Information Systems Research
Vol. 23, No. 2, June 2012, pp. 340–355
ISSN 1047-7047 (print) | ISSN 1526-5536 (online)
http://dx.doi.org/10.1287/isre.1100.0345

Relative Industry Concentration and Customer-Driven IT Spillovers

Zhuo (June) Cheng
School of Accounting and Finance, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, afzcheng@inet.polyu.edu.hk

Barrie R. Nault
Haskayne School of Business, University of Calgary, Calgary, Alberta T2N 1N4, Canada, nault@ucalgary.ca

We examine how one industry's productivity is affected by the IT capital of its customers and how this effect depends on industries' relative concentration. These customer-driven IT spillovers result from customers' IT investments in various information systems that reduce transaction costs through information sharing and coordination and lead to more efficient production and logistics upstream. The magnitude of IT spillovers depends on relative industry concentration because customers in more concentrated industries relative to those of their suppliers are better able to retain the benefits from their IT investments. We model customer-driven effects based on production theory and empirically test the model using two industry-level data sets covering different and overlapping time periods (1987–1999 and 1998–2005), different scopes of the economy (manufacturing only versus all industries), and different levels of industry aggregation. We find that, given an increase in a downstream industry's IT capital, there is a significant increase in downstream industry output as well as significant increases in upstream industry output. Moreover, the magnitude of IT spillovers is related to relative industry concentration: A 1% decrease in a customer's relative industry concentration increases spillovers by roughly 1%. Thus, further increases in IT capital can be justified along the supply chain, and an industry's relative concentration—which can reflect market power—in part determines the distribution of productivity benefits.

Key words: business value of IT; IT-enabled supply chains; economics of IS; spillovers; production function framework; input-output tables; industry concentration
History: Anitesh Barua, Senior Editor; Chris Forman, Associate Editor. This paper was received on April 27, 2009, and was with the authors $7\frac{1}{2}$ months for 2 revisions. Published online in *Articles in Advance* April 8, 2011.

1. Introduction

Over the past decades, much research has been devoted to quantifying the impact of information technology (IT) on organizational performance. This research has largely focused on the impact of *own* IT investment. We believe that one industry's productivity can also be positively affected by the IT investment of upstream or downstream supply chain partners. Cheng and Nault (2007a) studied supplier spillovers from IT investment upstream and found that supplier IT investment significantly increased productivity in downstream industries through the quality of intermediate input. In this research, we examine whether an industry's productivity can be affected by the IT investment of its downstream customers, and we study whether these effects depend on relative industry concentration along the supply chain. We build on the production theory framework and add a spatial component to reflect industry positions in the supply chain to capture the interindustry effects.

The reason we expect an impact of customers' IT investments on a specific industry's productivity is because industries rely on various information systems (IS) to coordinate activities ranging from requests for quotations through production planning and execution to final delivery. This coordination greatly reduces an array of transaction costs and allows the supply chain to function with the efficiency of an integrated firm. For suppliers, information sharing and coordination through such systems can help to more accurately forecast demand, increase production efficiency, improve logistics, and reduce excessive inventories. In this way, these benefits or productivity gains that are brought by IT investments move from customers to suppliers along the value chain.[1] To illustrate, Safeway (a large grocery retailer) shares information electronically with suppliers about shelf space, inventory, and forecasts within

[1] Hereafter, we use benefits and productivity gains interchangeably.

its supermarkets so that suppliers can track demand for their products, adjust production, and adjust the timing and size of deliveries (Laudon and Laudon 2003, p. 59). In this way, Safeway's suppliers benefit from the improved information sharing and coordination enabled by Safeway's IT investment.

Critical to the distribution of productivity gains from IT among supply chain partners is their relative industry concentration. Relative industry concentration may reflect market power that is in part determined by outside options—alternative sources of supplies for customers and alternative buyers for suppliers. Outside options are usually fewer, and the value of these options is usually lower the more concentrated the industry with which a firm transacts relative to the industry of the firm itself. In other words, if the supplying industry is highly concentrated compared to the downstream industry, then competition among downstream customers can give suppliers greater market power. An example of concentration leading to market power is the airline industry, where mergers among healthy firms increased concentration. This in turn led to market power in the form of higher prices (Kim and Singal 1993). Market concentration as a proxy for market power has been used to explain bank profitability (Berger 1995) and research and development (R&D) spending (Vossen 1999). In a study of systematic risk, results showed that large firms are better able to exercise market power in concentrated markets (Alexander and Thistle 1999). Courts typically use measures of market share or market concentration to make inferences about market power (Cameron and Glick 1996). Consequently, we expect the relative concentration of industries in the supply chain to impact the magnitude of customer-driven IT spillovers.

To quantify the impact of IT investments downstream, we employ the economywide input-output tables together with industry productivity data on output and inputs including IT capital and create two separate industry-level data sets: one for Standard Industrial Classification (SIC)-defined manufacturing industries from 1987–1999 and the other for North American Industrial Classification System (NAICS)-defined industries from 1998–2005. The "use" version of the input-output tables obtained from the Bureau of Labor Statistics (BLS) is critical to our analysis as the "use" tables provide the value of output produced in one industry that is "used" by another industry for each pair of industries in the economy. As such, the "use" tables show where different industries' outputs are used by other industries as inputs into production and provide a measure of transaction volumes between industries that are value chain partners. To operationalize market power among supply chain partners, we examine the effect of differences in industry concentration between supplying and buying industries on our customer-driven IT spillovers using standard and well-recognized measures such as the Herfindahl-Hirschman Index and the 20-firm concentration ratio.

Using an empirical productivity model formulated to include the effects of customer IT investment and relative industry concentration, we find customer-driven IT spillovers to be both positive and significant: For each additional dollar increase in a downstream industry's IT capital, there is a significant increase of between \$0.73 and \$1.14 in downstream industry output and a significant increase of between \$0.13 and \$0.38 in upstream industry output. More importantly, we find that the magnitude of customer-driven IT spillovers depends on relative industry concentration: A 1% decrease in a customer's relative industry concentration increases spillovers by roughly 1%. Our results are robust to different econometrics adjustments, alternative model specifications, and a falsification test. Our results also suggest that there has been underinvestment in IT capital along the supply chain, which may be in part because of the fact that downstream competition makes it more difficult for customers to retain the benefits of their IT investments.

The rest of this paper is organized as follows. In the next section, we describe the sources of customer-driven IT spillovers and the impact of relative industry concentration. Following that, we develop the model we use to estimate these spillovers effects. We then present our empirical results. The last section discusses our contributions.

2. Customer-Driven IT Spillovers and Relative Market Power with IT

2.1. Coordination-Based Customer-Driven IT Spillovers

Our model of IT spillovers effects draws upon the literature on the contribution of IT investment using the production function framework. Since the 1990s, considerable research has evaluated the contribution of IT investments, treating IT capital and/or IT labor as separate inputs. These studies converged on a positive *own* IT contribution (Dedrick et al. 2003, Cheng and Nault 2007a). Part of this contribution is in the form of coordination within the firm, which made production more efficient.

In early implementations of supply chain IS such as those using electronic data interchange (EDI), some models showed that customers would not only provide a price premium to suppliers using EDI but may also be better off subsidizing EDI adoption (Wang and Seidmann 1995). In other models, a supplier was shown to have incentives to subsidize customer IT adoption at the same time as the value of the transacted good was increased and customers paid premium prices (Nault 1997)—price premiums that in some cases were well-documented (Nault and Dexter 1995). Hence, the value of information sharing and coordination along the supply chain was priced in the transacted good and technologies for coordination could be subsidized.

As such, IT also enhances coordination between a firm and its external partners. For example, IT reduces the coordination costs that are involved in searching for suppliers, evaluating bids, carrying out negotiations, arranging logistics, and administering contracts (Lewis 2001). IT capability used in conjunction with interorganizational coordination mechanisms in supply chains has been found to be important in explaining firm performance (Bharadwaj et al. 2007). Transparency, visibility, and communication ability allow supply chain partners to share information and coordinate planning and fulfillment activities. Moreover, with the evolution of industry standards, organizations can become loosely coupled: IT allows for greater reliance on external partners (Sahaym et al. 2007) who can take advantage of network effects and overcome adoption costs (Zhu et al. 2006).

We view customer-driven IT spillovers as resulting from information sharing and coordination through various IS between suppliers and customers. One of the most well-known applications of IT-based coordination along the supply chain is collaborative planning, forecasting, and replenishment (CPFR). A variety of technologies support CPFR (Danese 2006): Web-based collaboration involving process and information sharing of forecasts, promotions, point-of-sale (POS) data, and logistics requirements; event management and analysis that monitors, alerts, and resolves exceptions; and tracking and reporting for management planning. IT sophistication and hence IT investments increase with the number of interacting units in the supply chain and with the depth of collaboration.

