ESSAYS ON THE ROLE OF NETWORKS IN FIRM PRODUCTIVITY AND INTERNATIONAL TRADE

By

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To my parents, my blueprints for excellence,
and my sisters, who showed me how to follow them.

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CHAPTER I

Estimating Productivity in the Presence of Spillovers: Firm-level Evidence from the US Production Network

I.1 Introduction

Production function estimation is at the heart of a number of important questions in economics. From examining changes to market power, assessing the impact of trade liberalization, to decomposing the sources of aggregate productivity growth, understanding firms' decisions and their implications on market outcomes often hinges on the accurate measurement of total factor productivity (TFP).

A significant finding of the literature on firm-level productivity is that businesses exhibit marked differences in TFP, even within narrowly-defined industries, and a vast body of work seeks to explain this dispersion.[1] One possible explanation is that firms may affect each other in ways that do not show up in the prices of intermediate goods and services; they may experience spillovers from knowledge transfers or agglomeration externalities. For example, in the trade literature, firms have been found to impact the productivity of counterparts through activities such as foreign direct investment (FDI) and exporting.[2] Javorcik (2004) finds that FDI in Lithuania has a positive effect on the productivity of domestic firms through backward linkages, while Keller and Yeaple (2009) document the existence of horizontal spillovers from multinationals to US firms. Likewise, Alvarez and López (2008) provide evidence from Chile of positive productivity spillovers from domestic and foreign-owned exporters on their suppliers, and Alfaro-Urena et al. (2019) finds TFP gains of $6-9\%$ among Costa Rican firms after they begin to supply to multinational corporations.

My paper quantifies the transmission of productivity gains through buyer-supplier relationships in the United States, and examines how the existence of spillovers affects the measurement of TFP. I consider spillovers not just from firm activities, but directly from productivity as well. A firm's TFP could increase or decline due to the productivity of the firms with which it has a relationship. The expected direction of this effect is not immediately clear: firms could learn from their peers and become more productive or might free-ride on their trading partners' efficiency. Empirical investigations into direct efficiency spillovers are relatively new. Serpa and Krishnan (2018) examine this question with data on firm-level buyer-supplier relationships in the US, while Bazzi et al. (2017) use input-output matrices to construct measures of the relationships between Indonesian firms. Both studies find that firms enjoy significant boosts to productivity from their relationships with more productive counterparts.

However, an important gap exists in the literature on productivity spillovers. Many studies assess the existence of spillovers using TFP estimates obtained from semi-parametric proxy variable/control function approaches. Introduced by Olley and Pakes (1996) and refined in Levinsohn and Petrin (2003), Wooldridge (2009) and Ackerberg et al. (2015) (hereafter OP, LP, Wooldridge and ACF respectively), these methods rely on an assumption that a firm's future productivity depends only on its own past productivity and characteristics. Alternative methods like Gandhi et al. (2020) rely on first order conditions for identification, but still rely on the same assumption on the productivity evolution process. This implies that each firm's productivity evolves independently, and implicitly rules out the existence of anticipated spillovers.

The contributions of this paper are three-fold. First, I show that when productivity spillovers exist, failing to account for this interdependence could lead to biased estimates of production function elasticities and TFP. Using Monte Carlo experiments, I demonstrate that input elasticities are generally not consistent when the law of motion for productivity precludes spillovers. As De Loecker (2013), De Loecker et al. (2016), and Garcia-Marin and Voigtländer

[1] See Syverson (2011) for a review.
[2] See Keller (2010) for a review of the evidence on spillovers from FDI and exporting.

(2019) point out, our conclusions about what drives changes in productivity are sensitive to how it is measured. De Loecker (2013) shows that measuring TFP under standard assumptions can lead us to underestimate the impact of exporting on productivity. In Garcia-Marin and Voigtländer (2019), the downward bias in learning-by-exporting estimates comes from revenue-based productivity measures that cannot disentangle the lower prices firms charge upon entry into export markets from their increased efficiency. Unfortunately, the direction of bias in spillover estimates is not so clear-cut. I find that, depending on the structure of the network and persistence of productivity over time, estimating spillovers on mismeasured TFP can lead us to *overestimate* network effects in some cases and *underestimate* them in others.

Secondly, I propose a modification to standard control function and first order condition approaches that flexibly accounts for the presence of spillovers. To do so, I apply results from the peer effects and spatial econometrics literatures Lee (2003); Bramoullé et al. (2009); Lee and Yu (2016), with an important distinction: these papers deal with outcomes that are observed, whereas I jointly estimate the outcome and spillovers. This comes at the cost of a few additional assumptions that are, nonetheless, compatible with both the standard production function and network effects frameworks. An advantage of the proposed method is that, even in the absence of spillovers, the estimator does not generate spurious network effects and provides consistent, albeit less precise, estimates of the input elasticities. It can also accommodate confounders such as common shocks to firms in the same network and the endogeneity of network formation. I extend the framework to examine heterogeneous spillovers in the manner of Dieye and Fortin (2017) and Patacchini et al. (2017), that vary by the nature of the relationship between firms and their characteristics.

Third, I apply this methodology to examine the transmission of efficiency gains through the production network of publicly listed firms in the United States from 1977 to 2016. I find evidence of positive productivity spillovers, with a stronger impact from suppliers to customers, and substantial heterogeneity by sector and firm size. Estimates suggest that if the most connected firm in a given year was 10 percent more productive, spillovers would lead to an increase in aggregate TFP of 0.2 to 1.9 percent. Furthermore, the cumulative impact of spillovers over time implies that the average firm in 1978 would be 16 percent more productive by 2016 due to spillovers alone. Decomposing the spillovers by sector, shows that electronics manufacturers have benefited from almost all other sectors and while retailers are important sources of efficiency gains.

My results highlight an additional channel for industrial policy to affect economic growth. Given that a substantial portion of these spillovers can be attributed to distribution and information technology, policymakers could target high-growth sectors that can generate these second-order effects. Furthermore, the centrality of a few firms to the production network suggests that policies adversely impacting such firms could have broader negative ramifications for the US economy.

In the next section, I describe the data and features of the sample of the US production network that I observe. Section I.3 presents my empirical framework and discusses the biases that arise from ignoring spillovers in the standard control function approach. In section I.4, I propose a procedure for estimating production functions in the presence of various network effects and clarify the assumptions needed to obtain valid estimates. I introduce a model of network formation in section I.5 to account for endogenous network selection. Section I.6 demonstrates the advantages of my approach over existing methods using Monte Carlo experiments. I consider extensions to the benchmark model including a gross output production function in section I.7. Section I.8 presents my empirical results and section I.9 concludes.

I.2 Data: The US Production Network

I begin by describing the data with which I characterize the firm-level production network within the United States, to highlight features that will be important for my empirical methodology. To examine the magnitude and origins of productivity spillovers in the US, I rely on a panel of publicly-listed firms in the *Compustat* database from 1977 to 2016. *Compustat* collects companies' financial statements from form 10-K reports filed with the US Securities and Exchange Commission (SEC). This provides detailed information on firms' sales, capital stock, expenses and employees. I supplement this with industry-level deflators and wages from the US Bureau of Economic Analysis (BEA) to construct the necessary variables for estimating a production function.[3]

Information on buyer-supplier links also comes from 10-K reports. Statement no. 14 issued in December 1976 by the Financial Accounting Standards Board (FASB) requires each firm to report any customers that are responsible for 10% or more of its sales within a fiscal year. I conservatively match the reported customer names to company financial data. The resulting network contains 18,872 unique buyer-supplier pairs and 66,052 dyad-year observations.[4]

I restrict the firm-level sample to the businesses that either report or are reported as customers, and have positive values of sales, capital stock, labor and materials. I discard firms in agriculture, forestry and fishing, because these industries have too few observations in both the firm- and dyad-level datasets. This yields an unbalanced panel of 8,353 firms and 55,047 firm-year observations.

Table I.1 reports average firm characteristics by decade and over the full sample. Due to the nature of the firms in question, and the restriction to companies with customer or supplier data, firms in the sample tend to be large, averaging 19,000 employees and $6.08 billion in annual sales. Based on the BEA's classification of large enterprises as firms employing 500 or more workers, about two-thirds of the sample are large firms. As shown in table I.2, manufacturers comprise more than half of the firms in the sample. Information and Services are the next largest sectors represented in the sample.[5]

The observed sample of the production network is sparse; that is, the number of connections per firm is low. Figure I.1 shows that firms report 1 or 2 customers on average, while the same customers are reported by about 3 or 4 suppliers. Consistent with the 10% sales reporting requirement, reported customers tend to be large; the average customer realizes about eight times as much in sales as the average supplier in the data (see figure I.5). This may be due to two factors: relatively small firms are likely to have major customers and larger firms are likely to be major customers. However, although the value traded in the average reported relationship is sizable and increases over time, figure I.2 indicates each individual relationship makes up a declining share of suppliers' sales.

In figure I.4, I examine features of the network that affect the identification of spillovers within my framework. Network density, measured by the number of observed links as a fraction of all possible links, does not exceed 0.28% in any year. The network gets sparser at the beginning of the sample and denser after the mid-90's. At the same time, network transitivity, the number of observed triads as a share of all possible triads, trends upwards throughout the sample, but does not exceed 1.2%. In sections I.3 and I.4, I discuss the importance of density and transitivity for both the biases in input elasticities from standard approaches and the performance of my proposed estimator.

Each year, the production network is often dominated by a large cluster of firms connected to each other. Figure I.3 shows that the number of edges in the largest connected component as a share of all edges in the network ranges from 56 to 70%. This is largely due to the presence of a few well-connected firms while the remainder of the network consists of peripheral small clusters.

Variations in clustering patterns over time reflect changes in the relative importance of each industry. Figure I.7 reports the 10 most central firms as measured by the number of links a firm has as a share of all observed links. In the first 10 years of the sample, manufacturers of automotives and other durable goods dominated the list. In the next decade, AT&T rose to the top of the list, and electronics manufacturers like IBM had begun to emerge. In the 1997-

[3] See section A.4 in the appendix for further details on variable construction.

[4] Other studies that have used this dataset to study the US production network include Atalay et al. (2011), Lim et al. (2017) and Serpa and Krishnan (2018). I am grateful to the authors of Atalay et al. (2011) for graciously sharing their matched buyer-supplier data with me.

[5] See section A.4 for a full list of industries in each sector.

2006, Walmart had risen to the top the list, and while automotive and electronics manufacturers still featured at the top of the centrality distribution, their centrality had declined relative to earlier decades. By the end of the sample, most manufacturers had been superseded by retailers and wholesalers had become the most connected firms, with Walmart continuing to top the list.

Figure I.6 shows the relationship between a firm's labor productivity, as measured by the natural log of sales per employee and that of its average buyer or seller. The slope of the fitted regression line is 0.38, indicating a strong positive correlation between the two quantities. Interpreting this relationship would require distinguishing between several possible explanations. Foremost is the question of direction: does a firm become more efficient by learning from its neighbors, or does causation move in the opposite direction? And if a firm is simultaneously affected by and affecting its partners, how can one pin down the magnitude of the effect? On the other hand, this relationship may be driven by the sorting of firms; if more productive firms trade with each other, then this correlation is evidence of network formation rather than spillovers. Yet another possibility is that supply chains are a channel for the transmission of production and demand shocks, inducing the revenues of connected firms to move in the same direction.

Each of these explanations has different implications for how productivity is measured: if there are spillovers due to learning, then firms' input decisions will likely be influenced by the efficiency of their suppliers or buyers, whereas unanticipated common shocks are unlikely to affect input choices to the same degree. In the next section, I introduce an empirical framework with the goal of distinguishing between these channels, examining how they impact the measurement of TFP, and quantifying the direction and magnitude of productivity spillovers.

Table I.1: Firm Characteristics

	1977-1986	1987-1996	1997-2006	2007-2016	Full Sample
Sales	3.29	3.65	6.45	10.57	6.08
	(12.27)	(14.64)	(22.17)	(28.9)	(21.03)
Sales per 1000 employees	0.29	0.34	0.51	0.83	0.5
	(1.16)	(0.82)	(3.63)	(7.19)	(4.12)
Value Added	0.93	1.02	1.88	3.47	1.85
	(2.9)	(3.04)	(5.34)	(8.23)	(5.47)
Capital stock	3.23	3.52	4.89	9.79	5.4
	(12.01)	(14.49)	(18.13)	(33.22)	(21.41)
Materials	2.53	2.85	4.73	7.12	4.37
	(11.06)	(13.45)	(18.86)	(22.98)	(17.56)
Employees (thousands)	15.35	13.9	19.15	27.22	18.95
	(48.73)	(43.41)	(61.46)	(84.71)	(62.02)
Large firm (employees $\geq$ 500)	0.65	0.63	0.68	0.77	0.68
Observations	10339	15268	15495	13455	54557

This table reports average characteristics of firms in the sample. Standard deviations are in parentheses. All monetary values are in 2009 billion USD.

Table I.2: Industry Composition

	1977-1986	1987-1996	1997-2006	2007-2016	Full Sample
Mining	9.2	5.8	4.0	7.4	6.3
Utilities	6.9	5.3	2.8	3.4	4.4
Construction	0.9	0.8	0.9	1.0	0.9
Durables Manufacturing	25.4	21.4	19.1	16.8	20.4
Non-Durables Manufacturing	17.6	17.7	18.6	19.7	18.4
Electronics Manufacturing	14.9	17.9	19.7	16.8	17.6
Wholesale	3.3	4.7	4.3	3.7	4.1
Retail	3.6	4.3	4.6	4.7	4.4
Transport and Warehousing	4.4	3.3	3.4	4.3	3.8
Information	5.5	8.9	10.5	10.2	9.0
Finance, Insurance & Real Estate	2.7	2.8	3.3	4.9	3.5
Services	5.6	7.1	8.9	6.9	7.3
Total	100	100	100	100	100

This table reports the distribution of firms in the sample by primary sector as determined by the BEA industry classification.

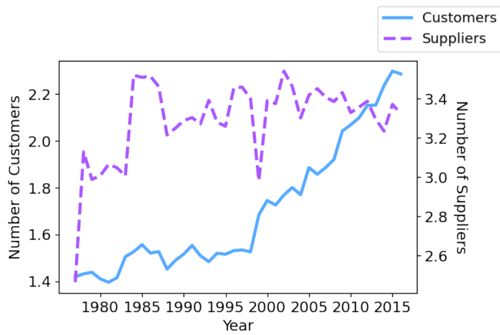


Figure I.1: Average Firm Degree

This figure shows annual average out- and in-degrees (customers and suppliers) for firms in the sample.

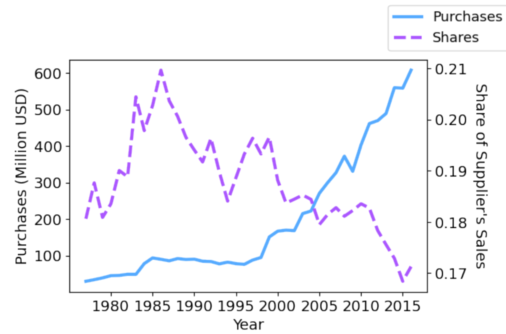


Figure I.2: Value Traded in Relationships

This figure shows the annual average value traded by each buyer-supplier pair in nominal Million USD and as share of the each seller's total sales.

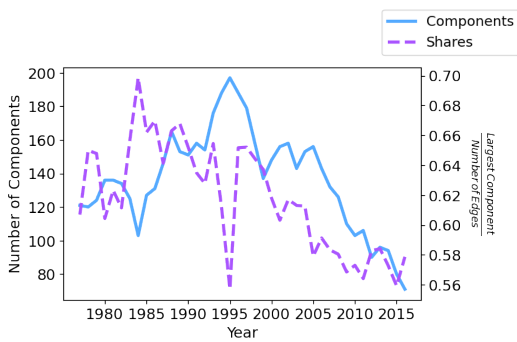


Figure I.3: Network Clustering and Components

This figure shows the number of connected components and the largest component as share of all edges in the network sample over time.

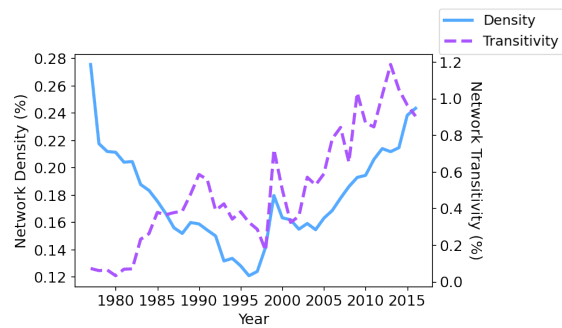


Figure I.4: Network Density and Transitivity

This figure shows the density and transitivity of the network sample over time.

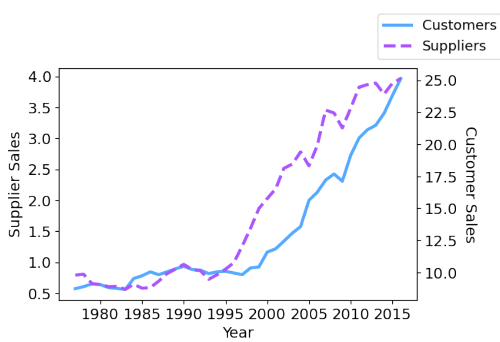


Figure I.5: Customer and Supplier Sales

This figure shows annual average sales (in 2009 Billion USD) of firms reporting and reported as customers in the sample.

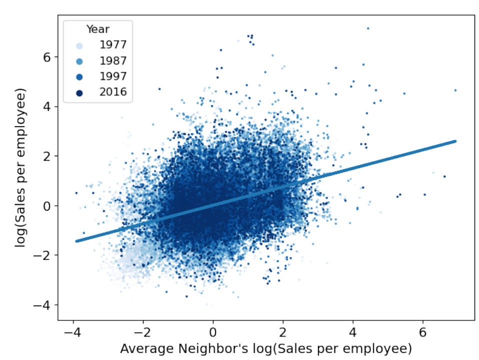


Figure I.6: Relationship between Labor Productivity of Firms and their Trading Partners

This figure shows the relationship between the labor productivity of a firm and its buyers and suppliers. The slope of the fitted regression line is 0.38.

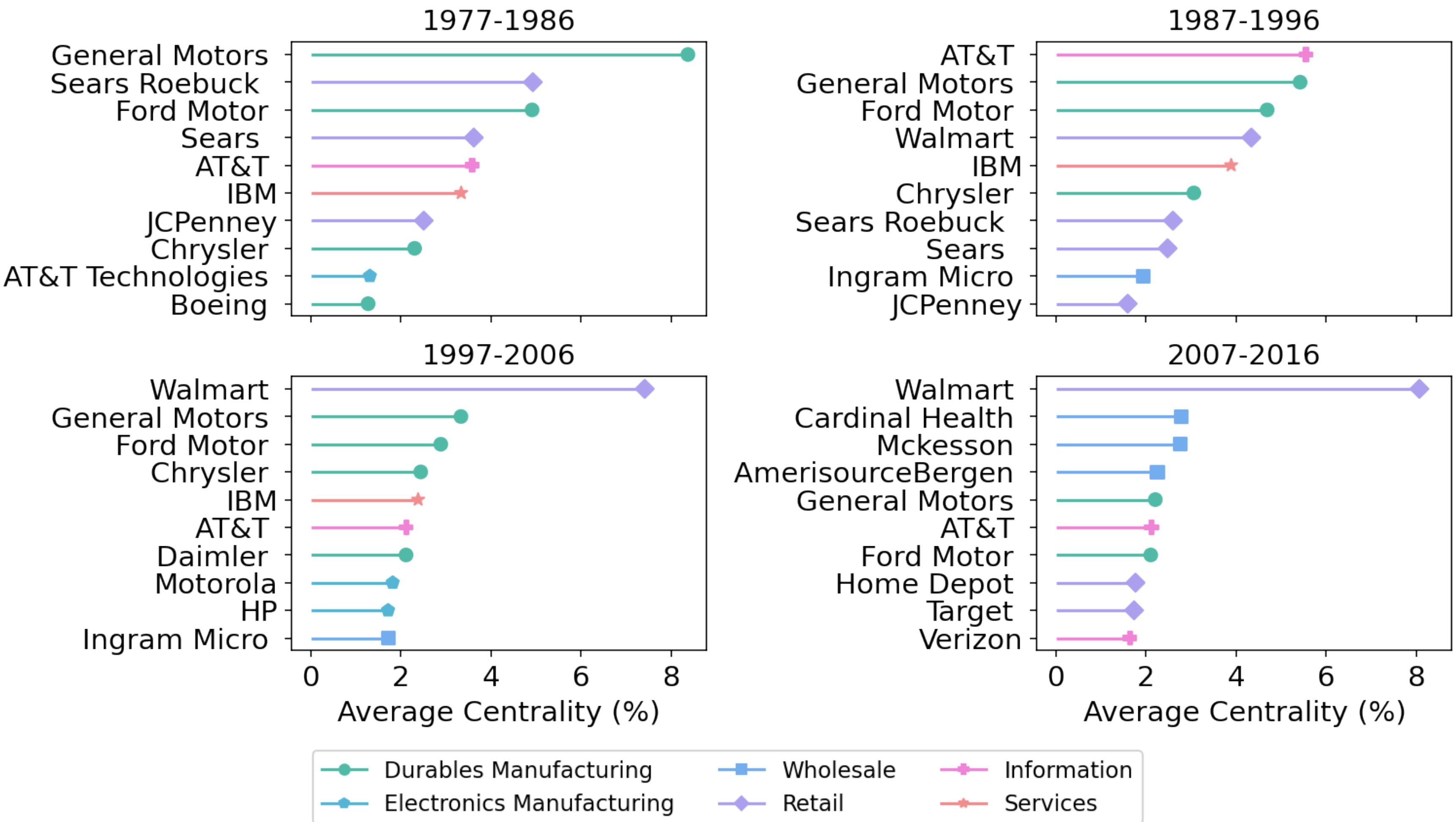


Figure I.7: Firm Centrality

This figure shows the top 10 firms by average centrality in each period.

I.3 Empirical Framework

Consider a production technology for firm i in period t in which productivity is Hicks-neutral:

$$Y_{it} = F(L_{it}, K_{it})e^{\omega_{it}+\varepsilon_{it}} \tag{I.1}$$

where output Y_{it} is a function of labor, L_{it} and capital, K_{it}. Output is shifted by an exogenous shock $e^{\varepsilon_{it}}$ independent of all variables known to the firm by the end of the period, the information set $\mathscr{I}_t$. $e^{\omega_{it}}$ is firm-specific TFP that is unobserved by researchers but known to the firm when making production decisions. $F(\cdot)$ is known up to some parameters. Taking the natural log of (I.1) yields:

$$y_{it} = f(L_{it}, K_{it}) + \omega_{it} + \varepsilon_{it} \tag{I.2}$$

The main limitation to estimating $f(\cdot)$ is a simultaneity problem: firms choose their inputs based on the realization of ω_{it}. Therefore, simply regressing a firm's output on its inputs would lead to a biased estimate of $f(\cdot)$.

To address this issue, the control function/proxy variable approach makes a set of assumptions on timing, a proxy variable and how productivity evolves over time. The existence of spillovers primarily poses a problem for the last set of assumptions. Productivity is typically assumed to follow a first-order Markov process:

$$\omega_{it} = h(\omega_{it-1}) + \eta_{it} \tag{I.3}$$

where $h(\cdot)$ is unknown and η_{it} is mean independent of firm's information set at the beginning of the period $\mathscr{I}_{t-1}$. Suppose instead that ω_{it} is affected by some other firm j either through its past decisions $\boldsymbol{x}_{jt-1}$ and/or its current productivity ω_{jt}:

$$\omega_{it} = h(\omega_{it-1}, \boldsymbol{x}_{jt-1}, \omega_{jt}) + \zeta_{it} \tag{I.4}$$

where $E[\zeta_{it} \mid \mathscr{I}_{t-1}] = 0$. The effect of $\boldsymbol{x}_{jt-1}$ represents spillovers from firm $j's$ activities such as research and development (R&D), FDI, exporting, etc. The inclusion of ω_{jt} indicates that j being more productive could contemporaneously influence i's productivity. Since firm j's TFP is also determined by its past productivity ω_{jt}, this representation indirectly allows for spillovers from productivity to occur with a one-period lag, but also accommodates the possibility that firm i is also affected by random shocks to j's productivity, ζ_{jt} within the same period. In addition, it enables researchers to differentiate between direct effects of firm activities

When researchers estimate TFP under the assumption in (I.3) whereas the true process is represented by (I.4), then the effect of firm j on i is attributed to η_{it}, which now violates the conditional independence assumption. In the following subsections, I examine the biases arising from standard control function approaches in greater detail.

Accounting for $\boldsymbol{x}_{jt-1}$ is fairly straightforward if we assume that it is known to i at the beginning of the period; that is, $\boldsymbol{x}_{jt-1} \in \mathscr{I}_{t-1}$. However, ω_{jt} poses a more serious problem because it is jointly realized with ω_{it} and cannot therefore be assumed to be in $\mathscr{I}_{t-1}$. In section I.4, I outline the assumptions needed to properly account for the effect of ω_{jt} on ω_{it} when estimating production functions.

I.3.1 Control Function Approach

Suppose $f(\cdot)$ takes the form of a simple Cobb-Douglas production function as in Ackerberg et al. (2015):[6]

$$y_{it} = \alpha_\ell \ell_{it} + \alpha_k k_{it} + \omega_{it} + \varepsilon_{it} \tag{I.5}$$

where y_{it}, k_{it}, and ℓ_{it} are the logs of value-added[7], capital and labor respectively. Obtaining consistent estimates of $\boldsymbol{\alpha}$ and ω_{it} requires three sets of assumptions.

The first relates to the timing of firms' decisions. Capital is a state variable, determined in the preceding period as a deterministic function of the firm's previous capital stock and its investment decision: $k_{it} = \kappa(k_{it-1}, i_{it-1})$. Labor, on the other hand, may or may not have dynamic implications. It may be fully adjustable and chosen after productivity is realized, or partly (or wholly) determined in the previous period. It, however, needs to be chosen prior to the intermediate input decision. Based on its current capital stock, workforce and productivity, the firm chooses intermediate inputs according to the following function:

$$m_{it} = \mathbb{M}(k_{it}, \ell_{it}, \omega_{it})$$

Next, one needs to assume that the demand for materials, $g(\cdot)$ is strictly monotonic in productivity, and that productivity is the only unobservable component of the input demand function. This guarantees that TFP can be expressed solely as a function of observables $\omega_{it} = \mathbb{M}^{-1}(k_{it}, \ell_{it}, m_{it})$. Substituting into the production function yields:

$$y_{it} = \alpha_\ell \ell_{it} + \alpha_k k_{it} + \mathbb{M}^{-1}(k_{it}, \ell_{it}, m_{it}) + \varepsilon_{it} \tag{I.6}$$

Although α_k and α_ℓ are not identified in this equation, we can obtain consistent estimates of the firm's expected value-added:

$$E[y_{it}|\mathscr{I}_{it}] = \varphi_{it} = \alpha_\ell \ell_{it} + \alpha_k k_{it} + \omega_{it} \tag{I.7}$$

This disentangles productivity from the idiosyncratic shock ε_{it}. In order to identify capital and labor elasticities, the evolution process for productivity must be specified. A standard assumption is that productivity follows a first-order Markov process given its information set $\mathscr{I}_{it-1}$ in the previous period:

$$\omega_{it} = h(\omega_{it-1}) + \eta_{it} \tag{I.8}$$

where $E[\omega_{it}|\mathscr{I}_{it-1}] = E[\omega_{it}|\omega_{it-1}] = h(\omega_{it-1})$. $h(\cdot)$ is known to the firm but unobserved by the researcher, while η_{it} is idiosyncratic. Given (I.7) I can write lagged productivity as:

$$\omega_{it-1} = \varphi_{it-1} - \alpha_k k_{it-1} - \alpha_\ell \ell_{it-1}$$
$$\implies \omega_{it} = h(\varphi_{it-1} - \alpha_k k_{it-1} - \alpha_\ell \ell_{it-1}) + \eta_{it}$$

Substituting into the production function yields:

$$y_{it} = \alpha_\ell \ell_{it} + \alpha_k k_{it} + h(\varphi_{it-1} - \alpha_k k_{it-1} - \alpha_\ell \ell_{it-1}) + \eta_{it} + \varepsilon_{it}$$

[6] I choose ACF because it allows for relatively flexible assumptions on the data-generating process for output, capital, labor and materials. However, this critique applies more broadly to OP, LP, Wooldridge and first order condition approaches such as Gandhi et al. (2020) that rely on similar assumptions on the productivity evolution process.

[7] Output minus intermediate inputs.

Since $E[\varepsilon_{it}|\mathscr{I}_{it}] = 0$ and $E[\eta_{it}|\mathscr{I}_{it-1}] = 0$ by assumption, then we can identify α_k, α_ℓ based on the moment restriction:

$$E[\varepsilon_{it} + \eta_{it}|\mathscr{I}_{it-1}] = E[y_{it} - \alpha_k k_{it} - \alpha_\ell \ell_{it} - h(\varphi_{it-1} - \alpha_k k_{it-1} - \alpha_\ell \ell_{it-1})|\mathscr{I}_{it-1}] = 0 \tag{I.9}$$

Using this equation, we can derive moment conditions to estimate the elasticities. Since, there are three unknowns, $(\alpha_k, \alpha_\ell, h(\cdot))$, a typical set of moments would be:

$$E[(\eta_{it} + \varepsilon_{it})k_{it}, \ell_{it-1}, \varphi_{it-1}] = 0 \tag{I.10}$$

I.3.2 Network Effects

To examine biases due to the existence of spillovers, we need to first understand how network effects are characterized. Within a given year, relationships between n_t firms result in a network. This can be represented by an $n_t \times n_t$ adjacency matrix A_t such that $A_{ij,t} = 1$ if firm i has a relationship with firm j in that year and zero otherwise. These relationships could be transactional (i sells inputs to j) or some other form of firm interdependence, such as i and j sharing a board member. The adjacency matrix need not be symmetric. As is standard in the peer-effects literature, I impose $A_{ii,t} = 0$ for all i so that a firm cannot have a spillover effect on itself.

In most examples, I focus on buyer-supplier networks, but this framework could apply to other types of inter-firm relationships.[8] Suppose we are interested in how upstream firms are affected by the productivity of their downstream network. Let N_{it} be the set of i's customers in period t and $n_{it} = |N_{it}|$.[9] We would like to estimate the following network effects equation:

$$\omega_{it} = \beta_1 + \rho\,\omega_{it-1} + \boldsymbol{x}_{it-1}\boldsymbol{\beta_x} + \lambda \frac{1}{n_{it}} \sum_{j \in N_{it}} \omega_{jt} + \frac{1}{n_{it}} \sum_{j \in N_{it}} \boldsymbol{x}_{jt-1}\boldsymbol{\beta}_{\bar{x}} + c_{\psi_t} + \zeta_{it} \tag{I.11}$$

where x_{it-1} is a $1 \times k$ vector of exogenous firm characteristics that could influence productivity, such as past R&D or exporting.

In this equation, there are three ways in which firm i's network could be related to its productivity. In the terminology of Manski (1993), the first channel is *endogenous network effects*: a firm's productivity is affected by the average productivity of its neighbors. This is measured by λ.

The second mechanism is *contextual effects* captured by $\boldsymbol{\beta}_{\bar{x}}$. Firms may be influenced by the characteristics or activities of their neighbors. For example, a firm's R&D could generate positive productivity spillovers on its business partners.

A firm's relationships could also result in *correlated effects*, productivity shocks common to all firms in a network cluster. Let ψ_t index the sub-components of a network in period t, that is firms who are at least indirectly connected to each other. Then c_{ψ_t} is a correlated effect for all firms in component ψ_t.

An underlying assumption here is that the network is exogenous; that is, firms do not select partners in ways that are systematically correlated with their productivity. For now, I abstract from network selection and address it in section I.5.

For the rest of this discussion, it would be convenient to rewrite these equations in matrix notation. Define the

[8] Provided the network satisfies certain conditions for identification. See the rest of this section for details.

[9] Note that for some final goods producers and retailers, $n_{it} = 0$. These firms may not experience spillovers from others, but could still affect their suppliers.

interaction matrix G_t as the row-normalized form of A_t.[10] Equation (I.11) can be rewritten as:

$$\omega_t = \beta_1 \iota + \rho \omega_{t-1} + \boldsymbol{x}_{t-1} \boldsymbol{\beta}_{\boldsymbol{x}} + \lambda G_t \omega_t + G_t \boldsymbol{x}_{t-1} \boldsymbol{\beta}_{\bar{x}} + c_{\psi_t} + \zeta_t \tag{I.12}$$

The reduced form is as follows:

$$\omega_t = (1 - \lambda G_t)^{-1} \left(\beta_1 \iota + \rho \omega_{t-1} + \boldsymbol{x}_{t-1} \boldsymbol{\beta}_{\boldsymbol{x}} + G_t \boldsymbol{x}_{t-1} \boldsymbol{\beta}_{\bar{x}} + c_{\psi_t} + \zeta_t \right) \tag{I.13}$$

$|\lambda| < 1$ implies that we can represent $(I - \lambda G_t)^{-1}$ as a geometric series.

$$\omega_t = \sum_{s=0}^{\infty} \lambda^s G_t^s \left(\beta_1 \iota + \rho \omega_{t-1} + \boldsymbol{x}_{t-1} \boldsymbol{\beta}_{\boldsymbol{x}} + G_t \boldsymbol{x}_{t-1} \boldsymbol{\beta}_{\bar{x}} + c_{\psi_t} + \zeta_t \right) \tag{I.14}$$

Bramoullé et al. (2009) prove that (I.12) is identified if the identity matrix I, G and G^2 are linearly independent. The presence of intransitive triads[11] guarantees that linear independence holds. Production networks naturally have this structure because supply-chains tend to be unidirectional. Therefore, if ω_t was observed, one could estimate (I.12) using 2SLS (Lee, 2003; Bramoullé et al., 2009), QMLE (Lee and Yu, 2016) or Bayesian methods in (Goldsmith-Pinkham and Imbens, 2013).

Measuring productivity adds a layer of complexity to the problem. A typical strategy as in Javorcik (2004) and Serpa and Krishnan (2018), is to first obtain TFP values by estimating a production function such as using a method described above, and use these estimates in the network effects equation in (I.12). However, these approaches implicitly rule out the presence of spillovers, and the resulting TFP estimates are incompatible with the a wide set of network models nested in the peer effects model above.

I.3.3 Biases due to Network Effects

When productivity is affected by network effects, the independence assumption on the productivity shock is violated. However, the impact on the estimation of production function elasticities will differ by the type of effect.

Suppose TFP is estimated under the exogeneity assumption in (I.3) but the true process is given by equation (I.12). This implies:[12]

$$E[\eta_t|\mathscr{I}_{t-1}] = \boldsymbol{x}_{t-1} \boldsymbol{\beta}_{\boldsymbol{x}} + \lambda G_t E[\omega_t \mid \mathscr{I}_{t-1}] + G_t \boldsymbol{x}_{t-1} \boldsymbol{\beta}_{\bar{x}} + E[c_{\psi_t} \mid \mathscr{I}_{t-1}]$$

In general, this expression is not equal to zero. $\boldsymbol{x}_{t-1}$ is a source of omitted variable bias but De Loecker (2013) and Gandhi et al. (2020) show that the productivity process can be modified to account for its impact, as long as $\boldsymbol{x}_{t-1}$ is in the firm's information set at the beginning of the period.[13] Contextual effects can be accounted for in the same way under similar assumptions. Provided that network formation is exogenous, including $G_t \boldsymbol{x}_{t-1}$ in equation (I.3) would eliminate bias from this dimension.

$G_t E[\omega_t|\mathscr{I}_{t-1}]$ poses a serious challenge because in general, $E[\omega_t|\mathscr{I}_{t-1}] \neq 0$. Consider the correlation between neighbors' current productivity and current capital stock. Using the reduced form of $G_t \omega_t$:

$$E[G_t \omega_t \circ k_t] = E[G_t (1 - \lambda G_t)^{-1} (\beta_1 \iota + \rho \omega_{t-1} + \boldsymbol{x}_{t-1} \boldsymbol{\beta}_{\boldsymbol{x}} + G_t \boldsymbol{x}_{t-1} \boldsymbol{\beta}_{\bar{x}} + \zeta_t) \circ k_t]$$

[10] $G_{ij,t} = 1/n_{it}$ if $A_{ij,t} = 1$ and zero otherwise.

[11] An intransitive triad in a graph is a set of nodes i, j, k, such that i is connected to j and j to k, but k is not connected to i.

[12] Here, I assume that G_t, $\{\boldsymbol{\omega}_{jt-1}\}_{j \in N_{it}}$ and $\{\boldsymbol{x}_{jt-1}\}_{j \in N_{it}}$ are in firm i's information set at the beginning of the period. I discuss this assumption explicitly in the next section.

[13] For example, as De Loecker (2013) notes, including firm's current export status would not be valid because that is dependent on productivity in the same period, but using previous export status would satisfy this condition.

where $\circ$ is the Hadamard product.[14] Even though capital stock was determined in the previous period, it is still correlated with current productivity spillovers because productivity persists over time, and investment in the previous period was a function of productivity at the time. That is $k_(it) = \kappa(k_{t-1}, i_{t-1}(\omega_{t-1}))$ and therefore, $E[G_t \omega_t \times k_t] \neq 0$. The same argument can be made for labor which is a function of productivity in the same period: $l_{t-1}(\omega_{t-1}) \implies E[G_t \omega_t \circ \ell_{t-1}] \neq 0$.

The direction of bias will depend on the sign and size of λ and the relationship between capital, labor and productivity. For example, if networks generate positive productivity externalities and capital stock is increasing in productivity, then α_k will be biased upwards. If λ is small enough, then the size of bias will be minimal. TFP values will be underestimated but the direction of bias on λ is unclear.

On their own, correlated effects or network fixed effects do not introduce bias in the estimation of α_k and α_ℓ. Since the common component shocks are idiosyncratic each period, then k_t and ℓ_{t-1}, which were determined in the previous period are independent of c_{ψ_t}. However, to the extent that network components and links do not vary much over time, failing to account for $c_{\psi_t t}$ would bias α_k and α_ℓ estimates.

To illustrate the bias from ignoring endogenous network effects, consider the following process:

$$\omega_t = \rho(I - \lambda G_t)^{-1}\omega_{t-1} + (I - \lambda G_t)^{-1}\zeta_{it} = \rho \sum_{s=0}^{\infty} \lambda^s G_t^s \omega_{t-1} + \sum_{s=0}^{\infty} \lambda^s G_t^s \zeta_{it} \tag{I.15}$$

Then the second stage of ACF is equivalent to estimating:[15]

$$\implies y_t = \alpha_\ell \ell_t + \alpha_k k_t + \rho \sum_{s=0}^{\infty} \lambda^s G_t^s (y_{t-1} - \alpha_\ell \ell_{t-1} - \alpha_k k_{t-1} - u_{t-1}) + \sum_{s=0}^{\infty} \lambda^s G_t^s \zeta_t + \varepsilon_t$$

Let $\Delta^G x_t = x_t - \rho \sum_{s=0}^{\infty} \lambda^s G_t^s x_{t-1}$, $\Delta_{x_t}^{err} = \rho \sum_{s=1}^{\infty} \lambda^s G_t^s x_{t-1}$ and $\Delta x_t = x_t - \rho x_{t-1} = \Delta^G x_t + \Delta_{x_t}^{err}$. This implies:

$$\Delta^G y_t = \alpha_\ell \Delta^G \ell_t + \alpha_k \Delta^G k_t + \sum_{s=0}^{\infty} \lambda^s G_t^s \zeta_t + \Delta^G \varepsilon_t \tag{I.16}$$

This is equivalent to the dynamic panel approach in Blundell and Bond (2000). However, growth in output, labor and capital have been purged of the variation from network effects in the previous period. When we assume no spillovers, we estimate:

$$\Delta y_t = \alpha_\ell \Delta \ell_t + \alpha_k \Delta k_t + u_t \tag{I.17}$$

Therefore, in the linear AR1 case, ignoring spillovers is equivalent to introducing non-classical measurement error into both output and inputs. Bias from ignoring spillovers can also be characterized as an omitted variables problem. By estimating equation (I.17), where $u_t = \rho \sum_{s=1}^{\infty} \lambda^s G_t^s \omega_{t-1} + \sum_{s=0}^{\infty} \lambda^s G_t^s \zeta_t + \varepsilon_t$. That is, the standard ACF procedure succeeds in eliminating the endogeneity problem that arises from input decisions depending on the firm's own productivity, but is unable to account for the influence of its network's past productivity. In either case, an instrumental variable approach would help to eliminate the problem. The key would be to find variables that are correlated with changes to labor and capital but uncorrelated with output, particularly the input choices and output of other firms.

