

ABSTRACT

Title of dissertation: FIRMS' ORGANIZATION OF
 GLOBAL PRODUCTION:
 THEORY AND EVIDENCE

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It is increasingly common for firms to break up their production process across different regions and countries. While the existing literature credits improvements in communication technology with enabling fragmentation, there is practically no empirical evidence on the determinants of firms' sourcing strategies. In this dissertation, I document the roles of communication technology, distance to suppliers, and labor cost differences in a firm's decisions about i) whether to fragment production across distinct geographic locations; ii) whether to offshore fragmented production; and iii) how much to offshore. To do so, I construct an original dataset about U.S. plants' and firms' fragmentation choices. The data yield a rich set of new facts about firms' sourcing decisions which I incorporate into a theoretical model. I then use the new data to test the model's predicted equilibrium relationships and to assess the relative importance of communication technology, distance, and labor costs in firms' sourcing strategies.

I construct the fragmentation dataset using new information about U.S. manufacturing plants' decision to contract for manufacturing services from domestic or foreign suppliers in 2007. Chapter two describes these data and presents ten new stylized facts about plants' and firms' sourcing decisions. Most notably, the data show that fragmentation: (i) is 13 times more prevalent from domestic than foreign suppliers; (ii) is done mostly by larger and more productive plants; and (iii) varies substantially within industries. The new facts are also consistent with the premise that firms fragment to access cheaper labor but that they pay a fixed cost to do so.

In the third chapter, I incorporate these new facts into a model of heterogeneous firms that decide where to locate the various stages of their production process. Firms fragment production to access cheaper labor, but breaking up production is costly. Firms incur a fixed cost to establish a supply network and additional per-task costs to coordinate production and transport inputs. The fixed costs deliver standard productivity sorting predictions, while the marginal costs add a new dimension of heterogeneity in firms' organization of production. In particular, firms with access to better communication technology, or in locations closer to their potential suppliers, will find fragmentation relatively more profitable. The model also shows that firms in high wage locations have more to gain from fragmentation, while firms in low wage states must offshore to access cheaper wages.

The fourth chapter provides an empirical assessment of the model's predicted equilibrium relationships. I estimate the relative importance of labor cost savings, technology, and distance to suppliers in a plant's decision to fragment production. The estimates indicate that plant use of electronic networks (as a proxy for com-

munication technology) is associated with an 18 percentage point increase in the probability of fragmentation, and a ten point increase in the probability of locating fragmented production offshore. While wage differences and distance to suppliers also have statistically significant relationships with plants' sourcing strategies, communication technology accounts for five times more of the explained variation than wages and distance combined. In contrast, for the decision about how much to offshore, wage differences are relatively more important than distance, and technology explains almost none of the observed variation. Because plant technology may be endogenous, I estimate the differential impact of plants' use of electronic networks on fragmentation in industries whose production process can be codified electronically more easily. As expected, plant use of electronic networks has a bigger impact on fragmentation in industries that are better able to specify production processes electronically. However, plants that use networks in industries with high electronic codifiability are less likely to locate their fragmented production offshore. Estimates from firm-country level import data suggest that successful electronic communication depends upon suitable technology in the sourcing location. The results support the premise that technology facilitates production fragmentation, but uncover substantial heterogeneity in technology's effectiveness across firms, industries, and sourcing locations.

FIRMS' ORGANIZATION OF GLOBAL PRODUCTION:
THEORY AND EVIDENCE

by

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Table of Contents

List of Tables	v
List of Figures	vii
List of Abbreviations	viii
1 Introduction	1
2 New Facts about Fragmentation	9
2.1 Introduction	9
2.2 Plant level fragmentation data	9
2.2.1 Description of the CMS sample	13
2.2.2 Aggregating to the firm level	14
2.2.3 Additional plant-level variables	15
2.3 New empirical facts	16
2.3.1 Plant and firm-level participation shares	16
2.3.2 Plant characteristics by CMS purchase status	18
2.3.3 Industry distribution of CMS purchases	19
2.3.4 Geographic distribution of CMS purchases	20
2.3.5 Firm import patterns	20
2.4 Manufacturing and wholesale firms	24
2.4.1 CMS data for wholesale establishments	25
2.4.2 Firm-level CMS participation shares	25
2.4.3 Firm-level imports	26
2.5 Conclusion	27
3 Model of Production Fragmentation	36
3.1 Introduction	36
3.2 Demand	36
3.3 Production	37
3.4 Profits within an integrated plant	38
3.5 Production with fragmentation across locations	39
3.5.1 Benefits from fragmentation	39
3.5.2 Costs of fragmentation	40
3.6 Profits with fragmentation	41
3.7 Equilibrium sourcing strategy	44
3.8 The likelihood of fragmentation	48
3.8.1 Variation in producer's technology	48
3.8.2 Variation in the home wage	49
3.9 Domestic versus offshore sourcing	51
3.10 Share of fragmentation	53
3.11 Conclusion	54

4	Testing the Model's Predictions	58
4.1	Introduction	58
4.2	The fragmentation decision	59
4.2.1	Main results for fragmentation	64
4.2.2	Differential impact of communication technology across industries	66
4.2.3	Additional controls	70
4.3	Domestic versus offshore fragmentation	71
4.3.1	Main results for offshoring	72
4.3.2	Differential impact of communication technology across industries	73
4.3.3	Additional controls	75
4.4	Robustness checks for probability of fragmenting and offshoring	75
4.5	Extent of offshored production	77
4.6	Location of offshore production	81
4.7	Assessing the relative importance of technology, distance and wages	85
4.8	Conclusion	88
A	Appendix	103
A.1	Substitutability of CMS purchases and standardized inputs	103
A.2	Proofs	104
A.2.1	Share of fragmentation and distance	104
A.2.2	Share of fragmentation and technology	104
A.2.3	Homogeneous task production	104
A.2.4	Multi-dimensional task costs	105
A.3	Hurdle models	106
B	Data Appendix	108
B.1	Contract Manufacturing Question	108
B.2	Missing Data	108
B.3	Variable Descriptions	109
B.3.1	Electronic networks	109
B.3.2	CAD Industry Intensity	110
B.3.3	U.S. Wage Data	111
B.3.4	Foreign Wages	113
B.3.5	Skill measures	115
B.3.6	Manufacturing service providers	115
B.3.7	Water Ports	116
B.3.8	Border Crossings	117
B.4	Probit estimation results	118

List of Tables

2.1	Plant participation shares by contract manufacturing service purchase status	29
2.2	Manufacturing firm participation shares by contract manufacturing service purchase status	29
2.3	Plant means by contract manufacturing service purchase status . . .	30
2.4	Industry distribution of the share of establishments that purchase contract manufacturing services	30
2.5	Plant participation shares within average state wage terciles, by CMS purchase status	31
2.6	Manufacturing firm imports, by contract manufacturing service purchase status	31
2.7	Manufacturing firms' import behavior, by contract manufacturing service purchase status	32
2.8	Manufacturing firm participation shares, by contract manufacturing service purchase status and firm type	33
2.9	Manufacturing firm imports, by contract manufacturing service purchase status and firm type	34
2.10	Manufacturing firms' import behavior, by contract manufacturing service purchase status and firm type	35
4.1	Average distance between a plant and its closest potential suppliers, by CMS purchase status	92
4.2	Plant use of electronic networks, by year and 2007 CMS purchase status	93
4.3	Share of plants in each 2007 CMS status, by 2002 electronic network use and 2002 CMS purchase status	93
4.4	Share of plants in each 2007 CMS status, by 2002 electronic network use and 2002 offshore CMS purchase status	93
4.5	Probability that a plant fragments production	94
4.6	First stage regressions for the probability of fragmentation	95
4.7	Correlations between industry CAD intensity and industry-level variables	96
4.8	Probability that a plant offshores, conditional on fragmentation . . .	97
4.9	First stage regressions for probability of offshoring	98
4.10	Robustness checks for probability of fragmenting and offshoring . . .	99
4.11	Extent of offshored production	100
4.12	Offshore sourcing location selection	101
4.13	Variance decomposition results: Contributions of wages, technology, and distance	102
B.1	Plant characteristics by response status	119
B.2	List of excluded wholesale industries	120
B.3	Water Ports with Imports	121

B.4 U.S. Counties with Land Entry Ports 122
B.5 Probit Regressions for probability of fragmentation and offshoring . . 123

List of Figures

3.1	Integrated production and domestic fragmentation	55
3.2	Integrated production, domestic fragmentation, or offshoring	56
3.3	Integrated production, domestic fragmentation and offshoring	57
4.1	Differential impact of electronic networks, by industry CAD intensity	90
4.2	Differential impact of firm technology on probability of sourcing from country s , by country technology	91
4.3	Differential impact of country technology on probability of sourcing from country s , by industry CAD intensity	92

List of Abbreviations

ASM	Annual Survey of Manufactures
BEA	Bureau of Economic Analysis
CAD	Computer Aided Design
CAM	Computer Aided Manufacturing
CM	Census of Manufactures
CMS	Contract Manufacturing Services
CNUS	Computer Survey Network Use Supplement
DOC	Department of Commerce
EDI	Electronic Data Interchange
EIN	Employer Identification Number
FDI	Foreign Direct Investment
IO	Input-Output
IV	Instrumental Variable
LBD	Longitudinal Business Database
LPM	Linear Probability Model
NAICS	North American Industrial Classification System
OLS	Ordinary Least Squares
OMB	Office of Management and Budget

Chapter 1

Introduction

There is increasing interest in firms' decisions to break up or fragment parts of their production processes. The importance of fragmenting across countries, i.e., offshoring, is evidenced by the large share of intermediate inputs in international trade (Yeats, 2001; Hummels, Ishii, and Yi, 2001), and is frequently attributed to new communication technology.¹ However, there is little systematic evidence of the impact of communication technology on offshoring, or of its importance relative to traditional trade or labor cost saving motives. In addition, much of the discussion has centered on offshoring because of its potential to harm domestic employment and wages, but some of these potential costs would be absent, or at least mitigated, by domestic rather than foreign fragmentation. We have even less evidence on firms' decisions to fragment domestically, though it may be an alternative to offshoring with very different implications for domestic workers.

In this dissertation I assess the role of technology, relative to wage differences and transportation costs, in a firm's decision to break up its production across foreign and domestic locations. Using original micro data from the 2007 U.S. Census

¹For example, Grossman and Rossi-Hansberg (2008) state "Revolutionary advances in transportation and communications technology have weakened the link between labor specialization and geographic concentration, making it easier to separate tasks in time and space" (p. 1978); Rodríguez-Clare (2010) says, "Falling costs of coordination and communication have allowed firms in rich countries to fragment their production process and offshore an increasing share of the value chain to low-wage countries" (abstract); and Baldwin and Venables (2010) attribute fragmentation of production to " ...revolutionary advances in information and communications technology that massively lowered the cost of organising complex activities over distances" (p. 1).

of Manufactures (CM), I uncover novel facts about the fragmentation of inputs that are customized to meet a firm's specific production criteria. This type of customized fragmentation requires communicating specifications across locations, so that the data are uniquely suited to assess the role of communication technology in fragmentation. I develop a theoretical framework that incorporates the new facts and delivers predictions about the trade-off that firms face between labor cost savings and fragmentation costs. Additional tests support the theory and suggest that communication technology is the most important factor in a firm's decision about whether or not to fragment or offshore, while wage differences matter most in determining the extent to which it does so.

The second chapter presents a set of stylized facts from a new dataset about U.S. plants' production fragmentation decisions. The new data are from the CM and identify whether a plant purchased contract manufacturing services (CMS) from other plants (within its company or from another company) to process its inputs; and if so, whether the plant primarily purchased these services domestically or abroad. I combine these data with additional information from the CM, the Longitudinal Business Database (LBD), and firm-level imports, to document a number of new facts about plants that fragment their customized production process. First, a substantial share of plants do not fragment production across locations. In addition, despite the secular increase in imported inputs mentioned above, the majority of plants that fragment primarily source from domestic suppliers. The share of plants that fragments production domestically is 13 times higher than the share of plants that offshores, and domestic fragmenters employ almost nine times more workers.

The data also show that plants that fragment production to any location are larger and more productive, particularly so if they offshore.² These aggregate patterns also hold within industries and reveal substantial heterogeneity in firms' sourcing strategies that are not explained by sectoral differences in production requirements. Finally, I find considerable differences in the geographical distribution of fragmenting plants. Most importantly, 22 percent of plants in low wage states fragment domestically, compared to 30 percent in high wage states.

In the third chapter, I incorporate the stylized facts into a model of heterogeneous firms that can fragment production across domestic and foreign locations. The model extends Grossman and Rossi-Hansberg (2008) to incorporate domestic fragmentation and non-participation within industries, two key findings in the data. More specifically, firms make their final good from a set of production tasks, and these tasks can be performed in foreign or domestic locations in which labor costs are lower. However, breaking up production is hard to do because firms must incur a fixed cost to establish a supply network and per-task costs to communicate product specifications and transport output.³ The model assumes that per-task fragmentation costs are decreasing in firms' communication technology and proximity to suppliers. As a result, firms that with access to better technology and those closer

²The finding of a productivity premia for offshorers is consistent with Kurz (2006), who analyzes U.S. plant-level data on foreign purchases of materials by manufacturers in 1987 and 1992; and Tomiura (2007), who creates productivity rankings for Japanese firms' sourcing choices. This paper extends those findings by showing they hold for fragmentation of customized inputs.

³In Antràs, Garicano, and Rossi-Hansberg (2006) and Antràs, Garicano, and Rossi-Hansberg (2008), communication technology affects how heterogeneous agents sort into international production teams. In those papers, the focus is on the interaction of skill and technology differences, and all offshoring takes place within the boundary of the firm. I do not model skill differences and offshoring can take place within or outside the firm.

to potential suppliers are more likely to fragment. In addition, firms in high wage states have the largest number of lower cost sourcing options, while firms in low wage states must offshore to access cheaper labor. Firms also differ in the efficiency of their final good production, so that the fixed costs of fragmentation lead to standard productivity sorting predictions. While the productivity sorting is similar to Antràs and Helpman (2004) and Helpman, Melitz, and Yeaple (2004), heterogeneity in firms' per-task fragmentation costs and potential for labor cost savings is entirely new.

In the fourth chapter, I test the equilibrium predictions of the model. Guided by the theory, I estimate the relative importance of labor cost savings, communication technology, and transportation costs in plants' decisions to fragment production and offshore. The estimates suggest that plant use of electronic networks to coordinate shipments (as a measure of communication technology) increases the probability of fragmentation by 18 percentage points, comparable to the effect of doubling the home wage. Conditional on fragmenting, the probability that a plant will offshore is ten percentage points higher for plants that use electronic networks. This effect is similar in magnitude to the 12 point decrease in the probability of offshoring fragmented production associated with a doubling of the plant's home wage. The negative relationship between a fragmenting plant's home wage and the probability it will offshore is consistent with the theoretical prediction that plants fragmenting production in lower wage states search for cheaper labor offshore. Plants that are farther away from foreign entry ports are also less likely to fragment offshore, supporting the premise that transportation costs affect plants' sourcing strategies.

Using the linked census-import data, I also examine the intensive margin of offshoring. As expected, I find that conditional on positive offshoring, the extent of offshored production is decreasing in the relative foreign wage and firms' distance to ports. This extends Hanson, Mataloni, and Slaughter (2005), who find that U.S. multinationals offshore more from low wage countries, and when transport costs are low. The analysis here adds a measure of communication technology and includes fragmentation that is outside the boundary of the firm. More importantly, this paper compares key determinants' impact on the extent of offshoring to their impact on whether or not to offshore in the first place. While the estimated coefficients suggest that communication technology, wages, and distance are all important factors in a firm's decision to fragment and offshore, the observed variation in producers' electronic network usage accounts for five times more of the explained variation than wages and distance combined. In contrast, for firms' decision about how *much* to offshore, wage differences are relatively more important than distance, and technology explains almost none of the observed variation.

A plant's use of communication technology may depend upon the fragmentation strategy it plans to adopt.⁴ To address this issue, I assume that electronic networks lower fragmentation costs at least in part by facilitating communication about production requirements. If this mechanism is at work, the effect of communication technology on fragmentation will depend upon a firm's ability to codify its product specifications in an electronic format. Computer Aided Design (CAD)

⁴See Bustos (2011) for a model in which firm technology is an endogenous choice that affects the firm's export decision.

and Computer Aided Manufacturing (CAM) software enables plants to codify specifications in an electronic format that can be sent to suppliers, but the extent to which plants can use CAD/CAM depends upon their industry's production process characteristics.⁵ I find that plants using networks in the most CAD/CAM intensive industries are over 20 percentage points more likely to fragment production than plants using networks in the least CAD/CAM intensive industries. Exploiting differences in communication and information technology across industries is similar to Bloom, Garicano, Sadun, and Reenen (2011), who estimate the differential effect of communication technology and CAD/CAM on firms' hierarchy structure. While those authors argue that CAD/CAM empowers local managers, thereby decentralizing decision-making, I show that it increases communication technology's effectiveness in transmitting information and thus facilitates production fragmentation.⁶

Although plants that use electronic networks in CAD/CAM intensive industries are more likely to fragment, the results also show that they are *less* likely to locate their fragmented production offshore. A potential explanation is that the effectiveness of plants' communication technology also depends upon suppliers' ability to receive and process electronic communications. Consistent with this hypothesis, estimates from firm-country level import data show that firm communi-

⁵Conversations with contract manufacturing suppliers at the Mid-Atlantic Design-2 Part Show in April 2011 suggest that communication technology makes fragmentation easier when it can be used in conjunction with CAD/CAM software.

⁶The complementarity I find between electronic communication and CAD/CAM may explain why Bloom et al. (2011) do not obtain statistically significant estimates on their measure of electronic communication for the effect of communication technology on decentralization within a firm.

cation technology and industry CAD intensity are associated with an increase in the probability of sourcing from more technologically advanced countries. This analysis extends Yeaple (2003), who finds that FDI in skill intensive industries is more likely to occur in skill abundant countries.⁷ The results support the premise that technology facilitates production fragmentation, but uncover substantial heterogeneity in its effectiveness across firms, industries, and sourcing locations.

A significant contribution of this dissertation is to document an empirical relationship between communication technology and firms' fragmentation and offshoring decisions. To my knowledge, this is the first systematic evidence on a relationship that is assumed in much of the existing theory, and which has the potential to affect a number of the theory's policy implications. The results suggest that improvements in communication technology matter more than wage differentials and distance to suppliers in U.S. producers' decisions about whether to fragment and offshore. In contrast, labor cost savings are the most significant factor in firms' decision about how much to offshore. The analysis also shows that the impact of communication technology varies significantly across industries and countries. Incorporating this variation into existing theory may lead to nuanced, but also richer and more informative, predictions about offshoring. While I do not calculate the welfare implications of fragmentation and offshoring, the dissertation does provide a framework to help inform policy makers. In particular, I show both theoretically

⁷The results also relate to Head, Jing, and Ries (2011), who show that Chinese cities tend to import from multiple countries, but that cities vary in their propensity to source from a given country. The authors posit that the nationality of foreign affiliates may drive a city's orientation towards a given country. This paper suggests an alternative explanation. Firms differ in their technological capabilities, and this variation may drive their compatibility with different sourcing locations.

and empirically that domestic and offshore fragmentation are potential substitutes and that a firm's decision depends upon the relative costs of each option. As a result, factors that increase the costs of domestic fragmentation without affecting offshoring costs may lead to more offshoring.⁸ Finally, the dissertation highlights the importance of geographic heterogeneity in producers' fragmentation costs and benefits and shows how this variation is related to firms' organization of production.

In the next chapter, I describe the new data and explain why fragmentation is a difficult but important activity to measure. The chapter also presents new stylized facts about plants and firms that fragment their production and describes the main phenomena the model should capture. I develop a heterogeneous firms model in Chapter 3 in which firms choose whether to produce in a single location, fragment domestically, or offshore. In Chapter 4, I assess the model's predicted equilibrium relationships along both the extensive and intensive margins. The chapter concludes with an assessment of the relative importance of labor cost savings, distance to suppliers, and communication technology for each fragmentation margin.

⁸The recent case in which Boeing faced charges for opening a new plant in South Carolina is an example of additional potential domestic fragmentation costs.

Chapter 2

New Facts about Fragmentation

2.1 Introduction

A major obstacle to conducting empirical work on the determinants of firms' sourcing strategies has been the lack of data about production fragmentation. Existing work on fragmentation has generally relied on aggregate input-output tables to impute the amount and importance of trade in intermediate inputs. While these data provide useful information about aggregate trends, they may mask significant firm-level heterogeneity. In this chapter, I describe new plant level data about both domestic and foreign fragmentation. These data yield ten new facts about firms' fragmentation strategies.

2.2 Plant level fragmentation data

The fragmentation data are based on a new question in the 2007 Census of Manufactures (CM). The question asks: "Did this establishment purchase contract manufacturing services from other companies or other establishments of your company to process materials or components that this establishment owns or controls?" Establishments that answer yes are also asked whether they primarily purchase these

services domestically or abroad.¹ I cannot provide any actual examples of firms or contract manufacturing service (CMS) purchases in the Census data because the data are confidential and respondents' identities cannot be revealed. However, hypothetical examples of CMS purchases include the manufacturing of company A's MP-3 player components as instructed by company A; the assembly of company B's computer processing chips in B's overseas plants using specified inputs and a precise design criterion; and the production of company C's shoes in non-affiliated factories using soles provided and materials specified by company C. In each case, the purchaser furnishes production specifications to the manufacturing service provider.

