The Different Effects of Hardware and Software on Production Interdependence in Manufacturing

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Make or buy decisions are often decisions between investing in capital for production or building supply chain relationships upstream. These are strategic decisions about production interdependence: the degree to which materials and services are provided internally versus purchased externally. Information technology (IT) has increased productivity with hardware and software such as robotics and flexible manufacturing systems. IT has also improved information sharing and coordination along the supply chain by integrating business processes with software. Within manufacturing, we examine whether hardware and software are related to choices of make versus buy differently. From a transaction cost perspective this can be due to differential impacts on reducing internal production costs versus external coordination costs. We find that in U.S. manufacturing industries from 1998-2016, hardware favors internal production suggesting hardware reduces costs of internal provision more; software increased purchases from upstream suppliers suggesting software reduces costs of external provision more. This result shows that hardware and software complementarity has limits in that each has distinct productivity targets, and that empirically the decision of make versus buy is manifested by investments in these different types of IT capital. That is, when facing strategic decisions about make versus buy in manufacturing, hardware and software have opposite impacts.

Keywords: Make versus buy; production interdependence; direct backward linkage (DBL); productivity; transaction costs; information technology; supply chains.

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1. Introduction

One of the most fundamental decisions in manufacturing is how much of the inputs to make and how much to buy. This determines firm's production interdependence: the degree to which materials and services used to produce final goods are provided internally versus purchased externally. The result leads to a level of production interdependence, which is an important dimension of the structure of supply chains and the economy in aggregate: it defines the boundary of firms and of industries, it determines bargaining power and competition, and it dictates the depth (i.e., number of tiers) of supply chains. It also determines the distribution of value added across the supply chain. Thus, make versus buy decisions are strategic.

As part of these decisions industries have invested heavily in information technology (IT). According to the U.S. Bureau of Labor Statistics (BLS), IT capital stock by the manufacturing sector climbed steadily from $73.04 billion in 1987, reaching $305.09 billion in 2018 (in 2012 dollars from capital tables released March 24, 2020.). This IT capital, which from an acquisition perspective can be separated into hardware and software where the former accounts for over 50% in manufacturing, reflects how industries have developed best practices to engineer operations and business processes.

IT capital has also changed how production is organized. Previous studies have found that IT has an impact on various measures of organizational structure. For example, IT leads to smaller firm size (Brynjolfsson et al. 1994), and IT is related to decreases in vertical integration and increases in diversification (Hitt 1999). These studies use IT capital as an aggregate. In the context of manufacturing, we presume that IT hardware and software may have different impacts on how production is organized, making different IT investments strategic in a way that is distinct from making IT investments with the goal of straightforward increases in productivity.

Every system is a combination of hardware and software. However, some are predominantly hardware and others are predominantly software. On one hand, IT implementations that are predominantly hardware in manufacturing like industrial process instruments, robotics, sensors, radio-frequency identification (RFID), computer numerical control (CNC), and flexible manufacturing systems (FMS), together with more general computers and communications, have yielded increased productivity on the shop floor. This hardware allows flexibility in production and scalability at low cost; links functional unit information systems to shop floor manufacturing technology; increases productivity through automation of routine tasks; improves designer productivity through computer-aided design; and enables greater process consistency and reliability, thereby improving product quality using CNC and FMS (Swamidass and Winch 2002).[1] Consequently, as hardware in manufacturing favors internal production, we expect that more hardware is associated with more internal provision, which translates into less interdependence.

On the other hand, IT implementations that are predominantly software, such as interorganizational systems (IOS) that enable strategies such as just-in-time (JIT) production has supported industries becoming increasingly integrated with their suppliers' business processes (Dong et al. 2009). The range of software includes tools like data analytics and machine learning incorporated in organization procedures and management methods. These are embedded in software-supported processes such as total quality management, JIT production, materials requirements planning (MRP), and supply chain management (SCM) – all of which are used to connect customers and suppliers (Burgess and Gules 1998). Consequently, industries in a manufacturing supply chain may have become more interdependent as software investments have grown.

[1] As we explain in detail in the subsection "IT Capital, Non-IT Capital, and Labor", of our aggregated hardware measure (HW), approximately one half can be considered information technology for manufacturing. In addition, we further decompose our measure of hardware (HW) into two components, R1HW (computers and related equipment and communication equipment) and R2HW (other information processing equipment). Of the latter disaggregated measure of hardware capital, 79.3% is "nonmedical instruments" related to manufacturing. Our results are consistent across the different measures of hardware.

Our focus: To help guide IT investments in support of make versus buy decisions and to better understand the impact of hardware and software subcomponents of IT on production interdependence, we examine how an industry's IT capital impacts its production dependence measured as direct backward linkage (DBL) with upstream suppliers. We disaggregate IT capital into hardware and software, and we examine their differential effects on DBL. Our definition of hardware and software is developed by the BLS. Hardware includes generic IT hardware such as computers and communication equipment, as well as manufacturing technology consisting of computer-aided industrial process instruments and related machines in manufacturing, such as those described above; the former accounts for roughly one third and the latter two thirds of hardware investment. Software includes pre-packaged, custom, and own-account software that includes application software such as ERP, IOS, SCM, etc., also described above. Some system software is firmware and, as such, is bundled with hardware.

We use production theory and develop an estimation model where we separate the direct effects of IT capital on DBL and the indirect effects of different IT capital subcomponents on DBL through intermediate inputs. To capture the indirect effects we allow the output elasticity of intermediate inputs to depend on different IT capital subcomponents, yielding a set of specifications. We then estimate that model with U.S. manufacturing industry-level data over 19 years: 1998-2016. As Aigner and Chu (1968) explain, any firm production function can be obtained from optimal parameter values at the industry-level, and estimation of an industry-level production function represents that of an average firm in the industry. This is certainly the case when firms follow industry best-practice.

Highlights of our results: First, we find that IT capital in aggregate has a negative direct effect on DBL across our different specifications. This is because IT capital expands output (make) relative to intermediate inputs (buy), corresponding to lower interdependence.

Next, disaggregating IT capital into hardware and software subcomponents, we develop a specification that isolates the indirect effects of hardware and of software through intermediate inputs.

We find that the indirect effect of hardware reduces DBL, and that, in contrast, the indirect effect of software increases DBL. Moreover, the indirect effect of software is greater than the direct effect of aggregate IT capital. Thus, we find that hardware capital favors internal production and reduces interdependence, whereas software capital favors external purchasing and increases interdependence with supply chains upstream. This seemly surprising result shows that hardware and software complementarity where investments in hardware are viewed as necessitating investments in software and vice versa, has limits in that each has distinct productivity targets, and that empirically the decision of make versus buy is manifested by these different IT capital investments. In other words, when it comes to impacts on interdependence, hardware and software have opposite effects.

Further, we disaggregate hardware capital into separate measures of general computers and communications, and of manufacturing technology. We find that the indirect effects of both hardware measures relate to lower interdependence, indicating complementarity between different categories of hardware persists in their effects on interdependence, and the effects remain opposite to those of software.

The remaining sections are organized as follows: section 2 explores literature related to our work; section 3 develops our conceptual, theoretical, and estimation models; section 4 presents our empirical estimation including a description of the data, variables, and econometric adjustments; section 5 presents our estimation results; and section 6 provides our conclusions.

2. Related Literature

2.1. IT and the Organizational Structure of Production

Many studies have examined the impact of IT on the organizational structure of production based on transaction cost theory. Theoretically, Malone et al. (1987) provide an analytical framework about how the relative importance of production and coordination costs affect organization forms. Based on the framework, they argue that IT leads to a shift from hierarchies to markets by reducing coordination costs. Gurbaxani and Whang (1991) provide a theoretical framework to assess the impact of IT on firm size and the allocation of decision rights based on agency theory and transaction cost theory. They analyze two opposing effects of IT on firm size: reducing external coordination costs favors markets and leads to smaller firm size, whereas reducing internal coordination costs results in vertically and horizontally larger firm size. Clemons et al. (1993) argue that IT could reduce coordination costs without increasing transaction risks in supplier-buyer relationships and contribute to a move to more outsourcing from a smaller set of suppliers with long-term relationships. Bakos and Kemerer (1992) gives an overview of early research in the field.

