Technology and Production Fragmentation: Domestic vs. Foreign Sourcing, *by* Teresa C. Fort

A Data Appendix–For online publication only

A.1 Import behavior by CMS purchase status

The CMS data do not provide information on the countries from which offshoring firms source. I therefore use the linked CMS-firm data to provide richer information on foreign sourcing decisions. Table A.6 presents the average extent to which firms offshore, measured as firms' imports over sales. Column 1 shows that domestic fragmenters source a relatively small share of their production offshore. Their average imports over sales is only three percent, compared to 20 percent for firms that primarily offshore. Somewhat surprisingly, firms with no CMS purchases import an average of nine percent of their sales. To assess whether this high share may result from industry compositional differences or sales in other sectors, I calculate firms' share of imports over sales relative to the average share of their modal industry. Excluding firms with employment outside of manufacturing, the relative shares are 0.67, 0.68 and 3.9 for non-purchasers, domestic fragmenters, and offshorers respectively. Offshoring firms' share of imports over sales is almost four times their industry average, while non-purchasers and domestic fragmenters' share is less than their industry mean. Column 2 shows firms' share of imports from low-income countries. I classify countries as low income if they are in the bottom two per-capita GDP terciles.[1] Firms with no CMS purchases and domestic CMS purchases import 28 and 19 percent of their manufactured good imports from low-income countries respectively. In contrast, offshorers source almost half of their imports from low-income countries.

Table A.6 also presents information about the products and countries from which firms import. Column 2 shows that the median count of distinct ten digit Harmonized System (HS) codes imported by firms is zero for firms with no CMS purchases and one for domestic fragmenters. In contrast, firms that purchase CMS offshore import a median of eight distinct products, and firms with both domestic and offshore purchasing plants import a median of 123 products. Column 3 shows that this pattern holds for the subset of importing firms in each category. Columns 4 and 5 provide the same statistics for the number of countries from which a firm imports. Firms with no CMS purchases import from a median of zero countries, domestic fragmenters import from a median of one, and offshorers import from a median of three. Firms with a mix of plants that source domestically and others that source offshore import from a median count of 20 countries. Conditional on importing, firms that source primarily offshore still import from more countries than firms that fragment domestically or not all.

[1] I obtain countries' per-capita GDP in 2007 from the International Monetary Fund. The GDP data are unavailable for a small number of countries that represent less than one percent of imports in each CMS category.

A.2 Variable Descriptions

Electronic Networks: I measure whether a plant used electronic networks in 2007 with a dummy variable equal to one for plants that report using an electronic network to control or coordinate shipments. The precise question from the 2007 Census of Manufactures is:

❻ E-SHIPMENTS

A. Did this plant use any electronic network to control or coordinate the flow of any of the shipments of goods reported in ❺, line A? Or, were the orders for any of the shipments reported in ❺, line A received over an electronic network?

Electronic networks include:

- Electronic Data Interchange (EDI)
- E-mail
- Internet
- Extranet
- Other online systems

0181 ☐ Yes - *Go to line B* 0182 ☐ No - *Go to* ❼

2007	2006

Although the question asks about establishments' use of electronic networks to control or coordinate shipments, data from the the 1999 Annual Survey of Manufactures (ASM) Computer Survey Network Use Supplement (CNUS) show that plants' use of electronic networks to sell goods is correlated with their use of networks to purchase inputs. I find that plants' acceptance of online orders for their manufactured products has a correlation coefficient of .23 with their use of networks to purchase materials or supplies. In addition, 32 percent of plants that sell goods over networks also use networks to provide information about their design specifications to external suppliers, compared to only 16 percent of plants that do not sell goods over networks. The same pattern (30 percent vs. 16 percent) holds for plants that do or do not use networks to purchase inputs. These findings support the premise that plant use of electronic networks to control or coordinate shipments is a good proxy for a plant's use of technology to communicate with suppliers.

I measure plants' use of electronic networks in 2002 using data from this similar question in the 2002 Census of Manufactures:

E-COMMERCE SALES, SHIPMENTS, RECEIPTS, OR REVENUE

A. Did any of the amount reported in ❹, line A include e-commerce sales, shipments, or receipts? *(E-commerce sales, shipments, or receipts are online orders for products from customers where price and/or terms of the sale are accepted or negotiated over an Internet, Extranet, Electronic Data Interchange (EDI) network, electronic mail, or other online system. Payment may or may not be made online.)*

0181 ☐ Yes - *Go to line B* 0182 ☐ No - *Go to* ❻

2002

CAD/CAM Industry Intensity: I measure industry intensity of Computer Aided Design (CAD) and Computer Aided Engineering (CAE) using the Computer Survey Network Use Supplement (CNUS) from the 1999 Annual Survey of Manufactures (ASM). The CNUS asked manufacturing establishments a number of questions about their use of different types of technology. I use the following question to identify whether a particular establishment used CAD/CAE software in 1999:

For each of the following **computer networked business processes**, please indicate below whether this **plant** currently uses or plans to begin using by December 2002.	Uses now	Plans to use by 12/2002	No plans to use by 12/2002

c. Production Management	**(1)** Integrated CAD/CAE (Computer Aided Design/Computer Aided Engineering)	○	○	○
	(2) Design of the production process	○	○	○
	(3) Production scheduling	○	○	○
	(4) Production monitoring	○	○	○
	(5) Test and acceptance of product	○	○	○
	(6) Outsourcing of research and development	○	○	○

I construct an indicator for all plants that used CAD in 1999 and calculate the share of plants in an industry using CAD relative to plants that did not use CAD and had no plans to use it by 2002. I do not include plants that report planning to use CAD by 12/2002. The ASM is not a representative sample, so I use weights provided in the CNUS to avoid any potential selection bias. I calculate the CAD measure at the NAICS 6 level.

Industry CAD intensity ranges from almost zero to one, with a mean of 0.44 and standard deviation of 0.25. The least CAD intensive industries are food manufacturing and textiles, while automotive, aerospace and machinery manufacturing are all CAD intensive. Table A.1 presents correlation coefficients of industry CAD intensity and various industry-level measures. Consistent with the premise that CAD facilitates communication about design specifications, the share of plants in an industry that use CAD software is highly correlated with the industry fraction of plants that report using electronic networks to share their product designs with suppliers, as well as with the fraction that share designs electronically with other company units. The correlation coefficients with CAD intensity are 0.49 and 0.54 respectively, with p-values of 0.00.

Industry CAD intensity is also positively correlated with industry capital intensity and skill intensity, with correlation coefficients of 0.09 and 0.16 respectively.[2] CAD intensity also seems to be higher in industries that use more differentiated inputs. The correlation coefficient between industry CAD intensity and the fraction of inputs not sold on an exchange and not reference priced, as calculated by Nunn (2007), is 0.26 and significant at the one percent level. Finally, I investigate whether CAD-intensive industries may have already experienced significant offshoring of the entire physical transformation process. To do so, I calculate the ratio of industry imports by wholesale firms relative to domestic production. There is a significant contingent of plants classified in the wholesale sector that design goods and coordinate production processes in foreign locations (see Bernard and Fort, 2015, for details on these firms). The second to last row of Table A.1 shows that the ratio of industry imports by wholesale firms with no U.S. manufacturing plants relative to the value of U.S. manufacturers' production is unrelated to industry CAD intensity. The bottom row shows a similar result for imports by all wholesale firms, including those with U.S. manufacturing establishments.