The CMS question was designed to identify manufacturing establishments that do not perform all of the physical transformation activities required to complete their final good. When an establishment pays another firm to perform some of its manufacturing activities, that establishment is both fragmenting and "outsourcing" production. If multiple plants within the same firm perform different stages of production, that firm is not outsourcing, but it is fragmenting production. According to the Office of Management and Budget (OMB), accurate measures of economic activity require identifying fragmentation both within and outside the firm, because "When producers subcontract portions of the production process to separate affiliated or unaffiliated units, the production function changes at the establishment level" (OMB (2009), p. 766).² Fragmentation is also important because it is a

¹An establishment denotes a single physical location where business transactions take place and for which payroll and employment records are kept. It is synonymous with a plant. The question as it appeared on the Census form is presented in Data Appendix B.

²The OMB (2011) notes that fragmentation and the resulting changes in the production function affect industry and sector classifications which in turn have an impact on measures such as the Bureau of Labor Statistics' Producer Price Index, productivity indices, employment, and

necessary step for firms that relocate part of their production process overseas, or “offshore.” Offshoring takes place within and outside the boundaries of the firm and has received ample attention in the literature. There are numerous ways in which offshoring has been measured, but to my knowledge, none are comparable to the CMS data analyzed here.

The CMS data provide new information about fragmentation since they differ from existing measures along several dimensions. First, the data include a comprehensive domestic fragmentation measure. Much of the existing literature on fragmentation focuses only on offshoring, but ignoring domestic fragmentation may confound factors that affect breaking apart the production process with factors that affect locating a portion of production overseas. Second, the data are collected at the plant level and reveal substantial intra-industry heterogeneity in plants’ and firms’ fragmentation decisions. Third, the data contain both outsourced and vertically integrated production, unlike measures of foreign direct investment that consist only of the latter. The inclusion of both types of fragmentation is important since, as noted in Feenstra (1998), “looking within multinational firms alone does not give a full perspective on what is happening” (p. 36).³ Fourth, the data do not rely on imported intermediates as a measure of foreign fragmentation. Identifying intermediate trade often relies on input-output tables that are relatively coarse and therefore unlikely to identify intermediate inputs exclusively or entirely.⁴ Imports of interme-

wages; and the Bureau of Economic Analysis’ industry accounts, national income accounts, and regional accounts. Houseman, Kurz, Lengermann, and Mandel (2011) also discuss how ignoring fragmentation may lead to systematic productivity mismeasurement in the U.S economy.

³A limitation of the data is that they do not distinguish between fragmentation that takes place within or outside the firm so that it is not possible to assess theory about optimal firm boundaries.

⁴Two new approaches for identifying intermediate trade are proposed by Sitchinava (2008) and

diates are also a limited measure since they exclude final goods that are assembled overseas and then re-imported into the home country. Finally, imported inputs can include raw commodities and standardized “off-the-shelf” inputs. Commodity trade is generally not considered offshoring, and it is unclear whether intermediate goods sold in the marketplace represent production fragmentation. While the degree of specificity needed to classify input trade as fragmentation is ambiguous, the data I use clearly identify trade in inputs (of goods and services, such as assembly) that are specialized for the purchaser, and therefore warrant classification as fragmentation.

The CMS data only capture fragmentation of production that is customized to meet buyers’ specifications, and in that sense may represent a subset of overall production fragmentation. Since this type of fragmentation requires communicating product specifications and coordinating input production so that all components fit together, it is especially relevant for assessing the effect of technology on coordination and communication costs across separate production locations. Understanding customized fragmentation is also valuable since it is a relatively new phenomenon;⁵ disruptions in the supply of customized inputs are extremely costly;⁶ and recent trends in U.S. manufacturing suggest that customized production will form an increasingly significant part of economic activity.⁷

Wright (2011).

⁵Trade in standardized inputs, and especially commodities, has been common for hundreds of years. For example, see chapters six and seven in Findlay and O’Rourke (2007).

⁶The recent earthquake in Japan provides a stark example.

⁷According to of Forrester Research, “We’re entering a new era in which mass customization will lead a number of consumer product categories...” Gowdner (2011).

2.2.1 Description of the CMS sample

The CM is conducted in years that end in 2 and 7. It covers the universe of manufacturing establishments in the U.S, though not every establishment is asked the CMS question. While all large plants and all plants that belong to multi-unit firms were asked the CMS question, only a random sample of small and medium-sized plants was asked the question. Data for the smallest manufacturing plants, generally those with less than five employees, are based only on administrative records and therefore do not include any information about those plants' CMS purchases.⁸ Since the administrative records are often based on imputed data, have no information about CMS purchases, and account for only 1.5% of sales and three percent of employment in the manufacturing sector, I exclude them from the entire analysis. All establishments that receive a census form in the mail are legally required to return the completed form. Despite the legal requirement, a fraction of establishments did not respond to the CMS question.

I assess the observable characteristics of plants outside the CMS sample to address potential issues from sample selection. While the CMS sample covers 54 percent of manufacturing establishments (excluding the administrative records), it includes 75 percent of sales and 71 percent of employment. Appendix B provides information on the plants outside the CMS sample. To correct for differences between the sample and the population of potential respondents, I estimate the probability

⁸The CM uses both short and long form questionnaires, and only the long forms ask the CMS purchase questions. While all large and multi-unit firm establishments receive the long form, only a random sample of small, single-unit firms receive the long form. Data for the smallest establishments is imputed from Federal tax returns and industry averages.

that an observation is in the CMS sample. Following Cameron and Trivedi (2005), I use the inverse probability as a weight in the empirical analyses.⁹ Details of the missing data and weights estimation are in Data Appendix B.

2.2.2 Aggregating to the firm level

To assess firm-level sourcing decisions, I aggregate the plant data to the firm level. The census data have a variable, *firmid*, that identifies the firm to which a given establishment belongs. This variable is superior to the employer identification number (EIN) used in other datasets to identify ownership. Since a single firm can use multiple EINs to file its tax returns, EINs may only identify part of a large firm. I classify firms with at least one offshoring plant and no domestic fragmenters as “Offshore Purchases.” Firms with at least one domestic fragmenting plant and no offshoring plants are classified as “Domestic Purchases.” Firms with at least one plant that purchases domestic CMS and at least one plant that purchases foreign CMS are classified as “Domestic and Offshore Purchases.” Finally, firms that have no plants that purchase CMS, and have at least one plant that reported no purchases of CMS are designated as “No Purchases.” Note that, due to the question design, an establishment can only source primarily domestically or primarily offshore, while multi-unit firms can potentially do both.

⁹Cameron and Trivedi recommend using weights (“that are inversely proportional to the probability of inclusion in the sample”) for a descriptive or data summary approach. They note that if a regression model is correctly specified then sample weighted and unweighted estimates should have the same probability limit, Cameron and Trivedi (2005) pp. 817-21.

2.2.3 Additional plant-level variables

I supplement the production fragmentation data with plants' total value of sales, number of employees and industry from the CM. I match the census data to the LBD to obtain the firms' employment in all other sectors; and to the Business Register to identify plants' latitude and longitude.¹⁰ By linking the firm-level data to the U.S. Customs import transactions data, I also identify the value, country, and product of firms' imports.¹¹ I restrict the import data to imports of manufactured products since imports of inputs that correspond to fragmented production should be classified in manufacturing.

I construct a value-added labor productivity measure for plant i as $vap_i = va_i/te_i$, where va denotes value-added and te denotes total employment. Plant sales, employment, and productivity all vary significantly across industries. To make meaningful comparisons of these variables across plants in different industries, I calculate a relative measure $x_{i,g}/\bar{x}_g$, where \bar{x}_g is the mean of variable x in the six digit NAICS industry g . I use the relative productivity measures to construct firm-level productivity. In Section 2.3, I also use these relative measures to compare plant characteristics across CMS purchase types.

¹⁰The LBD is a longitudinal panel of every private, non-farm establishment with at least one employee in the U.S. See Jarmin and Miranda (2002) for details on the LBD.

¹¹It is not possible to link the trade transactions data to individual establishments for multi-unit firms. See Bernard, Jensen, and Schott (2009) for a detailed description of the import data.

2.3 New empirical facts

The census data provide new information about which plants and firms fragment their production. The data also highlight within industry patterns about producers' sourcing decisions. The linked firm-import data show the relationship between importing and offshoring and provide evidence on the foreign locations from which firms purchase CMS. This section presents the new information summarized in ten stylized facts.

2.3.1 Plant and firm-level participation shares

Table 2.1 presents plant participation shares by CMS purchase status. The first column shows that 27 percent of plants fragment primarily domestically, while only two percent fragment primarily offshore. The majority of plants do not purchase CMS, and of those that do, only a small fraction primarily offshore.¹² Columns 2 and 3 provide the shares of sales and employment respectively by plants' CMS purchase status, weighted by the inverse probability of being in the CMS sample. The percentages of sales and employment at plants that offshore doubles to four percent, while the percent of sales and employment at plants that fragment domestically jumps to 39 percent and 35 percent respectively. These findings are summarized as

¹²Low participation shares are consistent with Hillberry and Hummels (2008), who examine the 1997 Commodity Flow Survey data and find that most U.S. manufacturing plants do not ship goods across large distances. Limited offshore sourcing for customized production is in line with results in Tomiura (2007), who finds that only 2.68 percent of Japanese manufacturing firms outsource production offshore. There is almost no existing evidence on plants' domestic fragmentation, but Fally (2011) uses aggregate input-output tables to calculate the average number of sequential stages of domestic production, weighted by each stage's value-added. He finds the average number of manufacturing stages is less than two. See Appendix A, Section A.1 for a discussion about the potential of substituting CMS purchases with standardized inputs.

the following facts:

Fact 1: The majority of plants do not fragment their production process for customized inputs, even on a sales or employment-weighted basis.

Fact 2: Domestic fragmentation is far more prevalent than offshoring.

Although most plants are single-unit firms, approximately 40 percent of the plants in the CMS sample belong to multi-unit firms. Table 2.2 illustrates important differences between the plant and firm-level shares. While a majority of sales and employment take place at plants that do not purchase CMS, columns 2 and 3 show that firms that do not purchase CMS account for only 31 percent of sales and 42 percent of manufacturing employment. The differences between the plant and firm level results are largely driven by the high sales and employment shares of firms with some plants that source domestically and others that source offshore. These firms account for only one percent of manufacturing firms, but cover 24 percent of sales and 16 percent of manufacturing employment.¹³

Table 2.2 provides additional support for *Fact 2*. Domestic fragmentation is more prevalent than offshoring at both the plant and firm level. Firms with plants that purchase CMS primarily domestically account for 55 percent of manufacturing employment, while firms with at least some offshoring plants account for 19 percent. In contrast, employment and sales participation shares differ between the plant and firm-level measures. Activity-weighted firm participation shares suggest that production fragmentation is a significant phenomenon in economic activity. While not all plants within a firm fragment production, fragmenting firms account for

¹³Data Appendix B decomposes this table into firms with and without wholesale establishments.

a significant share of both domestic and employment and sales. This finding is summarized by:

Fact 3: The majority of U.S. manufacturing sales and employment takes place at firms with at least one plant that purchases CMS.

2.3.2 Plant characteristics by CMS purchase status

Table 2.3 presents weighted means for plant sales, employment and the log of value-added labor productivity by CMS purchase status. Columns 1 and 2 show that the average plant that fragments production is larger in terms of both sales and employment than the average non-fragmenting plant. In addition, plants that fragment production offshore are larger than domestic fragmenters. The average sales at manufacturing plants with no CMS purchases is approximately \$19 million, while the average sales at offshoring plants is over \$50 million. Column 3 shows a similar pattern for productivity. Domestic purchasers are more productive than plants with no fragmentation, while offshorers are the most productive. Columns 4-6 present averages by CMS purchase status for relative industry measures. As described in Section 2.2.3, the relative measures capture within industry heterogeneity and ensure that patterns across categories are not driven by industry compositional differences. The same patterns hold for the within-industry measures. Plants with no purchases are smaller and less productive than plants that purchase CMS domestically; and offshoring plants are the largest and most productive plants. These results lead to two more stylized facts:

Fact 4: Plants that fragment production are larger and more productive than non-fragmenters.

Fact 5: Plants that fragment production offshore are larger and more productive than domestic fragmenters.

2.3.3 Industry distribution of CMS purchases

To explore variation in fragmentation within industries, Table 2.4 presents the industry distribution of the share of plants that purchase CMS domestically and offshore. I calculate participation shares within each of the 86 four digit North American Classification System (NAICS) manufacturing industries. The first column shows that there are two industries in which no plants offshore production. In one of these non-offshoring industries, 10-20 percent of the plants purchase CMS domestically, while in the other industry 20-35 percent of plants do. The first striking observation from Table 2.4 is that all industries have a positive share of plants that purchase domestic CMS. At least five percent of the plants in every industry fragment domestically. Table 2.4 also shows substantial non-participation in every industry. The highest observed share of fragmenting plants is almost 60 percent. These findings are summarized by:

Fact 6: There is substantial within industry heterogeneity in plants' sourcing strategies.

Examining the diagonal of Table 2.4, it is evident that every industry has a higher share of domestic fragmenters than offshoring plants. This finding provides

additional support for *Fact 2*. Domestic sourcing is more prevalent than offshoring within all NAICS 4 industries.

2.3.4 Geographic distribution of CMS purchases

Plant participation shares also vary across U.S. states. I calculate the average production worker wage per state and classify states as low wage, medium wage, and high wage depending upon the tercile to which their wage corresponds.¹⁴ Table 2.5 presents the average share of plants within each wage category by CMS purchase status. While two percent of plants offshore in all wage categories, domestic fragmentation varies substantially. Only 22 percent of plants purchase CMS domestically in low wage states, while 30 percent fragment domestically in high wage states. This finding leads to an additional stylized fact:

Fact 7: Domestic fragmentation is more prevalent in high wage states.

2.3.5 Firm import patterns

The CMS data capture the subset of fragmentation in which inputs are customized to meet buyers' specifications. To compare this customized offshoring to measures based on imports, Table 2.6 shows data on manufacturing firms' imports of manufactured goods, by firms' CMS purchase status. Column 1 indicates that firms with one or more plants that purchase CMS account for 67 percent of imports. Domestic fragmenters import 36 percent of imports, while offshoring firms import 31 percent. Columns 2 and 3 show that average imports by domestic fragmenters

¹⁴See Data Appendix B for details on the wage measure.

are \$7.2 million, compared to \$18.7 million for offshorers and \$429 million for firms with a mix of plants that fragment domestically and abroad. While it is impossible to measure the exact extent to which imports correspond to CMS purchases, offshoring firms' high share of imports and large average imports suggest that offshore CMS purchases constitute an important trade activity.

Table 2.6 also presents the average extent to which firms offshore, measured as firms' imports over sales.¹⁵ Column 4 shows that domestic fragmenters rely little on imported inputs. 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. This leads to an additional fact:

Fact 8: Firms that source customized inputs primarily offshore have a disproportionately high ratio of imports to sales.

Much of the existing literature has focused on imported intermediate inputs as a measure of offshoring. Column 4 in Table 2.6 presents the average share of each

¹⁵Since a significant portion of manufacturing firms that import have wholesale establishments, I include firms' sales in manufacturing and wholesale in the denominator. Firms may have sales in other sectors, but these data are not readily available. Data Appendix B provides a decomposition between firms with and without wholesale trade establishments.

firm's intermediate inputs over total imports.¹⁶ On average, 65 percent of offshoring firms' imports consist of intermediate inputs. This share is slightly higher than the share of intermediates in total imports at domestic fragmenters (62 percent) and non-fragmenters (60 percent). The data suggest that while the majority of CMS imports comprise intermediate inputs, fragmentation may also entail trade in final goods.

Although the CMS data lack specific details about the products and locations from which firms fragment, the trade data provide information about the products and countries of firms' imports. Column 1 in Table 2.7 shows that about 40 percent of firms that do not purchase CMS import manufactured goods. Imports by firms that do not purchase CMS may reflect purchases of standardized materials, inputs, or final goods that are sold in the marketplace; or they may reflect imports that relate to activities in other sectors in which the firm is active. About half of all firms that purchase domestic CMS import goods, while 90 percent of offshoring firms import. Firms that purchase CMS offshore but do not import may be offshoring the final assembly of goods that they sell overseas.¹⁷ Nearly all firms that purchase CMS both domestically and offshore import manufactured goods. Table 2.6 also 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.¹⁸ Column 2 shows

¹⁶A firm's intermediate inputs are determined based on the HS commodity codes identified as inputs in the BEA I-O tables for the firm's four digit NAICS code or codes.

¹⁷Almost all of these firms export goods. It is also possible that some firms are erroneously classified as non-importers due to an inability to link the import data to the census data. This should not be a big issue, however, as I match 92 percent of the transactions and 91 percent of the value of imports.

¹⁸I 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

that 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. This leads to the following fact:

Fact 9: Offshoring firms import relatively more from low-income countries than domestic fragmenters and non-fragmenters.

Table 2.7 also provides 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 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.

The firm-level import patterns in Tables 2.6 and 2.7 provide a reassuring validation of the CMS data. The vast majority of firms that purchase CMS primarily

in each CMS category.

offshore import manufactured goods. In addition, these firms import a wider range of products from a greater number of countries compared to firms that purchase CMS primarily domestically or not at all. Table 2.7 also shows that firms that purchase CMS offshore tend to source from multiple countries. These findings are summarized by a final stylized fact:

Fact 10: Offshoring firms are more likely to source multiple goods and from multiple countries than domestic fragmenters and non-fragmenters.

2.4 Manufacturing and wholesale firms

In the previous section, I provide summary statistics for all manufacturing firms. Since the evidence suggests that some of these firms have extensive activities in other sectors, I now break down the import summary statistics for manufacturers into the set of firms with and without wholesale establishments. This distinction is important because the U.S. wholesale sector has evolved to include establishments that design, market, and sell their own goods. Because these establishments perform little or no physical transformation activities, they are classified as wholesalers. From an economic theory perspective, however, the firms are essentially manufacturers that have offshored all of their physical transformation activities. Unfortunately, data limitations for wholesalers make it impossible to assess the portion of manufacturing-wholesale firms' activities that have been fully offshored. To ensure that these firms do not introduce a systematic bias in the subsequent empirical analysis, it is therefore important to compare manufacturing firms *with* wholesale

establishments to those *without* wholesale plants. If these firms' observable characteristics are markedly different, then a cleaner analysis in Chapter 4 should use only the former.

2.4.1 CMS data for wholesale establishments

The CMS question was asked not only of plants in the manufacturing sector, but also of establishments in wholesale trade. For wholesale trade, every establishment in 49 of the 71 NAICS industries was asked the CMS question. The firm level statistics I report are based on both the wholesale and manufacturing plants' CMS purchase status with a firm.¹⁹

2.4.2 Firm-level CMS participation shares

Table 2.8 provides firm level participation shares by CMS purchase status. The top panel covers all firms with at least one manufacturing establishment. This panel is identical to Table 2.2 but is included here for easy comparison. The bottom panel of Table 2.8 decomposes the firm level numbers between manufacturing firms with no wholesale establishments and manufacturing firms with wholesale establishments. Shares at firms without wholesale plants are quite similar to the plant level shares, while firms with both manufacturing and wholesale establishments have relatively higher sales and employment figures. Participation shares for firms that source both domestically and offshore exhibit the largest difference between firms with and

¹⁹Table B.2 in Appendix B provides a list of the excluded wholesale industries. Calculating the manufacturing firms' summary statistics based solely on a firm's manufacturing plants' CMS status yields almost identical results.

without wholesale plants. While firms that source domestically and offshore account for only two percent of sales for the former group, they account for 31 percent of sales for the latter.

2.4.3 Firm-level imports

Table 2.9 shows the share of manufacturing firms' imports of manufactured goods, by firms' CMS purchase status. The top panel is identical to the first three columns of Table 2.6. The bottom panel of Table 2.9 decomposes the aggregate firm statistics between manufacturing firms with and without wholesale establishments. For manufacturing only firms, fragmenting firms account for 44 percent of manufactured good imports by the sample, still a non-trivial amount. Average import patterns are similar to the aggregate numbers; offshoring firms have a higher average quantity of imports and a higher average share of imports over sales.

Table 2.10 provides information about the share of firms that import, the products they import and the countries from which they import, by firm CMS purchase status. The top panel is comparable to Table 2.7. The bottom panel decomposes manufacturing firms into those with and without wholesale establishments. For firms with no wholesale establishments, Column 1 shows that almost 40 percent of firms that do not purchase CMS import manufactured goods. About half of all firms that purchase CMS primarily domestically import goods, while almost 90 percent of offshoring firms import. Nearly all firms that purchase CMS both domestically and offshore import manufactured goods. Manufacturing firms with wholesale establish-

ments are much more globally integrated. 88 percent of these firms import goods, and those that purchase CMS domestically and offshore import a median count of 177 products from a median of 25 countries.