Empirically, Brynjolfsson et al. (1994) examine the relationship between IT and firm size and find that IT is associate with a decrease in firm size. They explain the relationship between IT and firm size based on firms' make versus buy decisions: when IT reduces external coordination costs more than internal, or IT reduces coordination costs more than product costs, firms buy more things externally and firm size shrinks. Hitt (1999) finds that IT is related to decreases in vertical integration and weak increases in diversification, and suggests that IT could reduce both internal and external coordination costs. Based on plant-level data, Forman and McElheran (2017) examine the impact of upstream, downstream, and internal IT use on firm boundaries. They find that externally-focused IT use is related to a reduction in downstream vertical integration. In a recent study, McElheran and Forman (2019) focus on the relationship between IT use and the vertical transfers within the firm and find that an increase in using the internet for external coordination is associated with a net shift toward market-based exchange. At the industry level, Gong et al. (2016) provide empirical evidence that the Internet-enabled move to the market in the provision of logistics, suggesting the internet-enabled IT reduced external transaction costs relatively more than internal governance costs.

There are many studies that suggest IT can reduce the costs of external coordination. Information sharing along the supply chain can reduce search costs, mitigate various threats from opportunism, and lower uncertainty. IT has improved interorganizational coordination and collaboration in production and in new product development (Bharadwaj et al. 2007, Peng et al. 2014). IT also facilitates supply chain process integration and improves supply chain performance (Rai et al.

2006, Devaraj et al. 2007). An industry's IT investments in IOSs, such as JIT systems, supply chain management systems, and collaborative planning, forecasting and replenishment (CPFR), allow information sharing and coordination downstream and upstream. This leads to visibility of inventory in a supply chain as well as the removal of redundant inventory and logistics activities across tiers of production. Early versions of Chrysler's Electronic Data Exchange systems, for example, allowed information about planning, production, and delivery to be transmitted instantly within and between supply chain partners, thereby facilitating the implementation of JIT (Mukhopadhyay et al. 1995). All of these software examples reduce external coordination costs.

Additionally, IT can reduce costs of internal production and management coordination. Traditional hardware together with newer manufacturing technologies like robotics and process control instruments directly improve productivity through automation of routine tasks, reducing labor costs, rework costs, and work-in-process (WIP) inventories (Zammuto and O'Connor 1992, Swamidass and Winch 2002). Higher productivity also results from IT-based interoperability in the integration of a sequence of technologies (Angst et al. 2011), and investments in software such as Enterprise Resource Planning (ERP) allow cross-functional processes and real-time information sharing across departments, enabling better forecasting and scheduling. There is substantial evidence that IT increases productivity by leveraging non-IT inputs and resources (e.g., Jeffers et al. 2008, Mittal and Nault 2009, Kleis et al. 2014, Peng and Zhang 2020), and Hitt et al. (2002) show higher performance across a wide variety of financial metrics after ERP implementation.

To summarize, this stream of studies has found that IT impacts various organizational structure measures, such as firm size, vertical integration, firm boundary, etc. These studies suggest that IT can reduce different types of costs in transactions, including internal and external coordination costs. However, few studies examined the impact of IT on the direct economic outcome of make versus buy decisions, for example, how much proportion of economic activities to buy from suppliers when organizing production. Also, different types of IT, such as hardware and software, may reduce various kinds of costs in transactions differently, which leads to the changes in the economics of make versus buy.

2.2. Production Interdependence as a Measure of Production Structure

In a seminal paper in the area of production interdependence, Chenery and Watanabe (1958) define two related measures of interdependence among productive sectors based on the input-output model: (1) the ratio of purchased inputs to the value of total production; and (2) the ratio of intermediate to total demand for a given product. Using the measures, Chenery and Watanabe (1958) find a similar production interdependence pattern among sectors across four developed countries. Since then, many studies have investigated the international and inter-temporal comparisons of production structure using similar measures. For instance, Santhanam and Patil (1972) compare India's production structure with that of selected advanced countries, and Song (1977) compare Korea's production structure with other countries' and also with its past production structure.

Jones (1976) relates the concepts of production interdependence and one of the varieties of Hirschmanian linkages—the input-provision or backward linkage effects—and points out that linkage concepts are based on industrial interdependence. Both DBL and production interdependence could be measured as the ratio of purchased inputs to the value of total production (Jones 1976). Reviewing the development of linkage measures, Dietzenbacher (1992) and Miller and Blair (2009) highlights the validity of the measure for DBL.

The DBL is usually used to identify key industries in an economy for economic development and policymaking (Drejer 2002, Kim et al. 2002, Miller and Blair 2009). Little attention has been drawn to the source of difference in DBL, a measure of production structure. The structure of production results from the interaction of a variety of forces, such as country and industry characteristics, technological development, and production type (Chenery and Watanabe 1958). A few studies have explored the relationship between IT and DBL. Rim et al. (2005) define an IT capital stock backward multiplier of an industry based on the industry's DBL and IT capital intensity, and find that the backward multipliers of IT capital are the highest in the manufacturing industry. Gong (2015) examines the relationship between IT and production interdependence and finds that IT as a whole reduces DBL and the reduction in DBL contributes to value-added by improving its total factor productivity (TFP).

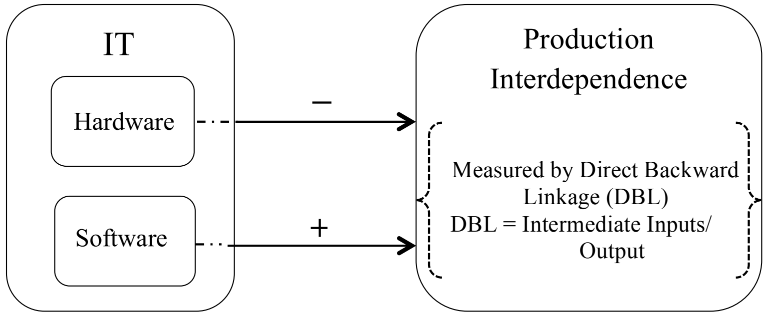

Figure 1 **Our Conceptual Model: IT and DBL**

In summary, we integrate the key measure of production independence, DBL, with earlier described elements of transaction costs as follows. If an industry can purchase intermediate inputs from other industries or can produce them itself, then a high DBL for a given industry suggests that external coordination costs are relatively low and that the industry depends heavily on suppliers for providing intermediate inputs including materials, energy, and services. A low DBL for a given industry suggests internal governance and production costs are relatively low and that fewer intermediate inputs are needed to produce a certain amount of output.

3. Conceptual, Theoretical, and Estimation Models

In the production function framework, an industry invests IT capital, non-IT capital, and labor into production, as well as purchases materials, energy, and services from upstream industries which are collectively called intermediate inputs. The four inputs (IT capital, non-IT capital, labor, and intermediate inputs) are combined in a production function to model the production of output. The ratio of an industry's intermediate inputs over its output, DBL, indicates an industry's production interdependence with upstream suppliers. IT capital can contribute to production directly as an input (Brynjolfsson and Hitt 1996) and indirectly through complementing, substituting, and augmenting other inputs (Dewan and Min 1997, Chwelos et al. 2010, Mittal and Nault 2009, Zhang et al. 2015). Specific to our focus, IT capital can contribute to output via internal production and to the amount of intermediate inputs needed to produce that output via external provision, thereby affecting production interdependence.

Transaction cost theory posits that make-versus-buy decisions hinge upon the trade-off between internal production cost and external transaction cost (Coase 1937, Williamson 1981). The amount of intermediate inputs purchased, and thus DBL, depends on the outcomes of make-versus-buy decisions: the more intermediates purchased the higher is the upstream dependency. Clemons et al. (1993) further decompose external transaction costs into coordination costs and transaction risk. Coordination costs are, for example, the cost of transmitting information about demand such as price, product characteristics, and availability. Transaction risk is the possibility of opportunistic behavior by trading partners to willfully misrepresent/withhold information or underperform. Information asymmetries, differences in bargaining power, and the number of potential suppliers all contribute to transaction risk. There are also strategic elements to balance between in-sourcing (make) and outsourcing (buy). Holcomb and Hitt (2007) argue that transaction cost characteristics such as asset specificity, small numbers bargaining, and technological uncertainty, together with strengths and weaknesses in production relative to the competition, causes the make or buy decision to be strategic as it is part of developing unique capabilities. In this way, choices of IT investments can reflect strategic capability development decisions, as well as resilience to supply disruptions (Ambulkar et al. 2015, Kim et al. 2015).