With information from customers as part of CPFR, suppliers are better able to forecast demand, improving their own production and logistics and therefore obtaining inventory and cost reductions (Lee et al. 2000). Sharing demand information electronically counters amplification of demand variability along the supply chain and avoids problems from inaccurate demand forecasts such as low capacity utilization, excess inventory, and errors and delays from data entry of purchase orders and payments. A classic example is the CPFR system implemented between Procter & Gamble (P&G) and its downstream retailers such as Wal-Mart. Wal-Mart's "continuous replenishment system" sends orders for new merchandise directly to suppliers as soon as consumers pay for their purchases at the point of sale (POS). P&G uses POS data to track demand for its products, plan production based on actual demand, and trigger shipments to retailers. It was estimated that the CPFR system helped P&G reduce inventory and cycle time by 10%. Sales increased by 2% as well because P&G was able to take immediate actions to prevent stock out (Laudon and Laudon 2003, pp. 2–3). Because supply chain IS require IT investment by both business partners, customers' IT investments in these systems improves information sharing and coordination (e.g., increases information accuracy, timeliness, and reliability) and benefits suppliers.

In practice, supply chain IS are increasingly based on Web technology, providing even greater sharing of information and coordination. For example, the Supplier Partner Information Network (SPIN) implemented by Chrysler Corporation allows Chrysler's suppliers to access portions of its intranet to get the most current data on design changes, parts shortages, packaging information, and invoice tracking (Kachadourian 2000). General Motors' private industrial network, GMSupplyPower, gives suppliers access to the latest information on production scheduling, inventory, and the quality of their parts (Rosencrance 2002). IS can also help suppliers collect payments from downstream customers faster. General Electric (GE) developed a new system that enabled its suppliers to be paid in 15 days instead of the usual 60 days (Laudon and Laudon 2003, p. 105).

In addition to direct spillovers through coordination and efficiency, there may be indirect spillovers from the transfer of knowledge.[2] For example, suppliers to Wal-Mart may become better at using IT through learning how Wal-Mart has used IT. One way suppliers to Wal-Mart may learn how IT has been used is by the movement of IT workers along the supply chain; there is some evidence that there are knowledge spillovers from IT workers moving among firms (Tambe and Hitt 2009). There may also be an accumulation of knowledge within an industry that could spill over to other industries and our industry-level analysis may capture these spillovers. However, firm-level analysis suggests that within-industry IT knowledge spillovers are overstated (Hitt and Tambe 2006).

2.2. Relative Industry Concentration and Market Power with IT

Historically, some partners have had concerns that IT can impact their relative market power along the supply chain. In consumer packaged goods markets, retailers resisted POS and other automated information sharing because they feared they would

[2] We thank an anonymous reviewer for this suggestion.

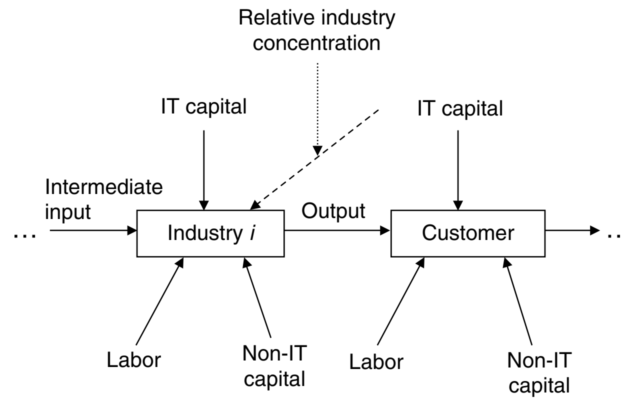
lose bargaining power (Clemons and Row 1993). In business-to-business (B2B) electronic markets, loss of data confidentiality can offset benefits of information transparency (Zhu 2004). Indeed, the tradeoff between benefits from the adoption of increasingly sophisticated systems and the loss of bargaining power is made more acute by requiring IT investment incentives between each link in the supply chain. The literature on "number of suppliers" (e.g., Bakos and Brynjolfsson 1993, Wang and Seidmann 1995) shows how a single buyer with market power needs to motivate IT investments among suppliers in order to capture benefits from using IT to coordinate the supply chain. Thus, although relative industry concentration between customers and suppliers is only one element of market power—other elements include switching costs and availability of substitutes—we believe it is an important element in explaining the distribution of benefits from the use of IT-based coordination technologies.

Recent developments in IT have greatly facilitated efficient information sharing and tight coordination among supply chain partners. Each additional dollar of IT investment is effective not only at the point where the investment is made but also along the entire supply chain. Research by Barua et al. (2004) looks at financial performance improvements from increased customer and supplier-side digitization, and measures local returns to firms' own IT initiatives in conducting sales and purchases online. The working paper by Mun and Nadiri (2002) shows that IT investment by an industry's customer and supplier industries reduces both labor and material costs of the industry. Our paper examines the productivity gain induced by downstream IT investment and also investigates the role of the relative industry concentration between upstream and downstream industries in the distribution of productivity gains. Cheng and Nault (2007a) focus on supplier-driven IT spillovers that occur through IT-related quality improvement in the intermediate input. In this paper, as detailed above, customer-driven IT spillovers occur through different mechanisms, i.e., through IT-enabled information sharing and coordination.

3. A Model of Customer-Driven IT Spillovers

Our conceptual model of customer-driven IT spillovers is a model of productivity along the supply chain and is shown in Figure 1. Industry i takes non-IT capital, labor, IT capital, and intermediate inputs and produces output that it supplies as intermediate goods to its customers. Industry i benefits from its customers' IT investments and these customer-driven IT spillovers are moderated by the relative industry concentration of the upstream and downstream industries.

Figure 1 The Customer-Driven IT Spillovers



In mathematical form, our model of customer-driven IT spillovers is derived from the simple Cobb-Douglas function relating inputs—including intermediate inputs—to output, with an added input representing customers' IT capital to capture the effects of downstream IT investment on upstream productivity:

$$Y = AK^{\alpha}L^{\beta}Z^{\gamma}M^{\theta}C^{\psi},$$

where Y is the quantity of output and K, L, Z, M, and C are the quantities of non-IT capital, labor, IT capital, intermediate inputs, and customers' IT capital, respectively. A is the technological change parameter and α, β, γ, θ, and ψ are the output elasticities of non-IT capital, labor, IT capital, intermediate inputs, and customers' IT capital, respectively.

To capture effects along the supply chain, we employ the "use" input-output table that shows which industries use output from other industries. The input-output table not only identifies the customer industries of a specific industry (a nonzero ijth element indicates that j is the customer of i) but also provides the relative importance of each customer's industry in the form of dollar transaction volume where a higher transaction volume indicates a more important customer. We define V_{ij} as the transaction volume in dollars that moves through the supply chain from industry i to industry j. For each industry i, we construct the weight

$$w_{ij} = \frac{V_{ij}}{\Sigma_{j\neq i} V_{ij}}$$

to capture the relative size of customer industry j in the total transactions made downstream by industry i.

For industry i, we use these weights to construct an aggregation of customers' IT capital stock

$$C_i = \Sigma_{j\neq i} w_{ij} Z_j = \Sigma_{j\neq i} \frac{V_{ij}}{\Sigma_{j\neq i} V_{ij}} Z_j,$$

where Z_j is the IT capital of the jth customer and w_{ij} is the weight on IT capital of the jth customer. We name this aggregation of customers' IT capital as the customer-driven IT spillovers of industry i. Our construction of the customer-driven IT spillovers is consistent with that of Mun and Nadiri (2002) and with the structure of the supplier IT spillovers in Cheng and Nault (2007a).

Taking (natural) logs of our Cobb-Douglas production function, we have

$$y_i = a + \alpha k_i + \beta l_i + \gamma z_i + \theta m_i + \psi c_i, \qquad (1)$$

where k_i, l_i, z_i, m_i, and c_i are the logs of non-IT capital, labor, IT capital, intermediate inputs, and customer-driven IT stock, respectively. ψ measures the customer-driven IT spillovers effect.

To incorporate the impact of relative industry concentration along the supply chain on our customer-driven IT spillovers, we use measures of industry concentration that compare the concentration of a given industry with concentration in those downstream industries with whom it has transactions. We model the impact by making the output elasticity of customer-driven IT spillovers a function of relative industry concentration $\psi = \psi(r_i)$, where r_i is a measure of relative industry concentration. We define the function $\psi(r_i)$ as linear in r_i:

$$\psi(r_i) = \mu + \eta r_i.$$

This form is the simplest form we can employ that allows for an element of pure spillovers μ and an element that depends on relative industry concentration.