These tables suggest that there are important differences between manufacturing firms with and without wholesale establishments. In particular, a combination of domestic and offshore sourcing is far more prevalent among firms with wholesale establishments. In addition, firms with wholesale establishments import more goods and from a wider range of countries. Given the existing data constraints for the wholesale sector, the empirical analysis in Chapter 4 is based on the subset of manufacturing firms without wholesale plants. This focus ensures that plants' and firms' manufacturing activities are correctly measured and do not exclude the portion of the firms' manufacturing activities that have been completely relocated offshore. Understanding the role of wholesale establishments in firms' offshoring decisions, however, remains a potentially fruitful avenue for future work.

2.5 Conclusion

The new CMS data provide key insights into plant and firm level fragmentation strategies. A substantial share of plants and firms do not break apart their production of customized inputs, and the vast majority of those that do primarily source domestically. Plants that fragment production are larger and more productive than non-fragmenters, and plants that source offshore are the largest and most productive. These patterns persist within industries, indicating substantial within

industry heterogeneity in firms' sourcing strategies. In addition, high wage states have the largest share of plants that fragment production domestically. Finally, offshoring firms have a higher ratio of imports to sales, a higher share of imports from low income countries, and import a greater range of products from more countries.

Tables

Table 2.1: Plant participation shares by contract manufacturing service purchase status

	Plants	Sales	Emp
No Purchases	0.71	0.57	0.61
Domestic Purchases	0.27	0.39	0.35
Offshore Purchases	0.02	0.04	0.04

Notes: Approximately 106,500 manufacturing plants in the CMS sample. Sales and employment shares weighted by the inverse probability of inclusion in the CMS sample.

Table 2.2: Manufacturing firm participation shares by contract manufacturing service purchase status

	Firms	Sales	Emp
No Purchases	0.69	0.31	0.42
Domestic Purchases	0.28	0.42	0.39
Offshore Purchases	0.02	0.03	0.03
Domestic & Offshore	0.01	0.24	0.16

Notes: Manufacturing firms are all firms in the CMS sample with one or more plants classified in manufacturing. Sales and employment shares weighted by the inverse probability of inclusion in the CMS sample.

Table 2.3: Plant means by contract manufacturing service purchase status

	Raw Means			Relative Industry Means		
	Sales ^a	Emp	ln(VAP)	Sales	Emp	ln(VAP)
No Purchases	19,487	51.3	4.51	0.87	0.91	-0.03
Domestic Purchases	37,077	79.8	4.63	1.28	1.20	0.07
Offshore Purchases	51,457	137	4.74	2.17	1.69	0.20
All Plants	24,686	60.4	4.55	1.00	1.00	0.00

Notes: Weighted by the inverse probability of inclusion in the CMS sample. ^a Sales in \$000s.

Table 2.4: Industry distribution of the share of establishments that purchase contract manufacturing services

86 Manufacturing Industries (NAICS 4)

Domestic Purchases (% of estabs in industry)	Offshore Purchases (% of estabs in industry)				Total
	0%	0-5%	5-10%	10-20%	
5-10%	0	2	0	0	2
10-20%	1	22	2	0	25
20-35%	1	31	6	2	40
35-50%	0	13	4	1	18
50-60%	0	1	0	0	1
Total	2	69	12	3	86

Note: Categories defined such that $LHS < \%estabs \leq RHS$

Table 2.5: Plant participation shares within average state wage terciles, by CMS purchase status

	State wage tercile		
	Low	Medium	High
No Purchases	0.76	0.73	0.68
Domestic Purchases	0.22	0.25	0.30
Offshore Purchases	0.02	0.02	0.02

Table 2.6: Manufacturing firm imports, by contract manufacturing service purchase status

	Total imports (share)	Average imports (millions \$s)	$\frac{\text{Imports}}{\text{Sales}}$ (mean)	$\frac{\text{Intermed Imports}}{\text{All Imports}}$ (mean)
No Purchases	0.33	2.5	0.09	0.60
Domestic Purchases	0.36	7.2	0.03	0.62
Offshore Purchases	0.07	18.7	0.20	0.65
Domestic & Offshore	0.24	428.5	0.16	0.75

Notes: Manufacturing firms are all firms in the CMS sample with one or more plants classified in manufacturing. Imports are of manufactured goods only. Measures weighted by the inverse probability of inclusion in the CMS sample.

Table 2.7: Manufacturing firms' import behavior, by contract manufacturing service purchase status

	Importer (share)	Low income ^a (share)	Median count of			
			HS Products ^b		Countries ^c	
			All Firms	Importers	All Firms	Importers
No Purchases	0.41	0.28	0	3	0	2
Domestic Purchases	0.53	0.19	1	4	1	2
Offshore Purchases	0.90	0.48	8	11	3	4
Domestic & Offshore	$\approx 1.0^d$	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. *a* Share of imports from low-income countries, where countries in the bottom two per capita GDP terciles are classified as low income. *b* Count of distinct 10 digit Harmonized System codes a firm imports. *c* Count of distinct countries from which a firm imports. *d* Rounded for disclosure avoidance.

Table 2.8: Manufacturing firm participation shares, by contract manufacturing service purchase status and firm type

	Firms	Sales	Emp
<hr/>			
All Manufacturers			
No Purchases	0.69	0.31	0.42
Domestic Purchases	0.28	0.42	0.39
Offshore Purchases	0.02	0.03	0.03
Domestic & Offshore	0.01	0.24	0.16
<hr/>			
Manufacturing Firms With			
No Wholesale Plants			
No Purchases	0.70	0.57	0.61
Domestic Purchases	0.28	0.38	0.35
Offshore Purchases	0.02	0.04	0.03
Domestic & Offshore	0.00	0.02	0.01
Wholesale Plants			
No Purchases	0.52	0.23	0.18
Domestic Purchases	0.37	0.43	0.45
Offshore Purchases	0.05	0.03	0.03
Domestic & Offshore	0.07	0.31	0.34

Notes: Manufacturing firms are all firms in the CMS sample with one or more plants classified in manufacturing. Sales and employment shares weighted by the inverse probability of inclusion in the CMS sample.

Table 2.9: Manufacturing firm imports, by contract manufacturing service purchase status and firm type

	Total imports (share)	Average imports (millions \$s)	$\frac{Imports}{Sales}$ (mean)
<hr/>			
All Manufactures			
No Purchases	0.33	2.5	0.09
Domestic Purchases	0.36	7.2	0.03
Offshore Purchases	0.07	18.7	0.20
Domestic & Offshore	0.24	428.5	0.16
<hr/>			
Manufacturing Firms With			
No Wholesale Establishments			
No Purchases	0.56	0.7	0.09
Domestic Purchases	0.31	1.0	0.03
Offshore Purchases	0.09	4.4	0.19
Domestic & Offshore	0.03	41.4	0.15
Wholesale Establishments			
No Purchases	0.29	64.5	0.12
Domestic Purchases	0.37	123.6	0.13
Offshore Purchases	0.06	153.4	0.30
Domestic & Offshore	0.28	542.0	0.16

Notes: Manufacturing firms are all firms in the CMS sample with one or more plants classified in manufacturing. Imports are of manufactured goods only. Measures weighted by the inverse probability of inclusion in the CMS sample.

Table 2.10: Manufacturing firms' import behavior, by contract manufacturing service purchase status and firm type

	Share of Importers	Median count of			
		HS Products ^a		Countries ^b	
		All Firms	Importers	All Firms	Importers
All Manufacturers					
No Purchases	0.41	0	3	0	2
Domestic Purchases	0.53	1	4	1	2
Offshore Purchases	0.90	8	11	3	4
Domestic & Offshore	≈ 1.00 ^c	123	124	20	20
Manufacturing Firms With					
No Wholesale Establishments					
No Purchases	0.39	0	3	0	2
Domestic Purchases	0.49	0	3	0	2
Offshore Purchases	0.89	7	9	3	3
Domestic & Offshore	> .89 ^c	36	37	9	9
All Firms	0.43	0	3	0	2
Wholesale Establishments					
No Purchases	0.82	7	11	3	4
Domestic Purchases	0.92	23	28	7	8
Offshore Purchases	0.99	42	42	10	10
Domestic & Offshore	1.00	177	177	25	25
All Firms	0.88	15	20	5	6

Notes: Manufacture firms are all firms in the CMS sample with one or more plants classified in manufacturing. Firm imports are limited to manufactured goods. ^a Count of distinct 10 digit Harmonized System codes a firm imports. ^b Count of distinct countries from which a firm imports. ^c Rounded for disclosure avoidance.

Chapter 3

Model of Production Fragmentation

3.1 Introduction

In this chapter, I develop a static partial equilibrium model of firms' production fragmentation decisions. It is a model of heterogeneous firms with an exogenous wage similar to Helpman et al. (2004) and Antràs and Helpman (2004), but incorporates the concept of task production with costly fragmentation originally introduced by Grossman and Rossi-Hansberg (2008). The model incorporates the stylized facts presented in Section 2.3 and provides a framework to assess the costs and benefits associated with fragmenting production across different locations.

3.2 Demand

Consumers are identical with preferences represented by

$$U = \prod_{j=1}^J Q_j^{\lambda_j}, \quad \sum_j \lambda_j = 1,$$

where Q_j is an index of aggregate consumption in industry j , and λ_j is an exogenous share of income spent on industry j . Aggregate consumption in industry j is a

constant elasticity of substitution function

$$Q_j = \left(\int_{i \in j} q(i)^\sigma di \right)^{1/\sigma},$$

where $\varepsilon = \frac{1}{1-\sigma} > 1$ denotes the elasticity of substitution between goods in a given industry. For now I drop the j subscripts with the understanding that all industry variables refer to industry j .

These CES preferences lead to demand for a particular variety i in a given industry,

$$q(i) = Ap(i)^{-\varepsilon}, \quad A = \frac{\lambda E}{\int_{i \in j} p(i)^{1-\varepsilon} di} \quad (3.1)$$

where $p(i)$ is the price of variety i and E is aggregate expenditure.

3.3 Production

There is an exogenous mass of producers, N_{jh} , in each industry and geographic home state h . In the model, producers' location is exogenous to their sourcing arrangement. In the empirical section, I consider the possibility that producers choose their location based on their anticipated sourcing strategy and use several approaches to address the potential biases that could result.

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 in each industry requires a continuum of tasks, normalized to one and indexed by k . Producers combine task output via a Leontief production function to produce a single com-

posite input M . More formally, $M = \min_k \{m_k\}$, $k \in [0, 1]$, where m_k denotes the output of task k .¹

Producers have heterogeneous productivity denoted by $\varphi > 0$. They transform the composite input M into their product via: $q = \varphi M$. As a result, the production of one unit of q requires q/φ units of M . Productivity can therefore represent production efficiency (same quality at lower cost) or product quality (higher quality at equal cost). The key assumption here is that productivity heterogeneity affects the transformation of the input M into output q , but does not alter firms' ability to convert labor into task output.²

3.4 Profits within an integrated plant

Consider an integrated plant, defined as one that performs all of its own production tasks within a single plant. With CES preferences, the optimal final goods' price is a mark-up over marginal cost and is 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 for the integrated producer is $C_i = w_h$, and its profits are:

$$\pi_I = \frac{(1 - \sigma)A}{\sigma^{(1-\varepsilon)}} \left[\frac{\varphi}{w_h} \right]^{(\varepsilon-1)}. \quad (3.2)$$

¹The assumption of single composite input with a Leontief production function is based on the set-up in Rodríguez-Clare (2010). 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.

²This assumption is similar to Antràs and Helpman (2004) where a firm's productivity does not affect the productivity of its input suppliers. See Appendix Section A.2.3 for additional discussion.

As is standard in this class of models, the most productive producers are also the biggest and most profitable producers.

3.5 Production with fragmentation across locations

When fragmentation is possible, final good producers can purchase task output from manufacturing service providers (MSPs) in different locations.³ MSPs specialize in the production of a single task that they customize for multiple final good producers. By specializing, the MSP is more efficient at the production of a given task than an integrated plant.

3.5.1 Benefits from fragmentation

The MSP efficiency gain is captured by its use of $\alpha < 1$ units of labor to produce one unit of m_k .⁴ MSPs are located in a domestic state, D , or offshore, O . There is free entry and perfect competition among MSPs so that the price of a task purchased from an MSP in sourcing location s is simply equal to its local production cost:

$$P_s(m_k) = \alpha w_s, \text{ where } s \in \{D, O\}. \quad (3.3)$$

By purchasing tasks from an MSP, a final good producer benefits from the gain in specialization, α , and can access potentially cheaper labor in the MSP's location.

³MSP is the term used by practitioners and by the U.S. Census Bureau to describe these specialized suppliers.

⁴The model could be extended to allow α to vary across sourcing locations. Grossman and Rossi-Hansberg (2009) argue that countries may differ in their productivities for given activities due to external economies of scale. Lafontaine and Sivadasan (2009) find that differences in labor market institutions across countries affect within firm labor productivity.

3.5.2 Costs of fragmentation

Although purchasing tasks from MSPs allows a final good producer to enjoy efficiency gains and perhaps access to 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 $f_D \leq f_O$. These costs are paid in the final good producer's home wage.

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:

$$\tau(\delta_{is}, \omega_k, \eta_i, \eta_s, \rho_j) \geq 1 \quad (3.4)$$

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, of the output from task k . $\frac{\partial \tau}{\partial \omega} > 0$ reflects task-specific differences in fragmentation costs attributable to these inherent differences. η_i captures producer i 's information technology, while η_s reflects the state of technology 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. In the empirical section, I assume that electronic communication about the production process lowers fragmentation costs

so that $\frac{\partial^2 \tau}{\partial \eta \partial \rho} < 0$. In addition, firms with better technology enjoy greater fragmentation cost savings when they source from locations with better technology so that $\frac{\partial^2 \tau}{\partial \eta_i \partial \eta_s} < 0$.

Final good producers pay the task specific fragmentation costs in units of labor from sourcing location s .⁵ The per-unit cost to final good producer i for task k purchased from an MSP in location s is then:

$$c_{kis} = \alpha w_s \tau(\delta_{is}, \omega_k, \eta_i, \eta_s, \rho_j). \quad (3.5)$$

3.6 Profits with fragmentation

Final good producers can perform all tasks within a single integrated plant, I , or can source an endogenous share of tasks from an MSP in another domestic state, D , or offshore location, O . To determine which sourcing strategy maximizes total profits, producers first maximize variable profits for each strategy. They then compare total profits across strategies by subtracting the respective fixed costs associated with fragmentation to a given location.

Fragmenting only maximizes variable profits if it results in lower costs of task production. Order tasks such that fragmentation costs are strictly increasing in the

⁵Payment of fragmentation costs in units of foreign labor is based on the offshoring cost set-up in Grossman and Rossi-Hansberg (2008).

index k .⁶ A necessary, though not sufficient, condition for fragmentation is then

$$w_h > \alpha w_D \tau_D(0) \text{ or} \tag{3.6a}$$

$$w_h > \alpha w_O \tau_O(0), \tag{3.6b}$$

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 (3.6) 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 (3.6a) holds, then for offshoring to be potentially viable, it must also be the case that

$$\frac{w_O}{w_D} < \frac{\tau_D(0)}{\tau_O(0)}. \tag{3.7}$$

In this case, the decision to offshore is independent of the home wage and depends only the relative costs and benefits of sourcing from the lowest cost domestic location relative to the lowest cost foreign location. I assume that the distance to an offshore location is greater than the distance to a domestic location, and/or that domestic technology is superior to foreign technology so that $\tau_D(k) < \tau_O(k) \forall k$.

From Equation (3.7), this assumption means that $w_O < w_D$ for offshoring to occur.

I also assume that $\frac{\partial \tau_D(\cdot)}{\partial k} \leq \frac{\partial \tau_O(\cdot)}{\partial k}$. As domestic fragmentation costs increase in the

⁶For this ordering to hold across locations, the task-specific component of fragmentation costs, ω_k , can interact with distance or technology, but not both. Under this assumption, the ordering is without loss of generality and the ordering of tasks' fragmentation costs, though not their absolute size, is the same across locations. See the appendix for further discussion. Assuming costs are strictly increasing in k is not without loss of generality. The appendix in Grossman and Rossi-Hansberg (2006) addresses the possibility of flat portions in the offshoring cost function in a model of homogeneous firms and perfect competition.

task index, k , offshoring costs increase at least as much.

Equations (3.6) and (3.7) 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. The other potential corner solution is $w_h > \alpha w_s \tau_s(1)$, where $s \in \{D, O\}$. In this case, producers fully fragment. Since the focus of this paper is on U.S. manufacturers that still perform some fraction of their physical transformation activities, I assume w_h is sufficiently low so that full fragmentation does not occur.

If a producer only fragments to one location s , then its optimal share of fragmented tasks, \bar{k}_s , is implicitly defined by

$$w_h = \alpha w_s \tau_s(\bar{k}_s), \text{ where } s \in \{D, O\}. \quad (3.8)$$

With sourcing from one location, the cost of the composite input M , for producer i sourcing from s is now:

$$C_{is} = (1 - \bar{k}_s)w_h + \alpha w_s \int_0^{\bar{k}_s} \tau_{is}(k) dk, \text{ where } s \in \{D, O\}. \quad (3.9)$$

If a producer sources domestically and offshore, then its share of offshored tasks is \bar{k}_O which is implicitly defined by

$$\frac{w_O}{w_D} = \frac{\tau_D(\bar{k}_O)}{\tau_O(\bar{k}_O)}, \quad (3.10)$$

while \bar{k}_D is given by Equation (3.8). In this case, the producer's home wage has no effect on its share of offshored tasks. When a producer sources domestically and offshore, the cost of the composite input M is then

$$C_i = (1 - \bar{k}_D)w_h + \alpha w_O \int_0^{\bar{k}_O} \tau_O(k) dk + \alpha w_D \int_{\bar{k}_O}^{\bar{k}_D} \tau_O(k) dk, \quad (3.11)$$

where \bar{k}_O is the share of tasks offshored and $\bar{k}_O - \bar{k}_D$ is the share of tasks fragmented domestically.

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

$$\pi_{is} = \frac{(1 - \sigma)A}{\sigma^{(1-\varepsilon)}} \left(\frac{\varphi}{C_{is}} \right)^{(\varepsilon-1)} - \sum_s w_h f_s, \text{ where } s \in \{D, O, DO\}. \quad (3.12)$$

3.7 Equilibrium sourcing strategy

In equilibrium, final good producer i chooses the sourcing location s that maximizes profits $\max_s \{\pi_{is}\}$, where $s \in \{I, D, O, DO\}$. Since fragmentation entails a fixed cost, it will never occur if Equation (3.6) 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; and (iii) a mixed strategy of domestic and offshore fragmentation 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 3.1a illustrates this cost scenario. In the figure, C_D , the cost of the composite M defined in Equation (3.9), is simply the area under the bold line. Because domestic fragmentation also entails a fixed cost, Figure 3.1b 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 φ , but the fixed cost to fragment means that, of the producers in the set N_D , only those with productivity above the threshold

$$\tilde{\varphi}_D = \left[\frac{\sigma^{1-\varepsilon}}{(1-\sigma)A} \left(\frac{w_h f_D}{C_D^{1-\varepsilon} - w_h^{1-\varepsilon}} \right) \right]^{\frac{1}{\varepsilon-1}}, \quad (3.13)$$

find it optimal to fragment domestically.

*Empirical prediction 1: All else equal, a firm will fragment domestically if doing so maximizes its **variable** profits and the firm's productivity is sufficiently high (i.e., $\varphi_i > \tilde{\varphi}_{iD}$).*

When $c_{kiD} < c_{kiO} \forall k$ for some firms, ignoring the domestic fragmentation option will overpredict the amount of offshoring, while underpredicting total fragmentation. Figure 3.1a shows that if offshoring were the only option, the share of fragmented tasks would be lower ($\bar{k}_O < \bar{k}_D$), as would the production cost savings.

The subset of producers for whom offshore fragmentation maximizes variable profits, N_O , face costs $c_{kiD} > c_{kiO} \forall k$. Figure 3.2a 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 3.1b, 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 3.2b depicts this case. Producers in the subset N_O , with productivity between $\tilde{\varphi}_D$ and $\tilde{\varphi}_O$, fragment domestically, while those with productivity above $\tilde{\varphi}_O$ offshore, where

$$\tilde{\varphi}_O = \left[\frac{\sigma^{1-\varepsilon}}{(1-\sigma)A} \left(\frac{w_h(f_O - f_D)}{C_O^{1-\varepsilon} - C_D^{1-\varepsilon}} \right) \right]^{\frac{1}{\varepsilon-1}}. \quad (3.14)$$

*Empirical prediction 2: All else equal, a firm will offshore production if doing so maximizes its **variable** profits and the firm's productivity is sufficiently high (i.e., $\varphi_i > \tilde{\varphi}_{iO}$).*

In this case, ignoring the domestic fragmentation margin would again overpredict the amount of offshoring and underpredict the overall amount of fragmentation. Let $\hat{\varphi}_O$ denote the offshoring threshold in a world with no domestic fragmentation.

Figure 3.2b shows that $\tilde{\varphi}_D < \hat{\varphi}_O < \tilde{\varphi}_O$. As a result, producer i with productivity $\tilde{\varphi}_D < \varphi_i < \hat{\varphi}_O$ would no longer fragment if domestic fragmentation were not an option, while producer l with productivity $\hat{\varphi}_O > \varphi_l < \tilde{\varphi}_O$ would now offshore instead of fragmenting domestically.