U.S. Wage Data: I use 2006 U.S. wage data from the Bureau of Labor Statistics' Occupational Employment Statistics (OES) Survey to measure production worker wages by state and industry. The state level data provide the mean wage by six-digit occupation. I limit the data to the 110 "Production occupations" and match them to national OES data on occupations and four-digit NAICS industries.

[2] Capital intensity is measured as total assets owned by plants in an industry at the beginning of 2007 relative to the industry's total employment. Skill intensity is the share of non-production workers in an industry relative to total employment. All variables are from the 2007 U.S. Census of Manufactures.

I use the national data to determine the occupational intensity of each industry, which I calculate as the share of workers in a given occupation in the industry's total employment of production occupation workers. I match the national share of each occupation within an industry to the state-occupation level wage data. I then compute the state-industry wage as the average, weighted by the national industry share, of each occupation's wage within an industry. The wage for industry j in state h is then:

$$wage_{hj} = \sum_{o \in j} [wage_{o,h} \times \frac{emp_{o,j,US}}{emp_{j,US}}], \tag{A.1}$$

where o denotes occupations. In principle, this methodology avoids attributing wage differences across industries and states to compositional differences in a state's employees. In practice, occupations are unevenly distributed across states so that some states do not have employment, and therefore wage values, for certain occupations. For example, only three states have nuclear power operators, seven have shoe machine operators, and 15 have semiconductor processors.[3] In addition, some states are missing wage data for some of their occupations. To ensure that the shares of employment in each state-industry combination sum to one, I use the average state wage for the five-digit occupation (or four-digit occupation if the five-digit occupation wage is missing) to which the missing occupation belongs.

Relative Foreign Wages: The foreign wage data are from the International Labor Organization and available for 1983-2003. I use monthly wages in US $s provided by Oostendorp (2005). I construct relative foreign wages for each industry-occupation as w^*/w_{US}, where w^* denotes the wage in a foreign country. This relative wage follows the theoretical framework and provides a unit free measure that applies to specific industries and occupations. To the extent that skill varies by industry and occupation, the relative wage controls for compositional differences in countries' wages that are driven by workers of varying skill levels. I primarily use wages from 2000 because it is the most recent year of complete data. When the 2000 data are missing for a given country-industry-occupation, I use data from the closest year. Because the relative wage is unit free, it is not affected by dollar inflation, though significant changes in the exchange rate over time may cause measurement problems for data substitution from other years. I match the ILO data to NAICS industries by hand and average over industries to obtain a relative foreign wage in a given NAICS industry. The industries vary from three-digit to six-digit NAICS. Despite substituting missing values with data from alternate years, there are still missing data. When available, I replace missing data with the average wage for a higher level of NAICS aggregation in a given country. There are some countries for which no data are available. Since identifying sourcing locations is a primary focus of this paper, country-specific characteristics are critical and I therefore do not impute data for the missing countries.

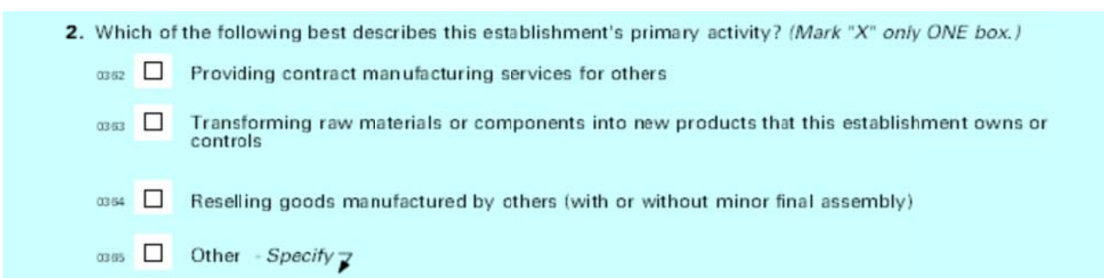
Skill measures: I measure state worker skill as the share of workers with at least a college degree using the 2007 data from the American Community Survey (ACS).

[3] The uneven distribution of occupations across the country is consistent with production fragmentation. It also suggests an important role for the substitutability of labor in a given location, for a given industry. I do not address this dimension of variation as a determinant of fragmentation.

Deep Water Ports: I identify all potentially relevant water ports using data from the Maritime Administration's Port Import Export Reporting Service (PIERS).[4] The data are collected from vessel manifests and bills of lading and provide imports, measured by number of shipping containers in twenty-foot equivalent units (TEUs), by port. To ensure the ports correspond to viable import channels, I restrict the ports to deep water ports with a value of imports greater than 100 TEUs. (I except Anchorage, Alaska from this exclusion criterion since it imported 92 TEUs in 2007, but is the largest viable import port in Alaska.) Latitude and longitude for each port are from the Intermodal Terminal Facility database from the Research and Innovative Technology Administration's Bureau of Transportation Statistics (RITA/BTS) National Transportation Atlas Databases (NTAD) 2010.[5] This database is missing Port Manatee, FL and the Port of Honolulu, HI so I obtain latitude and longitude for these ports from: `www.worldportsource.com/states.php`. The final port data are available at `http://faculty.tuck.dartmouth.edu/teresa-fort/data`.

Border Crossings: I identify all potential border crossings with Canada and Mexico using border crossing/entry data from RITA/BTS.[6] The data originate from the U.S. Department of Homeland Security, Customs and Border Protection, OMR database. There are 86 Canadian and 25 Mexican entry ports into the U.S. I exclude the crossings that had no truck traffic in 2007 to obtain 82 Canadian and 22 Mexican potential crossing points. I attach latitudes and longitudes to these crossings using the centroid for the county in which the port is located. The final data are available at `http://faculty.tuck.dartmouth.edu/teresa-fort/data`.

Domestic suppliers The CMS sample also has information about plants' primary activity. Treating all plants that identify their primary activity as "Providing contract manufacturing services to others", I calculate the distance between each manufacturing plant in the CMS sample and the closest manufacturing service provider (MSP). The precise question I use to identify MSPs is provided below.



2. Which of the following best describes this establishment's primary activity? *(Mark "X" only ONE box.)*

0362 ☐ Providing contract manufacturing services for others

0363 ☐ Transforming raw materials or components into new products that this establishment owns or controls

0364 ☐ Reselling goods manufactured by others (with or without minor final assembly)

0365 ☐ Other *- Specify*

[4]The data are available here: `www.marad.dot.gov/library_landing_page/data_and_statistics/Data_and_Statistics.htm`.

[5]Data available here: `www.bts.gov/publications/national_transportation_atlas_database/`.

[6]The data can be downloaded here: `http://www.bts.gov/programs/international/transborder/TBDR_BC/TBDR_BCQ.html`.