Although IT reduces internal production and external coordination costs, we hypothesize that hardware, especially manufacturing technology, reduces internal production costs relatively more than external coordination costs, and that this causes industries to produce a greater range of the needed inputs – effectively making these inputs internal costs, which in turn reduces their production dependence on upstream suppliers. On the other hand, software reduces external coordination costs relatively more than internal production costs by facilitating the exchange of product information such as price, product characteristics, availability, and delivery updates with upstream suppliers. As a result, industries purchase a greater range of the inputs they need, which in turn increases their production dependence on upstream suppliers. Figure 1 describes the relationship between hardware, software, and production interdependence measured as DBL.

3.1. The Production and Estimation Models

We develop our theoretical model based on production theory and implement it using the Cobb-Douglas production function. The Cobb-Douglas form is theoretically supported as coming from the accounting identity—output equals intermediate inputs plus the wage bill plus the total return on capital (Kundisch et al. 2014). A standard Cobb-Douglas function with output on the left-hand side is

$$Y_{it} = AK^{\alpha} L^{\beta} Z^{\gamma} M^{\theta}, \tag{1}$$

and the log form is

$$y = a + \alpha k + \beta l + \gamma z + \theta m. \tag{2}$$

Y is the quantity of output of industry i in year t, A is total factor productivity (TFP) representing technological change, and K, L, Z, M represent the quantities of non-IT capital, labor, IT capital, and intermediate inputs, respectively. $\alpha, \beta, \gamma, \theta$ are the output elasticities of non-IT capital, labor, IT capital, and intermediate inputs, respectively. Lower-case variables represent the log form of upper-case variables.

When using production theory it is tempting to overlay causality or infer a sequence of decisions such as choosing capital levels, optimizing output, and then whether to purchase or produce resulting in levels of labor and intermediate inputs. Our model is not meant to reflect causality or sequence. Rather, our production function estimation, rooted in production theory, relates inputs to output and assesses the marginal product through output elasticities of each input towards output. Many articles over 25 years of IT productivity research estimate output as a function of inputs (mostly with the Cobb-Douglas or variant) to obtain marginal products without overlaying sequence or causality of decision-making.

We conjecture that an industry's IT investment is related to its output through both a direct effect and indirect effect. The direct effect is captured by γ in (2), the output elasticity of IT capital, and the indirect effect is through the contribution of intermediate inputs, an effect captured by a in (2) where a is the log of TFP. The contribution of intermediate inputs measured as the output elasticity of intermediate inputs, θ, determines the percentage change in output in response to a one-percent change in intermediate inputs.

To explicitly specify the relationship between IT and the output elasticity of intermediate inputs we employ a varying-coefficient model, which allows the coefficient θ to change smoothly with the value of hardware and software subcomponents of IT capital. There are variants of varying-coefficient models (Hastie and Tibshirani 1993, Fan and Zhang 1999, Park et al. 2015). For our research purposes, we focus on the varying-coefficient model that formulates the relationship between IT capital subcomponents and the coefficient θ, which is directly related to the measure of DBL. Thus, we assume that the impact of IT capital subcomponents on the coefficients of non-IT capital and labor are constant (Hastie and Tibshirani 1993), $\alpha(hw, sw) = \alpha$ and $\beta(hw, sw) = \beta$, respectively. In addition, we assume a linear relationship between the two forms of IT capital (hardware and software) and the output elasticity of intermediate inputs, θ. We choose a linear form for simplicity and to embed the fewest assumptions about the relationship; any non-linear form usually has a linear term. Use of logs ensures consistency with other variables in terms of magnitude. We specify the relationship as

$$\theta(hw, sw) = \omega + \nu hw + \eta sw, \tag{3}$$

where hw and sw are the natural logarithm of hardware and software, respectively, and ν and η represent their indirect effects, respectively. The parameter ω becomes the direct effect of intermediate inputs on production. Treating $\theta(\cdot)$ as an output elasticity, it can be interpreted as

$$\theta(hw, sw) = \%\Delta Y / \%\Delta M \tag{4}$$

where Y and M are in dollars. If $\theta(\cdot)$ increases, then the marginal return of output Y from intermediate inputs M is higher, and the optimal choices of Y and M that result from the underlying profit maximization involving (1) are higher.

Bringing (3) into (2), we have

$$y = \tilde{a} + \tilde{\alpha}k + \tilde{\beta}l + \tilde{\gamma}z + \omega m + \nu[hw \times m] + \eta[sw \times m], \tag{5}$$

where we use "×" to denote the interaction terms. DBL is calculated as described earlier, and thus, the log form of DBL, $log(DBL)$, is written as

$$log(DBL) = log\frac{\sum_{j\neq i} inputs_{ji}}{Y} = log\frac{M}{Y} = m - y, \tag{6}$$

where $inputs_{ji}$ is the intermediate inputs required from industry j by industry i. Bringing (5) into (6), after transformation we have

$$\begin{aligned} log(DBL) &= -\tilde{a} - \tilde{\alpha}k - \tilde{\beta}l - \tilde{\gamma}z + [1-\omega]m - \nu[hw \times m] - \eta[sw \times m] \\ &= b_0 + b_1 k + b_2 l + b_3 z + b_4 m + b_5[hw \times m] + b_6[sw \times m]. \end{aligned} \tag{7}$$

In our production model, the equation in (7), IT has two types of effects on DBL. The total effects of a change in hardware on interdependence can be written as

$$\frac{\partial log(DBL)}{\partial hw} = b_3 \frac{\partial z}{\partial hw} + b_5 m, \tag{8}$$

and for software on interdependence can be written as

$$\frac{\partial log(DBL)}{\partial sw} = b_3 \frac{\partial z}{\partial sw} + b_6 m, \tag{9}$$

noting that a small difference in the log of a variable is approximately a percentage change in the variable. We begin by considering the impact of an increase in either hardware or software as in (8) and (9), respectively, on DBL. The direct effect can be assessed by b_3 in the first term on the right-hand side, and is similar in kind to the impact of labor and non-IT capital. The parameter b_3 reflects the (negative of) output elasticity of IT, $\tilde{\gamma}$, in (5). An increase in hardware or software increases IT capital, so $\partial z/\partial hw, \partial z/\partial sw = 1 > 0$. An increase in IT capital z increases output y. As long as there is a less than proportional increase, or even a reduction in intermediate inputs (e.g., greater efficiency), m, then with $log(DBL) = m - y$ this should result in a negative b_3. Thus, the direct effect of investments in IT capital is to reduce interdependence.

The indirect effect of an increase in hardware is in the second term on the right-hand side of (8). The parameter b_5 reflects the (negative of) change in the output elasticity of intermediate inputs, $\theta(\cdot)$, resulting from a change in hardware. If our conjecture that hardware reduces internal production costs relatively more than external coordination costs is correct, then an industry would need fewer intermediate inputs to produce a certain level of output – choosing to make more inputs than it buys. We therefore expect the estimate of b_5 to be negative. A negative b_5 indicates that an increase in hardware increases both the level of intermediate inputs and of output, where the increase in output is greater than the increase in intermediate inputs. As a consequence, this indirect effect of hardware is to reduce production interdependence, reinforcing the direct effect of IT capital.

The indirect effect of an increase in software is in the second term on the right-hand side of (9). The parameter b_6 reflects the (negative of) change in the output elasticity of intermediate inputs, $\theta(\cdot)$, resulting from a change in software. If our conjecture that software reduces external costs of provision relatively more than internal production costs is correct, then an industry would need more intermediate inputs to produce a certain level of output – choosing to buy more inputs than it makes. Thus, we expect the estimate of b_6 to be positive. A positive b_6 indicates that an increase in software increase both the level of intermediate inputs and output, where the increase in intermediate inputs is greater than the increase in output. As a consequence, this indirect effect serves to raise production interdependence. However, if the direct effect of IT capital reduces interdependence, then the combined effect is ambiguous.

4. Empirical Estimation

4.1. Data and Variables

Our Dataset is based on the 3-digit 2007 North American Industry Classification Systems (NAICS) codes and covers 19 years from 1998 to 2016. As our goal is to examine U.S. manufacturing, we make use of data for the 18 3-digit NAICS manufacturing industries. Table 1 provides a list of manufacturing industries.