A third potential scenario may lead to domestic and offshore fragmentation by the same producer. If the difference between the domestic versus offshore cost is not the same for each task (i.e., $\partial\tau_D(\cdot)/\partial k < \partial\tau_O(\cdot)/\partial k$), then a single producer may find both offshoring and domestic fragmentation optimal. Figure 3.3a depicts this case. The lowest cost for the composite input is attained by offshoring \bar{k}_O , and fragmenting $\bar{k}_D - \bar{k}_O$ domestically. The bold line is the graphical equivalent of Equation (3.11), where the area underneath the line represents the cost of M under a mix of domestic and offshore fragmentation. If fixed costs are high relative to fragmentation cost savings, then integrated production, domestic fragmentation, offshoring, and a mix of domestic and foreign sourcing are the four possible profit maximizing strategies. Figure 3.3b depicts these profit functions. Here, producers in the subset N_{DO} with productivity above $\tilde{\varphi}_{DO}$ fragment both domestically and offshore, where

$$\tilde{\varphi}_{DO} = \left[\frac{\sigma^{1-\varepsilon}}{(1-\sigma)A} \left(\frac{w_h f_D}{C_{OD}^{1-\varepsilon} - C_O^{1-\varepsilon}} \right) \right]^{\frac{1}{\varepsilon-1}}. \quad (3.15)$$

In this scenario, ignoring the domestic fragmentation option would still overpredict the extent of offshoring and underpredict total fragmentation. Let \hat{k}_O denote the share of offshored tasks when domestic fragmentation is not an option, where $w_h = \alpha w_O \tau_O(\hat{k}_O)$ implicitly defines \hat{k}_O . Figure 3.3a shows that for each producer

that would have fragmented both domestically and offshore, $\hat{k}_O < \bar{k}_D$ (recall from Equation (3.11) that \bar{k}_D represents total fragmented production). In addition, there is no longer a domestic fragmentation profit function, so the new productivity threshold is once again $\tilde{\varphi}_D < \hat{\varphi}_O < \tilde{\varphi}_O$. More producers offshore, but fewer fragment.

3.8 The likelihood of fragmentation

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.

3.8.1 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:

$$\frac{\partial C_s}{\partial \eta} = \frac{\partial \bar{k}_s}{\partial \eta} [\alpha w_s \tau(\bar{k}_s) - w_h] + \alpha w_s \int_0^{\bar{k}_s} \frac{\partial \tau(k)}{\partial \eta} dk < 0. \quad (3.16)$$

The term in square brackets in Equation (3.16) is equal to zero from Equation (3.8).⁷ The second term represents the inframarginal savings that result from better

⁷This 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 3.1a shows that the derivative may not capture the effect of large changes in η on task production costs.

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:

$$\frac{\partial \pi_s}{\partial \eta} = (1 - \varepsilon)B[C_s]^{-\varepsilon} \frac{\partial C_s}{\partial \eta}. \quad (3.17)$$

Plugging in Equation, (3.16), 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. An individual firms is now more likely to exceed that threshold, so that:

Empirical prediction 3: All else equal, plants with better communication technology will be more likely to fragment production.

3.8.2 Variation in the home wage

For fragmentation to occur, the home wage must be sufficiently high so that some tasks are cheaper to purchase from another location. In particular, Equation (3.6) is more likely to hold when w_h is large. As a result, the measure of producers for which fragmentation has the potential to maximize total profits is increasing in the home wage.

An increase in the home wage may also make fragmentation relatively more

profitable for the subset of producers for whom fragmentation already maximizes variable profits. Consider the effect of a change in the producer's home wage, w_h . The change in integrated profits relative to fragmented profits is

$$\frac{\partial \pi_I / \partial w_h}{\partial \pi_s / \partial w_h} = \frac{[w_h]^{-\varepsilon}}{(1 - \bar{k}_s)[C_s]^{-\varepsilon} + f_s / (\varepsilon - 1)B}. \quad (3.18)$$

where

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

For a producer that is indifferent between integrated and fragmented production before the wage change, the relative decrease in integrated profits exceeds the decrease in fragmented profits as long as:

$$f_s < B \left(\frac{\varepsilon - 1}{\varepsilon} \right) C_s^{-\varepsilon} \left[\frac{1}{\tau(\bar{k}_s)} \int_0^{\bar{k}} \tau(k) dk \right].$$

This condition reflects the fact that fixed costs from fragmentation are paid in the home wage. If fixed costs are greater than this threshold, an increase in the home wage results in additional fixed costs that swamp the marginal cost benefits from fragmentation. This result leads to the following prediction:

Empirical prediction 4: All else equal and assuming fixed costs are not too large, the profitability of fragmentation is increasing in producers' home wage.

3.9 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

$$\frac{\partial \tilde{\varphi}_O^{\varepsilon-1}}{\partial \delta} = \left[\frac{\partial C_O}{\partial \delta} - \frac{\partial C_D}{\partial \delta} \right] \left(\frac{w_h(f_O - f_D)}{[C_O^{1-\varepsilon} - C_D^{1-\varepsilon}]^2} \left(\frac{\sigma^{2-\varepsilon} A}{(1-\sigma)^2} \right) (C_O^{-\varepsilon} - C_D^{-\varepsilon}) \right). \quad (3.19)$$

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 (3.19) is positive. The offshoring threshold is therefore higher, leading to the following prediction:

Empirical prediction 5: All else equal, plants that are closer to potential offshore sourcing locations will be more likely to offshore.

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

$$\frac{\partial \tilde{\varphi}_O^{\varepsilon-1}}{\partial \eta} = \left[\frac{\partial C_O}{\partial \eta} - \frac{\partial C_D}{\partial \eta} \right] \left(\frac{w_h(f_O - f_D)}{[C_O^{1-\varepsilon} - C_D^{1-\varepsilon}]^2} \left(\frac{\sigma^{2-\varepsilon} A}{(1-\sigma)^2} \right) (C_O^{-\varepsilon} - C_D^{-\varepsilon}) \right) \quad (3.20)$$

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 (3.16) shows that an improvement in communication technology will make offshoring relatively more prof-

itable 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 3.2 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 3.20 can be expressed as

$$\alpha w_O \int_{\bar{k}_D}^{\bar{k}_O} \frac{\partial \tau_O(k)}{\partial \eta} dk + \alpha w_O \int_0^{\bar{k}_D} \frac{\partial \tau_O(k)}{\partial \eta} dk - \alpha w_D \int_0^{\bar{k}_D} \frac{\partial \tau_D(k)}{\partial \eta} dk. \quad (3.21)$$

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.

Empirical prediction 6: All else equal, communication technology affects the likelihood of offshoring, but its impact depends upon technology's effect on domestic versus offshore costs.

Finally, the home wage affects the likelihood that a fragmenting producer sources offshore. To see why, suppose there is one high wage domestic state, one low wage state and one offshore location, where $w_O < w_L < w_H$. For simplicity, assume that $\tau_O(\cdot) = \tau_L(\cdot) = \tau_H(\cdot)$ so that $\alpha w_O \tau_O(\cdot) < \alpha w_L \tau_L(\cdot) < \alpha w_H \tau_H(\cdot)$.

With this set-up, all producers in the high wage state face the scenario depicted in Figure 3.2a. Offshoring maximizes variable profits, but only those producers with productivity above $\tilde{\varphi}_O$ will source offshore, while those with $\tilde{\varphi}_D < \varphi < \tilde{\varphi}_O$ will fragment domestically. In contrast, no producers in the low wage state will fragment domestically, while those with $\varphi > \tilde{\varphi}_O$ will offshore.⁸ This leads to a final prediction about fragmenting producers' decision to offshore:

Empirical prediction 7: All else equal, the likelihood a fragmenting plant will offshore is decreasing in its home wage.

3.10 Share of fragmentation

In equilibrium, the share of tasks a final good producer fragments depends on the relative wage differences across locations. If a producer only sources from one location, then Equation (3.8) shows that the share fragmented by producers for whom $\pi_s > \pi_I$ is increasing in their relative home wage. More formally,

$$\frac{d\bar{k}}{d(w_s/w_h)} = -\frac{\alpha\tau_s(\bar{k}_s)^2}{\partial\tau_s(\bar{k})/\partial\bar{k}}. \quad (3.22)$$

It is important to note, however, that for a producer sourcing from multiple locations, Equation (3.10) shows that the share of tasks offshored is independent of the home wage and depends only the wage differences between sourcing alternatives.

This leads to the following prediction:

⁸If the gain from specialization is sufficiently high (i.e., α is sufficiently below 1), firms in low wage states may still fragment in their own state.

Empirical prediction 8: The share of tasks purchased from location s is decreasing in the location's wage relative to alternate sourcing location wages.

A decrease in fragmentation costs will also result in an increased share of fragmentation (i.e., $\frac{d\bar{k}}{d\delta} > 0$ and $\frac{d\bar{k}}{d\eta} > 0$).⁹ This yields the additional prediction:

Empirical prediction 9: The share of tasks producer i fragments will be increasing in the producer's communication technology and decreasing in its distance to suppliers.

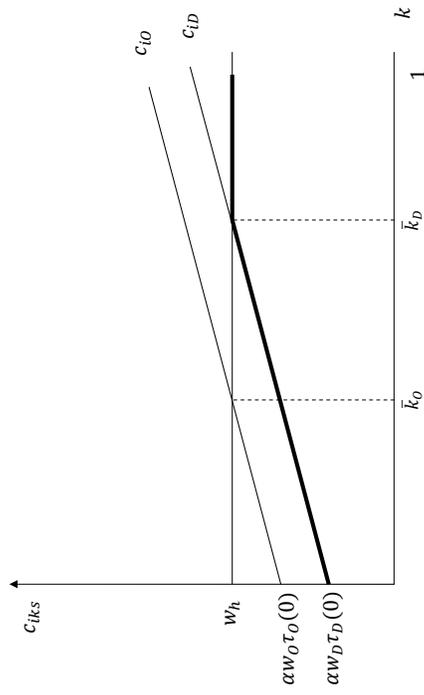
3.11 Conclusion

The model makes predictions about the extensive and intensive margins of producers' equilibrium fragmentation strategies. More productive producers with better information technology and located in higher wage states are more likely to fragment production. Of these fragmenting producers, the most productive and those that are relatively closer to foreign sourcing locations are more likely to offshore. In contrast, fragmenting producers' propensity to offshore is decreasing in their home wage, since producers in low wage states are less likely to find other domestic locations that provide lower labor costs. Finally, the degree to which producers fragment their production process depends upon the relative wages in their sourcing sites and the fragmentation costs they incur.

⁹See appendix sections A.2.1 and A.2.2 for full derivatives.

Figure 3.1: Integrated production and domestic fragmentation

(a) Variable costs per task



(b) Profits

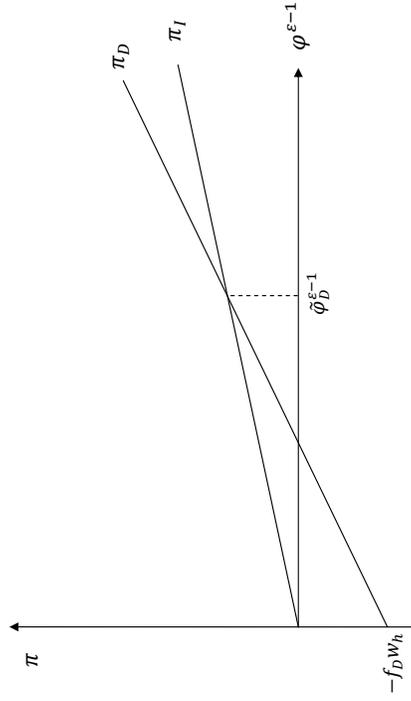
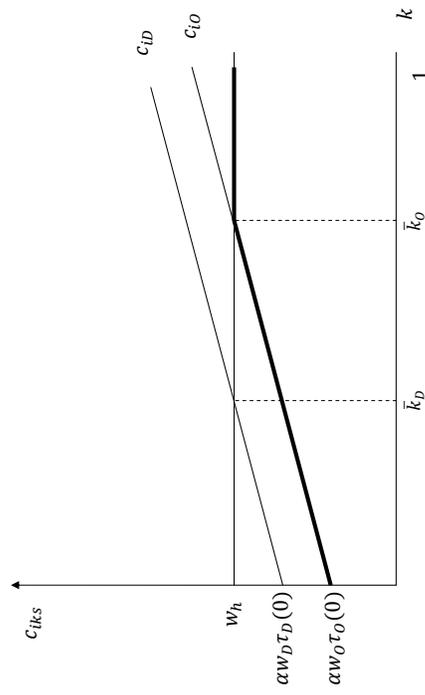


Figure 3.2: Integrated production, domestic fragmentation, or offshoring

(a) Variable costs per task



(b) Profits

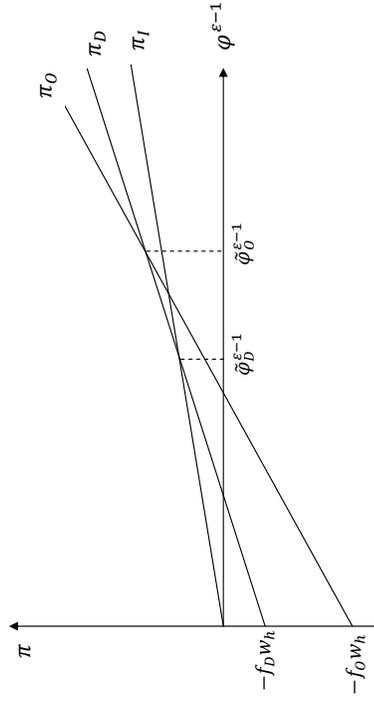
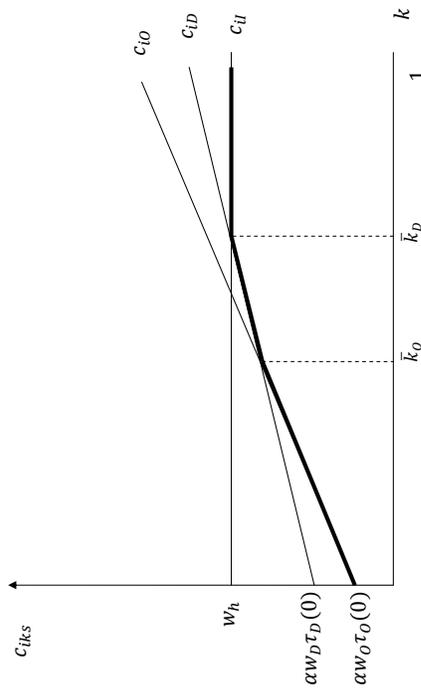
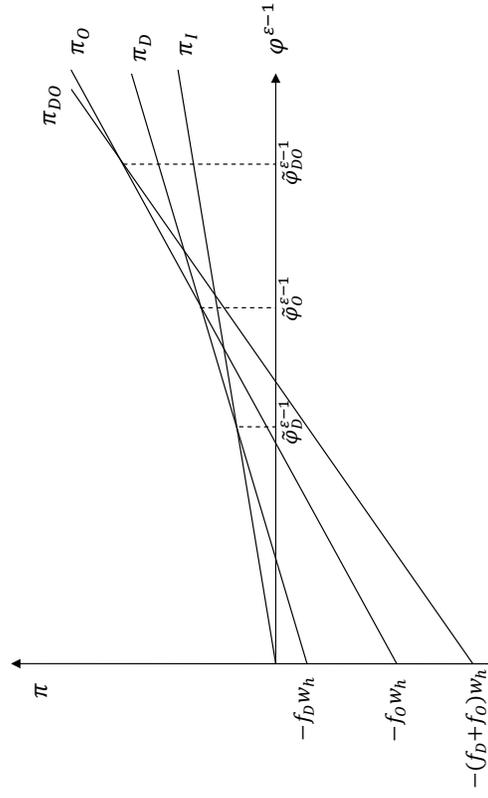


Figure 3.3: Integrated production, domestic fragmentation and offshoring

(a) Variable costs per task



(b) Profits



Chapter 4

Testing the Model's Predictions

4.1 Introduction

In this chapter, I use the new fragmentation dataset to test the equilibrium relationships predicted by the model. First I focus on the extensive margins and estimate determinants of the probability that a plant purchases contract manufacturing services (CMS), as well as the probability that a fragmenting plant will offshore. I then use the linked import data to assess the relationship between firm characteristics and the extent of offshore production. Although the theoretical framework in Chapter 3 shows that a firm's decisions about whether and how much to fragment and offshore are made simultaneously, I estimate each margin separately. This estimation strategy is driven by the relevance of each margin, the theory's implications about how margins are likely to be related to each other, and by practical data limitations. I explain these factors in each section. Finally, I disaggregate the firm import data by country to determine whether the effects of firm characteristics on sourcing strategies depend upon location specific factors.

4.2 The fragmentation decision

In this section, I estimate the probability that a plant will fragment production. To my knowledge, this specification provides the first evidence on the determinants of a producer's decision to break up its production process across distinct geographic locations. Since the theory suggests that domestic and foreign fragmentation may be substitutes for some firms, grouping both types of fragmentation together avoids violating the independence of irrelevant alternatives assumption that would arise from multinomial logit estimation.¹ I evaluate the importance of technology, distance and labor cost savings in a plant's decision to fragment its production process by estimating:

$$Pr(y_{i,j,h} = 1|X_{i,j,h}) = \beta_J + \beta_T Tech_i + \beta_w wage_h + \sum \beta_D Dist_i + \sum \beta_P Prod_i, (4.1)$$

where $y_{i,j,h}$ equals one if plant i in industry j and home state h purchases CMS. $Tech_i$ is a plant level measure of communication technology. $wage_h$ is the producer's home state wage, $Dist_i$ is a set of distance measures from plant i to domestic suppliers, ports and borders, and $Prod_i$ denotes plant productivity terciles. I include a full set of six digit NAICS industry dummies, β_J , as controls.

I measure plants' local labor costs with state-industry level U.S. wages constructed from the Bureau of Labor Statistics' Occupation Employment Statistics. To minimize any potential bias arising from the relationship between wages and

¹I have also estimated the probability of no fragmentation, domestic fragmentation, and offshoring jointly in a multinomial logit specification. While the the estimated coefficients change, their economic interpretation is qualitatively similar.

skill, the wage measure is based solely on production worker occupations and the mix of these occupations for a given industry is fixed across states. As a result, the variation in wages across states is attributable to differences in states' wages for detailed occupations.² Averaged over industry, the mean state wage is \$14.58, with a standard deviation of \$1.08. The lowest wages are \$12.44 and \$12.96 in South Dakota and Mississippi respectively, while the highest wage is \$17.97 in Alaska, followed by Delaware, Washington, Michigan and Connecticut, all with average wages above \$16.

To capture distance to potential domestic suppliers, I calculate the distance between each plant and the closest manufacturing service provider (MSP). I identify a potential supplier as the closest manufacturing establishment that specifies its primary activity as "Providing contract manufacturing services to others."³ I construct three additional measures to capture the distance between an individual plant and foreign sourcing locations. First, I calculate the distance between each plant and the closest deep water port. I also calculate the distances between each plant and the closest border crossing with Mexico and the closest crossing with Canada.⁴ Table 4.1 presents the average distance, by CMS purchase status, between a plant and the closest MSP, deep water port, and border crossings. The average minimum distance to an MSP is only two miles for the entire sample, though the average distance for non-fragmenting plants is 2.2 miles compared to 1.6 miles for fragmenters.

²Additional information on the wage data is presented in Data Appendix B.

³The 2007 CM asked all plants in the CMS sample to identify their primary activity from four choices. "Providing contract manufacturing services to others" is one of the four options. Additional details of the variable construction, as well as the exact question from the Census, are provided in Data Appendix B.

⁴Details for the port and border crossing locations are in Data Appendix B.

On average, plants that purchase CMS primarily offshore are 50 miles closer to a deep water port than plants that purchase CMS domestically. Offshoring plants are also 78 miles closer to Mexican border crossings relative to domestic fragmenters. In contrast, domestic fragmenters are over 50 miles closer to border crossings with Canada.

I construct productivity terciles using the log of plants' value-added labor productivity. I use terciles to follow the model's prediction that producers must exceed a productivity threshold for profits from fragmentation to exceed profits from integrated production. One implication of the model is that a plant for which fragmentation is optimal will be larger if it fragments.⁵ As a result, plants' measured productivity may be subject to reverse causality. Plants that fragment production are larger, as a result of fragmentation, and therefore have higher measured productivity. To address this issue, I instrument for plant productivity in 2007 using lagged values from 2002. I discuss the IV strategy in more detail below.