A.3 Fragmentation and industry characteristics

Table A.2 shows how fragmentation and offshoring, as well as their relationship with technology, relate to industry characteristics. Each column in Panel A reports the results from a series of bivariate ordinary least squares regressions in which industry shares, listed in the left column, are regressed ex-post on the industry characteristic listed at the top of the column. I also calculate an industry-specific estimate of the relationship between plant technology and fragmentation (or offshoring). To do so, I regress a fragmentation (or offshoring) indicator on an industry-by-plant technology indicator. Panel B reports results from a series of bivariate regressions in which these industry-by-technology fragmentation and offshoring estimates are regressed ex-post on industry characteristics. Finally I regress an indicator equal to one if an offshoring firm sources from a particular country on industry-by-technology-by-country human capital tercile indicators, with middle skill countries as the omitted category. Panel C reports results from regressing these industry-by-technology-by country human capital estimates on industry characteristics. The industry regressions are all weighted by the number of plants in an industry and I report Huber-White standard errors to allow for heteroskedasticity.

A.4 Robustness of wages and distance results

Table A.4 presents several robustness tests for the wage and distance estimates presented in Table 4. If local demand and wages are correlated, then the estimated wage coefficient will be biased. I assess this potential issue by controlling for personal income in the plant's economic area, as defined by the Bureau of Economic Analysis (BEA) economic areas.[7] Columns 1 and 4 in Table A.4 show that controlling for local demand does not affect the estimated coefficients.

Another potential concern is that the wage estimate is biased by differences in worker skill across states. Although the wage measure is based on wage differences within detailed occupation codes across states, it may still reflect skill heterogeneity. To assess the extent to which the wage estimate is biased by skill, I construct skill measures that vary by state. Columns 2 and 5 in Table A.4 show that the wage coefficient is robust to these controls.[8]

As an alternative measure of the distance to domestic suppliers, I construct a weighted average to a plant's input suppliers. First, I use I-O tables to determine the requisite inputs of production for each industry and to calculate the fraction of expenditure on each of these inputs. I assume that all plants in an industry use all of the inputs listed in the I-O tables in their production process with the same weights. Using the plant-level Census of Manufactures data, I then calculate the distance between each plant in my sample and the closest manufacturing plant that produces each input, where a plant's production is based on the plant's industry. As an example, suppose that car manufacturing

[7]There are 179 BEA economic areas. These areas are designed to capture relevant regional markets surrounding metropolitan or micropolitan statistical areas.

[8]I have also estimated equation (3.1) controlling for the share of state workers with an associate's degree and a high school degree, and the share of production workers with a college degree and an associate's degree. In all cases, the estimated coefficients on the variables of interest are largely unchanged.

uses tires (10 percent), glass (5 percent), and metal (85 percent). I calculate the distance to the closest tire, glass, and metal manufacturers and then construct a single weighted distance for each car manufacturing plant, where the weights are the value of each type of input in total input costs for the plant's industry.

Columns 3 and 6 in Table A.4 show that the weighted distance measure suggests an even more important role for distance than the

B Theory Appendix–For online publication only

In this appendix, I present a model of domestic and foreign fragmentation by heterogeneous firms. Because the purpose of the model is to understand firm-level decisions, I do not aggregate the model to solve for the industry equilibrium.

Let E denote aggregate expenditure in a representative industry (I omit industry subscripts for notational simplicity). Preferences across varieties for the representative industry have the standard CES form, with an elasticity of substitution $\varepsilon = \frac{1}{1-\sigma} > 1$. These preferences lead to demand for a particular variety i in a given industry,

$$q(i) = Ap(i)^{-\varepsilon}, \ A = \frac{E}{\int_{i \in j} p(i)^{1-\varepsilon} di} \tag{B.1}$$

where $p(i)$ is the price of variety i and A is exogenous to an individual firm.

Labor is the only factor of production and is supplied inelastically. Producers use one unit of labor to produce one unit of task output. Production requires a continuum of tasks, indexed by k. Producers combine task output via a Leontief production function to produce a single composite input M, as in Rodríguez-Clare (2010). More formally, $M = min_k\{m_k\}$, $k \in [0, 1]$, where m_k denotes the output of task k.[9] For expositional simplicity, I normalize the number of tasks in the representative industry to one. Since tasks are defined by a unit labor requirement, the empirical analysis controls for the potential that industries differ in the number of tasks required to produce M. Producers have heterogeneous productivity, denoted by $\varphi > 0$, and transform the composite input M into their product via: $q = \varphi M$.

B.1 Profits with no fragmentation

With CES preferences, the optimal final good price is a mark-up over marginal cost given by $p_i(\varphi) = C_i/\varphi\sigma$, where C_i denotes the marginal cost of the input M for firm i. Let w_h denote the wage in the producer's home state. Because producers make m_k one-to-one from labor, the cost of one unit of M

[9] The assumption of no substitutability between tasks that use the same factor of production is common in the literature and simplifies the analysis. The model could be extended so that the composite input is produced via a constant elasticity of substitution technology that depends on the intensity with which each task is performed.

at the integrated producer is $C_i = w_h$ and its profits are:

$$\pi_I = \frac{(1-\sigma)A}{\sigma^{(1-\varepsilon)}} \left[\frac{\varphi}{w_h}\right]^{(\varepsilon-1)}. \tag{B.2}$$

B.2 Profits with fragmentation

Fragmentation allows producers to purchase task output from a manufacturing service provider (MSP) in another location with potentially lower labor costs.[10] The assumption that wage differences exist within a country for the same quality of labor is supported by empirical evidence (e.g., Bernard et al., 2013). I assume perfect competition among MSPs so that the price of a task purchased from an MSP in another domestic (D) or offshore (O) sourcing location s is given by $P_s(m_k) = w_s$, where $s \in \{D, O\}$.[11] By assuming that a firm can only source from a domestic or foreign location, the model does not address the role of interdependencies in firms' sourcing decisions. See Blaum et al. (2013) and Antràs et al. (2014) for a discussion of these extensive margin interdependencies and how to address them.

While fragmentation allows a producer to access cheaper labor, it also entails certain costs. Establishing a supply network incurs a fixed cost f_D when the MSP is domestic and f_O when the MSP is foreign, with $f_D < f_O$. Fragmentation also incurs a task specific cost due to the additional transportation and coordination needs associated with breaking up the production function across locations. The fragmentation cost for firm i in industry j to source task k from location s is represented by the function:

$$\tau(\delta_{is}, \omega_k, \eta_i, \gamma_s, \rho_j) \geq 1, \tag{B.3}$$

which I assume is continuously differentiable in all its arguments. δ_{is} denotes the distance between the final good producer and the sourcing location s. Transportation costs are increasing in distance so that $\frac{\partial\tau}{\partial\delta} > 0$. ω_k represents an inherent characteristic, such as weight or complexity, of the output from task k. Tasks can be ordered on the continuum from zero to one such that $\frac{\partial\tau}{\partial\omega} > 0$ reflects task-specific differences in fragmentation costs attributable to these inherent differences. This attribute of the cost function is similar to Grossman and Rossi-Hansberg (2008). η_i captures producer i's information technology, and γ_s reflects the human capital in the sourcing location. I assume technology lowers fragmentation costs so that $\frac{\partial\tau}{\partial\eta} < 0$. ρ_j represents the extent to which production technology in industry j is amenable to electronic communication. If electronic communication about the production process lowers fragmentation costs, then $\frac{\partial^2\tau}{\partial\eta\,\partial\rho} < 0$. Intuitively, a firm's communication technology will have a bigger impact on costs when its production process can be codified in an electronic format. A sourcing location's human capital may also have an impact on the effectiveness of technology. If so, then we expect the cost-reducing effect of firm and industry technology to increase in the

[10] MSP is the term used by practitioners and the U.S. Census Bureau to describe these suppliers.