To measure relative industry concentration r_i, we use the ratio of a weighted sum of customer industry concentration to own industry concentration. The concentration of downstream industries is aggregated the same way as the customers' IT by using the input-output tables as the weight matrix:

$$CUSCONCN_i = \Sigma_{j\neq i} \frac{V_{ij}}{\Sigma_{j\neq i} V_{ij}} CONCN_j,$$

where $CONCN_j$ is the jth industry's concentration. Hence, $cusconcn_i$ measures the average level of customer industry concentration. Using the ratio $r_i = CUSCONCN_i/CONCN_i$, our estimation (Equation (1)) can now be written as

$$y_i = a + \alpha k_i + \beta l_i + \gamma z_i + \theta m_i + \mu c_i + \eta r_i c_i, \qquad (2)$$

where the last two terms together are the customer-driven IT spillovers with one element of pure spillovers and another element that also depends on relative industry concentration. The form in (2), derived from the Cobb-Douglas specification, focuses on the effect of relative industry concentration through customer-driven IT spillovers rather than including various forms of industry concentration that might be directly related to output. As detailed in our model derivation, r_i enters into our model through its effects on the coefficient of customer IT index. Similar model specifications can be found in econometrics textbooks (e.g., Wooldridge 2003, p. 236).

4. Empirical Estimation

4.1. Data Description

Our data includes two data sets, each covering different overlapping time periods and different scopes of the economy and sets of industries at different levels of aggregation.

4.1.1. Data Set I: 1987–1999. The first data set is similar to that used in Cheng and Nault (2007a) and consists of the multifactor productivity (MFP) data set for 3-digit SIC code manufacturing industries from 1987 to 1999 and the input-output tables from 1983 to 1999. Both are obtained from the BLS. Matching the MFP data set and the input-output tables, we have complete data from 1987 to 1999. This period has the advantage of no special events such as the "dotcom" crash or the 9/11 terrorist attacks. The MFP data set contains 140 3-digit SIC code manufacturing industries and provides the series of output and intermediate purchase compensation in millions of current dollars and the corresponding output deflator and intermediate purchase price deflator. Deflating the series gives us measures in millions of 1987 dollars, output Y and intermediate inputs M. The MFP data set has labor input in millions of hours L.

For capital stock, we obtained a breakdown of 30 asset types for each 3-digit SIC code manufacturing industry including computers and related equipment; office equipment; and communications, instruments, photocopying, and related equipment. We aggregated the productive stock of computers and related equipment, office equipment, communications, instruments, and photocopy and related equipment as the IT capital stock in millions of 1987 dollars Z. As these are measures of gross investment in IT, they should capture the IT investments used for supply chain coordination. To get the non-IT capital stock K, we total the equipment and structure components of the asset types and subtract the IT capital stock.

The input-output tables contain industries in addition to those in manufacturing, and some of the rows/columns are the combination of more than one SIC code manufacturing industry. In order to match the MFP data set and the input-output tables, we eliminated all the nonmanufacturing industries from the input-output tables and aggregated the MFP data set according to the industries represented in the input-output tables. We also dropped industries with missing data and industries that do not supply other industries. The result is a balanced panel of 84 industries across 13 years. Table 1 lists the 84 manufacturing industries, the SIC codes, and the industry numbers (IndNumb) used in the input-output tables.

In data set I, we use the Herfindahl-Hirschman Index (HHI) to measure the industry concentration. We obtained the HHI concentration data for the 4-digit SIC manufacturing industries in 1992 from the U.S. Census Bureau website. HHI is the sum of squares of the market shares of all firms in the industry. The data set also has a column of value of shipments (or total sales). We use the HHI multiplied by the square of value of shipments to get the sum of squares of the sales of all firms in the industry. We then aggregate this number and the value of shipments of 4-digit SIC industries into 3-digit SIC industries. The 3-digit industry HHI is the aggregate sum of squared sales divided by the squared aggregate value of shipments. The U.S. Census Bureau only reports the concentration data every five years and the concentration data from 1997 onward is classified by NAICS codes, which are very difficult to match with the SIC codes. We use the 1992 HHI data to proxy the concentration data for all the years in data set I. Our assumption of industry concentration being relatively stable in our sample period is justified by the high correlation between the 1987 HHI and 1992 HHI (correlation = 0.95). For a robustness check, we also applied the 1987 HHI for the years 1987–1991 and the 1992 HHI for the years 1992–1999, and our results for Data set I are similar to the ones we report.[3]

We set the diagonals in the input-output tables to zero in order to isolate the customer-driven effects from other industries. The summary statistics of the 1,092 observations are provided in the first part of Table 3.

4.1.2. Data Set II: 1998–2005. The second data set is a more recent data set and covers almost all industries in the economy. We acquired the input-output tables at the 3-digit 1997 NAICS level directly from the Bureau of Economic Analysis (BEA) website. We obtained capital stock, IT capital stock, and the labor hours for the 3-digit NAICS industries used in the input-output tables directly from the BLS. There are four categories for IT capital stock: computers, software, communications, and other. We aggregated the productive capital stock of these four categories and used it as Z. For non-IT capital stock, similar to the first data set, we totaled the equipment and structure components of the asset types and subtracted the IT capital stock from this number. We also acquired the gross domestic product by industry from the BEA website. Deflating this number by the chain-type quantity indexes for output from the BEA website gives us the real gross output Y. Similarly, deflating intermediate input series by the chain-type quantity indexes for intermediate inputs from the BEA website gives us the real intermediate inputs M for the 3-digit NAICS industries.

We obtained firm concentration data for the three-digit NAICS industries in 2002 from the U.S. Census Bureau website. As the HHI is only available for manufacturing industries and our data set II covers industries besides manufacturing, we use the 20-firm concentration ratio (CR20) instead. CR20 is defined as the sum of the percent market share of the largest 20 firms. Similar to what we did with data set I, we used the 2002 CR20 to proxy the concentration data for all the years in data set II.

In matching the input-output tables, productivity data, and concentration ratios, we dropped nine industries with missing concentration ratio data and one industry that does not supply to other industries. The result is a balanced panel of 49 industries over 8 years. Table 2 describes the 49 industries. The summary statistics of the 392 observations are provided in the second half of Table 3.[4]

The differences between data set I and data set II are worth noting. First, data set II covers a more recent period. Second, it covers a broader cross-section of the economy that includes not only manufacturing but also other industries. Third, data set II is at a more aggregate level: the 3-digit NAICS level (or subsector level) corresponds roughly to the 2-digit SIC level (or major group level) whereas data set I is at the 3-digit SIC level. Fourth, slightly different definitions of IT capital are used in the two data sets. In data set II, IT capital stock includes software while in data set I, it does not. By using the two data sets, we are able to test our model using different time periods on different scopes of the economy at different levels of industry aggregation and with different definitions of IT capital.

In both data sets I and II, we find that the pattern of industry transactions changes little over the sample period. We calculated the correlations between each

[3] An alternative way to obtain industry concentration is by using firm-level sales data from Compustat. Because Compustat reports sales data yearly, we can calculate a yearly industry concentration this way. However, Compustat data covers only the public firms in an industry whereas the U.S. Census measures are based on all public and private firms in an industry. Ali et al. (2009) found that the industry concentration measures calculated with Compustat data have correlations of only 13% with the corresponding U.S. Census measures and concluded that concentration measures calculated with Compustat are poor proxies for actual industry concentration.

[4] The correlation tables of the variables in each of our data sets are available upon request.

Table 1 **Data Set I (1987–1999): 3-Digit SIC Manufacturing Industry Description**