I measure a plant's use of communication technology with an indicator variable equal to one if the plant used electronic networks to control or coordinate its shipments in 2007. Specifically, the indicator identifies plants that negotiate the price or terms of sale for their shipments over an Internet, Extranet, Electronic Data Interchange (EDI) network, electronic mail, or other online system. Although this measure directly relates to shipments rather than input purchases, it is a useful proxy for plants' general use of communication technology. Using data collected

⁵Recall that for fragmentation to be optimal, the marginal cost of fragmented production must be less than the marginal cost of integrated production. With price set to a constant mark-up over marginal cost and downward sloping demand, a plant with the same underlying productivity parameter will therefore be larger if it fragments.

in the 1999 Annual Survey of Manufactures (ASM) Computer Survey Network Use Supplement (CNUS), the U.S. Department of Commerce (DOC) 2001 *E-Stats report* finds that just over half of the manufacturing plants that used networks to coordinate shipments in 1999 also used networks to make input purchases. Additional calculations from the CNUS show that 32 percent of plants that sold goods over networks also used networks to provide information about their design specifications to external suppliers, compared to only 16 percent of plants that did not sell goods over networks.⁶

An obvious problem with estimating Equation (4.1) is that a plant's communication technology may be endogenous to its sourcing strategy. If a plant installs a technology platform and adapts its business processes to use electronic networks because it is planning to fragment production, an unobserved positive shock to fragmentation may increase electronic network use. If this occurs, the estimated coefficient on technology will be biased. Since a plant's use of electronic networks to control or coordinate its shipments is driven by multiple factors, some of which are unrelated to fragmentation, one way to address the potential reverse causality problem is to instrument for plants' use of networks in 2007 with lagged values of their use in 2002. Table 4.2 presents the shares of plants that used these networks by plants' 2007 CMS purchase status. 36 percent of non-fragmenters, 51 percent of domestic fragmenters, and 61 percent of offshorers used electronic networks in 2007.

⁶Plants that do not use networks to control or coordinate shipments may still use the internet. For example, the DOC (2001) shows that approximately 87 percent of manufacturing plants in the 1999 ASM sample used an electronic network at their plant. In contrast, only 31 percent and 33 percent of the ASM plants accepted or placed orders online respectively. These data are only available in 1999. Additional details on electronic network use data are provided in Data Appendix B.

In 2002, these shares are lower by a factor of roughly half for each CMS category.

For the lagged instrument to be valid, plants' use of networks in 2002 must be determined by factors other than their decision to fragment production in 2007. For example, the instrument can identify a causal relationship if plants that used networks in 2002 to facilitate sales decide to fragment in 2007 because their existing communication technology makes fragmentation relatively more profitable. There are concrete reasons to believe that factors other than fragmentation play an important role in plants' use of networks to control or coordinate shipments. According to the DOC (2001), almost half of the plants that used networks to control or coordinate shipments in 1999 did not use networks to purchase inputs. McElheran (2010) also investigates the relationship between E-buying and E-selling and finds that, although both processes share the same technology platforms, E-selling generally entails more complex organizational changes. Finally, Table 4.2 shows that in 2007, 36 percent of plants that did not fragment production used electronic networks.

To identify a causal relationship using lagged values as instruments, it is also necessary for plants' fragmentation status in 2007 to differ from their fragmentation status in 2002. In particular, the instrument's power to identify a causal relationship depends upon the existence of plants that used networks in 2002 but did not fragment production. Although the 2002 CM did not ask the 2007 CMS purchase question, I use two similar questions from 2002 to assess differences between plants' 2002 and 2007 fragmentation strategies. The 2002 CM asked an establishment: 1) whether it contracted with another firm for any of its production using materials owned by the respondent; and 2) whether it sent any partially completed products to

a foreign facility for processing that were then returned to the respondent. Respondents had the option to check YES or NO to both of these questions. I compare the 2007 fragmentation status of single-units to their 2002 contract purchases.⁷ Table 4.3 decomposes plant shares for each 2007 CMS category according to 2002 electronic network use and fragmentation status. Columns 3 and 4 in the second row show that 15 percent of plants that purchase CMS domestically in 2007 used networks in 2002, and almost half of these plants did not fragment production in 2002. The third row shows that 28 percent of plants that offshore in 2007 used networks in 2002, and half of these plants did not fragment in 2002. Table 4.4 presents similar shares for 2002 electronic network use and offshore CMS purchase status. The third row shows that 31 percent of offshoring plants in 2007 used networks in 2002, though less than 20 percent of these plants offshored in 2002. These tabulations suggest the data contain sufficient variation in fragmentation status across electronic network use for the lagged values to be suitable instruments. To substantiate the use of lagged instruments further, Section 4.4 includes a robustness check in which the sample consists only of single unit plants that did not fragment production in 2002.

4.2.1 Main results for fragmentation

Table 4.5 reports results from estimating Equation (4.1). Column 1 provides OLS estimates from a regression on all plants in the CMS sample, weighted by the inverse probability of inclusion in the sample.⁸ The second column reports

⁷I limit the comparison to single unit firms since the 2002 question asks only about contract purchases from another firm.

⁸The weighted and unweighted estimates are almost identical.

OLS results for the IV sample. Since the instruments are lagged 2002 values, the IV sample consists of plants that existed in the same physical locations in 2002. I estimate a linear probability model (LPM) rather than logit or probit because of the large number of industry fixed effects, and so that the results are more comparable to the IV estimates; however, Appendix Table B.5 shows that marginal effects from probit estimation are quite similar.⁹ Column 3 presents results for the IV estimation. I focus on these results since they correspond to the preferred specification.

The estimated coefficient on electronic networks suggests that plants using electronic networks are 18 percentage points more likely to fragment. The coefficient is larger than the OLS estimate, consistent with the measure of network use to coordinate shipments being a noisy proxy for plant communication technology that facilitates communication with input suppliers. The estimated coefficient on the state wage is positive and significant and suggests that a plant in Washington state is 4.3 percentage points more likely to fragment than an otherwise identical plant in Mississippi, where average production worker wages are almost 30 percent lower. Productivity also has the expected positive relationship. Relative to plants in the lowest productivity tercile, plants in the second and third terciles are 12 and 16 points more likely to fragment respectively. Hillberry and Hummels (2008) detect significant non-linearities in the role of distance in shipments between plants, so I create indicators for different distance categories. Relative to plants that have a

⁹Because the endogenous technology variable and productivity measures are discrete, the IV regression cannot be estimated via IV probit. In addition, probit fixed effect estimates are inconsistent due to the incidental parameters problem. While it is possible to estimate a conditional logit model with fixed effects, estimating partial effects on the response probabilities with this specification requires plugging in values for the industry indicators (p. 492 Wooldridge (2002)). This exercise would not be practical in the analysis here.

manufacturing service provider (MSP) within a five mile radius, plants that are 5-10 miles away from the closest MSP are 2.1 percentage points less likely to fragment production, while those over 20 miles away are 2.8 points less likely to fragment. Plants' distance to a deep water port or a Canadian border crossing has a negligible relationship with the likelihood of fragmentation. In contrast, plants that are more than 50 miles from a border crossing with Mexico face a 2.8 percentage point decrease in the probability of fragmentation, relative to plants that are within 50 miles of the border.

There are three first stage regressions, two for productivity terciles two and three, and one for the electronic networks variable. The first three columns in Table 4.6 present the estimated coefficients and standard errors for the instruments in each first stage regression. The lagged instrument is always significant in its own first stage regression, with the expected positive coefficient. Each column reports Shea's partial R-squared for that column's endogenous variable. These range from 0.03 to 0.11.¹⁰ Each column also reports the F-Statistic for the null hypothesis that the instruments are jointly equal to zero. These F-statistics are well above the threshold of 10 proposed in Stock, Wright, and Yogo (2002).

4.2.2 Differential impact of communication technology across industries

In this section, I take an additional step towards identifying the causal effect of technology on the probability of fragmentation by focusing on a specific

¹⁰See Shea (1997) for a discussion of the partial R-squared as an indicator of weak instruments.

mechanism through which technology lowers fragmentation costs. In the model, technology lowers fragmentation costs by making it easier to communicate design criteria and production specifications across locations. In practice, a plant's use of electronic networks for these purposes depends upon its ability to codify the design and production requirements in an electronic format. If this ability varies across industries, electronic networks will lower fragmentation costs more in those industries in which the production process is amenable to electronic codification. The interaction between a plant's communication technology and its industry electronic codifiability identifies the marginal benefit of communicating design criteria and production specifications electronically.¹¹

I measure variation in industry electronic codifiability as the share of plants in a NAICS 6 industry that used Computer Aided Design (CAD) and Computer Aided Manufacturing (CAM) software in 1999.¹² This software allows plants to codify their input design criteria and the requisite physical transformation processes in an electronic format. Use of CAD/CAM software varies substantially across industries. The variation is driven by the complexity and extent to which the physical transformation process can be codified electronically. There is little benefit to creating a CAD file for a non-complex product whose specifications can be described

¹¹This approach is similar to the identification strategy in Rajan and Zingales (1998) who assess the effect of financial development on country growth by estimating the differential impact financial development has on growth in industries that are dependent on external financing. Those authors note "One way to make progress on causality is to focus on the details of theoretical mechanisms through which financial development affects economic growth, and document their working" (p.560).

¹²Conversations with various manufacturing service providers and their customers at the Mid-Atlantic Design-2-Part Show in Phoenixville, PA on April 14, 2011 suggest that electronic communication facilitates fragmentation most when it can be used in conjunction with CAD/CAM software. The CAD/CAM data were collected by the U.S. Census Bureau as part of the 1999 CNUS. Additional details are in Appendix B.

in a simple text file, while certain production process are simply not amenable to electronic codification in CAM software.¹³

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 4.7 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.¹⁴ 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

¹³For example, spring and wire manufacturing requires a continuous physical transformation process that cannot be performed by machines run by CAM software.

¹⁴Capital 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.

so, I calculate the ratio of industry imports by wholesale firms relative to domestic production. As described in chapter 2, firms that design goods and coordinate production processes in foreign locations are classified in the wholesale sector. The second to last row of Table 4.7 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.

Column 4 in Table 4.5 reports results from estimating Equation (4.1) with an additional interaction term between plant use of electronic networks and industry CAD intensity. I do not include the CAD variable directly because it is fully absorbed by the industry fixed effects. The interaction term has a positive and statistically significant coefficient, supporting the hypothesis that electronic communication lowers fragmentation costs more in industries in which plants are better able to specify production requirements electronically. To gauge the magnitudes and implied economic significance of the coefficients, Figure 4.1a plots the full effect of electronic networks evaluated at different levels of CAD intensity. The figure depicts a strong increasing relationship. Relative to plants that do not use electronic networks, plants that use networks in "other apparel" manufacturing (CAD intensity of 4 percent) are only 4.5 percentage points more likely to fragment, while plants using networks in the "semiconductor machinery" manufacturing (CAD intensity of 98 percent) are 32 percentage points more likely to fragment than plants not using networks. The differential impact of electronic networks between these two indus-

tries is thus about 27 percentage points. The coefficients on wage and distance are largely unchanged in this specification.

The right panel in Table 4.6 presents the estimated coefficients and standard errors for the instruments in each first stage regression. The lagged instrument is always significant in its own first stage regression, with the expected positive coefficient. Shea's partial R-squared measure ranges from 0.03 to 0.14, while F-statistics for the null hypothesis that the instruments are jointly equal to zero are well above 10.

4.2.3 Additional controls

There are several additional concerns that arise when estimating Equation (4.1). First, the model assumes that aggregate expenditure is identical across locations, though in reality this is clearly not the case. Since firm size depends upon aggregate expenditure, firms in areas with higher demand might be more likely to overcome the fixed costs of fragmentation. If 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).¹⁵ Column 5 in Table 4.5 shows that controlling for local demand does not affect the estimated coefficients.

Another potential concern is that the estimated effect of wages is biased by differences in worker skill across states. Although the wage measure is based on

¹⁵There are 179 BEA economic areas. These areas are designed to capture relevant regional markets surrounding metropolitan or micropolitan statistical areas.

wage differences within detailed occupation codes across states, these differences 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. Column 6 in Table 4.5 presents estimates of Equation (4.1) controlling for the state's share of workers with a college degree and the share of production workers with a high school degree. The inclusion of these skill measures does decrease the estimated wage coefficient, but it is still positive and statistically significant.¹⁶ The estimate now implies that, compared to an otherwise identical plant in Mississippi, a plant in Washington state is 2.4 percentage points more likely to fragment.¹⁷

4.3 Domestic versus offshore fragmentation

I now analyze a plant's decision to locate its fragmented production offshore. I estimate a variant of Equation (4.1), where the dependent variable is equal to one if plant i in industry j and home state h purchases CMS primarily offshore. I restrict the analysis to plants that fragment production so that the estimated coefficients reflect the impact of covariates on the probability of offshoring, relative to domestic fragmentation. The estimates for the probability of fragmentation therefore capture the determinants of breaking up the production process, while results in this section reflect the costs and benefits of locating fragmented production offshore. Because

¹⁶If fragmentation results in the fragmenting plant performing the higher skilled tasks while the lower skilled tasks are performed elsewhere, then the estimated coefficient on skills will be positive.

¹⁷I have also estimated Equation (4.1) 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.

the analysis is conditional on fragmentation, these estimates do not confound the effect of covariates on the likelihood of breaking up the production process with their effect on the likelihood of offshoring. However, to gain a complete picture of plants' offshoring decision, the estimates from both the fragmentation and offshoring regressions must be considered together.¹⁸

4.3.1 Main results for offshoring

Table 4.8 reports the results from estimating Equation (4.1) on the subset of fragmenting plants. As before, columns 1 and 2 provide OLS estimates for the full and IV samples respectively, while column 3 reports the IV estimates. The IV estimates suggest that plants using electronic networks to coordinate shipments are ten percentage points more likely to locate their fragmented production offshore. Based on the prediction from the model, this suggests that electronic communication has a differential impact of fragmentation costs that is increasing in distance. The estimated wage coefficient also has the expected negative sign. The probability that a fragmenting plant in Mississippi will purchase CMS offshore is 3.5 percentage points higher than the probability that a fragmenting plant in Washington state will do so. Consistent with the model, plants in the top productivity tercile are 3.8 percentage points more likely to offshore relative to the least productive plants.

While distance to the nearest MSP was an important factor in plants' decision to fragment, it does not seem to play a role in their decision to offshore. The

¹⁸An alternative specification would be the nested logit model in which the first branch is a plant's decision to fragment or not. For plants that fragment, the second branch would be the decision to source domestically or offshore. Estimating a nested logit, however, requires alternative-specific variables which are not available for these data.

estimated coefficients for being 5-20 miles and over 20 miles from the closest MSP are both close to zero. In contrast, distance to international entry ports does appear to affect plants' decision to offshore production. Plants that are over 200 miles away from a deep sea port are 2.4 percentage points less likely to fragment, relative to plants within 50 miles of the closest port. The estimates also show that plants over 50 miles from a border crossing with Mexico are 9.4 percentage points less likely to source their fragmented production from a foreign country relative to plants that are within 50 miles of the border. Being close to Canada, however, does not have a statistically significant relationship with the probability a fragmenting plant will source offshore.

Table 4.9 presents the estimated coefficients, standard errors and weak instrument tests for all instruments in each first stage regression. The lagged instrument is always positive and significant and the F-Statistic for the null hypothesis that the instruments are jointly equal to zero is well-above the threshold of 10 for each first stage regression.

4.3.2 Differential impact of communication technology across industries

I also estimate the differential impact of electronic networks across industries on the probability of offshoring. As in Section 4.2.2, I allow the effect of electronic networks to vary by industry CAD intensity. Column 4 in Table 4.8 presents the estimates. In contrast to results for the probability of fragmentation, the inter-

action between plant use of electronic networks and CAD industry intensity for the probability of offshoring is negative. Figure 4.1b depicts the full effect of networks, evaluated at different levels of CAD intensity. While electronic network use is associated with a higher probability of offshoring for all levels of CAD intensity, networks' impact appears to decrease with CAD intensity. The full effect is imprecisely estimated at low and intermediate levels of CAD, but the negative interaction is significant for the high CAD industries. A possible explanation for this result is that the average state of technology in foreign sourcing locations is below the average U.S. level. Receiving CAD/CAM files and using them correctly requires sophisticated equipment and workers. As a result, CAD software's potential to reduce coordination and communication costs across locations when used in conjunction with electronic networks cannot be fully realized if a given location does not have the ability to use it. Below, I investigate this possibility using the import data disaggregated by country.

The finding that electronic communication has a differential impact on the probability of relocating fragmented production offshore adds a new dimension to our understanding of the determinants of offshoring. Rather than treating technology as a single parameter that affects all firms and industries the same way, the results in Tables 4.5 and 4.8 uncover heterogeneous responses within and across industries. In addition, technological change does not necessarily make offshoring more likely. Technological improvements that facilitate domestic fragmentation may render offshoring less profitable if foreign sourcing locations are not properly equipped to exploit new infrastructure or techniques.

4.3.3 Additional controls

As in the fragmentation regressions, I ensure that the results are robust to controlling for local expenditure and state skill measures. Column 5 in Table 4.8 shows that controlling for the level of personal income in the plant's economic area does not affect the estimated coefficients. When I control for skill, the coefficient on the share of production workers in a state with at least a high school degree is negative and significant and the wage coefficient decreases slightly. While these results suggest skill may play a role in plants' decision to source their fragmented production offshore, the qualitative relationships predicted by the model are robust to controlling for observed skill heterogeneity.¹⁹

4.4 Robustness checks for probability of fragmenting and offshoring

In the model, producer's location is exogenous to their sourcing strategy. This assumption is plausible if firms' location is based on historic patterns. In the long-run, however, producers' location may depend upon their anticipated sourcing strategy. While the IV regressions are based on plants that existed in a given location for at least five years, this time frame could still include firms that chose their location with a fragmentation strategy in mind. I therefore repeat the analysis using the subsample of plants that had already existed in their 2007 location for at least ten years. Columns 1 and 4 in Table 4.10 show that the estimated IV coefficients in the fragmentation and offshoring regressions are largely unchanged, relative to the

¹⁹This is true for the six variants of state skill measures I constructed.

estimates in the baseline IV specification.

I also re-estimate Equation (4.1) excluding plants in the automotive industry. The automotive industry has the highest share of domestically fragmented plants and is often considered a leader in the new methods for fragmenting production. Columns 2 and 5 in Table 4.10 show that the automotive industries are not driving the results. The estimated coefficients retain the same magnitude and statistical significance.

Finally, I revisit concerns about firms' use of electronic networks being endogenous to their sourcing strategy. As discussed in Section 4.2, I can identify single unit firms' fragmentation status in 2002. To ensure that IV estimates of firms' use of networks are not driven by correlation in fragmentation status over time, I conduct a robustness check in which I limit the sample to single unit firms that did not fragment in 2002. I then instrument for firms' use of networks to coordinate shipments in 2007 with their use of networks to coordinate shipments in 2002. Although the sample is considerably smaller (the restriction to single unit firms alone cuts the sample almost in half), the main results are robust. Columns 3 and 6 in Table 4.10 show that plants using electronic networks are more likely to fragment production and offshore. The estimated coefficients on wages, distance, and productivity are all qualitatively similar to benchmark results as well.

4.5 Extent of offshored production

In this section, I turn to the intensive margin of firms' offshoring decision. To assess the relationship between producer characteristics and the extent of fragmented production, I estimate:

$$\ln(\text{share}_f) = \beta_J + \beta_T \text{Tech}_f + \beta_w \text{wage}_{f,s/US} + \sum \beta_D \text{Dist}_f + \beta_{Pln}(\text{Prod}_f) + \varepsilon_{i,j,h} \quad (4.2)$$

for firm f in industry j . The data do not provide information about the total share of fragmented production, and the import data are only available at the firm level, so I use firm imports over sales as a proxy for the extent of production sourced offshore.

As discussed in Chapter 2, a firm's imports do not necessarily reflect offshored or fragmented production. To maintain the focus on firms that fragment customized production processes, I limit the analysis to the subsamples of manufacturing firms with positive import values that purchase CMS primarily offshore and primarily domestically.²⁰ I estimate Equation (4.2) separately for the offshoring and domestic fragmenters to allow the estimated coefficients to vary by firm sourcing strategy. Separate estimations for each sample are appropriate since Section 4.3 shows significant roles for distance, wages, and communication technology in plants' decision to source primarily offshore versus primarily domestically. For the estimates to be consistent, I rely on the assumption that, conditional on being in the sample, the

²⁰I limit the analysis to manufacturing firms without wholesale establishments so that the empirical analysis tracks the theory more closely. There are not enough manufacturing firms with both domestic and offshore purchases to disclose those regression results.

log import to sales ratio follows a classical linear model. This assumption underpins a “hurdle” or “two-tiered” model that is often used to address corner solution outcomes such as those present here. Using this methodology, the probability of offshoring is estimated in the first step, and the log import share equation is estimated in a second, independent step via OLS. The estimates presented in this section therefore correspond to estimates of the second step in a hurdle model.²¹

Multi-unit firms may span multiple industries, so I control for industry using the firm’s share of employment in each four digit NAICS code. I construct an import-weighted average relative foreign wage for each firm using country-industry-occupation wages from the International Labor Organization.²² This wage measure is clearly endogenous to firms’ sourcing choices, so the estimates provide an assessment of the equilibrium relationship in the model between wages, fragmentation costs and the extent of offshored production, but do not uncover any causal effect. Although the model does not specify a role for productivity in determining the share of offshored production, I include the log of value added firm productivity as a control to ensure that the electronic network use indicator is not biased by its correlation with productivity. As before, I measure firms’ distance to foreign entry ports, using the minimum distance over all establishments for multi-unit firms. In the specification that includes the electronic networks and CAD intensity interac-

²¹The total impact of an independent variable on the extent of offshored production is then a combination of its effect on the probability of offshoring and its effect on the import share. I do not calculate the combined effect here since the extensive margin decision estimates are based on plant-level data and I am limited to firm-level data for the intensive margin analysis. Wooldridge (2002) pp. 536-7 describes the hurdle model in detail. See Appendix A, Section A.3 for a discussion about the limitations and benefits of a hurdle model in this analysis relative to Tobit or Heckman selection models.

