purpose machines** | 8 | 0 | 1 | 6 | 22 | 18 | 34 | 1 | 6 |

Observing the tables, it is worth noting that although the simulation does not make perfect predictions, it performs better than one might expect for a model of its simplicity. It certainly appears to perform better than a fully random model, or an overly simplistic model in which firms only produce what they produced in the previous period (which would generate a matrix of zeros).

In some categories, the predictions of the simulation are actually very close to what we observe in the data. It predicts 279 electrical machinery firms will add products in their own sector, compared with 259 in the data. Its prediction of 143 general purpose machinery firms adding products within their sector is also close to the observed 155. Many other categories also closely match the data. In broad terms, it captures that there are few products being added in sectors 72, 73, and 74, and few products being by firms specializing in those sectors.

However, the simulation also highlights some weaknesses of the model. The most notable difference from the data seems to be the model's over-prediction of the number of products being added in the machinery sectors (75, 76, and 77), except in a few cases. This disparity seems most pronounced when examining firms in sector 71 (Iron, steel, and articles thereof).

That said, given the simplicity of the model, and the small number of parameters we estimated, one would not expect the model to perform perfectly. We used a very simple regression to determine potential revenues, coupled with a cost structure with only four parameters (recall we excluded the vertical connectedness measure, $\zeta_3^{sc}$, from the simulation). Furthermore, we applied a sweeping estimation technique generally to all firms in all industries.

With a process as complex and varied as the evolution of product scope, we cannot hope to fully capture all of the nuances of firms' decisions with one procedure. There are certainly many other factors that could be affecting their choices, and it seems natural to believe that our model would not be a good fit for every sector in every industry. Nevertheless, for some sectors, the model seems to perform fairly well, producing predictions that are qualitatively and quantitatively similar to what we observe in the data.

## 7.3 Network Density Regression

As we mentioned in the introduction, one of the key results found by Hidalgo et al. (2007) was that the network of connections linking products together in terms of their relatedness is not evenly distributed. Rather, it dense (meaning, with many close connections) in some areas, and very sparse in others. Therefore, countries (or in our context, firms) positioned in the dense part of the network are in a position to take advantage of many more cost abatement opportunities than those in the sparse part of the network.

In the work by Hidalgo et al. (2007), they presented a visual representation of the areas of these areas of density by providing a picture of their network linking products together. Our network is substantially more complicated to represent, because the connections we analyze are between firms and products,

not between the products themselves. Therefore, we proxy for this density by measuring exactly how much abatement each firm receives from its position within the network for its sector.

Specifically, we compute for each firm and year, the normalized distance of the firm to each product within its sector along each of the dimensions in our study, and multiply this by the median of the $\zeta^{SC}$ abatement parameter associated with that distance. Summing these figures together for all products gives the total number of dollars of potential startup cost abatement that the firm receives for that year. We call this number the "Network Density."

We then regress the number of profitable products the firm has each year on: the network density just described, the firm-year fixed effect from the first stage regression (representing the firm's idiosyncratic productivity shock for that year), and the size of the firm's product basket in the given year. The results are given in Table 10.

**Table 10 – Network Density Regression**

| Regressor | Number of Profitable Products |
|---|---|
| Network Density | 0.0052*** |
| | (0.00005) |
| Firm-Year Productivity | 23.14*** |
| | (0.091) |
| Basket Size | 2.264*** |
| | (0.134) |
| Constant | 50.87*** |
| | (0.345) |
| Observations | 136608 |
| $R^2$ | 0.405 |

*Notes: Heteroskedasticity-robust standard errors reported in parentheses. "Network Density" is measured in terms of ₹100,000s of startup-cost abatement within the firm's own sector only.*
**** Significant at the 1% level*

Even controlling for the number of current products and the firm productivity, the network density is still highly significant (the t-statistic for that coefficient is 107). The seemingly small value of the coefficient should be interpreted in the light of the very large values of the network density measure.[24]

It should come as no surprise that the amount of cost abatement a firm receives is positively correlated with the number of potentially profitable products it has available. Rather, the purpose of this exercise was merely to highlight, in rather unsophisticated way, that different firms receive different benefits

[24] The average firm received ₹585,000,000 of abatement, and even the least-benefited firm had over ₹2,400,000.

from their connections due to the density or sparsity of the network around them. This is to reiterate and expand upon the lesson of section 7.1, that the value and meaning of the coefficients found in this paper must be viewed within the context of the network of firm-product connections they interact with.

# 8 Conclusion

We approached the question of how firm's product mixes evolve with the hypothesis that connections between firms and potential products were driving their decisions about which products to produce. We proposed several potential channels by which these connections might manifest, and tested their relative significance by observing the actual behavior of firms as they added new products and measuring the degree to which those products were connected to the firm along each of these dimensions. The model was estimated using moment inequalities, a novel econometric technique that allowed us to approach a large-scale choice problem of this nature in a computationally feasible manner.