In the OP/LP case where the labor elasticity is consistently estimated in the first stage, the second stage is equivalent

[14] Element-wise multiplication.

[15] See section A.1 for derivation.

to estimating:

$$\Delta^G \widetilde{y}_t = \alpha_k \Delta^G k_t + \sum_{s=0}^{\infty} \lambda^s G_t^s \zeta_t + \Delta^G \varepsilon_t \tag{I.18}$$

$$\tag{I.19}$$

where $\widetilde{y}_t = y_t - \widehat{\alpha}_\ell \ell_t$. Then by estimating $\Delta\widetilde{y}_t = \alpha_k \Delta k_t + u_t$ under the standard assumption of no-spillovers:

$$plim\ \widehat{\alpha}_k = \frac{cov(\Delta k_t, \Delta\widetilde{y}_t)}{var(\Delta k_t)} \tag{I.20}$$

$$= \alpha_k \left(1 - \rho \sum_{s=1}^{\infty} \lambda^s \frac{cov(\Delta k_t, G_t^s k_{t-1})}{var(\Delta k_t)}\right) + \rho \sum_{s=1}^{\infty} \lambda^s \frac{cov(\Delta k_t, G_t^s \widetilde{y}_{t-1})}{var(\Delta k_t)} \tag{I.21}$$

On one hand, α_k is re-scaled by the covariance between the firm's capital growth and its network's previous capital. If this covariance is positive, then it would shrink $\widehat{\alpha}_k$ or even reverse its sign. Higher ρ will increase the attenuation factor, as will λ if it is positive. When λ is negative, it leads to an alternating series that dampens attentuation. The network structure also plays a role: when long chains exist, $G_t^s k_{t-1} > 0$ even for high values of s. By contrast, a network in which firms are paired off, so that the longest chain has length 1. Then $G_t^s k_{t-1} = 0$ for all $s > 1$ and attentuation would be lower under this scenario.

On the other hand, there is another source of bias that depends on the covariance between the firm's capital growth and its network's previous output purged of the variation from labor. When this covariance is positive, $\widehat{\alpha}_k$ overestimates α_k, and the effects of ρ, λ and G_t now work in the opposite direction. Depending on the signs and magnitudes of these covariances, it is possible to obtain estimates of α_k close to the true value if the two opposing effects cancel out.

Even in this simplified setting, the direction and magnitude of bias are not easily predictable *ex-ante*. This means that one cannot merely apply a bias correction to estimates obtained under standard assumptions. It motivates a modification to the estimation procedure that can flexibly account for a variety of productivity processes and network effects. I propose a modification to the ACF procedure that achieves this without many additional assumptions.

I.4 Accounting for Spillovers

I.4.1 Endogenous and Contextual Effects

Assuming network exogeneity and no correlated effects, I write a more general form of the linear-in-means equation (I.12) above:

$$\omega_t = h(\omega_{t-1}, \boldsymbol{x}_{t-1}, G_t \boldsymbol{x}_{t-1}) + \lambda G_t \omega_t + \zeta_t \tag{I.22}$$

Note that $h(\cdot)$ is unknown and can be estimated using a polynomial approximation. This allows for flexible interactions between ω_{t-1}, $\boldsymbol{x}_{t-1}$ and $G_t \boldsymbol{x}_{t-1}$. The key requirement is that the endogenous effect enters linearly. This leads to the reduced form:

$$\omega_t = (I - \lambda G_t)^{-1} h(\omega_{t-1}, \boldsymbol{x}_{t-1}, G_t \boldsymbol{x}_{t-1}) + (I - \lambda G_t)^{-1} \zeta_t \tag{I.23}$$

$|\lambda| < 1$ implies that we can approximate $(I - \lambda G_t)^{-1}$ by a geometric series.

$$\omega_t = \sum_{s=0}^{\infty} \lambda^s G_t^s h(\omega_{t-1}, \boldsymbol{x}_{t-1}, G_t \boldsymbol{x}_{t-1}) + \sum_{s=0}^{\infty} \lambda^s G_t^s \zeta_t \tag{I.24}$$

This yields a consistent estimate of the conditional expectation of TFP:

$$E[\omega_t | \mathscr{I}_{t-1}] = \sum_{s=0}^{\infty} \lambda^s G_t^s h(\omega_{t-1}, \boldsymbol{x}_{t-1}, G_t \boldsymbol{x}_{t-1}) \tag{I.25}$$

since the resulting error term satisfies the mean independence condition:

$$E\left[(I - \lambda G_t)^{-1} \zeta_t \middle| \mathscr{I}_{t-1}\right] = E\left[\sum_{s=0}^{\infty} \lambda^s G_t^s \zeta_t \middle| \mathscr{I}_{t-1}\right] = 0$$

.

Note that equation (I.24) also indicates how λ can be identified. Given the reduced-form equation, $G_t \omega_t$ can be written as:

$$G_t \omega_t = G_t h(\omega_{t-1}, \boldsymbol{x}_{t-1}, G_t \boldsymbol{x}_{t-1}) + \sum_{s=1}^{\infty} \lambda^s G_t^{s+1} h(\omega_{t-1}, \boldsymbol{x}_{t-1}, G_t \boldsymbol{x}_{t-1}) + \sum_{s=0}^{\infty} \lambda^s G_t^{s+1} \zeta_t \tag{I.26}$$

As long as productivity is sufficiently persistent, we can use the current network's past productivity $G_t \omega_{t-1}$ as an instrument for the impact of network's current productivity $G_t \omega_t$. This is because a firm is only affected by its current neighbors' past productivity through the neighbors' current productivity. Therefore, λ is identified from the variation in $G_t \omega_t$.

Equation (I.26) indicates that there are additional instruments available to identify the endogenous network effect. These are more common in the network effects literature and rely on the existence of intransitive triads in the network (Lee, 2003; Bramoullé et al., 2009). For example $G_t^2 \omega_t$ and $G_t^2 \boldsymbol{x}_{t-1}$ is one set of possible instruments because G_t^2 captures the neighbors of a firm's neighbors, and these indirect connections affect the firm only through the firm's direct relationships.

Note however, that the relevance of these additional instruments relies on the strength of the endogenous effect. Whereas $G_t \omega_{t-1}$ is a good instrument as long as productivity is persistent, $G_t^2 \omega_{t-1}$ requires both persistence and $|\lambda| > 0$ while $G_t^2 \boldsymbol{x}_{t-1}$ requires that both endogenous and contextual network effects be nonzero.

Substituting the reduced form equation into the vectorized production function:

$$y_t = \alpha_k k_t + \alpha_\ell \ell_t + (1-\lambda G_t)^{-1}\left[h(\varphi_{t-1} - \alpha_k k_{t-1} - \alpha_\ell \ell_{t-1}, \boldsymbol{x}_{t-1}, G_t \boldsymbol{x}_{t-1}) + \zeta_t\right] + \varepsilon_t \tag{I.27}$$

which leads to the polynomial expansion:

$$y_t = \alpha_k k_t + \alpha_\ell \ell_t + \sum_{s=0}^{\infty} \lambda^s G_t^s h(\varphi_{t-1} - \alpha_k k_{t-1} - \alpha_\ell \ell_{t-1}, \boldsymbol{x}_{t-1}, G_t \boldsymbol{x}_{t-1}) + \sum_{s=0}^{\infty} \lambda^s G_t^s \zeta_t + \varepsilon_t \tag{I.28}$$

Accounting for network effects in the estimation procedure comes at the cost of additional assumptions. The first, as seen above, is that the endogenous effect enters the productivity process linearly. This would not hold if there were non-monoticities in spillovers. For instance, if firms are likely to free-ride on very productive neighbors and are also negatively affected by very unproductive networks, but are able to learn from moderately productive firms, then the linearity assumption would not hold. However, there is reason to believe that linearity is, at the very least, a good approximation for understanding the network effect and it is a common assumption in the peer effects literature. Furthermore, one need not assume linearity if endogenous spillovers are not contemporaneous. For example, if we assume firms are affected by the past productivity of the previous network $(G_{t-1}\omega_{t-1})$, or the past productivity of their current network $(G_t \omega_{t-1})$, then either of these terms could enter $h(\cdot)$ non-linearly without posing a problem for identification.

Secondly, we need to assume that $\{G_{i,jt}\}_{j \in N_{it}}$ is in the firm's information set $\mathscr{I}_{it-1}$ at the beginning of the period. This is consistent with a network that is fixed over time: $G_t = G \;\forall\; t = 1...T$ or any network formation processes that takes place at the beginning of every period before productivity is realized. For example, in the context of production networks, if all firms choose their suppliers at the beginning of each year, this condition would be met. The key here is the timing: firms make production decisions based on their realized productivities inclusive of spillovers. In addition, $\omega_{jt-1}, \boldsymbol{x}_{jt-1} \in \mathscr{I}_{it-1} \forall j \in N_{it}$. That is, firms can observe the past productivity and decisions of their neighbors. This likely holds true for buyer-supplier relationships in which buyers often do due diligence on future suppliers, and would need to be examined in other contexts such as geographic proximity, family networks, affiliate relationships, interlocking boards, and so on.

Third, I assume that correlations between the TFPs of connected firms are generated by spillovers rather than common shocks. I relax this assumption in the next section.

Finally, this procedure requires that G_t is exogenous, that is, network formation and productivity are not driven by factors that firms observe but we do not. This assumption can also be relaxed but will require the network formation process to be specified. I do so in section I.5.

I.4.2 Correlated Effects

Although network fixed effects alone do not bias the estimates of capital and labor elasticities, if endogenous or contextual spillovers are also present, failing to account for common shocks will lead to the mismeasurement of TFP. Therefore, given a productivity process with a component-year-specific fixed effect:

$$\omega_t = h(\omega_{t-1}, \boldsymbol{x}_{t-1}, G_t \boldsymbol{x}_{t-1}) + \lambda G_t \omega_t + c_{\psi_t} + \zeta_t \tag{I.29}$$

c_{ψ_t} can be eliminated by differencing using a matrix J_t such that $J_t)c_{\psi_t} = 0$. Bramoullé et al. (2009) suggest two ways to define J_t. The first is *within local differencing* by setting $J_t = I - G_t$. This subtracts the mean of a firm's neighbors' variables from the its own. An alternative would be *global differencing*, which subtracts not just the mean of a firm's neighbors, but all the firms in the component. That is, define J_t such that $H_{ij,t} = 1 - \frac{1}{n_{\psi_t}}$ if $i, j \in \psi_t$ and 1 otherwise.

Local differencing would suffice in an undirected network because if two firms are linked, then the link is reported in $G_{ij,t}$ and $G_{ji,t}$. However in directed networks, there may be some firms that are in the same sub-component and are therefore facing component-specific shocks but $\sum_{j\in N_{it}} G_{ij,t} = 0$, because the firm only has connections coming from one direction. For example, in a study of how customers affect the productivity of their suppliers, firm i may be a final goods producer whose productivity generates upstream spillovers but does not supply to any downstream firms. Yet it would be exposed to any shocks that affects the entire supply chain. If edges in G_t are classified as links from suppliers to customers, $G_{ij,t} = 0\,\forall j$ and $(I-G_t)c_{\psi_t} = c_{\psi_t}$. In this case, local differencing would not eliminate the correlated effect, but global differencing would.

When J_t is chosen appropriately, then transforming equation (I.29) yields:

$$J_t\omega_t = J_t h(\omega_{t-1}, \boldsymbol{x}_{t-1}, G_t\boldsymbol{x}_{t-1}) + \lambda J_t G_t \omega_t + J_t\zeta_t$$

with the corresponding reduced form:

$$J_t G_t \omega_t = \sum_{s=0}^{\infty} \lambda^s J_t G_t^s h(\omega_{t-1}, \boldsymbol{x}_{t-1}, G_t\boldsymbol{x}_{t-1}) + \sum_{s=0}^{\infty} \lambda^s J_t G_t^s \zeta_t$$

Note that differencing the productivity process will require that the production function be transformed as well. That is:

$$\begin{aligned} J_t y_t =& \alpha_k J_t k_t + \alpha_\ell J_t \ell_t + \sum_{s=0}^{\infty} \lambda^s J_t G_t^s h(\varphi_{t-1} - \alpha_k k_{t-1} - \alpha_\ell \ell_{t-1}, \boldsymbol{x}_{t-1}, G_t\boldsymbol{x}_{t-1}) \\ &+ \sum_{s=0}^{\infty} \lambda^s J_t G_t^s \zeta_t + J_t \varepsilon_t \end{aligned} \tag{I.30}$$

I.4.3 Estimation Procedure

I summarize my benchmark estimation procedure and outline modifications to deal with correlated effects. Estimation is a two-stage process. The first stage is the same as in Ackerberg et al. (2015). Estimate equation (I.6): $y_t = \alpha_k k_t + \alpha_\ell \ell_t + \mathbb{M}^{-1}(k_t, \ell_t, m_t) + \varepsilon_t$, using a polynomial approximation.[16] This yields estimates $\widehat{\varphi}_t = y_t - \widehat{\varepsilon}_t$.

In the second stage, estimate equation (I.28) by GMM with $k_t, \ell_t, \widehat{\varphi}_{t-1}, G_t\widehat{\varphi}_{t-1}$ as instruments. Alternatively, to reduce computational complexity, one can concentrate out the parameters in $h(\cdot)$ and proceed as follows. Start with guesses of the production function elasticities: $\alpha_k^*, \alpha_\ell^*$ and compute $\omega_t^* = \widehat{\varphi}_t - \alpha_k^* k_t - \alpha_\ell^* \ell_t$. Estimate the productivity process by 2SLS:

$$\omega_t^* = h(\omega_{t-1}^*, \boldsymbol{x}_{t-1}, G_t\boldsymbol{x}_{t-1}) + \lambda G_t \omega_t^* + u_t \tag{I.31}$$

with a polynomial approximation of $h(.)$ and $[G_t\omega_{t-1}, G_t^2\omega_{t-1}, G_t^2\boldsymbol{x}_{t-1}]$ as instruments for $G_t\omega_t$. Using predicted values, $E[\omega_t^*|\mathscr{I}_{t-1}]$ from the regression, compute the residual in the productivity process:

$$u_t^* = \omega_t^* - h^*(\omega_{t-1}^*, \boldsymbol{x}_{t-1}, G_t\boldsymbol{x}_{t-1}) - \lambda^* G_t \omega_t^*$$

Then solve for a new set of $(\alpha_k^*, \alpha_\ell^*)$ that satisfy the sample moment conditions:

$$E_{nt}[u_t^* \circ k_t, \ell_{t-1}] = 0 \tag{I.32}$$

Iterate through all steps of the second stage until the parameters converge to values $[\widehat{\alpha}_1, \widehat{\alpha}_k, \widehat{\alpha}_l]$. The corresponding

[16]Like ACF, this estimation procedure can be used with other value-added production function specifications such as the translog.

second stage parameters, $\widehat{\lambda}$ and the parameters in $\widehat{h}(\cdot)$ are consistent estimates of network effects. Standard errors can be obtained by residual-based or vertex bootstrapping. See section A.6 in the appendix for details on bootstrapping network data.

To account for correlated effects, estimate the first stage as in the benchmark procedure, and apply the J_t transformation to all variables in the second stage.

I.5 Network Endogeneity

So far, I have assumed that the network is exogenous, but it is also possible that a firm's productivity may be correlated with how it forms relationships. This issue is reminiscent of the selection problem in Olley and Pakes (1996) – firms are only observed if their productivity is above some threshold. In this case, observed interfirm relationships may depend on TFP. To address this issue, I incorporate the network selection model in Arduini et al. (2015) and Qu et al. (2017) into the benchmark estimation procedure above.

I.5.1 Network Selection Model

Endogenous network formation as modeled by Qu et al. (2017) and Arduini et al. (2015) highlights a possible link between a firm's TFP and the nature of its network. Shocks to productivity are correlated with the chances of meeting potential partners. For example, firms that are better able to search for buyers or suppliers may also be more productive. In this case, a positive relationship between a firm's TFP and its networks' TFP or choices would be a result of the improved search rather than any spillovers.[17]

At the beginning of each period, firms i and j consider the surplus of a link $V_i(A_{ij,t})$. Both firms want to form a link if $V_i(A_{ij,t}=1)-V_i(A_{ij,t}=0)>0$.[18] I parametrize this difference in surplus as:

$$V_i(A_{ij,t}=1)-V_i(A_{ij,t}=0)=U_{ijt}(\gamma)+\xi_{ijt}$$

where ξ_{ijt} is i.i.d and follows a logistic distribution.

$$U_{ijt}(\gamma)=\gamma_1+z_{it}\boldsymbol{\gamma}_i+z_{jt}\boldsymbol{\gamma}_j+z_{ijt}\boldsymbol{\gamma}_{ij}+\gamma_h H_{ijt} \tag{I.33}$$

Note that despite the slight abuse of notation, $\boldsymbol{\gamma}_i,\boldsymbol{\gamma}_j,\boldsymbol{\gamma}_{ij}$ are not random coefficients. They are parameters whose subscripts denote that they correspond to i, j or the dyad's characteristics.

$\boldsymbol{z}_{it}$ may include ω_{it-1},x_{it-1} and other variables such as industry that influence a firm's relationship decision but may have no direct impact on productivity. $\boldsymbol{z}_{ijt}$ usually includes the distance between i and j's characteristics: $|\boldsymbol{z}_{it}-\boldsymbol{z}_{jt}|$ or some other dyad-specific measures, such as the physical distance between the firms, industry input-output shares, etc. A negative coefficient on $|\boldsymbol{z}_{it}-\boldsymbol{z}_{jt}|$ indicates that firm i wants to match with firms that are similar. H_{ijt} measures past linkages; a large and positive γ_h indicates that firm i prefers to stick with its previous partners. Past linkages can be specified broadly; for instance, $H_{ijt}=A_{ij,t-1}$ would mean that firm i only considers linkages from the previous period,

[17] Other studies such as Goldsmith-Pinkham and Imbens (2013) and Hsieh and Lee (2016) model network endogeneity as a correlation between unobserved variables in the network selection model and the error term of the outcome equation. The interpretation differs; in this setting selection would be driven by unobserved synergies such as common business philosophies. If these factors are also correlated with productivity, then estimated spillovers would capture the effect of assortativity in these unobserved characteristics (see Serpa and Krishnan (2018)) for an application to productivity spillovers. I choose the Arduini et al. (2015) model for two reasons. First, it allows me to explicitly highlight the dual role that productivity may play in search and interfirm spillovers. Secondly, the reduction of the problem to a selection correction term preserves the usual structure of the estimator, while the Goldsmith-Pinkham and Imbens (2013) and Hsieh and Lee (2016) relies on Bayesian estimation of a full likelihood model.

[18] This model can apply to both directed and undirected networks. For example, in a buyer-supply network, the the surplus from i supplying j would be considered differently from the reverse direction.

while $H_{ijt} = \mathbb{1}\left(\sum_{s=1}^{m} A_{ij,t-s} > 0,\ m \leq t\right)$ measures whether i and j were connected in any of the last m periods.[19]

The probability that a link $A_{ij,t}$ forms is given by:

$$P(A_{ij,t} = 1 \mid \mathscr{I}_{t-1}) = P(U_{ijt}(\gamma) + \xi_{ijt} > 0) = \frac{e^{U_{ijt}(\gamma)}}{1 + e^{U_{ijt}(\gamma)}}$$

The specified model, coupled with a logistic distribution implies that, conditional on firm and dyad characteristics, historical connectivity, and the unobserved ξ_t, the probability that i wants to form a link with j is independent of its decision to connect with some other firm k. While this may be restrictive, it is analytically and computationally tractable, and still manages to capture important features of real-world networks.

For example, this model allows for the possibility that a firm can choose multiple partners; i need not prefer j to all other firms, it just needs to prefer matching with j to not matching. This is useful for characterizing production networks, in which a non-negligible number of firms trade with more than one partner. As in Goldsmith-Pinkham and Imbens (2013), this model can also accommodate some interdependence in the linking decision through the choice of variables such as the number of links in the previous period, whether the firms had neighbors in common etc.

Network endogeneity arises from the relationship between ξ_{ijt} and the error term in the productivity process, ζ_{it}. Let $\xi_{it}' = \{\xi_{ijt}\}_{j \neq i}^{n_t}$ be a row vector of the error terms from all the dyadic regressions with links originating from i. $(\zeta_{it}, \xi_{it}') \sim i.i.d.(0, \Sigma_{\zeta\xi})$ where $\Sigma_{\zeta\xi} = \begin{pmatrix} \sigma_\zeta^2 & \sigma_{\zeta\xi}' \\ \sigma_{\zeta\xi} & \Sigma_\xi \end{pmatrix}$ is positive definite, σ_ζ^2 is a scalar, $\sigma_{\zeta\xi}$ is an $n_t - 1$ column vector of covariances, and $\Sigma_\xi = \sigma_\xi^2 I_{n_t-1}$. Stacking all the ξ_{it}'s in a matrix:

$$\Xi_t = \begin{bmatrix} \xi_{1t}' \\ \vdots \\ \xi_{n_t t}' \end{bmatrix}$$

then the error term in the productivity process can be written as:

$$\zeta_{it} = \Xi_t \boldsymbol{\delta} + \nu_t$$

where $\boldsymbol{\delta} = \Sigma_\xi^{-1} \sigma_{\zeta\xi}$, ν_t is independent of ξ_{it} and $\sigma_\nu^2 = \sigma_\zeta^2 - \sigma_{\zeta\xi}' \Sigma_\xi^{-1} \sigma_{\zeta\xi}$. Therefore, the productivity process becomes:

$$\omega_t = h(\omega_{t-1}, \boldsymbol{x}_{t-1}, G_t \boldsymbol{x}_{t-1}) + \lambda G_t \omega_t + \Xi_t \boldsymbol{\delta} + \nu_t \tag{I.34}$$

G_t is endogenous when $\sigma_{\zeta\xi} \neq 0$ and the selectivity bias is equal to $\Xi_t \boldsymbol{\delta}$.

I.5.2 Accounting for Selection

To the estimate model, assume ζ_{it} is normally distributed. Then Arduini et al. (2015) shows that the selectivity bias can be controlled for using a Heckman-type mills ratio:

$$\begin{aligned} \mu_{it} &= \sum_{j \neq i}^{N_t} g_{ij,t} \frac{\phi(\Phi^{-1}(p))}{\Phi(\Phi^{-1}(p))} + (1 - g_{ij,t}) \frac{\phi(\Phi^{-1}(p))}{1 - \Phi(\Phi^{-1}(p))} \\ &= \sum_{j \neq i}^{N_t} g_{ij,t} \frac{\phi(\Phi^{-1}(p))}{p} + (1 - g_{ij,t}) \frac{\phi(\Phi^{-1}(p))}{1 - p} \end{aligned} \tag{I.35}$$

[19] There are alternative models such as Graham (2017) that include firm-year fixed effects in the dyadic regression model. Estimation of such models will depend on the sparsity of the network.

where $p = P(A_{ij,t} = 1 \mid \mathscr{I}_{t-1})$, and ϕ and Φ are the probability and cumulative density functions for a standard normal variable. The i.i.d assumption on ξ_{ijt}'s dispenses with the need to estimate all $N_t - 1$ parameters in $\boldsymbol{\delta}$. Instead, due to the summation above, one only has to estimate a single parameter $\delta = \frac{\sigma_{\zeta\xi}}{\sigma_\xi^2}$.

I.5.3 Estimation Procedure

Incorporating the selection model is similar to the Olley and Pakes (1996) correction for attrition. The first stage of my benchmark procedure is unchanged with the estimation of $\widehat{\varphi}_{it}$ and $\widehat{\varepsilon}_{it}$ using the proxy variable. In the second stage, starting with the initial guesses of the labor and capital coefficients $(\alpha_k^*, \alpha_\ell^*)$, compute $\omega_{it-1}^* = \widehat{\varphi}_{it-1} - \alpha_k^* k_{it-1} - \alpha_\ell^* \ell_{it-1}$.

Using ω_{it-1}^* and other variables that could determine the observed links between firms, estimate the selection model in equation (I.33) to obtain γ^*. Next, compute the predicted probabilities $p^* = \frac{e^{U_{ijt}(\gamma^*)}}{1+e^{U_{ijt}(\gamma^*)}}$ and the selection correction term $\mu_{it}^* = \sum_{j\neq i}^{N_t} g_{ij,t} \frac{\phi(\Phi^{-1}(p^*))}{p^*} + (1-g_{ij,t})\frac{\phi(\Phi^{-1}(p^*))}{1-p^*}$. Include this correction term as one of the explanatory variables in the productivity process equation:

$$\omega_t^* = \sum_{s=0}^{\infty} \lambda^s G_t^s h(\omega_{t-1}^*, \boldsymbol{x}_{t-1}, G_t \boldsymbol{x}_{t-1}) + \delta \sum_{s=0}^{\infty} \lambda^s G_t^s \mu_{it}^* + u_t \tag{I.36}$$

The resulting residuals are now purged of the omitted variable bias arising from network selection and can be used to construct the sample moments in (I.31) for identification of the elasticities.[20]

I.6 Monte Carlo Experiments

I conduct three sets of experiments to assess the performance of the standard ACF estimator and my modified procedure when various types of network effects are present. In the first set of experiments, I examine how each type of network effect individually affects the bias and efficiency of capital and labor elasticity estimates obtained using the ACF procedure. Next, I demonstrate how my modified procedure performs when endogenous, contextual and correlated effects are cumulatively present and consider the sensitivity of the estimates from my benchmark procedure to misspecification. Finally, I compare the performance of ACF and my benchmark procedure as the size of the endogenous effect, the persistence of productivity and the density of the network vary.

For all three experiments, I draw a balanced sample of 1000 firms over 10 years. I use a Cobb-Douglas production function in logs:

$$y_{it} = \alpha_\ell \ell_{it} + \alpha_k k_{it} + \omega_{it} + \varepsilon_{it}$$

where $\varepsilon_{it} \sim \mathscr{N}(0, \sigma_\varepsilon^2)$. I set $\alpha_\ell = 0.6, \alpha_k = 0.4$ and $\sigma_\varepsilon^2 = 1$.[21] The productivity process varies depending on the experiment. To avoid the impact of arbitrary initial values, I simulate 20 periods and discard the first 10.

To induce variation in cluster (component) size and the length of supply chains, I split the firms into four industries with 400, 300, 200, and 100 firms in the first, second, third and fourth industries respectively and construct an inter-industry trade structure as follows: Industry 1 sells 17, 33 and 44 percent of its output to industries 2, 3 and 4 respectively. 2 sells to 50 percent each to 3 and 4, while industry 3 sells all its output to 4. The fourth industry sells

[20] In principle, the selection model would be re-estimated for each value of ω_{it-1}^* as the values $(\alpha_k^*, \alpha_\ell^*)$ are updated in each iteration. However, this significantly increases the computational cost of the procedure. As long as the initial guesses of the elasticities, such as those obtained from an OLS regression, are reasonably close to their true values measurement error in the lagged TFP variable should not have an outsized effect on the estimates of the selection correction term. In my Monte Carlo simulations, results were quite similar when selection was estimated only once and when it was re-estimated in each iteration.

[21] See section A.2 for further details on the Monte Carlo setup.

nothing to other firms. This structure is fixed over time, and does not represent the actual network but is a measure of industry compatibility that I use to generate both exogenous and endogenous networks as described below.[22]

I.6.1 Experiment 1: Bias in Standard ACF estimates due to Network Effects

I simulate five data generating processes (DGPs) to demonstrate the bias in standard ACF estimates of the input elasticities from each type network effect—endogenous, contextual and correlated—and network endogeneity separately.

The productivity process is:

$$\omega_t = \beta_1 \iota + \rho \omega_{t-1} + \beta_x x_t + \lambda G_t \omega_t + \beta_{\bar{x}} G_t x_t + c_{\psi_t} + \zeta_t \tag{I.37}$$

where $\zeta_{it} \sim \mathcal{N}(0, \sigma_\zeta^2)$. To induce a non-linear relationship between x and capital, I generate it according to $x = 0.5\ln(\sqrt{K}_{t-1}) + \widetilde{x}$, where $\widetilde{x} \sim \mathcal{N}(-2, \sigma_{\widetilde{x}}^2)$. Since it depends on K_{t-1}, it is not correlated with ζ_t. I set $\beta_1 = 0.5, \rho = 0.6, \beta_x = 0.4, \sigma_\zeta^2 = 1.25$, and $\sigma_{\widetilde{x}}^2 = 5$.

For DGPs 1 to 4, I generate an exogenous directed network in each period by randomly assigning links with probability $P(A_{ijt} = 1) = \frac{indshare_{ij}}{indsize_j}$ where $indshare_{ij}$ is the compatibility of i and j's industries obtained from the industry compatibility matrix described above, while $indsize_j$ is the number of firms in j's industry. DGP 1 has no network effects ($\lambda = 0, \beta_{\bar{x}} = 0, c_{\psi_t} = 0$) and exogenous network formation, and ACF estimates should be consistent. DGP 2 features only the endogenous effect ($\lambda = 0.3, \beta_{\bar{x}} = 0, c_{\psi_t} = 0$) while DGP 3 features only the contextual effect ($\lambda = 0, \beta_{\bar{x}} = 0.3, c_{\psi_t} = 0$). In DGP 4, I draw component fixed effects in each period from a normal distribution with a mean of 1 and a standard deviation of 1 ($\lambda = 0, \beta_{\bar{x}} = 0, c_{\psi_t} \mathcal{N}(1,1)$). For DGP 5, I start with an exogenous network in the first period, then simulate future networks using the model in section I.5 with the coefficient of the selection term $\delta = \frac{\sigma_{\zeta\xi}}{\sigma_\xi^2} = 0.003$, while there are no other network effects ($\lambda = 0, \beta_{\bar{x}} = 0, c_{\psi_t} = 0$).

I estimate the production function using standard ACF with a second-degree polynomial approximation in the first and second stages. The results are shown in table I.3. The largest bias comes from the presence of an endogenous effect. It leads to a capital coefficient estimate that is almost 25% higher than the true value. In comparison, a contextual effect of the same size has a negligible impact on the capital coefficient. As expected, correlated effects reduce precision but do not have a sizable impact on bias. In the absence of any other network effects, endogenous network formation has no impact on bias or efficiency of the estimated input elasticities. Therefore, of all the network effects, ignoring endogenous spillovers introduces the greatest bias in the production function elasticities.

[22] I have set up data-generating processes for my Monte Carlo experiments to be as simple as possible while allowing for network effects. However, it is worth noting that these DGPs do not reflect important features of firm-level empirical data, particularly fat-tailed productivity and network degree distributions. Exploring how these features would affect bias and precision on my estimator is left for future work.

Table I.3: Bias due to Network Effects with Standard ACF Procedure

DGP		α_ℓ	α_k
	True values	0.6	0.4
No network effects	Mean	0.599	0.4
	Std. Dev.	(0.025)	(0.061)
Endogenous Effect ($\lambda = 0.3$)	Mean	0.596	0.495
	Std. Dev.	(0.032)	(0.066)
Contextual Effect ($\beta_{\bar{x}} = 0.3$)	Mean	0.598	0.414
	Std. Dev.	(0.04)	(0.063)
Correlated Effect ($c_{\psi_t} \sim \mathscr{N}(1,1)$)	Mean	0.58	0.38
	Std. Dev.	(0.171)	(0.271)
Endogenous Network $\left(\frac{\sigma_{\zeta\xi}}{\sigma_\xi^2} = 0.003\right)$	Mean	0.6	0.391
	Std. Dev.	(0.014)	(0.082)

Based on 1000 replications.This table reports production function elasticites obtained using the procedure in Ackerberg et al. (2015). Each row includes a separate network effect in the law of motion on productivity.

I.6.2 Experiment 2: Comparison of Estimates from Standard and Modified ACF Procedures

Next, I compare the performance my estimator against standard ACF in table I.4 using four DGPs. The Monte Carlo setup is essentially the same as in experiment 1 above. However, I introduce network effects cumulatively rather than individually. DGP 1 favors the ACF procedure with no network effects and exogenous network formation, while DGP 2 introduces both endogenous and contextual network effects. DGP 3 is similar to the second DGP but with the addition of correlated effects, while DGP 4 has all the previous network effects with endogenous network formation.

I consider 4 estimators. The first is a standard ACF that assumes no network effects. Using the TFP measure obtained from ACF, I estimate network effects with the generalized 2SLS procedure described in section I.4.3. This is the approach typically used in empirical studies of productivity spillovers. ACF-N is my modified procedure that jointly estimates productivity and network effects. ACF-ND uses global differencing to eliminate correlated effects, and ACF-NDS accounts for selection using the network formation model in section I.5.3. All estimators use a second-degree polynomial in capital, labor and materials in the first stage, and a linear productivity process in the second.

Under DGP 1, all estimators perform well when estimating both the production function and the productivity process. Furthermore, precision is not diminished. It is important to note that allowing for spillovers under the modified procedure does not introduce spurious network effects. With the combined impact of endogenous and contextual effects in DGP 2, ACF significantly overestimates the capital coefficient but still gives reasonable estimates of network effects in the productivity process, although the endogenous effect is slightly overestimated. All three modified procedures yield estimates of the input elasticities that are close to the truth but slightly underestimate λ.

When there are network fixed effects, my benchmark procedure, ACF-N overestimates the labor coefficient and underestimates capital elasticity, the persistence parameter, and the endogenous effect. In these respects, ACF performs better because when correlated effects are unaccounted for, all network terms containing G_t introduce bias because they are correlated with the error term. Differencing improves both consistency and precision, with standard deviations up to 60 times smaller than under ACF and ACF-N. Bias due to endogenous network formation is negligible, presumably

Table I.4: Comparison of Estimates from Standard ACF and Modified ACF Procedures

DGP	Estimator		Elasticities		Productivity Process Coefficients				
			α_ℓ	α_k	ρ	β_x	$\beta_{\bar{x}}$	λ	$\frac{\sigma_{\zeta\xi}}{\sigma_\xi^2}$
DGP 1		True values	0.6	0.4	0.6	0.4	0.0	0.0	0.0
	ACF	Mean	0.599	0.4	0.6	0.401	0.	-0.001	
		Std. Dev.	(0.025)	(0.061)	(0.015)	(0.026)	(0.009)	(0.01)	
	ACF-N	Mean	0.602	0.392	0.601	0.398	0.	-0.001	
		Std. Dev.	(0.018)	(0.061)	(0.016)	(0.019)	(0.009)	(0.01)	
	ACF-ND	Mean	0.603	0.389	0.601	0.397	-0.	-0.	
		Std. Dev.	(0.024)	(0.064)	(0.016)	(0.024)	(0.01)	(0.011)	
	ACF-NDS	Mean	0.603	0.39	0.601	0.397	-0.	0.	-0.
		Std. Dev.	(0.024)	(0.064)	(0.016)	(0.025)	(0.01)	(0.012)	(0.002)
DGP 2		True values	0.6	0.4	0.6	0.4	0.1	0.3	0.0
	ACF	Mean	0.595	0.516	0.556	0.402	0.092	0.332	
		Std. Dev.	(0.035)	(0.07)	(0.017)	(0.035)	(0.016)	(0.042)	
	ACF-N	Mean	0.601	0.401	0.596	0.399	0.121	0.242	
		Std. Dev.	(0.018)	(0.046)	(0.016)	(0.018)	(0.013)	(0.026)	
	ACF-ND	Mean	0.602	0.398	0.595	0.397	0.118	0.249	
		Std. Dev.	(0.028)	(0.055)	(0.016)	(0.028)	(0.014)	(0.026)	
	ACF-NDS	Mean	0.602	0.396	0.596	0.397	0.115	0.257	-0.004
		Std. Dev.	(0.027)	(0.055)	(0.016)	(0.028)	(0.014)	(0.026)	(0.002)
DGP 3		True values	0.6	0.4	0.6	0.4	0.1	0.3	0.0
	ACF	Mean	0.616	0.496	0.479	0.362	0.121	0.357	
		Std. Dev.	(0.169)	(0.417)	(0.171)	(0.161)	(0.102)	(0.496)	
	ACF-N	Mean	0.741	0.162	0.514	0.257	0.082	0.222	
		Std. Dev.	(0.154)	(0.215)	(0.269)	(0.154)	(0.072)	(0.62)	
	ACF-ND	Mean	0.614	0.368	0.605	0.385	0.109	0.266	
		Std. Dev.	(0.032)	(0.052)	(0.017)	(0.032)	(0.012)	(0.018)	
	ACF-NDS	Mean	0.614	0.368	0.605	0.385	0.108	0.269	-0.002
		Std. Dev.	(0.032)	(0.052)	(0.018)	(0.032)	(0.012)	(0.018)	(0.002)
DGP 4		True values	0.6	0.4	0.6	0.4	0.1	0.3	0.003
	ACF	Mean	0.607	0.35	0.603	0.374	0.128	0.255	
		Std. Dev.	(0.138)	(0.239)	(0.147)	(0.166)	(0.109)	(0.122)	
	ACF-N	Mean	0.705	0.183	0.637	0.291	0.067	0.236	
		Std. Dev.	(0.137)	(0.213)	(0.184)	(0.142)	(0.056)	(0.2)	
	ACF-ND	Mean	0.619	0.368	0.61	0.383	0.091	0.281	
		Std. Dev.	(0.073)	(0.116)	(0.056)	(0.07)	(0.023)	(0.037)	
	ACF-NDS	Mean	0.621	0.362	0.612	0.38	0.09	0.28	0.001
		Std. Dev.	(0.078)	(0.129)	(0.064)	(0.076)	(0.026)	(0.037)	(0.002)

Based on 1000 replications. Estimators are based on Ackerberg et al. (2015) with ACF denoting the standard procedure, while N, D, and S indicate modifications to account for network effects, network differencing, and network selection respectively. Data generating processes are outlined above (see appendix A.2 for details). DGP1 has no network effects, DGP2 has correlated and endogenous effects, DGP3 includes correlated, endogenous and network fixed effects, while DGP4 features all 3 network effects and an endogenous network formation process.

because the coefficient $\frac{\sigma_{\zeta\xi}}{\sigma_{\xi}^2}$ on the omitted variable, is small. Other than reduced precision when compared with ACF-ND, estimates of the productivity process and input elasticities are not different from when selection is accounted for with ACF-NDS.

I.6.3 Experiment 3: Effect of Network Density on Bias and Precision

Since the first experiment shows that most important source of bias is the endogenous effect, I further explore how precision and consistency vary with network density in the presence of an endogenous spillover. I employ a quadratic AR1 process for productivity:

$$\omega_t = \beta_1 + \rho_1 \omega_{t-1} + \rho_2 \omega_{t-1}^2 + \lambda G_t \omega_t + \zeta_t \tag{I.38}$$

where $\zeta_{it} \sim \mathcal{N}(0, \sigma_\zeta^2)$. I set $\beta_1 = 0.5, \rho_2 = -0.01$, and $\sigma_\zeta^2 = 5$. The quadratic term is necessary to explore high values of λ and ρ_1. If productivity is persistent and the endogenous spillover is also large, then simulated values of productivity grow quite large for some firms, and the resulting investment series soon tends to infinity for highly productive firms.[23]. The quadratic term serves as a dampener to control the size ω_t in the simulation.[24] Additionally, it allows for the comparison of ACF and my modified procedure when the productivity is process not linear.

To vary network density, I draw random exogenous networks using Erdős and Rényi (1960) graphs, also known as binomial graphs. Firms are edges are formed $A_{ijt} \overset{i.i.d.}{\sim} \text{Bern}(p)$ and the density of the graph is equal to the probability of an link forming between two firms, p. This class of graphs has several features worth noting. First, intransitivity rises as the density falls. This is an advantage because intransitivity helps with identification of the endogenous network effect, so we can expect more precise estimates as the network gets more sparse. Secondly, when $p > \frac{1}{N_t}$, a giant component emerges that contains more vertices than any other component of the network. In my Monte Carlo experiments, this means that for graphs with density > 0.001 the infinite series of terms G_t^s will go to zero much more slowly than with density ≤ 0.001. Therefore, one would expect the potential bias to be greater as density increases, particularly once it crosses the 0.001 threshold. However, it is worth noting that the resulting degree distribution is binomial $B(N_t - 1, p)$, which is approximately normal whereas buyer-supplier networks have empirically been found to follow a Pareto (power-law) degree distribution (Bernard and Moxnes, 2018).