IndNumb	1987 SIC code	Industry title	IndNumb	1987 SIC code	Industry title
13	242	Sawmills and planing mills	56	371	Motor vehicles and equipment
14	243	Millwork, plywood, and structural members	60	375,379	Miscellaneous transportation equipment
15	244, 249	Wood containers and misc. wood products	62	382	Measuring and controlling devices
16	245	Wood buildings and mobile homes	63	384	Medical equipment, instruments, and supplies
17	251	Household furniture	64	385	Ophthalmic goods
18	254	Partitions and fixtures	65	386	Photographic equipment and supplies
19	252, 253, 259	Office and misc. furniture and fixtures	66	387	Watches, clocks, and parts
20	321–323	Glass and glass products	67	391	Jewelry, silverware, and plated ware
21	324	Hydraulic cement	69	393, 395, 396, 399	Manufactured products, nec
22	325, 326, 328, 329	Stone, clay, and misc. mineral products	70	201	Meat products
23	327	Concrete, gypsum, and plaster products	71	202	Dairy products
24	331	Blast furnaces and basic steel products	72	203	Preserved fruits and vegetables
25	332	Iron and steel foundries	73	204, 207	Grain mill products, fats and oils
26	333	Primary nonferrous smelting and refining	74	205	Bakery products
27	334, 339	All other primary metals	75	206	Sugar and confectionery products
28	335	Nonferrous rolling and drawing	76	208	Beverages
29	336	Nonferrous foundries	77	209	Miscellaneous foods and kindred products
30	341	Metal cans and shipping containers	79	221–224, 226, 228	Weaving, finishing, yarn and thread mills
31	342	Cutlery, handtools, and hardware	80	225	Knitting mills
32	343	Plumbing and nonelectric heating equipment	81	227	Carpets and rugs
33	344	Fabricated structural metal products	82	229	Miscellaneous textile goods
34	345	Screw machine products, bolts, rivets, etc.	83	231–238	Apparel
35	346	Metal forgings and stampings	84	239	Miscellaneous fabricated textile products
36	347	Metal coating, engraving, and allied services	85	261–263	Pulp, paper, and paperboard mills
38	349	Miscellaneous fabricated metal products	86	265	Paperboard containers and boxes
39	351	Engines and turbines	87	267	Converted paper products except containers
40	352	Farm and garden machinery	92	275, 276	Commercial printing and business forms
41	353	Construction and related machinery	94	278	Blankbooks and bookbinding
42	354	Metalworking machinery and equipment	95	279	Service industries for the printing trade
43	355	Special industry machinery	96	281, 286	Industrial chemicals
44	356	General industrial machinery and equipment	97	282	Plastics materials and synthetics
45	357	Computer and office equipment	98	283	Drugs
46	358	Refrigeration and service industry machinery	99	284	Soap, cleaners, and toilet goods
47	359	Industrial machinery, nec	100	285	Paints and allied products
48	361	Electric distribution equipment	101	287	Agricultural chemicals
49	362	Electrical industrial apparatus	102	289	Miscellaneous chemical products
50	363	Household appliances	103	291	Petroleum refining
51	364	Electric lighting and wiring equipment	104	295, 299	Miscellaneous petroleum and coal products
52	365	Household audio and video equipment	105	301	Tires and inner tubes
53	366	Communication equipment	106	302, 5, 6	Rubber products, plastic hose, and footwear
54	367	Electronic components and accessories	107	308	Miscellaneous plastics products, nec
55	369	Miscellaneous electrical equipment	109	311, 315–317, 319	Luggage, handbags, and leather products, not elsewhere classified

Note. IndNumb is the industry number used in the input-output tables.

row of the input-output tables of 1987 and 1999 for data set I—the average correlation is 0.96. Similarly, the average correlation for the beginning and ending years of data set II is 0.99. The fact that the industry transaction pattern changes little over time is not surprising because industries have stable mixes of inputs and outputs and this is how they are classified under the SIC and NAICS systems. This finding is consistent with Mun and Nadiri (2002).

When using measures of industry IT capital and industry concentration, there is a possible identification problem in that most industries are of high IT intensity and high concentration (or vice versa) so that the off-diagonal elements are underrepresented and there is insufficient variation.[5] We used IT capital over non-IT capital as a measure of IT intensity and divided high and low using median levels, and the distribution for each of the two data sets is provided in Table 4.[6] As we can see from Table 4, the industries are fairly equally distributed across the four cells. Moreover, the correlation between IT intensity and concentration is not high (0.14 for data set I and −0.06 for data set II). This suggests that we have enough variation in our sample across the two measures.

4.1.3. Level of Aggregation. There are issues in using industry-level data versus firm-level data. Firm-level data would allow us to tie a specific firm's IT

[5] We thank the review team for this suggestion.

[6] The distribution is similar when using IT capital over output as the IT intensity measure. Later, in the robustness tests and alternative specifications section, we discuss our results from using IT capital over non-IT capital as an alternative spillovers measure.

Table 2 Data Set II (1998–2005): 3-Digit NAICS Industry Description

IndNumb	1997 NAICS code	Industry title
5	22	Utilities
7	311, 312 (311FT)	Food and beverage and tobacco products
8	313, 314 (313TT)	Textile mills and textile product mills
9	315, 316 (315AL)	Apparel and leather and allied products
10	321	Wood products
11	322	Paper products
12	323	Printing and related support activities
13	324	Petroleum and coal products
14	325	Chemical products
15	326	Plastics and rubber products
16	327	Nonmetallic mineral products
17	331	Primary metals
18	332	Fabricated metal products
19	333	Machinery
20	334	Computer and electronic products
21	335	Electrical equipment, appliances, and components
22	336	Transportation equipment
23	337	Furniture and related products
24	339	Miscellaneous manufacturing
25	42	Wholesale trade
26	44, 45 (44RT)	Retail trade
27	481	Air transportation
29	483	Water transportation
30	484	Truck transportation
31	485	Transit and ground passenger transportation
32	486	Pipeline transportation
33	487, 488, 492 (487OS)	Other transportation and support activities
34	493	Warehousing and storage
35	511	Publishing industries (includes software)
36	512	Motion picture and sound recording industries
39	521, 522 (521CI)	Federal Reserve banks, credit intermediation, and related activities
40	523	Securities, commodity contracts, and investments
41	524	Insurance carriers and related activities
42	525	Funds, trusts, and other financial vehicles
43	531	Real estate
44	532, 533 (532RL)	Rental and leasing services and lessors of intangible assets
45	5411	Legal services
46	5412–5414, 5416–5419 (5412OP)	Miscellaneous professional, scientific, and technical services
47	5415	Computer systems design and related services
49	561	Administrative and support services
50	562	Waste management and remediation services
51	61	Educational services
52	621	Ambulatory health care services
54	624	Social assistance
55	711, 712 (711AS)	Performing arts, spectator sports, museums, and related activities
56	713	Amusements, gambling, and recreation industries
57	721	Accommodation
58	722	Food services and drinking places
59	81	Other services, except government

Notes. IndNumb is the sequence in which the industries appear in the input-output tables. Codes in parentheses are the ones used in the input-output tables, if different from the NAICS codes.

investments to IT spillovers in the supply chain, and the resulting managerial implications would be based on data closer to where those IT investment decisions are made. Firm-level data is also less subject to aggregation error, both in the data and as a representation of a firm's production function. Nonetheless, such aggregation errors exist when moving from product level to firm level.

Industry-level data allows us to examine a much broader segment of the economy. In addition, with industry-level data sets at different levels of aggregation and with different measures of IT capital, consistent results in our analysis mitigate the chance that our results are because of aggregation versus real effects between firms along the supply chain. A study by Kundisch et al. (2009) has also shown that

Table 3 Summary Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Data set I (1987–1999)					
Output (in millions of 1987 dollars)	1,092	30,292.60	46,315.43	557.62	738,130.80
Non-IT capital stock (in millions of 1987 dollars)	1,092	20,613.36	22,970.83	461.80	135,540.60
Labor (in millions of hours)	1,092	413.82	344.66	12.20	2,350.90
IT capital stock (in millions of 1987 dollars)	1,092	1,763.91	3,149.87	30.30	27,661.10
Intermediate inputs (in millions of 1987 dollars)	1,092	17,017.56	21,118.91	313.18	202,082.50
Customer-driven IT spillovers (C) (index)	1,092	3,076.025	2,631.97	69.16	21,739.58
Log of customer-driven IT spillovers (c) (index)	1,092	7.71	0.85	4.24	9.99
Herfindahl-Hirschman Index (HHI) of 1992 (index)	1,092	268.02	364.70	11.52	2,408
Customer industry concentration (CUSHHI) of 1992 (index)	1,092	343.88	255.17	30.34	1,176.49
Relative industry concentration (r = CUSHHI/HHI) of 1992 (ratio)	1,092	3.83	6.15	0.04	37.59
Data set II (1998–2005)					
Gross output (in millions of 2000 dollars)	392	277,491.60	295,906.30	24,423.90	1,782,986
Non-IT capital stock (in millions of 2000 dollars)	392	172,433.30	242,302.50	9,376	1,449,984
Labor (in millions of hours)	392	3,195.27	4,365.01	84	25,773
IT capital stock (in millions of 2000 dollars)	392	24,681.21	31,885.17	468	154,685
Intermediate inputs (in millions of 2000 dollars)	392	126,467.30	113,970.50	7,687	510,563.80
Customer-driven IT spillovers (C) (index)	392	37,460.97	14,704.97	747.57	102,651.10
Log of customer-driven IT spillovers (c) (index)	392	10.45	0.41	8.92	11.54
20-firm concentration ratio (CR20) of 2000 (percentage)	392	34.70	20.94	6.30	100
Customer industry concentration (CUSCR20) of 2002 (index)	392	31.01	7.88	16.53	58.62
Relative industry concentration (r = CUSCR20/CR20) of 2002 (ratio)	392	1.35	1.07	0.27	5.12

estimates using Cobb-Douglas-related forms do not have aggregation issues. There is the possibility that parts of the supply chain are within industries—for example, different tiers in the automotive industry are within a single industry as we measure it. However, this would bias our analyses toward not finding significant spillovers.