[11] In this setup, fragmentation lowers production costs only through a cheaper wage. In practice, MSPs also enjoy gains to specialization that provide an incentive for fragmentation even when wages are the same. The model can easily be extended to capture this by assuming MSPs require $\alpha < 1$ units of labor per task output.

sourcing location's human capital ($\frac{\partial^2 \tau}{\partial \eta_i \partial \gamma_s} < 0$ and $\frac{\partial^2 \tau}{\partial \rho_j \partial \gamma_s} < 0$.) Finally, the effect of electronic communication on fragmentation costs may also depend upon country human capital. In other words, the differential effect across industries of firm technology may be an increasing function of human capital ($\frac{\partial^3 \tau}{\partial \eta_i \partial \rho_j \partial \gamma_s} < 0$).

An important limitation of these assumptions is that the model allows for a differential impact of human capital on the cost-lowering effects of firm and industry technology, but not on production costs across countries. In other words, the model assumes that wage differences reflect unit labor costs that are adjusted for differences in worker output due to skill or other factors. In the empirical implementation, it will be important to control for skill differences and other factors that could lower production costs across countries.

Final good producers pay the task specific fragmentation costs in units of labor from sourcing location s. The per-unit cost to final good producer i for task k purchased from an MSP in location s is:

$$c_{kijs} = w_s \tau(\delta_{is}, \omega_k, \eta_i, \eta_s, \rho_j). \tag{B.4}$$

Fragmenting only maximizes variable profits if it results in lower costs of task production. Without loss of generality, order tasks such that fragmentation costs are strictly increasing in the index k for a given location. A necessary, though not sufficient, condition for fragmentation is then

$$w_h > w_D \tau_D(0) \text{ or} \tag{B.5a}$$

$$w_h > w_O \tau_O(0), \tag{B.5b}$$

where D and O denote the lowest cost domestic and offshore locations respectively, and $\tau(0)$ denotes the fragmentation cost of task $k = 0$. Equation (B.5) simply states that the task with the lowest fragmentation cost must be cheaper to fragment, either domestically or offshore, than to produce in an integrated plant. Whenever equation (B.5a) holds, then for offshoring to be potentially viable, it must also be the case that

$$\frac{w_O}{w_D} < \frac{\tau_D(0)}{\tau_O(0)}. \tag{B.6}$$

In this case, the decision to offshore is independent of the home wage and depends only on the relative costs and benefits of sourcing from the firm's lowest cost domestic location relative to its lowest cost foreign location.

Equations (B.5) and (B.6) highlight the role of relative wages and costs in determining whether fragmentation and offshoring take place. If the wage differential is not sufficiently high relative to fragmentation costs, then producers will not fragment and non-participation arises without any role for fixed costs and productivity.[12]

When a producer only sources from one location s, then its optimal share of fragmented production,

[12]The other potential corner solution is $w_h > w_s \tau_s(1)$, where $s \in \{D, O\}$. In this case, producers fully fragment. Since the focus of this paper is on U.S. manufactures that still perform some fraction of their physical transformation activities, I assume w_h is sufficiently low relative to costs so that full fragmentation does not occur.

$\bar{k}_s$, is implicitly defined by

$$w_h = w_s \tau_s(\bar{k}_s), \text{ where } s \in \{D, O\}. \tag{B.7}$$

The cost of the composite input M, for producer i sourcing from s is then:

$$C_{is} = (1 - \bar{k}_s) w_h + w_s \int_0^{\bar{k}_s} \tau_{is}(k)\, dk, \text{ where } s \in \{D, O\}. \tag{B.8}$$

Figure B.1a illustrates the case where offshoring maximizes variable profits by minimizing the cost of producing M.

This new cost for the composite input M results in the following profits for producer i:

$$\pi_{is} = \frac{(1-\sigma)A}{\sigma^{(1-\varepsilon)}} \left(\frac{\varphi}{C_{is}} \right)^{(\varepsilon-1)} - f_s, \text{ where } s \in \{D, O\}. \tag{B.9}$$

B.3 Derivations of the productivity thresholds

In equilibrium, final good producer i chooses the sourcing location s that maximizes profits $max_s\{\pi_{is}\}$, where $s \in \{I, D, O\}$. Since fragmentation entails a fixed cost, it will never occur if Equation (B.5) does not hold. In this section, I determine the optimal fragmentation strategy for the subsets of producers in a geographic state for whom: (i) domestic fragmentation maximizes variable profits; (ii) offshoring maximizes variable profits. I first determine producers' optimal share of fragmented tasks, and then identify those producers' profit maximizing decision.

Producers who face costs $c_{kiD} < c_{kiO}$ $\forall k$ represent the subset of producers for whom domestic fragmentation maximizes variable profits, N_D. Figure B.2a illustrates this cost scenario. In the figure, C_D, the cost of the composite M defined in Equation (B.8), is simply the area under the bold line. Because domestic fragmentation also entails a fixed cost, Figure B.2b depicts the optimal sourcing strategy for firms with these wage and cost conditions. Fragmentation lowers marginal costs and therefore results in a profit function that is steeper in $\varphi^{\varepsilon-1}$, but the fixed cost to fragment means that, of the producers in the set N_D, only those with productivity above the threshold

$$\tilde{\varphi}_D = \left[\frac{\sigma^{1-\varepsilon}}{(1-\sigma)A} \left(\frac{f_D}{C_D^{1-\varepsilon} - w_h^{1-\varepsilon}} \right) \right]^{\frac{1}{\varepsilon-1}}, \tag{B.10}$$

find it optimal to fragment domestically.

The subset of producers for whom offshore fragmentation maximizes variable profits face costs $c_{kiD} > c_{kiO}$ $\forall k$. Figure B.1a depicts this situation. C_O, the cost of the composite input M, is the area under the bold line. The cost of M under offshoring is clearly lower than the cost with domestic fragmentation, which is the lower than the cost from integrated production. If the relative fixed costs are small compared to the relative costs of M under domestic versus offshore fragmentation, then optimal profits are similar to those in Figure B.2b, except here only integrated production or offshoring take place. However, if relative fixed costs are large compared to relative savings, or

$$\frac{f_O}{f_D} > \frac{C_O^{1-\varepsilon} - w_h^{1-\varepsilon}}{C_D^{1-\varepsilon} - w_h^{1-\varepsilon}},$$

then integrated production, domestic fragmentation, and offshoring are all possible profit maximizing strategies. Figure B.1b depicts this case. Producers with productivity between $\tilde{\varphi}_D$ and $\tilde{\varphi}_O$, fragment domestically, while those with productivity above $\tilde{\varphi}_O$ offshore, where

$$\tilde{\varphi_O} = \left[\frac{\sigma^{1-\varepsilon}}{(1-\sigma)A}\left(\frac{(f_O - f_D)}{C_O^{1-\varepsilon} - C_D^{1-\varepsilon}}\right)\right]^{\frac{1}{\varepsilon-1}}. \tag{B.11}$$

B.4 Comparative Statics

The model provides a framework in which to assess how changes in producer technology, distance to suppliers, and labor cost differences affect the decision to fragment production. This section assesses how these factors affect: (i) whether or not fragmentation is potentially feasible (i.e., the impact on variable profits), and (ii) total profits.