Table I.5 shows the results of varying network density. ACF estimates of the capital elasticity appear unbiased for densities ≤ 0.001 and increases to over 50% of the true value for densities above 0.001. Estimates of λ increase with density while ρ_1 moves in the opposite direction. In comparison, my benchmark procedure ACF-N provides stable and consistent estimates of both the elasticities and productivity process at most densities. When the network is very sparse, however, my procedure underestimates λ and does so with less precision because the instrument $G_t^2 \omega_{t-1}$ is weaker when there are fewer triads in the network.

In section A.3 in the appendix, I also examine how my approach performs as the persistence of productivity and the size of the endogenous network effect vary. Unsurprisingly, my procedure yields more consistent and precise estimates as productivity gets more persistent, increasing the relevance of $G_t \omega_{t-1}$ as an instrument, and as the endogenous spillover gets larger, raising the relevance of the $G_t^2 \omega_{t-1}$ instrument. Importantly, even when $\lambda = 0$, my procedure still yields consistent estimates as long as ρ is sufficiently large.

[23]See details on optimal investment in section A.2.5 in the appendix

[24]It is also worth mentioning that in empirical applications, estimating flexible forms of the productivity process may be necessary. Otherwise, linearity of the Markov process may force estimates of λ to be small or negative.

Table I.5: Effect of Sparsity on Bias and Precision (Quadratic AR1)

Density	Estimator	Elasticities		Productivity Process Coefficients			
		α_ℓ	α_k	β_1	ρ_1	ρ_2	λ
		0.6	0.4	0.5	0.8	-0.01	0.3
0.0001	ACF	0.603	0.358	-0.125	0.809	-0.01	0.087
		(0.024)	(0.239)	(2.369)	(0.216)	(0.003)	(0.106)
	ACF-N	0.617	0.413	-0.23	0.76	-0.01	0.226
		(0.057)	(0.165)	(2.845)	(0.196)	(0.022)	(0.109)
0.0003	ACF	0.604	0.359	0.122	0.81	-0.01	0.113
		(0.024)	(0.216)	(1.975)	(0.19)	(0.003)	(0.12)
	ACF-N	0.632	0.381	0.379	0.764	-0.011	0.241
		(0.093)	(0.113)	(1.456)	(0.195)	(0.038)	(0.238)
0.0005	ACF	0.605	0.377	0.209	0.798	-0.01	0.132
		(0.024)	(0.195)	(1.691)	(0.169)	(0.003)	(0.126)
	ACF-N	0.641	0.371	0.412	0.753	-0.009	0.25
		(0.106)	(0.113)	(1.226)	(0.217)	(0.034)	(0.097)
0.0007	ACF	0.606	0.387	0.271	0.791	-0.01	0.159
		(0.027)	(0.182)	(1.509)	(0.158)	(0.003)	(0.137)
	ACF-N	0.646	0.362	0.51	0.745	-0.007	0.243
		(0.116)	(0.116)	(0.506)	(0.237)	(0.046)	(0.1)
0.0009	ACF	0.606	0.411	0.266	0.771	-0.01	0.18
		(0.03)	(0.168)	(1.359)	(0.147)	(0.004)	(0.145)
	ACF-N	0.635	0.371	0.532	0.767	-0.011	0.252
		(0.101)	(0.098)	(0.308)	(0.2)	(0.037)	(0.085)
0.001	ACF	0.606	0.423	0.243	0.761	-0.01	0.196
		(0.032)	(0.161)	(1.295)	(0.147)	(0.007)	(0.152)
	ACF-N	0.63	0.377	0.539	0.778	-0.009	0.225
		(0.09)	(0.088)	(0.305)	(0.203)	(0.031)	(1.04)
0.003	ACF	0.602	0.617	-0.343	0.523	-0.017	0.261
		(0.053)	(0.114)	(1.261)	(0.137)	(0.011)	(0.184)
	ACF-N	0.611	0.389	0.585	0.815	-0.01	0.283
		(0.038)	(0.049)	(0.256)	(0.06)	(0.009)	(0.035)
0.005	ACF	0.605	0.637	-0.109	0.462	-0.019	0.312
		(0.067)	(0.138)	(0.987)	(0.161)	(0.017)	(0.201)
	ACF-N	0.608	0.388	0.509	0.818	-0.01	0.291
		(0.03)	(0.057)	(0.298)	(0.05)	(0.007)	(0.042)
0.007	ACF	0.606	0.639	-0.405	0.47	-0.026	0.545
		(0.073)	(0.149)	(13.879)	(0.694)	(0.207)	(6.696)
	ACF-N	0.607	0.385	0.437	0.818	-0.01	0.294
		(0.027)	(0.068)	(0.339)	(0.053)	(0.002)	(0.027)
0.009	ACF	0.606	0.638	0.132	0.448	-0.018	0.339
		(0.073)	(0.154)	(2.354)	(0.217)	(0.05)	(1.188)
	ACF-N	0.606	0.386	0.405	0.815	-0.01	0.302
		(0.03)	(0.077)	(0.393)	(0.06)	(0.005)	(0.175)
0.01	ACF	0.606	0.639	0.011	0.452	-0.019	0.388
		(0.072)	(0.153)	(1.8)	(0.2)	(0.046)	(0.925)
	ACF-N	0.606	0.386	0.404	0.815	-0.01	0.301
		(0.031)	(0.078)	(0.404)	(0.061)	(0.005)	(0.14)
0.03	ACF	0.605	0.644	-0.23	0.478	-0.011	0.317
		(0.069)	(0.149)	(5.307)	(1.216)	(0.238)	(2.909)
	ACF-N	0.605	0.387	0.417	0.813	-0.01	0.298
		(0.032)	(0.083)	(0.398)	(0.064)	(0.004)	(0.061)
0.05	ACF	0.606	0.643	0.054	0.414	-0.024	0.446
		(0.072)	(0.152)	(3.357)	(0.782)	(0.151)	(1.833)
	ACF-N	0.605	0.388	0.417	0.813	-0.01	0.299
		(0.032)	(0.084)	(0.399)	(0.065)	(0.004)	(0.062)
0.07	ACF	0.606	0.643	0.005	0.423	-0.022	0.419
		(0.073)	(0.154)	(1.994)	(0.457)	(0.085)	(1.053)
	ACF-N	0.604	0.388	0.42	0.813	-0.01	0.297
		(0.03)	(0.084)	(0.4)	(0.064)	(0.003)	(0.049)
0.09	ACF	0.606	0.643	0.001	0.426	-0.021	0.413
		(0.071)	(0.154)	(1.774)	(0.406)	(0.074)	(0.928)
	ACF-N	0.604	0.388	0.42	0.813	-0.01	0.297
		(0.03)	(0.084)	(0.401)	(0.063)	(0.003)	(0.049)
0.1	ACF	0.606	0.642	-0.003	0.425	-0.021	0.417
		(0.073)	(0.157)	(1.812)	(0.417)	(0.077)	(0.952)
	ACF-N	0.604	0.388	0.42	0.814	-0.01	0.296
		(0.028)	(0.083)	(0.403)	(0.061)	(0.003)	(0.032)
0.3	ACF	0.605	0.644	-0.048	0.437	-0.019	0.388
		(0.07)	(0.15)	(1.033)	(0.184)	(0.025)	(0.454)
	ACF-N	0.603	0.389	0.422	0.813	-0.01	0.296
		(0.027)	(0.084)	(0.409)	(0.062)	(0.003)	(0.032)
0.5	ACF	0.606	0.644	-0.054	0.435	-0.019	0.392
		(0.072)	(0.153)	(1.048)	(0.189)	(0.027)	(0.468)
	ACF-N	0.604	0.389	0.421	0.813	-0.01	0.296
		(0.027)	(0.083)	(0.412)	(0.062)	(0.003)	(0.032)
0.7	ACF	0.607	0.643	-0.025	0.427	-0.021	0.416
		(0.074)	(0.156)	(1.63)	(0.365)	(0.066)	(0.827)
	ACF-N	0.604	0.388	0.42	0.814	-0.01	0.296
		(0.027)	(0.084)	(0.413)	(0.062)	(0.003)	(0.032)
0.9	ACF	0.607	0.642	-0.054	0.435	-0.019	0.392
		(0.074)	(0.156)	(1.063)	(0.189)	(0.027)	(0.478)
	ACF-N	0.604	0.388	0.422	0.813	-0.01	0.297
		(0.029)	(0.085)	(0.414)	(0.063)	(0.004)	(0.052)

Based on 1000 replications. Estimators are based on Ackerberg et al. (2015) with ACF denoting the standard procedure and ACF-N indicating the modified procedure to account for network effects. Networks are exogenous erdos-renyi (binomial) graphs with densities as shown. The data-generating process for productivity is quadratic AR1 with endogenous network effects. True values of the parameters are at the top of the table. Standard deviations are in parentheses.

I.7 Extensions

I.7.1 Gross Production Functions

So far, I have only considered a structural value-added production function, which often requires the assumption that the production function is Leontief with respect to intermediate inputs. In this section I consider a framework exploiting first order conditions on intermediate input choices as in Gandhi et al. (2020, GNR hereafter). Under similar assumptions as in the proxy variable approach above, the standard GNR procedure can be modified to jointly estimate network effects and productivity.

Like ACF, the GNR methodology assumes that TFP enters the production function in a Hicks-neutral fashion. However, intermediate inputs now enter directly into the production function:

$$\begin{aligned} Y_t &= F(L_t, K_t, M_t)e^{\omega_t+\varepsilon_t} \\ \iff y_t &= f(\ell_t, k_t, m_t) + \omega_t + \varepsilon_t \end{aligned} \tag{I.39}$$

For simplicity, assume that materials are flexible while both labor and capital have dynamic implications.

The procedure consists of two stages. The first stage exploits first order conditions from profit maximization to estimate the elasticity of intermediate inputs with respect to output. Given the production technology above, the firm chooses materials to maximize profits:

$$\max_{M_t} P_t E[F(L_t, K_t, M_t)e^{\omega_t+\varepsilon_t}] - P_t^M M_t \tag{I.40}$$

where P_t and P_t^M are the prices of output and materials respectively. The static first order condition with respect to materials is:

$$P_t \frac{\partial}{\partial M_t} F(L_t, K_t, M_t)e^{\omega_t}\mathscr{E} = P_t^M \tag{I.41}$$

where $\mathscr{E} \equiv E[e^{\varepsilon_t} \mid \mathscr{I}_t] = E[e^{\varepsilon_t}]$ which relies on the assumption that the error terms are unconditionally independent.[25]

It is also pertinent to note that this first order condition makes an implicit assumption about market structure: that the firm is a price-taker in both input and output markets. Therefore, this framework cannot directly examine impacts of or effects on market power. I retain this assumption in my modified procedure.

$$\begin{aligned} &\frac{\partial}{\partial M_t} F(L_t, K_t, M_t)e^{\omega_t}\mathscr{E} = \frac{P_t^M}{P_t} \\ &\frac{M_t}{Y_t}\frac{\partial}{\partial M_t} F(L_t, K_t, M_t)e^{\omega_t}\mathscr{E} = \frac{P_t^M M_t}{P_t Y_t} \\ &\ln\left(\frac{\partial}{\partial m_t} f(\ell_t, k_t, m_t)\right) - \varepsilon_t + \ln(\mathscr{E}) = s_t \end{aligned} \tag{I.42}$$

where $s_t \equiv \ln(\frac{P_t^M M_t}{P_t Y_t})$ is the log of the intermediate input expenditure share of revenue.

$$E[\varepsilon_t \mid \mathscr{I}_t] = 0 \implies E[s_t \mid \mathscr{I}_t] = \ln\left(\frac{\partial}{\partial m_t} f(\ell_t, k_t, m_t)\right) + \ln(\mathscr{E}) \tag{I.43}$$

Let $D^{\mathscr{E}}(\ell_t, k_t, m_t) \equiv \frac{\partial}{\partial m_t} f(\ell_t, k_t, m_t) \times \mathscr{E}$. Then given the moment of ε_t in (I.43) above, $\ln D^{\mathscr{E}}(\ell_t, k_t, m_t)$ can be estimated by non-linear least squares regression of the materials expenditure share on the log of a polynomial in labor,

[25] See Gandhi et al. (2020) for details on estimation under a relaxed conditional independence assumption.

capital and materials. Furthermore:

$$\begin{aligned} \varepsilon_t = \ln D^{\mathscr{E}}(\ell_t, k_t, m_t) - s_t \implies e^{\varepsilon_t} &= D^{\mathscr{E}}(\ell_t, k_t, m_t) e^{-s_t} \\ \mathscr{E} = &E[e^{\varepsilon_t}] = E[D^{\mathscr{E}}(\ell_t, k_t, m_t) e^{-s_t}] \end{aligned} \tag{I.44}$$

Using the estimates of $D^{\mathscr{E}}$ from the share regression, we can replace the moment in (I.44) with its empirical equivalent and compute the constant $\mathscr{E}$. This enables us obtain an estimate of the materials elasticity:

$$D(\ell_t, k_t, m_t) = \frac{\partial}{\partial m_t} f(\ell_t, k_t, m_t) = \frac{D^{\mathscr{E}}(\ell_t, k_t, m_t)}{\mathscr{E}} \tag{I.45}$$

The second stage of GNR requires assumptions on the productivity process to estimate the rest of the production function. By the fundamental theorem of calculus:

$$\int \frac{\partial}{\partial m_t} f(\ell_t, k_t, m_t) dm_t = f(\ell_t, k_t, m_t) + \mathscr{C}(\ell_t, k_t) \tag{I.46}$$

The goal is to estimate $\mathscr{C}(\cdot)$ since we can compute $\int \frac{\partial}{\partial m_t} f(\ell_t, k_t, m_t) dm_t$ using $D(\ell_t, k_t, m_t)$ from the first stage. By substituting for $f(\ell_t, k_t, m_t)$ using equation (I.39):

$$\begin{aligned} \int \frac{\partial}{\partial m_t} f(\ell_t, k_t, m_t) dm_t &= y_t - \omega_t - \varepsilon_t + \mathscr{C}(\ell_t, k_t) \\ \mathscr{Y}_t \equiv y_t - \int \frac{\partial}{\partial m_t} f(\ell_t, k_t, m_t) dm_t - \varepsilon_t &= -\mathscr{C}(\ell_t, k_t) + \omega_t \end{aligned} \tag{I.47}$$

It is at this point that the assumption on the productivity evolution process comes into play. GNR maintains the same first-order Markov assumption as ACF:

$$\omega_t = h(\omega_{t-1}) + \eta_t, \qquad \text{where } E[\eta_t \mid \mathscr{I}_{t-1}] = 0 \tag{I.48}$$

$$\begin{aligned} \omega_{t-1} &= \mathscr{Y}_{t-1} + \mathscr{C}(\ell_{t-1}, k_{t-1}) \\ \implies \mathscr{Y}_t &= -\mathscr{C}(\ell_t, k_t) + h(\mathscr{Y}_{t-1} + \mathscr{C}(\ell_{t-1}, k_{t-1})) + \eta_t \end{aligned} \tag{I.49}$$

We can estimate $\mathscr{C}(\cdot)$ and $h(\cdot)$, normalizing the former to contain no constant, based on unconditional moments derived from $E[\eta_t \mid \mathscr{I}_t$:

$$\begin{aligned} E[\eta_t \ell_t^{\tau_\ell} k_t^{\tau_k}] &= 0 \\ E[\eta_t \mathscr{Y}_{t-1}^{\tau_{\mathscr{Y}}}] &= 0 \end{aligned} \tag{I.50}$$

where τ_ℓ, τ_k and $\tau_{\mathscr{Y}}$ are determined by the degrees of the polynomial approximations for $\mathscr{C}(\cdot)$ and $h(\cdot)$ respectively.

I.7.1.1 Accounting for Network Effects

As with the modified ACF approach, I maintain the same assumptions and procedure in the first stage of GNR. Network effects come into play at the second stage when the law of motion on productivity is required for identification.

Note however, that by maintaining the same assumptions in the first stage, I do not account for ways in which the firm's network could potentially influence its intermediate input choices. For now, I focus specifically on network effects that operate through productivity spillovers and leave the implications for materials demand for future work.

I replace the productivity evolution process in (I.48) with one that allows for a linearly additive endogenous network effect:[26]

$$\omega_t = h(\omega_{t-1}) + \lambda G_t \omega_t + \zeta_t \qquad \text{where } E[\zeta_t \mid \mathscr{I}_{t-1}] = 0$$
$$\implies \omega_t = \sum_{s=0}^{\infty} \lambda^s G_t^s h(\omega_{t-1}) + \sum_{s=0}^{\infty} \lambda^s G_t^s \zeta_t$$

The equation (I.49) becomes:

$$\mathscr{Y}_t = -\mathscr{C}(\ell_t, k_t) + \sum_{s=0}^{\infty} \lambda^s G_t^s h(\mathscr{Y}_{t-1} + \mathscr{C}(\ell_{t-1}, k_{t-1})) + \sum_{s=0}^{\infty} \lambda^s G_t^s \zeta_t \tag{I.51}$$

This yields an additional set of moments from which the endogenous effect λ can be identified:

$$E[\zeta_t G_t^s \mathscr{Y}_{t-1}^{\tau_{\mathscr{Y}}}] = 0 \qquad \text{where } s \geq 1 \tag{I.52}$$

I.7.2 Alternative Network Effect Specifications

The modified ACF procedure introduced in section I.4 can accommodate specifications of the productivity process that account for other ways in which spillovers may occur. In this section, I consider some of these specifications, and how they affect the estimator and what additional assumptions are needed, if any.

I.7.2.1 Local-Aggregate Endogenous Effect

The linear-in-means equation considered so far is also known as the local-average model because it assumes that the average productivity and characteristics of a firm's neighbors is the key source of spillovers. Another model is the local-aggregate model as in Liu and Lee (2010) and Liu et al. (2014), that considers the sum rather than the average. That is:

$$\omega_t = h(\omega_{t-1}, \boldsymbol{x}_{t-1}, A_t \boldsymbol{x}_{t-1}) + \lambda A_t \omega_t + \zeta_t \tag{I.53}$$

where A_t is the adjacency matrix. This model has different implications from the local-average model. There are also hybrid models that include local-average contextual effects and local-aggregate endogenous effects:

$$\omega_t = h(\omega_{t-1}, \boldsymbol{x}_{t-1}, G_t \boldsymbol{x}_{t-1}) + \lambda A_t \omega_t + \zeta_t \tag{I.54}$$

or both local-average and local-aggregate endogenous effects:

$$\omega_t = h(\omega_{t-1}, \boldsymbol{x}_{t-1}, G_t \boldsymbol{x}_{t-1}) + \lambda_A A_t \omega_t + \lambda_G G_t \omega_t + \zeta_t \tag{I.55}$$

See Liu and Lee (2010) and Liu et al. (2014) for further discussion of the conditions under which these network effects are identified. In general as long as the matrix inversion conditions to obtain a reduced form and the information set conditions hold, my benchmark procedure only needs to be modified by changing the network matrix where necessary.

I.7.2.2 Heterogeneous Network Effects

So far, my model of network effects has assumed homogeneous spillovers. However, the model can account for a finite set of heterogeneous network effects. If I partition the network into a finite set of B groups such as buyers and suppliers, industries, or based on firm size, then I can estimate:

$$\omega_t = h(\omega_{t-1}, \boldsymbol{x}_{t-1}, \{G_{b,t} \boldsymbol{x}_{t-1}\}_{b=1}^{B}) + \sum_{b=1}^{B} \lambda_b G_{b,t} \omega_t + \zeta_t \tag{I.56}$$

[26] For clarity of exposition, I leave out contextual and correlated effects, but they can be included in much the same way as with ACF.

Note that $\boldsymbol{x}_{t-1}, \{G_{b,t}\boldsymbol{x}_{t-1}\}_{b=1}^{B}\omega_t = \lambda G_t \omega_t$ where λ is a weighted average of the heterogeneous effects. Therefore, my benchmark procedure can still be used to consistently estimate TFP without any modification. Afterwards, the heterogeneous network effect parameters can be obtained using the specification above. Dieye and Fortin (2017) and Patacchini et al. (2017) discuss the identification conditions and estimation procedures for this model in greater detail.

I.8 Results

In this section, I use my empirical framework to examine the magnitude of endogenous productivity spillovers through vertical relationships in the US production network. I explore how these spillovers vary over time, industry and firm size and document substantial heterogeneity in the sources and recipients of network effects.

I estimate a gross production function with a linear intermediate input share equation and a second-degree polynomial in capital and labor in the second stage.[27] I also estimate a value-added Cobb Douglas production function with materials as the proxy variable and a second-degree polynomial in the first stage. In both specifications, I assume a linear productivity process that includes an endogenous network effect and recover both production function elasticities and productivity spillovers from my modified approach. Because spillovers imply that TFP is jointly determined for linked firms across industries, the production function cannot be estimated separately for each industry. Therefore, I control for industry and year fixed effects in the productivity equation. In addition, due to the observed variation in the network structure over time, I estimate both specifications separately for each decade in the sample.

I compare my estimates with results from standard GNR and ACF approaches with industry and year fixed effects in the productivity equation for comparability. Because standard approaches do not yield estimates of productivity spillovers, I use TFP estimates from these procedures in a second stage. To obtain network effect coefficients, I apply the generalized 2SLS (G2SLS) approach in Lee (2003) and Bramoullé et al. (2009). In the first step, I estimate λ^* by 2SLS using $[G_t\omega_{t-1}, G_t^2\omega_{t-1}]$ as instruments for $G_t\omega_t$. I compute $E^*[G_t\omega_t|\mathscr{I}_{t-1}]$ using the reduced form equation in (I.13). This is the feasible estimate of the best instrumental variable (IV) for $G_t\omega_t$. Then I estimate 2SLS again, this time with $E^*[G_t\omega_t|\mathscr{I}_{t-1}]$ instrumenting for $G_t\omega_t$. To eliminate component-year fixed effects, I apply global differencing described in section I.4.2 to both standard and modified procedures.

As discussed in section I.2, the buyer-supplier network is only partially observed because firms only need to report their major customers; only about 18% of links fall below the 10% sales threshold. To address this, I rely on information about link intensity: I weight each relationship by the value traded between the two firms in that year. This mitigates some of the bias from missing links, because links that fall below the 10% threshold are would have weights close to zero. There is also the added advantage of allowing more important trading partners to have a larger impact on a firm's productivity.[28]

I.8.1 Production Function Elasticities

Tables I.6 and I.7 report the estimated elasticities of output with respect to inputs from gross output and value-added production functions, respectively. GNR/ACF refer to the standard procedures, GNR-N/ACF-N denote my modified approach that accounts for endogenous productivity spillovers, and GNR-ND/ACF-ND indicate specifications that account for both endogenous network effects and component-year fixed effects. Because I assume that the network does not affect intermediate input demand in the gross output specification, the elasticity of output with respect to materials does not vary across specifications.

Estimated capital and labor elasticities are also quite similar with and without accounting for network effects. The relative importance of each input varies over time; in the gross output specification, the elasticity of output with respect to labor falls from about 0.49 between 1977-1986 by 0.26 in the 2007-2016 period. By contrast, results from in the value-added specification move in the opposite direction, with labor elasticity rising from about 0.62 to 0.68 over the same time horizon.

[27] This specification implies a translog production function.

[28] As a robustness check, I estimate all specifications with an unweighted network in section A.5.2 of the appendix. The results are similar in magnitude, indicating that major trading partners are the more salient sources of spillovers.

Table I.6: Gross Production Function Elasticities

Period	Estimator	Capital	Labor	Materials
	GNR	0.280	0.489	0.341
1977-1986	GNR-N	0.271	0.497	0.341
	GNR-ND	0.279	0.493	0.341
	GNR	0.267	0.382	0.489
1987-1996	GNR-N	0.266	0.383	0.490
	GNR-ND	0.271	0.379	0.490
	GNR	0.159	0.278	0.529
1997-2006	GNR-N	0.173	0.269	0.529
	GNR-ND	0.170	0.273	0.529
	GNR	0.183	0.263	0.508
2007-2016	GNR-N	0.194	0.257	0.508
	GNR-ND	0.191	0.262	0.508
	GNR	0.210	0.321	0.500
All	GNR-N	0.219	0.318	0.500
	GNR-ND	0.221	0.317	0.500

This table reports the average input elasticities from a gross output production function estimated on US firms in Compustat. Estimators are based on Gandhi et al. (2020): GNR denotes the standard procedure with a linear first stage, a second-degree polynomial in the second stage, and a linear productivity process. GNR-N and GNR-ND are modifications to accommodate network effects and network differencing respectively. All specifications include industry and year fixed effects in the productivity process.

Table I.7: Value-Added Production Function Elasticities

Period	Estimator	Capital	Labor
	ACF	0.395	0.632
1977-1986	ACF-N	0.398	0.629
	ACF-ND	0.405	0.623
	ACF	0.441	0.606
1987-1996	ACF-N	0.437	0.614
	ACF-ND	0.429	0.626
	ACF	0.362	0.670
1997-2006	ACF-N	0.361	0.672
	ACF-ND	0.347	0.685
	ACF	0.327	0.670
2007-2016	ACF-N	0.326	0.671
	ACF-ND	0.316	0.686
	ACF	0.384	0.644
All	ACF-N	0.383	0.646
	ACF-ND	0.375	0.657

This table reports input elasticities of a Cobb-Douglas value-added production function (in logs) estimated on US firms in Compustat. Estimators are based on Ackerberg et al. (2015): ACF denotes the standard procedure with a second-degree polynomial in the first stage and a linear productivity process. ACF-N and ACF-ND are modifications to accommodate network effects and network differencing respectively. All specifications include industry and year fixed effects in the productivity process.

I.8.2 Endogenous Productivity Spillovers

I now turn to estimates of productivity spillovers. First, I define the network as undirected: a firm j belongs in firm i's neighborhood if it either buys from or sells to the firm. Table I.8 and figure I.8 show the endogenous network effects from gross output TFP.

Based on TFP measures from the standard GNR approach, the results suggest that a firm's productivity rises by 0.084 percent in the short run when its average buyer or seller gets 10 percent more productive. Accounting for endogenous productivity spillovers in TFP estimation raises the point estimate to 0.09 percent, but differencing out common shocks to productivity lowers the estimate to 0.076 percent. The persistence of TFP over time also implies a substantial long-run effect of having more trading partners in one period. An estimated coefficient of 0.9 on ln TFP_{t-1}, means that transacting with a 10 percent more efficient firm in a single period results in a long-run efficiency gain of 0.76 percent. In the value-added specification, the impact of correlated effects is striking; the estimated short-run impact of a 10 percent rise in the average neighbor's TFP goes from 0.07 percent with standard ACF to 0.01 when I account for both endogenous and correlated effects in the production function estimation.

Across all specifications, estimates from the standard approach and my modified procedure are often statistically indistinguishable. This is consistent with the discussion in section A.1 and results from the Monte Carlo experiment in table I.5: standard approaches yielded estimates of productivity spillovers that were closest to the true effect when the network density was between 0.1 and 0.3 percent. As shown in figure I.4, the density of the observed network in my sample ranges from 0.12 to 0.28 percent and lies within the region with the least bias in estimated spillovers.

It is worth noting, however, that because these spillovers have a cumulative impact over time and space, even small differences in these point estimates could have result in substantially different implications. To illustrate this, I simulate a growth path for the average firm in 1978 under the assumption that it is connected to the median firm in the same year. For simplicity, I assume there are no shocks to productivity and the average firm is also its partner's only connection, and this relationship remains the same for all periods. Then I compute:

$$\widetilde{\omega}_t = \left(I - \widehat{\lambda} G\right)^{-1} \left(\widehat{\beta}_1 + \widehat{\rho}\,\widetilde{\omega}_{t-1}\right), \qquad G = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \tag{I.57}$$

where $t = \{1979 \ldots 2016\}$, $\widehat{\beta}_1 = 0.203$, and $\widehat{\rho} = 0.9$. $\widehat{\lambda}$ takes on three possible values: the point estimates from GNR, GNR-N and GNR-ND. I difference the cumulative TFP growth from what it would be in a no-spillover scenario in which $\widehat{\lambda} = 0$. Figure I.12 shows that an endogenous effect of 0.0076, as obtained from GNR-ND, implies that the average firm would grow an additional 16.3 percent due to spillovers by 2016. Standard GNR would overstate the cumulative impact of spillovers, implying 18 percent additional growth, while accounting for network effects without eliminating common productivity shocks would suggest a cumulative spillover effect of 19.6 percent.

To understand the economic importance of these spillovers in the cross-section, I compute a back-of-the-envelope estimate of the impact of the most connected firm in each year on aggregate TFP through spillovers. Let j denote the most central firm in year t. I sum up j's contribution to the network average for each of its connections, weighting by firm i's nominal revenues in that period, and multiply that by the spillover estimate. That is:

$$\text{Contribution}_{jt} = \widehat{\lambda} \sum_{it} weight_{it} G_{ijt} \tag{I.58}$$

whew $weight_{it} = \frac{Revenue_{it}}{Avg\,Revenue_t}$. Figure I.14 shows that for $\widehat{\lambda} = 0.002$, a 10 percent increase in the TFP of the most central firm would correspond with a 0.25 to 1.9 percent rise in aggregrate TFP through spillovers alone.

I.8.2.1 Relationship Direction and Dynamics

Next, I examine how spillovers depend on the nature of the relationship between firms. Figure I.10 and table I.10 show that productive suppliers have almost 5 times the impact on their customers as productive buyers have on their suppliers: a 10 percent more productive supplier raises efficiency by 0.095 percent while customers raise productivity by 0.02 percent. As depicted in figure I.13, having a more productive supplier implies that the average firm would grow an additional 19.3 percent over the sample period due to spillovers, as compared to 4.3 percent from a more productive customer.[29]

To investigate how much this is driven by maintaining old relationships as opposed to forming new ones, I decompose the interaction matrix into buyers/sellers that the firm traded with in both the current and the previous year ($G_t \cap G_{t-1}$), and new links ($G_t \setminus G_{t-1}$). The results in table I.12 suggest that both old and new suppliers are important sources of spillovers, while new customers are the primary sources of buyer-to-seller spillovers.

Estimates from value-added specifications do not show a significant difference between spillovers from buyers to sellers or vice versa. In figure I.11 and table I.11, a 10 percent more efficient supplier is associated with a 0.016 percent rise in productivity while the effect of buyers is 0.011 percent. These effects are statistically indistinguishable from each other. For the rest of this discussion, I focus on estimates from gross output production functions, but additional results from value-added specifications are in section A.5.1 in the appendix.

I.8.2.2 Heterogeneity by Sector

In this section, I investigate how the spillovers transmit within and across sectors. I estimate a gross output production function with endogenous and correlated effects, allowing spillovers to vary by the sector of the firm and its trading partners. I classify sectors based on the share of observed links that are from sellers to buyers, or from buyers to sellers respectively. If 50 percent or more of links between sector u and sector v are from suppliers in u to customers in v, then the spillovers from u to v are classified as downstream, while the impact of sector v on firms in u is considered an upstream spillover. Figures I.15 and I.16 depict estimates of downstream and upstream spillovers, respectively that are significant at the 5 percent level. Table I.13 reports the full set of estimates.

These results highlight the important role of information technology (IT), retailers and services in productivity growth within the US. As shown by figure I.15, the substantial downstream spillovers occur within the electronics manufacturing sector. Furthermore, the synergies between electronics manufacturing and the finance, insurance and real estate sector is primarily driven by technology patent holders (SIC 6794 and NAICS 533110) such as InterDigital Inc. which provides mobile technology research services to mobile phone manufacturers such as Apple. Manufacturers also tend to amplify the impact of productivity growth in other sectors because they enjoy efficiency boosts from both directions: electronics manufacturers from mainly customers and manufacturers of non-durables from their suppliers (see figure I.16). Retailers are an import source of upstream spillovers, while transport and warehousing firms generate downstream spillovers. None of these sectors receives efficiency boosts from other sectors, and in fact, experience negative network effects. Negative endogenous effects suggests free-riding or, given that I use deflated sales as a measure of output, downward pressure on prices by more profitable firms.

I.8.2.3 The Role of Firm Size

Finally, I consider the role of firm size in the transmission of efficiency gains through the production network. I classify firms as large if they have 500 or more employees, the definition used by the US BEA. The results are reported in table I.14 and figure I.17 highlights estimates that are significant at the 5% level. Large productive suppliers are an important source of productivity gains for both large and small firms, with small customers benefiting nearly twice as much as large buyers. Small efficient suppliers also have a substantial impact on their large customers. The effect of customer efficiency on their suppliers is driven solely by large firms.

Given that the average firm in my sample is larger than the average firm in the US, at least 60 percent or more the sample can be classified as large based on this definition. In table I.15, I check how sensitive these results are to different classifications of firm size. I consider three alternative definitions based on the number of employees: greater than or equal to 1000, 5000 or an industry-year specific median. The results are similar across definitions except that, as excepted, the impact of large firms diminishes while that of small firms rises.

[29] Larger confidence intervals in the 1977-1986 period are likely due to a combination of fewer firms in the sample, a denser network, and fewer reported links.

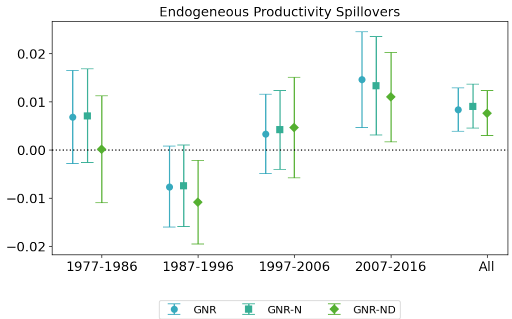


Figure I.8: Spillover Estimates (Gross-Output)

This figure shows point estimates and 95% confidence intervals of endogenous productivity spillovers from a gross output production function. See table I.8 for standard errors.

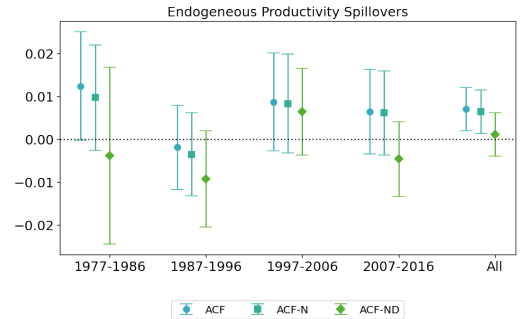


Figure I.9: Spillover Estimates (Value-Added)

This figure shows point estimates and 95% confidence intervals of endogenous productivity spillovers from a value-added production function. See table I.9 for standard errors.

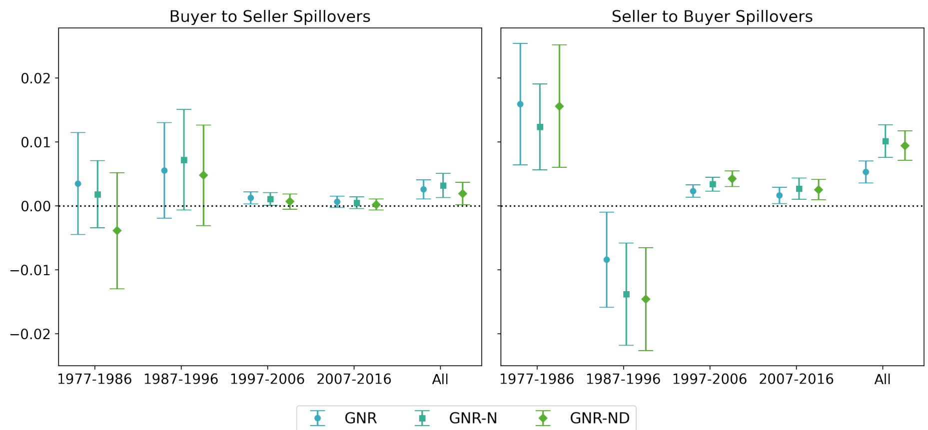


Figure I.10: Spillover Estimates by Relationship Direction (Gross-Output)

This figure shows point estimates and 95% confidence intervals of endogenous productivity spillovers by direction of the relationship from a gross output production function. See table I.10 for standard errors.

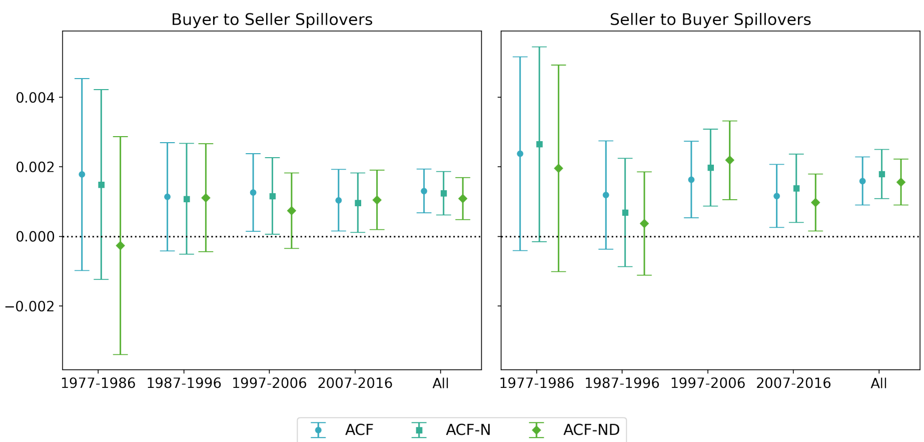


Figure I.11: Spillover Estimates by Relationship Direction (Value-Added)

This figure shows point estimates and 95% confidence intervals of endogenous productivity spillovers by direction of the relationship from a value-added production function. See table I.11 for standard errors.

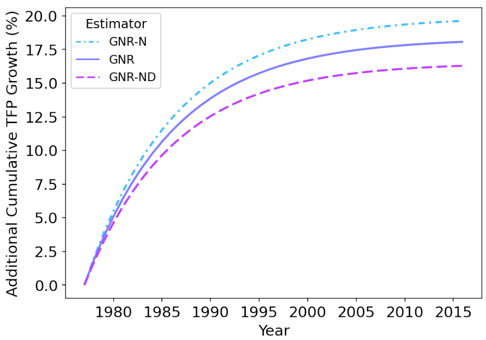


Figure I.12: Cumulative Impact of Endogenous Productivity Spillovers over Time
This figure depicts a simulated path of log(TFP) for a firm with productivity equal to the 1978 average, assuming it is connected to the median firm in the same year. Endogenous productivity spillovers are assumed to be 0.0084, 0.009 and 0.0076 obtained from GNR, GNR-N and GNR-ND respectively. The bottom dotted line assumes that the firm experiences no spillovers.

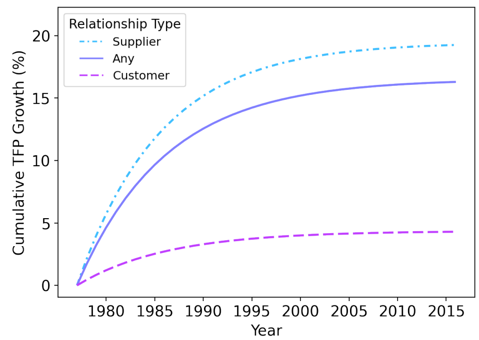


Figure I.13: Cumulative Impact of Endogenous Productivity Spillovers by Relationship Type
This figure depicts a simulated path of log(TFP) for a firm with productivity equal to the 1978 average, assuming it is connected to the median firm in the same year. Endogenous productivity spillovers are assumed to be 0.002, 0.0095 and 0.0076 for customers, suppliers or either, respectively. The bottom dotted line assumes that the firm experiences no spillovers.