Our measures of IT capital are aggregates across asset types rather than measures of specific application types such as the IT used for supply chain coordination. Ideally, we would like to measure IT investment that is directed to such coordination. Unfortunately, with system implementations becoming increasingly integrated—for example, the same systems monitor and plan internal production as well as share production information with supply chain partners—it is not possible to determine which IT investments are used for external coordination even from firm-level data. To account for this in our empirical specification, we use a production function that includes IT capital as both an input to production and a source of spillovers, and we thereby capture both internal and external returns from IT. For a robustness check, we also considered subsets of our measures of IT capital—communications-only and computer and communications-only types of IT capital stock—to construct customer-driven IT spillovers and our results are qualitatively similar in both sign and significance level.[7]

Table 4 Distribution of Data Set I and Data Set II

Number of industries	Low concentration	High concentration	Total
Data set I (1987–1999)			
Low IT intensity	27	15	42
High IT intensity	15	27	42
Total	42	42	84
Data set II (1998–2005)			
Low IT intensity	13	11	24
High IT intensity	11	14	25
Total	24	25	49

Notes. Low (high) IT intensity is defined as the industries with IT intensity (IT capital over output) below (above) the median level in the sample. Low (high) concentration is defined as the industries with industry concentration (HHI for data set I and CR20 for data set II) below (above) the median level in the sample.

4.2. Methodologies

We estimate our model of customer-driven IT spillovers using (2). We center the variables c_i and r_i to better interpret the interaction and to reduce possible multicollinearity between the interaction and the main effects. Because our data set is a cross-sectional time series, we anticipate autocorrelated and heteroskedastic error terms. Using the Wooldridge test for autocorrelation in a panel data set, we find that first-order autocorrelation (AR1) is present at all reasonable levels of significance in both data set I and data set II (F-statistic = 28.93 for data set I and 82.56 for data set II). In addition, the AR1 process is likely to differ across the industries, that is, AR1 could be panel specific (PSAR1). We find that in our customer-driven model, with relative industry concentration the null hypothesis of common AR1 coefficients is rejected at all

[7] The IT subset results are available upon request.

Table 5 Regression Results—Data Set I (1987–1999)

	Baseline		Alternative econometrics adjustments					Alternative model specifications		Falsification test
Columns	1	2	3	4	5	6	7	8	9	10
Variables	He + PSAR1	He + PSAR1	IT producing dummies	2-digit SIC dummies	Random effects	Year dummies	SYS-GMM	He + PSAR1	He + PSAR1	He + PSAR1
K	0.0550***	0.0843***	0.0759***	0.0625***	0.0762***	0.0846***	0.0370***	0.0833***	0.0901***	0.0710***
	(0.0101)	(0.00960)	(0.00965)	(0.0149)	(0.0280)	(0.00938)	(0.00303)	(0.00953)	(0.0103)	(0.0107)
L	0.258***	0.234***	0.251***	0.234***	0.240***	0.227***	0.282***	0.242***	0.239***	0.254***
	(0.00903)	(0.00853)	(0.0103)	(0.0143)	(0.0277)	(0.00769)	(0.00267)	(0.00831)	(0.00951)	(0.0104)
Z	0.0716***	0.0663***	0.0484***	0.0575***	0.0657***	0.0741***	0.124***	0.0676***	0.0622***	0.0680***
	(0.00496)	(0.00551)	(0.00796)	(0.00955)	(0.0167)	(0.00595)	(0.00136)	(0.00528)	(0.00582)	(0.00468)
M	0.661***	0.652***	0.655***	0.689***	0.684***	0.648***	0.626***	0.649***	0.650***	0.646***
	(0.0105)	(0.0104)	(0.0109)	(0.0147)	(0.0237)	(0.00955)	(0.00380)	(0.0100)	(0.0110)	(0.0107)
C		0.0132***	0.0229***	0.0101	0.0385**	0.0211***	0.0356***	0.0179***	0.0173***	0.0138*
		(0.00470)	(0.00553)	(0.00706)	(0.0160)	(0.00567)	(0.00231)	(0.00457)	(0.00505)	(0.00705)
$R \times C$		−0.00318***	−0.00249***	−0.00291***	−0.00536***	−0.00293***	−0.00525***		−0.00273***	−0.00312**
		(0.000964)	(0.000941)	(0.00105)	(0.00169)	(0.000787)	(0.000436)		(0.000898)	(0.00128)
R									−0.00215**	
									(0.000857)	
C_K										0.00236
										(0.0118)
$R \times C_K$										−0.0009
										(0.00303)
Obs.	1,092	1,092	1,092	1,092	1,092	1,092	1,092	1,092	1,092	1,092

Notes. K, non-IT capital; L, labor; Z, IT capital; M, intermediate inputs; C, customer-driven IT spillovers; R, relative industry concentration. C_K, customer-driven non-IT spillovers (used in the falsification test). He, heteroskedastic error structure; PSAR1, panel specific AR1 error structure. Dummy variables are suppressed for brevity. IT-producing dummies, 2-digit SIC dummies, and year dummies regressions are adjusted for He + PSAR1. Standard errors are in parentheses.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

reasonable levels of significance in data set I ($\chi^2 = 700.50$), but the null hypothesis could not be rejected in data set II ($\chi^2 = 7.93$). Therefore, we adjust for PSAR1 in data set I and for only AR1 in data set II. We use the likelihood ratio test for the presence of panel-level heteroskedasticity and find that for our model the null hypothesis of no panel-level heteroskedasticity is rejected at all reasonable levels of significance in both data sets ($\chi^2 = 302.51$ for data set I and 226.19 for data set II).

Consequently, in data set I, we estimate our model using specifications for heteroskedastic errors and industry-specific AR1 coefficients (He + PSAR1). In data set II, we use specifications for heteroskedastic errors and a common AR1 coefficient (He + AR1). To generate our estimates, we use cross-sectional time series generalized least-squares (GLS) regressions implemented in Stata software. Later, in the subsection following the next, we detail how we verified that our results are robust to different econometric adjustments, to alternative model specifications, and to a falsification test.

4.3. Regression Results—Baseline

The baseline regression results of our model of customer-driven IT spillovers in (2) are reported in Column 2 for data set I of Table 5 and in Column 2 for data set II ofTable 6. The regression results for the simple Cobb-Douglas production function are included for data sets I and II in Column 1 of Table 5 and Table 6, respectively, for comparison. These simple Cobb-Douglas results are similar across the two data sets and they are similar to those in previous studies (see Cheng and Nault 2007a). In our customer-driven IT spillovers model, the output elasticity estimates for non-IT capital, labor, IT capital, and intermediate inputs are similar to the results from the simple Cobb-Douglas function. As a result, we focus our attention on the customer-driven IT spillovers effect and the effect of relative industry concentration on customer-driven IT spillovers.

4.3.1. Interpretation of the Estimates of the Spillovers Coefficient. The estimates of the coefficient for the customer-driven IT spillovers, μ in (2), are positive and significant at the 1% level for both data set I (Column 2 of Table 5) and data set II (Column 2 of Table 5). This indicates that there are significant effects of downstream IT capital on upstream productivity. We should exercise caution when interpreting the coefficient μ in the presence of our interaction term $\eta r_i c_i$ in (2). The coefficient μ is the partial effect of the customer-driven IT spillovers on output *at the mean level of relative industry concentration*. Recall that

Table 6 Regression Results—Data Set II (1998–2005)