B.4.1 Variation in producer's technology

The model predicts that plants with better communication technology, η, will face lower fragmentation costs. In particular, the cost of the composite input M for a producer fragmenting from location s is decreasing in technology, according to:

$$\frac{\partial C_s}{\partial \eta} = \frac{\partial \bar{k}_s}{\partial \eta}\left[\alpha w_s \tau(\bar{k}_s) - w_h\right] + \alpha w_s \int_0^{\bar{k}_s} \frac{\partial \tau(k)}{\partial \eta}\, dk < 0. \tag{B.12}$$

The term in square brackets in Equation (B.12) is equal to zero from Equation (B.7).[13] The second term represents the inframarginal savings that result from better technology. Holding distance and wage differences constant, an improvement in communication technology decreases fragmentation costs. This decrease means that fragmentation is now potentially viable for a larger set of firms.

Producers for whom fragmentation already maximized variable profits are also more likely to fragment production in response to improvements in their communication technology. The change in fragmentation profits from an improvement in technology η is:

$$\frac{\partial \pi_s}{\partial \eta} = (1-\varepsilon)B[C_s]^{-\varepsilon}\frac{\partial C_s}{\partial \eta}, \tag{B.13}$$

[13] This is essentially the envelope condition in that the impact of changes in the share of tasks fragmented on profits is zero to the first order. As is true for all derivatives, this expression holds for small changes in η. Figure B.2a shows that the derivative may not capture the effect of large changes in η on task production costs.

where

$$B \equiv \frac{(1-\sigma)A}{(\sigma\varphi)^{1-\varepsilon}}.$$

Plugging in Equation, (B.12), better technology increases fragmentation profits. Since π_I is unaffected by the change, this implies a lowering of the productivity threshold above which fragmentation is optimal.

B.4.2 Variation in the home wage

An increase in the producer's home wage, w_h, makes fragmentation relatively more profitable. The change in integrated profits relative to fragmented profits is

$$\frac{\partial \pi_I/\partial w_h}{\partial \pi_s/\partial w_h} = \frac{[w_h]^{-\varepsilon}}{(1-\bar{k}_s)[C_s]^{-\varepsilon}}. \tag{B.14}$$

Plugging in the equation for C_s and simplifying shows that the decrease in profits from integrated production is always greater than the decrease from fragmented production whenever

$$(1-\bar{k}) + \frac{1}{\tau(\bar{k})}\int \tau(k)dk > (1-\bar{k})^{(1/\varepsilon)}, \tag{B.15}$$

which is a condition that always holds whenever $\bar{k} > 0$.

B.5 Domestic versus offshore sourcing

Of the firms that fragment production, only those with productivity above $\tilde{\varphi}_O^{\varepsilon-1}$ do so offshore. Since the slope of the offshoring profit function depends upon fragmentation costs, the likelihood of exceeding $\tilde{\varphi}_O^{\varepsilon-1}$ is also decreasing in the distance between a firm and its potential offshore sourcing locations. More formally

$$\frac{\partial \tilde{\varphi}^{\varepsilon-1}}{\partial \delta} = \left[\frac{\partial C_O}{\partial \delta} - \frac{\partial C_D}{\partial \delta}\right]\left(\frac{w_h(f_O - f_D)}{\left[C_O^{1-\varepsilon} - C_D^{1-\varepsilon}\right)^2}\left(\frac{\sigma^{2-\varepsilon}A}{(1-\sigma)^2}\right)\left(C_O^{-\varepsilon} - C_D^{-\varepsilon}\right)\right). \tag{B.16}$$

The three terms inside the parentheses are positive, so the effect on the offshoring threshold depends upon the sign of the terms in the square brackets. If a decrease in distance to foreign suppliers does not affect plants' distance to domestic suppliers, then the second term is zero and Equation (B.16) is positive. The offshoring threshold is therefore higher, leading to the following prediction:

The offshoring threshold also depends upon communication technology. Specifically, the effect of changes in technology on the productivity threshold is given by

$$\frac{\partial \tilde{\varphi}^{\varepsilon-1}}{\partial \eta} = \left[\frac{\partial C_O}{\partial \eta} - \frac{\partial C_D}{\partial \eta}\right]\left(\frac{w_h(f_O - f_D)}{\left[C_O^{1-\varepsilon} - C_D^{1-\varepsilon}\right]^2}\left(\frac{\sigma^{2-\varepsilon}A}{(1-\sigma)^2}\right)\left(C_O^{-\varepsilon} - C_D^{-\varepsilon}\right)\right) \tag{B.17}$$

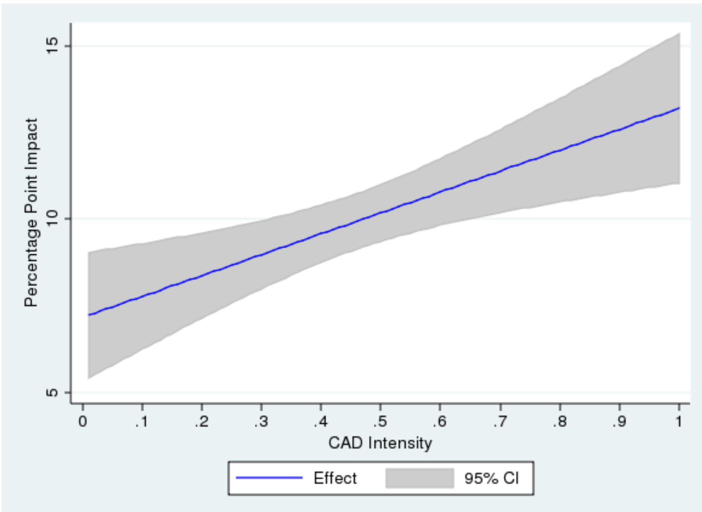
The terms in parentheses are positive, so the offshoring threshold is decreasing in technology as long as $\frac{\partial C_O}{\partial \eta} < \frac{\partial C_D}{\partial \eta}$. Plugging in Equation (B.12) shows that an improvement in communication technology will make offshoring relatively more profitable than domestic fragmentation if the inframarginal cost savings from offshored production exceed the inframarginal cost savings of domestic fragmentation. Consider the case depicted in Figure B.1a where $c_{iD} > c_{iO}$. In this case, offshoring maximizes variable profits, but the higher fixed cost to offshore induces domestic fragmentation over some range of φ. Under these conditions, the terms in the first set of brackets in Equation B.17 can be expressed as

$$\alpha w_O \int_{\bar{k}_D}^{\bar{k}_O} \frac{\partial \tau_O(k)}{\partial \eta}\, dk + \alpha w_O \int_{0}^{\bar{k}_D} \frac{\partial \tau_O(k)}{\partial \eta}\, dk - \alpha w_D \int_{0}^{\bar{k}_D} \frac{\partial \tau_D(k)}{\partial \eta}\, dk. \tag{B.18}$$

