The Strategic Value of IT in Setting Productive Capacity

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Capacity is the maximum short run output with capital in place under normal operations, and capital investment increases capacity. Excess capacity can be used as an economic strategy for entry deterrence by lowering average costs over a greater range of output, and as an operations strategy providing value through flexibility to manage demand fluctuations and production disturbances. Our primary focus is to study the way that information technology (IT) can contribute to a strategy of holding excess capacity by comparing the relationship between IT capital and capacity with that of non-IT capital and capacity. Using production theory-based empirical analyses, we find that increases in IT capital yield almost four-fold greater expansion in capacity than do increases in non-IT capital. Thus, as both types of capital are constraints on capacity, for a strategy of holding excess capacity IT capital is a more valuable constraint to relax than non-IT capital. In addition, since the late 1990s, IT capital, and to a lesser extent non-IT capital, have reduced capacity utilization (output/capacity), meaning increasing levels of excess capacity are being held across manufacturing industries and utilities across the economy.

Keywords: capacity, capacity utilization, information technology, production function

History: Revision date: March 4, 2019; This paper was first submitted on October 2, 2015 and has been with the authors for 15 months for 3 revisions.

1. Introduction

The capacity of industries to produce goods and services, and the utilization of that capacity, is a critical determinant of our collective quality of life. Firms invest in different types of capital to enable levels of productive capacity (hereafter, capacity) that allow production of goods and services at minimum efficient scale where average costs are minimized, and for the most part these low costs are ultimately passed along to consumers. At the same time, the levels of capacity utilization (CU), both for industries and in aggregate for the economy, reflect demand pressure where high demand pressure usually results in inflation pressure. As capacity is determined by the amounts of different types of capital in place, capital investments take a central role.

We examine a previously overlooked strategic use of information technology (IT): how IT can be used as part of a strategy to hold excess capacity. We adopt the definition of capacity from the Federal Reserve Board (FRB) which defines capacity as the *"sustainable maximum output - the greatest level of output a plant can maintain within the framework of a realistic work schedule, after factoring in normal downtime and assuming sufficient availability of inputs to operate the capital in place"* (Corrado, Gilbert, and Raddock 1997). CU is then the ratio of actual output to a sustainable maximum output, or capacity. Capacity is inherently a short-run concept, constrained by capital in place and achieved by adding variable inputs to the limit of what the capital in place can accommodate.

There are a few things worth noting in this definition of capacity. First, these are maximum output levels that can be maintained over time. Next, capacity is not profit-maximizing output – output that should depend on prices. This definition is not necessarily profit-maximizing capacity, although it could be if capital investments are made inter-temporally with this objective. This definition also determines what is fixed and what is variable in the short-run, where short-run is understood to be one year. Capital, both IT and non-IT, is fixed in the short-run – in practice this means the capital in place and the annual capital plan that all firms have. Labor and intermediate inputs (e.g., materials, energy, purchased services) are variable.

For capacity to increase, the cost structure of production must change as a result of an increase in capital. As capital costs such as interest and depreciation do not change with output, they are fixed costs. Consequently, minimum average costs are reached at a higher level of output, and diminishing returns ultimately cause the short-run average costs curve to increase with increasing output until it reaches capacity. An increase in capacity means a change in flexibility to increase output. Sufficient capacity enables firms to avoid installation of new capital such as technology or machinery, and the calibration of newly-installed production processes, both that require lead-time. Thus, higher levels of capacity allow output to be expanded more before needing new capital.

Our underlying message is that IT can be used strategically as part of a greater strategy of holding excess capacity. For example, CiscoSystems, Inc. invested in Enterprise IT and internet applications around 1994 to streamline processes, enhance capacity, and maximize employee productivity. These IT investments consequently empowered Cisco with enhanced capability to seize new market opportunities, deter entries and thus strengthen its leadership position in the telecommunications equipment market. Dell Inc. also invested heavily in IT to revamp its supply chain management and electronic commerce to implement the direct-sales model and mass customization. Part of the goal with such investments in IT is to substantially improve efficiency, production flexibility, and capacity which could serve as entry barriers and protect market shares. As a result, between 1994 and 1998, Dell grew twice as fast as its major rivals in the personal computer market and tripled its market share. More recently, the popularity of smart manufacturing empowered by advanced IT has the potential to greatly improve capacity and thus firms' responsiveness to fluctuating marketing demand.

From the above industrial examples, we see that the strategy of investing in IT to hold excess capacity plays out in two ways. The first is excess capacity as entry deterrence, a strategy that has been studied in economics for over 30 years (e.g., Kamien and Schwartz 1972, Spence 1977, Dixit 1980, Spulber 1981, Bulow et al. 1985). Capital investments such as IT are irreversible preemptive commitments that can last for years. Incumbent firms with excess capacity can increase output in the short-run, increasing supply and consequently reducing price, either deterring new entry or causing a new entrant with lesser capacity to exit. Indeed, in the entry game the excess capacity may remain idle, acting simply as a deterrent. A side benefit of excess capacity is greater entry upstream and downstream: excess capacity signals commitment to a more stable, reliable, and profitable supply chain (von Ungern-Sternberg 1988).

Excess capacity can also be used as an operations strategy providing value through flexibility. Responding to demand fluctuations and production disturbances requires cost-efficient output flexibility from excess capacity (Sheshinski and Dreze 1976, Gabszewicz and Poddar 1997). Capital investments in technology are often viewed as a hedge against demand fluctuations, allowing output to vary over time (Yang et al. 2011, Yang et al. 2014). Excess capacity allows flexible output expansion at lower average costs, and with shorter lead-times: lead-time to increase capacity (capital) creates shortage risk (Ryan 2004). Facing demand fluctuations, excess capacity provides buffers for scheduling and inventory in interconnected production systems like just-in-time. Indeed, a focus in operations has been on capacity expansion or optimal capacity in the presence of high demand uncertainty (see Luss (1982), for a survey of capacity expansion models and Zhang, Roundy, Cakanyildirim, and Huh (2004) on capacity planning).

As an important economic indicator, CU is a more common context in which government, firms and researchers take notice of capacity. It is a key determinant of corporate profitability and an indicator of macroeconomic performance (Paraskevopoulos and Pitelis 1995). CU has been employed in empirical studies to explain inflation, unemployment, investment, productivity measurement, and inventory, and as we indicated earlier, is often used as an indicator of aggregate demand pressure (Schultze 1963, Greenwood, Hercowitz and Huffman 1988, Shapiro, Gordon and Summers 1989, Gordon 1989, 1998, Dexter, Levi and Nault 2005, etc.).