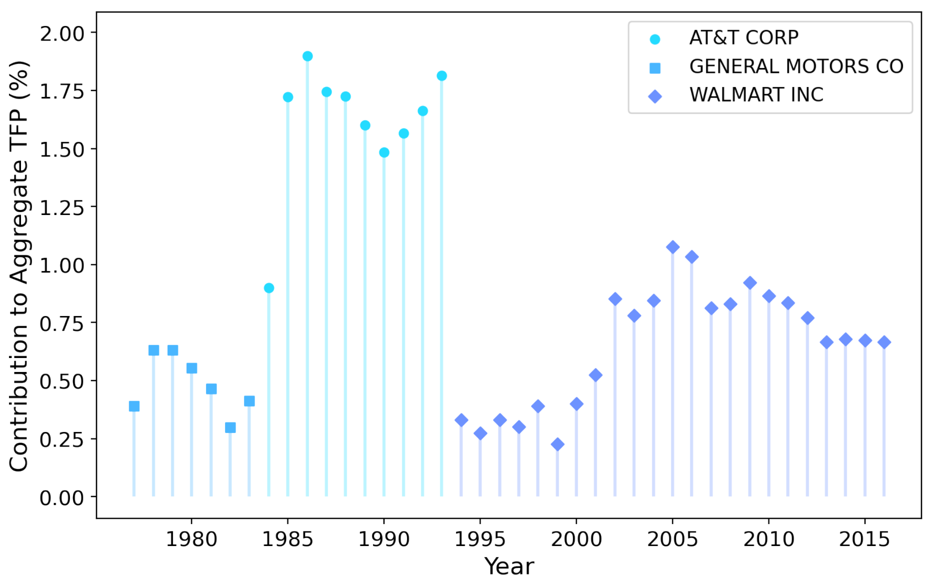
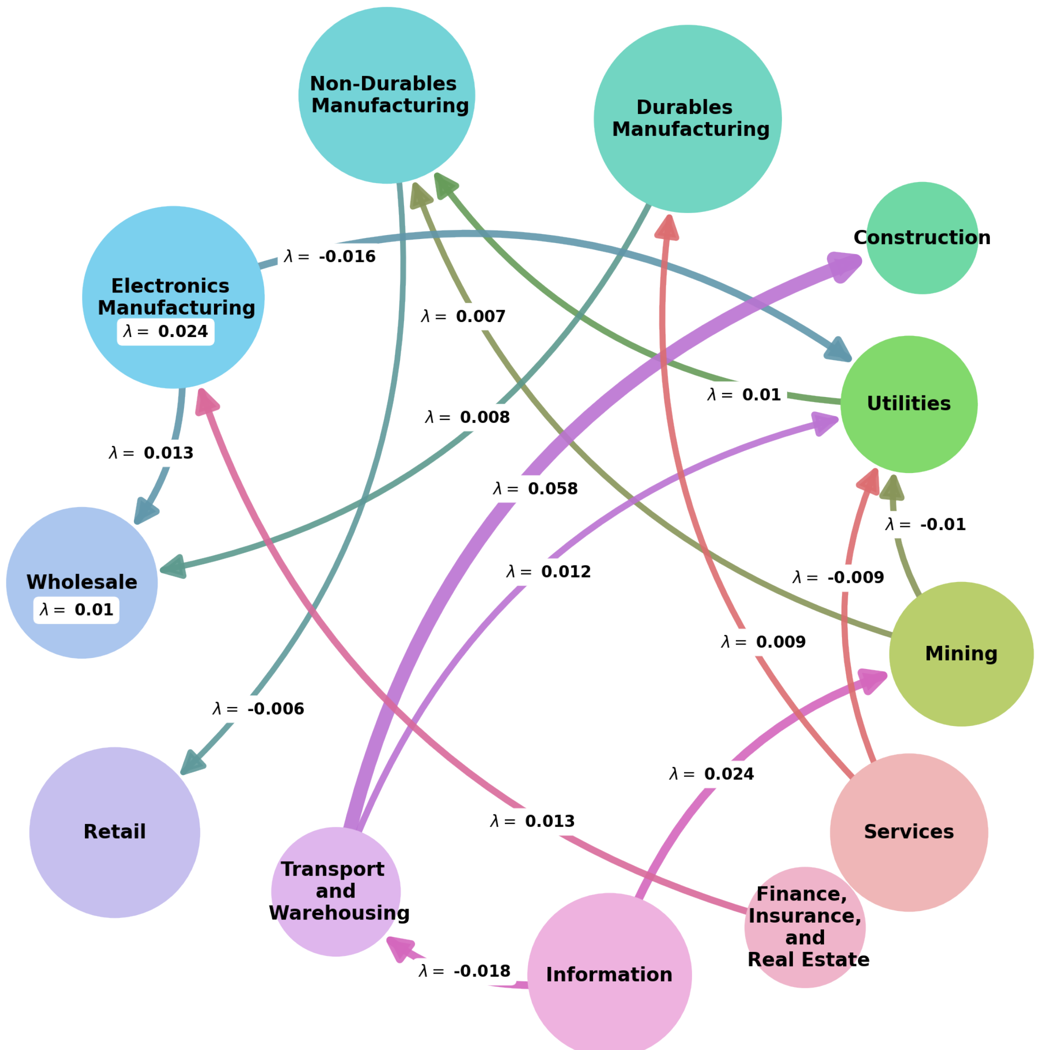


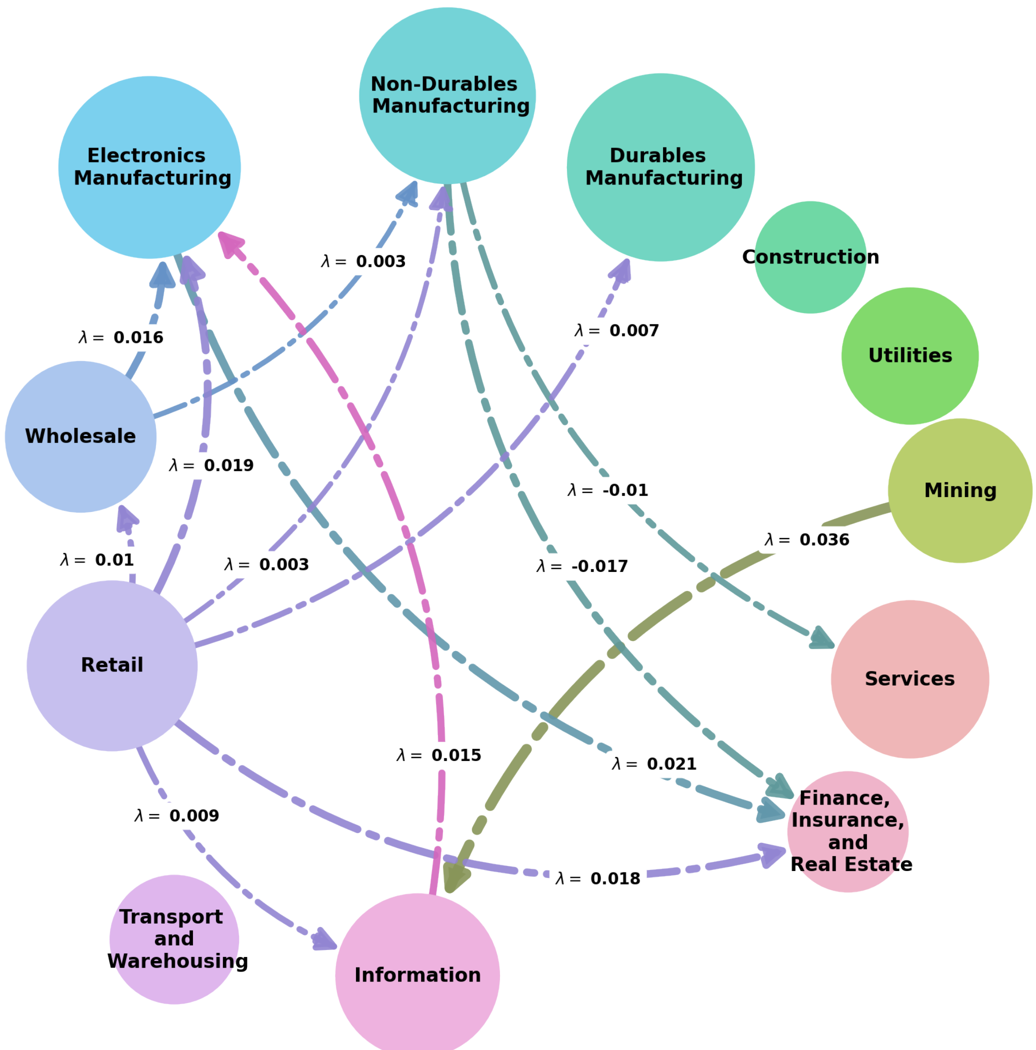
Figure I.14: Contribution of Most Central Firms to Aggregate TFP
This figure shows the impact of a 10% increase in the TFP of the most central firm in each year to aggregate productivity through spillovers. The contribution of the most central firm j in year t is calculated as $\widehat{\lambda} \sum_{it} weight_{it} G_{ijt}$ where $\widehat{\lambda} = 0.02$ and $weight_{it} = \frac{Revenue_{it}}{Avg\,Revenue_t}$

Figure I.15: Downstream Productivity Spillovers by Sector



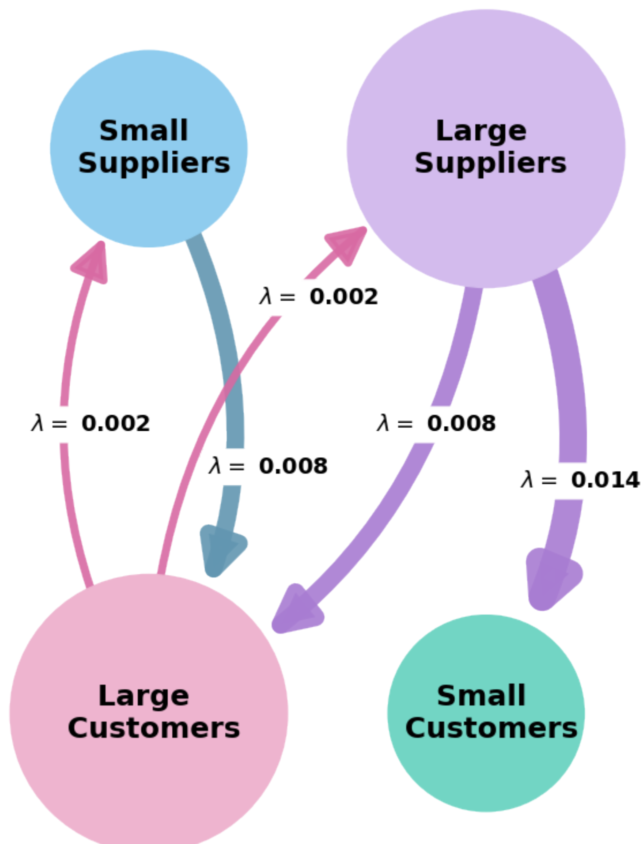
This figure shows downstream productivity spillovers (λ) that vary by the sector of the firm and its trading partners. Estimates are significant at the 5% level. Sector nodes are weighted by the total number of connections originating from or going to firms in the sector, across all time periods. See table I.13 for the full set of coefficients.

Figure I.16: Upstream Productivity Spillovers by Sector



This figure shows upstream productivity spillovers (λ) that vary by the sector of the firm and its trading partners. Estimates are significant at the 5% level. Industry nodes are weighted by the total number of connections originating from or going to firms in the sector, across all time periods. See table I.13 for the full set of coefficients.

Figure I.17: Endogenous Productivity Spillovers by Firm Size



This figure shows endogenous productivity spillovers that vary by firm size. Estimates are significant at the 10% level. See table I.10 for the full set of coefficients.

Table I.8: Endogenous Productivity Spillovers (Gross Output)

Dependent Variable: $\ln\mathrm{TFP}_t$			
Period	Estimator	$\ln\mathrm{TFP}_{t-1}$	Neighbors' $\ln\mathrm{TFP}_t$
1977-1986	GNR	0.8401 (0.0205)	0.0068 (0.0049)
	GNR-N	0.839 (0.0207)	0.007 (0.0049)
	GNR-ND	0.8257 (0.0227)	0.0001 (0.0057)
1987-1996	GNR	0.8313 (0.0244)	-0.0077 (0.0043)
	GNR-N	0.8312 (0.0244)	-0.0075 (0.0043)
	GNR-ND	0.8229 (0.0271)	-0.0109 (0.0044)
1997-2006	GNR	0.858 (0.013)	0.0033 (0.0042)
	GNR-N	0.8585 (0.0134)	0.0041 (0.0042)
	GNR-ND	0.8586 (0.0147)	0.0046 (0.0053)
2007-2016	GNR	0.8957 (0.0215)	0.0145 (0.005)
	GNR-N	0.8963 (0.0214)	0.0133 (0.0052)
	GNR-ND	0.8918 (0.023)	0.0109 (0.0048)
All	GNR	0.9035 (0.0067)	0.0084 (0.0023)
	GNR-N	0.9025 (0.0067)	0.009 (0.0023)
	GNR-ND	0.8996 (0.0073)	0.0076 (0.0024)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a gross output production function (in logs) estimated with the standard Gandhi et al. (2020) procedure (GNR), or with modifications to accommodate network effects (GNR-N) and network differencing (GNR-ND). Network effects for GNR are estimated using the generalized 2SLS procedure in Lee (2003); Bramoullé et al. (2009). Standard errors are in parentheses. All specifications include industry and year fixed effects.

Table I.9: Endogenous Productivity Spillovers (Value-Added)

Dependent Variable: $\ln\mathrm{TFP}_t$			
Period	Estimator	$\ln\mathrm{TFP}_{t-1}$	Neighbors' $\ln\mathrm{TFP}_t$
1977-1986	ACF	0.8169 (0.0207)	0.0123 (0.0065)
	ACF-N	0.8168 (0.0207)	0.0097 (0.0062)
	ACF-ND	0.807 (0.0214)	-0.0039 (0.0105)
1987-1996	ACF	0.8472 (0.0135)	-0.002 (0.005)
	ACF-N	0.8479 (0.0134)	-0.0036 (0.0049)
	ACF-ND	0.8482 (0.0121)	-0.0093 (0.0057)
1997-2006	ACF	0.8679 (0.0116)	0.0086 (0.0058)
	ACF-N	0.8682 (0.0116)	0.0083 (0.0059)
	ACF-ND	0.8685 (0.0104)	0.0064 (0.0051)
2007-2016	ACF	0.8774 (0.0321)	0.0063 (0.005)
	ACF-N	0.8776 (0.032)	0.0061 (0.005)
	ACF-ND	0.8691 (0.0358)	-0.0046 (0.0044)
All	ACF	0.8687 (0.0095)	0.007 (0.0026)
	ACF-N	0.8688 (0.0095)	0.0064 (0.0026)
	ACF-ND	0.8663 (0.0101)	0.001 (0.0026)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a value-added production function (in logs) estimated with the standard Ackerberg et al. (2015) procedure (ACF), or with modifications to accommodate network effects (ACF-N) and network differencing (ACF-ND). Network effects for ACF are estimated using the generalized 2SLS procedure in Lee (2003); Bramoullé et al. (2009). Standard errors are in parentheses. All specifications include industry and year fixed effects.

Table I.10: Productivity Spillovers by Relationship Direction (Gross Output)

		Dependent Variable: $\ln\text{TFP}_t$	
Period	Estimator	Customers' $\ln\text{TFP}_t$	Suppliers' $\ln\text{TFP}_t$
1977-1986	GNR	0.0035 (0.0041)	0.0159 (0.0048)
	GNR-N	0.0019 (0.0027)	0.0124 (0.0034)
	GNR-ND	-0.0038 (0.0046)	0.0156 (0.0049)
1987-1996	GNR	0.0056 (0.0038)	-0.0084 (0.0038)
	GNR-N	0.0072 (0.004)	-0.0138 (0.0041)
	GNR-ND	0.0048 (0.004)	-0.0145 (0.0041)
1997-2006	GNR	0.0013 (0.0005)	0.0023 (0.0005)
	GNR-N	0.0011 (0.0005)	0.0034 (0.0006)
	GNR-ND	0.0007 (0.0006)	0.0043 (0.0006)
2007-2016	GNR	0.0007 (0.0004)	0.0017 (0.0006)
	GNR-N	0.0005 (0.0005)	0.0027 (0.0008)
	GNR-ND	0.0002 (0.0004)	0.0026 (0.0008)
All	GNR	0.0026 (0.0008)	0.0053 (0.0009)
	GNR-N	0.0032 (0.001)	0.0102 (0.0013)
	GNR-ND	0.002 (0.0009)	0.0095 (0.0012)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a gross output production function (in logs) estimated with the standard Gandhi et al. (2020) procedure (GNR), or with modifications to accommodate network effects (GNR-N) and network differencing (GNR-ND). Network effects for GNR are estimated using the generalized 2SLS procedure for heterogenous peer effects in Dieye and Fortin (2017); Patacchini et al. (2017). Standard errors are in parentheses. All specifications include industry and year fixed effects.

Table I.11: Productivity Spillovers by Relationship Direction (Value-Added)

		Dependent Variable: $\ln\text{TFP}_t$	
Period	Estimator	Customers' $\ln\text{TFP}_t$	Suppliers' $\ln\text{TFP}_t$
1977-1986	ACF	0.0018 (0.0014)	0.0024 (0.0014)
	ACF-N	0.0015 (0.0014)	0.0027 (0.0014)
	ACF-ND	-0.0003 (0.0016)	0.002 (0.0015)
1987-1996	ACF	0.0011 (0.0008)	0.0012 (0.0008)
	ACF-N	0.0011 (0.0008)	0.0007 (0.0008)
	ACF-ND	0.0011 (0.0008)	0.0004 (0.0008)
1997-2006	ACF	0.0013 (0.0006)	0.0016 (0.0006)
	ACF-N	0.0012 (0.0006)	0.002 (0.0006)
	ACF-ND	0.0007 (0.0006)	0.0022 (0.0006)
2007-2016	ACF	0.001 (0.0005)	0.0012 (0.0005)
	ACF-N	0.001 (0.0004)	0.0014 (0.0005)
	ACF-ND	0.0011 (0.0004)	0.001 (0.0004)
All	ACF	0.0013 (0.0003)	0.0016 (0.0004)
	ACF-N	0.0012 (0.0003)	0.0018 (0.0004)
	ACF-ND	0.0011 (0.0003)	0.0016 (0.0003)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a value-added production function (in logs) estimated with the standard Ackerberg et al. (2015) procedure (ACF), or with modifications to accommodate network effects (ACF-N) and network differencing (ACF-ND). Network effects for ACF are estimated using the generalized 2SLS procedure for heterogenous peer effects in Dieye and Fortin (2017); Patacchini et al. (2017). Standard errors are in parentheses. All specifications include industry and year fixed effects.

Table I.12: Productivity Spillovers by Relationship Dynamics (Gross Output)

		Dependent Variable: $\ln\text{TFP}_t$			
Period	Estimator	Continuing Customers' $\ln\text{TFP}_t$	New Customers' $\ln\text{TFP}_t$	Continuing Suppliers' $\ln\text{TFP}_t$	New Suppliers' $\ln\text{TFP}_t$
1977-1986	GNR	0.0032 (0.0033)	0.0006 (0.0039)	0.0143 (0.0037)	0.0073 (0.0038)
	GNR-N	0.0 (0.0017)	0.0001 (0.0018)	0.0087 (0.002)	0.0052 (0.0018)
	GNR-ND	-0.0004 (0.0023)	-0.0019 (0.0022)	0.0113 (0.0024)	0.0049 (0.0023)
1987-1996	GNR	0.0072 (0.0035)	0.0033 (0.0039)	-0.0035 (0.0041)	-0.0118 (0.0035)
	GNR-N	0.0074 (0.0041)	0.0082 (0.0049)	-0.009 (0.0049)	-0.0194 (0.004)
	GNR-ND	-0.0128 (0.0046)	0.0101 (0.0064)	-0.0009 (0.0101)	-0.0175 (0.0081)
1997-2006	GNR	-0.0007 (0.0004)	0.0005 (0.0004)	0.0003 (0.0003)	0.0013 (0.0003)
	GNR-N	-0.0009 (0.0004)	0.0003 (0.0004)	0.0014 (0.0004)	0.0025 (0.0004)
	GNR-ND	-0.0011 (0.0005)	0.0002 (0.0005)	0.0019 (0.0005)	0.0031 (0.0004)
2007-2016	GNR	0.0005 (0.0004)	0.0006 (0.0004)	0.0015 (0.0005)	0.0013 (0.0004)
	GNR-N	0.0005 (0.0005)	0.0004 (0.0005)	0.0031 (0.0008)	0.0026 (0.0006)
	GNR-ND	0.0003 (0.0005)	0.0003 (0.0005)	0.0031 (0.0009)	0.0027 (0.0007)
All	GNR	0.0008 (0.0006)	0.0017 (0.0006)	0.0028 (0.0006)	0.0038 (0.0006)
	GNR-N	0.001 (0.0007)	0.0017 (0.0007)	0.0067 (0.0009)	0.0077 (0.0008)
	GNR-ND	0.0005 (0.0007)	0.0013 (0.0008)	0.0071 (0.001)	0.0082 (0.0009)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a gross output production function (in logs) estimated with the standard Gandhi et al. (2020) procedure (GNR), or with modifications to accommodate network effects (GNR-N) and network differencing (GNR-ND). Network effects for GNR are estimated using the generalized 2SLS procedure for heterogenous peer effects in Dieye and Fortin (2017); Patacchini et al. (2017). Standard errors are in parentheses. All specifications include industry and year fixed effects.

Table I.13: Productivity Spillovers by Sector (Gross Output)

	Dependent Variable: lnTFP$_t$											
	Firm's Sector											
Partners' Sector	Mining	Utilities	Constr	Durables	Non-Durables	Electronics	Wholesale	Retail	Trans & WH	Info	FIRE	Services
Mining	-0.0084	-0.0096	-0.0064	0.0017	0.0075	-0.0161	0.0172	0.0094	0.0102	0.0357	0.0042	0.0028
	(0.0064)	(0.0038)	(0.0331)	(0.005)	(0.0027)	(0.0326)	(0.0104)	(0.008)	(0.0092)	(0.0111)	(0.0085)	(0.008)
Utilities	-0.0032	-0.0007	0.0061	0.003	0.01	0.0134	0.0041	-0.0028	0.0018	-0.0024	-0.0038	0.0105
	(0.0059)	(0.0028)	(0.0104)	(0.0027)	(0.0021)	(0.0082)	(0.0083)	(0.0084)	(0.0065)	(0.0125)	(0.0178)	(0.006)
Construction	-0.0192	0.0014	0.0147	0.0055	-0.0058	-0.0079	0.0113	-0.0075	0.017	0.0043	-0.0005	0.0282
	(0.0312)	(0.0041)	(0.0115)	(0.0059)	(0.0036)	(0.0133)	(0.0076)	(0.009)	(0.0228)	(0.0035)	(0.0061)	(0.0218)
Durables Mfg	0.0077	0.0002	0.0265	0.0025	0.0012	-0.0036	0.0079	-0.0016	0.0029	0.0039	0.0052	0.0032
	(0.0065)	(0.003)	(0.0231)	(0.0022)	(0.0016)	(0.0024)	(0.0027)	(0.0016)	(0.0035)	(0.0034)	(0.0063)	(0.0034)
Non-Durables Mfg	-0.0061	-0.0014	-0.0028	0.0001	-0.001	-0.0067	0.0034	-0.0062	-0.0065	-0.0026	-0.0175	-0.0102
	(0.0052)	(0.0028)	(0.0132)	(0.0018)	(0.0013)	(0.0048)	(0.0027)	(0.0016)	(0.0038)	(0.0044)	(0.0085)	(0.0038)
Electronics Mfg	-0.0433	-0.0157	-0.0275	-0.0003	-0.0043	0.0244	0.013	0.0021	0.0079	0.0007	0.0207	0.0001
	(0.0501)	(0.0055)	(0.0355)	(0.0046)	(0.0038)	(0.0029)	(0.0031)	(0.0032)	(0.0058)	(0.0031)	(0.0091)	(0.0043)
Wholesale	-0.0052	0.0126	0.0121	0.0022	0.0032	0.0165	0.01	0.0017	0.0033	0.0022	-0.0132	0.0027
	(0.0118)	(0.0075)	(0.0164)	(0.0021)	(0.0012)	(0.0021)	(0.0038)	(0.0014)	(0.0104)	(0.0024)	(0.0118)	(0.004)
Retail	0.0113	-0.0037	-0.0075	0.0074	0.003	0.0194	0.0104	0.0012	-0.0013	0.009	0.018	0.0017
	(0.0118)	(0.0104)	(0.016)	(0.0028)	(0.0013)	(0.0036)	(0.0019)	(0.0026)	(0.004)	(0.0041)	(0.0046)	(0.0044)
Transport and	0.0079	0.0116	0.0575	0.0037	0.0033	0.0067	0.0078	0.0022	-0.0031	0.0007	-0.0088	0.0
Warehousing	(0.0094)	(0.0034)	(0.0184)	(0.0041)	(0.002)	(0.0059)	(0.0109)	(0.0039)	(0.0042)	(0.0081)	(0.0073)	(0.0103)
Information	0.0244	-0.0023	0.0085	-0.0035	-0.001	0.0151	0.0064	-0.001	-0.018	0.0041	0.0066	-0.0074
	(0.0118)	(0.0069)	(0.017)	(0.0039)	(0.0028)	(0.0025)	(0.0049)	(0.0026)	(0.0048)	(0.0028)	(0.0047)	(0.004)
Finance, Insur &	0.0004	0.005	-0.0134	0.0	-0.0044	0.0134	-0.0026	0.0017	0.0045	0.0042	-0.0021	0.0048
Real Estate	(0.0112)	(0.0143)	(0.0128)	(0.0044)	(0.0025)	(0.0034)	(0.0149)	(0.002)	(0.0043)	(0.0031)	(0.0043)	(0.0036)
Services	0.0035	-0.0088	0.0083	0.0088	0.0042	0.0022	0.0084	0.0042	0.0025	0.0052	0.009	0.0025
	(0.0117)	(0.0036)	(0.0253)	(0.0023)	(0.0023)	(0.0028)	(0.0072)	(0.0026)	(0.005)	(0.0031)	(0.0048)	(0.0037)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a gross output production function (in logs) estimated with the standard Gandhi et al. (2020) procedure (GNR), or with modifications to accommodate network effects (GNR-N) and network differencing (GNR-ND). Network effects for GNR are estimated using the generalized 2SLS procedure for heterogenous peer effects in Dieye and Fortin (2017); Patacchini et al. (2017). Sectors are determined according to the BEA industry classification. Standard errors are in parentheses. All specifications include industry and year fixed effects.

Table I.14: Productivity Spillovers by Firm Size & Relationship Direction (Gross Output)

			Dependent Variable: $\ln\text{TFP}_t$				
Partner Size	Relationship	Firm Size	1977-1986	1987-1996	1997-2006	2007-2016	All
Large	Customers	Large	0.0012	0.0033	-0.0001	0.0003	0.002
			(0.0031)	(0.0073)	(0.0004)	(0.0004)	(0.0008)
		Small	-0.0032	-0.0028	0.0005	-0.0004	0.0021
			(0.0037)	(0.0056)	(0.0006)	(0.0006)	(0.001)
	Suppliers	Large	0.0141	-0.0226	0.0024	0.0026	0.0083
			(0.0032)	(0.0103)	(0.0004)	(0.0007)	(0.001)
		Small	0.0509	-0.0638	0.0046	-0.005	0.0143
			(0.0273)	(0.0208)	(0.0024)	(0.0025)	(0.0077)
Small	Customers	Large	-0.0115	-0.0701	-0.0058	-0.0059	-0.0091
			(0.0106)	(0.0447)	(0.0026)	(0.0064)	(0.0076)
		Small	-0.0004	-0.0387	0.0	-0.0008	-0.0045
			(0.0127)	(0.0329)	(0.0021)	(0.0027)	(0.0052)
	Suppliers	Large	0.0122	-0.0124	0.0021	0.0023	0.0081
			(0.0034)	(0.0054)	(0.0004)	(0.0006)	(0.0009)
		Small	0.0502	-0.0144	0.0032	0.0	0.0075
			(0.0227)	(0.0133)	(0.0019)	(0.003)	(0.0053)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a gross output production function (in logs) estimated with the standard Gandhi et al. (2020) procedure (GNR), or with modifications to accommodate network effects (GNR-N) and network differencing (GNR-ND). Network effects for ACF are estimated using the generalized 2SLS procedure for heterogenous peer effects in Dieye and Fortin (2017); Patacchini et al. (2017). Large firms are businesses with 500 or more employees.Standard errors are in parentheses. All specifications include industry and year fixed effects.

Table I.15: Productivity Spillovers by Varying Firm Size Cutoffs (Gross Output)

			Dependent Variable: $\ln\text{TFP}_t$			
			Firm's Sector			
Partner Size	Relationship	Firm Size	500	1000	5000	Median
Large	Customers	Large	0.002	0.0017	0.0015	0.0011
			(0.0008)	(0.0008)	(0.0008)	(0.0008)
		Small	0.0021	0.0036	0.0019	0.0015
			(0.001)	(0.0011)	(0.001)	(0.001)
	Suppliers	Large	0.0083	0.008	0.006	0.0088
			(0.001)	(0.001)	(0.0008)	(0.001)
		Small	0.0143	0.0094	0.0086	0.0093
			(0.0077)	(0.0036)	(0.0027)	(0.0016)
Small	Customers	Large	-0.0091	-0.001	-0.0038	0.0019
			(0.0076)	(0.0061)	(0.0039)	(0.0015)
		Small	-0.0045	-0.0051	0.0007	0.0026
			(0.0052)	(0.0036)	(0.0012)	(0.0012)
	Suppliers	Large	0.0081	0.0086	0.008	0.0074
			(0.0009)	(0.001)	(0.0012)	(0.0011)
		Small	0.0075	0.0074	0.0091	0.0088
			(0.0053)	(0.0033)	(0.0013)	(0.0013)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a gross output production function (in logs) estimated with the standard Gandhi et al. (2020) procedure (GNR), or with modifications to accommodate network effects (GNR-N) and network differencing (GNR-ND). Network effects for GNR are estimated using the generalized 2SLS procedure for heterogenous peer effects in Dieye and Fortin (2017); Patacchini et al. (2017). Large firms are defined by having at least as many employees as the cutoffs indicated above. The median cutoff is determined by industry and year. Standard errors are in parentheses. All specifications include industry and year fixed effects.

I.9 Conclusion

This paper examines how efficiency gains are transmitted through vertical relationships. The existence of spillovers implies a form of firm interdependence that matters for consistent estimation of production functions. Using Monte Carlo experiments, I show that endogenous spillovers—the effect of the average productivity of a firm's neighbors on its own productivity—are an important source of bias when not accounted for in TFP estimation. Furthermore, the direction of this bias cannot always be clearly predicted *a priori*, and varies by the density of the network and the persistence of productivity. However, for moderately sparse networks, standard approaches may deliver reasonably unbiased estimates of production function elasticities and spillovers.

Under additional assumptions on firms' information sets and the structure of the network, I propose a methodology that can flexibly accommodate various network effects and endogenous network formation, and can be applied to both gross output and value-added production functions. I show experimentally that it performs better than standard approaches as long as the network is not too dense and productivity is sufficiently persistent.

Using data from *Compustat* on supplier-customer relationships in the US, I investigate the extent of productivity spillovers in from 1977 to 2016. I find that firms benefit from having more productive buyers and sellers, with both large and small suppliers having a larger effect than customers. Furthermore, the cumulative impact of spillovers over the 4 decades in the sample could mean a 16 percent difference in efficiency when compared to a no-spillover scenario.

Estimates suggest that if the most connected firm in a given year was 10 percent more productive, spillovers would lead to an increase in aggregate TFP of 0.2 to 1.9 percent. This also works in the opposite direction: a significant decline in productivity of central firms could mean substantial second-order impacts to US aggregate efficiency due to the interdependence of firms' activities through supply chains. This suggests that industrial and trade policies that could potentially affect the productivity of well-connected firms needs to account for potential indirect effects both upstream and downstream.

The sectoral composition of the production network plays a large role in the size and transmission of productivity gains. I find substantial heterogeneity in the size and spillovers between and within sectors, with electronics manufacturers benefiting from efficiency gains from most sectors, while retailers and services boost other sectors.

Consistent with my Monte Carlo experiments, estimates from standard approaches empirically yielded estimates of network effects that were similar to those obtained from my procedure, because the observed network density fell within the region where bias in spillover estimates was minimized. While this is reassuring for studies conducted on networks with similar levels of sparsity, caution should be taken when networks are much sparser or denser.

Results differed between gross output and value-added specifications. As discussed in Gandhi et al. (2017), value-added and gross output productivity measures may vary significantly and lead to substantively different policy implications about the dispersion of firm productivity. My paper reveals that the choice of production function also matters for the estimation of productivity spillovers.

CHAPTER II

Home-Country Productivity Spillovers from US Multinational Activity

II.1 Introduction

For a long time, scholars and policymakers have sought to understand how the activities of multinational enterprises (MNEs) shape the economic landscapes of the countries in which they operate. Of particular interest has been the prospect of multinationals as drivers of international technology diffusion, the idea that firms could gain productivity-enhancing knowledge through interactions with producers from other countries. In this regard, inward foreign direct investment (FDI) by MNEs has received considerable attention: if multinationals generate positive externalities on domestic firms in foreign (host) countries, then there is a policy rationale for attracting inward FDI.[1]

The effect of outward FDI has been explored to a lesser extent and researchers have focused primarily on the impacts on home-country employment, investment and exporting (Lipsey, 2004; Desai et al., 2009). However, policies promoting and subsidizing outward FDI have recently gained traction in developing countries, particularly in China (Perea and Stephenson, 2017). Proponents of such policies highlight the potential for productivity spillovers from multinational parent companies to domestic firms in the home country.

In this paper, I examine the impact of outward FDI in the US by estimating how much the productivity of US firms varies by their exposure to US multinationals through horizontal and vertical linkages. Using data from 1989 to 2016 on publicly-listed companies in *Compustat*, I document a positive relationship between an MNE's productivity and its activities abroad. To examine spillovers, I construct firm-specific measures of exposure to MNEs through vertical buyer-supplier relationships and horizontal product-market competition. My results show that domestic customers and competitors of MNEs tend to be more productive, while MNE suppliers within the US experience a negative impact on their total factor productivity (TFP).

The rest of this paper proceeds as follows: in the next section, I provide an overview of the existing literature. Section II.3 outlines my empirical approach, and section II.4 describes the data. Results are presented in section II.5. Section II.6 concludes.

II.2 Background and Related Literature

The basis for home-country productivity spillovers from outward FDI relies on the existence of an "own-firm effect", that is, the impact of an MNE's activities abroad on the its own productivity. Navaretti and Castellani (2004) and Borin and Mancini (2016) find that Italian firms become more productive after investing abroad, and Hijzen et al. (2011) find weaker productivity impacts for French MNEs. There are several reasons why one could expect a positive own-firm effect of FDI on productivity. MNEs may be become more productive due to scale economies, affiliate specialization within the firm, or knowledge acquired as result of deliberate technology-sourcing[2] in the host-country, and the parent company subsequently learning from its affiliates.

The knowledge or technology acquisition channel is the more salient source of potential home-country productivity spillovers. If an MNE's performance is improved by knowledge acquired abroad, domestic firms in the home country could benefit from relationships with the parent company in the same way that foreign firms in host countries could benefit from relationships with its affiliates. That is, transmission channels for spillovers from outward FDI are likely to be similar to those discussed in the literature on inward FDI. Within an industry, greater domestic productivity could be

[1] See Smeets (2008), Harrison and Rodríguez-Clare (2010), Havranek and Irsova (2011) and Alfaro (2017) for reviews of the literature.

[2] For instance, early work by Kogut and Chang (1991) and Yamawaki (1993) suggests Japanese firms' investments in the US were aimed at tapping into the technological capacity of innovative US industries.

driven by competitive pressures, imitation of manufacturing processes or managerial strategies (Wang and Blomström, 1992), and workers moving to domestic firms with knowledge retained from experience in MNEs (Glass and Saggi, 2002). Vertical spillovers across buyer-supplier relationships could also be generated by customers of MNEs gaining access to higher-quality inputs, or suppliers benefiting from being integrated into MNEs' more efficient supply chains (Javorcik, 2004; Alfaro-Urena et al., 2019).

Empirical evidence of home-country productivity spillovers from outward FDI is limited. At the macroeconomic level, Potterie and Lichtenberg (2001) estimates the impact of changes in a country's R&D stock on its trade and investment partners, and finds larger spillovers from investing in R&D-intensive countries than from being invested in by those countries. Castellani and Pieri (2016) study a set of European countries, and finds that home-country labor productivity growth is positively correlated with outward investments in sales and distribution, but negatively correlated with outward investments in manufacturing activities. At the firm level, Braconier et al. (2001) find no relationship between Swedish firms' labor productivity and research and development (R&D) in foreign countries, while Globerman et al. (2000) show that domestic firms are more likely to cite patents from foreign locations in which Swedish multinationals have greater investments. Using data from on Estonian enterprises, Vahter et al. (2007) find a positive own-firm effect of outward FDI but weak evidence of intra-sectoral spillovers. My paper is most closely related to work by Tang and Altshuler (2015), who find a positive relationship between the productivity of domestic publicly-listed companies in the US and multinational activities in downstream industries.

In addition to providing further evidence on the existence of outward FDI spillovers, I improve upon existing work by exploiting firm-level variation in exposure to multinationals within the same product space and in buyer-supplier relationships. There are several advantages of firm-specific linkages over industry-level proxies. Firstly, it enables me to detect spillovers that would otherwise be masked by sector aggregation. This has been shown to be quantitatively meaningful in the inward FDI literature. For instance, Newman et al. (2015) find that domestic Vietnamese firms who purchase inputs from MNE affiliates have higher productivity, whereas industry-level forward spillovers from MNEs is negative. Secondly, by observing the interfirm linkages, I avoid making assumptions about the MNEs' input sourcing behavior which, as Barrios et al. (2011) point out, are implicit in standard industry-level measures.

Furthermore, I am able to explore richer interactions between vertical and horizontal effects. Consider a scenario represented in Figure II.1, suppliers A and B in the upstream sector sell to competitor A and the MNE respectively, while customers A and B in the downstream sector buy from the MNE and competitor B, respectively. Supplier B could experience direct backward spillovers (BS_{MB}) due to its trading relationship with the MNE. Supplier A, on the other hand, is only indirectly affected by the MNE, either through the horizontal spillovers from Supplier B or the horizontal impact of the MNE on Competitor A (BS_{MAA}) who purchases from Supplier A. Industry-level measures of MNE exposure would only recover a composite estimate of the direct and indirect vertical spillovers, while my approach is able to distinguish between them and quantify the relative importance of each channel.

An additional contribution of my work is that I distinguish between general productivity spillovers in the US economy and the specific effects of MNE activities. Many of the mechanisms through which home-country spillovers from MNEs may occur are not exclusive to outward FDI; knowledge acquired by any other means could be transmitted in much the same way as technical expertise gained abroad. To the extent that exposure to more productive firms has differential impacts from interacting with less productive firms, estimated effects of transacting or competing with MNEs may have more to do with their producitivity than their international activities. Existing studies show theoretically (Helpman et al., 2004) and empirically (Wagner, 2011) that more productive firms engage in FDI. Furthermore, as discussed above, outward FDI may also raise the productivity of multinationals themselves due to scale economies rather than knowledge transfers. This is an important distinction because the policy implications significantly differ. If outward FDI results knowledge transfers or spillovers, this would be reflected in both the impact of MNEs themselves

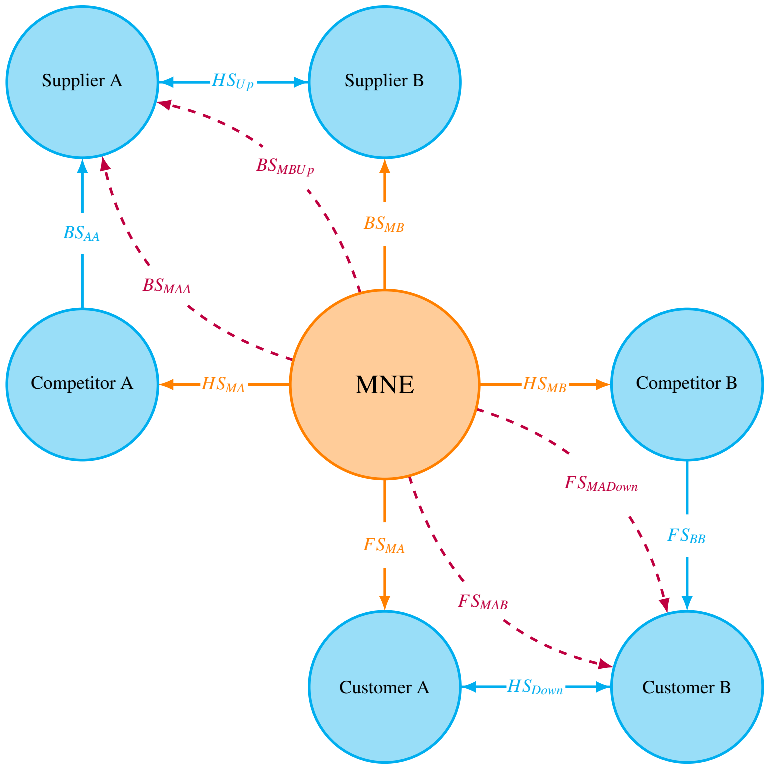


Figure II.1: Possible interactions between horizontal and vertical spillovers.