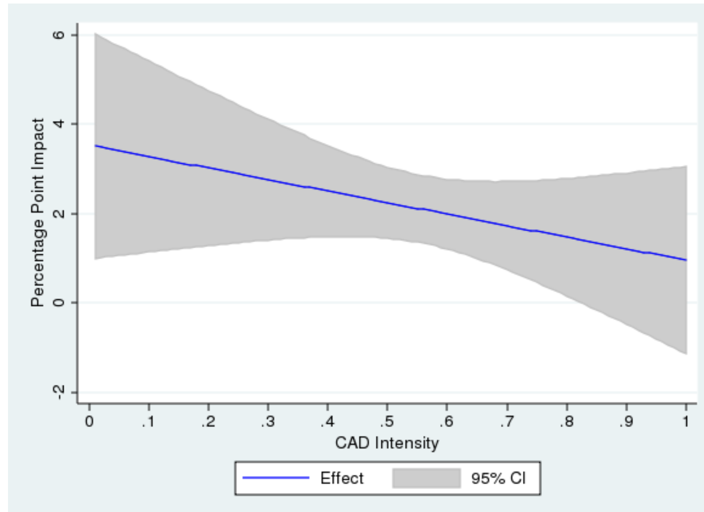
The first term is always negative, while the second two terms offset each other if the technology shock affects all tasks and domestic and offshore costs equally. When this occurs, a technology improvement will lower a firm's offshoring threshold, making it more likely that the firm offshores. In contrast, if the technology shock lowers domestic fragmentation costs relatively more than offshoring costs, the offshoring threshold may rise, thereby decreasing the likelihood that a given firm will exceed the threshold.

Online Appendix Figures and Tables

Figure A.1: Differential impact of electronic networks, by industry CAD intensity



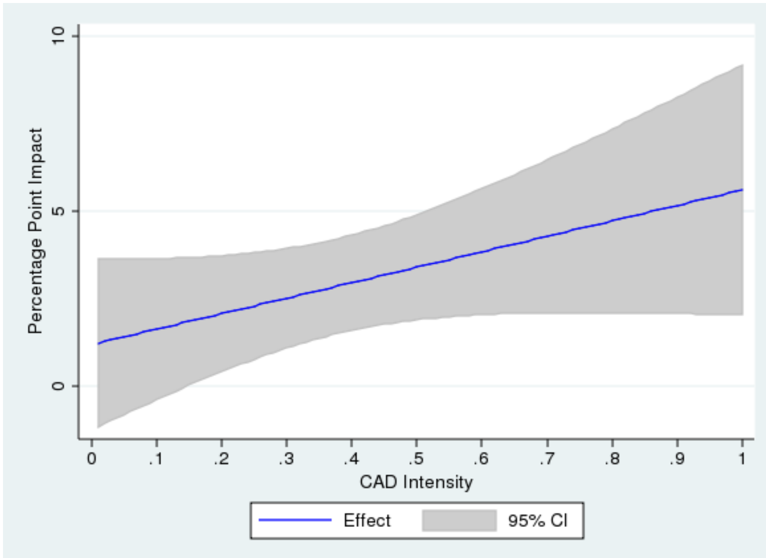
(a) Fragmentation



(b) Offshoring | Fragmentation

Notes: Effect of plant use of electronic networks evaluated at different levels of industry CAD/CAM intensity. Based on the estimates reported in columns 3 and 6 of Table 4.

Figure A.2: Differential impact of change in electronic network use, by industry CAD intensity



Notes: Effect of plant use of electronic networks evaluated at different levels of industry CAD/CAM intensity. Based on the panel estimates reported in column 5 of Table 6.

Table A.1: Correlations between industry CAD intensity and industry-level variables

	CAD	ShrDesSup	ShrDesCo	KI	SI	DI	Off
Share designs	0.49						
w/suppliers	*0.00*						
Share designs	0.54	0.23					
w/comp. units	*0.00*	*0.00*					
Capital Intensity	0.09	-0.24	0.20				
	0.04	*0.00*	*0.00*				
Skill Intensity	0.16	0.25	0.10	0.00			
	0.00	*0.00*	*0.02*	*0.99*			
Diff Inputs	0.26	0.35	0.12	-0.37	0.37		
	0.00	*0.00*	*0.01*	*0.00*	*0.00*		
Wholesale imports	-0.03	-0.02	0.05	-0.08	0.01	0.15	
to sales	*0.57*	*0.62*	*0.27*	*0.10*	*0.92*	*0.00*	
Whole/Manf imports	-0.03	-0.02	0.10	-0.07	-0.01	0.16	0.92
to sales	*0.54*	*0.70*	*0.03*	*0.13*	*0.81*	*0.00*	*0.00*

Notes: Correlation coefficients between industry CAD intensity, the share of manufacturing plants that use electronic networks to share designs with suppliers, the share that use networks to share designs with other company units, capital intensity, skill intensity, share of differentiated inputs, and wholesale firm imports relative to domestic manufactures' sales. Details on industry variables are provided in the text. P-values reported in italics.

Table A.2: Fragmentation and offshoring industry and industry-by-technology estimates

	CAD intensity	Share diff inputs	Skill intensity	Log capital intensity	Routineness
Panel A: Industry Shares					
Fragmentation	0.345***	0.357***	0.510***	-0.008	-0.357*
	(0.089)	(0.070)	(0.121)	(0.018)	(0.197)
Offshoring	0.032***	0.054***	0.106***	0.004	-0.065*
	(0.011)	(0.012)	(0.025)	(0.005)	(0.038)
Offshoring | Fragmentation	0.027	0.100***	0.163**	0.007	-0.059
	(0.035)	(0.032)	(0.065)	(0.012)	(0.105)
Panel B: Industry by Technology Coefficients					
Fragmentation	0.053*	0.047	0.016	0.003	0.124
	(0.031)	(0.052)	(0.070)	(0.008)	(0.103)
Offshoring	0.003	0.041***	-0.003	-0.005	0.045
	(0.013)	(0.012)	(0.027)	(0.004)	(0.053)
Offshoring | Fragmentation	-0.031	0.066*	-0.154*	-0.023*	0.115
	(0.035)	(0.035)	(0.081)	(0.012)	(0.130)
Panel C: Industry-by-Technology-by-Country Human Capital Coefficients					
Low Skill Country Offshoring	-0.030	0.020	-0.135***	-0.015***	0.127***
	(0.021)	(0.022)	(0.034)	(0.006)	(0.045)
High Skill Country Offshoring	0.060*	0.017	0.296***	0.043***	-0.267**
	(0.033)	(0.049)	(0.069)	(0.012)	(0.102)

Notes: Each column reports the coefficient and Huber-White robust standard error from a bivariate regression of the estimated industry fragmentation or offshoring coefficient in the left column on the industry characteristic listed at the top of the column. Panel A reports results for industry fragmentation and offshoring shares. Panel B reports results for estimated industry-by-technology fragmentation and offshoring coefficients. Panel C reports results for estimated industry-by-technology-by-country human capital tercile coefficients. There are 86 NAICS 4 manufacturing industries, though Panel C includes only 79 industries. Routineness is only available for 77 industries (70 for Panel C). Regressions are weighted by the number of plants in each industry.