Where does IT come in? A wide variety of IT capital affects capacity. Milgrom and Roberts (1990) suggest that IT drives modern manufacturing that emphasizes quality and a speedy response to market conditions. Indeed, manufacturing technologies such as numerically controlled machines (CNC), flexible manufacturing systems, computer-integrated manufacturing, robotics, programmable controllers, and modular assemblies, as well as automated adaptive scheduling all make it easier to adjust the level and composition of output. Inter-organizational information systems, Enterprise Resource Planning, E-commerce platforms, and supply chain management systems all help to reduce cost and improve efficiencies independent of output scale. With the maturity of

Internet standards these systems further reduce transaction costs and enable better coordination and business processes (Gong, Nault and Rahman, 2016).

Research on IT productivity suggests that IT capital is a general-purpose technology, which differs from most non-IT capital. Some argue that IT enables complementary organizational investments such as business processes and work practices leading to cost reductions and quality improvements (Brynjolfsson and Hitt 2000). For example, IT capital is an enabler of more advanced manufacturing strategies, and to some degree, it is the strategies enabled by IT that results in increased productivity and capacity. Higher levels of IT are associated with increased delegation of powers to smaller units and greater levels of workforce skills and education (Bresnahan, Brynjolfsson and Hitt 2002). IT has also substituted for routine labor tasks and complemented non-routine cognitive tasks (Autor, Levy and Murnane 2003). Apart from the direct business value IT generates, IT augments non-IT capital and labor (Mittal and Nault 2009), and IT capital from adjacent industries has significant spillover effects as IT investment made upstream (downstream) significantly impacts productivity downstream (upstream) (Cheng and Nault 2007, 2012).

Although additional IT capital increases capacity, IT can have conflicting effects on CU. In some cases, IT capital may lead to more efficient production and increased CU. For example, CNC provides opportunities to increase CU by making manufacturing more flexible such that machines can be used for a variety of operations (Koltai and Stecke, 2008). Barua, Kriebel and Mukhopadhyay (1995) find that IT improved intermediate process-level measures such as CU and inventory turnover. Through case studies in elevators, retailing, telecommunications and investment banking, Nightingale et al. (2003) show that IT-based control systems that are commonly used to coordinate the flow of goods, traffic, materials, funds, services or information can effectively improve the allocation of system traffic, thus increasing CU. Hubbard (2003) finds that on-board computers reduce idle time and improve efficiency in trucking, also increasing CU. These studies examine a particular IT application or group of applications, and concentrate on increased utilization of existing capacity without necessarily incorporating the effects of IT on expanding capacity.

In contrast to all of the studies cited above that mostly focused on pre-2000 examples, and in contrast to the pre-2000 results on CU that we find based on productivity theory, Bansak, Morin and Starr (2007) find that increased use of technology reduces CU, albeit by a small amount. Their analysis is based on a subset of manufacturing industries and relies on a simple estimation model by amassing an ad hoc collection of variables on the right-hand-side (other than IT) that the authors thought might influence or control for the relationship between IT and CU.

Our Focus: We study the way that IT can contribute to a strategy of holding excess capacity by comparing the relationship between IT capital and capacity with that of non-IT capital and capacity. With actual output commonly understood and capacity defined as above, we can illustrate our analyses using the graphs in Figures 1a and 1b, and Figure 2a and 2b.

We concentrate on the impact of quasi-fixed (i.e., unchangeable in the short-run) input constraints on capacity that come from IT capital and non-IT capital. Moreover, we focus exclusively on the production side of the story. That is, we do not study how firms manage their capacity or CU rate to match market demand. Rather, we examine the impact of IT capital relative to non-IT capital on capacity and CU from a production theory perspective.

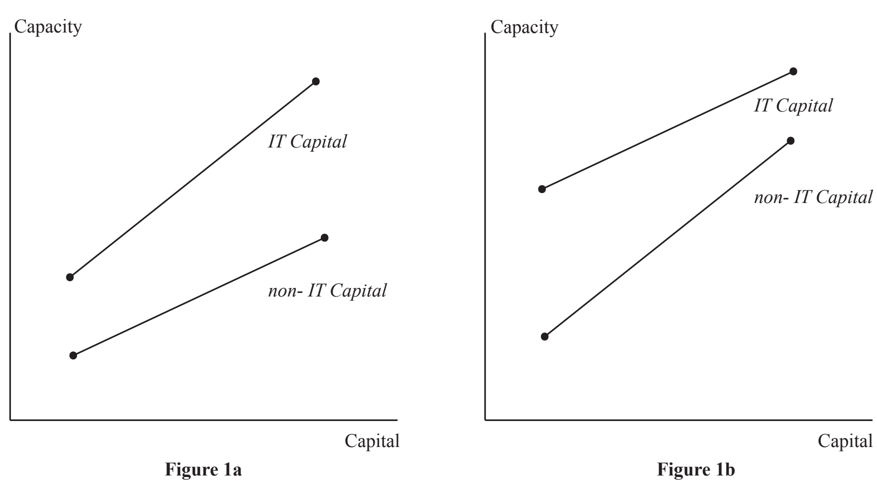

Figure 1 Capacity response to IT and non-IT capital

In Figures 1a and 1b capacity increases in response to increases in IT and non-IT capital: in Figure 1a capacity increases at a greater rate in response to IT capital increases than it does in response to non-IT capital increases, and Figure 1b shows the opposite effects. The lines in Figure 1a and 1b differ in their steepness in response to increases in the different types of capital. Thus, if our results support Figure 1a, then additional investments in IT capital better support a strategy of holding excess capacity than additional investments in non-IT capital. Determining increases in capacity from increases in IT capital relative to increases in non-IT capital is the main focus and contribution of our analyses. A priori it is reasonable to expect that the marginal returns to each type of capital are not significantly different for output in a long-run equilibrium, and consequently should not be for capacity. Finding differences in marginal returns to capacity from changes in different capitals suggest that IT capital versus non-IT capital are being used differently and strategically in the setting of capacity.