The results speak strongly in favor of our hypothesis—that product connections matter, and are part of the driving force behind the observed co-production correlations between products. The success of the estimation also shows that history matters for firms' product choice, since each of the distance measures looked at connections between firms and products in the year prior to actual production. Finally, we were able to gain some insight into the nature of which connections matter most in which sectors—physical distance seems to matter the most, followed by input similarity. Vertical connectedness ranks as the least important measure of relatedness, in every industry.

There were, however, several drawbacks to our estimation. The first is that our estimates, based primarily on firms adding products within their own industries, are not easily generalizable to firms moving across industries. The second is that, due to data limitations and the constraints of our estimation method, we were unable to account for a lot of richness that is obviously a factor in firms' production decisions (such as the presence of specialized capital, credit constraints, or demand complementarities). Our model and estimation method also do not account for potential effects from cannibalism or credit constraints, which could be relevant in a developing country setting.

Nevertheless, the results we found should be an important first step in unraveling a very rich problem, and should prove useful to those seeking to understand how firms (and potentially by extension, countries) expand their product scope and migrate from one industry to another during their process of development. Our paper also makes a methodological contribution, demonstrating how a traditional trade model coupled with a relatively new econometric technique can be used to analyze a problem of potential interest to both economists and policymakers.

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## Appendix

The appendix will include details on how we performed some of the calculations in the paper, as well as providing the results from alternative ways of estimating the model. Section A.1 will review how certain terms in the first stage regression were calculated, as well as providing the regression results. Section A.2 discusses our method for calculating the physical distance between firms and products. Section A.3 presents the results for some alternative specifications. Section A.4 presents the moments used in the preferred specification. Section A.5 gives the results from the Kolmogorov-Smirnov tests comparing the firm-choice and population distributions for firm-product distances discussed in section 6 of the paper.

### A.1. Marginal Cost Regression

#### A.1.1. $PL_j$

$PL_j$ is the price of a unit of labor in production of product *j*. Computation of this variable requires computing the labor costs for each firm, and using that to impute the labor costs of each product.

We began by calculating the labor inputs (in rupees) for every firm-year. Because we are interested in workers actually involved in the production process, we only included workers in the following categories in Block E of the ASI data:

1. Male workers employed directly
2. Female workers employed directly
3. Child workers employed directly
4. Workers employed through contractors
5. Supervisory and Managerial Staff
6. Other employees

These categories excludes unpaid family members/proprietor/coop. members. The total wage bill was calculated as the sum of the wages/salaries paid to employees in the included categories, excluding bonuses, contributions to Provident and other funds, and workman and staff welfare expenses.

To calculate the labor cost for a product, we need to make an assumption regarding how labor costs are assigned to given products within multi-product firms. We assumed that firms allocate labor expenses to products proportional to that product's share of the firm's total revenue from all products. So the labor costs allocated by firm *f* to product *j* in period *t* are:

$$Labor\ Costs_{fjt} = Labor\ Costs_{ft} * \frac{Revenue_{fjt}}{\sum_j Revenue_{fjt}} \tag{28}$$

We need to define what we will call a "unit" of labor for the purposes of our production function, so we can calculate the cost of such a unit. We use man-days as our unit of choice, and we use an analogous

relationship to the one given in equation (28) to assign man-days to products within multi-product firms (that is, we assume man-days are proportional to revenue).

We then computed values for the price of labor (defined as labor costs divided by man-days) of each product on the firm-year level. The median of these firm-year specific labor intensities was then taken as the ultimate value for the product-level labor intensity:

$$PL_j = \underset{ft}{\text{median}}\{PL_{fjt}\} \tag{1}$$

### A.1.2. $PIC_{fjt}$ (Intermediate Input Costs)

The calculation of the intermediate input costs for each firm-product-year combination requires several steps, which we will go through in turn. We first need to compute an input-output table for products at the 5-digit ASICC level[25], we then use this table to assign inputs to outputs at the firm level. Finally, having the quantity of the given inputs assigned to each output, we find the cost of these inputs by multiplying the unit value of the input provided in the data.

#### A.1.2.1. Input-Output Table

There is a vast literature on the computation of input-output tables. As described in Bohlin and Widell (2006), an assumption needs to be made about technology in order for an input-output table to be identified. The two most common assumptions in the literature are the Product-Technology Assumption (PTA) and the Industry-Technology Assumption (ITA). The PTA assumes that production of a particular product requires the same inputs, regardless of which industry it is made in. The ITA assumes that, within an industry, the same input mix is used for every product produced by the industry.

Almon (2000) provides a discussion about the merits and weaknesses of both of these assumptions, as well as a demonstration of the types of input-output tables that would be produced as a result of each of them. As one might expect, the ITA fares very poorly, and Almon describes the tables produced by such an assumption to be "massive nonsense."

We use the PTA for our input-output table, and generate it using the linear constraints in the technique developed in Bohlin and Widell (2006). This method was chosen because it allows the use of the PTA while avoiding the problem of negative flows (i.e. negative inputs being used in some outputs), as well as allowing generalization to the use of rectangular "Make" and "Use" tables[26].