Table A.3: Marginal Effects for Nested Logit Estimation

	ME on Probability of			
	None	Domestic	Offshore	Off | Frag
A. Baseline Specification				
$ln(Distance_{is})$				
Domestic	0.011	-0.017	0.007	0.023
	0.003	*0.008*	*0.006*	*0.016*
Offshore	0.010	-0.009	-0.002	-0.003
	0.003	*0.002*	*0.002*	*0.002*
$ln(wage_h)$	-0.156	0.143	0.013	
	0.044	*0.040*	*0.012*	
$Elec.\ networks_i$	-0.100	0.090	0.010	0.005
	0.028	*0.025*	*0.009*	*0.004*
$ln(VAProd_i)$	-0.041	0.033	0.008	0.013
	0.012	*0.010*	*0.007*	*0.009*
B. Baseline Specification, with CAD Interaction				
$ln(Distance_{is})$				
Domestic	0.006	-0.011	0.005	0.017
	0.002	*0.006*	*0.005*	*0.011*
Offshore	0.006	-0.005	-0.001	-0.002
	0.002	*0.001*	*0.001*	*0.001*
$ln(wage_h)$	-0.225	0.207	0.017	
	0.064	*0.056*	*0.015*	
$Elec.\ networks_i$	-0.092	0.095	-0.003	-0.029
	0.026	*0.028*	*0.004*	*0.019*
$ln(VAProd_i)$	-0.041	0.033	0.008	0.014
	0.012	*0.009*	*0.007*	*0.009*

Notes: Average marginal effects (AMEs) for the Nested Logit specifications reported in Table A.2. Standard deviations of AMEs reported in italics.

Table A.4: Robustness estimates of the probability of fragmentation and offshoring

Dependent variable is an indicator equal to one if plant i:

	Fragments Production			Offshores | Fragmentation		
	1	2	3	4	5	6
	Demand	Skill	IO Dist	Demand	Skill	IO Dist
$Elec.\ networks_i$	0.097***	0.097***	0.097***	0.023***	0.023***	0.023***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$ln(wage_h)$	0.187***	0.161***	0.175***	-0.096***	-0.106***	-0.093***
	(0.028)	(0.029)	(0.027)	(0.026)	(0.027)	(0.026)
$ln(VAProd_i)$ Q2	0.044***	0.043***	0.043***	0.007**	0.007**	0.007**
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Q3	0.077***	0.077***	0.077***	0.028***	0.028***	0.028***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
MSP 5-20 miles away	-0.020***	-0.020***		0.006	0.006	
	(0.005)	(0.005)		(0.006)	(0.006)	
20+ miles away	-0.016	-0.017		0.002	0.000	
	(0.011)	(0.011)		(0.016)	(0.016)	
Port 51-200 miles	-0.017***	-0.015***	-0.011***	-0.004	-0.004	-0.005
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
200+ miles away	0.002	0.007	0.005	-0.014***	-0.013***	-0.016***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)
50+ miles to Mexico	-0.016	-0.015	-0.021*	-0.097***	-0.095***	-0.095***
	(0.012)	(0.012)	(0.012)	(0.018)	(0.018)	(0.018)
50+ miles to Canada	-0.010	-0.011	-0.009	-0.011*	-0.011*	-0.011*
	(0.008)	(0.008)	(0.008)	(0.007)	(0.006)	(0.007)
ln(Personal income)	0.000			0.001		
	(0.001)			(0.002)		
College Degree		0.036***			0.019	
		(0.012)			(0.014)	
Input wtd. dist is 10-50 miles			-0.018***			0.001
			(0.004)			(0.003)
50+ miles			-0.024***			0.002
			(0.008)			(0.007)
NAICS6 Fixed Effects	yes	yes	yes	yes	yes	yes
Adj. R2	0.09	0.09	0.09	0.08	0.08	0.08

Notes: Demand controls for personal income in the plant's BEA Economic Area. Skill controls for the share of workers with a college degree. IO dist is the weighted distance to each closest input supplier based on the plant's industry and the implied inputs from the BEA Input-Output tables. CAD is the CAD/CAM intensity in a plant's industry. MSP denotes manufacturing service provider. Standard errors clustered by state. *, **, *** denote 10%, 5% and 1% significance respectively. Results are also robust to clustering by industry. N suppressed for disclosure avoidance.