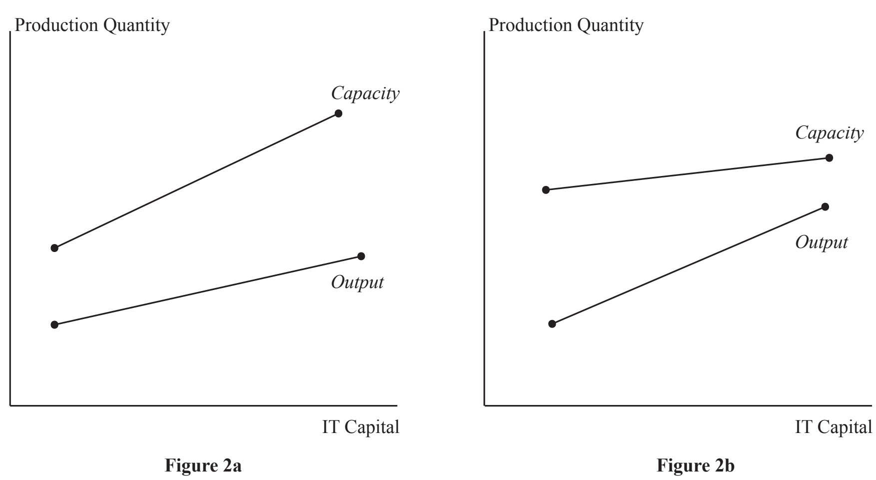

Figure 2 Output and capacity response to increased IT capital

In addition, there are two directions in which recent technological changes such as an increase in IT capital may have an impact on CU. The first is using investments in IT capital to increase excess capacity - operating at lower average utilization – to be able to handle demand fluctuations. In this way, the scalability of IT capital is used to extend economies of scale in production, effectively extending the lower portion of the average cost curve to higher levels of production. Bansak, Morin and Starr (2007) also suggest automated design and modular units make capacity expansion faster and cheaper, an argument consistent with higher levels of excess capacity. Alternatively, IT capital may allow firms to use capacity more efficiently, effectively lowering the lower portion of the average cost curve so that firms can produce higher levels of output more cost effectively before hitting the capacity limit. Of course, IT capital both changes capacity via increasing quasi-fixed assets and changes the average marginal product of capital. In Figures 2a and 2b output and capacity are increasing in IT capital. In Figure 2a the rate of increase in capacity from increases in IT capital is larger than that of output. Consequently, increases in IT capital have a greater impact on capacity than on output, and as a result when IT capital is expanded CU decreases. The alternative whereby the rate of increase in output is greater than that of capacity when IT capital is increased is shown in Figure 2b. In this case, when IT capital is expanded CU increases.

Organization of the Analysis: We first explain the distinction between output and capacity, which highlights the roles of quasi-fixed and variable inputs. Then, we use two industry examples – a pulp and paper plant, and a molding factory – to explain how the variable inputs to production (labor and intermediate inputs) would not be expanded in a straightforward way (say, proportionally) as production is expanded to capacity. We then derive separate estimation forms for actual output, capacity, and CU based on the Cobb-Douglas production function. Next, we estimate our models using cross-sectional time series industry-level datasets that cover mainly U.S. manufacturing industries across broad 13-year and 16-year time periods. Industry-level data is appropriate as an industry can be viewed as a set of organizations that are homogeneous in technology, production, and operations, and thus need to maintain a healthy level of capacity for similar reasons (Chiasson and Davidson 2005).

We find that both IT and non-IT capital have significant contributions to capacity. More importantly, increases in IT capital yield approximately four-fold greater changes in capacity than do increases in non-IT capital. Thus, as a constraint determining capacity, IT capital is a more valuable constraint to relax than non-IT capital, and is the dominant investment choice when implementing a strategy of holding excess capacity. We also confirm that both IT and non-IT capital have helped to reduce the CU rate since the late 1990's, seemingly after the advent of the Internet and the growth of enterprise software applications. We then examine a series of potential threats to our estimations using an extensive set of robustness tests that effectively confirm our results, making these available in our Appendix. We end with a summary of our conclusions, and a discussion of our contributions, implications, potential limitations and future research.

2. Our Model

2.1. Output and Capacity

We use production theory to illustrate the distinctions between actual output (hereafter, output) and capacity. This distinction is best described at the firm level, and the resulting output and capacity aggregates to the industry level.

To begin, we follow convention and take output and capacity as measures defined over the short-run such as a calendar or fiscal year. CU is then defined as output divided by capacity. In the short-run capital is quasi-fixed, meaning that IT capital and non-IT capital do not change in the short-run (Corrado et al 1997). Although in reality IT capital and non-IT capital do change throughout a year due to new capital investment and retirement/depreciation, these are typically the result of a capital plan set at the start of the year. Consequently, in practice IT capital and non-IT capital are pre-determined at the start of the year. We measure the capital stocks at a single point in time during the year, typically the end of the year.

Next, viewing the firm as a production function defines output as a function of inputs, typically IT and non-IT capital stocks that are quasi-fixed, and labor and intermediate inputs that can be adjusted to achieve a given level of output. Production as a function of the inputs takes input and output prices as constant over the short run – in practice this can be an annual average output price, an average wage rate and an average cost of intermediate inputs. A production function is not meant to reflect a sequence of decisions between inputs and output, rather it relates inputs to output and assesses the marginal product of each input.

Producing at capacity follows a systematically different production process than producing profit-maximizing output in terms of productivity of the inputs. Because firms are profit-maximizing entities, the output we observe is the level of output a firm produces in order to maximize their profits. This output results from levels of labor and intermediate inputs that are selected in order to maximize profits, and these levels of labor and intermediate inputs are the inputs we observe. These profit-maximizing levels of output, labor and intermediate inputs are unlikely to fully utilize the quasi-fixed inputs, IT and non-IT capital. It is worth recognizing that profit-maximizing output depends on a variety of factors including market demand, strategic decisions, financial restrictions, etc., factors we take as reflected in output prices and inputs prices.

For capacity, however, firms produce their "sustainable maximum output" (see Introduction) by increasing labor and intermediate inputs to the point that additional labor or intermediate inputs cannot generate further production, and as such the quasi-fixed inputs, IT and non-IT capital, are fully utilized. As capacity is a hypothetical measure, we do not observe capacity nor the levels of labor and intermediate inputs necessary to reach capacity, although we do measure the capital stocks. The FRB and other organizations obtain estimates of capacity, which we can observe, but they do not obtain estimates of the labor and intermediate inputs necessary to provide for sustainable maximum output.

IT productivity research has predominantly focused on IT's impact on profit-maximizing output. However, the output and capacity are distinct in the way inputs are managed and utilized for production. Therefore, we expect that the output elasticities of inputs and total factor productivity (TFP) all differ when firms are producing at the hypothetical "sustainable maximum output" level, or at capacity, as compared to profit-maximizing output.

Expanding Labor and Intermediate Inputs for Capacity: The degree to which labor and intermediate inputs are expanded to produce at capacity not only differ between industries, it is also non-linear within industries. Our first example, and a straightforward illustration of the former, is a modern capital-intensive pulp and paper plant. Such plants only require a fixed number of workers to produce across a range of output levels due to high levels of automation. Thus, increasing from profit-maximizing output to capacity may involve no additional labor, and at the same time may require additional intermediate inputs (energy, chemicals, wood chips). If a second shift is required, then labor doubles while production (and intermediate inputs) is increased continuously.