Table 1: The List of Manufacturing Industries

Manufacturing industries	BEA Codes	NAICS	Industry Title
Durable Manufacturing Industries	321	321	Wood Products
	327	327	Nonmetallic Mineral Products
	331	331	Primary Metal Products
	332	332	Fabricated Metal Products
	333	333	Machinery
	334	334	Computer and Electronic Products
	335	335	Electrical Equipment, Appliances, and Components
	336	336	Transportation Equipment
	337	337	Furniture and Related Products
	339	339	Miscellaneous Manufacturing
Non-Durable Manufacturing Industries	311FT	311312	Food and Beverage and Tobacco Products
	313TT	313314	Textile Mills and Textile Product Mills
	315AL	315316	Apparel and Leather and Applied Products
	322	322	Paper Products
	323	323	Printing and Related Support Activities
	324	324	Petroleum and Coal Products
	325	325	Chemical Products
	326	326	Plastics and Rubber Products

Output, Intermediate Inputs, and DBL: From the GDP by industry accounts available on the Bureau of Economic Analysis (BEA) website, we obtain the nominal values of gross output and total intermediate inputs, along with the corresponding deflators. Consistent with the BEA's methodology of converting nominal to real, we use chain-type quantity indices available at the 3-digit NAICS level as deflators to obtain the real values of gross output, Y, and total intermediate inputs, M_{tot}, by multiplying the 2009 current-dollar value of the series of gross output and intermediate inputs by the corresponding chain-type quantity indices, then dividing by 100, respectively.

In order to isolate the intermediate inputs an industry purchased from within its own industry, for each industry-year we employ the input-output use tables from the BEA to capture the intermediate inputs provided by the given industry to itself. To match the input-output tables with the multi-factor productivity data we describe next, we combine NAICS 3361MV and NAICS 3364OT in input-output tables as one industry named NAICS 336. From the input-output table, we obtain the nominal value of an industry's intermediate inputs purchased from within its own industry. We then apply the chain-type quantity indices for gross output of the given industry and follow the same procedure as above to obtain the real value of intermediate inputs from the given industry itself, M_{own}. The real value of intermediate inputs purchased from other supplying industries, M_{ext}, is the difference between M_{tot} and M_{own}. We take M_{ext} as our measure of intermediate inputs, M, and calculate DBL for each industry by dividing M_{ext} (or M) by Y.

IT Capital, Non-IT Capital, and Labor: We obtain our data on capital stock from the multi-factor productivity databases on the BLS website, which provides detailed capital measures, information capital measures, and intellectual property capital measures. Information capital stock is called information processing equipment by the BLS, and is made up of three broad classes: *computers and related equipment*, *communications equipment*, and *other information processing equipment*. As all components of this information capital stock are equipment, we use the total information capital stock as hardware in the context of manufacturing, HW.

Software was previously classified as a type of information capital for industries based on NAICS codes. Since 2013 it has been reclassified as a component of intellectual property capital measures (Smith and Holdren 2013), where intellectual property capital also includes research and development ($R\&D$), as well as entertainment, literary, and artistic originals. We extract the productive capital stock for software from intellectual property capital measures and use it as the measure of software, SW. The sum of hardware and software is total IT capital, Z.

Based on the data about capital stock and IT capital, we calculate non-IT capital, K. Total capital stock includes equipment, structures, intellectual property products, rental residential capital, inventories, and land. For the years prior to the reclassification of software, productive capital stock is calculated by aggregating equipment and structures. Non-IT capital is then computed as productive capital stock less IT capital, where the latter included hardware and software. For the years post-reclassification, where software is no longer included in equipment, we calculate non-IT capital, K, as equipment and structures less hardware (HW). Both IT capital and non-IT capital stock are in millions of 2009 dollars.

The BLS further details its hardware classes: the BLS class *computers and related equipment* includes mainframe computers, personal computers, printers, terminals, tape drives, storage devices, and integrated systems; the BLS class *communications equipment* is not further detailed; and the BLS class *other information processing equipment* includes medical equipment and related instruments, nonmedical instruments, photocopying and related equipment, and office and accounting machinery.

In manufacturing industries the first two classes, *computers and related equipment* and *communication equipment*, are IT that can be used for the purpose of general information processing. The class *other information processing equipment* is mostly used for the purpose of computer-aided manufacturing. Of the hardware for manufacturing industries, *computers and related equipment* together with *communication equipment* accounts for 39.4%, and *other information processing equipment* accounts for 60.6%. Of this latter class, 79.3% is "nonmedical instruments". To clarify the components of "nonmedical instruments", we refer to the 2002 Bridge Table to Private Fixed Investment in Equipment and Software (PES) (U.S. Bureau of Economic Analysis (BEA) 2007), which contains the input-output commodity composition at the detailed level for private fixed investment in equipment and software. It suggests that "nonmedical instruments" is primarily manufacturing industrial instruments and related products for measuring, displaying, transmitting, and controlling process variables in manufacturing.

To better separate information technology capital for manufacturing from the aggregate of hardware, we refine hardware into two measures. The first is the sum of the classes *computers and related equipment* and *communication equipment*, which we call $R1HW$, that is the 39.4% of hardware (HW) described above. The second is *other information processing equipment*, which we call $R2HW$, that is the 60.6% of hardware described above. Of this latter disaggregated measure of hardware capital, $R2HW$, 79.3% is "nonmedical instruments" related to manufacturing. It is worth noting that of our aggregated hardware measure defined in the prior paragraph (HW), approximately one half can be considered information technology for manufacturing (e.g., 60.6% * 79.3% = 48.1%). Table 2 provides detailed descriptions of hardware and software by asset type.

Table 2: Descriptions on Hardware and Software by Asset Type

Information Capital		**BLS Asset Code**	**Asset Type**
Hardware (HW)	Computers and Peripheral Equipment	32	Mainframe Computers
		33	Personal Computers (PCs)
		34	Direct Access Storage Devices
		35	Printers
		36	Terminals
		37	Tape Drives
		38	Storage Devices
		39	Integrated Systems
	Communication Equipment	16	Communication Equipment
	Other	26	Instruments: Photocopying and Related Equipment
		27	Medical Equipment and Related Equipment
		28	Electromedical Instruments
		29	Nonmedical Instruments
		14	Office and accounting equipment
Software (SW)		40	Pre-packaged
		41	Custom
		42	Own-account

Note: The descriptions are created based on the type of asset codes in the Appendix C of Rental Price Tables from the BLS and the overview of capital inputs for the BLS multifactor productivity measures.

Our measure of labor input, L, is measured as Full-Time Equivalent (FTE) employees in thousands and is obtained from the BEA National Income and Product Accounts. The number of FTE employees is the sum of the number of employees on full-time schedules and the number of part-time employees converted to a full-time basis according to their weekly hours (BEA).

Capacity Utilization and Industry Concentration: As we describe in the next subsection, we control for fluctuations in business cycles with capacity utilization and for industry competitiveness with industry concentration. Our data sources are described below.

The data on capacity utilization (CU) for our 18 manufacturing industries based on 3-digit NAICS over 1998-2016 is obtained from the Federal Reserve Economic Data (FRED), which is a database maintained by the Federal Reserve Bank of St. Louis. According to the explanatory notes from the Federal Reserve, for a given industry in a certain year, capacity utilization is measured as a seasonally adjusted output index divided by a capacity index.

For industry concentration we use $CR20$ which is the market share of the largest 20 firms in an industry. As the $CR20$ data were in 2002 and 2007 by the US Economic Census, we obtain the 2002

Table 3: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Gross Output (in millions of 2009 dollars)	280725.3	234677.5	17739	959887
Intermediate Inputs (in millions of 2009 dollars)	182649.2	163028.3	7728	691774
Non-IT Capital Stock (in millions of 2009 dollars)	162189	113298.7	19715	410717
Labor (Full-Time Equivalent Employees in Thousands)	756.822	490.090	109	2076
IT Capital Stock (in millions of 2009 dollars)	14249.61	22787.06	810	123745
Hardware (in millions of 2009 dollars)	8543.804	12729	459	63304
R1HW (in millions of 2009 dollars)	2895.795	4082.001	141	23628
R2HW (in millions of 2009 dollars)	5647.997	9071.013	223	39757
Software (in millions of 2009 dollars)	5705.81	11122.68	227	61650
Direct Backward Linkage	0.513	0.113	0.143	0.912
Capacity Utilization in Percentage	75.422	7.269	46.929	92.727
Average concentration ratio in Percentage	24.822	7.540	1.720	38.140

Notes: R1HW is the sum of computers and communication equipment, and R2HW is the other information processing equipment. The number of observations is 342.