[25] This is a greater level of disaggregation than is available from the Indian government.

[26] The Make table is the mapping from producers to outputs. In our case, it is an $F \times J$ matrix, where F is the total number of firms, and J is the total number of products. The element $M_{fj}$ in the matrix gives the quantity of product *j* that was made by firm *f* in the given year (we have one Make table for each year). The Use table is analogous, but for inputs rather than outputs.

We make use of the constraints in their minimization problem to harvest the usage coefficients that can be exactly identified from the data. So computing the input-output table comes down to solving the following set of linear constraints:

$$U_{uf} = \sum_{m \in \mathcal{M}} \alpha_{umf} M_{mf}$$
$$\alpha_{umf} \geq 0 \qquad (2)$$
$$\alpha_{um} = \underset{f}{\text{mean}}(\alpha_{umf})$$

In the above equations, $U_{uf}$ is the quantity of input *u* that is used by firm *f*. $M_{mf}$ is the quantity of output *m* that is made by firm *f*. $\alpha_{umf}$ is the usage coefficient, which is the number of units of the input good *u* needed to make one unit of the output good *m*. $\alpha_{umf}$ is firm-specific. The average of those coefficients is $\alpha_{um}$, which becomes an element of the input-output table. The set $\mathcal{M}$ is all of the products that the firm actually makes (in other words, we only apply the constraints for $M_{mf} > 0$).

Intuitively, the outputs of a firm $M_{mf}$, times the quantity of input *u* that is needed to produce that output $\alpha_{umf}$, must equal the total amount of *u* that is used by the firm.

In the above equation, both $U_{uf}$ and $M_{mf}$ are known from the data, and we must determine $\alpha_{umf}$. We do this only for those $\alpha_{umf}$'s that are exactly identified from the constraints above. This happens in two cases.

In the first case, $\mathcal{M}$ is a singleton, so the firm only makes one product. Thus, $\alpha_{umf}$ is defined for every *u* for that firm and product (with $\alpha_{umf} = 0$ for those products the firm does not use).

In the second case, $U_{uf} = 0$ for some *u* and *f*. In that case, even if $\mathcal{M}$ is *not* a singleton, we can determine that $\alpha_{umf} = 0$ for that (*u,f*) because $\alpha_{umf} \geq 0$ and $M_{mf} > 0$.

Intuitively, this method is roughly equivalent to using single-product firms to identify the elements of our input-output table, although the current methodology allows us to identify more elements of the table than merely using single-product firms.[27]

[27] The above methodology allowed us to create a complete input profile for 3919 of our 5367 products, and a partial input profile for an additional 1099 of those products, leaving only 349 products for which no input data could be determined. Since many of our 5367 products only appear as inputs in the data (never outputs), this means we were able to calculate input data for almost all outputs in the dataset. With respect to the accuracy of this methodology, it is worth noting two points: 1) When computing the Gollop and Monahan (1991) distance measure between products, the distances looked qualitatively indistinguishable whether they were calculated using the input-output table above, or whether they were computed using firm input mixes (as in Kugler and Verhoogen [2012]), which incorporate multi-product firms and bypass the use of the input-output table (the formula for which is described in the "Theoretical Framework" section of the paper); and 2) The first-stage regression, which used intermediate inputs from the input-output table to predict marginal costs showed the coefficient on those inputs to be large and highly significant. Both of these facts lead us to conclude that this

An input-output table was calculated using the above method for every year in the data. The final input-output table was then the median of the yearly tables.

### A.1.2.2. Assigning Inputs to Outputs at the firm level

Our estimation is performed on single- as well as multi-product firms, so we need a method to map a firm's inputs to its outputs in order to determine the input costs for a particular output.

Previous authors, such as Foster, Haltiwanger, and Syverson (2008) and DeLoecker (2011) address the problem of assigning inputs to outputs in multiproduct firms by assigning them in proportion to the number of products produced. We perform a similar operation, but unlike the aforementioned authors, we have the advantage of an input-output table which we can use to inform our assignment of inputs. We therefore modify their approach and weight the assignment of inputs according to the values found in the input-output table.

To do this, we assume there is a scaling factor $\gamma$, that relates firm-specific $\alpha$'s to the general economy-wide $\alpha$'s found in the input-output table, and that this scaling factor is constant for every product the firm uses. Consider the following illustration:

| $\alpha$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|
| $U_1$ | .5 | 1 | $\alpha_{13}$ |
| $U_2$ | $\alpha_{21}$ | $\alpha_{22}$ | $\alpha_{23}$ |
| $U_3$ | $\alpha_{31}$ | $\alpha_{32}$ | $\alpha_{33}$ |

| Use | Quant |
|---|---|
| $U_1$ | 10 |
| $U_2$ | 15 |
| $U_3$ | 10 |

| Make | Quant |
|---|---|
| $M_1$ | 5 |
| $M_2$ | 10 |
| $M_3$ | 0 |

The $\alpha$ table is the economy-wide input-output table, in which we have only filled in two of the elements for this example, because we are only considering how to assign the input $U_1$ to the firm's outputs. The Use table shows the quantity of each input used by our example firm, and the Make table shows the quantities of its outputs.