Our second example illustrates a more involved setting adapted from part of the Harvard Business Case "Capacity Analysis: Sample Problems" (9-696-058). Consider a molding factory that produces an automobile component. There are ten in-house software-controlled molding machines equipped with advanced technologies. Each machine requires a single full-time operator whose job includes loading, unloading, actively monitoring, and making necessary adjustments to the machines. Profit-maximizing output only requires six molding machines and their operators run a single shift in a given day. To assemble all the molded parts produced in a given day together with other parts, which are freely available, requires fifteen assemblers working a single shift to make the final components.

In order to produce at capacity during a single shift, the factory would need an additional four operators; and in order to assemble the molded parts from 10 molding machines, the assembly line needs to be running at its fastest speed requiring twenty workers at the same time. Therefore, the factory would need at least another five workers on the assembly line during a single shift. During this short-run production boost from output to capacity, a two-thirds increase, the total amount of IT and non-IT capital stock remain fixed. However, the increase in labor input varies from two-thirds more operators to only one-third more assemblers.

What we see from these two examples is that it is not a simple matter to determine the economies of scale for labor and intermediate inputs as production is expanded from profit-maximizing output to capacity, and that these economies of scale depend on the capacity of the quasi-fixed capital in place. Referring to our molding factory example, additional labor can be used only to the degree that there are more machines in place. Furthermore, if the molding machines are of less advanced technology requiring two full-time operators at the same time, using more materials to run at the same rate as the more advanced technology machines, then there is a doubling of labor and an increase in intermediate inputs without an increase in capacity. Therefore, IT and non-IT capital constrain the sustainable maximum output by bounding the maximum amount of usable labor and intermediate inputs.

Beyond these types of examples, there are subtle effects on the productivity of inputs as production is expanded that depend on the different types of capital. For example, as we noted in the Introduction, IT capital may affect organizational efficiency (Brynjolffson and Hitt 2000), and IT capital has been shown to augment labor and non-IT capital (Mittal and Nault 2009) and have supply chain spillover effects on quality and coordination (Cheng and Nault 2007, 2012).

Both of our examples are at the plant-level, our entry deterrence and production flexibility strategies are at the firm level, and as will be seen below, our analysis of capacity and CU are aggregated at the industry level. To understand how our approach bridges these levels, we first recognize that the FRB uses plant-level surveys (Survey of Plant Capacity) as the major input to its calculations of industry capacity and industry capacity utilization. Therefore, the measures we use are aggregated from the plant-level.

Second is disaggregating from the industry-level to the firm-level. Following classic work from economics, results from the industry-level can be applicable to the firm-level: "$\cdots$ *the production function for any particular firm may conceptually be obtained from the industry function in terms of the firm's ability to implement optimal values of parameters in the industry*" (Aigner and Chu 1968, p. 826). Aigner and Chu (1968) further argue that an industry-level production function can be understood as the production function of an "average" firm in the industry: "$\cdots$ *we can approximate an "average" firm production function when we have data only on industry aggregates* $\cdots$*, the latter points is especially important because in practice data at the firm level are usually not available*" (p. 830).

2.2. Estimation model

Productive capacity and CU are conditional on the firm's stock of quasi-fixed inputs, that is, inputs that are not adjustable within a given year. We consider a firm that produces only one output with two variable inputs and two quasi-fixed inputs. In order to be comparable and compatible with the bulk of research on the productivity of IT, our production function for output is based on a simple Cobb-Douglas (CD) form,

$$Y = AL^{\alpha}K^{\beta}Z^{\gamma}M^{\theta}, \tag{1}$$

where Y is output measured in real dollars, L is labor hours or full-time equivalents, K is the stock of non-IT capital measured in real dollars, Z is the stock of IT capital measured in real dollars, and M is intermediate inputs also measured in real dollars. The simple CD form represents production for a defined period of time, for example a year. Output, labor and intermediate inputs are flows, and the two capitals are stocks. In some formulations, the capital stocks are converted to flows by the rental price method, although there is generally little effect on the estimates. A is the technical change parameter, usually representing TFP. The parameters α, β, γ and θ are the output elasticities of labor, non-IT capital, IT capital, and intermediate inputs respectively. The output elasticities represent the percentage increase in output from a marginal percentage increase in the input. Using lower-case letters to represent the (natural) logs of the corresponding upper-case letters, the simple CD production function in logs is

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

Notice that the variables in (1) and (2) are the actual values of inputs that were used by industries and the actual values of output that were produced.

We chose the simple CD form because there is research that provides a theoretical basis for the CD form based on the income accounting identity, and a recent application of this in the context of IT can be found in Kundisch et al., 2014. This work shows that the CD form is flexible in various dimensions such as aggregation, and that many of the restrictions some researchers worry about in the CD form are captured in TFP. Consequently, the simple CD form is well-suited as a production function for output. Given that we use the CD form in our estimation of output, we also use it in our estimation form for capacity below. Although the theoretical basis in Kundisch et al. (2014) was only empirically tested on output, the well-known advantages of the CD form in the economic interpretation of the estimates (output elasticities) also apply to its use in estimating capacity. Moreover, as we show below, using the CD form for both output and capacity allow us to derive a clean estimation form for CU.

To model the relationship between inputs and capacity (rather than output) we take IT and non-IT capital as quasi-fixed, and labor and intermediate inputs as variable inputs that are available in sufficient quantities and at current market prices as to achieve sustainable maximum output. These definitions are consistent with the measures obtained from the FRB, which we discuss in more detail in the data description below.

With our measure of capacity, which we write as Y_c or y_c in log form, and using a CD-based production function form in order to make our estimates comparable with the output equation in (1), we represent capacity production as

$$Y_c \;=\; A_c L_c^{\alpha_c} K^{\beta_c} Z^{\gamma_c} M_c^{\theta_c}, \tag{3}$$

and in logs

$$y_c \;=\; a_c \;+\; \alpha_c l_c \;+\; \beta_c k \;+\; \gamma_c z +\; \theta_c m_c. \tag{4}$$

In (3) and (4) we use the subscript c to denote terms in the capacity model, and our interest is in the two output elasticities of capital, β_c and γ_c. As we discussed earlier, producing at capacity follows a systematically different production process than producing profit-maximizing output in terms of productivity of the inputs. Labor and intermediate inputs as variable inputs are marked with the subscript c to indicate their levels when producing at capacity, and the two types of capital – the quasi-fixed inputs, are kept at the same levels as they are when producing at the level of profit-maximizing output. Thus, (4) captures the relationship between the inputs, some variable and some fixed, required to produce a level consistent with maximum sustainable output. In other words, given fixed IT capital and non-IT capital, (4) embodies the increased levels of labor and intermediate inputs needed to produce at capacity.