²²Details about the data and wage construction are in Appendix B.

tion, I measure firm CAD intensity as an employment-weighted share of each firm's industry CAD intensity. Because the industry controls are no longer fully co-linear with the CAD industry measure, I include the level of CAD intensity by firm. To ensure that the CAD intensity measure is not confounded by the extent to which an industry uses more complex or differentiated inputs, I also control for the share of differentiated inputs for a firm's industry mix using the industry measure from Nunn (2007).²³

Columns 1 and 2 in Table 4.11 report results from estimating Equation (4.2) on the subsets of firms that source offshore and domestically respectively. Firm use of electronic networks does not have a statistically significant relationship with the extent of offshored production for firms that primarily offshore. In contrast, for firms that primarily source domestically, use of electronic networks is associated with an 8.5 percent increase in their import share. For both samples, adding an interaction between electronic networks and CAD intensity results in a statistically insignificant relationship between communication technology and the degree of offshoring.

The estimated coefficients also suggest that the extent of offshore production by firms that primarily source from foreign locations is independent of firms' distance to a deep water port or border crossing. Although three of the four distance coefficients have the expected negative sign, they are all imprecisely estimated and therefore not statistically different from zero. It is important to interpret these results in context of the estimates in Section 4.3. Firms that source primarily offshore

²³I use the liberal definition of the fraction of inputs not sold on an exchange and not reference priced.

are closer to deep water ports and Mexican border crossings, but their import share is independent of these distances. In contrast, the extent of offshored production is significantly decreasing in distance from a deep water port for firms that primarily fragment domestically. Relative to firms that are 50 miles from a port, the import share by firms that are 50 to 200 miles away is 15 percent lower, and the share for firms over 200 miles away is 27 percent lower. The import share is also 34 percent lower for domestic fragmenters that are more than 50 miles from a Canadian border crossing.

The relative foreign wage has the expected negative sign and is statistically significant for both firms that primarily offshore and for firms that primarily source domestically. For offshoring firms, a ten percent increase in their average relative foreign wage is associated with a 1.8 percent lower import share. For firms that source primarily domestically, a ten percent increase in their average relative foreign wage is associated with a 2.7 percent decrease in their import share. This association is consistent with the model's prediction, but as explained above, should not be interpreted as proof of a causal relationship.

Thus far, the empirical results are consistent with many of the model's predicted equilibrium relationships. Labor cost saving motives are evident in producers' decision about whether or not to fragment production and offshore, as well as the extent to which they offshore, conditional on fragmentation. Distance to foreign entry points is also an important factor in whether or not a producer offshores the majority of its fragmented production. For firms that fragment primarily domestically, distance is also related to the extent to which firms offshore production.

The role of technology is more nuanced. Technology facilitates communication between producers and suppliers about inputs' design and production requirements, thereby increasing the probability a producer will fragment production. However, producers' ability to leverage the communication advantages that technology confers appears to be higher when sourcing from domestic rather than foreign locations. This relationship is evident in the extensive margin results where, conditional on fragmenting, plants that use electronic networks in CAD intensive industries are less likely to offshore. The intensive margin results in this section also suggest that communication technology has a limited impact on the degree to which a firm offshores its production. In the next section, I use firm-country level import data to assess whether the the apparent decreased effectiveness of communication technology in sourcing from offshore relative to domestic locations may be driven by heterogeneity in foreign locations' technology.

4.6 Location of offshore production

In this section, I re-assess firms' decision about where to locate their fragmented production using variation in firms' foreign sourcing locations. I aggregate the import data to the firm-country level and construct an indicator equal to one if a firm sources from a given country. The dataset includes an observation for every potential firm-country import combination. I regress the indicator on firm characteristics (X_F), country characteristics (X_S), and firm-country interactions

$(X_F \times X_S)$:

$$Pr(y_{i,s} = 1|X_{i,s}) = \theta + \beta_F X_F + \beta_S X_S + \beta_{FS}(X_F \times X_S), \quad (4.3)$$

where $y_{i,s} = 1$ if firm i imports from country s . The firm variables, X_F , include the log of value added productivity, electronic network use, the interaction between electronic networks and industry CAD intensity, and the industry share of differentiated inputs.²⁴ The country variables, X_S , include relative wages, human capital, and a country technology measure. I interact the firm level technology variables with country technology to assess whether the impact of firm technology on the probability of sourcing from a given location depends upon that country's level of technology. The interaction terms, $X_F \times X_S$, also include the minimum distance between each firm and country.

I measure country technology as the number of secure internet servers in 2007 in each country from the World Bank World Development Indicators. This variable is similar to one used by Freund and Weinhold (2002), who find an important role for a country's internet penetration in explaining variation in countries' growth of U.S. services trade. The number of internet servers in a country represents a measure of countries' communication technology infrastructure. In this dimension, an assessment of its importance in trade complements Limão and Venables (1999), who show that transportation infrastructure is a significant determinant of trade

²⁴Since the focus of this analysis is on the interaction terms, I use a continuous productivity measure to facilitate the disclosure analysis.

flows.²⁵ I calculate the minimum distance between each firm and each country using latitudes and longitudes from the CEPII.²⁶ The relative foreign wage comes from the same data described in Section 4.5, but here each firm faces the same wage for a given industry-country combination. Because the model assumes homogeneous labor, I control for country human capital with an updated version of the Hall and Jones (1999) measure.²⁷

Since the objective of this section is to assess whether the effectiveness of firm level technology depends upon the level of technology in a given country, I use country or firm fixed effects and focus on the interaction terms. This approach controls for all possible omitted country or firm characteristics and is therefore less susceptible to reverse causality and spurious correlation problems. As in Section 4.2, I estimate Equation (4.3) using a linear probability model.²⁸

Table 4.12 presents results from estimating Equation (4.3) on the subset of firms that primarily purchase CMS from offshore and domestic locations respectively. Columns 1 and 2 report estimates using country fixed effects, which allow for a quantification of the role of firm technology in the probability of sourcing from

²⁵The measure of country communication technology also relates to Golub, Jones, and Kierzkowski (2007), who document a role for countries' technology infrastructure in exports and FDI.

²⁶The data are available here: www.cepii.fr/anglaisgraph/bdd/distances.htm. I use latitude and longitude for the largest city in each country. Firm latitude and longitude is based on the closest manufacturing plant in the firm.

²⁷I use the education data from Barro and Lee (2000) to construct a measure for 2000 since this is the most recent data available. Human capital measures tend to be correlated over time, but this measure is more relevant than the original Hall and Jones (1999) variable based on 1989 data.

²⁸OLS is preferable in this context due to the inclusion of firm and country fixed effects. Probit estimates with fixed effects are inconsistent. In addition the marginal effects for interaction terms vary by observation making them difficult to summarize (see Ai and Norton (2003)). Finally, both probit and logit models suffer from perfect separation that occurs when a firm or country dummy predicts an outcome perfectly. There is no appealing solution for the separation problem in the analysis here with fixed effects. See Zorn (2005) for a discussion of this issue.

a given country. The interactions between firm and country technology are positive and significant for both samples. Figure 4.2a plots the full effect of electronic network use for offshoring firms evaluated at different levels of country technology. While using electronic networks has a zero or negative effect on the probability of sourcing from countries with a small number of servers, such as Bangladesh, their use increases the probability of sourcing from a high technology country like Japan by over two percentage points. Figure 4.2b depicts a similar relationship between industry CAD intensity and country technology. To illustrate magnitudes, increasing CAD intensity from its level in the “other apparel” industry to its level in the “semi-conductor machinery” industry is associated with no increase in the probability of sourcing from a country with Bangladesh’s technology, but a 6.6 percentage point increase in the probability of sourcing from a country with Japan’s level of technology.

Columns 3 and 4 in Table 4.12 report estimates of Equation (4.3) with firm fixed effects. The firm-country interactions are positive and statistically significant in this specification as well. Figure 4.3 shows the differential impact of country technology on firms’ sourcing strategies. The figure plots the percentage point impact of a one unit increase in log of servers on the probability a firm will source from a particular country and shows how this impact varies by firm and industry technology. The probability a firm will source from a given country is increasing in the number of servers in that country, but the effect of servers is larger for firms that use electronic networks and is increasing in industry CAD intensity. To illustrate the implied magnitudes from the figure, an increase in country technology equiva-

lent to increasing Bangladesh's number of servers to the level in Japan is associated with a 14 percentage point increase in the probability a firm in the "other apparel" industry sources from that country, and a 25 percentage point increase for a firm in the "semi-conductor machinery" industry.

The results presented in Table 4.12 are also consistent with an important role for distance. The estimates with country fixed effects, presented in columns 1 and 2, exploit differences in firms' distance to a given country that arise from variation in firms' geographic distribution across the U.S. They suggest that doubling the firm-specific distance to a country is associated with 2.6 or 1.9 percentage point decrease in the probability of sourcing from that country for offshoring and domestic fragmenters respectively. The estimates with firm fixed effects exploit the variation in distance to different countries for a given firm. Although the coefficients have the expected negative sign, they are not statistically significant.

4.7 Assessing the relative importance of technology, distance and wages

In this section, I assess the relative importance of wages, technology, and distance in firms' fragmentation and offshoring decisions. To perform the analysis, I calculate the share of the explained variation attributable to each of these key determinants. For example, to assess the importance of wage variation in a given estimation, I first calculate \hat{y} , the predicted value of the dependent variable for each observation, using actual values of independent variables. Next, I re-calculate

predicted values using the actual wage values for each observation, but holding all other independent variables at their sample means. Letting \hat{y}_{iw} denote this predicted value for observation i , the share of the explained variation accounted for by the actual wage variation in the data is then the sample analogue of $VAR(\hat{y}_{iw})/VAR(\hat{y}_i)$. When multiple variables capture the effect of distance or technology, I calculate the predicted values with all distance or technology variables evaluated at actual values and all other independent variables held at their means. Since these calculations do not incorporate covariances between independent variables, they do not represent a perfect decomposition and the fractions of the variation explained by different variables will not necessarily add to one. However, the analysis provides an informative quantification of the relative importance of the key explanatory variables.

Table 4.13 presents results of the simplified variance decomposition for the main results from each set of estimations. The top panel corresponds to the IV estimates for the probability a plant will fragment production (Table 4.5) and the probability it will offshore (Table 4.8). The first row reports results for the specification with no interaction between plant use of electronic networks and industry CAD intensity and shows that wage variation accounts for one and two percent of the explained variation in fragmentation and offshoring decisions respectively. Technology, measured by plant use of electronic networks, accounts for 28 percent of the explained variation in plants' fragmentation decision and 24 percent of the explained variation in offshoring. Distance explains only one percent of the variation in the fragmentation decision, and two percent of the explained variation of

offshoring.²⁹ The second row shows that when the effect of electronic networks is allowed to vary by CAD intensity, technology accounts for 36 and 47 percent of the explained variation in fragmentation and offshoring respectively. Variation in communication technology accounts for much larger shares of the explained variation in plants' decision to break up their production process or source from overseas, relative to both distance and labor cost savings motives.

The bottom panel of Table 4.13 presents shares of the explained variation of firms' imports over sales for the four specifications in Table 4.11. The left hand side shows variance shares for firms that purchase CMS primarily domestically, while the right hand side has shares for firms that primarily offshore. For both types of firms, wages account for the largest share of variation. Depending upon the specification, wages' share of the explained variation ranges from .11 to .17. Variation in distance between a firm and the closest foreign entry points is also important, accounting for approximately 5 percent of the explained variation in all specifications. Technology only accounts for a non-trivial portion of the explained variation when it includes the electronic networks interaction, and since these interactions are statistically insignificant, the share of explained variation is less instructive. These results suggest that while technology is the most relevant determinant in producers' decision about whether or not to fragment and offshore, labor cost differences are most the important factor in explaining the degree to which firms offshore, conditional on fragmentation.

²⁹The distance measure is more relevant for the relative costs of foreign sourcing. The low share of explained variation may simply reflect the limitation of the distance measures for domestic sourcing.

4.8 Conclusion

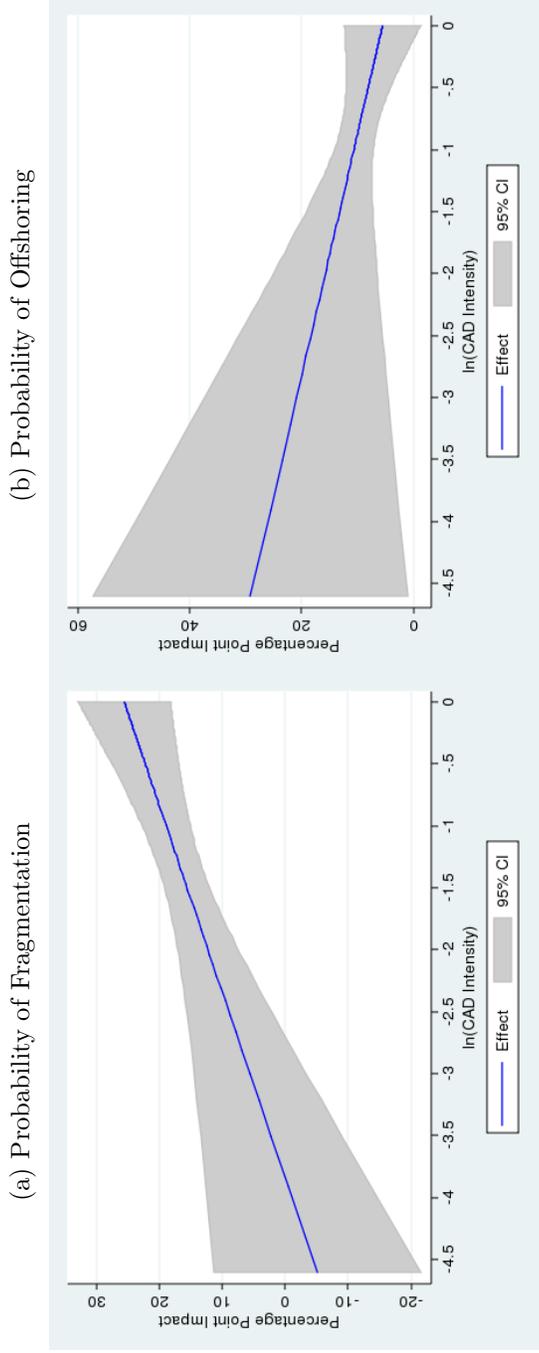
Communication technology has the potential to lower fragmentation costs by facilitating coordination and communication across locations. Consistent with this notion, the empirical results show that plant use of electronic networks to coordinate shipments increases the probability of fragmentation by 18 percentage points. To address the possibility of endogenous technology choice, I focus on the ability of communication technology to facilitate fragmentation through improved communication about product specifications and production processes. Using industry variation in CAD intensity as a measure of a firm's ability to specify its production process in an electronic format, I find evidence consistent with this mechanism. The differential impact of electronic communication on the probability of fragmenting in CAD intensive industries is almost 20 percentage points higher than the impact in low CAD industries.

While the evidence in this chapter is consistent with a strong role for communication technology in a firm's fragmentation decision, it also shows that technology's impact on the probability of offshoring is more nuanced. In particular, firms that use electronic networks in CAD intensive industries are less likely to offshore their fragmented production than firms in low CAD industries. One explanation for this result is that successful use of electronic communication and CAD technology depends upon the quality of technology in the sourcing country. Since offshore locations' average technology is lower than U.S. technology, this could drive the lower impact of electronic networks on the probability of offshoring by firms in CAD in-

tensive industries. Consistent with this hypothesis, estimates using disaggregated country-import data show that the effect of firm communication and information technology on the probability of offshoring is increasing in country level technology. As a result, a single parameter is unlikely to capture the true impact of technological improvements, since this impact varies substantially across firms, industries, and countries.

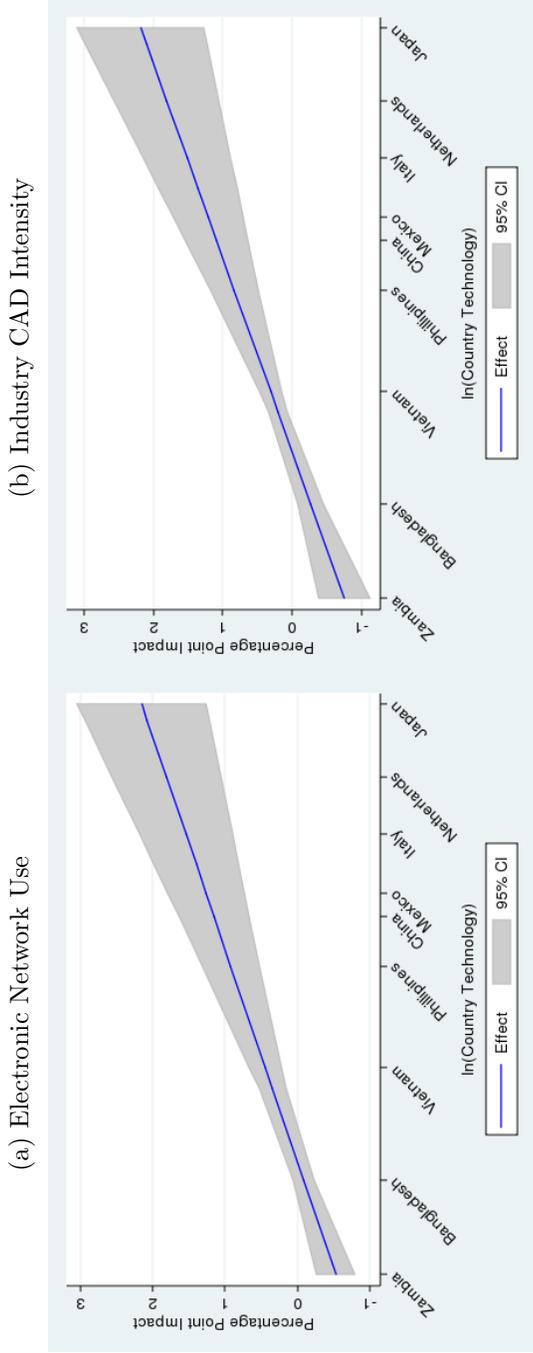
The results in this chapter also indicate that potential labor cost savings are a significant determinant of firms' fragmentation decisions. Plants in high wage locations are more likely to fragment production domestically, while conditional on fragmentation, plants in low wage states are more likely to offshore. These results suggest that plants are geographically differentiated with arbitrage opportunities to purchase labor from other locations. The paper shows that the arbitrage opportunities depend on communication technology. Given the rapid progress in developing communication technology to date, fragmentation is likely to become more common in the future as more firms seek to exploit its potential to lower production costs. To the extent that technological advances require matching technology or skills in the sourcing location, however, these advances will not necessarily displace U.S. jobs, but instead may lead to substantial shuffling of employment across U.S. states.

Figure 4.1: Differential impact of electronic networks, by industry CAD intensity



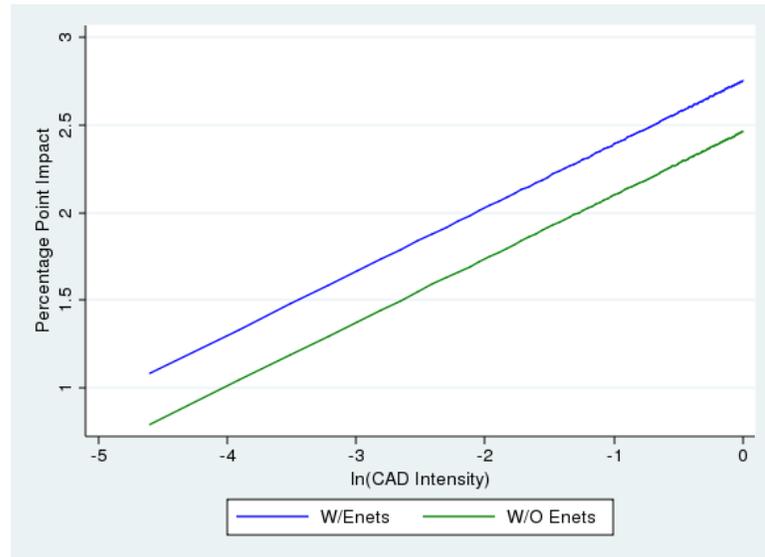
Notes: Estimates based on IV regressions of the probability an establishment fragments and offshores.

Figure 4.2: Differential impact of firm technology on probability of sourcing from country s , by country technology



Notes: Estimates based on regressions of the probability a firm imports from a given country, with country fixed effects.

Figure 4.3: Differential impact of country technology on probability of sourcing from country s , by industry CAD intensity



Notes: Estimates based on regressions of the probability a firm imports from a given country, with firm fixed effects.