An *average* firm would need the following quantities of $U_1$ to make the products of this example firm:

- $\underbrace{5}_{M_1} \times \underbrace{0.5}_{\alpha_{11}}$ = 2.5 = amount of $U_1$ needed to make 5 units of $M_1$
- $\underbrace{10}_{M_2} \times \underbrace{1}_{\alpha_{12}}$ = 10 = amount of $U_1$ needed to make 10 units of $M_2$

method, while not perfectly accurate, as at least a very good approximation to the "true" input-output matrix for these products.

This firm would therefore need 12.5 units of $U_1$ to make its existing set of outputs, but it only uses 10. We therefore apply our scaling factor:

$$\gamma \underbrace{(M_1\alpha_{11} + M_2\alpha_{12})}_{12.5} = \underbrace{U_1}_{10}$$

In this example, $\gamma = 0.8$, so for the purposes of calculating the input costs for this firm, we would assume 2 units of $U_1$ were used for $M_1$, and 8 units of $U_1$ were used for $M_2$. When applying this method to the dataset, $\gamma$ is allowed to vary by firm and use-product.

We use the above method to define a price for the total aggregated input basket used in production of each product at the firm-year level. Since most products in the data do not have units given in terms of quantity of items sold, we define a unit of output as being one rupee. We therefore divide the aggregated input costs for each product by the ex-factory value of output to determine the unit price for the input basket.

### A.1.3 Regression Results

| | $\ln(r_{fjt})$ |
|---|---|
| $\beta_L^{mc}$ | -0.779*** |
| | (0.039) |
| $\beta_{IC}^{mc}$ | -0.130*** |
| | (.003) |
| $firm \times year\ FE$ | Yes |
| N | 296677 |
| $R^2$ | 0.75 |

*** denotes 1% significance.
Robust standard errors are in parentheses.

Above are the results from the regression in equation (17), the first stage in our estimation procedure.

## A.2. Physical Distance Calculation

### A.2.1. Mapping firms to districts

There are two difficulties to be overcome in determining the location of the firms at the district level. The first is that the ASI panel data, which contains unique identifiers for firms, only gives firm location down to the state level, which is far less precise. Districts are available in the cross-section data, but there is no direct mapping from the cross-section to the panel. The second difficulty is that MOSPI

changed their state and district codes in 2001. This required us to make two mappings: The first from the panel data to the cross-section, the second from pre-2001 district codes to post-2001 district codes.

To create the first mapping, from panel data to cross-section, we followed the technique used in Harrison et al. (2013), and matched the closing net value of fixed assets found in the panel and the cross-section, dropping any values of 0 or 1, and any duplicates, which could potentially lead to ambiguous matches.

To create the second mapping, we made the assumption that firms (factories in the data), do not change their location from year to year. Thus, by observing the location codes of individual firms prior to and post-2001, we were able to create a concordance linking the two sets of codes.

### A.2.2. Calculating the Distance

For each of the districts, longitude and latitude coordinates were obtained from Wikipedia's GeoHack tool. In the instances when coordinates were not available for a district, or when the available coordinates were obviously false, the coordinates for the district capital were used instead.

The coordinates were linked to the post-2001 district codes, because we did not have a list linking pre-2001 codes to district names. There were a few instances in which several pre-2001 codes were merged into one post-2001 code. In such cases, all of the pre-2001 codes were assigned the same coordinates.

Distances between the districts were calculated using the haversine formula for great circle distance, with the radius of the earth set to be 6372.8 km. Distances between firms were then defined to be the distance between the firms' associated districts, measured in kilometers, with a distance of 0 if the firms were located in the same district.

The distance between a firm and a product is then defined as the distance to the closest firm producing that product:

$$D_{fjb_{t-1}} = \min_{f' \in \mathcal{F}_{j,t-1}} d_{ff'} \tag{3}$$

Where $d_{ff'}$ is the physical distance between firms $f$ and $f'$, $D^2_{fjb_{t-1}}$ is the physical distance between firm *f* and product *j* at period *t-1*, and $\mathcal{F}_{j,t-1}$ is the set of all firms producing *j* at *t-1*.

We then construct our measure of proximity by dividing by the maximum distance between any two points in India (to get the measure between 0 and 1), and flipping it, so that nearby products have a proximity measure of 1 instead of 0.

$$\phi^2_{fjb_{t-1}} = \left| \frac{D_{fjb_{t-1}}}{\max_{f,f'} d_{ff'}} - 1 \right| \tag{4}$$

Where |.| is the absolute value operator.