Arrows show the direction of spillovers. Solid and dashed lines indicate direct and indirect spillovers respectively. BS, HS, and FS denote backward, horizontal and forward spillovers respectively.

and the indirect effect of their increased productivity, and could justify outward FDI promotion policies. However, if outward FDI does not generate any additional knowledge, there could still be positive spillovers operating through MNEs' raised productivity, but would make a less compelling case for the promotion of outward FDI in particular.

II.3 Empirical Approach

In this section, I describe my empirical strategy for recovering MNE spillover effects, which involves jointly estimating a firm-level production function and a productivity process that depends on a firm's interactions with MNEs and across industries. I incorporate spillovers into the productivity estimation process because, as I demonstrate in the previous chapter, failing to account for the way spillovers could affect a firm's input choices and output through its productivity may bias estimates TFP and spillovers. In section II.3.1, I present a specification of the firm's productivity process, then outline how I embed it within the production function estimation procedure in II.3.2.

II.3.1 The Productivity Process with MNE Spillovers

To estimate the relationship between a firm's productivity and its exposure to multinationals, researchers typically estimate an equation of the form:

$$\omega_{ist} = \beta_1 + \beta_H Horizontal_{st} + \beta_B Backward_{st} + \beta_F Forward_{st} + \beta_s + \beta_t + \eta_{it} \tag{II.1}$$

where ω_{ist} is the natural log of the Total Factor Productivity (TFP) of firm i in industry s at time t, and $Horizontal_{st}$, $Backward_{st}$, and $Forward_{st}$ are industry-level measures of multinational activity in the same, downstream and upstream industries respectively. β_s and β_t are industry and year fixed effects.

However, in order to disentangle direct and indirect effects, as well as distinguish between general and MNE-specific spillovers, I estimate the following specification:

$$\begin{aligned}\omega_{ist} = \quad & \alpha_1 + \delta \text{MNE}_{ist-1} + \gamma_H Horizontal_{ist} + \gamma_B Backward_{ist} + \gamma_F Forward_{ist} \\ & + \rho\,\omega_{ist-1} + \lambda_H \overline{\omega}^{H_i}_{jst} + \lambda_B \overline{\omega}^{B_i}_{jst} + \lambda_F \overline{\omega}^{F_i}_{jst} + \alpha_{st} + \eta_{ist} \end{aligned} \tag{II.2}$$

where, as before, ω_{ist} is the firm's log(TFP) in the period, and MNE_{ist-1} is the firm's multinational status in the previous period. I use lagged MNE status to allow reverse technology transfer from affiliates to take place with a one-period lag, and δ captures the *own-firm* effect of multinational experience. $Horizontal_{ist}$, $Backward_{ist}$, and $Forward_{ist}$ are the shares of a firm i's current product-market competitors, customers, and suppliers that were multinationals in the previous year. Therefore, γ_H, γ_B and γ_F measure the direct spillover effects of competing and transacting with multinationals.

To account for general productivity spillovers, I include $\overline{\omega}^{H_i}_{jst}$, $\overline{\omega}^{B_i}_{jst}$, and $\overline{\omega}^{F_i}_{jst}$ which are averages of the log(TFP) of firm i's current competitors, customers and suppliers, respectively. The corresponding λ_H, λ_B, and λ_F are *endogenous network effects*, that reflect the impact of competing and trading with more productive firms.

Note that, by using firm-specific measures, I am able to include industry-year fixed effects α_{st} to account for time-varying industry-wide changes in productivity and MNE exposure. Finally, I include firm i's lagged productivity ω_{ist-1} to specify an AR-1 productivity process that can be embedded in the TFP estimation procedure.

Following the network effects literature,[3] I represent (II.2) in a vectorized form by constructing interaction matrices: G^H_t, G^B_t and G^F_t, where element G^H_{ijt} is a weight specifying firm j's proximity to firm i in the product-market space, G^B_{ijt} is firm i's sales to firm j as a share of firm i's sales to all other firms, and G^F_{ijt} is firm i's purchases from firm j as a share of firm i's purchases from all other firms. Note that these matrices are time-varying, allowing for changes in the existence and importance of firm-to-firm links. Then equation (II.2) becomes:

$$\begin{aligned}\omega_t = \quad & \alpha_1 \iota + \delta \text{MNE}_{t-1} + \gamma_H G^H_t \text{MNE}_{t-1} + \gamma_B G^B_t \text{MNE}_{t-1} + \gamma_F G^F_t \text{MNE}_{t-1} \\ & + \rho\,\omega_{t-1} + \lambda_H G^H_t \omega_t + \lambda_B G^B_t \omega_t + \lambda_F G^F_t \omega_t + \alpha_{st} + \eta_t \end{aligned} \tag{II.3}$$

where each variable x_t is a column vector of x_{ist}'s and ι is a vector of ones.

The reduced form of this vectorized equation allows for closer examination of potential direct and indirect impacts of MNE activities. Let I be the identity matrix, $\boldsymbol{\lambda} = (\lambda_H, \lambda_B, \lambda_F)'$, $\boldsymbol{\gamma} = (\gamma_H, \gamma_B, \gamma_F)'$, $G_t(\boldsymbol{\lambda}) = \lambda_H G^H_t - \lambda_B G^B_t - \lambda_F G^F_t$, and $G_t(\boldsymbol{\gamma}) = \gamma_H G^H_t - \gamma_B G^B_t - \gamma_F G^F_t$. If $|\lambda_H| < 1, |\lambda_B| < 1,$ and $|\lambda_F| < 1$, then equation (II.3) can be rewritten as:[4]

$$\begin{aligned}(I - G_t(\boldsymbol{\lambda}))\omega_t &= \delta \text{MNE}_{t-1} + G_t(\boldsymbol{\gamma})\text{MNE}_{t-1} + \rho\,\omega_{t-1} + \alpha_{st} + \eta_t \\ \Longrightarrow \omega_t &= (I - G_t(\boldsymbol{\lambda}))^{-1} \left[\delta \text{MNE}_{t-1} + G_t(\boldsymbol{\gamma})\text{MNE}_{t-1} + \rho\,\omega_{t-1} + \alpha_{st} + \eta_t\right] \\ \omega_t &= \sum_{\tau=0}^{\infty} G_t(\boldsymbol{\lambda})^{\tau} (\delta I + G_t(\boldsymbol{\gamma}))\,\text{MNE}_{t-1} + \rho \sum_{\tau=0}^{\infty} G_t(\boldsymbol{\lambda})^{\tau} \omega_{t-1} + \sum_{\tau=0}^{\infty} G_t(\boldsymbol{\lambda})^{\tau} (\alpha_{st} + \eta_t) \end{aligned} \tag{II.4}$$

Equation II.4 implies that a firm's productivity is influenced by an infinite series of combinations of direct and indirect spillovers from multinational activity in its network. Given the assumption that the λ's are bounded in absolute value by 1, then the indirect effects, operating through the endogenous network effects, lessen in importance as the degrees

[3] See Lee (2003) and Bramoullé et al. (2009).

[4] The constant has been suppressed for ease of exposition.

of separation between firms within the network increases. Taking a closer look at the first two terms in the first summation on the right-hand side of equation (II.4):

$$\begin{aligned}\sum_{\tau=0}^{1} G_t(\boldsymbol{\lambda})^{\tau}\left(\delta I + G_t(\boldsymbol{\gamma})\right)\mathrm{MNE}_{t-1} &= \left(\delta I + G_t(\boldsymbol{\gamma}) + \delta G_t(\boldsymbol{\lambda}) + G_t(\boldsymbol{\lambda})G_t(\boldsymbol{\gamma})\right)\mathrm{MNE}_{t-1} \\ &= \delta \mathrm{MNE}_{t-1} + G_t(\delta\boldsymbol{\lambda}+\boldsymbol{\gamma})\mathrm{MNE}_{t-1} + G_t(\boldsymbol{\lambda})G_t(\boldsymbol{\gamma})\mathrm{MNE}_{t-1} \end{aligned} \tag{II.5}$$

$G_t(\delta\boldsymbol{\lambda}+\boldsymbol{\gamma})\mathrm{MNE}_{t-1}$ in equation II.5 shows that without controlling for general productivity spillovers among firms, the total effect of interacting with MNEs can be decomposed into a direct effect (γ) that is MNE-specific and an indirect effect ($\delta\boldsymbol{\lambda}$) that operates through the impact of an MNE's activities on their own productivity. $G_t(\boldsymbol{\lambda})G_t(\boldsymbol{\gamma})\mathrm{MNE}_{t-1}$ also highlights some of the rich second-order interactions of spillover effects such as $\lambda_F\gamma_H G_t^F G_t^H \mathrm{MNE}_{t-1}$, which is the effect of a firm's suppliers competing with multinationals or $\lambda_B^2(G_t^B)^2\mathrm{MNE}_{t-1}$, the effect of a firm supplying inputs to MNEs' suppliers.

II.3.2 Estimating TFP

To recover firm-level TFP estimates, along with the spillover coefficients, I use my modification of the Gandhi et al. (2020) approach for estimating gross output production functions introduced in the previous chapter. I estimate a Hicks-neutral production function of labor, capital, and intermediate inputs:

$$\begin{aligned} Y_t &= F(L_t,K_t,M_t)e^{\omega_t+\varepsilon_t} \\ \Longleftrightarrow y_t &= f(\ell_t,k_t,m_t)+\omega_t+\varepsilon_t \end{aligned} \tag{II.6}$$

I assume materials are flexible, labor and capital have dynamic implications and the error terms ε_t are unconditionally independent.

The procedure consists of two stages. The first stage exploits first order conditions from profit maximization to estimate the elasticity of intermediate inputs with respect to output. Given the production technology above, the firm chooses materials to maximize profits:

$$\max_{M_t} P_t E[F(L_t,K_t,M_t)e^{\omega_t+\varepsilon_t}] - P_t^M M_t \tag{II.7}$$

where P_t and P_t^M are the prices of output and materials respectively. The static first order condition with respect to materials implies:

$$s_t = \ln\left(\frac{\partial}{\partial m_t} f(\ell_t,k_t,m_t)\right) + \ln(\mathscr{E}) - \varepsilon_t \tag{II.8}$$

$$\Longrightarrow\ s_t = \ln D^{\mathscr{E}}(\ell_t,k_t,m_t) - \varepsilon_t \tag{II.9}$$

where $s_t \equiv \ln(\frac{P_t^M M_t}{P_t Y_t})$ is the log of materials expenditure share of revenue, $D^{\mathscr{E}}(\ell_t,k_t,m_t) \equiv \dfrac{\partial}{\partial m_t} f(\ell_t,k_t,m_t)\times\mathscr{E}$ and $\mathscr{E} \equiv E[e^{\varepsilon_t} \mid \mathscr{I}_t] = E[e^{\varepsilon_t}]$. I approximate $D^{\mathscr{E}}(\ell_t,k_t,m_t)$ by a second-degree polynomial in labor, capital and materials, and estimate equation (II.9) using non-linear least squares. Using the estimated coefficients, I compute the implied materials elasticity:

$$\widehat{D}(\ell_t,k_t,m_t) = \frac{\widehat{D}^{\mathscr{E}}(\ell_t,k_t,m_t)}{\widehat{\mathscr{E}}} \tag{II.10}$$

where $\widehat{\mathscr{E}}$ is the mean of the first-stage residuals. By the fundamental theorem of calculus:

$$\int D(\ell_t, k_t, m_t) dm_t = f(\ell_t, k_t, m_t) + \mathscr{C}(\ell_t, k_t) \tag{II.11}$$

$$\implies y_t - \int D(\ell_t, k_t, m_t) dm_t - \varepsilon_t = -\mathscr{C}(\ell_t, k_t) + \omega_t \tag{II.12}$$

Therefore I can compute:

$$\widehat{\mathscr{Y}_t} = y_t - \int \widehat{D}(\ell_t, k_t, m_t) dm_t - \widehat{\varepsilon}_t \tag{II.13}$$

In the second stage of the procedure, I approximate $\mathscr{C}(\cdot)$ by a second-degree polynomial, normalized to contain no constant, and estimate it using two-step generalized method of moments (GMM) as follows. Starting with a guess $\widetilde{\mathscr{C}}(\cdot)$,[5] I compute:

$$\widetilde{\omega}_t = \widehat{\mathscr{Y}_t} - \widetilde{\mathscr{C}}(\ell_t, k_t)$$
$$\text{and } \widetilde{\omega}_{t-1} = \widehat{\mathscr{Y}_{t-1}} - \widetilde{\mathscr{C}}(\ell_{t-1}, k_{t-1})$$

Then estimate:

$$\widetilde{\omega}_t = \alpha_1 \iota + \rho \widetilde{\omega}_{t-1} + G_t(\boldsymbol{\lambda})\widetilde{\omega}_t + \delta \text{MNE}_{t-1} + G_t(\boldsymbol{\gamma})\text{MNE}_{t-1} + \alpha_{st} + \eta_t$$

by two-stage least squares, with $G_t^H \widetilde{\omega}_{t-1}$, $G_t^B \widetilde{\omega}_{t-1}$, $G_t^F \widetilde{\omega}_{t-1}$ and $\{G_t^q G_t^r MNE_{t-1}\}_{r,q \in \{H,B,F\}}$ as instruments for $G_t^H \widetilde{\omega}_t$, $G_t^B \widetilde{\omega}_t$, $G_t^F \widetilde{\omega}_t$. Then I find a new set parameters of $\widetilde{\mathscr{C}}(\cdot)$ that satisfy the moments:

$$E[\eta_t \circ \ell_t, k_t, \ell_t k_t, \ell_t^2, k_t^2] = 0 \tag{II.14}$$

where $\circ$ is the Hadamard product and the empirical moments are constructed using $\widetilde{eta}_t$ obtained the estimation above. The process is repeated until the parameters converge to a solution $\widehat{\mathscr{C}}(\cdot)$ and $(\widehat{\rho}, \widehat{\delta}, \widehat{\alpha}_1, _{\widehat{\gamma}}, \widehat{\boldsymbol{\lambda}})$.

II.4 Data

In this section, I describe the sources of data used in my analysis, examine the characteristics of my sample, and discuss some of the advantages and limitations of the data.

II.4.1 Data Sources

This study uses *Compustat* data from 1989-2016 on non-agricultural publicly-listed companies in the US. Firms' financial information is obtained from their annual reports filed with the Securities and Exchange Commission (SEC). I construct measures of inputs and output from the firms' reported expenditures and sales, deflated by industry-level price indices from the Bureau of Economic Analysis (BEA).[6] I restrict the sample to domestic US firms and multinationals with US-based parent companies by dropping firms with headquarters located outside the US.

Information on firms' international activities are collected from the *Compustat* Business Segments file containing information on the geographic segments in which the firm operates. I classify a firm as a multinational if it has

[5] I use OLS estimates as starting values.

[6] See the appendix for details on variable construction.

subsidiaries in any non-US location. Therefore, $MNE_{t-1} = 1$ if a firm had any subsidiaries outside the US in the previous year, and is 0 otherwise.

Firm-level buyer-supplier linkages are obtained from the *Compustat* Customer Segments file. Financial Accounting Standards no. 14 requires firms to report major customers that are responsible for 10% or more of a firms' sales in a year. I use the matches constructed in the preceding chapter, similar to the dataset used in Atalay et al. (2011). This enables me to directly identify multinationals' buyers and suppliers, rather than relying on input-output tables. As Barrios et al. (2011) show, industry-based vertical spillover measures of exposure to multinationals are sensitive to assumptions about the use of domestic and imported inputs, as well as MNEs' input-sourcing decisions.

Horizontal linkages between firms are obtained from Hoberg and Phillips (2010) and Hoberg and Phillips (2016) which measures proximity within the product-market space based on the similarity between firms' business descriptions. Identifying competitors in this way is particularly advantageous in my setting for two reasons. First, this yields granular measures of who multinationals' competitors are. Secondly, unlike typical industry classifications, the product similarity measure does not impose transitivity: that firms i and j, and j and k are close competitors does not automatically imply that i and k are also close competitors. Therefore, the interaction matrix constructed using this product-market similarity measure satisfies the linear independence condition needed to identify endogenous productivity spillovers described in Chapter 1.

I restrict the sample period to 1989-2016 because 1989 is the first year in which the horizontal linkage data is available and 2016 is the last year with matched customer-supplier data. I also drop firms with no vertical or horizontal links. The resulting sample is a set of 5,466 unique firms and 33,723 firm-year observations. The vertical relationship data contains 12,139 unique buyer-supplier links and 47,468 dyad-year observations, while the horizontal network consists of 138,303 unique competitor pairs and 572,303 horizontal links across all years.

II.4.2 Descriptive Statistics

Table II.1 summarizes some characteristics of firms in the sample across all years. Because this study only examines publicly-listed companies, firms in the sample tend to be large across the board, and MNEs comprise more than half of firm-year observations. MNEs are, on average, larger than domestic firms with about 7.65 billion (2009 USD) in annual sales over the sample period, compared to 3.2 billion for domestic firms. MNEs also tend to have larger capital stocks, purchase more intermediate inputs, and hire more employees on average than their domestic counterparts. However, they also tend to vary more in size, with higher standard deviations across all of these measures.

The network characteristics in Table II.1 are all weighted sums or averages, with weights corresponding to the product-space similarity scores for the horizontal links, and dyad-specific sales for the vertical links. Domestic firms are less likely to reported as major customers, with an average in-degree of 0.69 while about 1.49 suppliers are identified per MNE. There does not appear to be a substantial difference between the number of major customers reported by domestic firms and MNEs. Firms of both types also tend to have similar shares of MNEs among their customers. However, MNEs have a higher average share of MNEs as suppliers at 21% compared to 9% for domestic firms. This may again be function of the reporting threshold, with domestic firms less likely to be reported by larger MNEs than by smaller domestic firms.

The horizontal network is much denser than the vertical network, with about 14.65 and 17.29 competitors on average for domestic and multinational firms respectively. MNEs tend to compete closely with each other, with an average of 12.22 horizontal links to MNEs and with multinationals comprising 59% of their competitors on average. Domestic firms also predominantly compete with other domestic firms, with MNEs only making up 25% of their competitors on average. These sorting patterns in the product-market space would be obscured by industry-level measures, which typically assume that all firms within the same industry face equal exposure to MNEs.

II.5 Results

II.5.1 TFP Estimates

This section presents results of the model presented in section II.3 on the data described above. I estimate three specifications: the first includes network effects from MNE exposure but no endogenous productivity spillovers, the second contains MNE-specific and general network effects, and the third accounts for both types of spillovers and controls for network cluster-specific productivity shocks in each year. All specifications include industry-year and region fixed effects, and control for a firm's MNE status in the production function.

The estimated production function parameters are similar across all specifications, with elasticities of output with respect to labor, capital and intermediate inputs at about 0.25, 0.15 and 0.52 respectively. Figure II.2 depicts the distribution of estimated productivity in 2016 from each specification, which does not differ substantially in mean or variance.

Estimated productivity does differ across MNEs and domestic firms, and between domestic firms that compete or trade with MNEs and those that do not. Figure 3 shows how average log(TFP) from the third specification compares over the sample period across firm types. In the first panel, I compare all firms based on their multinational status. MNEs are more productive than domestic firms on average, except for the period between 2000 and 2005 when average productivity growth for both types of firms proceeded at a similar pace. In the other three panels, I only examine domestic firms, and categorize them by whether or not they have at least one MNE customer, supplier or competitor. Throughout the sample period, domestic firms that purchase from MNEs tend to be more productive than their counterparts that do not, while the opposite pattern holds for domestic suppliers of MNEs. MNE competitors and non-competitors are on similar productivity growth paths at the beginning of the sample, but their trajectories begin to diverge in 2000, with MNE competitors exhibiting greater productivity.

II.5.2 Productivity Spillovers from MNEs

These patterns reflect the productivity process coefficients and spillovers estimates in Tables II.2 and II.3. In Table II.3, Columns (1) and (2) are network effects estimated within the same productivity process for domestic firms and MNEs without endogenous network effects, the next two columns report coefficients from the second specification with endogenous effects, and columns (5) and (6) reports estimates from the third specification that accounts for common productivity shocks with network fixed effects. In Table II.2, each column represents the three respective specifications mentioned above.

My results suggest that the own-firm effect is positive: MNEs are about 0.7 to 1% more productive in the short run. Given that productivity is highly persistent with an AR1 parameter of 0.89, this implies a long-run effect of 7 to 10%. Across all specifications, firms that have a higher share of MNEs among their competitors or suppliers are more productive, while firms with a greater share of MNE customers are less productive.

However, the magnitudes of these effects differ depending on whether or not endogenous effects are included in the productivity process. Results in column (1) of Table II.3 suggest that domestic firms who only compete with MNEs are about 2.8% more productive than domestic firms who compete only with other domestic firms, but columns (3) and (5) indicate an effect size of about 1.5%. The difference is even starker for multinational firms: without accounting for endogenous effects, there is 1% productivity advantage of competing with only other MNEs as compared to only domestic firms, but it diminishes to a statistically insignificant 0.2% when we factor in the effect of being in a more competitive product-market in general.

Focusing on the third specification reported in columns (5) and (6) of Table II.3, spillover estimates vary between MNEs and domestic firms. Multinational firms experience a smaller positive impact of competing with MNEs and negative effect of supplying to MNEs than domestic firms do. The opposite holds for the impact of purchasing from a greater share of MNEs; the effect is higher for multinationals who experience a short-run 1.3% productivity boost compared to 0.96% for domestic firms.

These disparities are further exacerbated by the differences in the actual observed interactions with MNEs. The average multinational for whom MNEs comprise 21% of its suppliers experiences a 0.27% productivity gain compared to the average domestic firm's gain of 0.086% from the MNEs that make up 9% of its suppliers. Furthermore, when I consider spillovers to the average domestic firm from its interactions with MNEs across vertical and horizontal linkages, the overall effect is quite modest: a 0.375% gain from 25% of its competitors, a 0.581% decline due to 45% of its customer base, and a 0.086% effect from 9% of its suppliers, yields a combined negative impact of 0.12%.

Indirect impacts of trading and competing with multinationals are also relatively muted in comparison to the direct spillovers. Given the own-firm effect in Table II.2 and the endogenous productivity spillovers in Table II.3, domestic firms that compete with only MNEs get an additional 0.0012% productivity boost due to the increased TFP that MNEs enjoy from their international activities.

My results differ from the findings by Tang and Altshuler (2015) who find positive but insignificant horizontal spillovers from US multinationals to domestic firms, significant positive spillovers from MNEs in downstream sectors to domestic firms upstream (backward spillovers), and marginally significant negative forward effects of MNEs in upstream industries on domestic firms downstream (forward spillovers). There are several reasons for these differences. First, as discussed earlier, Tang and Altshuler (2015) construct measures of MNE exposure at the industry level. In my case, I focus on firm-specific exposure based on the observed interactions between firms. Therefore, the inclusion of industry-year fixed effects eliminates the kind of variation that was used to identify spillovers in Tang and Altshuler (2015). Finally, I estimate a gross output production function on all non-agricultural sectors, rather than a value-added production function on the manufacturing sector.

The positive impact of MNEs on their customers rather than their suppliers is the reverse of what has been found in the literature on host-country effects. This may suggest an important difference between the value of MNE operations at home and abroad: an MNE in a foreign country may be substantially closer to the technological frontier than domestic firms and can serve as an important source of innovation for their suppliers, whereas in the home country, MNEs and their domestic suppliers may be proximate in the technology space. Therefore, the added benefit of MNEs at home may arise mainly from their ability to supply inputs at a lower cost, higher quality, or more efficient pace to their customers, due to their experience with organizing complex supply chains globally.

II.5.3 Alternative Measures of MNE Exposure

So far, I have measured multinational activity by whether or not a firm reported a foreign subsidiary in the previous year. Now, I consider how my results change if multinational status is measured by how active these foreign affiliates are, as proxied by their sales abroad. I construct two alternative measures: an indicator for whether the firm had any international sales in the preceding year and a firm's foreign sales as a share of total revenue. Table II.4 reports estimates from a specification including both endogenous productivity spillovers and network fixed effects.

Both measures yield qualitatively similar results: positive horizontal and forward spillovers, and negative backward spillovers for both domestic firms and MNEs. However, intensity of foreign activity as captured by the share of international sales, appears to matter. Compared to the benchmark 1.5% short-run productivity boost to domestic firms from competiting exclusively with MNEs, there is a 4.67% gain if those multinationals are predominantly active abroad (i.e. have a foreign sales share close to 1).

II.6 Conclusion

Overall, the findings of this study suggest that there are home-country spillovers from MNEs to domestic firms in the United States. By using observed horizontal and vertical relationships between firms, I am able to identify effects that operate directly and indirectly through these linkages. These results do not, however, provide a strong case for subsidizing outward FDI. For the average domestic firm, the combined impact of all types of interactions with MNEs is modest and negative.

Nevertheless, the findings of this study should interpreted with caution because of several limitations. First, the composition of the sample and observed vertical links means that the findings here may not be representative of the population of US firms. Secondly, I cannot directly test the channels through which these spillovers occur. For example, this study does not distinguish between the transmission of exchange-rate shocks and productivity gains. Future work could examine the impact of additional factors such as affiliate location: if reverse technology transfers from affiliates to the parent company are taking place, then one would expect greater spillovers from firms with subsidiaries in technologically advanced locations.

Another limitation, shared by many other studies of productivity spillovers, is that I estimate productivity using revenues rather than physical output. Consequently, my estimates reflect overall impacts on profitability rather than simply physical productivity. Given that the observed vertical linkages tend to be between firms and their major customers, this may partly explain the negative backward spillovers, especially if MNEs are adept at securing discounts from their suppliers.

Table II.1: Firm Characteristics

	Domestic		Multinational	
	Mean	SD	Mean	SD
Sales	3.2	10.04	7.65	23.68
Employees (thousands)	10.62	32.93	22.69	80.08
Capital stock	3.08	10.62	5.2	20.08
Materials	2.26	7.53	5.51	20.06
No. of suppliers	0.69	2.6	1.49	5.73
No. of customers	1.13	1.13	1.08	1.36
No. of competitors	14.65	22.54	17.29	23.99
No. of MNE suppliers	0.31	1.66	1.03	4.67
No. of MNE customers	0.69	0.85	0.85	1.17
No. of MNE competitors	5.12	10.43	12.22	18.27
MNE share of suppliers	0.09	0.27	0.21	0.39
MNE share of customers	0.45	0.47	0.5	0.48
MNE share of competitors	0.25	0.31	0.59	0.39
Observations	16443		17280	

This table reports means and standard deviations of characteristics of firms in the sample over the period 1989-2016. Monetary values are in 2009 billion USD. All supplier, customer and competitor characteristics are weighted by the value purchased, value sold, and product-market distance respectively.

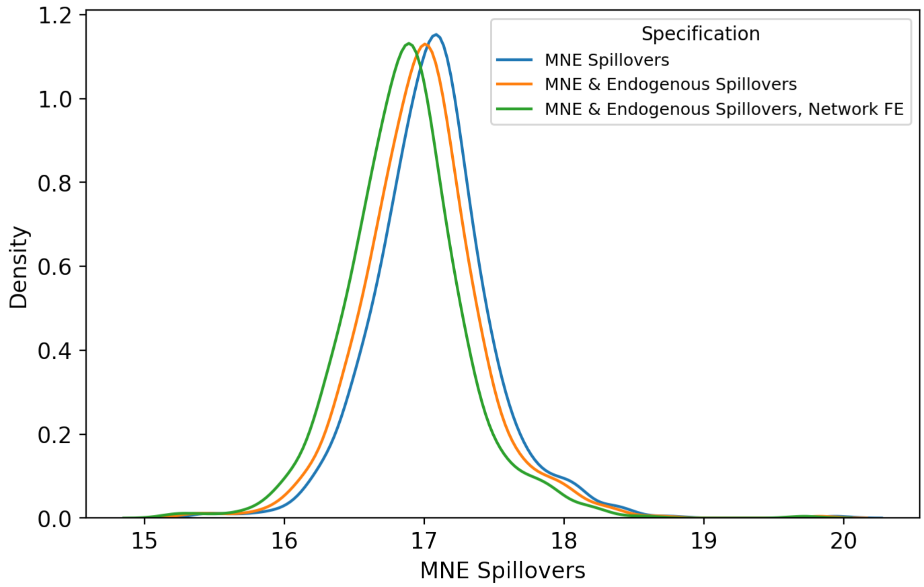


Figure II.2: Distribution of ln(TFP) in 2016

This figure shows the distributions of ln(TFP) in 2016, estimated on a sample of firms in *Compustat* using the Iyoha (2021) modification of the Gandhi et al. (2020) procedure to allow for productivity spillovers from MNEs, endogenous network effects, and network fixed effects.

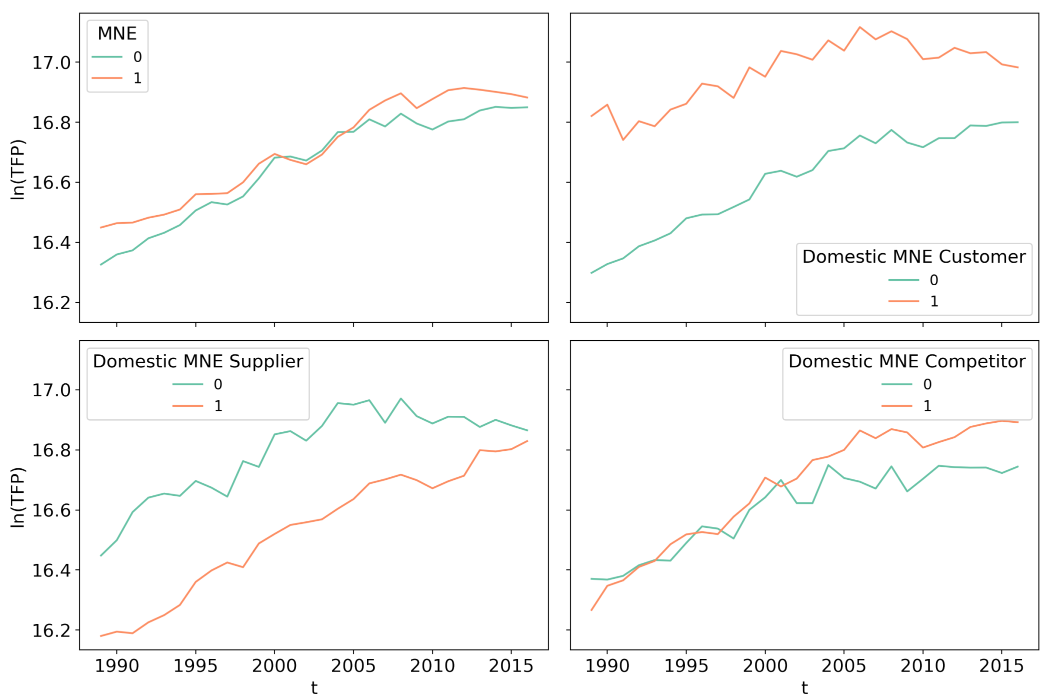


Figure II.3: Average Productivity by Firm Type and Trading Partner

The first panel of this figure compares estimated productivity of all firms by MNE status. The other three panels compare domestic firms by whether or not they buy from, supply to or compete with at least one MNE.

Table II.2: Productivity Process Coefficients

	Dependent Variable: $\ln\text{TFP}_t$		
	(1)	(2)	(3)
$\ln(TFP)_{t-1}$	0.887	0.887	0.886
	(0.005)	(0.005)	(0.005)
MNE_{t-1}	0.007	0.011	0.012
	(0.004)	(0.005)	(0.005)
Constant	1.947	1.88	1.878
	(0.093)	(0.09)	(0.091)
Network FE	No	No	Yes

This table reports coefficients of a linear productivity process from a productionfunction estimated on US firms in Compustat (in logs) with the Iyoha (2021) modification of the Gandhi et al. (2020) procedure. Standard errors are in parentheses. All specifications include industry-year and region fixed effects.

Table II.3: Productivity Spillovers

	Dependent Variable: $\ln\text{TFP}_t$					
	Domestic	MNE	Domestic	MNE	Domestic	MNE
	(1)	(2)	(3)	(4)	(5)	(6)
Competitors' MNE_{t-1}	0.0278	0.0104	0.0149	0.0024	0.0151	0.0016
	(0.005)	(0.0035)	(0.0059)	(0.0049)	(0.006)	(0.0049)
Customers' MNE_{t-1}	-0.014	-0.0098	-0.0129	-0.0108	-0.0129	-0.0104
	(0.0038)	(0.0029)	(0.0047)	(0.0047)	(0.0047)	(0.0047)
Suppliers' MNE_{t-1}	0.0137	0.0228	0.009	0.0122	0.0096	0.0127
	(0.004)	(0.003)	(0.0045)	(0.0038)	(0.0046)	(0.0039)
Competitors' $\ln(TFP)_t$			0.001	0.0008	0.001	0.0007
			(0.0002)	(0.0003)	(0.0002)	(0.0003)
Customers' $\ln(TFP)_t$			0.0006	0.0005	0.0006	0.0005
			(0.0003)	(0.0003)	(0.0003)	(0.0003)
Suppliers' $\ln(TFP)_t$			0.001	0.0013	0.001	0.0013
			(0.0003)	(0.0002)	(0.0003)	(0.0003)
Network FE	No	No	No	No	Yes	Yes

This table reports network effects from a production function estimated on US firms in Compustat (in logs) with the Iyoha (2021) modification of the Gandhi et al. (2020) procedure.Standard errors are in parentheses. All specifications include industry-year and region fixed effects.

Table II.4: Productivity Spillovers with Alternative Measures of MNE Exposure

	Dependent Variable: $\ln\text{TFP}_t$			
	Domestic	MNE	Domestic	MNE
	(1)	(2)	(3)	(4)
Competitors' any foreign sales$_{t-1}$	0.0154	0.0007		
	(0.006)	(0.0049)		
Competitors' foreign sales share$_{t-1}$			0.0467	0.0024
			(0.0137)	(0.008)
Customers' any foreign sales$_{t-1}$	-0.0132	-0.0102		
	(0.0047)	(0.0046)		
Customers' foreign sales share$_{t-1}$			-0.0373	-0.0225
			(0.0102)	(0.007)
Suppliers' any foreign sales$_{t-1}$	0.0104	0.0131		
	(0.0046)	(0.0039)		
Suppliers' foreign sales share$_{t-1}$			0.0228	0.023
			(0.0121)	(0.0069)
Competitors' $\ln(TFP)_t$	0.001	0.0007	0.0011	0.0007
	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Customers' $\ln(TFP)_t$	0.0006	0.0005	0.0005	0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Suppliers' $\ln(TFP)_t$	0.001	0.0012	0.001	0.0014
	(0.0003)	(0.0003)	(0.0003)	(0.0002)

This table reports network effects from a production function estimated on US firms in Compustat (in logs) with the Iyoha (2021) modification of the Gandhi et al. (2020) procedure. Standard errors are in parentheses. All specifications include network, industry-year, and region fixed effects.

CHAPTER III

The Impact of the US-China Trade War on Latin America: Evidence from Importer-Exporter Linkages

III.1 Introduction

In 2018, the United States Trump Administration enacted a series of protectionist policies against several of its major trade partners, including a series of tariffs targeting about $247 billion in imports from China (Fajgelbaum et al., 2020). Many countries responded to these policies by imposing retaliatory tariffs and filing cases against the US at the World Trade Organization (WTO). The scope of these tariff increases has renewed interest in third-country effects of bilateral trade policies. These impacts are typically analyzed in the context of trade liberalization, when countries enter into bilateral trade agreements; the events of 2018 provide an opportunity for examining the third-country effects of protectionism as well.

In this paper, I focus specifically on restrictions placed by the US and China on imports from each other, and empirically investigate the short-run third-country effects of the trade war on importer-exporter relationships between the US, China, and a subset of Latin American countries. Specifically, I examine trade diversion and trade deflection to Mexico and Colombia. I find very little evidence that trade between Colombia and the US or China, in goods subject to the tariffs, changed significantly as a result of the trade war. I also find no evidence of changes in maritime trade between Mexico and the US or China in the affected goods.

The rest of this chapter proceeds as follows: section III.2 provides background on the US-China trade war and a review of related literature. In section III.3, I discuss my estimation strategy for quantifying trade diversion and deflection, while section III.4 describes the data used in the empirical analysis. I present my results in section III.5. Section III.6 concludes.

III.2 Background and Literature

III.2.1 The US-China Trade War

The US-China trade war began in early 2018 with US-imposed tariffs on imports of solar panels and washing machines in February, and steel and aluminum in March. These tariffs applied to a broad set of countries, including China. In April, China responded with retaliatory tariffs on imports of aluminum, wine, fruit and meat from the US.[1] Between July and September, the trade war intensified with both the US and China imposing additional tariffs that raised the average tariff on US imports of goods from China from 3.8 to 12 percent, and on China's imports of US goods from 7.2 to 18.3 percent (Bown, 2019).

There are several reasons why the US-China trade war offers a useful setting for studying third-country effects. As Amiti et al. (2019) points out, the 2018 tariffs provide an exogenous shock to international trade because the election of President Trump was unexpected, and there was substantial uncertainty about the specific components of his administration's trade policies. Secondly, the breadth of goods affected by import tariffs during the trade war increases the range of countries that could potentially be alternative import sources or export destinations.

Much of the research on the trade war has focused on the direct impacts of the tariffs on the US and China. Fajgelbaum et al. (2020) assess the short-run impact of the 2018 tariffs and find an aggregate welfare loss of 0.04% GDP in the US. Amiti et al. (2019) also find that the tariffs led to a rise in prices of US-made intermediate and final goods, complete pass-through of tariffs to domestic prices of imported goods, and a decrease in the number of imported varieties. Analysis by Cavallo et al. (2021) suggests that tariff incidence has fallen mainly on US firms, with lowered

[1] Other countries, including Mexico, also imposed retaliatory tariffs during this period.

margins for US retailers, while Handley et al. (2020) find that US exporters affected by import tariffs experienced a decline in export growth in 2018 and 2019, with a larger effect in 2019.

III.2.2 Trade Diversion and Deflection

Trade diversion considerations were introduced to the economics literature by Viner (1950) who discussed potential negative welfare effects of preferential trade agreements (PTAs): although PTAs could increase welfare by creating trade between the members, import source diversion could reduce welfare as firms in member countries switch from trading with non-members. With respect to protectionism rather than PTAs, I extend the discussion in Bown and Crowley (2007) on potential impacts of an anti-dumping duty to the import tariffs in the trade war. US tariffs on Chinese imports would generate trade diversion if US importers reduce their purchases of the affected goods from China, and increase their imports of those goods from other countries. These same tariffs would result in trade deflection if Chinese exporters that would otherwise have supplied goods to the US, sell those goods in other countries instead.

In this study, I consider trade diversion and deflection as a result of both US tariffs on imports from China, and China's tariffs on imports from the US. Specifically, I assess whether US importers substituted away from Chinese producers and towards Mexican and Colombian exporters, and if Chinese exporters sold more products to Mexican and Colombian importers as a result of US-imposed tariffs. Similarly, I estimate the impact that China's tariffs on US-produced goods had on the Mexico and Colombia's exports to China and imports from the US.

Researchers have documented trade diversion and deflection as a result of other US trade policies. Flaaen et al. (2020) find that after antidumping import duties were imposed on US imports of washing machines from Korea and Mexico in 2012, US firms switched to sourcing from China, and after safeguard tariffs were passed against washer imports from China in 2016, US import sourcing moved to Thailand and Vietnam. These shifts were primarily driven by the relocation decisions of washing machine producers. A notable result of the Flaaen et al. (2020) study is that the 2018 tariffs on washers also led to an increase in the price of dryers, a tariff-exempt but complementary good. This indicates that the third-country effects of the trade war could also show up in close substitutes and complements. I discuss how my empirical strategy takes this into account in the next section. There is also evidence of trade deflection from US anti-dumping duties. Bown and Crowley (2007) studied the US imposition of antidumping duties on Japan, and found that it led to an increase of Japan's exports of the same products to the average third country market.