	Baseline		Alternative econometrics adjustments					Alternative model specification		Falsification test
Columns	1	2	3	4	5	6	7	8	9	10
Variables	He + AR1	He + AR1	Sector dummies	Finer sector dummies	Random effects	Year dummies	SYS-GMM	He + AR1	He + AR1	He + AR1
K	0.0753***	0.0849***	0.132***	0.174***	0.131***	0.0784***	0.109***	0.0862***	0.0802***	0.0759***
	(0.0189)	(0.0177)	(0.0192)	(0.0189)	(0.0291)	(0.0142)	(0.00338)	(0.0182)	(0.0159)	(0.0168)
L	0.280***	0.289***	0.256***	0.238***	0.267***	0.262***	0.180***	0.277***	0.255***	0.265***
	(0.0139)	(0.0119)	(0.0139)	(0.0135)	(0.0215)	(0.00996)	(0.00373)	(0.0129)	(0.0136)	(0.0123)
Z	0.0865***	0.0649***	0.0517***	0.0159	0.0306*	0.0660***	−0.0511***	0.0676***	0.0853***	0.0800***
	(0.0104)	(0.0110)	(0.0107)	(0.0116)	(0.0181)	(0.00949)	(0.00329)	(0.0120)	(0.00981)	(0.0116)
M	0.563***	0.589***	0.596***	0.594***	0.545***	0.636***	0.820***	0.590***	0.607***	0.593***
	(0.0146)	(0.0152)	(0.0157)	(0.0154)	(0.0212)	(0.0142)	(0.00449)	(0.0152)	(0.0150)	(0.0154)
C		0.0510***	0.0458***	0.0566***	0.0769***	0.151***	0.565***	0.0458***	0.0456***	0.0500***
		(0.0123)	(0.0111)	(0.0118)	(0.0171)	(0.0204)	(0.00472)	(0.0130)	(0.0117)	(0.014)
$R \times C$		−0.0441***	−0.0302***	−0.0374***	−0.0489***	−0.0407***	−0.0736***		−0.0361***	−0.0383***
		(0.00666)	(0.00973)	(0.0101)	(0.0114)	(0.00793)	(0.00941)		(0.0110)	(0.00801)
R									0.0494***	
									(0.0111)	
C_K										−0.0218
										(0.022)
$R \times C_K$										−0.0194
										(0.0183)
Obs.	392	392	392	392	392	392	392	392	392	392

Notes. K, non-IT capital; L, labor; Z, IT capital; M, intermediate inputs; C, customer-driven IT spillovers; R, relative industry concentration. C_K, customer-driven non-IT spillovers (used in the falsification test). He, heteroskedastic error structure; AR1, AR1 error structure. Dummy variables are suppressed for brevity. Sector dummies, finer sector dummies, and year dummies regressions are adjusted for He + AR1. Standard errors in parentheses.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

the relative industry concentration is centered when we estimate (2) and so, at the mean level of relative industry concentration, $r_i = 0$.

The impact on overall productivity of increases in downstream IT capital can be seen when computing marginal products. Recall that the expression for customer-driven IT spillovers is a weighted sum of all customers' IT capital. If all the customers of industry i increase their IT capital by \$1.00, then the downstream industry's own output increases by $Y/Z \times \gamma$ or \$1.14 on average in data set I and \$0.73 on average in data set II. Critical to our arguments, we find that, because of customer-driven IT spillovers, such an increase in downstream IT capital results in an output increase in upstream industries of $Y/C \times \mu$ or \$0.13 on average in data set I and \$0.38 on average in data set II. Thus, the total effect of a \$1.00 increase in IT capital is \$1.27 and \$1.11 for our two data sets, respectively, at the mean level of relative industry concentration.

4.3.2. Effects of Relative Industry Concentration on Customer-Driven IT Spillovers. The estimates of the coefficient of the interaction term between customer-driven IT spillovers and relative industry concentration, η in (2), are negative and significant at the 1% level for both data set I (Column 2 of Table 5) and data set II (Column 2 of Table 6). The significant negative coefficient of this interaction term means that the greater the downstream concentration relative to own industry concentration, the lesser the customer-driven IT spillovers. This is consistent with our expectations because more concentrated industries have greater market power, all things being equal, and are better able to retain the benefit from their IT investments when dealing with industries with lower concentration. The magnitude of η is not directly comparable between the two data sets because we use different measures of industry concentration.

As noted before, the variables c_i and r_i are centered so that we can interpret them at the mean level. In data set I at the mean level of r_i, which is 3.83 from Table 3, the magnitude of the customer-driven IT spillovers effect is $\mu = 0.0132$. If a customer's relative industry concentration r_i decreases by 1%, then the customer-driven IT spillovers effect μ would be increased by 0.92% ($\eta/\mu \times r_i$). In data set II at the mean level of r_i, which is 1.35 from Table 3, the magnitude of the customer-driven IT spillovers effect is $\mu = 0.051$. If a customer's relative industry concentration r_i decreases by 1%, then the customer-driven IT spillovers effect μ would be increased by 1.17% ($\eta/\mu \times r_i$).

Using our estimates, we can calculate the value of downstream customer competition in the form of industry concentration. In data set I, we use the HHI as our measure of customer industry concentration. If the HHI downstream of industry i decreases by 1% and if industry i's HHI remains constant, then r_i decreases by 1%. This decrease in downstream HHI would create an increase in upstream output through its effect on customer-driven IT spillovers by 0.094% ($\eta \times r_i \times c_i$).

Similarly, using our estimates for data set II, we can calculate the value of downstream customer competition where, in this data set, we use the 20-firm concentration ratio (CR20) as our measure of customer industry concentration. If the CR20 downstream of industry i decreases by 1% and industry i's CR20 remain constant, then r_i decreases by 1%. This decrease in downstream CR20 would create an increase in upstream output through its effect on customer-driven IT spillovers by 0.62% ($\eta \times r_i \times c_i$).

4.4. Robustness Tests and Alternative Specifications

As can be seen, our results are consistent across two data sets from different time periods, different sets of industries, different levels of aggregation, and different definitions of IT capital. To further check the robustness of our results, we carried out additional data analyses with different econometric adjustments and alternative model specifications.[8]

4.4.1. Estimates with Fixed Effects. To control for any unobservable, industry-specific, time-invariant differences in the production process, we ran our model with fixed effects and controlled for AR1. Fixed-effects estimation allows different intercepts to be estimated for different industries and can be obtained by including industry dummies. Consistent with Stiroh's (2004) observation that, historically, fixed-effects estimation has led to disappointing results with insignificant capital coefficients and implausibly low returns to scale, in our estimations with industry fixed effects the non-IT capital and IT capital coefficients become insignificant in data set I as does the IT capital coefficient in data set II. However, our customer-driven IT spillovers effect remains positive and significant in the estimations for both data sets, and the interaction effect remains negative and significant for data set II.

Fixed-effects estimation uses a great deal of degrees of freedom as different intercepts are estimated for each industry. To alleviate this problem, we used sector dummies instead of industry dummies, recognizing the fact that industries in the same sector share relatively similar production processes.[9]

Our data set I only includes manufacturing industries, and we classify these industries into sectors in two different ways. We first classify the manufacturing industries into IT producing, IT using, and other. Following Stiroh (2002), our IT-producing industries are the 17 industries with the first two digits of SIC code being 35 (industrial machinery and equipment) or 36 (electronic and other electric equipment). IT-using industries are the 31 industries that are not IT producing and whose IT intensity (IT capital stock over gross output) is above the sample median. The remaining 36 industries are classified as other. As a second way of classifying industries into sectors, we group the industries with identical 2-digit subheadings together into 1 sector, which results in 19 2-digit SIC sectors in data set I. The results of our regression with the dummies for the above two sets of classifications and controlling for heteroskedasticity and PSAR1 are reported in Columns 3 and 4, respectively, of Table 5. Again, we can see that the estimates are very close to those of the baseline regressions in Column 2, except for the insignificance of the IT spillovers term in the 2-digit SIC dummy regression. Yet the IT spillovers term is very close to being significant (t-stat $= 1.43$).

In data set II, we classify the industries into five sectors: manufacturing (NAICS codes 31–33); transportation, communications, and public utilities (NAICS codes 22 and 48–49); wholesale and retail trade (NAICS codes 42, 44–45, and 72); finance, insurance, and real estate (NAICS codes 52–53); and services (NAICS codes 51, 54, 56, 61, 62, 71, and 81). This classification corresponds roughly to the SIC division structure used by the U.S. Census Bureau. The results of our regression with sector dummies (fixed effects) and controlling for heteroskedasticity and AR1 are reported in Column 3 of Table 6. As we can see, the estimates are very close to those of the baseline regressions in Column 2. In addition, we tried a finer sector classification with the industries grouped into nine sectors; similar results were obtained and are reported in Column 4 of Table 6.[10]

[8] We also ran our model with possible outliers excluded. The results are consistent with our baseline results and are available upon request.

[9] We thank an anonymous reviewer for this suggestion.

[10] The nine sectors were: manufacturing (NAICS codes 31–33); transportation, communications, and public utilities (NAICS codes 22 and 48–49); wholesale trade (NAICS codes 42); retail trade (NAICS codes 44–45); accommodation, food services, and drinking places (NAICS code 72); finance, insurance, and real estate (NAICS codes 52–53); entertainment (NAICS codes 51 and 71); professional services (NAICS codes 54, 56, and 81); and educational services, health care, and social assistance (NAICS codes 61–62).

4.4.2. Estimates with Random Effects. Although estimates with fixed effects assume that any omitted variables are constant over time, estimates with random effects allow any omitted variables to vary over time. Conceptually, the term random effects is related to panel-specific AR1 where each industry can have a different autocorrelation function, but it is different in its estimation specification and because it is not autocorrelation based. We ran our model with random effects and controlling for AR1. The regression results are reported in Column 4 of Table 5 for data set I and Table 6 for data set II. The results are very close to those of our baseline regressions in Column 2 of Tables 5 and 6 with similar parameter estimates and almost identical significance.