Our focus is on the marginal products of non-IT capital and IT capital, β_c and γ_c. This is because comparing the marginal products allows us to conclude which type of capital is a more valuable constraint on capacity to relax. Specifically, the output elasticities represent the effects of the inputs on capacity in terms of percentages, whereas the marginal products demonstrate such effects in terms of dollar returns. If the marginal product of IT (non-IT) capital is greater than that of non-IT (IT) capital, then a dollar spent increasing IT (non-IT) capital yields a greater increase in capacity. Because capacity is defined as sustainable maximum output, (3) and (4) are essentially results of a constrained optimization where the amounts of non-IT capital and IT capital are the constraints. Therefore, another way to understand the output elasticities (marginal products) of the two capitals is shadow prices: they represent the marginal return in percentage (actual dollars) to capacity by relaxing the constraint of keeping capital fixed from (2) to (4) by one percent (one dollar).

For estimating our capacity equation in (4) we have data for the inputs when producing actual output, and a measure of capacity. Two of the inputs, IT capital and non-IT capital, remain the same when producing at output or at capacity. For the other two inputs, labor and intermediate inputs, we do not have data for when producing at capacity. The figures we need for labor and intermediate inputs are hypothetical in that they are quantities of labor and intermediate inputs needed to produce at capacity. The question is how to scale up labor and intermediate inputs to the hypothetical figures they might assume when producing at capacity. Our examples of the pulp and paper plant and of the molding factory discussed earlier make it clear that any mathematically systematic scaling would not hold across heterogeneous industries, and that the scaling for labor likely differs from that for intermediate inputs.

Recognizing industry heterogeneity in how labor and intermediate inputs would be scaled up from producing output to producing at capacity, we use industry dummy variables to scale up labor and intermediate inputs so that the scale up for each of labor and intermediate inputs varies across industries. Essentially, we resolve the scale up problem by allowing the data to estimate the scale ups in the context of a CD production function form. Using industry-level data, we can allow any industry to be the base industry, and estimate a variant of (4),

$$y_c \;=\; a_c \;+\; \delta_{c,0} l + \sum_{i \neq 0} \delta_{c,i} d_i l \;+\; \beta_c k \;+\; \gamma_c z + \; \eta_{c,0} m + \sum_{i \neq 0} \eta_{c,i} d_i m, \tag{5}$$

where the summation is over the total number of industries minus one, d_i is an industry dummy variable with i representing a specific industry, and $\delta_{c,j}$ and $\eta_{c,j}$ $(j \in \{0, i\})$ are to be estimated. Here $\delta_{c,0}$ and $\eta_{c,0}$ capture the scaled levels and output elasticities of the variable inputs for the base industry, and $\delta_{c,i}$ and $\eta_{c,i}$ capture the scaled levels and output elasticities of the variable inputs for industry i $(i \neq 0)$ relative to the base industry.

Due to the industry dummy variables, we estimate different coefficients for each industry for both labor and intermediate inputs. Putting this together, in (5) we use $\delta_{c,0} l + \sum_{i \neq 0} \delta_{c,i} d_i l$ as an approximation for the product of scaled labor and its output elasticity, which is $\alpha_c l_c$ in (4). It is worth observing that $\delta_{c,0}$ is a base industry mixture of output elasticity and scale up, and $\delta_{c,i}$, which can assume any sign, is a mixture of output elasticity and scale up for industry i relative to the base industry. We do the same for intermediate inputs (m). It is also worth recognizing that the values of $\delta_{c,j}$ and $\eta_{c,j}$ $(j \in \{0, i\})$ in (5) are not of particular interest and are not easily interpretable because they are a mixture of output elasticities and scaling. They simply serve to scale up the variable inputs to arrive at estimates of the output elasticities of non-IT capital and IT capital, β_c and γ_c, respectively. That is, we are not trying to estimate industry-specific output elasticities for labor and intermediate inputs but rather are scaling the variable inputs in order to obtain cross-sectional estimates for the output elasticities of IT capital and non-IT capital that apply to capacity, which can be compared to those from the output equation in (1).

We considered other scaling methods for the variable inputs, however, none of them work in our context because production functions represent an optimal input mix to produce a profit-maximizing level of output. Although we can derive marginal products of labor and intermediate inputs or simply scale them up proportionally from the levels we observe that are needed for output to that for capacity, these marginal products or proportional scaling are unlikely to hold through an expansion from actual output to capacity – especially so given capital is fixed. Our pulp and paper plant and molding factory examples show the difficulty of using current level of marginal product to calculate the extra labor and intermediate inputs needed in order to produce at capacity. Therefore, only in special circumstances would the variable inputs demonstrate constant returns to scale or some other easily identifiable scaling moving from actual output production to capacity. Moreover, from an econometric perspective, scaling up labor and intermediate inputs using marginal products or proportional scaling would involve capacity, which is the dependent variable in (4), creating a problem for the estimation.

Given (1) and (3), we are able to develop a reduced estimation form for CU starting from

$$CU = \frac{Y}{Y_c} = \frac{A}{A_c}\frac{L^{\alpha}}{L_c^{\alpha_c}}K^{\beta-\beta_c}Z^{\gamma-\gamma_c}\frac{M^{\theta}}{M_c^{\theta_c}},$$

where CU is the ratio of output over capacity, each represented by a CD production function. To linearize the form, we take its log

$$logCU = (a - a_c) + \alpha l - \alpha_c l_c + (\beta-\beta_c)k + (\gamma-\gamma_c)z + \theta m - \theta_c m_c,$$

where l_c and m_c are again hypothetical and thus not directly observable. We apply the same scaling method as in (5) to replace l_c and m_c and obtain our estimation form for CU that combines our output and capacity equations

$$logCU = a_u + \delta_{u,0}l + \sum_{i\neq 0}\delta_{u,i}d_i l + \beta_u k + \gamma_u z + \eta_{u,0}m + \sum_{i\neq 0}\eta_{u,i}d_i m, \tag{6}$$

where $a_u = a - a_c$, $\beta_u = \beta - \beta_c$, and $\gamma_u = \gamma - \gamma_c$. The subscript u on the coefficients represent that they come from the CU equation, (6). Similar to (5), $\delta_{u,0}$ and $\eta_{u,0}$ represent the scaled effects of the variable inputs on $logCU$ for the base industry, and $\delta_{u,i}$ and $\eta_{u,i}$ capture the scaling of such effects for industry i ($i \neq 0$) in this particular equation. Again, as in (5), we are only interested in β_u and γ_u, which measure the elasticities of non-IT and IT capital on CU. Specifically, if the sign is negative, it means its corresponding capital helps to reduce CU by creating more capacity relative to output; if positive, then the effect is reversed leaving less slack capacity (e.g., increasing the corresponding capital generates more output relative to capacity). Although we can separately estimate β (γ) from (2) and β^c (γ^c) from (5), (6) allows us to estimate their difference as one term and test if it is statistically different from zero.