My results confirm the findings of Cigna et al. (2020) on trade diversion as a result of the 2018 US import tariffs. Using monthly product-level data, the authors find no evidence of widespread import source diversion by the US towards third countries as a result of tariffs levied against imports from China. I make two additional contributions: I assess trade diversion from China's retaliatory tariffs, and also examine trade deflection.

III.3 Empirical Strategy

To assess the third-country effects of the US-China trade war, I utilize an event-study difference-in-differences strategy that exploits the timing of the import tariff announcements. I aggregate firm-to-firm transaction-level data to the firm-product level and estimate the following specification:

$$\Delta \ln(z_{ijt}) = \sum_{\tau=-q}^{m} \beta_\tau E_{j\tau} + \gamma_{ij} + \gamma_{st} + \varepsilon_{ijt} \tag{III.1}$$

where i denotes a firm and j indexes an HS 6-digit product in quarter t. $E_{j\tau}$ is the treatment variable, and is equal to 1 from the quarter in which a tariff is imposed on product j, and 0 before that. For never-treated products, $E_{j\tau}$ is always equal to 0. q and m are the number of quarters before and after the tariff is imposed. The parameters of interest are the

β_τ's. γ_{ij} is a firm-product fixed effect and γ_{st} is a sector-time fixed effect, where sectors are defined at the HS 2-digit product-level, in order to exploit only variation within groups of related commodities. Standard errors are clustered at the HS 6-digit product level.

Although US-tariffs are imposed at the HS 10-digit level and China's tariffs are at the HS 8-digit level, I analyze effects on HS 6-digit product categories for two reasons. First, data on Mexico is only available at the HS 6-digit level. Secondly, as Cigna et al. (2020) points out, trade diversion effects are likely to show up in substitution towards closely-related goods or the increased purchases of complementary goods. Only looking at trade in the specific HS 10 commodities targeted could lead to the underestimation of these effects.

I account for seasonality by taking 4-quarter log differences of the dependent variable, which yields the year-on-year growth rate. I consider four variables for z_{ijt}: the average value traded per trading partner, the average quantity per trading partner, the average price (unit value) per trading partner, and the number of (unique) trading partners in the time period. I construct an unbalanced panel of firm-product pairs,[2] and use the inverse hyperbolic sine transformation, $\ln(z+\sqrt{z^2+1})$, to avoid dropping observations with zeros at t or $t-4$. Here, trading partners refer to other firms, rather than countries, and enables me to observe how the relationship between Mexican or Colombian importers and exporters, and their average supplier or buyer in the US and China is changing as a result of the trade war.

To examine trade diversion due to US import tariffs on Chinese goods, I estimate the effect of the tariff announcements on Mexico and Colombia's exports to the US. For trade deflection from US import tariffs, I estimate the impact of the tariff announcements on Mexico and Colombia's imports from China. Similarly, I use Mexico-China and Colombia-China exports to examine trade diversion due to China's import tariffs on US goods, and Mexico-US and Colombia-US imports to investigate trade deflection from these tariffs. I exclude products, such as steel and aluminum, that were subject to concurrent tariffs imposed on other countries by the US and retaliatory actions from those countries, to avoid the confounding effects of trade policies that were not specific to the US-China bilateral relationship.[3]

III.4 Data

This study employs transaction-level customs data on Colombia and Mexico obtained from Import Genius. The data spans most of the universe of maritime shipments by Mexico from 2015-2019, and all modes of transportation for Colombia. Each record contains the name of the shipper and recipient of the goods, as well as the source (destination) country for imports (exports). Colombian data reports HS 10-digit codes, while Mexican data reports products at the HS 6-digit level. The data also contains Total FOB values (in US dollars) for Colombian imports and exports, and Total CIF values for Mexican imports. Trade values are not reported in the Mexico export data. I use gross weight in metric tons as a measure of quantity, and prices are unit values derived by dividing the total value of shipments by their weight.

To obtain the number of unique trading partners for each firm, I match firm names using the TF-IDF (Term-Frequency Inverse Document Frequency) approach[4] to identify multiple shipments sent by the same exporter or received by the same importer. I clean the data by eliminating duplicate transactions between the same pair of firms, and of the same quantity and value in a single day. I also exclude records that are missing the name of the shipment's recipient or sender, or both the value and quantity of the shipment. I aggregate this data to the quarterly level for each

[2] A firm-product pair is included if it has a positive quantity traded in the current quarter, or in the same quarter in the preceding or subsequent year.

[3] There could be other policy confounders during this period that I do not directly address. For example, China also lowered the average tariff on its imports from the rest of the world by 1.3 percentage points in 2018 (Bown, 2019). However, to the extent that such policies are not highly correlated with US-China tariffs, I am able to assess the differential impact of the trade war on targeted goods as compared to non-targeted.

[4] This method converts firm names into vectors and assigns every pair of names a similarity score equal to the cosine of the angle between their vectors. I use a conservative cutoff of 0.99999 to identify matched firms.

Colombian and Mexican firm-product pair.

I use data on the US-China trade war from Fajgelbaum et al. (2020) to identify products affected by tariffs and the effective dates.[5] I aggregate import tariffs from the HS 10 level for the US and the HS 8 level for China to the HS 6 level. For HS 6 products with multiple effective dates, I assign treatment to begin at the earliest effective date. I exclude all products subject to tariffs imposed by the US on imports from countries other than China, and retaliatory tariffs imposed by other countries on imports from the US in 2018.

III.5 Benchmark Estimates

In this section, I present reduced form estimates of the impact of the US-China trade war on Colombia and Mexico's trade with the US and China. First I examine trade diversion and deflection due to US-imposed tariffs, and then assess the impact of China's retaliatory tariffs working in the opposite direction.

III.5.1 The Impact of US Tariffs on Chinese Imports

III.5.1.1 Trade Diversion

Figure III.1 shows estimates from the event study specification in equation III.1 for Colombian exports to the US. Since the tariffs were imposed between July and September, the estimated coefficients span the first quarter of 2016 to the fourth quarter of 2019, with 2018 Q2 normalized to zero. The pre-trends indicate that before the tariffs were announced, Colombia's exports to the US of goods subject to the tariffs had relatively higher growth rates than goods not targeted by the import tariffs. However, the gap between treated and untreated products declined after the tariffs were imposed. This suggests, if anything, a relative reduction in exports of target goods from Colombia to the US —the opposite of what one would expect to see if trade diversion was indeed occurring. There also does not appear to be any effect on the prices charged by Colombian exporters to US firms.

For Mexico, there is also weak evidence of trade diversion. The second panel of Figure III.2 does appear to indicate an uptick in the relative growth rate of the number of US firms importing treated goods from Mexican firms in the last two quarters of 2019. However, given a slightly upward pretend, it is not clear that this growth can be attributed to the trade war.

III.5.1.2 Trade Deflection

Turning to Colombia's imports from China, the first and third panels of Figure III.3 suggest a positive trend in the growth rate of the value imported and number of trading partners for targeted goods relative to non-targeted goods after the US import tariffs came into effect. However, this positive trend can also be observed in the pre-announcement period and can hardly be ascribed to the tariffs themselves. As with exports to the US, there does not appear to be any systematic changes in prices faced by Colombian importers for Chinese goods as a result of the trade war.

Price effects on Mexico's imports are similarly absent as illustrated in the fourth panel of Figure III.4. And while there is no discernible trend in the average value or quantity of importers per trading partner or the number of Chinese firms from which Mexican firms purchased targeted products, there is also little to indicate that the tariffs imposed by the US had a differential impact along the aforementioned dimensions.

III.5.2 The Impact of China's Import Tariffs on US Products

I now turn to the analysis of tariffs levied by China on the import of US products, and their effect on China's imports from Mexico and Colombia, as well as the latter countries' imports from the US. The tariffs in question were

[5] Tariffs went into effect shortly after they were announced. Therefore, for the purpose of this study, there is no substantive difference between announcement and effective dates.

announced in April 2018, and between July and September. Because the bulk of goods were treated in Q3 2018 (after excluding steel and aluminum), I trim the post-treatment period to four quarters after the tariff announcement.

III.5.2.1 Trade Diversion

Based on the coefficients in Figure III.5, there does not appear to any evidence that Chinese importers switched some of their sourcing from the US to Colombia after tariffs on US goods were announced. There does seem to be an upward trend in the relative growth of the number of trading partners in targeted goods that stalls after the tariffs are announced. While Colombian export prices of non-targeted goods tend to be rising more than target goods after the tariff increases, this appears to also have been the case in some quarters before the trade war began. Furthermore, export price reductions would not be consistent with trade diversion as a result of a positive demand shock from China.

Mexico's exports to China, as shown in Figure III.6, also bears no indication of trade diversion in the year after China's tariffs against the US were imposed.

III.5.2.2 Trade Deflection

With respect to Colombia's imports from the US, Figure III.7, shows a decline in the growth rate of value and quantity traded, as well as the number of trade partners for targeted goods relative to goods that were not subject to Chinese import tariffs. This would be inconsistent with the US deflecting exports to Colombia that would otherwise have gone to China. Interestingly, a spike in the growth rates of Colombia-US imports appears to have occurred about 3 to 6 quarters before the tariffs were announced, which was during 2017 Q1 to Q4 for most goods subject to the tariffs. In addition, although there is not clear evidence of pricing effects as a result of the tariffs, there does appear to be a spike in the growth rates of prices of targeted goods a year prior to the tariff announcements.

For Mexico, there is some indication in Figure III.8 that the value and quantity imported from the US grew at a faster pace for targeted goods in the quarter that import tariffs were imposed and in subsequent periods. The number of trading partners also appears to have been positively impacted, while price remained unaffected.

III.5.3 Robustness

The inclusion of observations with zero trade values in the benchmark specification may have impacted the estimates by biasing them toward a null effect, especially if firm-to-firm trade is infrequent. In Figures III.9 to III.16, I report impacts on value, quantity and number of trade partners where these outcomes are year-on-year differences of their natural logs. Therefore, each regression only includes firm-product pairs with positive values of the dependent variable.

The results either confirm the earlier findings of no relative changes, or even slight declines in the trade between Colombia/Mexico and the US or China. Taken together, they provide no evidence of trade diversion or deflection to Mexico or Colombia in the short run as a result of the US-China trade war.

III.6 Conclusion

Overall, this paper employs firm-level customs data from Colombia and Mexico to examine some third-country effects of the 2018 tariff increases during the US-China trade war. My results confirm an existing finding in the literature of no evidence of import source diversion in the short-run due to US-imposed tariffs. I also find very little to suggest that China imported more from or exported more to Mexico or Colombia as a result of the trade war.

This study does not necessarily rule out trade diversion or deflection in all context, but does so only for Mexico and Colombia. If these countries are not good substitute source or destination countries for US or Chinese imports and exports, then it is possible that the third-country effects absent here, manifested in other countries. Furthermore, given that a significant portion of trade between Mexico and the US occurs by land rather than shipping, I am unable to detect trade diversion that may have occurred through this mode of transport.

Beyond trade diversion and deflection, other third-country impacts could show up through global value chains. For example, declines in industrial output in the US and China due to the trade war may have reduced demand for crude oil from Colombia or in intermediate goods from Mexico. Future work could empirically investigate these effects.

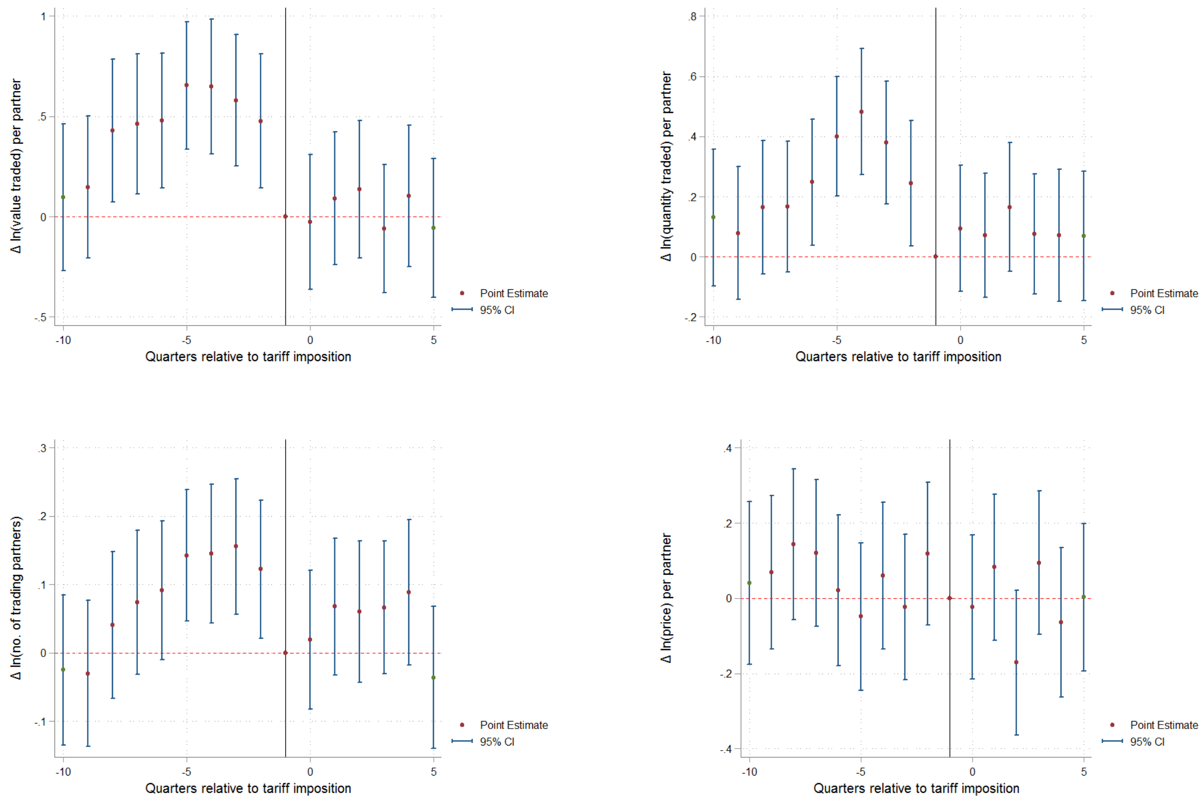


Figure III.1: Impact of US-China Import Tariffs on Colombia-US Exports

This figure plots event study estimates of differences in exports of treated vs. untreated goods from Colombian firms to US importers after the US imposed tariffs on imports from China. Observations are at the firm-product-quarterly level. Products are defined by HS 6-digit categories. All outcomes other than prices have been transformed using the inverse hyperbolic sine function and year-on-year differencing. Every specification includes firm-product and HS 2 sector-quarter fixed effects.

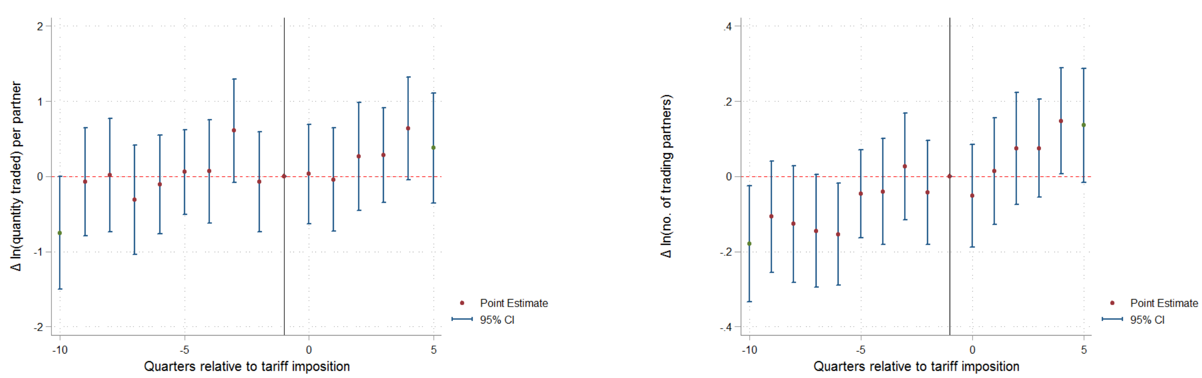


Figure III.2: Impact of US-China Import Tariffs on Mexico-US Exports

This figure plots event study estimates of differences in exports of treated vs. untreated goods from Mexican firms to US importers after the US imposed tariffs on imports from China. Observations are at the firm-product-quarterly level. Products are defined by HS 6-digit categories. All outcomes other than prices have been transformed using the inverse hyperbolic sine function and year-on-year differencing. Every specification includes firm-product and HS 2 sector-quarter fixed effects.

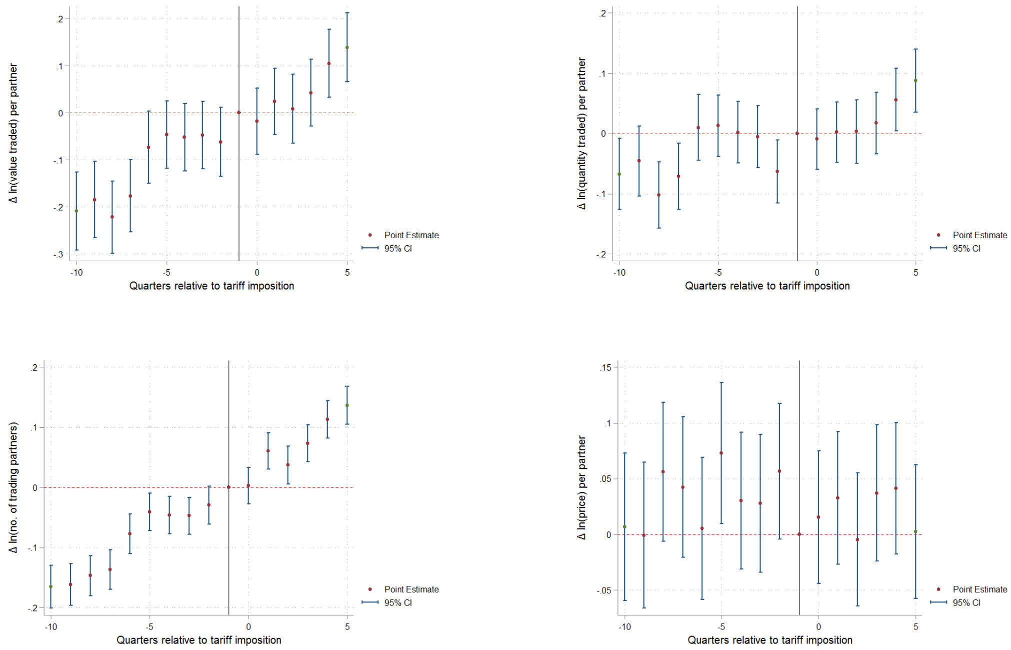


Figure III.3: Impact of US-China Import Tariffs on Colombia-China Imports

This figure plots event study estimates of differences in imports of treated vs. untreated goods by Colombian firms from Chinese exporters after the US imposed tariffs on imports from China. Observations are at the firm-product-quarterly level. Products are defined by HS 6-digit categories. All outcomes other than prices have been transformed using the inverse hyperbolic sine function and year-on-year differencing. Every specification includes firm-product and HS 2 sector-quarter fixed effects.

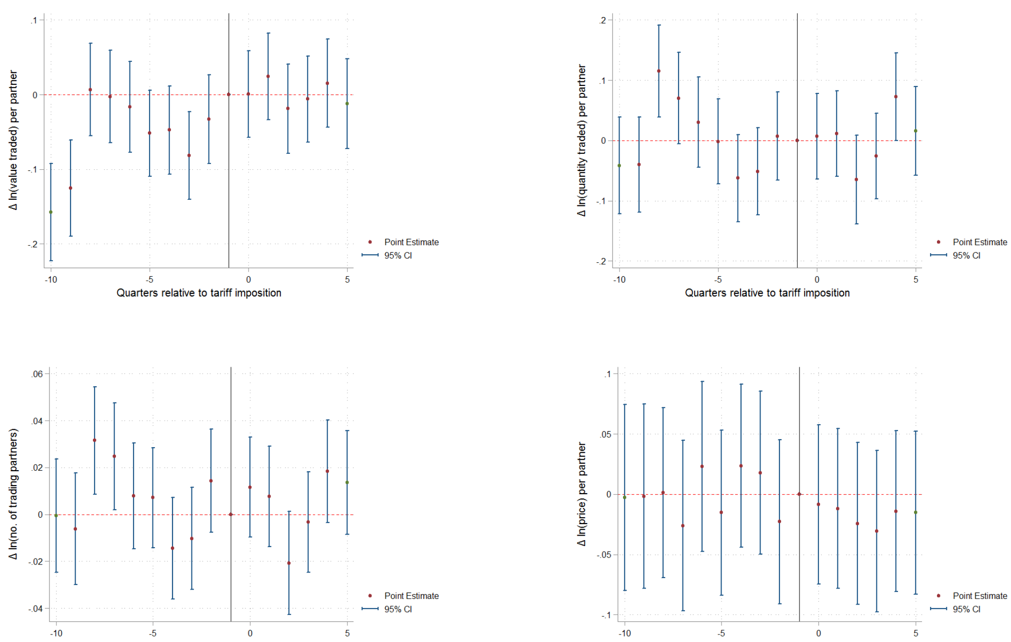


Figure III.4: Impact of US-China Import Tariffs on Mexico-China Imports

This figure plots event study estimates of differences in imports of treated vs. untreated goods by Mexican firms from Chinese exporters after the US imposed tariffs on imports from China. Observations are at the firm-product-quarterly level. Products are defined by HS 6-digit categories. All outcomes other than prices have been transformed using the inverse hyperbolic sine function and year-on-year differencing. Every specification includes firm-product and HS 2 sector-quarter fixed effects.

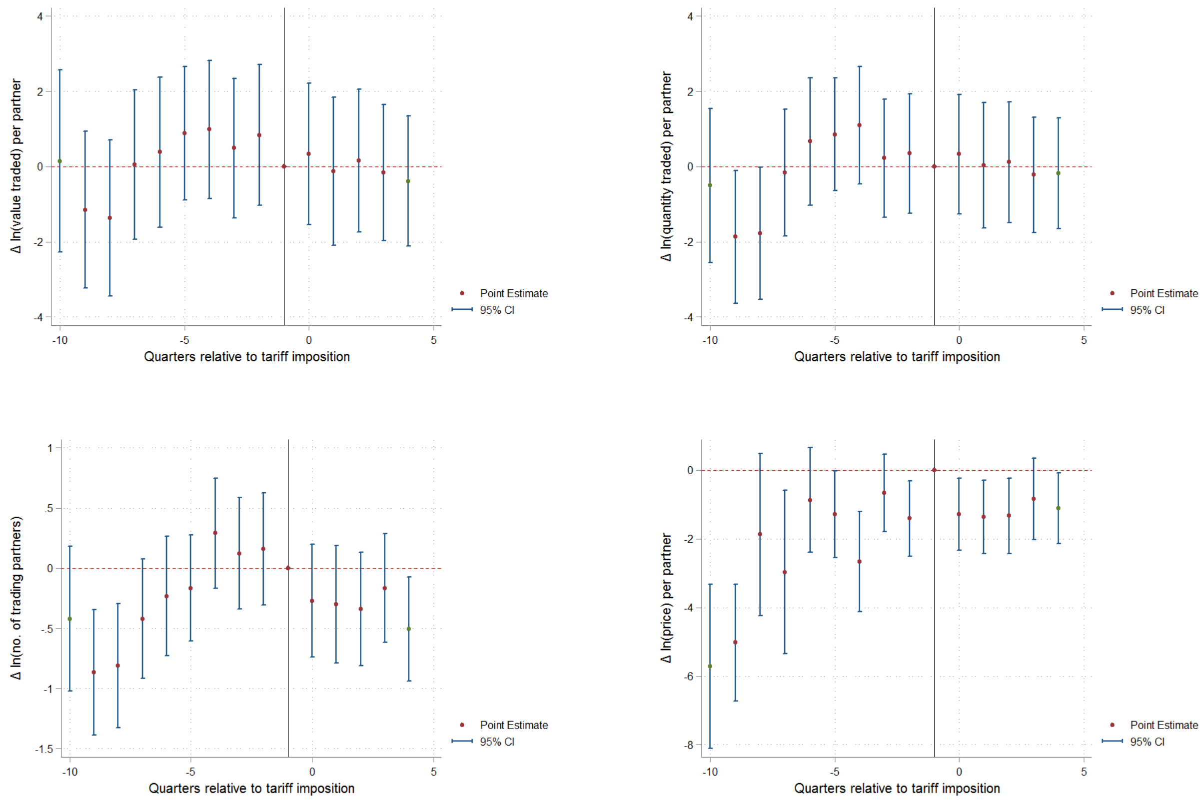


Figure III.5: Impact of China-US Import Tariffs on Colombia-China Exports

This figure plots event study estimates of differences in exports of treated vs. untreated goods from Colombian firms to Chinese importers after China imposed tariffs on imports from the US. Observations are at the firm-product-quarterly level. Products are defined by HS 6-digit categories. All outcomes other than prices have been transformed using the inverse hyperbolic sine function and year-on-year differencing. Every specification includes firm-product and HS 2 sector-quarter fixed effects.

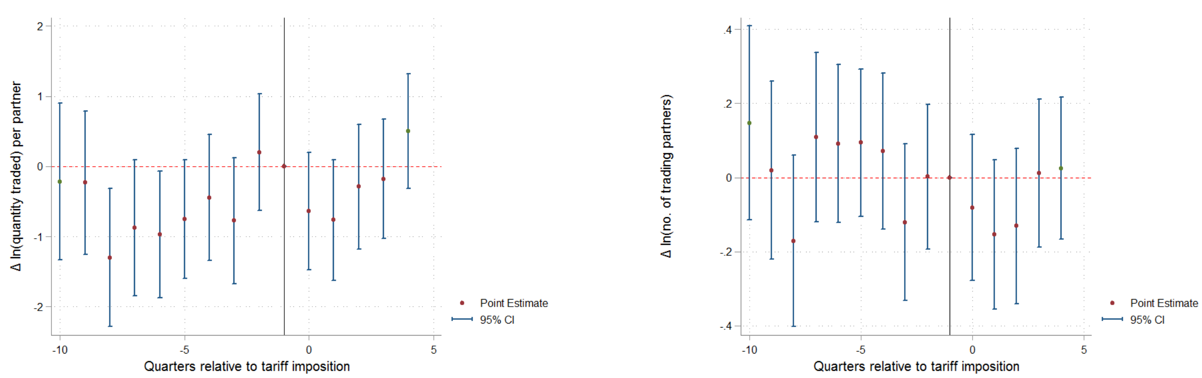


Figure III.6: Impact of China-US Import Tariffs on Mexico-China Exports

This figure plots event study estimates of differences in exports of treated vs. untreated goods from Mexican firms to Chinese importers after China imposed tariffs on imports from the US. Observations are at the firm-product-quarterly level. Products are defined by HS 6-digit categories. All outcomes other than prices have been transformed using the inverse hyperbolic sine function and year-on-year differencing. Every specification includes firm-product and HS 2 sector-quarter fixed effects.

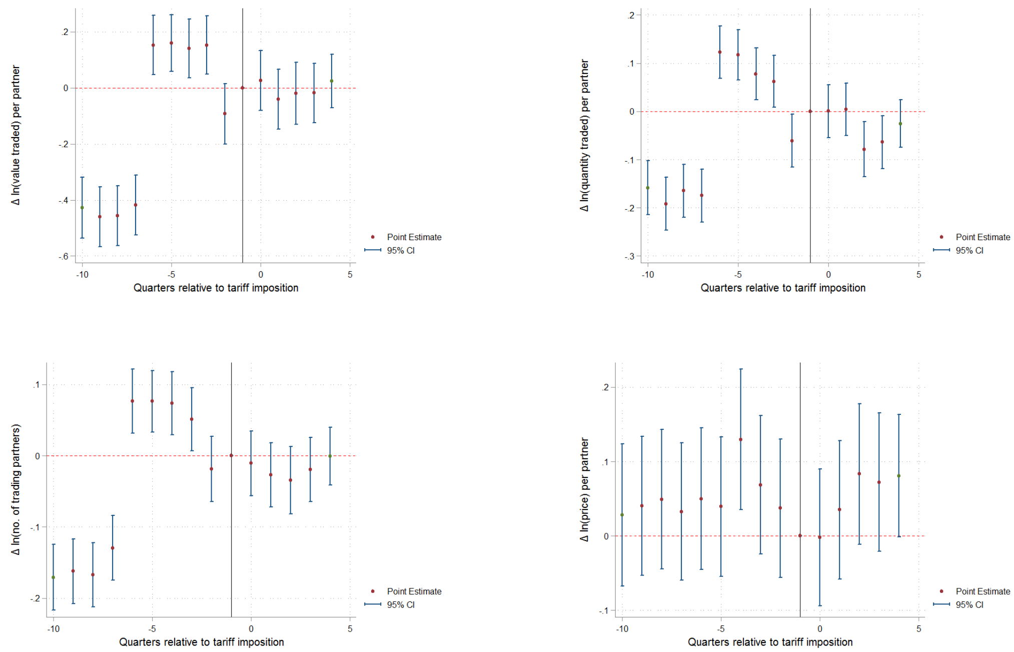


Figure III.7: Impact of China-US Import Tariffs on Colombia-US Imports

This figure plots event study estimates of differences in imports of treated vs. untreated goods by Colombian firms from US exporters after China imposed tariffs on imports from the US. Observations are at the firm-product-quarterly level. Products are defined by HS 6-digit categories. All outcomes other than prices have been transformed using the inverse hyperbolic sine function and year-on-year differencing. Every specification includes firm-product and HS 2 sector-quarter fixed effects.

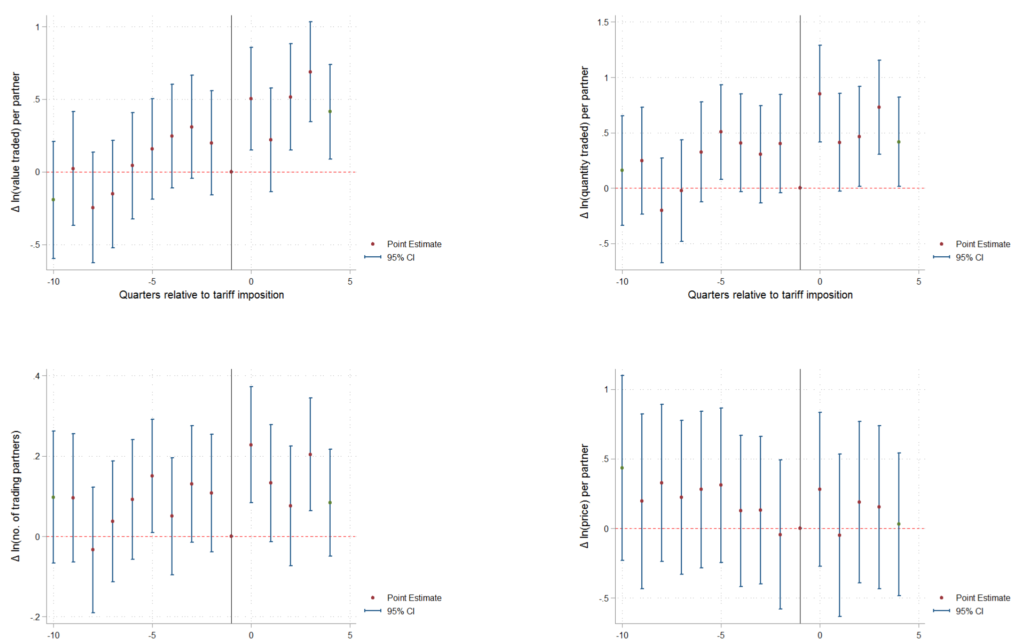


Figure III.8: Impact of China-US Import Tariffs on Mexico-US Imports

This figure plots event study estimates of differences in imports of treated vs. untreated goods by Mexican firms from US exporters after China imposed tariffs on imports from the US. Observations are at the firm-product-quarterly level. Products are defined by HS 6-digit categories. All outcomes other than prices have been transformed using the inverse hyperbolic sine function and year-on-year differencing. Every specification includes firm-product and HS 2 sector-quarter fixed effects.

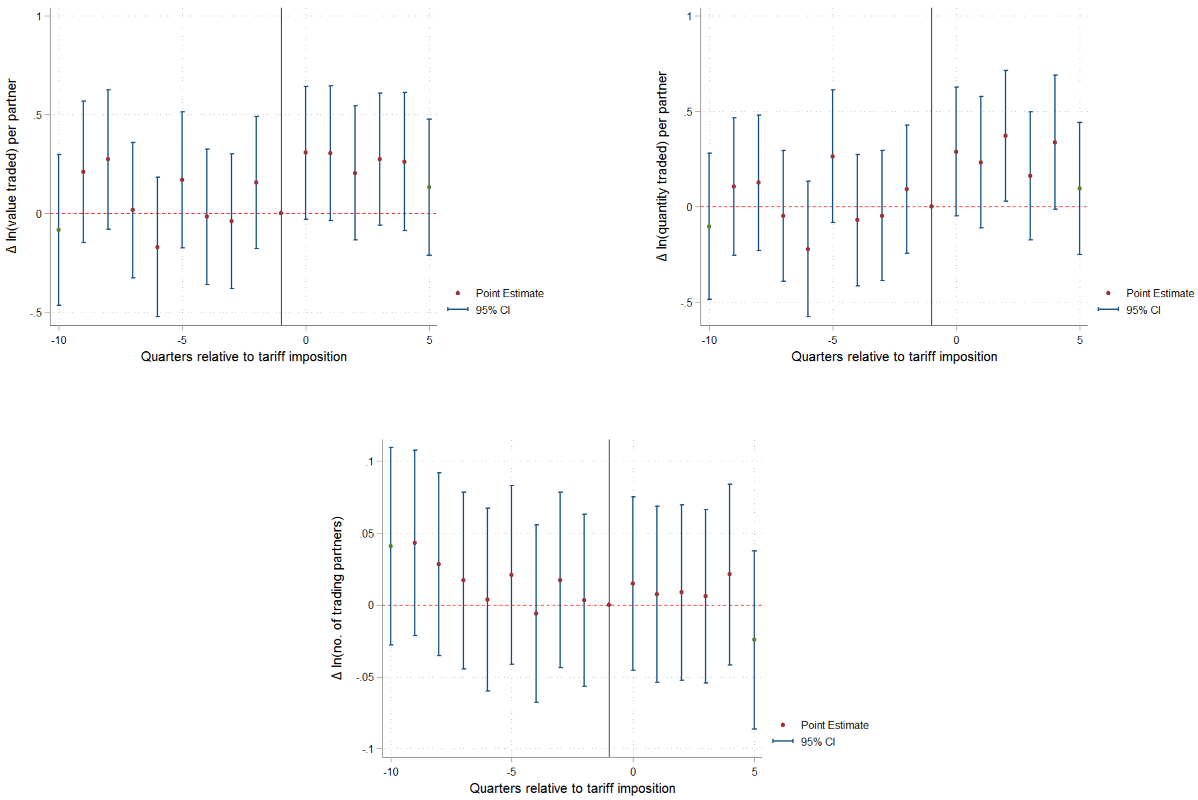


Figure III.9: Robustness: Impact of US-China Import Tariffs on Colombia-US Exports

This figure plots event study estimates of differences in exports of treated vs. untreated goods from Colombian firms to US importers after the US imposed tariffs on imports from China. Observations are at the firm-product-quarterly level. Products are defined by HS 6-digit categories. All outcomes are year-on-year log-differenced. Every specification includes firm-product and HS 2 sector-quarter fixed effects.

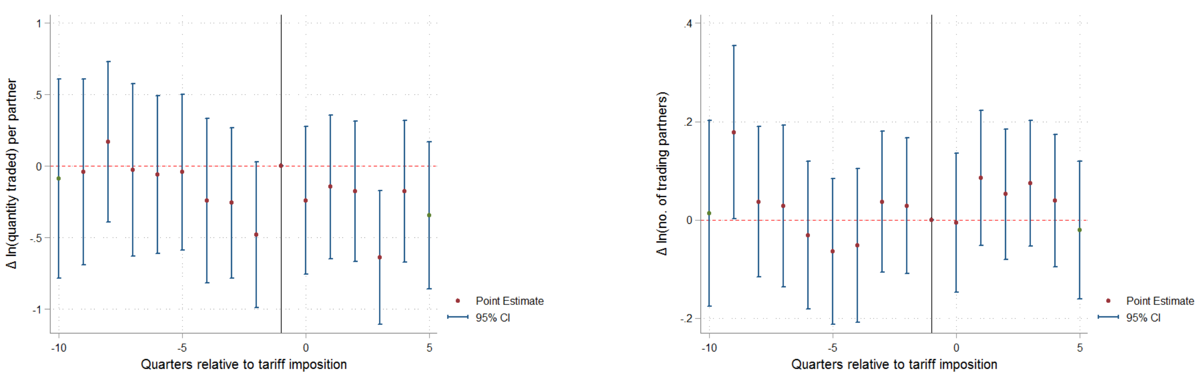


Figure III.10: Robustness: Impact of US-China Import Tariffs on Mexico-US Exports

This figure plots event study estimates of differences in exports of treated vs. untreated goods from Colombian firms to US importers after the US imposed tariffs on imports from China. Observations are at the firm-product-quarterly level. Products are defined by HS 6-digit categories. All outcomes are year-on-year log-differenced. Every specification includes firm-product and HS 2 sector-quarter fixed effects.

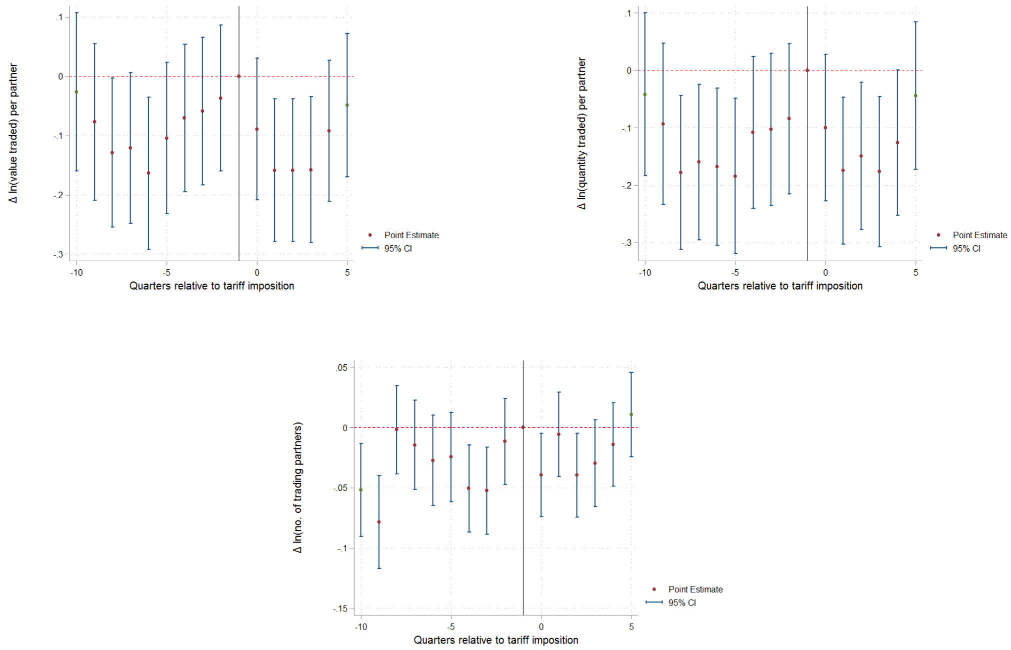


Figure III.11: Robustness: Impact of US-China Import Tariffs on Colombia-China Imports

This figure plots event study estimates of differences in imports of treated vs. untreated goods by Colombian firms from Chinese exporters after the US imposed tariffs on imports from China. Observations are at the firm-product-quarterly level. Products are defined by HS 6-digit categories. All outcomes are year-on-year log-differenced. Every specification includes firm-product and HS 2 sector-quarter fixed effects.