$CR20$ and 2007 $CR20$ by industry. In order to incorporate the updates in $CR20$ across years, we use the 2002 $CR20$ for industries from 1998 to 2002, and the 2007 $CR20$ for the industries from 2003 to 2016. We calculate the average concentration ratio, ACR, based on the $CR20$ of all suppliers weighted by the transaction volumes between a given industry and its suppliers in the input-output tables, which present the transactions among 60 manufacturing and non-manufacturing industries. When calculating ACR, we set the diagonals in the input-output tables to zero to extract the transactions with other industries, and then calculate ACR as a weighted average of the $CR20$ of upstream industries,

$$ACR20_{it} = \sum_{j \neq i} \frac{V_{ji}}{\sum_{j \neq i} V_{ji}} CR20_{jt},$$

where V_{ji} is the dollar transaction volume of purchases of industry i from the supplier industry j. Our construction of ACR is consistent with those in Mun and Nadiri (2002) and Cheng and Nault (2007).

Our final Dataset is a balanced panel of 18 manufacturing industries across 19 years. The summary statistics for our Dataset are provided in Table 3.

4.2. Controls and Econometric Adjustments

Business cycle controls - capacity utilization: Capacity utilization, CU, is defined as the ratio of actual output to the maximum potential output (Nelson 1989). According to modern business cycle theory, the business cycle refers to fluctuations in economic activity, and capacity utilization is a measure of the business cycle (Günter and Lorenz 1989). In our model, the utilization of intermediate inputs and the number of labor hours might be affected by fluctuations in business cycles. For example, when the economy has low or negative growth, an industry may reduce its purchases of intermediate inputs from suppliers. Although year-fixed effects (described below) partially control for the impact of business cycle fluctuations, each industry may have differing responses to business cycle fluctuations. In order to control for the heterogeneous effects of business cycle fluctuations on industries' production we add CU to our estimation model.

Controls for competition in the supplying market: The competition among suppliers could affect the value of purchases of a given industry, which in turn affects DBL. For example, when the supplying market is concentrated, a small number of supplying industries provide a large proportion of the goods and services. Thus, the given industry may have less bargaining power in negotiation and would have to purchase more to produce a certain output (increased interdependence). Concentration ratio is the measure of the market competition in an industry, and $CR20$ is one of the most common tools. Taking all the suppliers of a given industry as the supplying market (excluding itself as a supplier), we use the ratio of the transaction volume between a given industry and a supplier to the total transaction volumes between the given industry and all upstream suppliers as weights, and then apply the weighted average of $CR20$ of suppliers (ACR) to measure the level of competition in the supplying market.

Econometric adjustments - fixed effects, autocorrelation, and heteroscedasticity: The years contained in our datasets cover many changes in political and economic activities, such as the e-commerce boom in the late 1990s, the e-commerce collapse, the 9/11 terrorist attacks in 2001, and the financial crisis in 2008. These changes took place alongside the variations in fiscal, monetary, and trade policies. To control for any economy-wide time-specific shocks that could affect all industries, we include year-fixed effects in our estimation model.

In addition, there might be unobserved heterogeneity related to different types of manufacturing production processes, and this unobserved heterogeneity may be correlated to an industry's DBL.

We use sector dummies to control for time-invariant sector-specific effects instead of industry dummies as we use industry-level capacity utilization to control for industry-level. Our Dataset includes both durable manufacturing and non-durable manufacturing industries, which differ in production processes and organization. Thus, we use durable and non-durable manufacturing sector dummies to control for the effect due to unobserved heterogeneity in our Dataset.

Because our Dataset is a cross-sectional time-series, we test for the presence of autocorrelation and heteroskedasticity (HE). First, we anticipate autocorrelation in error terms as the output of any industry is highly correlated with its output in the previous year under relatively smooth business cycles. Following the Wooldridge test for autocorrelation in panel data (Wooldridge 2002), we reject the null hypothesis of no first-order autocorrelation (AR1) at all reasonable levels of significance (F (1, 17) = 37.31 for our estimation model below). In addition, autocorrelation could differ in magnitude for different industries if the magnitude of response to changes in business cycles differs across industries, so the AR1 process could be panel-specific AR1 (PSAR1). We use the likelihood ratio test to check whether AR1 coefficients are common across the industries (Greene 2008). The null hypothesis—that the regression with the correction of AR1 is nested in the regression with the correction of PSAR1—is rejected at all levels of significance ($\chi^2(17) = 95.30$ for our estimation model below). Considering that we use industry-level capacity utilization to control for industry-specific effects as we note above, we adjust for AR1 in order to avoid over-controlling for industry-specific effects.

We also test for panel-level HE using the likelihood ratio test (Greene 2008). It is reasonable to anticipate panel-level HE because the variances of the error terms for each industry are likely to fluctuate over time and the variances of the error terms could also differ across industries, resulting in panel-level HE. The null hypothesis of no panel-level HE is rejected at all levels of significance for our estimation model below ($\chi^2(17) = 431.85$).

Consequently, we estimate our models by adjusting for AR1 and panel-level HE. For each regression, we use feasible generalized least squares (FGLS) to generate our estimates (Wooldridge 2002).

To better interpret the interaction term and reduce possible multicollinearity between the interaction effect and the main effects (Wooldridge 2009, Ozer-Balli and Sørenson 2010), we center hardware hw, software sw, and intermediate inputs m when constructing the interactions terms in (7), $hw \times m$ and $sw \times m$. More generally, multicollinearity is less of a concern in our estimations as we have a theoretically-driven model and multicollinearity only affects efficiency and not bias. We address endogeneity issues which may bias our estimators later.

Estimation model: After controlling for fixed effects, the effect of business cycle fluctuations, and competition in the supplying market, our estimation models are specified as in (10) with the additional econometric adjustments where subscripts i, t, and j indicate industry, year, and sector, respectively:

$$\begin{aligned} log(DBL_{it}) = b_0 + b_1 k_{it} + b_2 l_{it} + b_3 z_{it} + b_4 m_{it} + b_5[hw_{it} \times m_{it}] + b_6[sw_{it} \times m_{it}] \\ + uCU_{it} + rACR_{it} + \sum_{t=1}^{T-1} d_t year_t + \sum_{j=1}^{L-1} s_j sector_j + \epsilon_1. \end{aligned} \quad (10)$$

5. Results

5.1. The Relationship Between Aggregated IT Capital and DBL

Before estimating the interaction effects of disaggregated IT, hardware and software, with intermediate inputs as we formulated in (10), we estimate a model where aggregated IT capital has the same direct effect described in (7), and an indirect effect where the output elasticity of intermediate inputs is defined as $\theta(z_{it}) = \omega + \mu z_{it}$. This yields the slightly aggregated analogue of (7),

$$\begin{aligned} log(DBL_{it}) &= -\tilde{a} - \tilde{\alpha} k_{it} - \tilde{\beta} l_{it} - \tilde{\gamma} z_{it} + [1-\omega] m_{it} - \mu[z_{it} \times m_{it}] \\ &= \hat{b}_0 + \hat{b}_1 k_{it} + \hat{b}_2 l_{it} + \hat{b}_3 z_{it} + \hat{b}_4 m_{it} + \hat{b}_5[z_{it} \times m_{it}], \end{aligned} \quad (11)$$

that we estimate with the same controls as (10).