Tables

Table 4.1: Average distance between a plant and its closest potential suppliers, by CMS purchase status

	MSP ^a	Deep water Ports	Border Crossings	
			Canada	Mexico
No Purchases	2.2	286	469	992
Domestic Purchases	1.6	302	431	1,028
Offshore Purchases	1.6	248	483	950
All Plants	2.0	290	459	1,001

Distances are in miles. ^a Closest manufacturing service provider.

Table 4.2: Plant use of electronic networks, by year and 2007 CMS purchase status

	Share of Plants	
	2002	2007
No Purchases	0.17	0.36
Domestic Purchases	0.22	0.51
Offshore Purchases	0.33	0.61

Table 4.3: Share of plants in each 2007 CMS status, by 2002 electronic network use and 2002 CMS purchase status

2007 CMS Purchases	Networks in 2002=NO 2002 CMS Purchases		Networks in 2002=YES 2002 CMS Purchases	
	No	Yes	No	Yes
None	0.72	0.17	0.08	0.03
Domestic Purchases	0.51	0.34	0.07	0.08
Offshore Purchases	0.41	0.30	0.14	0.14

Note: Table limited to single unit firms in 2007 since 2002 question only includes CMS purchases from another firm. 2002 CMS question asks whether plant purchased CMS from another firm.

Table 4.4: Share of plants in each 2007 CMS status, by 2002 electronic network use and 2002 offshore CMS purchase status

2007 CMS Purchases	Networks in 2002=NO 2002 Offshore Purchases		Networks in 2002=YES 2002 Offshore Purchases	
	No	Yes	No	Yes
None	0.82	0.03	0.14	0.01
Domestic Purchases	0.74	0.06	0.19	0.02
Offshore Purchases	0.57	0.12	0.25	0.06

Note: 2002 offshore question asks whether plant sent any partially completed products to a foreign facility for processing.

Table 4.5: Probability that a plant fragments production

Dependent variable is 1 if plant i in industry j and state h fragments production

	OLS Estimates		IV Estimates			
	All ^a (1)	IV sample (2)	Baseline (3)	CAD (4)	Demand (5)	Skill (6)
<i>Electronic networks_i</i>	0.107*** (0.008)	0.103*** (0.004)	0.183*** (0.019)	0.256*** (0.037)	0.255*** (0.038)	0.255*** (0.037)
× <i>ln(CAD_j)</i>				0.067*** (0.025)	0.066*** (0.025)	0.066*** (0.025)
<i>ln(wage_h)</i>	0.137** (0.051)	0.212*** (0.031)	0.170*** (0.029)	0.162*** (0.030)	0.167*** (0.030)	0.096*** (0.037)
<i>ln(VAProd_i)</i> Q2	0.039*** (0.007)	0.037*** (0.005)	0.117*** (0.023)	0.121*** (0.023)	0.121*** (0.023)	0.120*** (0.023)
Q3	0.067*** (0.009)	0.073*** (0.008)	0.155*** (0.014)	0.158*** (0.013)	0.159*** (0.013)	0.158*** (0.013)
Distance to MSP						
5-20 miles	-0.017** (0.008)	-0.022*** (0.006)	-0.022*** (0.004)	-0.021*** (0.004)	-0.023*** (0.005)	-0.023*** (0.004)
20+ miles	-0.033*** (0.009)	-0.029*** (0.007)	-0.028*** (0.006)	-0.028*** (0.006)	-0.032*** (0.006)	-0.031*** (0.006)
Distance to port ^c						
51-200 miles	-0.008 (0.010)	0.001 (0.008)	-0.006 (0.004)	-0.006 (0.004)	-0.009** (0.004)	-0.006 (0.005)
200+ miles	-0.001 (0.007)	0.014 (0.009)	0.009* (0.005)	0.008 (0.005)	0.004 (0.005)	0.007 (0.006)
50+ miles to border w/ Mexico	0.006 (0.007)	-0.019** (0.009)	-0.034*** (0.005)	-0.033*** (0.005)	-0.032*** (0.005)	-0.042*** (0.006)
Canada	-0.025 (0.024)	-0.010 (0.024)	-0.006 (0.008)	-0.006 (0.009)	-0.006 (0.007)	-0.006 (0.007)
<i>ln(BEA PI)</i>					-0.003** (0.002)	
<i>ln(Share college_h)</i> ^c						0.034* (0.018)
<i>ln(Share highschool_h)</i> ^d						0.069*** (0.025)
NAICS 6 controls	yes	yes	yes	yes	yes	yes
Adj. R-Squared	0.08	0.09	0.08	0.08	0.08	0.08
N	105,500	71,600	71,600	71,600	71,600	71,600

Notes: Standard errors clustered by state. *, **, *** denote 10%, 5% and 1% significance respectively. IV regressions instrument for electronic networks and productivity using lagged 2002 values. *a* Regression for full sample, weighted by the inverse probability of inclusion in sample. *b* Distance between plant i and closest deepwater port; plants within 50 miles is omitted category. *c* Share of all workers in state with at least a college degree. *d* Share of all production workers in state with at least a high school degree. N rounded for disclosure avoidance.

Table 4.6: First stage regressions for the probability of fragmentation

Each column is the first stage regression for the listed endogenous variable

Instruments	Electronic networks only			With CAD interaction			
	$\ln(VAP_i)$ Q2	$\ln(VAP_i)$ Q3	$Elec.Nets_i$ Indicator	$\ln(VAP_i)$ Q2	$\ln(VAP_i)$ Q3	$Elec.Nets_i$ Indicator	$\times \ln(CAD_j)$
$\ln(VAP_i)$ Q2	0.156*** (0.006)	0.089*** (0.004)	0.043*** (0.005)	0.156*** (0.006)	0.089*** (0.004)	0.043*** (0.005)	-0.060*** (0.007)
Q3	-0.049*** (0.006)	0.391*** (0.007)	0.063*** (0.005)	-0.049*** (0.006)	0.391*** (0.007)	0.063*** (0.005)	-0.082*** (0.008)
$Elec\ networks_i$	-0.007* (0.004)	0.039*** (0.004)	0.263*** (0.004)	-0.012** (0.006)	0.042*** (0.006)	0.277*** (0.006)	-0.088 (0.064)
$\times \ln(CAD_j)$				-0.004 (0.003)	0.003 (0.003)	0.013*** (0.003)	0.171*** (0.056)
Adj. R ²	0.08	0.27	0.14	0.08	0.27	0.14	0.51
Shea's Partial R ²	0.03	0.11	0.04	0.03	0.12	0.04	0.03
F-Statistic ^a	1431	374	1217	1083	281	938	736

Notes: Each column reports the coefficients and standard errors for the excluded instruments in the first stage regression of the respective endogenous variable. Instruments are 2002 lagged values. Standard errors clustered by state. *, **, *** denote 10%, 5% and 1% significance respectively. ^a F-Statistic is for a test of the null hypothesis that the instruments are jointly equal to zero.

Table 4.7: Correlations between industry CAD intensity and industry-level variables

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

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 4.8: Probability that a plant offshores, conditional on fragmentation

Dependent variable is 1 if plant i in industry j and state h primarily offshores production

	OLS Estimates		IV Estimates			
	All ^a (1)	IV sample (2)	Baseline (3)	CAD (4)	Demand (5)	Skill (6)
<i>Electronic networks_i</i>	0.023*** (0.004)	0.021*** (0.003)	0.100*** (0.016)	0.055 (0.035)	0.056 (0.035)	0.057 (0.035)
$\times \ln(CAD_j)$				-0.051 (0.038)	-0.051 (0.038)	-0.051 (0.038)
$\ln(wage_h)$	-0.140*** (0.033)	-0.116*** (0.043)	-0.125*** (0.044)	-0.122*** (0.043)	-0.125*** (0.045)	-0.106** (0.047)
$\ln(VAProd_i)$ Q2	0.003 (0.006)	0.006 (0.004)	-0.001 (0.018)	-0.003 (0.019)	-0.004 (0.019)	-0.004 (0.019)
Q3	0.020*** (0.007)	0.021** (0.009)	0.038*** (0.011)	0.036*** (0.011)	0.035*** (0.011)	0.035*** (0.011)
Distance to MSP						
5-20 miles	-0.002 (0.004)	0.000 (0.004)	0.001 (0.005)	0.000 (0.005)	0.002 (0.005)	0.002 (0.004)
20+ miles	-0.003 (0.005)	0.001 (0.005)	0.002 (0.006)	0.002 (0.006)	0.004 (0.006)	0.005 (0.005)
Distance to port ^c						
51-200 miles	-0.012** (0.006)	-0.007 (0.008)	-0.012 (0.008)	-0.012 (0.008)	-0.010 (0.008)	-0.009 (0.008)
200+ miles	-0.021*** (0.003)	-0.016*** (0.005)	-0.023*** (0.005)	-0.024*** (0.006)	-0.021*** (0.005)	-0.015*** (0.005)
50+ miles to border w/ Mexico	-0.093*** (0.032)	-0.123*** (0.036)	-0.094*** (0.017)	-0.095*** (0.017)	-0.097*** (0.017)	-0.088*** (0.018)
Canada	-0.013** (0.006)	-0.011* (0.005)	-0.010 (0.007)	-0.010 (0.007)	-0.010 (0.007)	-0.011* (0.006)
$\ln(BEA PI)$					0.002 (0.002)	
$\ln(Share\ college_h)^c$						0.024 (0.016)
$\ln(Share\ highschool_h)^d$						-0.055*** (0.020)
NAICS 6 controls	yes	yes	yes	yes	yes	yes
Adj. R-Squared	0.09	0.10	0.08	0.07	0.07	0.07
N	30,700	21,500	21,500	21,500	21,500	21,500

Notes: Standard errors clustered by state. *, **, *** denote 10%, 5% and 1% significance respectively. IV regressions instrument for electronic networks and productivity using lagged 2002 values. *a* Regression for full sample, weighted by the inverse probability of inclusion in sample. *b* Distance between plant i and closest deep water port; plants within 50 miles is omitted category. *c* Share of all workers in state with at least a college degree. *d* Share of all production workers in state with at least a high school degree. N rounded for disclosure avoidance.

Table 4.9: First stage regressions for probability of offshoring

Each column is the first stage regression for the listed endogenous variable

Instruments	Electronic networks only			With CAD interaction			
	$\ln(VAP_i)$ Q2	$\ln(VAP_i)$ Terciles Q3	$Elec.Nets_i$ Dummy	$\ln(VAP_i)$ Q2	$\ln(VAP_i)$ Terciles Q3	$Elec.Nets_i$ Dummy	$\times \ln(CAD_j)$
$\ln(VAP_i)$ Q2	0.140*** (0.011)	0.097*** (0.007)	0.013 (0.008)	0.140*** (0.011)	0.097*** (0.007)	0.013 (0.008)	-0.060*** (0.007)
Q3	-0.080*** (0.012)	0.398*** (0.011)	0.032*** (0.010)	-0.080*** (0.013)	0.397*** (0.011)	0.032*** (0.010)	-0.082*** (0.008)
$Elec\ networks_i$	-0.014* (0.008)	0.049*** (0.007)	0.240*** (0.006)	-0.030** (0.014)	0.061*** (0.011)	0.267*** (0.012)	-0.088 (0.064)
$\times \ln(CAD_j)$				-0.016 (0.010)	0.013* (0.008)	0.027** (0.012)	0.171*** (0.056)
Adj. R ²	0.09	0.25	0.12	0.09	0.25	0.12	0.51
Shea's Partial R ²	0.04	0.11	0.04	0.03	0.11	0.05	0.04
F-Statistic ^a	570	176	481	462	137	371	403

Notes: Each column reports the coefficients and standard errors for the excluded instruments in the first stage regression of the respective endogenous variable. Instruments are 2002 lagged values. Standard errors clustered by state. *, **, *** denote 10%, 5% and 1% significance respectively. *a* F-Statistic is for a test of the null hypothesis that the instruments are jointly equal to zero.

Table 4.10: Robustness checks for probability of fragmenting and offshoring

Dependent variable is 1 if plant i in industry j and state h :

	Fragments production			Offshores, conditional on fragmenting		
	10+ yr. olds	Non-auto	Adopters	10+ yr. olds	Non-auto	Adopters
<i>Elec. networks_i</i>	0.173*** (0.017)	0.185*** (0.022)	0.126*** (0.034)	0.095*** (0.017)	0.094*** (0.018)	0.150*** (0.038)
$\ln(wage_h)$	0.172*** (0.030)	0.167*** (0.029)	0.124*** (0.039)	-0.119** (0.048)	-0.131*** (0.047)	-0.177** (0.075)
$\ln(VAProd_i)$ Q2	0.126*** (0.024)	0.113*** (0.025)	0.074* (0.039)	0.007 (0.019)	0.002 (0.019)	-0.011 (0.049)
Q3	0.157*** (0.013)	0.157*** (0.015)	0.061*** (0.021)	0.043*** (0.012)	0.042*** (0.012)	0.052* (0.028)
Distance to MSP						
5-20 miles	-0.021*** (0.004)	-0.023*** (0.004)	-0.021*** (0.006)	0.002 (0.004)	0.002 (0.005)	-0.006 (0.010)
20+ miles	-0.027*** (0.006)	-0.027*** (0.005)	-0.020* (0.011)	0.008 (0.006)	0.002 (0.006)	0.008 (0.013)
Distance to port ^c						
51-200 miles	-0.006 (0.005)	-0.003 (0.005)	0.010 (0.009)	-0.014* (0.008)	-0.012 (0.008)	-0.012 (0.012)
200+ miles	0.010* (0.005)	0.013** (0.005)	0.017** (0.007)	-0.023*** (0.005)	-0.022*** (0.005)	-0.024*** (0.007)
50+ miles to border w/						
Mexico	-0.034*** (0.006)	-0.033*** (0.012)	-0.097*** (0.011)	-0.084*** (0.015)	-0.096*** (0.018)	-0.091*** (0.030)
Canada	-0.002 (0.009)	-0.002 (0.007)	-0.006 (0.009)	-0.010 (0.007)	-0.011 (0.008)	-0.009 (0.014)
NAICS 6 controls	yes	yes	yes	yes	yes	yes
Adj.R-Squared	0.08	0.08	0.07	0.08	0.08	0.03
N	69,000	63,000	22,000	19,000	21,000	5,000

Notes: 10+ yrs consists of plants that have been in the same location for at least ten years. Non-auto excludes plants in automotive manufacturing industries. Adopters consists of all single-unit firms that did not fragment production in 2002. Standard errors clustered by state. *, **, *** denote 10%, 5% and 1% significance respectively. N rounded for disclosure avoidance.

Table 4.11: Extent of offshored production

Dependent variable is $\ln\left(\frac{\text{imports}}{\text{sales}}\right)$ for firm f in industry j

	CMS purchases primarily:			
	Offshore		Domestic	
<i>Electronic networks_f</i>	0.070	-0.145	0.085**	0.082
	(0.107)	(0.180)	(0.043)	(0.069)
$\times \ln(CAD_j)$		-0.232		-0.005
		(0.156)		(0.061)
$\ln(VA Prod_f)$	-0.004	-0.013	-0.043	-0.043
	(0.070)	(0.070)	(0.033)	(0.033)
<i>Distance_f to port^a</i>				
51-200 miles	0.150	0.154	-0.149**	-0.149**
	(0.151)	(0.150)	(0.066)	(0.065)
200+ miles	-0.053	-0.044	-0.254***	-0.252***
	(0.114)	(0.114)	(0.048)	(0.048)
> 50 miles from border w/ ^a				
Mexico	-0.287	-0.297	-0.232	-0.224
	(0.235)	(0.235)	(0.160)	(0.159)
Canada	-0.194	-0.217	-0.343***	-0.344***
	(0.203)	(0.203)	(0.075)	(0.075)
$\ln(wage_f/US)$	-0.182***	-0.175***	-0.265***	-0.265***
	(0.050)	(0.050)	(0.022)	(0.022)
$\ln(CAD_j)$		0.052		-0.084
		(0.165)		(0.066)
$\ln(Diff\ inputs_j)^b$		-1.902**		0.910***
		(0.751)		(0.296)
Industry controls	yes	yes	yes	yes
Adj. R-Squared	0.04	0.04	0.07	0.07
N	1,200	1,200	9,300	9,300

Notes: *, **, *** denote 10%, 5% and 1% significance respectively. *a* Distance between foreign entry point and the closest manufacturing establishment in the firm; firms with a plant within 50 miles is omitted category. *b* Firm's industry share of differentiated input use. N rounded for disclosure avoidance.

Table 4.12: Offshore sourcing location selection

Dependent variable is 1 if firm f , in industry j , imports from country s

	Firms' CMS purchases are primarily:			
	Offshore	Domestic	Offshore	Domestic
<i>Electronic networks_f</i>	-0.005*** (0.001)	-0.005*** (0.001)		
× $\ln(CAD_j)$	-0.000 (0.001)	0.000** (0.000)		
× $\ln(Servers_s)$	0.002*** (0.001)	0.002*** (0.000)	0.003*** (0.001)	0.003*** (0.001)
$\ln(CAD_j)$	-0.008*** (0.002)	-0.004*** (0.001)		
× $\ln(Servers_s)$	0.003*** (0.001)	0.001*** (0.000)	0.004*** (0.001)	0.002*** (0.000)
$\ln(VA Prod_f)$	0.002*** (0.000)	0.001*** (0.000)		
<i>Distance_{fs}^a</i>	-0.026** (0.011)	-0.019** (0.009)	-0.018 (0.030)	-0.026 (0.023)
$\ln(Diff inputs_j)$	0.007*** (0.001)	0.002*** (0.000)		
$\ln(w_s/w_{US})$			-0.021 (0.018)	-0.004 (0.005)
$\ln(Human Capital_s)$			-0.051 (0.035)	-0.024 (0.017)
$\ln(Servers_s)$			0.025*** (0.007)	0.009*** (0.002)
Country fixed effects	yes	yes	no	no
Firm fixed effects	no	no	yes	yes
Adj. R-Squared	0.21	0.11	0.10	0.09
N	270,000	363,900	103,000	1,382,000

Notes: Standard errors clustered by country. There are 185 country clusters in columns 1 and 2, and 70 country clusters in columns 3 and 4. *, **, *** denote 10%, 5% and 1% significance respectively. ^a Distance between a country's main city and the closest manufacturing establishment in the firm. N rounded for disclosure avoidance.

Table 4.13: Variance decomposition results: Contributions of wages, technology, and distance

Specification with:	Fragments			Offshores		
	Wages	Technology	Distance	Wages	Technology	Distance
No CAD interaction	0.01	0.28	0.01	0.02	0.24	0.02
With CAD interaction	0.01	0.36	0.01	0.02	0.47	0.02

Firm intensive margin estimations, dependent variable is $\ln(\frac{imports}{sales})$

Firms' CMS Purchases are Primarily:

Specification with:	Domestic			Offshore		
	Wages	Technology	Distance	Wages	Technology	Distance
No CAD interaction	0.17	0.00	0.05	0.14	0.00	0.05
With CAD interaction	0.16	0.01	0.05	0.11	0.05	0.04

Notes: The top panel corresponds to the IV estimates for the extensive margin presented in columns 4 and 5 in Tables 4.5 and 4.8. In the extensive margin estimations, the dependent variable in the left panel is an indicator for whether a plant fragments production; the dependent variable in the right panel is an indicator for whether a plant that fragments does so primarily offshore. The bottom panel corresponds to estimates from Table 4.11. In the intensive margin regressions, the dependent variable is the firm $\ln(\frac{imports}{sales})$. The left panel provides estimates for the subset of domestic fragmenters; the right panel provides estimates for the subset of offshores. In both panels, the top row is the specification with electronic networks only, while the bottom row includes networks and their interaction with CAD intensity.

Appendix A

Appendix

A.1 Substitutability of CMS purchases and standardized inputs

The CMS data correspond to fragmentation of customized production processes, so plants that report no purchases may perform all the requisite physical transformation activities to make their good, or they may be able to purchase standardized, off-the-shelf inputs. To assess whether CMS purchases can be substituted with standardized inputs, I examine their relationship with plants' purchases of materials. Plants' purchases of CMS are positively correlated with their material purchases, suggesting that CMS purchases are not substitutes for material inputs. To control for the possibility that standardized inputs are substitutes for CMS purchases in the empirical section, I use six digit NAICS industry fixed effects so that the estimates reflect within industry differences in the probability of fragmentation. The six digit NAICS industry controls represent a very detailed classification that should capture the importance of customized inputs in production. It is possible, however, that some firms within an industry produce higher quality goods that require more customized inputs. In this case, the estimated coefficients on productivity may reflect higher quality, rather than greater production efficiency. In firm-level regressions with multi-unit firms that span multiple industries, I can only control for industry at the four digit level. In these cases, I also include the Nunn (2007)

measure of an industry's need for differentiated inputs as a control for industries' demand for customized production processes.

A.2 Proofs

A.2.1 Share of fragmentation and distance

The effect on \bar{k} from an increase in distance between the firm and its sourcing location is

$$\frac{d\bar{k}}{d\delta} = -\frac{1}{\partial\tau(\bar{k})/\partial\bar{k}} \frac{\partial\tau(\bar{k})}{\partial\delta} < 0, \quad (\text{A.1})$$

as expected.