2.3. Data Description

As a result of the change in industry classifications implemented by U.S. Federal Government agencies in the late 1990s, we have two cross-sectional time-series datasets covering different time periods (1987-1999 and 1998-2013), variable definitions, and industries at different aggregation levels. Although not ideal, the two distinct datasets allows us to generalize our findings and further explore our research questions. Summary statistics for our two datasets and a detailed description of the industries in each dataset are provided in Tables A1-A3 in the Appendix.

1987-1999 Dataset: This earlier dataset is the result of matching a productivity dataset with a CU dataset, both from 1987 to 1999. The same productivity dataset is used in Cheng and Nault (2007), collected from the Bureau of Labor Statistics (BLS), and covers 140 three-digit Standard Industrial Classification (SIC) code manufacturing industries. The productivity dataset contains labor input (L), IT capital stock (Z), non-IT capital stock (K), intermediate inputs (M) and gross output (Y). The labor input is in millions of hours. The remaining three variables are converted to millions of 1987 dollars, by dividing their nominal values in millions by their corresponding deflators. The labor input incorporates IT labor and accounts for changes in both raw hours and in skill composition of the work force (i.e., education and work experience) (BLS 2007). IT capital stock is an aggregation of the stock of computers and related equipment, office equipment, communication, instruments, photocopy and related equipment. The instruments measure include most of the manufacturing instruments that are elements of automation. From a breakdown of asset types, non-IT capital stock is computed as the total of equipment and structures less IT capital stock.

To match the SIC-based productivity dataset, we requested SIC-based CU data from the FRB. It covers 45 SIC code manufacturing industries at the two-digit or three-digit level from 1987 to 1999. The FRB estimates of CU are developed from a combination of sources – about 22 percent are from government sources and trade sources, about 73 percent are based on responses to the Bureau of the Census's Survey of Plant Capacity and roughly 5 percent are based on trends through peaks in production. CU data from the FRB has been the most consistent over time, that is, a CU rate of 85 percent today means about the same degree of tightness in production that it meant in the past. Moreover, it covers a broad span of industries and sufficiently long time periods.

For each industry in a certain year, the CU index is the ratio of nominal output divided by nominal capacity for a given industry-year. We cannot directly use the capacity index data from FRB since it is not comparable between industries. We therefore calculate our capacity measure (Y_c) by dividing gross output (Y) in the productivity dataset by CU. Because Y is already in millions of 1987 dollars, Y_c is also in millions of 1987 dollars. As the SIC capacity dataset contains both two-digit and three-digit industries, we aggregate the productivity dataset to match the industries in the capacity dataset. The result is a balanced panel of 39 industries across 13 years.

To control for sector-level heterogeneity, we generated sector dummy variables following Stiroh (2002) and Cheng and Nault (2012): IT-producing industries are the 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 industries which are not IT-producing and whose IT intensity (IT capital stock over gross output) is above the sample median of the non-IT producing industries; the remaining industries are Others. This dataset yields 5 IT-producing, 16 IT-using, and 18 Others industries. Table A2 in the Appendix lists the 39 manufacturing industries and their SIC codes.

1998-2013 Dataset: This more recent dataset is based on the 2007 North American Industry Classification System (NAICS). We acquired data on capital stock, IT capital stock (Z), labor input (L), intermediate input (M), and GDP (Y) for 60 three-digit NAICS code industries from 1998 to 2013, directly from the BEA and BLS websites. All value-based variables have been converted to constant 2009 dollars using chain-type quantity indices provided by the BEA. IT capital is the aggregate stock of software and information processing equipment - which includes computer and peripheral equipment, communications, instruments, photocopy and related equipment, and office and accounting equipment. Non-IT capital (K) is obtained by subtracting IT capital from the total stock of private fixed assets. In this dataset, Labor is the number of total full-time equivalent employees, which equals the number of employees on full-time schedules plus the number of employees on part-time schedules converted to a full-time basis.

We collected NAICS-based CU data from the FRB website. The data are a mix of different digit levels. The definition of CU is the same as in our earlier dataset. This NAICS-based CU dataset covers 43 detailed industries in manufacturing, mining, and utilities. Because the CU data are aggregated from the establishment level for each industry, they are not additive across industries. Therefore, we aggregate the productivity dataset according to the levels of industries in the CU dataset, and then match the two datasets. The result is a balanced panel of 22 industries (19 in manufacturing, 3 in oil and gas and mining) across 16 years. As in our 1987-1999 dataset, we then generate capacity, Y_c. Unlike our 1987-1999 dataset, this dataset contains manufacturing and also oil and gas and mining industries. We classify the industries into two sectors: manufacturing (NAICS codes 31-33) and non-manufacturing, and create a sector dummy variable for the non-manufacturing sector to control for any sector-level heterogeneity. Table A3 in the Appendix lists the industries and their NAICS codes.

2.4. Econometric Adjustments

Heteroscedasticity and autocorrelation are the two econometric problems that commonly arise when using cross-sectional time series data. As our industries differ in size, organization, management, production technology, and response to economic shocks, we expect our datasets to exhibit industry-level heteroscedasticity, possibly correlated across industries. We use a Breusch-Pagan / Cook-Weisberg test to test for heteroscedasticity. We reject the null hypothesis of no heteroscedasticity in both datasets for the model of actual output (in (2), $\chi^2 = 31.09$ for our earlier dataset and 4.84 for our more recent dataset), for the model of capacity (in (5), $\chi^2 = 81.90$ for our earlier dataset and 135.51 for our more recent dataset), and for the model of CU (in (6), $\chi^2 = 4.77$ for our earlier dataset and 35.12 for our more recent dataset).

We also expect our datasets to exhibit first-order autocorrelation because with relatively smooth business cycles one year's output is highly correlated with the prior year. Using the Wooldridge test for autocorrelation in a panel dataset, we rejected the null hypothesis of no first-order autocorrelation (AR1) at reasonable levels of significance in both datasets for the model of actual output (in (2), F-statistic=10.97 for our earlier dataset and 33.86 for our more recent dataset), for the model of capacity (in (5), F-statistic=27.080 for our earlier dataset and 26.24 for our more recent dataset), and for the model of CU (in (6), F-statistic=76.251 for our earlier dataset and 68.87 for our more recent dataset). Moreover, if the response to changes in business cycles do not occur with the same magnitude in each industry, then each industry may differ in its magnitude of autocorrelation and the autocorrelation becomes industry-specific.