To begin, the direct effect of IT on DBL is assessed by $\hat{b}_3$, which is the (negative) analogue of $\tilde{\gamma}$ in (11), and it is negative and significant at the 1% level (Column 1 of Table 4). Recalling from (6) that $log(DBL_{it}) = m_t - y_t$, with a negative $\hat{b}_3$ an increase in IT capital results in an increase in output greater than the change in intermediate inputs – *a priori* it is not possible to determine

Table 4: The Main Estimation Results

Variable (Parameter)	DV Log (DBL) (Col 1)	DV Log (DBL) (Col 2)
Non-IT Capital (b_1)	-0.347*** (0.0251)	-0.349*** (0.0247)
Labor (b_2)	-0.118*** (0.0174)	-0.132*** (0.0178)
IT Capital (b_3)	-0.087*** (0.0142)	-0.087*** (0.0139)
Intermediate Inputs (b_4)	0.470*** (0.0187)	0.476*** (0.0184)
IT Capital × Intermediate Inputs ($\hat{b}_5$)	-0.007 (0.0086)	
HW × Intermediate Inputs (b_5)		-0.073*** (0.0212)
SW × Intermediate Inputs (b_6)		0.054*** (0.0170)
ACR (r)	0.004* (0.0012)	0.004*** (0.0011)
Capacity Utilization (u)	-0.005*** (0.0006)	-0.005*** (0.0005)
Constant	-0.155 (0.161)	-0.124 (0.158)
Observations	342	342

Notes: All variables listed in the column named as "Variable (Parameter)" are in natural logs, excluding "Capacity Utilization" and "ACR". We control for panel-level heteroskedasticity (HE) and first-order autocorrelation (AR1) for the Dataset. Details of the year-fixed effects and sector-fixed effects are suppressed for brevity. Standard errors are in parentheses following the estimated coefficients. *p<0.10, **p<0.05, ***p<0.01.

if intermediate inputs would increase or decrease. This direct effect of IT suggests an increase in IT capital favors make versus buy, decreasing production interdependence.

In contrast, the estimate of $\hat{b}_5$, which is the (negative) analogue of μ in (11), is not significant with an estimate of -0.007 (Column 1 of Table 4). Consequently, $\theta(z_{it}) = \omega + \mu z_{it} = \omega$, the output elasticity of intermediate inputs is unaffected by changes in IT capital, and there is no indirect effect. Empirically this suggests that although different components of IT are integrated together in production, they may affect DBL through intermediate inputs differently. Thus, our theoretical model approach of separately analyzing the impact of hardware and software by implying they may have different effects on DBL through intermediate inputs is reasonable.

5.2. The Relationship Between Disaggregated IT Capital (Hardware and Software) and DBL

We estimate the equation we formulate in (10) to empirically determine the interaction effects of disaggregated IT, hardware and software, with intermediate inputs. The total effect of hardware and software on DBL is shown by our estimates of the direct effect in b_3 and the indirect effect through intermediate inputs in b_5 and b_6, respectively.

The direct effect of increases in hardware or software (that increases IT capital) on DBL is negative through the estimate of b_3, which is significant at the 1% level (Column 2 of Table 4). The estimate b_3 is the (negative) analogue of $\tilde{\gamma}$ in (7), so that $\tilde{\gamma}$ is positive. Consequently, by this measure (DBL) of interdependence, the direct effect of an increase in hardware or software increases IT capital, which in turn favors make versus buy and reduces interdependence as was the case with aggregated IT capital.

The impact of hardware through intermediate inputs on DBL: The indirect effect of increases in hardware through intermediate inputs on DBL is shown by our estimate of b_5, which is negative and significant at the 1% level (Column 2 of Table 4). As (10) is transformed from (5), the coefficient of the interaction between hardware and intermediate inputs ($hw \times m$) in (5), ν, is positive. As discussed in the theoretical model, a negative b_5 indicates that an increase in hardware increases intermediate inputs and output, but the increase in output is greater than the increase in intermediate inputs, resulting in a decrease in DBL (see (6)). Consequently, the indirect effect of an increase in hardware through intermediate inputs reinforces the direct effect through IT capital: both favor make versus buy and reduce interdependence.

The impact of software through intermediate inputs on DBL: The indirect effect of increases in software through intermediate inputs on DBL is shown by our estimate of b_6, which is positive and significant at the 1% level (Column 2 of Table 4). As (10) is transformed from (5), the coefficient of the interaction between software and intermediate inputs ($sw \times m$) in (5), η, is negative. As discussed in the theoretical model, a positive b_6 indicates that an increase in software increases intermediate inputs and output, but the increase in intermediate inputs is greater than the increase in output, resulting in an increase in DBL (see (6)). Consequently, the indirect effect of an increase in software through intermediate inputs is opposite to the direct effect through IT capital: the former favors buy and increases interdependence, and the latter favors make and reduces interdependence.

In order to determine whether the indirect effect of software through intermediate inputs on DBL outweighs the direct effect of software on IT capital carrying through to DBL via b_3, we calculate the total effect of software on DBL. Using the average intermediate inputs from our cross-sectional time series dataset in Table 3 and our estimates in Table 4, recognizing that from (9) the term $\partial z_{it}/\partial sw_{it} = 1$, the total effect of an increase in software on DBL from (9) is

$$b_3 + b_6 logM = -0.087 + 0.054 * log(182649.2) = 0.567.$$

Regardless of which industry average for intermediate inputs we take (from Table 3 the minimum is \$7728 million in 2009 dollars) the estimates from Table 4 yield a positive total effect. This suggests that the indirect effect outweighs the direct effect, and on average an increase in software favors buy versus make and increases interdependence. Unfortunately, we do not have sufficient data to estimate (10) by industry, recognizing that industry-specific estimates of b_3, b_5, and b_6 may differ.

5.3. Robustness Tests

Estimation with disaggregated hardware: As we indicate in our description of our data, we define hardware broadly in the context of manufacturing to include computers and communication equipment for general information processing and other information processing equipment. Given that these two categories of hardware may be used for different purposes in manufacturing – one for more general computing applications and the other more specific to the manufacturing process – we consider our redefined hardware measures in the estimation. The first is the sum of computers and communication equipment, $R1HW$; the second is the other information processing equipment, $R2HW$. We estimate a model where aggregated IT capital has the same direct effect described in (7) and an indirect effect where the output elasticity of intermediate inputs depends on each of our disaggregated hardware measures and our measure of software, noting the lower case for the log form of the disaggregated hardware measures:

$$\theta(z_{it}) = \omega + \nu_1 r1hw + \nu_2 r2hw + \eta sw_{it}.$$

This yields a further disaggregated analogue of (7),

$$\begin{aligned} log(DBL_{it}) &= -\tilde{a} - \tilde{\alpha}k_{it} - \tilde{\beta}l_{it} - \tilde{\gamma}z_{it} + [1-\omega]m_{it} \\ &\quad -\nu_1[r1hw_{it} \times m_{it}] - \nu_2[r2hw_{it} \times m_{it}] - \eta[sw_{it} \times m_{it}] \\ &= \check{b}_0 + \check{b}_1 k_{it} + \check{b}_2 l_{it} + \check{b}_3 z_{it} + \check{b}_4 m_{it} \\ &\quad + \check{b}_{51}[r1hw_{it} \times m_{it}] + \check{b}_{52}[r2hw_{it} \times m_{it}] + \check{b}_6[sw_{it} \times m_{it}], \end{aligned} \tag{12}$$

that we estimate with the same controls as (10).

The estimation result is shown in Column 1 of Table 5. Both estimates $\check{b}_{51}$ and $\check{b}_{52}$, that correspond to (the negative of) ν_1 and ν_2, respectively, are negative and significant at the 1% level. The sum of the estimates is close to that of aggregated hardware in Table 4. In addition, the estimate of $\check{b}_6$ corresponding to (the negative of) η is close to that in Table 4, as is the estimate of $\check{b}_3$.

These results suggest that the impact of hardware and software on DBL through intermediate inputs are robust to different definitions of hardware. More importantly, each refinement of hardware reduces DBL. Consequently, both hardware used for more general computing applications and hardware that is more specific to the manufacturing process reduce interdependence. We speculate that hardware for general computing applications is integrated closely with hardware that is more specific to actual manufacturing such as industrial process variable equipment - for example, CNC machines - and that together this favors reducing internal production costs (make) thereby reducing interdependence. In other words, the subset of hardware containing manufacturing technology has the same effect as more general IT hardware, and that is to favor make versus buy and reduce production interdependence.