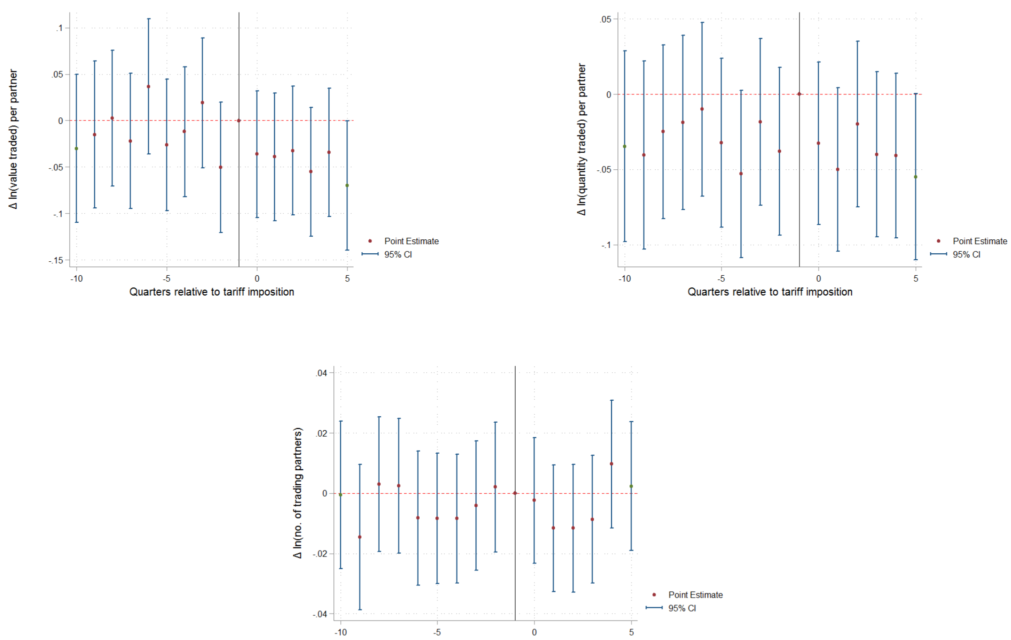


Figure III.12: Robustness: Impact of US-China Import Tariffs on Mexico-China Imports

This figure plots event study estimates of differences in imports of treated vs. untreated goods by Mexican firms from Chinese exporters after the US imposed tariffs on imports from China. Observations are at the firm-product-quarterly level. Products are defined by HS 6-digit categories. All outcomes are year-on-year log-differenced. Every specification includes firm-product and HS 2 sector-quarter fixed effects.

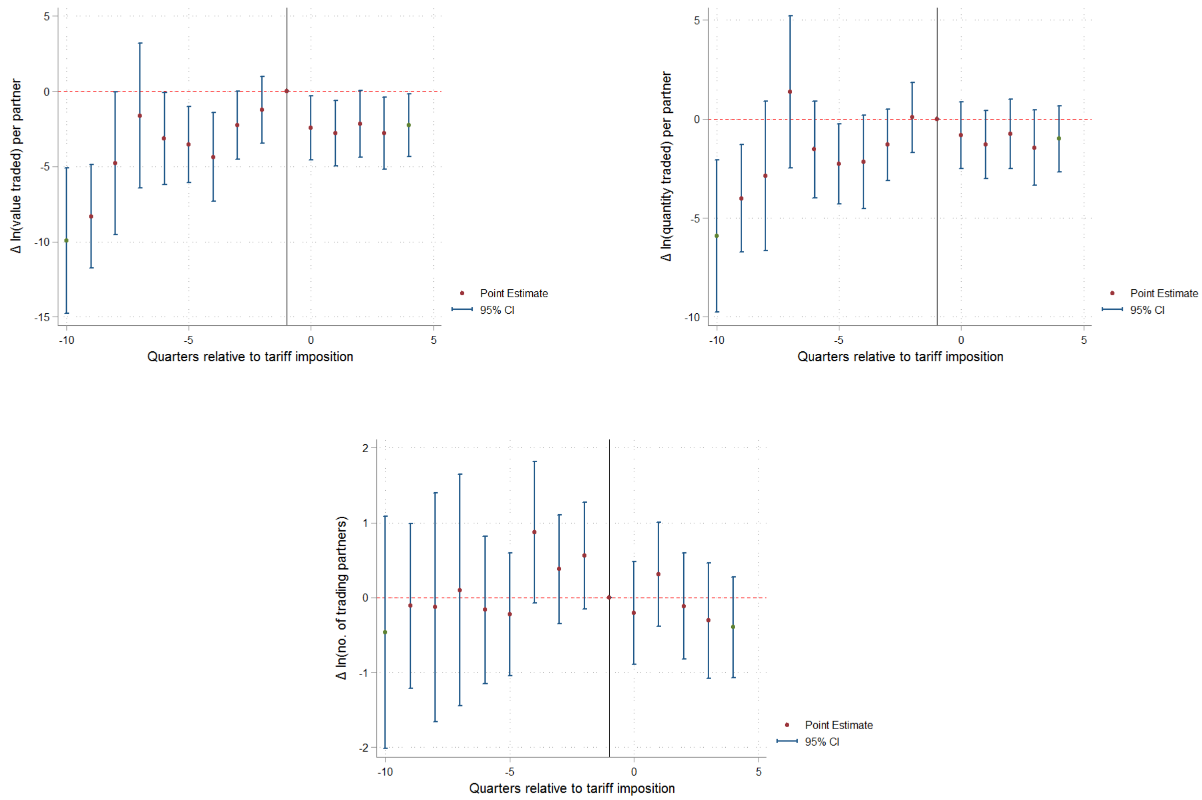


Figure III.13: Robustness: Impact of China-US Import Tariffs on Colombia-China Exports

This figure plots event study estimates of differences in exports of treated vs. untreated goods from Colombian firms to Chinese importers after China imposed tariffs on imports from the US. Observations are at the firm-product-quarterly level. Products are defined by HS 6-digit categories. All outcomes are year-on-year log-differenced. Every specification includes firm-product and HS 2 sector-quarter fixed effects.

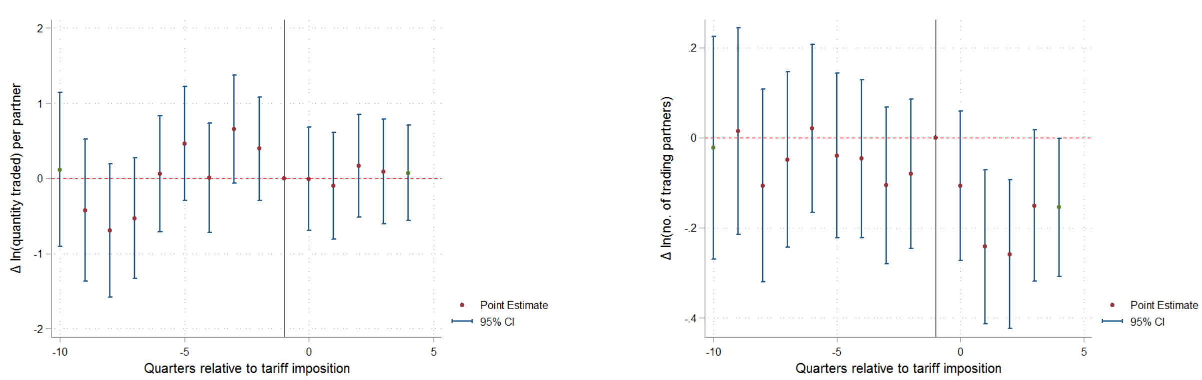


Figure III.14: Robustness: Impact of China-US Import Tariffs on Mexico-China Exports

This figure plots event study estimates of differences in exports of treated vs. untreated goods from Mexican firms to Chinese importers after China imposed tariffs on imports from the US. Observations are at the firm-product-quarterly level. Products are defined by HS 6-digit categories. All outcomes are year-on-year log-differenced. Every specification includes firm-product and HS 2 sector-quarter fixed effects.

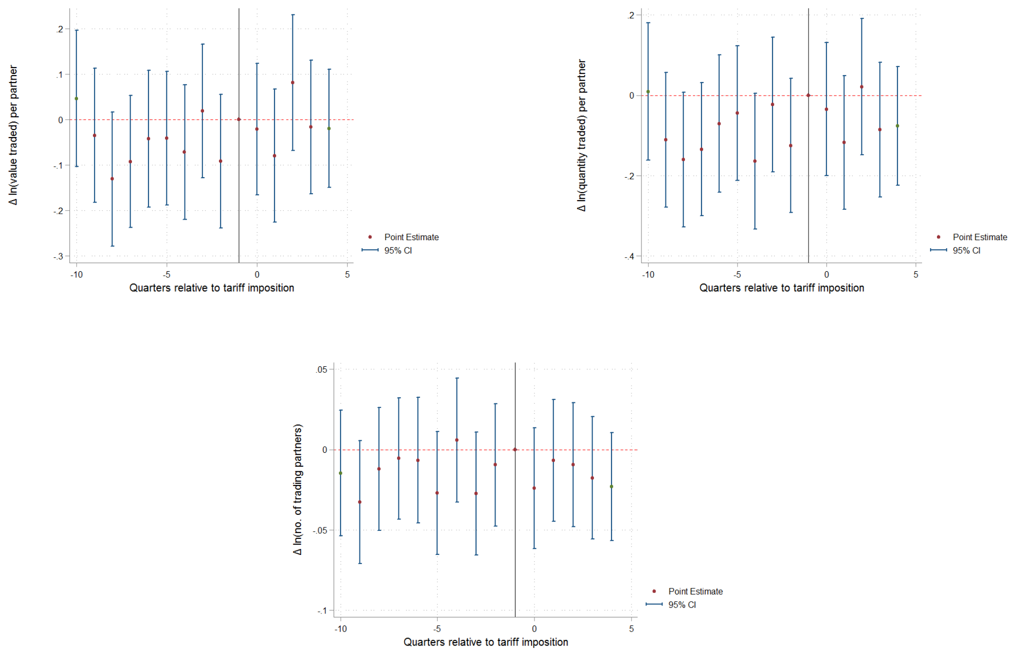


Figure III.15: Robustness: Impact of China-US Import Tariffs on Colombia-US Imports

This figure plots event study estimates of differences in imports of treated vs. untreated goods by Colombian firms from US exporters after China imposed tariffs on imports from the US. Observations are at the firm-product-quarterly level. Products are defined by HS 6-digit categories. All outcomes are year-on-year log-differenced. Every specification includes firm-product and HS 2 sector-quarter fixed effects.

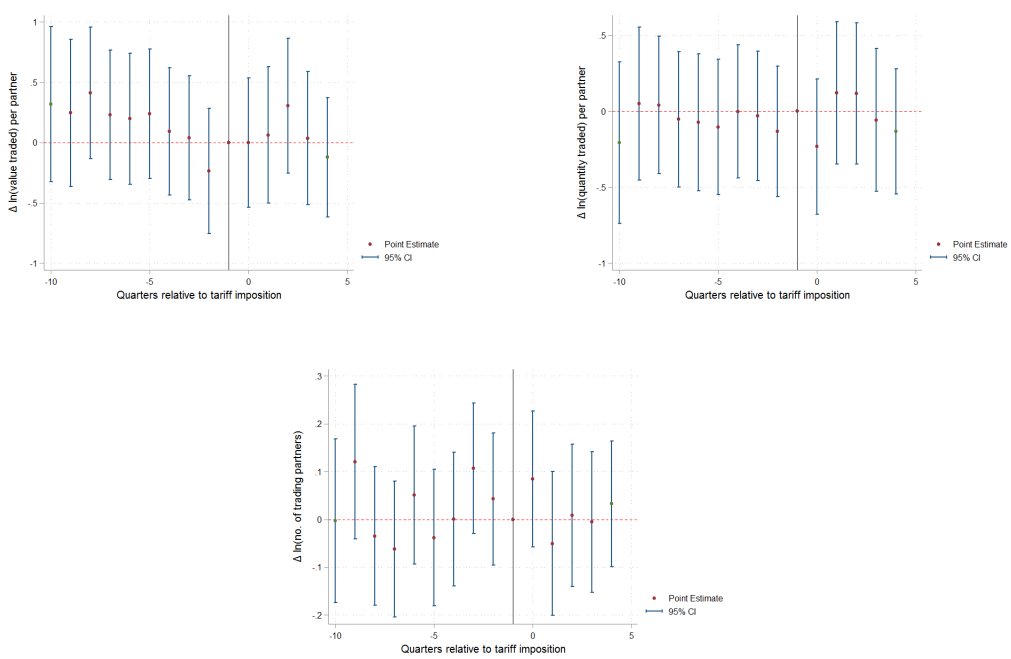


Figure III.16: Robustness: Impact of China-US Import Tariffs on Mexico-US Imports

This figure plots event study estimates of differences in imports of treated vs. untreated goods by Mexican firms from US exporters after China imposed tariffs on imports from the US. Observations are at the firm-product-quarterly level. Products are defined by HS 6-digit categories. All outcomes are year-on-year log-differenced. Every specification includes firm-product and HS 2 sector-quarter fixed effects.

Appendix A

Appendix

A.1 Derivation of Bias Terms

In this section, I derive expressions for the bias in production function elasticities shown in section I.3.3.

$$
\begin{aligned}
&y_t = \alpha_\ell \ell_t + \alpha_k k_t + \omega_t + \varepsilon_t \\
&\omega_t = \rho(I-\lambda G_t)^{-1}\omega_{t-1} + (I-\lambda G_t)^{-1}\zeta_{it} = \rho \sum_{s=0} \lambda^s G_t^s \omega_{t-1} + \sum_{s=0} \lambda^s G_t^s \zeta_t \\
&\implies y_t = \alpha_\ell \ell_t + \alpha_k k_t + \rho \sum_{s=0} \lambda^s G_t^s \omega_{t-1} + \sum_{s=0}^{\infty} \lambda^s G_t^s \zeta_t + \varepsilon_t \\
&\omega_{t-1} = \varphi_{t-1} - \alpha_\ell \ell_{t-1} - \alpha_k k_{it-1} \\
&\implies y_t = \alpha_\ell \ell_t + \alpha_k k_t + \rho \sum_{s=0} \lambda^s G_t^s (\varphi_{t-1} - \alpha_\ell \ell_{t-1} - \alpha_k k_{it-1}) + \sum_{s=0}^{\infty} \lambda^s G_t^s \zeta_{it} + \varepsilon_t \\
&y_{t-1} = \varphi_{t-1} + \varepsilon_t \\
&\implies y_t = \alpha_\ell \ell_t + \alpha_k k_t + \rho \sum_{s=0}^{\infty} \lambda^s G_t^s (y_{t-1} - \alpha_\ell \ell_{t-1} - \alpha_k k_{t-1} - u_{t-1}) + \sum_{s=0}^{\infty} \lambda^s G_t^s \zeta_t + \varepsilon_t
\end{aligned}
$$

Let $\Delta^G x_t = x_t - \rho \sum_{s=0}^{\infty} \lambda^s G_t^s x_{t-1}$, $\Delta_{x_t}^{err} = \rho \sum_{s=1}^{\infty} \lambda^s G_t^s x_{t-1}$ and $\Delta x_t = x_t - \rho x_{t-1} = \Delta^G x_t + \Delta_{x_t}^{err}$. This implies:

$$\Delta^G y_t = \alpha_\ell \Delta^G \ell_t + \alpha_k \Delta^G k_t + \sum_{s=0}^{\infty} \lambda^s G_t^s \zeta_t + \Delta^G \varepsilon_t \tag{A.1}$$

This is equivalent to the dynamic panel approach in Blundell and Bond (2000). However, growth in output, labor and capital have been purged of the variation from network effects in the previous period. When we assume no spillovers, we estimate:

$$\Delta y_t = \alpha_\ell \Delta \ell_t + \alpha_k \Delta k_t + u_t \tag{A.2}$$

Therefore, in the linear AR1 case, ignoring spillovers is equivalent to introducing non-classical measurement error into both output and inputs.

Bias from ignoring spillovers can also be characterized as an omitted variables problem. By estimating equation (A.2), where $u_t = \rho \sum_{s=1}^{\infty} \lambda^s G_t^s \omega_{t-1} + \sum_{s=0}^{\infty} \lambda^s G_t^s \zeta_t + \varepsilon_t$. That is, the standard ACF procedure succeeds in eliminating the endogeneity problem that arises from input decisions depending on its own productivity, but is unable to account for the influence of its network's past productivity.

In either case, an instrumental variable approach would help to eliminate the problem. The key would be to find variables that are correlated with changes to labor and capital but uncorrelated with output, particularly the input choices and output of other firms.

In the OP case where the labor elasticity is estimated in the first stage, the second stage is equivalent to estimating:

$$\Delta^G \widetilde{y}_t = \alpha_k \Delta^G k_t + \sum_{s=0}^{\infty} \lambda^s G_t^s \zeta_t + \Delta^G \varepsilon_t \tag{A.3}$$

$$\tag{A.4}$$

where $\widetilde{y}_t = y_t - \widehat{\alpha}_\ell \ell_t$. Then by estimating $\Delta\widetilde{y}_t = \alpha_k \Delta k_t + u_t$ under the standard assumption of no-spillovers:

$$plim\ \widehat{\alpha}_k = \frac{cov(\Delta k_t, \Delta\widetilde{y}_t)}{var(\Delta k_t)} \tag{A.5}$$

$$plim\ = \alpha_k \left(1 - \rho \sum_{s=1}^{\infty} \lambda^s \frac{cov(\Delta k_t, G_t^s k_{t-1})}{var(\Delta k_t)}\right) + \rho \sum_{s=1}^{\infty} \lambda^s \frac{cov(\Delta k_t, G_t^s \widetilde{y}_{t-1})}{var(\Delta k_t)} \tag{A.6}$$

When productivity is mismeasured by ignoring spillovers, the resulting estimates also result in incorrect conclusions about spillover effects. When (α_ℓ, α_k) are consistently estimated, and

$$\widehat{\omega}_t = \widehat{\varphi}_t - \widehat{\alpha}_\ell \ell_t - \widehat{\alpha}_k k_t \tag{A.7}$$

$$plim\ \widehat{\omega}_t = \varphi_t - \alpha_\ell \ell_t - \alpha_k k_t = \omega_t \tag{A.8}$$

However, when we estimate $(\widetilde{\alpha}_\ell, \widetilde{\alpha}_k) = \left(\widehat{\alpha}_\ell + \alpha_\ell^{err}, \widehat{\alpha}_k + \alpha_k^{err}\right)$, to obtain $\widetilde{\omega}_t = \widehat{\varphi}_t - \widetilde{\alpha}_\ell \ell_t - \widetilde{\alpha}_k k_t$. Then

$$\widetilde{\omega}_t = \widehat{\varphi}_t - \widetilde{\alpha}_\ell \ell_t - \widetilde{\alpha}_k k_t = \widehat{\varphi}_t - \widehat{\alpha}_\ell \ell_t - \widehat{\alpha}_k k_t - (\alpha_\ell^{err} \ell_t + \alpha_k^{err} k_t) = \widehat{\omega}_t - \omega_t^{err} \tag{A.9}$$

where $\omega_t^{err} = \alpha_\ell^{err} \ell_t + \alpha_k^{err} k_t$ In the generalized 2SLS procedure for estimating network effects, we estimate $\widetilde{\lambda}$ in the first stage by using $G_t \widetilde{\omega}_{t-1}$ as an instrument for $G_t \widetilde{\omega}_t$ in this equation:[1] The true model is:

$$\omega_t = \rho \omega_{t-1} + \lambda G_t \omega_t + \zeta_t$$

but we estimate:

$$\widetilde{\omega}_t = \rho \widetilde{\omega}_{t-1} + \lambda G_t \widetilde{\omega}_t + v_t$$

A.2 Monte Carlo Setup

The Monte Carlo setup closely follows Collard-Wexler and De Loecker (2016), Van Biesebroeck (2007) and Ackerberg et al. (2015) with modifications for network generation and the inclusion of spillovers in the productivity process. I generate a balanced panel of 1000 firms over 10 time periods.

A.2.1 Production Function

I use a structural value-added production function that is Leontief in materials.

$$Y_{it} = \min\{L_{it}^{\alpha_\ell} K_{it}^{\alpha_k} e^{\omega_{it}}, \alpha_m M_{it}\} e^{\varepsilon_{it}} \tag{A.10}$$

$$\implies Y_{it} = L_{it}^{\alpha_\ell} K_{it}^{\alpha_k} e^{\omega_{it} + \varepsilon_{it}} = \alpha_m M_{it} e^{\varepsilon_{it}} \tag{A.11}$$

$$\text{In logs, } y_{it} = \alpha_\ell \ell_{it} + \alpha_k k_{it} + \omega_{it} + \varepsilon_{it} \tag{A.12}$$

where $\varepsilon_{it} \sim \mathcal{N}(0, \sigma_\varepsilon^2)$. I set $\alpha_\ell = 0.6, \alpha_k = 0.4$ and $\sigma_\varepsilon^2 = 1$

A.2.2 Productivity Process and Network

Productivity evolves according to an AR1 process that allows for contemporaneous endogenous productivity spillovers. For ease of notation, I write the equation in vectorized form:

$$\omega_t = \beta_1 \iota + \rho \omega_{t-1} + \lambda G_t \omega_t + \zeta_t \tag{A.13}$$

[1] Further lags of the network effect can be used ($G_t^2 \widetilde{\omega}_t, G_t^3 \widetilde{\omega}_t$ and so on). However, for ease of exposition, I focus on the just-identified case.

where $\zeta_{it} \sim \mathcal{N}(0, \sigma_\zeta^2)$. I set $\sigma_\zeta^2 = 5$. I generate productivity using the reduced form of the above equation:

$$\omega_t = (\mathrm{I} - \lambda G_t)^{-1} (\beta_1 \iota + \rho \omega_{t-1} + \zeta_t) \tag{A.14}$$

G_t is the interaction matrix defined as in section I.3.2 derived from the network. I generate exogenous networks using Erdős and Rényi (1960) graphs, also known as binomial graphs. Firms are edges are formed $A_{ijt} \overset{i.i.d.}{\sim} \mathrm{Bern}(p)$.

A.2.3 Intermediate Input Demand

$$M_{it} = \frac{1}{\alpha_m} K_{it}^{\alpha_k} L_{it}^{\alpha_\ell} e^{\omega_{it}} \tag{A.15}$$

$$\text{In logs, } m_{it} = \alpha_k k_{it} + \alpha_\ell \ell_{it} + \omega_{it} - \ln(\alpha_m) \tag{A.16}$$

A.2.4 Labor Demand

Wages, W_{it} are firm-year specific and distributed log-normally: $\ln(W_t) \sim \mathcal{N}(0, \sigma_w^2)$. Then each firm chooses optimal labor according to:

$$L_{it} = \left(\alpha_\ell \frac{K_{it}^{\alpha_k}}{W_{it}} e^{\omega_{it}} \right)^{\frac{1}{1-\alpha_\ell}} \tag{A.17}$$

$$\text{In logs, } \ell_{it} = \frac{1}{1-\alpha_\ell} \left(\ln(\alpha_\ell) + \alpha_k k_{it} + \omega_{it} - \ln(W_{it}) \right) \tag{A.18}$$

A.2.5 Capital and Optimal Investment

Capital is accumulated as follows:

$$K_{it} = (1-\delta) K_{it-1} + I_{t-1} \tag{A.19}$$

I set the depreciation rate at $\delta = 0.2$.

Investment is subject to convex adjustment costs $c(I_{it}) = \frac{b}{2} I_{it}^2$ with $b = 0.3$. Optimal investment can be derived by setting up the profit maximization problem:[2]

$$\Pi_{it} = L_{it}^{\alpha_\ell} K_{it}^{\alpha_k} e^{\omega_{it}} - W_{it} L_{it} - \frac{b}{2} I_{it}^2 \tag{A.20}$$

Here, I assume perfect competition and normalize the price of output to 1. The firm's value function is :

$$V(L_{it}, K_{it}, W_{it}, \omega_{it}) = \max_{L_{it}, K_{it}} L_{it}^{\alpha_\ell} K_{it}^{\alpha_k} e^{\omega_{it}} - W_{it} L_{it} - \frac{b}{2} I_{it}^2 + \beta\, \mathbb{E}_{it} V(L_{it+1}, K_{it+1}, W_{it+1}, \omega_{it+1}) \tag{A.21}$$

$$\text{such that } K_{it+1} = (1-\delta) K_{it} + I_t \tag{A.22}$$

β is the discount factor and is fixed at 0.95. Optimal investment solves the Euler equation $\dfrac{\partial V}{\partial I} = 0$:

$$b I_{it} = \beta\, \mathbb{E}_{it} V_K(L_{it+1}, K_{it+1}, W_{it+1}, \omega_{it+1}) \tag{A.23}$$

[2] This derivation follows Collard-Wexler and De Loecker (2016) and Van Biesebroeck (2007).

The envelope condition yields:

$$V_K(L_{it},K_{it},W_{it},\omega_{it}) = \alpha_k L_{it}^{\alpha_\ell} K_{it}^{\alpha_k-1} e^{\omega_{it}} + \beta(1-\delta)\,\mathbb{E}_{it}\,V_K(L_{it+1},K_{it+1},W_{it+1},\omega_{it+1}) \tag{A.24}$$

Substituting in (A.17) and (A.23):

$$V_K(L_{it},K_{it},W_{it},\omega_{it}) = \alpha_k \alpha_\ell^{\frac{\alpha_\ell}{1-\alpha_\ell}} K_{it}^{\frac{\alpha_k+\alpha_\ell-1}{1-\alpha_\ell}} W_{it}^{\frac{-\alpha_\ell}{1-\alpha_\ell}} e^{\frac{\omega_{it}}{1-\alpha_\ell}} + b(1-\delta)I_{it} \tag{A.25}$$

Given a constant returns to scale technology ($\alpha_\ell + \alpha_k = 1$), the Euler equation becomes:

$$I_{it} = \frac{\beta\alpha_k}{b}\alpha_\ell^{\frac{\alpha_\ell}{1-\alpha_\ell}}\,\mathbb{E}_{it}\left[W_{it+1}^{\frac{-\alpha_\ell}{1-\alpha_\ell}} e^{\frac{\omega_{it+1}}{1-\alpha_\ell}}\right] + \beta(1-\delta)\,\mathbb{E}_{it}\,I_{it+1} \tag{A.26}$$

$$\implies I_{it} = \frac{\beta\alpha_k}{b}\alpha_\ell^{\frac{\alpha_\ell}{1-\alpha_\ell}} \sum_{\tau=0}^{\infty} \beta^\tau (1-\delta)^\tau\,\mathbb{E}_{it}\left[W_{it+1+\tau}^{\frac{-\alpha_\ell}{1-\alpha_\ell}} e^{\frac{\omega_{it+1+\tau}}{1-\alpha_\ell}}\right] \tag{A.27}$$

Since wages and productivity are drawn independently,

$$\mathbb{E}_{it}\left[W_{it+1+\tau}^{\frac{-\alpha_\ell}{1-\alpha_\ell}} e^{\frac{\omega_{it+1+\tau}}{1-\alpha_\ell}}\right] = \mathbb{E}_{it}\left[W_{it+1+\tau}^{\frac{-\alpha_\ell}{1-\alpha_\ell}}\right]\mathbb{E}_t\left[e^{\frac{\omega_{it+1+\tau}}{1-\alpha_\ell}}\right]$$

for all $\tau \geq 0$. Furthermore, $\ln(W_{it}) \sim \mathcal{N}(0,\sigma_w)^2 \implies \mathbb{E}_{it}\left[W_{it+1+\tau}^{\frac{-\alpha_\ell}{1-\alpha_\ell}}\right] = \exp\left(\frac{\alpha_\ell^2\sigma_w^2}{2(1-\alpha_\ell)^2}\right)$.

The value of $\mathbb{E}_t\left[e^{\frac{\omega_{t+1+\tau}}{1-\alpha_\ell}}\right]$ depends on the productivity process:

$$\begin{aligned}
\omega_{t+1+\tau} =& \rho(I-\lambda G_{t+\tau+1})^{-1}\omega_{t+\tau} + (I-\lambda G_{t+\tau+1})^{-1}\varepsilon_{t+1+\tau}\\
=& \rho^2(I-\lambda G_{t+\tau+1})^{-1}(I-\lambda G_{t+\tau})^{-1}\omega_{it+\tau-1} + \rho(I-\lambda G_{t+\tau+1})^{-1}(I-\lambda W_{t+\tau})^{-1}\varepsilon_{t+\tau}\\
&+ (I-\lambda G_{t+\tau+1})^{-1}\varepsilon_{t+\tau+1}\\
\omega_{t+1+\tau} =& \rho^{\tau+1}\prod_{r=0}^{\tau}(I-\lambda G_{t+\tau+1-r})^{-1}\omega_t + \sum_{r=0}^{\tau}\rho^r\prod_{s=0}^{r}(I-\lambda G_{t+\tau+1-s})^{-1}\varepsilon_{t+\tau+1-r}
\end{aligned} \tag{A.28}$$

$\mathbb{E}_t\left[e^{\frac{\omega_{t+1+\tau}}{1-\alpha_\ell}}\right]$ depends on the whether spillovers exist, and if they do, how firms form expectations about future links. When there are no spillovers $\lambda = 0$:

$$\mathbb{E}_t\left[e^{\frac{\omega_{it+1+\tau}}{1-\alpha_\ell}}\right] = \mathbb{E}_t\left[\exp\left(\frac{\rho^{\tau+1}\omega_{it}}{1-\alpha_\ell} + \frac{1}{1-\alpha_\ell}\sum_{r=0}^{\tau}\rho^r\varepsilon_{t+\tau+1-r}\right)\right] \tag{A.29}$$

$$= \exp\left(\frac{\rho^{\tau+1}\omega_{it}}{1-\alpha_\ell}\right)\prod_{r=0}^{\tau}\mathbb{E}_{it}\left[\exp\left(\frac{\rho^r\varepsilon_{it+\tau+1-r}}{1-\alpha_\ell}\right)\right] \tag{A.30}$$

$$= \exp\left(\frac{\rho^{\tau+1}\omega_{it}}{1-\alpha_\ell}\right)\prod_{r=0}^{\tau}\exp\left(\frac{\rho^{2r}\sigma_\zeta^2}{2(1-\alpha_\ell)^2}\right) \tag{A.31}$$

Let $\overline{G}$ represent the result of firms' beliefs about their future network. For example, if networks are non-stochastic or firms naively believe that $G_{t+\tau} = G_t\ \forall\tau > 0$, then we can set $\overline{G} = G_{t+1}$, which is deterministic given our previous assumption that $G_{t+1} \in \mathscr{I}_t$:

$$\begin{aligned}
\mathbb{E}_t\left[e^{\frac{\omega_{it+1+\tau}}{1-\alpha_\ell}}\right] &= \mathbb{E}_t\left[\exp\left(\frac{\rho^{\tau+1}}{1-\alpha_\ell}(I-\lambda\overline{G})^{-(\tau+1)}\omega_t + \frac{1}{1-\alpha_\ell}\sum_{r=0}^{\tau}\rho^r(I-\lambda\overline{G})^{-(r+1)}\varepsilon_{t+\tau+1-r}\right)\right] \\
&= \exp\left(\frac{\rho^{\tau+1}}{1-\alpha_\ell}(I-\lambda\overline{G})^{-(\tau+1)}\omega_t\right)\prod_{r=0}^{\tau}\mathbb{E}_{it}\left[\exp\left(\frac{\rho^r}{1-\alpha_\ell}(I-\lambda\overline{G})^{-(r+1)}\varepsilon_{t+\tau+1-r}\right)\right] \\
&= \exp\left(\frac{\rho^{\tau+1}}{1-\alpha_\ell}(I-\lambda\overline{G})^{-(\tau+1)}\omega_t\right)\prod_{r=0}^{\tau}\exp\left(\frac{\rho^{2r}\sigma_\zeta^2}{2(1-\alpha_\ell)^2}(I-\lambda\overline{G})^{-2(r+1)}\iota\right) \\
\mathbb{E}_{it}\left[e^{\frac{\omega_{it+1+\tau}}{1-\alpha_\ell}}\right] &= \exp\left(\frac{\rho^{\tau+1}}{1-\alpha_\ell}(I-\lambda\overline{G})^{-(\tau+1)}\omega_t\right)\prod_{r=0}^{\tau}\exp\left(\frac{\rho^{2r}\sigma_\zeta^2}{2(1-\alpha_\ell)^2(1-\lambda)^{2(r+1)}}\right) \qquad \text{(A.32)}
\end{aligned}$$

Therefore, optimal investment choice reduces to a function of parameters and current productivity:

$$\begin{aligned}
I_t =& \frac{\beta\alpha_k}{b}\alpha_\ell^{\frac{\alpha_\ell}{1-\alpha_\ell}}\exp\left(\frac{\alpha_\ell^2\sigma_w^2}{2(1-\alpha_\ell)^2}\right) \qquad \text{(A.33)} \\
&\times\sum_{\tau=0}^{\infty}\beta^\tau(1-\delta)^\tau\exp\left(\frac{\rho^{\tau+1}}{1-\alpha_\ell}(I-\lambda\overline{G})^{-(\tau+1)}\omega_t + \frac{\sigma_\zeta^2}{2(1-\alpha_\ell)^2(1-\lambda)^2}\sum_{r=0}^{\tau}\left(\frac{\rho}{1-\lambda}\right)^{2r}\right)
\end{aligned}$$

When there are no spillovers, this reduces to:

$$I_t = \frac{\beta\alpha_k}{b}\alpha_\ell^{\frac{\alpha_\ell}{1-\alpha_\ell}}\exp\left(\frac{\alpha_\ell^2\sigma_w^2}{2(1-\alpha_\ell)^2}\right)\sum_{\tau=0}^{\infty}\beta^\tau(1-\delta)^\tau\exp\left(\frac{\rho^{\tau+1}\omega_t}{1-\alpha_\ell} + \frac{\sigma_\zeta^2\sum_{r=0}^{\tau}\rho^{2r}}{2(1-\alpha_\ell)^2}\right) \qquad \text{(A.34)}$$

For alternative assumptions on the productivity process, such as a quadratic AR1 process, and endogenous network formation, it is not feasible to derive an closed-form solution as above. However, as long technology exhibits constant returns to scale, I approximate optimal investment as follows. Firstly, given $|\beta(1-\delta)| < 1$, then for some tolerance level close to zero, $\beta^\tau(1-\delta)^\tau <$ tolerance. Therefore, I can choose M sufficiently high such that $\sum_{\tau=0}^{M}\beta^\tau(1-\delta)^\tau\,\mathbb{E}_{it}\left[W_{it+1+\tau}^{\frac{-\alpha_\ell}{1-\alpha_\ell}}e^{\frac{\omega_{it+1+\tau}}{1-\alpha_\ell}}\right]$ is a good approximation for $\sum_{\tau=0}^{\infty}\beta^\tau(1-\delta)^\tau\,\mathbb{E}_{it}\left[W_{it+1+\tau}^{\frac{-\alpha_\ell}{1-\alpha_\ell}}e^{\frac{\omega_{it+1+\tau}}{1-\alpha_\ell}}\right]$. I set a tolerance level of e^{-4}, and given $\beta(1-\delta) = 0.95(1-0.2)$, then $M = 34$.

Next, at each time t, I draw 100 realizations of the sequence $\{\omega_{it+1+\tau}\}_{\tau=0}^{M}$ for each firm i and approximate $\mathbb{E}_{it}\left[exp\left(\frac{\omega_{it+1+\tau}}{1-\alpha_\ell}\right)\right] = \frac{1}{100}\sum_{s=0}^{100}exp\left(\frac{\omega_{it+1+\tau,s}}{1-\alpha_\ell}\right)$.

A.3 Additional Monte Carlo Experiments

In this section, I consider how bias and precision change with the size of the endogenous network effect, and the persistence of productivity over time. The Monte Carlo setup is the same as in section I.6.3.

When I vary λ, ACF and ACF-N perform similarly, yielding comparable estimates of the input elasticities and spillover effects. Low values of λ are difficult to detect, while at very high values, there is a sharp decline in efficiency, with the decline greater under ACF. Under the linear process with negative spillovers, ACF-N appears to perform better than ACF as λ rises in magnitude.

Finally, variations in ρ_1 have striking effects on the estimation of λ because it determines the strength of $G_t \omega_{t-1}$ as an instrument for $G_t \omega_t$. Intuitively, if productivity is not persistent, then neighbors' lagged TFP is a weak instrument for the contemporaneous effect of neighbors's productivity, because the intertemporal correlation is not strong. ACF-N is not immune to this issue, and loses efficiency in its estimates of λ unless ρ_1 is sufficiently high. However the input elasticities are relatively well estimated by ACF-N, while ACF leads to biased estimates for high values of ρ_1: overestimating the capital coefficient when $\rho_1 = 0.8$ and underestimating it when $\rho_1 = 0.9$.

Table A.1: Effect of λ on Bias and Precision (Quadratic AR1)

λ	Estimator		Elasticities		Productivity Process Coefficients			
			α_ℓ	α_k	β_1	ρ_1	ρ_2	λ
		True	0.6	0.4	0.5	0.8	-0.01	
0.01	ACF	Mean	0.603	0.353	-0.198	0.809	-0.01	0.
		Std. Dev.	(0.024)	(0.251)	(2.706)	(0.23)	(0.003)	(0.061)
	ACF-N	Mean	0.608	0.355	-0.038	0.811	-0.009	-0.02
		Std. Dev.	(0.037)	(0.234)	(2.394)	(0.212)	(0.027)	(0.337)
0.03	ACF	Mean	0.603	0.353	-0.182	0.809	-0.01	0.019
		Std. Dev.	(0.024)	(0.247)	(2.457)	(0.224)	(0.003)	(0.061)
	ACF-N	Mean	0.608	0.354	-0.03	0.812	-0.01	-0.009
		Std. Dev.	(0.035)	(0.23)	(2.218)	(0.206)	(0.003)	(0.686)
0.05	ACF	Mean	0.603	0.354	-0.16	0.808	-0.01	0.038
		Std. Dev.	(0.024)	(0.242)	(2.212)	(0.218)	(0.003)	(0.062)
	ACF-N	Mean	0.608	0.353	-0.027	0.813	-0.01	0.038
		Std. Dev.	(0.034)	(0.225)	(2.002)	(0.201)	(0.003)	(0.27)
0.07	ACF	Mean	0.604	0.354	-0.132	0.808	-0.01	0.057
		Std. Dev.	(0.024)	(0.237)	(1.978)	(0.212)	(0.003)	(0.062)
	ACF-N	Mean	0.607	0.354	0.013	0.814	-0.01	0.055
		Std. Dev.	(0.033)	(0.219)	(1.746)	(0.193)	(0.003)	(0.143)
0.09	ACF	Mean	0.604	0.357	-0.099	0.805	-0.01	0.076
		Std. Dev.	(0.024)	(0.23)	(1.759)	(0.204)	(0.003)	(0.063)
	ACF-N	Mean	0.607	0.355	0.044	0.814	-0.01	0.071
		Std. Dev.	(0.033)	(0.212)	(1.546)	(0.184)	(0.003)	(0.136)
0.1	ACF	Mean	0.604	0.36	-0.08	0.803	-0.01	0.086
		Std. Dev.	(0.024)	(0.226)	(1.65)	(0.2)	(0.003)	(0.063)
	ACF-N	Mean	0.607	0.356	0.059	0.814	-0.01	0.08
		Std. Dev.	(0.033)	(0.208)	(1.443)	(0.179)	(0.003)	(0.151)
0.3	ACF	Mean	0.606	0.643	0.054	0.414	-0.024	0.446
		Std. Dev.	(0.072)	(0.152)	(3.357)	(0.782)	(0.151)	(1.833)
	ACF-N	Mean	0.605	0.388	0.417	0.813	-0.01	0.299
		Std. Dev.	(0.032)	(0.084)	(0.399)	(0.065)	(0.004)	(0.062)
0.5	ACF	Mean	0.645	0.362	-5.659	0.723	-0.012	0.651
		Std. Dev.	(0.151)	(0.156)	(270.251)	(0.645)	(0.063)	(8.7)
	ACF-N	Mean	0.648	0.351	-3.503	0.77	-0.012	0.704
		Std. Dev.	(0.1)	(0.101)	(204.646)	(0.311)	(0.034)	(6.386)
0.7	ACF	Mean	0.682	0.318	-3.839	0.668	-0.012	1.148
		Std. Dev.	(0.19)	(0.19)	(217.5)	(4.683)	(0.616)	(11.871)
	ACF-N	Mean	0.685	0.314	4.003	0.592	-0.001	0.671
		Std. Dev.	(0.144)	(0.144)	(91.859)	(0.669)	(0.099)	(2.519)

Based on 1000 replications. Estimators are based on Ackerberg et al. (2015) with ACF denoting the standard procedure and ACF-N indicating the modified procedure to account for network effects. Networks are exogenous Erdos-Renyi (binomial) graphs with 0.05 density. The data-generating process for productivity is quadratic AR1 with endogenous network effects.