Table A.5: Fraction of Plants that Purchase CMS in each NAICS 4 Industry

Industry	Description	Share
3118	Bakeries and Tortilla Manufacturing	0.08
3273	Cement and Concrete Product Manufacturing	0.08
3211	Sawmills and Wood Preservation	0.10
3116	Animal Slaughtering and Processing	0.11
3253	Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	0.13
3212	Veneer, Plywood, and Engineered Wood Product Manufacturing	0.13
3279	Other Nonmetallic Mineral Product Manufacturing	0.14
3113	Sugar and Confectionery Product Manufacturing	0.14
3115	Dairy Product Manufacturing	0.14
3379	Other Furniture Related Product Manufacturing	0.15
3274	Lime and Gypsum Product Manufacturing	0.15
3241	Petroleum and Coal Products Manufacturing	0.15
3117	Seafood Product Preparation and Packaging	0.16
3111	Animal Food Manufacturing	0.16
3328	Coating, Engraving, Heat Treating, and Allied Activities	0.17
3112	Grain and Oilseed Milling	0.18
3121	Beverage Manufacturing	0.19
3271	Clay Product and Refractory Manufacturing	0.19
3114	Fruit and Vegetable Preserving and Specialty Food Manufacturing	0.19
3259	Other Chemical Product and Preparation Manufacturing	0.20
3251	Basic Chemical Manufacturing	0.20
3149	Other Textile Product Mills	0.21
3362	Motor Vehicle Body and Trailer Manufacturing	0.22
3255	Paint, Coating, and Adhesive Manufacturing	0.22
3219	Other Wood Product Manufacturing	0.22
3159	Apparel Accessories and Other Apparel Manufacturing	0.23
3366	Ship and Boat Building	0.23
3261	Plastics Product Manufacturing	0.23
3272	Glass and Glass Product Manufacturing	0.24
3221	Pulp, Paper, and Paperboard Mills	0.24
3119	Other Food Manufacturing	0.24
3371	Household and Institutional Furniture and Kitchen Cabinet Manufacturing	0.25
3141	Textile Furnishings Mills	0.25
3372	Office Furniture (including Fixtures) Manufacturing	0.26
3262	Rubber Product Manufacturing	0.26
3252	Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing	0.26
3122	Tobacco Manufacturing	0.27
3133	Textile and Fabric Finishing and Fabric Coating Mills	0.27
3313	Alumina and Aluminum Production and Processing	0.27
3314	Nonferrous Metal (except Aluminum) Production and Processing	0.27
3152	Cut and Sew Apparel Manufacturing	0.27
3161	Leather and Hide Tanning and Finishing	0.27
3131	Fiber, Yarn, and Thread Mills	0.27
3132	Fabric Mills	0.28
3391	Medical Equipment and Supplies Manufacturing	0.28
3169	Other Leather and Allied Product Manufacturing	0.28
3323	Architectural and Structural Metals Manufacturing	0.28
3151	Apparel Knitting Mills	0.29
3399	Other Miscellaneous Manufacturing	0.30
3365	Railroad Rolling Stock Manufacturing	0.30
3326	Spring and Wire Product Manufacturing	0.30
3334	Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	0.31
3231	Printing and Related Support Activities	0.32
3312	Steel Product Manufacturing from Purchased Steel	0.32
3324	Boiler, Tank, and Shipping Container Manufacturing	0.32
3254	Pharmaceutical and Medicine Manufacturing	0.32
3256	Soap, Cleaning Compound, and Toilet Preparation Manufacturing	0.33
3311	Iron and Steel Mills and Ferroalloy Manufacturing	0.34
3327	Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	0.35
3329	Other Fabricated Metal Product Manufacturing	0.36
3359	Other Electrical Equipment and Component Manufacturing	0.36
3222	Converted Paper Product Manufacturing	0.36
3315	Foundries	0.36
3346	Manufacturing and Reproducing Magnetic and Optical Media	0.36
3351	Electric Lighting Equipment Manufacturing	0.37
3352	Household Appliance Manufacturing	0.37
3322	Cutlery and Handtool Manufacturing	0.38
3344	Semiconductor and Other Electronic Component Manufacturing	0.38
3353	Electrical Equipment Manufacturing	0.38
3363	Motor Vehicle Parts Manufacturing	0.39
3332	Industrial Machinery Manufacturing	0.40
3333	Commercial and Service Industry Machinery Manufacturing	0.40
3321	Forging and Stamping	0.40
3335	Metalworking Machinery Manufacturing	0.41
3331	Agriculture, Construction, and Mining Machinery Manufacturing	0.41
3339	Other General Purpose Machinery Manufacturing	0.42
3343	Audio and Video Equipment Manufacturing	0.42
3325	Hardware Manufacturing	0.44
3369	Other Transportation Equipment Manufacturing	0.47
3345	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	0.47
3364	Aerospace Product and Parts Manufacturing	0.50
3336	Engine, Turbine, and Power Transmission Equipment Manufacturing	0.50
3341	Computer and Peripheral Equipment Manufacturing	0.50
3342	Communications Equipment Manufacturing	0.55
3361	Motor Vehicle Manufacturing	0.65
3162	Footwear Manufacturing	DDD

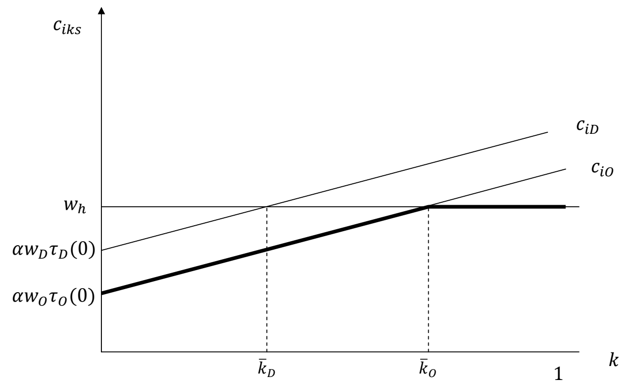
Notes: Shares weighted by inverse probability of being included in the sample. Sorted by share of plants that purchase CMS. DDD is supressed for disclosure avoidance.

Table A.6: Manufacturing firms' import behavior, by CMS purchase status

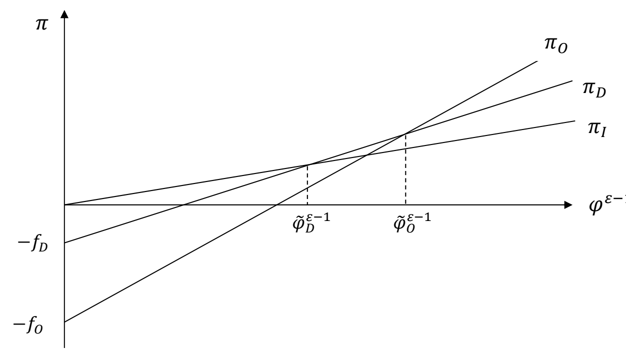
	$\frac{Imports}{Sales}$	Low-income (share)	Median count of Firm HS Products[c] All Firms	Median count of Firm HS Products[c] Importers	Median count of Firm Countries[d] All Firms	Median count of Firm Countries[d] Importers
No Purchases	0.09	0.28	0	3	0	2
Domestic Purchases	0.03	0.19	1	4	1	2
Offshore Purchases	0.2	0.48	8	11	3	4
Domestic & Offshore	0.16	0.19	123	124	20	20

Notes: Manufacturing firms are all firms in the CMS sample with one or more plants classified in manufacturing. Firm imports are limited to manufactured goods. $\frac{Imports}{Sales}$ is the average of total firm imports over sales. Low income is firms' average share of low income imports. *a* Count of distinct 10 digit Harmonized System codes a firm imports. *b* Count of distinct countries from which a firm imports.

Figure B.1: Integrated production, domestic fragmentation or offshoring

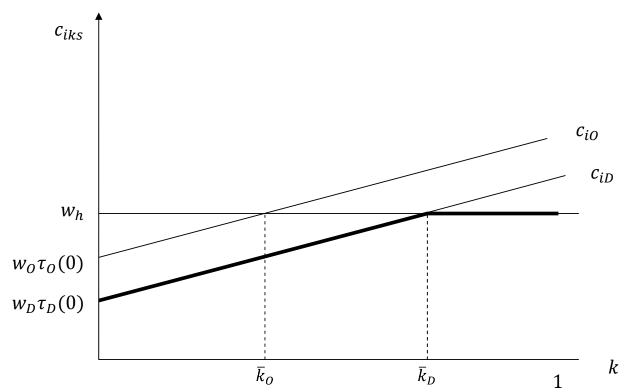


(a) Variable costs per task

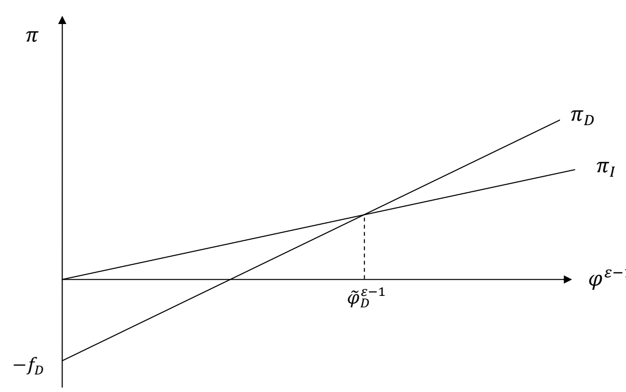


(b) Profits

Figure B.2: Integrated production and domestic fragmentation



(a) Variable costs per task



(b) Profits