Given our test results, both panel-specific autocorrelation and panel-level heteroscedasticity are suspected in both of our datasets. To adjust for these econometrically, we estimate our models using specifications for heteroscedastic errors and industry-specific AR1 coefficients (He + PSAR1). To generate our estimates, we use cross-sectional time series feasible generalized least-squares (FGLS) regressions (Wooldridge 2002) implemented in Stata. Furthermore, we add year dummies to control for potential economy-wide shocks, control for sector-specific heterogeneity by including sector dummies (i.e., IT-producing and IT-using for our 1987-1999 dataset, and non-manufacturing for our 1998-2013 dataset), and allowing for industry-specific autocorrelation. In addition, estimating our capacity equation, (5), and our CU equation, (6), the industry dummy variables used to scale up labor and intermediate inputs capture industry-level fixed effects to the degree that these effects are related to labor and/or intermediate inputs. We do not include controls for correlated industry-level heteroscedasticity as the number of industries is greater than the number of years in both of our datasets. We use the system GMM estimation as a test to address this feature.

It is worth pointing out that our estimation method allows each industry to have different scale up factors for labor and for intermediates. Although these scaling up factors are multiplicative with labor/intermediate inputs used to produce output, they are easily consistent with some non-linear process as they result from the time series that contains a variety of levels of output and inputs.

3. Results

3.1. Main Results

Our main results for the two datasets are reported in Table 1 (output elasticities) and Table 2 (marginal products). For each dataset, there are three sets of results corresponding to the output model in (2), the capacity model in (5), and the CU model in (6), respectively. The output results are included for comparison. Recall that our interests are the impacts of IT capital and non-IT capital, which are our primary focus throughout the results section.

Table 1 Main Results - Output Elasticities

	1987-1999			1998-2013		
	Output	Capacity	CU	Output	Capacity	CU
IT Capital	0.077 ***	0.133 ***	0.036	0.042 *	0.079 ***	-0.042 **
	(0.019)	(0.024)	(0.022)	(0.022)	(0.023)	(0.020)
Non-IT Capital	0.101 ***	0.437 ***	-0.634 ***	0.355 ***	0.450 ***	-0.430 ***
	(0.02)	(0.061)	(0.055)	(0.065)	(0.061)	(0.049)
Labor	0.264 ***			0.175 **		
	(0.018)			(0.022)		
Intermediate Inputs	0.571 ***			0.410 ***		
	(0.024)			(0.028)		
Returns to Scale	1.013			0.982		
N	507	507	507	352	352	352

Notes. Log dependent variable and input variables. Feasible Least Squares estimation. IT-producing, IT-using, and the year dummies are included for the 1987 -1999 dataset. Non-manufacturing and the year dummies are included for the 1998 -2013 dataset. Dummies and interaction terms are suppressed for brevity. Control for panel-specific heteroskedasticity (PSHe) and panel-specific autocorrelation (PSAR1) for both datasets

∗p<0.10, ∗∗p<0.05, ∗∗∗p<0.01. Standard errors in parentheses.

Table 2 Main Results - Marginal Products

	1987-1999			1998-2013		
	Output †	Capacity †	CU ‡	Output †	Capacity †	CU ‡
IT Capital	2.520 ***	5.220 ***	4.78%	2.261 *	5.611 ***	-1.07% **
	(0.622)	(0.943)	(0.029)	(1.184)	(1.633)	(0.005)
Non-IT Capital	0.155 ***	0.819 ***	-3.00% ***	0.731 ***	1.233 ***	-0.45% ***
	(0.031)	(0.114)	(0.003)	(0.134)	(0.167)	(0.001)
N	507	507	507	352	352	352

† Marginal products

‡ Marginal impact on industry-average CU per one billion dollar increase

∗p<0.10, ∗∗p<0.05, ∗∗∗p<0.01. Standard errors in parentheses.

Results on Output: Because of the aggregation necessary to match the productivity data with the capacity data, we examine estimates from the simple CD form to ensure they are comparable with prior IT productivity results that have used this form. Our estimates from the simple CD regression on output in (2) are reported in Column 2 for our 1987-1999 dataset and Column 5 for our 1998-2013 dataset in Table 1 (output elasticities) and Table 2 (marginal products). Our output elasticity of IT capital for the 1998-2013 dataset is comparable in magnitude with previous findings and significant at the 10% level; the output elasticity of labor is significant at the 5% level. The rest of our output elasticities across the two datasets are significant at the 1% level and conform roughly in magnitude to previous findings with industry-level data (for example, Table 4 in Cheng and Nault 2007) even though prior studies differ in data sources, aggregation, and econometric adjustments. Our measures of the returns to scale in Table 1 indicate roughly constant returns to scale in both datasets.

Results on Capacity: The estimates from our model on capacity in (5) are presented in Column 3 for our 1987-1999 dataset and Column 6 for our 1998-2013 dataset in both Table 1 (output elasticities) and Table 2 (marginal products).

From Table 1, the output elasticities of IT and non-IT capital in the capacity model, γ^c and β^c in (5), are both positive and significant at the 1% level in both datasets. Both of these output elasticities are greater in magnitude than their corresponding estimates in the simple CD model in (2): For IT capital the change is $\gamma^c - \gamma = 0.056$ in our earlier dataset and 0.037 in our more recent dataset); for non-IT capital the change is $\beta^c - \beta = 0.336$ in our earlier dataset and 0.095 in our more recent dataset. These changes indicate that despite the increase in labor and intermediate inputs, both IT and non-IT capital contribute to the production boost when increasing from output to capacity, and this reflects their increased value as constraints on capacity.

To answer our main question of whether IT capital or non-IT capital is a more valuable contributor at the margin to capacity, we convert the elasticities to marginal products (MP). From the capacity model results in Table 2, the MP for IT capital is much greater than that for non-IT capital, and statistically significant in both the earlier and later datasets. In the earlier dataset the MP for IT capital is 5.220 and for non-IT capital is 0.819, with $\chi^2(1) = 16.40$ for the Wald test on the statistical difference. Similarly, in the more recent dataset the MP for IT capital is 5.611 and for non-IT capital is 1.233 with $\chi^2(1) = 6.70$. Specifically, a \$1 million increase in IT capital is associated with a \$5.22 million increase in capacity for an average industry in the 1987-1999 dataset and a \$5.61 million increase in capacity in the 1998-2013 dataset. This indicates that a one dollar investment in IT capital has a return multiple of 4-6 times that of non-IT capital when investing to increase capacity. An alternative and equivalent interpretation is that the MPs are shadow prices for capacity: MPs represent the dollar gains in capacity by relaxing the capital constraint by one dollar. Our results show that relaxing the IT capital constraint yields a greater payoff for capacity than relaxing non-IT capital.