Estimation with total intermediate inputs: An industry may purchase intermediate inputs within its own industry and from other supplying industries. Given that within-industry purchases

Table 5: Robustness Testing Results with Different Estimations

DV: Log (DBL)	Disaggregated Hardware Estimation (Col 1)	Total Intermediate Inputs Estimation (Col 2)	GMM Estimation (Col 3)	HW and SW in Main Effects Estimation (Col 4)
Non-IT Capital (b_1)	-0.346*** (0.0247)	-0.231*** (0.0276)	-0.221*** (0.0144)	-0.342*** (0.0250)
Labor (b_2)	-0.120*** (0.0187)	-0.134*** (0.0201)	-0.132*** (0.0132)	-0.135*** (0.0175)
IT Capital (b_3)	-0.092*** (0.0144)	-0.098*** (0.0137)	-0.126*** (0.0157)	
HW (b_{31})				-0.103*** (0.0194)
SW (b_{32})				0.0090 (0.0156)
Intermediate Inputs (b_4)	0.474*** (0.0186)	0.418*** (0.0202)	0.373*** (0.0222)	0.469*** (0.0182)
HW × Intermediate Inputs (b_5)		-0.046*** (0.0155)	-0.196*** (0.0261)	-0.078*** (0.0203)
R1HW × Intermediate Inputs (b_{51})	-0.034** (0.0161)			
R2HW × Intermediate Inputs (b_{52})	-0.029** (0.0130)			
SW × Intermediate Inputs (b_6)	0.045*** (0.0172)	0.032** (0.0132)	0.150*** (0.0242)	0.055*** (0.0165)
ACR (r)	0.004*** (0.0011)	0.002** (0.0011)	0.006*** (0.0014)	0.004*** (0.0011)
Capacity Utilization (u)	-0.005*** (0.0006)	-0.004*** (0.0005)	-0.003** (0.0012)	-0.005*** (0.0005)
Constant	-0.171 (0.163)	-0.603*** (0.160)	-0.353** (0.167)	-0.0667 (0.162)
Observations	342	342	306	342

Notes: All variables are in natural logs, excluding "Capacity Utilization" and "ACR". R1HW is the sum of computers and communication equipment, and R2HW is the other information processing equipment. Details of the year-fixed effects and sector-fixed effects for both Datasets are suppressed for brevity. Standard errors are in parentheses following the estimated coefficients. *p<0.10, **p<0.05, ***p<0.01.

account for a small proportion of total intermediate inputs purchases in our data, 19.7% on average, our estimation uses between-industry purchases to focus on the production interdependence relationship across industries. However, it is possible that the exclusion of within-industry purchases could affect the estimation results as within-industry transactions may be a large proportion of total intermediate inputs purchases for certain manufacturing industries. In order to address this concern, we estimate our main model in (10) by using the total intermediate inputs including those within-industry. The results in Column 2 of Table 5 show that all our results are consistent with our main estimation results in Column 2 of Table 4. Consequently, our estimation results are robust when incorporating within-industry intermediate inputs.

Estimation with instrumental variables: There is the possibility of endogeneity problems in our estimation. In general, endogeneity can arise as a result of omitted variables, measurement errors, and simultaneity (Wooldridge 2002). It is possible that some omitted variables, such as other productivity-related organizational initiatives, may be correlated with the independent variables in our models. In addition, there is potential for measurement errors in variables relating to inputs and output due to aggregation, sampling, etc., such that DBL is likely subjected to measurement errors as well. There might also be concerns about endogeneity caused by simultaneity. Simultaneity arises when explanatory variables in our models are determined simultaneously with the dependent variables. For example, an increase in software increases DBL, so a given industry becomes more dependent on upstream suppliers, and thus it requires the given industry to invest more in IOS, SCM, and CPFR, to improve information sharing and coordination between them.

Our econometric adjustments for fixed effects, as well as controlling for capacity utilization and competition in the supplying market help relieve the above endogeneity concerns. We further address such concerns by providing estimates using instrumental variables (IVs). Firstly, we use lags of the variables as instrumental variables, similar to previous related studies (Stiroh 2002a, Han et al. 2011b, Cheng and Nault 2012, Han and Mithas 2013). Specifically, for the estimation of (10), we suspect that the main variables of interest, IT capital, intermediate inputs, and the interaction term "$HW \times IntermediateInputs$" and "$SW \times IntermediateInputs$", that is, $hw_{it} \times m_{it}$ and $sw_{it} \times m_{it}$, respectively in (10), might be endogenous, so we use one-year and two-year lags of those variables as excluded instrumental variables.

Secondly, we employ a two-step generalized method of moments (GMM) procedure and conduct the Hansen/Sargan C-test for the estimated model. The Hansen/Sargan C test (also known as the "GMM distance" test) allows to test the exogeneity of a subset of regressors or instrument when implemented using Stata's ivreg2 orthog option (Baum et al. 2003, 2007). The Hansen/Sargan C statistic fails to reject its null that the suspected main variables of interest in (10) may be treated as exogenous ($\chi^2(4) = 3.540, p = 0.472$). The two-step GMM procedure generates efficient estimates of the coefficients and consistent estimates of the standard errors in the presence of arbitrary heteroskedasticity. The estimates are presented in Column 3 of Table 5. All results are consistent with our main findings and consistent when we use system GMM (detailed results are available from the authors). The consistent GMM estimation results mitigate the possible omitted variable issue due to our assumption of the constant relationship between IT capital subcomponents and the coefficients of non-IT capital and labor.

Estimation with main effects of hardware and software: Traditionally, hardware and software are integrated in production, and thus the IS discipline usually uses total information capital for the IT capital input when estimating a production function to examine the direct effect of IT on productivity (e.g., Cheng and Nault 2007, 2012, Han et al. 2011b, Gong et al. 2016). Following this tradition, we consider the direct effect of IT capital in production, and we also develop the interaction effects of hardware and software with intermediate inputs through a varying-coefficient model instead of simply adding the interaction terms about "$HW \times IntermediateInputs$" and "$SW \times IntermediateInputs$" in the estimation model. Someone may argue that hardware and software should be included separately as main effect terms in order to interpret the interaction terms. To address this concern, we examine the main effect of HW and SW separately in the following specification, which is another analogue of (7). We estimate it with the same controls as (10).

$$log(DBL) = b_0 + b_1 k + b_2 l + b_{31} hw + b_{32} sw + b_4 m + b_5 [hw \times m] + b_6 [sw \times m]. \tag{13}$$

The results in Column 4 of Table 5 shows that the main effect of HW is significant, while the main effect of SW is not significant. The other estimates are consistent with our main estimation results in Column 2 of Table 4. When estimating the main effect of HW and SW separately, their estimated coefficients might be affected by their high correlation, 0.93. Generally high collinearity can cause the inflation of the variance of regression coefficients, resulting in less precise estimates or insignificant estimates (O'brien 2007). Thus, the insignificant main effect of SW might be due to the high correlation between HW and SW (in their log forms). It also suggests that it is reasonable to aggregate hardware and software when estimating the direct effect of IT capital on DBL in order to avoid insignificant estimates due to the high correlation between subcomponents.

Estimation with IT-intensity and IT-producing: IT intensity is an important industry characteristic and has drawn a lot of attention in IS literature (e.g., Stiroh 2002b, Mittal and Nault 2009, Han et al. 2011a,b). Previous studies have shown that IT-intensive industries may achieve higher productivity gains than other industries (Stiroh 2002b, Han et al. 2011a), and the value creation from IT may depentd on whether this industry is IT-intensive or not (Mittal and Nault 2009, Han et al. 2011b). The impact of IT hardware and software on production interdependence may differ between IT-intensive and non-IT-intensive industries. We examine this using two approaches: splitting our sample into IT-intensive and non-IT-intensive sectors, and adding an IT-intensive dummy in the estimation. We measure IT intensity as the ratio of IT capital to total capital (Stiroh 2002b) and classify an industry as IT-intensive when its IT intensity is above the median industry IT intensity. As shown in Columns 1 through 3 of Table 6, our main results are robust to differences in IT-intensity. Indeed, the impact of hardware and software on production interdependence is larger in IT-intensive industries, suggesting IT plays a relatively more important role in the make versus buying decisions in IT-intensive industries.

Previous studies also suggest that productivity growth might be mainly due to IT-producing industries. For instance, Acemoglu et al. (2014) found that IT-producing sector may drive the productivity growth in manufacturing industries. Chou and Shao (2014) found that IT service industries in 25 OECD countries experience a larger productivity growth than other service industries. To test if the IT-producing industry is responsible for our results, we drop the IT-producing industry named "Computer and Electronic Products" (NAICS 334). As shown in Column 4 of Table 6, the results suggest that the different impacts of hardware and software on DBL are consistent with or without considering IT-producing industries.