## A.3. Alternative Specifications

### A.3.1 Large Firms Only

**Table A.3.1.1: Estimates**

| | **Lower** | **Upper** | **Lower** | **Upper** | **Lower** | **Upper** | **Lower** | **Upper** |
|---|---|---|---|---|---|---|---|---|
| Industry: | Animal, Vegetable, Forestry | | Ores, minerals, gas, electricity | | Chemicals | | Rubber, plastic, leather | |
| $\mu_0^{fc}$ | 5.47 | 49.62 | 86.24 | 548.88 | 37.29 | 309.56 | 13.18 | 68.88 |
| $\mu_0^{sc}$ | 7.12 | 173.50 | 74.73 | 1,857.67 | 74.05 | 1,200.11 | 40.81 | 304.72 |
| $\zeta_1^{sc}$ | 0.00 | 111.06 | 0.00 | 862.52 | 0.00 | 489.51 | 0.00 | 115.00 |
| $\zeta_2^{sc}$ | 0.00 | 173.50 | 0.00 | 1,857.67 | 0.00 | 1,200.11 | 0.00 | 304.72 |
| $\zeta_3^{sc}$ | 0.00 | 62.86 | 0.00 | 602.68 | 0.00 | 362.92 | 0.00 | 79.11 |

| Industry: | Wood, cork, paper | | Textiles | | Metals, Machinery | | Railways, ships, transport | |
|---|---|---|---|---|---|---|---|---|
| $\mu_0^{fc}$ | 13.60 | 85.32 | 8.99 | 58.60 | 21.55 | 118.90 | 55.45 | 307.21 |
| $\mu_0^{sc}$ | 25.96 | 323.99 | 8.33 | 267.61 | 61.39 | 525.62 | 184.97 | 1,324.89 |
| $\zeta_1^{sc}$ | 0.00 | 167.76 | 0.00 | 112.29 | 0.00 | 176.23 | 0.00 | 452.14 |
| $\zeta_2^{sc}$ | 0.00 | 323.99 | 0.00 | 267.61 | 0.00 | 525.62 | 0.00 | 1,324.89 |
| $\zeta_3^{sc}$ | 0.00 | 104.35 | 0.00 | 71.34 | 0.00 | 133.60 | 0.00 | 328.64 |

*Notes: Values expressed in thousands of 1982 dollars. An exchange rate of 9 rupees per dollar was used for the conversion from rupees.*

These are the results of our estimation performed only on the set of firms with 200 or more employees. According to the sampling procedure for the ASI, these firms are sampled with probability 1 in every year of the data.

Many of the broad trends identified in the baseline estimation persist. The physical distance parameter ($\zeta_2^{sc}$) continues to have the largest upper bounds, followed by input similarity ($\zeta_1^{sc}$), then vertical connectedness ($\zeta_3^{sc}$). However, in this version of the estimation, both the lower bounds on the costs ($\mu_0^{fc}$ and $\mu_0^{sc}$)and the upper bounds on all parameters are substantially higher than in the baseline. This might be attributed to the larger scale operations happening at these firms, resulting in higher costs (but also potentially higher profits).

**Table A.3.1.2: Confidence Intervals**

| | **Lower** | **Upper** | **Lower** | **Upper** | **Lower** | **Upper** | **Lower** | **Upper** |
|---|---|---|---|---|---|---|---|---|
| Industry: | Animal, Vegetable, Forestry | | Ores, minerals, gas, electricity | | Chemicals | | Rubber, plastic, leather | |
| $\mu_0^{fc}$ | 5.47 | 62.72 | 86.24 | 673.19 | 37.29 | 417.22 | 13.18 | 81.70 |
| $\mu_0^{sc}$ | 7.12 | 209.57 | 74.73 | 2,054.56 | 74.05 | 5,228.11 | 40.81 | 329.44 |
| $\zeta_1^{sc}$ | 0.00 | 120.63 | 0.00 | 1,034.43 | 0.00 | 5,867.89 | 0.00 | 165.61 |
| $\zeta_2^{sc}$ | 0.00 | 262.14 | -0.03 | 2,602.22 | 0.00 | 4,802.56 | 0.00 | 373.71 |
| $\zeta_3^{sc}$ | 0.00 | 87.86 | 0.00 | 1,019.66 | 0.00 | 1,884.56 | 0.00 | 119.79 |

| Industry: | Wood, cork, paper | | Textiles | | Metals, Machinery | | Railways, ships, transport | |
|---|---|---|---|---|---|---|---|---|
| $\mu_0^{fc}$ | 13.60 | 117.18 | 8.99 | 70.99 | 21.55 | 142.27 | 55.45 | 372.90 |
| $\mu_0^{sc}$ | 25.96 | 471.04 | 8.33 | 303.40 | 61.39 | 591.89 | 184.97 | 1,797.89 |
| $\zeta_1^{sc}$ | 0.00 | 296.18 | 0.00 | 130.11 | 0.00 | 303.02 | 0.00 | 1,414.11 |
| $\zeta_2^{sc}$ | 0.00 | 560.47 | 0.00 | 349.90 | 0.00 | 650.08 | 0.00 | 1,770.89 |
| $\zeta_3^{sc}$ | 0.00 | 192.61 | 0.00 | 82.98 | 0.00 | 179.22 | 0.00 | 1,495.00 |

*Notes: Values expressed in thousands of 1982 dollars. An exchange rate of 9 rupees per dollar was used for the conversion from rupees. The left parameter in every column represents the single-sided 95% confidence interval on the lower bound, and the right parameter is the single-sided 95% confidence interval on the upper bound. Values account for correlation across observations, and were computed using 500 subsamples.*

The above table represents the confidence intervals for the specification including only firms with 200 or more employees. While for some sectors they are similar to the estimates themselves, in others (chemicals, ores, and transportation, for instance) they are much wider. This is likely attributed to fewer observations available in those sectors.