4.4.3. Estimates with Year Dummies. The years covered in our two data sets, 1987–1999 and 1998–2005, contain many changes in the overall political economy from the peace dividend at the end of the Cold War to the recession in the early 1990s, the e-commerce boom in the late 1990s, and the e-commerce bust and terrorist attacks shortly after 2000. These changes were accompanied by changes in trade, monetary, and fiscal policy. To control for any economy-wide shocks that affect all industries, we ran our model including year dummies (adjusted for He + PSAR1 in data set I and He + AR1 for data set II). The results are reported in Column 5 of Table 5 for data set I and Table 6 for data set II. Again, the parameter estimates and their significance are very close to those of the baseline regression in Column 2 of Tables 5 and 6.

4.4.4. Estimates with Instrumental Variables. Another potential issue is the endogeneity of the independent variables. There are three possible reasons for endogeneity: omitted variables, measurement error, and simultaneity (Wooldridge 2002, p. 50). Omitted variables and measurement error problems are statistically similar because measurement error is unobservable; this causes problems only when it is correlated with the independent variables. If there are omitted variables correlated with our inputs, these inputs would receive credit for variation in the omitted variables. However, to the extent that the omitted variables are industry specific, the adjustment with panel-specific AR1, fixed or random effects can help relieve this problem. Simultaneity arises when the independent variables are simultaneously determined along with the dependent variable. In particular, our different types of capital inputs—non-IT, IT, and customer IT—could be endogenous if an unexpected increase in output leads to further investment in these capital inputs. We can test this kind of endogeneity by using the one-year lags of our different types of capital—k_i, z_i, and c_i—as instruments. The Hansen/Sargan C-test statistic (Baum et al. 2003) could not reject the exogeneity of k_i, z_i, and c_i for both data sets ($\chi^2 = 3.44$ for data set I and 6.46 for data set II).[11] Labor and intermediate inputs could also be endogenous because shocks in output are likely to trigger contemporaneous adjustments in labor and intermediate inputs (Dewan and Kraemer 2000). We ran the same Hansen/Sargan C-test using one-year lags of output, labor, and intermediate inputs as the instruments, and the statistics could not reject the exogeneity of labor and intermediate inputs for both data sets either ($\chi^2 = 1.96$ for data set I and 1.38 for data set II).

For these tests, we use lagged variables as instruments. Finding other appropriate instruments is challenging. The instrumental variables need to be exogenous, that is, uncorrelated with the error term, and they need to be partially correlated with the endogenous variables. The production function literature has pursued several alternatives for the instrumental variables including "internal" instruments such as lagged independent variables and demand-side instruments like oil prices, defense spending shocks, and monetary policy shocks (Stiroh 2004). Stiroh (2004) compared these alternatives and found that the approach with the best performance is a "system GMM estimator" (SYS-GMM) developed by Blundell and Bond (1998). SYS-GMM estimates the parameters from a stacked system of first-difference equations (with lagged levels as instruments) and levels equations (with lagged first differences as instruments) (Stiroh 2004). We present our estimates of SYS-GMM in Column 6 of Table 5 for data set I and Table 6 for data set II. The significance and sign of the IT spillovers term and the interaction term remain unchanged from our baseline regression in Column 2 of Tables 5 and 6.

4.4.5. Alternative Model Specifications. Our estimation model of customer-driven IT spillovers in (2) does not include the main effect of relative industry concentration—that is, an additional term with r_i. There are two reasons for not including the main effect of relative industry concentration: First, our model is derived in such a way that relative industry concentration (r_i) enters through its effects on the coefficient (the output elasticity) of customer-driven IT spillovers (see the development of (2)). Second, we recognize that relative industry concentration is not an input factor in the production function and does not affect output directly. As mentioned before, similar specifications can be found in econometrics textbooks (e.g., Wooldridge 2003, p. 236).

However, one reason to include the main effect of relative concentration is to account for unobserved

[11] We also tried longer lags of the capital variables as instruments and the statistics remain insignificant.

heterogeneity that may be because of relative market power differences between industries. To test whether our results are robust to the alternative specification whereby relative industry concentration is considered an omitted variable and hence a source of unobserved heterogeneity, we ran the model with the main effect of relative industry concentration. As we can see from these results (Column 8 of Table 5 for data set I and Table 6 for data set II), the coefficients are similar to our baseline model in Column 2 of Tables 5 and 6. Also included are the estimates from another alternative specification with both the main effect of relative industry concentration and the interaction effect excluded (Column 7 of Table 5 for data set I and Table 6 for data set II); similar results are obtained as compared to the baseline in Column 1 of Tables 5 and 6. These results from the alternative specification are consistent with earlier results in Cheng and Nault (2007b).[12]

Another approach to address concerns of unobserved heterogeneity related to between-industry differences in the level of IT capital is considering a basis other than IT capital for the measure of IT spillovers. We examined a measure of IT intensity calculated as IT capital over non-IT capital. This measure of IT intensity better captures the degree to which IT is integral to production because it is a ratio of capital measures and is not subject to some of the scale-dampening effects of using output or labor in the denominator. The estimates of our model using this measure of IT intensity as the spillovers and using the same weighting method as earlier to develop the customer-driven IT spillovers yielded results consistent with those in our baseline results across both data sets.[13]

4.4.6. Falsification Test. We also consider that customer non-IT capital may have spillovers that are being picked up in the regressions by customer IT capital and that non-IT capital customer-driven spillovers overshadow customer-driven IT capital spillovers.[14] To examine these possibilities, we ran our specification in (2) with additional terms for customer-driven non-IT capital spillovers. The customer-driven non-IT capital spillovers is constructed the same way as the customer-driven IT spillovers. That is, we aggregate customer industries' non-IT capital with the input-output tables as the weighting matrix. The results are presented in Column 10 of Table 5 for data set I and Table 6 for data set II. We find that customer-driven IT capital spillovers remain significant as in our baseline model and that customer-driven non-IT capital spillovers are not significant. Thus, our customer-driven IT spillovers results—both direct and moderated by relative industry concentration—are not masking or being overshadowed by customer-driven non-IT capital spillovers. This can also be seen as evidence against the argument that scale-related downstream heterogeneity is driving our results because non-IT capital can be a proxy for scale.

5. Conclusion

Economists have long documented the importance of spillovers as a source of increasing returns and long-run productivity growth (Barro and Sala-i-Martin 2004). In this research, we provide evidence for significant and positive spillovers upstream from downstream IT investment and for the impact of relative industry concentration on the magnitude of this customer-driven IT spillovers. Our findings are consistent over different time periods, on different scopes of the economy, at different levels of industry aggregation, and with different definitions of IT capital. Our results are robust to different econometric adjustments, alternative model specifications, and a falsification test.

Our study has two important contributions. The first is providing an argument for and evidence of customer-driven IT spillovers. Customer-driven IT spillovers result from IT-enabled information sharing and coordination and possibly IT knowledge spillovers, all leading to more efficient production and logistic upstream. Our analysis conclusively shows that these effects are not only significant but are also substantial in that IT investment downstream has large effects on upstream output even after we control for the moderating effect of relative industry concentration. These IT spillovers are positive externalities to IT investment and, when unaccounted for in investment decisions, cause lower investment in IT and lower IT capital levels than would be optimal for production in a given supply chain and in the economy. Even though these spillovers may result in part from subsidized adoption and the promotion of standards, our results indicate that there are returns from additional IT investments.

The second and perhaps most novel contribution is that we show that relative industry concentration—which we believe reflects market power resulting from upstream versus downstream competition—affects how much of the returns from downstream investments in IT spill over to upstream industries. That is, we find that relatively more concentrated industries retain more of the returns from their IT

[12] First differencing can also remove unobserved time-invariant effects but at a cost of reduced variation, which can lead to large standard errors. Our first-difference regressions had larger standard errors but the coefficients had the same signs as our baseline results.

[13] These IT intensity regression results are available upon request.

[14] We thank an anonymous reviewer for this suggestion.

investments. The findings behind our contributions are not only consistent across our two data sets but are also consistent across a battery of robustness tests and alternative specifications.

The managerial implications of our findings come directly from our results that productivity from customer investment in IT is providing value upstream, and that the level of competition in the customer versus supplier industry—as captured by relative industry concentration—affects how much of the value spills over. The first suggests underinvestment in IT along the supply chain because all the payoffs to IT investment are not being retained by the investing industry. More complete contracting between customers and suppliers based on further sharing of verifiable information may make it possible to better coordinate joint investments in IT. The second suggests a role for policy along the lines of subsidies for IT investment to those industries that are more competitive (i.e., less concentrated). This would increase their returns to IT investment and perhaps motivate their IT investment to levels that make supply chain coordination more efficient.