Table 6: Robustness Testing Results with IT-Intensity and IT-Producing

DV: Log (DBL)	Sample Splitting Estimation: Non-IT-Intensive Industries (Col 1)	Sample Splitting Estimation: IT-Intensive Industries (Col 2)	IT-Intensive Dummy Estimation (Col 3)	Dropping IT-Producing Industry Estimation (Col 4)
Non-IT Capital (b_1)	-0.352***	-0.401***	-0.391***	-0.329***
	(0.0415)	(0.0504)	(0.0306)	(0.0214)
Labor (b_2)	-0.084***	-0.310***	-0.136***	-0.115***
	(0.0142)	(0.0530)	(0.0177)	(0.0158)
IT Capital (b_3)	-0.054	-0.061**	-0.046**	-0.096***
	(0.0336)	(0.0271)	(0.0212)	(0.0131)
Intermediate Inputs (b_4)	0.383***	0.701***	0.483***	0.436***
	(0.0182)	(0.0426)	(0.0185)	(0.0166)
HW × Intermediate Inputs (b_5)	-0.061**	-0.153***	-0.070***	-0.080***
	(0.0282)	(0.0341)	(0.0207)	(0.0196)
SW × Intermediate Inputs (b_6)	0.023	0.068**	0.053***	0.042***
	(0.0232)	(0.0342)	(0.0169)	(0.0156)
ACR (r)	0.001	0.010***	0.005***	0.003***
	(0.0012)	(0.0022)	(0.0012)	(0.0010)
Capacity Utilization (u)	-0.004***	-0.008***	-0.005***	-0.005***
	(0.0007)	(0.0009)	(0.0006)	(0.0005)
IT-Intensive Dummy			-0.089***	
			(0.0288)	
Constant	0.395*	-1.084***	-0.012	0.054
	(0.229)	(0.257)	(0.170)	(0.139)
Observations	171	171	342	323

Notes: All variables listed in the column named as "Variable (Parameter)" are in natural logs, excluding "Capacity Utilization" and "ACR". We control for panel-level heteroskedasticity (HE) and first-order autocorrelation (AR1) for the Dataset. Details of the year-fixed effects and sector-fixed effects are suppressed for brevity. FTE is Full-Time Equivalent employees in thousands. Standard errors are in parentheses following the estimated coefficients. The industries having an above-median IT-intensity are in the IT-intensive industries, and others are in the non-IT-intensive industries.*p<0.10, **p<0.05, ***p<0.01.

6. Conclusion

We examine the different effects of hardware and software on production interdependence resulting from make versus buy decisions, interdependence that we measure as DBL. We find that the direct effect of an industry's IT capital as an aggregate corresponds with lower production interdependence with suppliers, favoring making versus buying of inputs. When separating IT into hardware and software capital we find that the indirect effect of hardware through its interaction with intermediate inputs also corresponds with lower interdependence. This indirect effect persists if hardware is further disaggregated into more general hardware and manufacturing technology.

In contrast, the indirect effect of software corresponds with higher interdependence favoring buy versus make, and the indirect effect of software capital outweighs its direct effect. Therefore, we find that hardware capital reduces production interdependence and software capital increases production interdependence; that is, hardware favors making and software favors buying. Our finding of the opposite effects of hardware and software is surprising, especially in view of the complementary nature of hardware and software. This may be due to our focus on manufacturing sectors in the economy. In our BLS-based measure of hardware, two thirds are computer-aided industrial process instruments and related machineries, with the rest being general computers and communication equipment. Some of this hardware has embedded system software as firmware. The BLS measures software as capitalized software purchased or developed separately from hardware. Therefore, our measures of hardware and software are relatively independent. Bloom et al. (2014) also separate IT into two categories and find distinct effects of IT such as ERP for plant managers and computer-aided design/manufacturing for production workers and communication technology such as company intranets on worker and plant manager autonomy and span of control.

Our study makes three related contributions. First, we empirically examine the differential effects of IT hardware and software on production interdependence in manufacturing. Indeed, few articles separately analyze hardware and software. Notable exceptions are Gurbaxani and Mendelson (1987) and Gurbaxani and Mendelson (1992) that focus on hardware and software shares in the information system budgets, showing that hardware and software are net complements using data that substantially predates ours. As the components of IT, both hardware and software can reduce internal production costs and external coordination costs in production. Our results suggest that hardware increases automation in utilizing intermediate inputs from suppliers, which reduces costs of internal provision more than external provision, and this leads to decreased interdependence on upstream suppliers for intermediate inputs. Software increases information sharing and coordination within and between industries, which reduces costs of external provision more than internal provision, leading to increased interdependence. As a consequence of hardware being composed of mostly manufacturing technology there are important supply chain implications of different IT investments.

Second, our results contribute to the literature on the impact of IT on transaction costs. There is a large body of research that examines how IT affects various measures of organizational structure such as firm size, firm boundaries, vertical integration, and diversification (Gurbaxani and Whang 1991, Brynjolfsson et al. 1994, Hitt 1999). This research stream has taken IT capital as an aggregate. Our results show that disaggregated hardware and software have differential effects on internal production cost and external transaction cost, and thus on organization structure: aggregate IT capital reduces transaction costs, but hardware and software have different relative effects with hardware favoring reductions in internal transaction costs and software favoring reductions in external transaction costs. Our findings defy the wide-accepted notion that IT increases interdependence, suggesting that interdependence needs to be clearly defined and IT components should not be treated uniformly.

Third, we contribute to the literature on production interdependence. Previous studies have focused on the international and inter-temporal comparison of production structure at the country-level (Santhanam and Patil 1972, Song 1977). In contrast, we study the cross-sectional differences of production structure across industries/sectors. As shown in Table 3, DBL (our chosen measure of production structure) ranges from .157 to .993. The wide variation deserves attention and it remains largely unclear what contributes to the variation. Our study is an initial attempt to examine how IT affects production interdependence.

Managerial implications: One implication for the choice between make versus buy is that industries' IT can help both increase and decrease interdependence with upstream suppliers. Investment in IT within an industry is usually viewed as facilitating information sharing and coordination within and between industries, allowing integration of business processes among its supply chain partners, and enabling its synchronization with upstream suppliers in terms of product design, production scheduling, and inventory replenishment – all of which supports buying a greater proportion of intermediate inputs to output, which leads to greater interdependence. The surprising result in our study is that an industry's IT capital not only increases the integration between itself and its suppliers in terms of business processes, but by investing in hardware also reduces its production interdependence with upstream suppliers by substituting for goods and services purchased from suppliers and enhancing the efficiency of their use, supporting buying a lesser proportion of intermediate inputs to output and thus a greater value added.

As a consequence, manufacturers can strategically direct their investment in hardware or software in production. Thus, firms could preferentially direct their IT capital towards hardware, improving their operations through more efficient use of intermediate inputs to reduce their production interdependence with suppliers, effectively increasing their value added and their bargaining power. The latter could then be used to overcome hold-up problems in negotiations with upstream suppliers regarding joint investments in software that improves information sharing and coordination, such as SCM systems, CPFR, and big data and analytics – types of IT that have the potential of reducing costs across the supply chain. Alternatively, firms could potentially direct their IT capital towards software, enabling a form of virtual integration with suppliers, and mitigating problems due to double marginalization.

Limitations: A potential limitation is that our industry-level data does not allow a direct estimate of the impact of IT on firm-specific business processes and efficiency. Ideally, as firms are the locus of capital investment and production decisions, a firm-level analysis of the impacts of IT capital on production would be more closely matched to these decisions. However, because most firms of a sufficient scale are multi-product and possibly multi-divisional, firm-level data would be an aggregate of investment and production decisions. Moreover, as Aigner and Chu (1968) argues, industry-level estimates are generally applicable to firms, which is the case with industry best practices. Firm-level data that details which industries and which firms within those industries are a given firm's suppliers, and how much is purchased from those industries and firms, is rarely available.

However, a corresponding benefit of industry-level data is that our industry-level analysis allows us to investigate the impact of IT capital on DBL across the universe of manufacturing industries in our economy, which increases the generalizability of our results.

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