### A.4.1 Moments for Baseline specification

**Table A.4.1**

**Industry 1**

| | Bound | $\Delta\mu_0^{fc}$ | $\Delta\mu_0^{sc}$ | $\Delta\zeta_1^{sc}$ | $\Delta\zeta_2^{sc}$ | $\Delta\zeta_3^{sc}$ | $\Delta\nu$ | Obs. |
|---|---|---|---|---|---|---|---|---|
| $\mu_0^{fc}$ | upper | 1.00 | -0.65 | 0.12 | 0.00 | 0.04 | 403,710 | 25,472 |
| | lower | -1.00 | 0.21 | -0.05 | -0.01 | -0.02 | -28,299 | 8,363 |
| $\mu_0^{sc}$ | upper | 1.00 | 0.66 | -0.39 | -0.60 | -0.05 | 65,075 | 8,069 |
| | lower | -1.00 | -1.00 | 0.99 | 0.21 | 0.00 | -20,657 | 40,598,000 |
| $\zeta_1^{sc}$ | upper | 0.00 | -0.28 | -0.44 | 0.14 | -0.05 | -25,975 | 3,872,500 |
| | lower | 0.00 | -0.17 | 0.20 | 0.20 | -0.04 | 266,660 | 732,260 |
| $\zeta_2^{sc}$ | upper | 0.00 | -0.28 | -0.42 | 0.09 | -0.04 | -20,092 | 3,369,100 |
| | lower | 0.00 | -0.23 | -0.12 | 0.34 | -0.10 | 354,010 | 4,012,400 |
| $\zeta_3^{sc}$ | upper | 0.00 | -0.29 | -0.31 | 0.19 | -0.29 | -30,693 | 700,130 |
| | lower | 0.00 | -0.33 | -0.10 | 0.29 | 0.21 | 322,360 | 123,730 |

**Industry 2**

| | Bound | $\Delta\mu_0^{fc}$ | $\Delta\mu_0^{sc}$ | $\Delta\zeta_1^{sc}$ | $\Delta\zeta_2^{sc}$ | $\Delta\zeta_3^{sc}$ | $\Delta\nu$ | Obs. |
|---|---|---|---|---|---|---|---|---|
| $\mu_0^{fc}$ | upper | 1.00 | -0.58 | 0.13 | 0.00 | 0.09 | 1,648,400 | 4,058 |
| | lower | -1.00 | 0.19 | -0.06 | -0.01 | -0.01 | -218,380 | 2,017 |
| $\mu_0^{sc}$ | upper | 1.00 | 0.66 | -0.31 | -0.59 | -0.02 | 396,180 | 2,118 |
| | lower | -1.00 | -1.00 | 0.99 | 0.24 | 0.00 | -47,464 | 12,068,000 |
| $\zeta_1^{sc}$ | upper | 0.00 | -0.28 | -0.22 | 0.17 | -0.04 | -117,620 | 499,900 |
| | lower | 0.00 | -0.18 | 0.20 | 0.21 | -0.03 | 5,214,300 | 380,730 |
| $\zeta_2^{sc}$ | upper | 0.00 | -0.27 | -0.16 | 0.09 | -0.03 | -95,104 | 467,680 |
| | lower | 0.00 | -0.23 | -0.05 | 0.37 | -0.06 | 4,964,800 | 1,054,600 |
| $\zeta_3^{sc}$ | upper | 0.00 | -0.27 | -0.13 | 0.24 | -0.40 | -95,989 | 62,616 |
| | lower | 0.00 | -0.32 | -0.12 | 0.23 | 0.13 | 2,181,400 | 23,879 |