Table A.2: Effect of ρ on Bias and Precision (Quadratic AR1)

ρ	Estimator		Elasticities		Productivity Process Coefficients			
			α_ℓ	α_k	β_1	ρ_1	ρ_2	λ
		True	0.6	0.4	0.5		-0.01	0.3
0.1	ACF	Mean	0.644	0.413	-271.942	0.485	-0.047	52.923
		Std. Dev.	(0.138)	(0.384)	(8697.007)	(12.757)	(1.038)	(1683.731)
	ACF-N	Mean	0.65	0.39	2.029	0.113	-0.009	0.151
		Std. Dev.	(0.1)	(0.365)	(90.035)	(0.514)	(0.041)	(10.864)
0.2	ACF	Mean	0.634	0.362	3.014	0.255	-0.003	-0.094
		Std. Dev.	(0.131)	(0.234)	(30.083)	(1.139)	(0.109)	(5.893)
	ACF-N	Mean	0.647	0.343	-0.796	0.205	-0.01	0.14
		Std. Dev.	(0.099)	(0.219)	(37.532)	(0.127)	(0.031)	(7.268)
0.3	ACF	Mean	0.628	0.369	1.427	0.286	-0.001	0.069
		Std. Dev.	(0.109)	(0.161)	(6.855)	(0.587)	(0.166)	(3.382)
	ACF-N	Mean	0.645	0.345	-0.132	0.312	-0.009	1.074
		Std. Dev.	(0.095)	(0.151)	(31.101)	(0.103)	(0.03)	(24.603)
0.4	ACF	Mean	0.617	0.381	1.412	0.314	0.028	-0.083
		Std. Dev.	(0.086)	(0.122)	(15.72)	(2.994)	(1.188)	(11.549)
	ACF-N	Mean	0.638	0.354	0.251	0.409	-0.01	0.45
		Std. Dev.	(0.084)	(0.118)	(21.734)	(0.086)	(0.028)	(8.122)
0.5	ACF	Mean	0.609	0.389	0.831	0.518	-0.013	0.268
		Std. Dev.	(0.061)	(0.094)	(1.139)	(0.193)	(0.104)	(0.935)
	ACF-N	Mean	0.628	0.364	1.104	0.512	-0.011	0.105
		Std. Dev.	(0.072)	(0.103)	(13.659)	(0.066)	(0.022)	(7.008)
0.6	ACF	Mean	0.606	0.398	0.758	0.609	-0.009	0.253
		Std. Dev.	(0.044)	(0.082)	(0.549)	(0.053)	(0.017)	(0.146)
	ACF-N	Mean	0.619	0.373	1.087	0.613	-0.01	0.186
		Std. Dev.	(0.057)	(0.09)	(6.734)	(0.064)	(0.016)	(1.727)
0.7	ACF	Mean	0.601	0.465	0.575	0.665	-0.012	0.29
		Std. Dev.	(0.043)	(0.086)	(0.38)	(0.081)	(0.014)	(0.1)
	ACF-N	Mean	0.608	0.385	0.642	0.714	-0.01	0.279
		Std. Dev.	(0.036)	(0.081)	(2.109)	(0.053)	(0.005)	(0.47)
0.8	ACF	Mean	0.606	0.643	0.054	0.414	-0.024	0.446
		Std. Dev.	(0.072)	(0.152)	(3.357)	(0.782)	(0.151)	(1.833)
	ACF-N	Mean	0.605	0.388	0.417	0.813	-0.01	0.299
		Std. Dev.	(0.032)	(0.084)	(0.399)	(0.065)	(0.004)	(0.062)
0.9	ACF	Mean	0.708	0.113	-5.964	0.65	-0.028	0.346
		Std. Dev.	(0.093)	(0.273)	(33.081)	(4.953)	(0.367)	(4.293)
	ACF-N	Mean	0.603	0.386	0.024	0.922	-0.01	0.296
		Std. Dev.	(0.028)	(0.09)	(1.165)	(0.122)	(0.002)	(0.033)

Based on 1000 replications. Estimators are based on Ackerberg et al. (2015) with ACF denoting the standard procedure and ACF-N indicating the modified procedure to account for network effects. Networks are exogenous Erdos-Renyi (binomial) graphs with 0.05 density. The data-generating process for productivity is quadratic AR1 with endogenous network effects.

A.4 Variable Construction

- Sales: Net sales deflated by an industry deflator for GDP.
- Labor: Number of employees
- Capital: Total property, plant and equipment (gross) before depreciation. Following the method in İmrohoroğlu and Tüzel (2014), I deflate using the yearly implicit price deflator for fixed investment at the calculated age of capital. Capital age is computed as the ratio of accumulated depreciation to current depreciation, smoothed by taking a 3-year moving average. The year at which the deflator is applied is current year − average capital age. All years before 1929 are bottom-coded because that is the earliest year in the deflator data.
- Materials: Estimated as Cost of goods sold plus Selling, General and Administrative Expenses minus labor costs. Salaries and wage costs are missing for most firms, so I estimate labor costs by multiplying number of employees by 2-digit industry wages per full-time equivalent employee. Figure A.1 shows that these estimates strongly correlate with wage costs that were reported in the data. Estimated materials are deflated by the 2-digit industry price indices for intermediate inputs.
- Value-added: Sales minus materials, deflated by industry price indices for value-added.
- Exports: International Sales as reported in the geographic segments information on annual reports. These figures are often reported by location of the final customer, but do not always differentiate between exports from the US and sales by multinational firms within foreign countries. However, to the extent that this contains some measure of exporting, a dummy for exporting based on positive values of this variable should have minimal measurement error.
- Industry: Industry classifications are based on those used in input-output tables from the Bureau of Economic Analysis (BEA). There are 65 industries from before 1997 and 71 industries from 1997 onwards. These roughly correspond to 3-digit NAICS and 2-digit SIC codes. Compustat's annual financials only reports the latest industry classification, therefore, I obtain historical NAICS codes from the primary business segment. I also replace SIC codes for companies that are incorrectly coded as ”99” (unclassifiable) from annual reports in the EDGAR database and business segment data. These are then converted to BEA industry codes using the concordances provided by the bureau. All deflators, price indices and input-output tables are based on these BEA industry codes. However, in regressions I combine industries with too few observations. These include: transit and ground transportation with general transportation and warehousing, and other transportation and support activities; Funds, trusts and other financial vehicles combined with securities, commodity contracts and investments; Legal services with miscellaneous professional services; Ambulatory health, hospitals, nursing and residential care with social assistance. This results in 41 industry groups.

Table A.3: Sample Size by Industry and Sector

Sector	Industry	Observations
Mining	Mining, except oil and gas	445
	Oil and gas extraction	2323
	Support activities for mining	691
Utilities	Utilities	2427
Construction	Construction	481
Durables Manufacturing	Electrical equipment, appliances, and components	1063
	Fabricated metal products	1190
	Furniture and related products	303
	Machinery	2571
	Miscellaneous manufacturing	1490
	Motor vehicles, bodies and trailers, and parts	1975
	Nonmetallic mineral products	368
	Other transportation equipment	1059
	Primary metals	902
	Wood products	192
Non-Durables Manufacturing	Apparel and leather and allied products	1410
	Chemical products	3959
	Food and beverage and tobacco products	1561
	Paper products	601
	Petroleum and coal products	1068
	Plastics and rubber products	778
	Printing and related support activities	223
	Textile mills and textile product mills	448
Electronics Manufacturing	Computer and electronic products	9581
Wholesale	Wholesale trade	2215
Retail	Food and beverage stores	347
	General merchandise stores	574
	Motor vehicle and parts dealers	153
	Other retail	1303
Transport and Warehousing	Air transportation	422
	Other transportation and support activities	265
	Pipeline transportation	487
	Rail transportation	238
	Transit and ground passenger transportation	14
	Transportation and warehousing	22
	Truck transportation	322
	Warehousing and storage	13
	Water transportation	284
Information	Broadcasting and telecommunications	2213
	Data processing, internet publishing, and other information services	633
	Motion picture and sound recording industries	292
	Publishing industries, except internet (includes software)	1788
FIRE	Federal Reserve banks, credit intermediation, and related activities	554
	Funds, trusts, and other financial vehicles	25
	Insurance carriers and related activities	397
	Real estate	222
	Rental and leasing services and lessors of intangible assets	445
	Securities, commodity contracts, and investments	247
Services	Accommodation	117
	Administrative and support services	664
	Ambulatory health care services	263
	Amusements, gambling, and recreation industries	56
	Computer systems design and related services	1162
	Educational services	46
	Food services and drinking places	238
	Hospitals	76
	Legal services	4
	Miscellaneous professional, scientific, and technical services	998
	Nursing and residential care facilities	42
	Other services, except government	115
	Performing arts, spectator sports, museums, and related activities	30
	Social assistance	3
	Waste management and remediation services	159

This table reports the number firm-year observations in the sample by primary sector and industry as determined by the BEA industry classification.

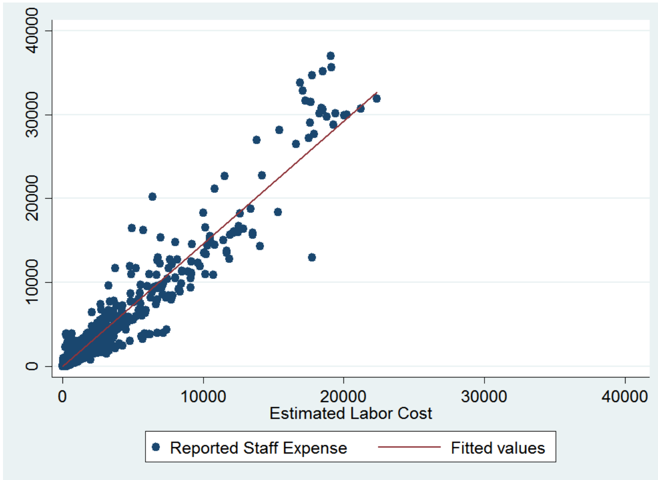


Figure A.1: Estimated and Reported Labor Expenses

This figure shows the correlation between labor expenses reported in *Compustat* and labor costs estimated using industry wage expenditure.

A.5 Additional Results and Robustness Checks

A.5.1 Value-Added Estimates

Table A.4: Productivity Spillovers by Relationship Dynamics (Value-Added)

		Dependent Variable: $\ln\text{TFP}_t$			
Period	Estimator	Continuing Customers' $\ln\text{TFP}_t$	New Customers' $\ln\text{TFP}_t$	Continuing Suppliers' $\ln\text{TFP}_t$	New Suppliers' $\ln\text{TFP}_t$
1977-1986	ACF	0.0009	0.0023	0.002	0.0005
		(0.0014)	(0.0014)	(0.0011)	(0.001)
	ACF-N	0.0008	0.0022	0.0021	0.0007
		(0.0014)	(0.0014)	(0.0011)	(0.001)
	ACF-ND	0.0008	0.001	0.003	0.0003
		(0.0016)	(0.0015)	(0.0013)	(0.0011)
1987-1996	ACF	0.0001	0.0003	-0.0006	0.001
		(0.0009)	(0.001)	(0.0007)	(0.0006)
	ACF-N	0.0002	0.0003	-0.0011	0.0005
		(0.0009)	(0.001)	(0.0007)	(0.0006)
	ACF-ND	0.0004	0.0004	-0.0012	0.0006
		(0.001)	(0.001)	(0.0007)	(0.0007)
1997-2006	ACF	0.0008	0.0004	0.0003	0.0014
		(0.0005)	(0.0005)	(0.0004)	(0.0004)
	ACF-N	0.0008	0.0004	0.0006	0.0017
		(0.0005)	(0.0005)	(0.0004)	(0.0004)
	ACF-ND	0.0005	0.0004	0.0006	0.002
		(0.0005)	(0.0004)	(0.0005)	(0.0004)
2007-2016	ACF	0.0012	0.0003	0.0011	0.0003
		(0.0006)	(0.0004)	(0.0004)	(0.0003)
	ACF-N	0.0011	0.0003	0.0013	0.0004
		(0.0006)	(0.0004)	(0.0004)	(0.0003)
	ACF-ND	0.0012	0.0003	0.0011	0.0002
		(0.0007)	(0.0004)	(0.0004)	(0.0003)
All	ACF	0.0007	0.0008	0.0006	0.0009
		(0.0003)	(0.0003)	(0.0003)	(0.0002)
	ACF-N	0.0007	0.0008	0.0008	0.001
		(0.0003)	(0.0003)	(0.0003)	(0.0002)
	ACF-ND	0.0007	0.0008	0.0007	0.0011
		(0.0004)	(0.0003)	(0.0003)	(0.0002)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a value-added production function (in logs) estimated with the standard Ackerberg et al. (2015) procedure (ACF), or with modifications to accommodate network effects (ACF-N) and network differencing (ACF-ND). Network effects for ACF are estimated using the generalized 2SLS procedure for heterogenous peer effects in Dieye and Fortin (2017); Patacchini et al. (2017). Standard errors are in parentheses. All specifications include industry and year fixed effects.

Table A.5: Productivity Spillovers by Sector (Value-Added)

	Dependent Variable: $\ln\text{TFP}_t$											
	Firm's Sector											
Partners' Sector	Mining	Utilities	Constr	Durables	Non-Durables	Electronics	Wholesale	Retail	Trans & WH	Info	FIRE	Services
Mining	0.0037	-0.0004	0.009	0.0027	0.0014	-0.0057	-0.0011	-0.0026	0.0121	0.0135	-0.001	-0.0035
	(0.0018)	(0.0011)	(0.0092)	(0.0013)	(0.0009)	(0.0081)	(0.0034)	(0.0025)	(0.0055)	(0.0068)	(0.0036)	(0.0025)
Utilities	0.0029	0.0025	0.0034	-0.0001	0.0022	0.0025	0.0052	-0.0023	0.0024	-0.0013	-0.003	0.0033
	(0.0018)	(0.001)	(0.004)	(0.001)	(0.0011)	(0.0021)	(0.0033)	(0.0028)	(0.0021)	(0.0054)	(0.0107)	(0.0034)
Construction	0.0151	0.0014	0.009	0.0013	-0.0014	-0.0018	-0.0107	-0.0057	0.0047	0.0004	0.001	0.0096
	(0.0172)	(0.0013)	(0.0049)	(0.0023)	(0.0009)	(0.0032)	(0.0068)	(0.0037)	(0.0091)	(0.001)	(0.0033)	(0.0107)
Durables Mfg	0.0008	-0.0007	0.0171	-0.0002	-0.0019	-0.0017	0.0013	-0.0014	-0.0002	-0.0011	0.0027	0.003
	(0.0018)	(0.0008)	(0.0084)	(0.0006)	(0.0006)	(0.0006)	(0.0012)	(0.0007)	(0.0013)	(0.0013)	(0.0035)	(0.0014)
Non-Durables Mfg	0.0023	0.0007	0.0048	-0.0011	-0.0011	-0.0006	0.003	-0.0043	0.0035	-0.0012	-0.0073	-0.0059
	(0.0019)	(0.0011)	(0.0061)	(0.0006)	(0.0005)	(0.0011)	(0.0012)	(0.0007)	(0.0019)	(0.0016)	(0.0035)	(0.0017)
Electronics Mfg	-0.0087	-0.0011	-0.008	0.0004	-0.0014	0.0012	0.0042	-0.0013	0.0008	-0.0006	0.0049	-0.0
	(0.0081)	(0.0014)	(0.0084)	(0.0006)	(0.0012)	(0.0006)	(0.0011)	(0.0013)	(0.0013)	(0.0008)	(0.004)	(0.0014)
Wholesale	0.0007	-0.0005	0.0214	0.0007	0.001	0.0024	0.0061	-0.002	-0.0022	-0.0004	-0.0068	-0.0012
	(0.0042)	(0.0013)	(0.0216)	(0.0007)	(0.0006)	(0.0008)	(0.0025)	(0.0009)	(0.0026)	(0.0012)	(0.0058)	(0.0015)
Retail	-0.0052	-0.0082	0.0023	0.0018	0.0006	0.005	0.0033	0.0001	-0.0012	0.0044	0.0086	0.0002
	(0.0039)	(0.0032)	(0.0169)	(0.0007)	(0.0006)	(0.0018)	(0.0016)	(0.0012)	(0.0013)	(0.0022)	(0.0032)	(0.0022)
Transport and Warehousing	0.0031	-0.0003	0.013	0.0006	0.0005	-0.0016	0.0162	0.0025	0.0004	-0.0	0.0161	-0.0034
	(0.0029)	(0.0008)	(0.0084)	(0.0013)	(0.0006)	(0.0029)	(0.0059)	(0.0019)	(0.0016)	(0.0019)	(0.0044)	(0.0024)
Information	0.0071	0.0002	0.0036	-0.0026	-0.0017	0.0011	0.0055	-0.0003	-0.0042	0.002	0.0029	-0.0022
	(0.0052)	(0.0013)	(0.0064)	(0.0012)	(0.0011)	(0.0007)	(0.0021)	(0.0014)	(0.0014)	(0.0009)	(0.0019)	(0.0015)
Finance, Insur & Real Estate	0.002	-0.0049	-0.0054	-0.0007	-0.0008	0.0031	0.0038	-0.0022	0.0027	-0.0013	-0.0008	0.0009
	(0.0034)	(0.0045)	(0.003)	(0.0012)	(0.0006)	(0.0009)	(0.0066)	(0.001)	(0.0012)	(0.0012)	(0.0017)	(0.0015)
Services	-0.0006	-0.0004	0.0055	0.0004	-0.001	0.0003	-0.0004	0.0003	-0.0014	0.0004	0.0011	0.0007
	(0.0027)	(0.001)	(0.015)	(0.0008)	(0.0006)	(0.0007)	(0.002)	(0.0016)	(0.0015)	(0.0012)	(0.0017)	(0.0015)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a gross output production function (in logs) estimated with the standard Ackerberg et al. (2015) procedure (ACF), or with modifications to accommodate network effects and network differencing (ACF-ND). Network effects for ACF are estimated using the generalized 2SLS procedure for heterogenous peer effects in Dieye and Fortin (2017); Patacchini et al. (2017). Sectors are determined according to the BEA industry classification. Standard errors are in parentheses. All specifications include industry and year fixed effects.

Table A.6: Productivity Spillovers by Firm Size & Relationship Direction (Value-Added)

Partner Size	Relationship	Firm Size	Dependent Variable: $\ln TFP_t$ 1977-1986	1987-1996	1997-2006	2007-2016	All
Large	Customers	Large	0.0002	0.0005	0.0002	0.0007	0.0008
			(0.0015)	(0.0007)	(0.0005)	(0.0004)	(0.0003)
		Small	0.0066	0.0007	-0.0021	-0.0001	0.002
			(0.0019)	(0.001)	(0.0007)	(0.0006)	(0.0004)
	Suppliers	Large	0.0002	-0.0009	0.0012	0.0007	0.0004
			(0.0013)	(0.0006)	(0.0004)	(0.0003)	(0.0002)
		Small	0.0339	0.0006	-0.0012	-0.0038	0.0028
			(0.018)	(0.005)	(0.0046)	(0.0031)	(0.0027)
Small	Customers	Large	-0.0033	-0.0046	-0.0088	-0.0043	-0.0054
			(0.0047)	(0.0048)	(0.004)	(0.0022)	(0.0023)
		Small	0.0125	-0.0059	-0.0021	0.0022	-0.0003
			(0.0071)	(0.0062)	(0.0029)	(0.0059)	(0.0028)
	Suppliers	Large	0.0013	-0.0001	0.0017	0.0005	0.0007
			(0.0011)	(0.0007)	(0.0005)	(0.0003)	(0.0002)
		Small	0.0218	-0.0004	0.0045	-0.0023	0.0039
			(0.0088)	(0.0046)	(0.0041)	(0.0046)	(0.0025)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a value-added production function (in logs) estimated with the standard Ackerberg et al. (2015) procedure (ACF), or with modifications to accommodate network effects (ACF-N) and network differencing (ACF-ND). Network effects for ACF are estimated using the generalized 2SLS procedure for heterogenous peer effects in Dieye and Fortin (2017); Patacchini et al. (2017). Large firms are businesses with 500 or more employees.Standard errors are in parentheses. All specifications include industry and year fixed effects.

Table A.7: Productivity Spillovers by Varying Firm Size Cutoffs (Value-Added)

			Dependent Variable: $\ln\text{TFP}_t$			
			Firm's Sector			
Partner Size	Relationship	Firm Size	500	1000	5000	Median
Large	Customers	Large	0.0008	0.0008	-0.0	0.0002
			(0.0003)	(0.0003)	(0.0003)	(0.0003)
		Small	0.002	0.003	0.0014	0.0022
			(0.0004)	(0.0004)	(0.0004)	(0.0004)
	Suppliers	Large	0.0004	0.0002	-0.0006	-0.0
			(0.0002)	(0.0002)	(0.0002)	(0.0002)
		Small	0.0028	0.0049	0.0037	0.0048
			(0.0027)	(0.0015)	(0.001)	(0.0006)
Small	Customers	Large	-0.0054	-0.002	-0.0009	-0.0003
			(0.0023)	(0.0015)	(0.0009)	(0.0005)
		Small	-0.0003	-0.0014	0.0004	0.0019
			(0.0028)	(0.0018)	(0.0006)	(0.0007)
	Suppliers	Large	0.0007	0.0006	-0.0001	0.0
			(0.0002)	(0.0002)	(0.0003)	(0.0003)
		Small	0.0039	0.0038	0.0039	0.0032
			(0.0025)	(0.0015)	(0.0006)	(0.0006)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a value-added production function (in logs) estimated with the standard Ackerberg et al. (2015) procedure (ACF), or with modifications to accommodate network effects (ACF-N) and network differencing (ACF-ND). Network effects for ACF are estimated using the generalized 2SLS procedure for heterogenous peer effects in Dieye and Fortin (2017); Patacchini et al. (2017). Large firms are defined by having at least as many employees as the cutoffs indicated above. The median cutoff is determined by industry and year. Standard errors are in parentheses. All specifications include industry and year fixed effects.

A.5.2 Unweighted Estimates

Table A.8: Endogenous Productivity Spillovers (Gross Output, Unweighted)

	Dependent Variable: $\ln\text{TFP}_t$		
Period	Estimator	$\ln\text{TFP}_{t-1}$	Neighbors' $\ln\text{TFP}_t$
1977-1986	GNR	0.8403	0.0068
		(0.0205)	(0.0049)
	GNR-N	0.8391	0.0074
		(0.0207)	(0.0049)
	GNR-ND	0.8248	-0.0001
		(0.0228)	(0.0058)
1987-1996	GNR	0.8314	-0.0065
		(0.0244)	(0.0039)
	GNR-N	0.8312	-0.0063
		(0.0244)	(0.0039)
	GNR-ND	0.8232	-0.0093
		(0.0271)	(0.0039)
1997-2006	GNR	0.8583	0.0001
		(0.013)	(0.0043)
	GNR-N	0.8588	0.0003
		(0.0132)	(0.0043)
	GNR-ND	0.8584	0.0002
		(0.0145)	(0.0055)
2007-2016	GNR	0.8964	0.0115
		(0.0214)	(0.0048)
	GNR-N	0.8964	0.0113
		(0.0214)	(0.005)
	GNR-ND	0.889	0.0096
		(0.0229)	(0.0047)
All	GNR	0.9038	0.0076
		(0.0066)	(0.0023)
	GNR-N	0.9027	0.0086
		(0.0067)	(0.0024)
	GNR-ND	0.8998	0.0069
		(0.0073)	(0.0025)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a gross output production function (in logs) estimated with the standard Gandhi et al. (2020) procedure (GNR), or with modifications to accommodate network effects (GNR-N) and network differencing (GNR-ND). Network effects for GNR are estimated using the generalized 2SLS procedure in Lee (2003); Bramoullé et al. (2009). Interaction matrices for network effects are unweighted. Standard errors are in parentheses. All specifications include industry and year fixed effects.

Table A.9: Productivity Spillovers by Relationship Direction (Gross Output, Unweighted)

	Dependent Variable: $\ln\text{TFP}_t$		
Period	Estimator	Customers' $\ln\text{TFP}_t$	Suppliers' $\ln\text{TFP}_t$
1977-1986	GNR	0.0036	0.0167
		(0.004)	(0.005)
	GNR-N	0.0022	0.017
		(0.0033)	(0.0045)
	GNR-ND	-0.0025	0.0127
		(0.0036)	(0.004)
1987-1996	GNR	0.0063	-0.008
		(0.004)	(0.0036)
	GNR-N	0.0079	-0.0122
		(0.0039)	(0.0035)
	GNR-ND	-0.0056	-0.012
		(0.0044)	(0.0079)
1997-2006	GNR	0.0013	0.0023
		(0.0005)	(0.0005)
	GNR-N	0.001	0.0033
		(0.0005)	(0.0005)
	GNR-ND	0.0006	0.0041
		(0.0006)	(0.0006)
2007-2016	GNR	0.0006	0.0016
		(0.0004)	(0.0006)
	GNR-N	0.0004	0.0024
		(0.0004)	(0.0008)
	GNR-ND	0.0002	0.0025
		(0.0004)	(0.0008)
All	GNR	0.0025	0.0053
		(0.0008)	(0.0009)
	GNR-N	0.0024	0.0079
		(0.0008)	(0.0011)
	GNR-ND	0.0015	0.008
		(0.0008)	(0.001)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a gross output production function (in logs) estimated with the standard Gandhi et al. (2020) procedure (GNR), or with modifications to accommodate network effects (GNR-N) and network differencing (GNR-ND). Network effects for GNR are estimated using the generalized 2SLS procedure for heterogenous peer effects in Dieye and Fortin (2017); Patacchini et al. (2017). Interaction matrices for network effects are unweighted. Standard errors are in parentheses. All specifications include industry and year fixed effects.

Table A.10: Productivity Spillovers by Relationship Dynamics (Gross Output, Unweighted)

		Dependent Variable: $\ln TFP_t$			
Period	Estimator	Continuing Customers' $\ln TFP_t$	New Customers' $\ln TFP_t$	Continuing Suppliers' $\ln TFP_t$	New Suppliers' $\ln TFP_t$
1977-1986	GNR	0.0037	0.001	0.0149	0.0092
		(0.0034)	(0.0039)	(0.0038)	(0.0039)
	GNR-N	0.0013	0.0004	0.0138	0.0095
		(0.0024)	(0.0026)	(0.0029)	(0.0028)
	GNR-ND	0.0001	-0.0028	0.0157	0.0088
		(0.0031)	(0.0031)	(0.0032)	(0.0035)
1987-1996	GNR	0.0077	0.0033	-0.003	-0.0121
		(0.0035)	(0.0039)	(0.0038)	(0.0037)
	GNR-N	-0.0036	0.0165	-0.0041	-0.0295
		(0.0048)	(0.0068)	(0.0081)	(0.0077)
	GNR-ND	-0.0116	0.0101	0.0006	-0.0214
		(0.0046)	(0.0065)	(0.009)	(0.0088)
1997-2006	GNR	-0.0007	0.0005	0.0003	0.0013
		(0.0004)	(0.0004)	(0.0003)	(0.0003)
	GNR-N	-0.0009	0.0003	0.0015	0.0026
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
	GNR-ND	-0.0011	0.0002	0.002	0.0031
		(0.0005)	(0.0005)	(0.0005)	(0.0004)
2007-2016	GNR	0.0005	0.0005	0.0015	0.0013
		(0.0004)	(0.0004)	(0.0005)	(0.0004)
	GNR-N	0.0004	0.0004	0.0025	0.0022
		(0.0004)	(0.0004)	(0.0007)	(0.0005)
	GNR-ND	0.0001	0.0003	0.0025	0.0022
		(0.0004)	(0.0004)	(0.0008)	(0.0006)
All	GNR	0.0008	0.0017	0.0029	0.0038
		(0.0006)	(0.0006)	(0.0006)	(0.0006)
	GNR-N	0.0009	0.0017	0.0066	0.0076
		(0.0007)	(0.0007)	(0.0009)	(0.0008)
	GNR-ND	0.0005	0.0012	0.007	0.0081
		(0.0007)	(0.0008)	(0.001)	(0.0009)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a gross output production function (in logs) estimated with the standard Gandhi et al. (2020) procedure (GNR), or with modifications to accommodate network effects (GNR-N) and network differencing (GNR-ND). Network effects for GNR are estimated using the generalized 2SLS procedure for heterogenous peer effects in Dieye and Fortin (2017); Patacchini et al. (2017). Interaction matrices for network effects are unweighted. Standard errors are in parentheses. All specifications include industry and year fixed effects.

Table A.11: Productivity Spillovers by Sector (Gross Output, Unweighted)

	Dependent Variable: $\ln\text{TFP}_t$											
	Firm's Sector											
Partners' Sector	Mining	Utilities	Constr	Durables	Non-Durables	Electronics	Wholesale	Retail	Trans & WH	Info	FIRE	Services
Mining	-0.0082	-0.0093	-0.0062	0.0017	0.0071	-0.0155	0.0165	0.0088	0.0098	0.0343	0.0042	0.0027
	(0.0062)	(0.0037)	(0.0317)	(0.0048)	(0.0026)	(0.0312)	(0.01)	(0.0077)	(0.0088)	(0.0107)	(0.0082)	(0.0077)
Utilities	-0.0031	-0.0006	0.006	0.0029	0.0097	0.0127	0.0041	-0.0027	0.0018	-0.0023	-0.0035	0.01
	(0.0057)	(0.0027)	(0.0102)	(0.0026)	(0.002)	(0.0079)	(0.008)	(0.0081)	(0.0063)	(0.0121)	(0.0173)	(0.0058)
Construction	-0.0189	0.0012	0.0144	0.0052	-0.0057	-0.0076	0.0109	-0.0072	0.0164	0.0041	-0.0002	0.0276
	(0.0303)	(0.004)	(0.0112)	(0.0057)	(0.0035)	(0.0128)	(0.0073)	(0.0087)	(0.0222)	(0.0034)	(0.0059)	(0.0213)
Durables Mfg	0.0074	0.0002	0.0255	0.0024	0.0012	-0.0036	0.0076	-0.0016	0.0028	0.0037	0.0049	0.003
	(0.0063)	(0.0029)	(0.0223)	(0.0021)	(0.0016)	(0.0023)	(0.0026)	(0.0016)	(0.0034)	(0.0033)	(0.0061)	(0.0033)
Non-Durables Mfg	-0.0059	-0.0014	-0.0028	0.0	-0.0009	-0.0065	0.0033	-0.006	-0.0063	-0.0025	-0.0169	-0.0098
	(0.005)	(0.0027)	(0.0129)	(0.0017)	(0.0013)	(0.0046)	(0.0026)	(0.0015)	(0.0037)	(0.0043)	(0.0082)	(0.0037)
Electronics Mfg	-0.0413	-0.015	-0.0262	-0.0001	-0.004	0.0231	0.0126	0.0021	0.0076	0.0005	0.0203	0.0002
	(0.0478)	(0.0053)	(0.034)	(0.0044)	(0.0036)	(0.0028)	(0.0029)	(0.0031)	(0.0055)	(0.0029)	(0.0089)	(0.0041)
Wholesale	-0.005	0.0122	0.0115	0.0021	0.0031	0.016	0.0096	0.0016	0.0032	0.0021	-0.0125	0.0026
	(0.0114)	(0.0073)	(0.0157)	(0.002)	(0.0012)	(0.002)	(0.0037)	(0.0013)	(0.0101)	(0.0023)	(0.0114)	(0.0038)
Retail	0.0109	-0.0035	-0.0072	0.0071	0.0029	0.0187	0.0101	0.0012	-0.0012	0.0086	0.0175	0.0016
	(0.0114)	(0.01)	(0.0154)	(0.0027)	(0.0013)	(0.0035)	(0.0018)	(0.0025)	(0.0038)	(0.004)	(0.0045)	(0.0043)
Transport and Warehousing	0.0075	0.0111	0.0536	0.0035	0.0031	0.0063	0.0074	0.0021	-0.003	0.0007	-0.0084	0.0
	(0.009)	(0.0032)	(0.0183)	(0.004)	(0.0019)	(0.0057)	(0.0105)	(0.0038)	(0.004)	(0.0079)	(0.007)	(0.01)
Information	0.0235	-0.0023	0.0083	-0.0034	-0.001	0.0145	0.0062	-0.001	-0.0174	0.004	0.0064	-0.0071
	(0.0114)	(0.0066)	(0.0165)	(0.0038)	(0.0027)	(0.0024)	(0.0047)	(0.0025)	(0.0046)	(0.0027)	(0.0046)	(0.0038)
Finance, Insur & Real Estate	0.0003	0.0048	-0.013	-0.0	-0.0044	0.0129	-0.0024	0.0017	0.0043	0.004	-0.0019	0.0047
	(0.0108)	(0.0137)	(0.0124)	(0.0043)	(0.0024)	(0.0033)	(0.0144)	(0.0019)	(0.0042)	(0.003)	(0.0042)	(0.0034)
Services	0.0032	-0.0086	0.0082	0.0084	0.004	0.0021	0.008	0.004	0.0023	0.005	0.0088	0.0024
	(0.0113)	(0.0035)	(0.0245)	(0.0022)	(0.0022)	(0.0027)	(0.0069)	(0.0025)	(0.0048)	(0.003)	(0.0047)	(0.0036)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a gross output production function (in logs) estimated with the standard Gandhi et al. (2020) procedure (GNR), or with modifications to accommodate network effects (GNR-N) and network differencing (GNR-ND). Network effects for GNR are estimated using the generalized 2SLS procedure for heterogenous peer effects in Dieye and Fortin (2017); Patacchini et al. (2017). Sectors are determined according to the BEA industry classification. Interaction matrices for network effects are unweighted. Standard errors are in parentheses. All specifications include industry and year fixed effects.

Table A.12: Productivity Spillovers by Firm Size & Relationship Direction (Gross Output, Unweighted)

Partner Size	Relationship	Firm Size	Dependent Variable: $\ln TFP_t$ 1977-1986	1987-1996	1997-2006	2007-2016	All
Large	Customers	Large	0.001	0.0028	-0.0001	0.0003	0.0019
			(0.0034)	(0.0073)	(0.0005)	(0.0004)	(0.0008)
		Small	-0.0039	-0.0019	0.0006	-0.0004	0.0019
			(0.0042)	(0.0056)	(0.0006)	(0.0006)	(0.001)
	Suppliers	Large	0.0151	-0.0252	0.0025	0.0026	0.0081
			(0.0036)	(0.0108)	(0.0004)	(0.0007)	(0.001)
		Small	0.0569	-0.0686	0.0047	-0.005	0.0139
			(0.0304)	(0.0216)	(0.0025)	(0.0025)	(0.0076)
Small	Customers	Large	-0.0134	-0.0778	-0.0063	-0.0059	-0.009
			(0.0117)	(0.0468)	(0.0028)	(0.0064)	(0.0075)
		Small	0.0002	-0.051	0.0	-0.0008	-0.0044
			(0.0143)	(0.0392)	(0.0022)	(0.0027)	(0.0052)
	Suppliers	Large	0.0138	-0.0125	0.0023	0.0022	0.008
			(0.0039)	(0.0058)	(0.0005)	(0.0006)	(0.0009)
		Small	0.0581	-0.0154	0.0033	0.0	0.0074
			(0.0272)	(0.0137)	(0.002)	(0.003)	(0.0052)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a gross output production function (in logs) estimated with the standard Gandhi et al. (2020) procedure (GNR), or with modifications to accommodate network effects (GNR-N) and network differencing (GNR-ND). Network effects for ACF are estimated using the generalized 2SLS procedure for heterogenous peer effects in Dieye and Fortin (2017); Patacchini et al. (2017). Large firms are businesses with 500 or more employees.Interaction matrices for network effects are unweighted. Standard errors are in parentheses. All specifications include industry and year fixed effects.

Table A.13: Productivity Spillovers by Varying Firm Size Cutoffs (Gross Output, Unweighted)

Dependent Variable: $\ln\mathrm{TFP}_t$						
			Firm's Sector			
Partner Size	Relationship	Firm Size	500	1000	5000	Median
Large	Customers	Large	0.0019	0.0016	0.0014	0.001
			(0.0008)	(0.0008)	(0.0008)	(0.0008)
		Small	0.0019	0.0033	0.0017	0.0014
			(0.001)	(0.0011)	(0.001)	(0.001)
	Suppliers	Large	0.0081	0.0078	0.006	0.0087
			(0.001)	(0.001)	(0.0008)	(0.001)
		Small	0.0139	0.0093	0.0084	0.0091
			(0.0076)	(0.0035)	(0.0027)	(0.0016)
Small	Customers	Large	-0.009	-0.001	-0.0039	0.0018
			(0.0075)	(0.006)	(0.0038)	(0.0015)
		Small	-0.0044	-0.0051	0.0007	0.0026
			(0.0052)	(0.0036)	(0.0012)	(0.0012)
	Suppliers	Large	0.008	0.0086	0.0079	0.0073
			(0.0009)	(0.001)	(0.0012)	(0.0011)
		Small	0.0074	0.0071	0.009	0.0087
			(0.0052)	(0.0032)	(0.0013)	(0.0013)

This table reports coefficients of a linear productivity evolution process with endogenous network effects estimated on US firms in Compustat. Each TFP measure is from a gross output production function (in logs) estimated with the standard Gandhi et al. (2020) procedure (GNR), or with modifications to accommodate network effects (GNR-N) and network differencing (GNR-ND). Network effects for GNR are estimated using the generalized 2SLS procedure for heterogenous peer effects in Dieye and Fortin (2017); Patacchini et al. (2017). Large firms are defined by having at least as many employees as the cutoffs indicated above. The median cutoff is determined by industry and year. Interaction matrices for network effects are unweighted. Standard errors are in parentheses. All specifications include industry and year fixed effects.

A.6 Bootstrap for Network Data

A.6.1 Residual-based resampling

Resampling network data needs to preserve the dependence structure between firms and across time. In my empirical application, I use the residual-based bootstrap whose asymptotic properties have been studied in the context of cross-sectional spatially correlated data by Jin and Lee (2012). I modify the procedure by treating my unbalanced panel as repeated cross-sections. I estimate the model, and obtain my first stage estimates $\widehat{\varphi}$ and residuals $\widehat{\varepsilon}_t$. If the residuals do not have zero mean, I subtract the empirical mean from each residual and obtain $\widetilde{\varepsilon}_t$. Then, for each $t = \{1, \cdots, T\}$ I draw samples of size n_t from $\widetilde{\varepsilon}_{nt}$. Sampling R times, I obtain $\{\varepsilon_t^{*r}\}_{r=1}^{R}$ and use these to generate psuedosamples:

$$y_t^{*r} = \widehat{\varphi}_t + \varepsilon_t^{*r}$$

I re-estimate both the production function and productivity process on these pseudo-samples, obtaining a set of elasticities $\{(\alpha_\ell^{*r}, \alpha_\ell^{*r})\}$ and productivity process parameters $\{(\rho^{*r}, \lambda^{*r}, \boldsymbol{\beta}^{*r})\}$ that I use to construct standard errors and confidence intervals.

A.6.2 Vertex Resampling

An alternative procedure is the vertex bootstrap introduced by Snijders and Borgatti (1999). Although this method is potentially more robust to model misspecification, the resulting adjacency matrices are not guaranteed to satisfy the linear independence conditions for consistency of the G2SLS peer effects estimator. The procedure is as follows: Let M be the set of unique firms across all years in the data, with cardinality m and let R be the number of bootstrap repetitions.

For each bootstrap repetition r, randomly select m firms from M with replacement to form a bootstrap sample M_r. Each firm k in M_r corresponds to a firm $i(k) \in M$; I include observations from all years in which $i(k)$ appears in the original dataset. This is the standard block bootstrapping procedure for panel data, which maintains the dependence structure across time within a firm.

Next, for each year, construct the adjacency matrix A_{rt} from the original A_t. Every pair of firms (k,h) in M_r corresponds to $(i(k), i(h))$ in M. Therefore, if $i(k) \neq i(h)$, then we can set

$$A_{kh,rt} = A_{i(k)i(h),t}$$

However, A_t does not provide information on edges between duplicated nodes ($i(k) = i(h)$), because in the original network, a firm could not buy from itself. But in the bootstrap sample, k and h are considered different firms. Therefore, I fill in these edges by uniformly sampling from all the elements of A_t. Finally, the interaction matrix G_{rt} is constructed by row-normalizing A_{rt}.

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