Our study has three notable limitations. First, our empirical analysis is at industry level. Firm-level data has the potential to provide greater managerial insights and is less subject to aggregation error; however, as we pointed out earlier, our industry-level analysis is broader and, with consistent results over different levels of industry aggregation and different definitions of IT capital, it is unlikely that our results are because of aggregation. Nevertheless, IT spillovers at the firm level remain an interesting topic for future research.

Second, we recognize that there is a gap between measuring relative concentration and whether that measure fully captures the concept of market power especially with aggregated data because there may be many firms in the subindustries of the industries we measure. The Federal Trade Commission appears to employ measures similar to ours when measuring market power except in cases where market power can be measured directly through price. Unfortunately, we do not have access to that level of data and it is not compatible with our production function-based analysis. However, our summary statistics on the CR20 give us a sense of scale: In the first part of our Table 3, we see that the average CR20 is over 30%. In this context, aggregating three equally-sized subindustries with different monopolists would yield an aggregate CR20 of 33%. Consequently, given the average size of our concentration measure, we are more confident that our measure of relative concentration is capturing many of the essential features of market power.

Third, firms, in recognition of the IT spillovers, may choose to operate strategically and only invest or share information to the extent that no spillovers occur. We do not explicitly capture that strategic interaction in our empirical model. Modeling strategic behavior and policy implications requires a prior analytical model such as Cachon and Lariviere (2001).

Future research could investigate the network structure of the supply chain (Burt 1982) and explore how IT is adopted and diffused in the supply chain network. Finally, this research, together with that of Cheng and Nault (2007a), focuses on IT spillovers along the supply chain. Future research could study IT spillovers that result through other mechanisms such as learning from peer industries or investing in R&D that makes IT more effective.

Acknowledgments

The authors are grateful to the Conference on Information Systems and Technology (CIST) 2007 review team and participants as well as Gerard Cachon, Jianqing Chen, Kunsoo Han, Robert J. Kauffman, Victoria L. Mitchell, Mohammad Rahman, Bin Srindhi, and Kevin Zhu for helpful comments. They thank the Natural Sciences and Engineering Research Council of Canada, the Social Sciences and Humanities Research Council of Canada, the Haskayne School of Business at the University of Calgary, and the School of Accounting and Finance at The Hong Kong Polytechnic University for support.

References

Alexander, D. L., P. D. Thistle. 1999. Market power, efficiency and the dispersion of systematic risk. *Rev. Indust. Organ.* **14**(4) 377–390.

Ali, A., S. Klasa, E. Yeung. 2009. The limitations of industry concentration measures constructed with Compustat data: Implications for finance research. *Rev. Financial Stud.* **22**(10) 3839–3871.

Bakos, J. Y., E. Brynjolfsson. 1993. Information technology, incentives, and the optimal number of suppliers. *J. MIS* **10**(2) 37–53.

Barro, R. J., X. Sala-i-Martin. 2004. *Economic Growth*. MIT Press, Cambridge, MA.

Barua, A., P. Konana, A. B. Whinston, F. Yin. 2004. An empirical investigation of net-based business value. *MIS Quart.* **28**(4) 585–620.

Baum, C. F., M. E. Schaffer, S. Stillman. 2003. Instrumental variables and GMM: Estimation and testing. Boston College working papers in Economics, RePEC:boc:bocoec:545. Boston College, Boston.

Berger, A. N. 1995. The profit-structure relationship in banking—Tests of market-power and efficient-structure hypotheses. *J. Money, Credit Banking* **27**(2) 404–431.

Bharadwaj, S., A. Bharadwaj, E. Bendoly. 2007. The performance effects of complementarities between information systems, marketing, manufacturing, and supply chain processes. *Inform. Systems Res.* **18**(4) 437–453.

Blundell, R. W., S. R. Bond. 1998. Initial conditions and moment restrictions in dynamic panel data models. *J. Econometrics* **87**(1) 115–143.

Burt, R. 1982. *Toward a Structural Theory of Action: Network Models of Social Structure, Perception, and Action*. Academic Press, New York.

Cachon, G. P., M. A. Lariviere. 2001. Contracting to assure supply: How to share demand forecasts in a supply chain. *Management Sci.* **47**(5) 629–646.

Cameron, D., M. Glick. 1996. Market share and market power in merger and monopolization cases. *Managerial and Decision Econom.* **17**(2) 193–201.

Cheng, Z., B. R. Nault. 2007a. Industry level supplier-driven IT spillovers. *Management Sci.* **53**(8) 1199–1216.

Cheng, Z., B. R. Nault. 2007b. Customer-driven IT spillovers and industry competition. *Proc. Fall 2007 INFORMS Conf. Inform. Systems Tech., Seattle*.

Clemons, E. K., M. C. Row. 1993. Limits to interform coordination through information technology: Results of a field study in consumer packaged goods distribution. *J. MIS* **10**(1) 73–95.

Danese, P. 2006. Collaboration forms, information and communications technologies, and coordination mechanisms in CPFR. *Internat. J. Production Res.* **44**(16) 3207–3226.

Dedrick, J., V. Gurbaxani, K. Kraemer. 2003. Information technology and economic performance: A critical review of the empirical evidence. *ACM Comput. Survey* **35**(1) 1–28.

Dewan, S., K. L. Kraemer. 2000. Information technology and productivity: Evidence from country-level data. *Management Sci.* **46**(4) 548–562.

Hitt, L. M., P. Tambe. 2006. Measuring spillovers from information technology investments. *Proc. Internat. Conf. Inform. Systems, Milwaukee*, 1793–1802.

Kachadourian, G. 2000. A new ANX for everyone. *Automotive Indust.* **180**(2) 113.

Kim, E. H., V. Singal. 1993. Mergers and market power: Evidence from the airline industry. *Amer. Econom. Rev.* **83**(3) 549–569.

Kundisch, D., N. Mittal, B. R. Nault. 2010. Measuring IT productivity using income accounting. Working paper, University of Calgary.

Laudon, K. C., J. P. Laudon. 2003. *Essentials of Management Information Systems*, 5th ed. Prentice Hall, Upper Saddle River, NJ.

Lee, H. L., K. So, C. Tang. 2000. The value of information sharing in a two-level supply chain. *Management Sci.* **46**(5) 626–643.

Lewis, I. 2001. Logistics and electronic commerce: An interorganizational systems perspective. *Transportation J.* **40**(4) 5–13.

Mun, S., M. I. Nadiri. 2002. Information technology externalities: Empirical evidence from 42 U.S. industries. National Bureau of Economic Research Working Paper 9272, Cambridge, MA.

Nault, B. R. 1997. Quality differentiation and adoption costs: The case for interorganizational information systems pricing. *Ann. Oper. Res.* **71** 115–142.

Nault, B. R., A. S. Dexter. 1995. Added value and pricing with information technology. *MIS Quart.* **19**(4) 449–463.

Rosencrance, L. 2002. Speed racers. *Computerworld* **36**(33) 12.

Sahaym, A., H. K. Steensma, M. A. Schilling. 2007. The influence of information technology on the use of loosely coupled organization forms: An industry-level analysis. *Organ. Sci.* **18**(5) 865–880.

Stiroh, K. J. 2002. Information technology and the U.S. productivity revival: What do the industry data say? *Amer. Econom. Rev.* **92**(5) 1559–1576.

Stiroh, K. J. 2010. Reassessing the impact of IT in the production function: A meta-analysis and sensitivity tests. *Contributions in Memory of Zvi Griliches*. National Bureau of Economic Research (NBER), Cambridge, MA.

Tambe, P., L. M. Hitt. 2009. Job hopping, knowledge spillovers, and regional returns to information technology investments. *Internat. Conf. Inform. Systems (ICIS) 2010 Proc., St. Louis*, 123.

Vossen, R. W. 1999. Market power, industrial concentration and innovative activity. *Rev. Indust. Organ.* **15**(4) 367–378.

Wang, E. T. G., A. Seidmann. 1995. Electronic data interchange: Competitive externalities and strategic implementation policies. *Management Sci.* **41**(3) 401–418.

Wooldridge, J. M. 2002. *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, MA.

Wooldridge, J. M. 2003. *Introductory Econometrics: A Modern Approach*, 2nd ed. South-Western, Mason, OH.

Zhu, K. 2004. Information transparency of business-to-business electronic markets: A game-theoretic analysis. *Management Sci.* **50**(5) 670–685.

Zhu, K., K. L. Kraemer, V. Gurbaxani, S. Xu. 2006. Migration to open standard interorganizational systems: Network effects, switching costs, and path dependency. *MIS Quart.* **30**(4) 515–525.