**Industry 3**

| | Bound | $\Delta\mu_0^{fc}$ | $\Delta\mu_0^{sc}$ | $\Delta\zeta_1^{sc}$ | $\Delta\zeta_2^{sc}$ | $\Delta\zeta_3^{sc}$ | $\Delta\nu$ | Obs. |
|---|---|---|---|---|---|---|---|---|
| $\mu_0^{fc}$ | upper | 1.00 | -0.59 | 0.38 | 0.00 | 0.05 | 1,336,600 | 9,150 |
| | lower | -1.00 | 0.19 | -0.14 | -0.01 | -0.01 | -162,720 | 3,706 |
| $\mu_0^{sc}$ | upper | 1.00 | 0.73 | -0.12 | -0.64 | -0.02 | 677,930 | 4,138 |
| | lower | -1.00 | -1.00 | 0.99 | 0.18 | 0.00 | -80,319 | 17,261,000 |
| $\zeta_1^{sc}$ | upper | 0.00 | -0.27 | 0.09 | 0.21 | -0.04 | -154,710 | 1,417,700 |
| | lower | 0.00 | -0.17 | 0.20 | 0.23 | -0.02 | 960,350 | 998,920 |
| $\zeta_2^{sc}$ | upper | 0.00 | -0.25 | 0.11 | 0.11 | -0.04 | -128,230 | 1,138,300 |
| | lower | 0.00 | -0.21 | 0.11 | 0.34 | -0.04 | 1,706,500 | 3,653,900 |
| $\zeta_3^{sc}$ | upper | 0.00 | -0.28 | 0.11 | 0.21 | -0.16 | -164,500 | 400,830 |
| | lower | 0.00 | -0.21 | 0.13 | 0.20 | 0.12 | 1,144,000 | 107,310 |

**Industry 4**

| | Bound | $\Delta\mu_0^{fc}$ | $\Delta\mu_0^{sc}$ | $\Delta\zeta_1^{sc}$ | $\Delta\zeta_2^{sc}$ | $\Delta\zeta_3^{sc}$ | $\Delta\nu$ | Obs. |
|---|---|---|---|---|---|---|---|---|
| $\mu_0^{fc}$ | upper | 1.00 | -0.54 | 0.33 | 0.00 | 0.04 | 594,480 | 4,491 |
| | lower | -1.00 | 0.16 | -0.10 | -0.01 | -0.01 | -60,811 | 3,177 |
| $\mu_0^{sc}$ | upper | 1.00 | 0.73 | -0.18 | -0.65 | -0.02 | 246,970 | 3,291 |
| | lower | -1.00 | -1.00 | 0.99 | 0.16 | 0.00 | -48,614 | 11,735,000 |
| $\zeta_1^{sc}$ | upper | 0.00 | -0.25 | -0.03 | 0.18 | -0.02 | -70,731 | 1,059,100 |
| | lower | 0.00 | -0.16 | 0.22 | 0.19 | -0.01 | 324,880 | 648,950 |
| $\zeta_2^{sc}$ | upper | 0.00 | -0.23 | 0.00 | 0.09 | -0.02 | -57,363 | 869,600 |
| | lower | 0.00 | -0.20 | 0.05 | 0.32 | -0.02 | 467,740 | 2,042,400 |
| $\zeta_3^{sc}$ | upper | 0.00 | -0.28 | -0.04 | 0.20 | -0.16 | -59,121 | 170,360 |
| | lower | 0.00 | -0.23 | 0.12 | 0.22 | 0.16 | 409,280 | 43,694 |

**Industry 5**

| | Bound | $\Delta\mu_0^{fc}$ | $\Delta\mu_0^{sc}$ | $\Delta\zeta_1^{sc}$ | $\Delta\zeta_2^{sc}$ | $\Delta\zeta_3^{sc}$ | $\Delta\nu$ | Obs. |
|---|---|---|---|---|---|---|---|---|
| $\mu_0^{fc}$ | upper | 1.00 | -0.61 | 0.25 | 0.00 | 0.02 | 283,990 | 4,860 |
| | lower | -1.00 | 0.18 | -0.09 | -0.01 | -0.01 | -36,280 | 2,204 |
| $\mu_0^{sc}$ | upper | 1.00 | 0.68 | -0.28 | -0.60 | -0.03 | 79,402 | 2,452 |
| | lower | -1.00 | -1.00 | 0.99 | 0.19 | 0.00 | -29,549 | 11,500,000 |
| $\zeta_1^{sc}$ | upper | 0.00 | -0.31 | -0.13 | 0.23 | -0.04 | -37,488 | 979,580 |
| | lower | 0.00 | -0.16 | 0.20 | 0.21 | -0.03 | 313,400 | 323,980 |
| $\zeta_2^{sc}$ | upper | 0.00 | -0.31 | -0.09 | 0.15 | -0.04 | -29,973 | 757,730 |
| | lower | 0.00 | -0.21 | -0.09 | 0.33 | -0.03 | 288,130 | 1,457,400 |
| $\zeta_3^{sc}$ | upper | 0.00 | -0.30 | -0.12 | 0.23 | -0.21 | -27,443 | 198,710 |
| | lower | 0.00 | -0.28 | 0.02 | 0.24 | 0.23 | 431,800 | 32,707 |