A.2.2 Share of fragmentation and technology

The effect on \bar{k} from a change in communication technology is:

$$\frac{d\bar{k}}{d\eta} = -\frac{1}{\frac{\partial\tau(\bar{k})}{\partial\bar{k}}} \left[\frac{\partial\tau(\bar{k})}{\partial\eta} + \frac{d\rho}{d\eta} \frac{\partial\tau(\bar{k})}{\partial\rho} \right] + \frac{1}{w_s \frac{\partial\tau(\bar{k})}{\partial\bar{k}}} \left[\frac{1}{\alpha} \frac{dw_h}{d\eta} - \tau(\bar{k}) \frac{dw_s}{d\eta} \right]. \quad (\text{A.2})$$

If wages are unaffected by technology, then the second set of square brackets are zero (but you see how skill-biased technological change would have interesting effects on offshored production). Here I assume that $\frac{d\rho}{d\eta} = 0$ which means $\frac{d\bar{k}}{d\eta} < 0$.

A.2.3 Homogeneous task production

The model assumes that productivity heterogeneity affects the transformation of the input M into output q , but does not alter firms' ability to convert labor into

tasks. This assumption is similar to Antràs and Helpman (2004), where all suppliers make inputs one-to-one from labor, regardless of the productivity of the firm that owns them. The effect of extending the impact of productivity to task production depends upon firms' sourcing choices. Under integrated production, heterogeneity in task production would amplify the profitability and size differences that productivity heterogeneity induces without changing the model's basic result. The effect of extending task productivity heterogeneity under fragmented production would depend upon whether, and the extent to which, firms transfer their productivity to their input suppliers. With costless transferability regardless of ownership, task heterogeneity would simply amplify the existing results. If firm ownership or supplier industry affect transferability, then firms will weigh these additional fragmentation costs against the benefits described above.¹

A.2.4 Multi-dimensional task costs

When firms can source each task from a different location and fragmentation costs vary along two task-specific dimensions, it is no longer possible to order tasks by their costs. Locations vary in terms of their distance to the firm, relative wage and technological capabilities. Task-specific cost factors, such as weight and complexity, may interact with location-specific variables to induce non-monotonicities in costs across locations and tasks. For example, suppose final good production requires complex plastic screws that are communication intensive but relatively light, and

¹See Fort (2010) for an analysis of how firms' ability to transfer productivity to new plants varies across industries.

large metal frames that are straightforward to construct but heavy. Plastic screws will be more expensive than frames to fragment from a nearby MSP, but metal frames will be relatively more costly to purchase from a distant supplier. Maximizing variable profits when there are three potential fragmentation strategies therefore entails identifying the lowest cost sourcing location for each task. A firm will prefer to source task k from location 1 over location 2 if:

$$\frac{w_{s_1}}{w_{s_2}} < \frac{\tau(\delta_{s_2}, \omega_k, \eta_{s_2})}{\tau(\delta_{s_1}, \omega_k, \eta_{s_1})}, \quad (\text{A.3})$$

conditional on $w_h > \alpha w_{s_1} \tau_k(\delta_{s_1}, \omega_k, \eta_{s_1}, \rho_j)$. Equation (3.7) shows that as long fragmenting is cheaper than integrated production, the decision to source from one location over another depends only the relative costs and benefits of those locations. The share of tasks fragmented from a given location s will simply be the total number of tasks for which s is the cheapest sourcing location over all tasks.

A.3 Hurdle models

Although the hurdle model relies on the assumption that $\ln(y)$ follows a classical linear model, it is more general than Tobit because it does not constrain the effect of the independent variables on the probability of $y > 0$ to have the same sign and relative magnitudes as the effect of the independent variables on the size of $\ln(y)$. Using a standard hurdle model approach, the $E(y|x) = \Phi(x\gamma) \exp(x\beta + \sigma^2/2)$, where γ are the coefficients from a probit of the probability that $y > 0$, β are the coefficients from the OLS regression of $\ln(y)$ on x for positive values of y , and σ are

the standard errors from the OLS regression.

Appendix B

Data Appendix

B.1 Contract Manufacturing Question

The CMS purchase question is the third part of the special inquiries section, question 26 on the Census of Manufacturers. The exact question is:

3. Did this establishment purchase contract manufacturing services from other companies or other establishments of your company to process materials or components that this establishment owns or controls?

0496 Yes, primarily with establishments WITHIN the 50 States and the District of Columbia

0497 Yes, primarily with establishments OUTSIDE of the 50 States and the District of Columbia

0498 No

B.2 Missing Data

Table B.1 presents information on plants in the CMS sample relative to those outside the sample. The first three columns provide participation shares and show that while the CMS sample comprise of 54 percent of U.S. manufacturing establishments (excluding administrative records), it covers 75 percent of sales and 71 percent of employment. The last three columns of Table B.1 present summary statistics by CMS non-response type. As expected, establishments not asked the CMS question are substantially smaller than plants in the sample. To address potential selection bias in the analyses, I use a number of establishment-level variables, including sales,

employment, age, firm age, multi-unit firm status, industry, and industry employment interactions, to estimate, via logit, the probability that an establishment will be in the CMS sample. I then predict the probability that an observation is in the sample and use the inverse of the predicted probability as a weight in the subsequent empirical analyses.

B.3 Variable Descriptions

This section provides detailed information about the data sources and construction methodology for variables used in chapters 2 and 4.

B.3.1 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:

6 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 **5**, line A? Or, were the orders for any of the shipments reported in **5**, line A received over an electronic network?

Electronic networks include:

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

0181 Yes - Go to line B 0182 No - Go to **7**

	2007	2006
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I measure plants' use of electronic networks in 2002 using data from this similar question in the 2002 Census of Manufactures:

Although the question asks about establishments' use of electronic networks to

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 ❺

2002

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 valid proxy for a plant's use of technology to communicate with suppliers.

B.3.2 CAD 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)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	(2) Design of the production process	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	(3) Production scheduling	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	(4) Production monitoring	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	(5) Test and acceptance of product	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	(6) Outsourcing of research and development	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

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. The mean of the 473 manufacturing industries is .44, with a standard deviation of .25 and a range of 1. The least CAD intensive industries are in food manufacturing, while the most CAD intensive are in machinery, aerospace, and automotive manufacturing.

B.3.3 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. 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. When an occupation is listed as an input into an industry but the employment information for the occupation is missing, I treat its employment share as zero.¹ 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:

$$wage_{hj} = \sum_{o \in j} [wage_{o,h} \times \frac{emp_{o,j,US}}{emp_{j,US}}], \quad (\text{B.1})$$

where o denotes occupations. While the missing employment information may lead to measurement error in an industry’s average wage, the error will be consistent across states.

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.² In addition, some states are missing wage data for some of their occupations. To ensure that the shares of employment in each

¹For example, the national OES file lists “Butchers and meat cutters” as an input for Animal Food manufacturing, but has no employment information for the occupation. I therefore assign a zero share to that occupation as an input into Animal Food manufacturing.

²The 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.

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.

The average production worker wage across states and industries is \$14.58. The lowest wage, \$9.67, is for workers in the Cut and Sew apparel industry in Montana. The highest wage, \$25.36, is for workers in the Petroleum and Coal Products manufacturing industry in Alaska. State fixed effects explain 33 percent of the variation in the wage, while industry fixed effects explain 56 percent of the wage variation in the data. Averaged over industry, the mean state wage is \$14.58, with a standard deviation of \$1.08. The lowest wages are \$12.44 and \$12.96 in South Dakota and Mississippi respectively, while the highest wage is \$17.97 in Alaska, followed by Delaware, Washington, Michigan and Connecticut, all with average wages above \$16.

B.3.4 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. When I construct the firm import-weighted average relative wage, I drop firms for which 50 percent or more of its imports have no wage. For the remaining firms, I re-normalize import shares to construct an import-weighted average relative wage according to:

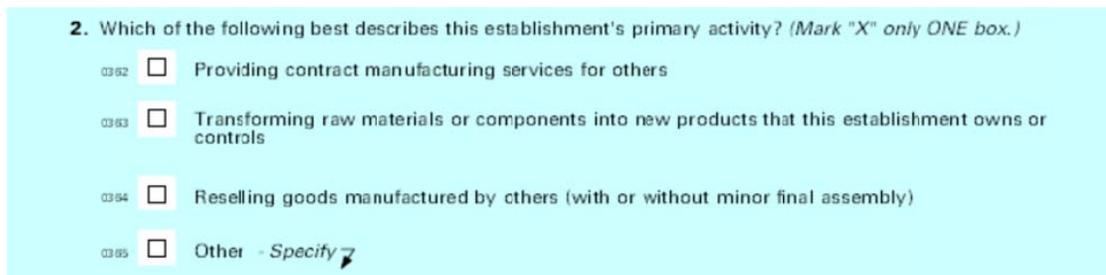
$$\left(\frac{w^*}{w_{US}}\right)_f = \frac{\sum_{s,j} [imports_{f,s,j} \times \frac{w_{s,j}}{w_{us,j}}]}{imports_f} \quad (\text{B.2})$$

B.3.5 Skill measures

I measure state skill differences using 2007 data from the American Community Survey (ACS). For both total workers in a state and for the subsample of production workers in a state, I calculate a) the share of workers with at least a college degree; b) the share of workers with at least an associate's degree; and c) the share of workers with at least a high school degree.

B.3.6 Manufacturing service providers

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.)

- Providing contract manufacturing services for others
- Transforming raw materials or components into new products that this establishment owns or controls
- Reselling goods manufactured by others (with or without minor final assembly)
- Other - Specify

I also calculate an alternative domestic distance measure as the weighted average of the minimum distance between a plant and all of its input suppliers. I use the 2002 BEA I-O tables to identify each plant's inputs based on the plant's four digit NAICS industry. I also use the I-O tables to calculate the share of each input in production, which I use as a weight. The weighted distance to input suppliers

is positively correlated with the distance to the closest MSP. Using the weighted distance in regression analyses in lieu of the MSP distance measure yields similar results.

B.3.7 Water Ports

I identify all potentially relevant water ports using data from the Maritime Administration's Port Import Export Reporting Service (PIERS).³ 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. There are 122 ports, including both government and non-government shipments by vessel into and out of U.S. foreign trade zones, the 50 states, District of Columbia and Puerto Rico. I exclude ports in Puerto Rico since my data are limited to the 50 states. I also exclude the Port of Gramercy, LA since its facility solely handles green and calcined petroleum coke (see www.jeinc.com/gramercy).

Shipping costs are generally increasing in the distance between a port and the final import destination, but rates at small ports tend to be substantially higher than rates at larger ports since they are served by fewer shipping lines. In addition, many container shipments must come through deep water ports.⁴ To ensure that my port list corresponds to viable import channels, I restrict the ports to those with

³The data are available here: www.marad.dot.gov/library_landing_page/data_and_statistics/Data_and_Statistics.htm.

⁴According to Richard Phillips, CEO of Pilot Freight Services, port-to-port shipping charges are decreasing in the number of shippers to a specific port. In addition, shipping companies offer discounts based on total customer volume. Because larger ports support more carriers from a greater range of sourcing locations, shipping costs at larger ports tend to be substantially lower than costs at smaller ports.

a value of imports greater than 100 TEUs. This criterion eliminates 71 ports, 45 with zero imports and only seven with more than 50 TEUs of imports. (I except Anchorage, Alaska from this exclusion criterion since it imported 92 TEUs in 2007, but is the largest viable import port in Alaska.) I also identify deep water ports using a combination of internet searches. Table B.3 lists the 46 ports with at least 100 TEUs of imports in 2007 and the Port of Anchorage. Column 4 identifies the 42 deep water ports.

I obtain latitude and longitude for each port using 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.

B.3.8 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

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

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

the county in which the port is located. Table B.4 lists the states and counties with border crossings.

B.4 Probit estimation results

In the paper, I estimate the probability of fragmentation and offshoring using a linear probability model. Table B.5 presents the marginal effects from estimation via probit. The estimated marginal effects evaluated at the mean are all similar to the estimated OLS coefficients.

Tables

Table B.1: Plant characteristics by response status

	Participation Shares			Sales ^a	Means	
	Plants	Sales	Emp		Emp	ln(VAP)
In CMS Sample	0.54	0.75	0.71	36,778	86	4.56
Out of CMS Sample						
Not Answered	0.21	0.23	0.24	29,548	77	4.61
Not Asked	0.25	0.02	0.05	2,314	13	4.25
No Info	0.00	0.00	0.00	21,147	61	4.75
All Manufactures	1.00	1.00	1.00	26,638	66	4.50

Notes: Approximately 196,800 manufacturing plants; excludes administrative records. ^a Sales in \$000s.

Table B.2: List of excluded wholesale industries

NAICS Code	NAICS Description
423210	Furniture Merchant Wholesalers
423220	Home Furnishing Merchant Wholesalers
423410	Photographic Equipment and Supplies Merchant Wholesalers
423420	Office Equipment Merchant Wholesalers
423440	Other Commercial Equipment Merchant Wholesalers
423450	Medical, Dental, and Hospital Equipment and Supplies Merchant Wholesalers
423460	Ophthalmic Goods Merchant Wholesalers
423490	Other Professional Equipment and Supplies Merchant Wholesalers
423710	Hardware Merchant Wholesalers
423720	Plumbing and Heating Equipment and Supplies (Hydronics) Merchant Wholesalers
423730	Warm Air Heating and Air-Conditioning Equip. and Supplies Merchant Wholesalers
423740	Refrigeration Equipment and Supplies Merchant Wholesalers
423840	Industrial Supplies Merchant Wholesalers
423990	Other Miscellaneous Durable Goods Merchant Wholesalers
424610	Plastics Materials and Basic Forms and Shapes Merchant Wholesalers
424690	Other Chemical and Allied Products Merchant Wholesalers
424710	Petroleum Bulk Stations and Terminals
424720	Petroleum and Petroleum Products Merchant Wholesalers
424910	Farm Supplies Merchant Wholesalers
424990	Other Miscellaneous Nondurable Goods Merchant Wholesalers
425110	Business to Business Electronic Markets
425120	Wholesale Trade Agents and Brokers

Note: These industries were not asked the CMS questions and are therefore excluded from all analyses.

Table B.3: Water Ports with Imports

	Intermodal Terminal Facility	City	State	Deep Water ^a	Imports (TEUs)
1	PORT OF ANCHORAGE	Anchorage	AK	1	92
2	BNSF-MOBILE-AL	Mobile	AL	1	34,968
3	PORT OF LONG BEACH	Long Beach	CA	1	3,686,191
4	PORT OF OAKLAND	Oakland	CA	1	798,762
5	PORT OF HUENEME	Port Hueneme	CA	1	17,533
6	YELLOW-SAN DIEGO-CA TERMINAL	San Diego	CA	1	48,137
7	PORT OF LOS ANGELES	San Pedro	CA	1	4,323,281
8	PORT OF BRIDGEPORT	Bridgeport	CT	1	3,002
9	PORT OF WILMINGTON	Wilmington	DE	1	141,731
10	PORT CANAVERAL	Cape Canaveral	FL	1	246
11	PORT OF FERNANDINA WHARF	Fernandina Beach	FL	1	4,126
12	PORT EVERGLADES	Fort Lauderdale	FL	1	312,427
13	PORT OF FORT PIERCE	Fort Pierce	FL		2,951
14	PORT OF JACKSONVILLE	Jacksonville	FL	1	44,005
15	PORT OF MIAMI	Miami	FL	1	348,394
16	PORT OF PANAMA CITY	Panama City	FL		21,532
17	PORT OF PALM BEACH	Riviera Beach	FL		47,223
18	PORT OF TAMPA	Tampa	FL	1	18,870
19	SAVANNAH-GA-373 N	Savannah	GA	1	1,077,771
20	NOT IN DATABASE	Honolulu	HI	1	23,583
21	PORT OF LAKE CHARLES	Lake Charles	LA	1	279
22	PORT OF NEW ORLEANS	New Orleans	LA	1	77,280
23	PORT OF BOSTON	Boston	MA	1	94,224
24	PORT OF BALTIMORE	Baltimore	MD	1	254,325
25	PORT OF PORTLAND, MAINE	Portland	ME	1	405
26	PORT OF GULFPORT	Gulfport	MS	1	104,009
27	PORT OF WILMINGTON-NC	Wilmington	NC	1	84,693
28	GLOUSTER CITY MARINE TERMINAL	Glouster City	NJ	1	3,136
29	THE PORT AUTHORITY OF NY & NJ	New York	NY	1	2,640,303
30	PORT OF PORTLAND	Portland	OR	1	104,545
31	TRANSFLO-CHESTER-PA	Chester	PA	1	52,082
32	PORT OF PHILADELPHIA AND CAMDEN	Philadelphia	PA	1	161,603
33	PORT OF CHARLESTON	Charleston	SC	1	768,774
34	PORT OF BEAUMONT	Beaumont	TX	1	296
35	PORT OF CORPUS CHRISTI AUTHORITY	Corpus Christi	TX	1	599
36	PORT OF FREEPORT	Freeport	TX	1	31,326
37	PORT OF GALVESTON	Galveston	TX	1	3,904
38	PORT OF HOUSTON AUTHORITY	Houston	TX	1	619,561
39	NEWPORT NEWS MARINE TERMINAL	Newport News	VA	1	28,589
40	NORFOLK INTERNATIONAL TERMINALS	Norfolk	VA	1	857,033
41	PORT OF RICHMOND-VA	Richmond	VA		23,179
42	PORT OF EVERETT	Everett	WA	1	190
43	PORT OF SEATTLE	Seattle	WA	1	785,643
44	PORT OF TACOMA	Tacoma	WA	1	722,450
45	PORT OF VANCOUVER, USA	Vancouver	WA	1	316
46	PORT OF MILWAUKEE	Milwaukee	WI		140
47	NOT IN DATABASE	Port Manatee	FL	1	4,127

Source: RITA/BTS National Transportation Atlas and the Maritime Administration. Water ports with 100 TEUs or more of imports in 2007 and Port of Anchorage. ^a Identification based on internet searches and port-specific websites.

Table B.4: U.S. Counties with Land Entry Ports

Ports on the Canadian Border					
State	County	State	County	State	County
ID	Boundary	MT	Blaine	VT	Orleans
ME	Aroostook	MT	Daniels	WA	Clallam
ME	Somerset	MT	Gallatin	WA	Ferry
ME	Washington	MT	Glacier	WA	King
MI	Chippewa	MT	Hill	WA	Okanogan
MI	Oakland	MT	Liberty	WA	Pend Oreille
MI	St. Clair	MT	Lincoln	WA	San Juan
MI	Wayne	MT	Phillips	WA	Skagit
MN	Cook	MT	Sheridan	WA	Stevens
MN	Kittson	MT	Toole	WA	Whatcom
MN	Koochiching	MT	Valley		
MN	Lake of the Woods	ND	Bottineau		
MN	Roseau	ND	Burke		

Ports on the Mexican Border					
State	County	State	County	State	County
NM	Dona Ana	NM	Dona Ana	TX	Presidio
NM	Luna	NM	Luna	TX	Starr
TX	Cameron	TX	Cameron	TX	Val Verde
TX	El Paso	TX	El Paso	TX	Webb
TX	Hidalgo	TX	Hidalgo		
TX	Maverick	TX	Maverick		

Source: Source: RITA/BTS border crossing/entry data. Based on entry ports with truck crossings in 2007.

Table B.5: Probit Regressions for probability of fragmentation and offshoring

Dependent variable is 1 if establishment

	Fragments		Offshores	
	All	IV Sample	All	IV Sample
<i>Electronic networks_i</i>	0.100*** (0.003)	0.097*** (0.003)	0.019*** (0.003)	0.019*** (0.003)
<i>ln(wage_h)</i>	0.189*** (0.037)	0.223*** (0.033)	-0.089*** (0.025)	-0.106*** (0.039)
<i>ln(VAProd_i)</i> Q2	0.048*** (0.005)	0.046*** (0.005)	0.006 (0.004)	0.006 (0.005)
Q3	0.083*** (0.005)	0.084*** (0.005)	0.024*** (0.006)	0.021*** (0.007)
Distance to MSP				
5-20 miles	-0.017*** (0.004)	-0.021*** (0.004)	0.005 (0.003)	0.004 (0.004)
20+ miles	-0.024*** (0.006)	-0.028*** (0.006)	0.004 (0.005)	0.006 (0.006)
Distance to port ^c				
51-200 miles	-0.013** (0.006)	-0.005 (0.005)	-0.006 (0.005)	-0.007 (0.006)
200+ miles	0.004 (0.005)	0.013** (0.006)	-0.015*** (0.003)	-0.018*** (0.005)
50+ miles to border w/ Mexico	-0.021*** (0.004)	-0.038*** (0.004)	-0.076*** (0.028)	-0.081*** (0.021)
Canada	-0.008 (0.009)	-0.005 (0.010)	-0.014 (0.010)	-0.011 (0.007)
NAICS 6 controls	yes	yes	yes	yes
N	105,400	71,500	29,100	19,500

Notes: Table reports the marginal effects that correspond to OLS estimates for the probability of fragmentation and offshoring presented in the paper. Standard errors clustered by state. *, **, *** denote 10%, 5% and 1% significance respectively. Probit sample is not identical to OLS sample because certain industry fixed effects predict outcome perfectly, in which case the observations are dropped from the probit estimation. ^a Distance between plant *i* and closest deep water port; plants within 50 miles is omitted category.

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