**Industry 6**

| | Bound | $\Delta\mu_0^{fc}$ | $\Delta\mu_0^{sc}$ | $\Delta\zeta_1^{sc}$ | $\Delta\zeta_2^{sc}$ | $\Delta\zeta_3^{sc}$ | $\Delta\nu$ | Obs. |
|---|---|---|---|---|---|---|---|---|
| $\mu_0^{fc}$ | upper | 1.00 | -0.52 | 0.18 | 0.00 | 0.06 | 429,470 | 10,946 |
| | lower | -1.00 | 0.15 | -0.06 | 0.00 | -0.03 | -54,524 | 8,661 |
| $\mu_0^{sc}$ | upper | 1.00 | 0.73 | -0.34 | -0.69 | -0.11 | 86,646 | 6,916 |
| | lower | -1.00 | -1.00 | 0.99 | 0.17 | 0.00 | -23,197 | 29,306,000 |
| $\zeta_1^{sc}$ | upper | 0.00 | -0.26 | -0.23 | 0.16 | -0.16 | -28,815 | 1,830,200 |
| | lower | 0.00 | -0.15 | 0.20 | 0.18 | -0.03 | 421,220 | 796,440 |
| $\zeta_2^{sc}$ | upper | 0.00 | -0.26 | -0.19 | 0.11 | -0.15 | -24,490 | 1,642,900 |
| | lower | 0.00 | -0.18 | -0.08 | 0.29 | -0.05 | 444,300 | 2,856,100 |
| $\zeta_3^{sc}$ | upper | 0.00 | -0.32 | -0.30 | 0.21 | -0.56 | -14,972 | 509,780 |
| | lower | 0.00 | -0.24 | -0.07 | 0.19 | 0.19 | 432,050 | 143,780 |

**Industry 7**

| | Bound | $\Delta\mu_0^{fc}$ | $\Delta\mu_0^{sc}$ | $\Delta\zeta_1^{sc}$ | $\Delta\zeta_2^{sc}$ | $\Delta\zeta_3^{sc}$ | $\Delta\nu$ | Obs. |
|---|---|---|---|---|---|---|---|---|
| $\mu_0^{fc}$ | upper | 1.00 | -0.54 | 0.35 | 0.00 | 0.04 | 911,670 | 19,401 |
| | lower | -1.00 | 0.15 | -0.11 | -0.01 | -0.01 | -91,434 | 15,278 |
| $\mu_0^{sc}$ | upper | 1.00 | 0.75 | -0.15 | -0.68 | -0.02 | 334,670 | 15,969 |
| | lower | -1.00 | -1.00 | 0.98 | 0.17 | 0.00 | -54,246 | 48,288,000 |
| $\zeta_1^{sc}$ | upper | 0.00 | -0.24 | 0.02 | 0.15 | -0.02 | -85,650 | 4,957,200 |
| | lower | 0.00 | -0.16 | 0.23 | 0.18 | -0.01 | 649,930 | 3,291,400 |
| $\zeta_2^{sc}$ | upper | 0.00 | -0.23 | 0.04 | 0.08 | -0.02 | -74,199 | 4,245,200 |
| | lower | 0.00 | -0.18 | 0.08 | 0.31 | -0.02 | 674,990 | 9,073,800 |
| $\zeta_3^{sc}$ | upper | 0.00 | -0.22 | -0.04 | 0.13 | -0.14 | -87,244 | 938,590 |
| | lower | 0.00 | -0.22 | 0.10 | 0.21 | 0.15 | 740,030 | 439,510 |

**Industry 8**

| | Bound | $\Delta\mu_0^{fc}$ | $\Delta\mu_0^{sc}$ | $\Delta\zeta_1^{sc}$ | $\Delta\zeta_2^{sc}$ | $\Delta\zeta_3^{sc}$ | $\Delta\nu$ | Obs. |
|---|---|---|---|---|---|---|---|---|
| $\mu_0^{fc}$ | upper | 1.00 | -0.55 | 0.36 | 0.00 | 0.01 | 3,619,500 | 2,334 |
| | lower | -1.00 | 0.15 | -0.11 | -0.01 | 0.00 | -223,200 | 1,536 |
| $\mu_0^{sc}$ | upper | 1.00 | 0.77 | -0.15 | -0.69 | 0.00 | 920,590 | 1,746 |
| | lower | -1.00 | -1.00 | 0.98 | 0.17 | 0.00 | -151,860 | 5,819,300 |
| $\zeta_1^{sc}$ | upper | 0.00 | -0.26 | 0.04 | 0.18 | -0.01 | -248,480 | 452,100 |
| | lower | 0.00 | -0.15 | 0.23 | 0.20 | 0.00 | 1,583,900 | 403,300 |
| $\zeta_2^{sc}$ | upper | 0.00 | -0.26 | 0.08 | 0.11 | 0.00 | -229,150 | 403,350 |
| | lower | 0.00 | -0.18 | 0.10 | 0.33 | 0.00 | 3,942,400 | 1,025,100 |
| $\zeta_3^{sc}$ | upper | 0.00 | -0.37 | 0.13 | 0.26 | -0.05 | -155,790 | 60,322 |
| | lower | 0.00 | -0.22 | 0.09 | 0.22 | 0.07 | 2,137,500 | 67,471 |

*Notes: Differences in profits are expressed in 1982 rupees. Besides the restrictions imposed above, we also impose the restrictions that the sum of the startup-cost-abatement parameters ($\zeta$) cannot be larger than the total startup cost $\mu_0^{sc}$, and that no costs in the estimation can be negative.*