The increase in MP going from the simple CD model to the capacity model is also much greater for IT capital as compared to non-IT capital – approximately \$3 for each dollar of investment in IT capital as compared to less than one dollar for each dollar of investment in non-IT capital. Thus, the high MPs for IT capital seen in many IT productivity studies when contributing to actual output are magnified relative to non-IT capital when contributing to capacity. Given our datasets, these results are very clear and have persisted for the last quarter century: IT capital has a higher MP in expanding capacity than non-IT capital both in absolute terms and relative to their contributions to actual output.

As we will cover in more detail in the Discussion and Conclusions section, for the strategy of holding excess capacity for entry deterrence or for cost-efficient short-term changes in output in response to demand fluctuations, at the margin IT capital is by far the more effective investment to increase capacity.

Results on CU: Columns 4 and 7 in Table 1 and Table 2 present the estimates for our model on CU in (6).

Beginning with our more recent dataset, 1998-2013, we find that the impact of additional investment in either IT capital or non-IT capital significantly decreases CU: at the 5% level for IT capital and at the 1% level for non-IT capital. When converted to MPs in Table 2 we see that these impacts can be substantial, and are twice as large for investments in IT capital as compared to those in non-IT capital: 1.07% decrease in CU as compared to a 0.45% decrease in CU for one billion dollars of additional capital investment. Thus, IT capital and non-IT capital both reduce the short-run CU rate because their effects on capacity outweigh those on output, and more so for IT capital.

In the earlier dataset, 1987-1999, the results for non-IT capital are consistent in sign with the more recent dataset and magnified: non-IT capital is negative and significant at the 1% level, and the impact of non-IT capital on CU is large: -3.00% in Table 2. This difference in magnitude between the two datasets may be explained by the earlier dataset having more finely defined industries, although there is no way to test this. In contrast, for the earlier dataset, 1987-1999, the results for IT capital are insignificant, that is, IT capital did not have a significant impact on CU.

To explore this insignificant result further, we spilt the earlier dataset based on pre- and post-Internet periods, 1987-1994 and 1995-1999, respectively, as was done in Gong et al. (2016). As we know, Internet significantly lowered the internal and external coordination costs of the firm and increased transparency for suppliers and customers. According to Hobbes' Internet Timeline 10.2 (Zakon 2011), business and media started to notice the Internet in 1994. The Internet was commercialized in 1995 when NSFNET (National Science Foundation Network) was decommissioned, removing the last restrictions on the use of the Internet to carry commercial traffic (Leiner et al. 1997). In addition, enterprise software applications also became popular in mid-1990s, coinciding with our timing of the Internet-based split (McAfee and Brynjolfsson, 2008). We expect significant a difference between the two sample splits in ways IT could contribute to capacity and CU because of the economies of scale of the Internet and enterprise software applications. Our tests for the two sub-periods suggest the presence of heteroscedasticity (He) for all three models in each sub-period, panel-specific autocorrelation (PSAR1) for the models of output and CU in the pre-Internet period and for the model of output in the post-Internet period, and common autocorrelation (AR1) for the rest of the models in each sub-period. We control for the same sector and year fixed effects as for the pooled dataset.

The results are in Tables 3 and 4. For non-IT capital the results on CU are consistent in sign and magnitude with those results from the full earlier dataset: non-IT capital is negative and significant at the 1% level, and the MP on CU is roughly −3.00%. In contrast, the impact of IT capital on CU is significant both pre- and post-Internet, 1% level and 5% level, respectively, and positive - declining substantially in MP terms from 17.36% to 7.00%. Even though higher levels of IT capital increases CU throughout the 1987-1999 period, we suspect that the large decline in MP and in significance between pre- and post-Internet is evidence of a regime change, and consequently why the impact of IT capital on CU was not significant in the full earlier dataset. We note that the impact of IT capital on capacity in the pre-Internet period is not significant, although it is in the post-Internet period. We return to this in the Discussion and Conclusion section.

3.2. Robustness Checks and Alternative Specifications

Although our two datasets differ in time span, set of industries, level of aggregation, and definition for IT capital, our main qualitative findings on capacity are consistent and on CU are mostly consistent across the two datasets and sample splits. To further check the robustness/validity of our results, we performed a substantial set of tests and analyses, and our main qualitative results stay unchanged. Specifically, we use fixed effects estimation to control for industry-level effects

Table 3 Results for Pre- and Post-Internet periods - Output Elasticities

	1987-1994			1995-1999		
	Output †	Capacity ‡	CU †	Output †	Capacity ‡	CU ‡
IT Capital	0.133 ***	0.014	0.112 ***	0.238 ***	0.095 **	0.074 **
	(0.013)	(0.023)	(0.026)	(0.019)	(0.042)	(0.032)
Non-IT Capital	0.037 ***	0.239 ***	-0.661 ***	0.048 ***	1.205 ***	-0.707 ***
	(0.011)	(0.072)	(0.071)	(0.017)	(0.098)	(0.074)
Labor	0.193 ***			0.173 ***		
	(0.01)			(0.015)		
Intermediate Inputs	0.627 ***			0.531 ***		
	(0.018)			(0.031)		
N	312	312	312	195	195	195

Notes. Log dependent variable and input variables. Feasible Least Squares estimation, control for IT-producing, IT-using, and the year dummies. Dummies and interaction terms are suppressed for brevity.

∗p<0.10, ∗∗p<0.05, ∗∗∗p<0.01. Standard errors in parentheses.

† control for panel-specific heteroskedasticity (PSHe) and panel-specific autocorrelation (PSAR1)

‡ control for panel-specific heteroskedasticity (PSHe) and common autocorrelation (AR1)

Table 4 Results for Pre- and Post-Internet periods - Marginal Products

	1987-1994			1995-1999		
	Output †	Capacity ‡	CU †	Output †	Capacity ‡	CU ‡
IT Capital	4.959 ***	0.628	17.36% ***	6.064 ***	2.887 **	7.00% **
	(0.485)	(1.031)	(4.03)	(0.484)	(1.276)	(3.027)
Non-IT Capital	0.051 ***	0.401 ***	-3.00% ***	0.086 ***	2.631 ***	-2.83% ***
	(0.015)	(0.121)	(0.322)	(0.031)	(0.214)	(0.296)
N	312	312	312	195	195	195

† Marginal products

‡ Marginal impact on industry-average CU per one billion dollar increase

∗p<0.10, ∗∗p<0.05, ∗∗∗p<0.01. Standard errors in parentheses.

that do not vary over time, and 2-stage least squares estimation (2SLS) as well as system-GMM estimation to deal with potential endogeneity.

Without controlling for industry-level fixed-effects, there may be long-run differences in output and capacity that are likely to be correlated with IT capital and non-IT capital. We note that our capacity and CU equations, (5) and (6), include industry dummy variables as part of the scale-up such that if these long-run differences are related to labor or intermediate inputs they are controlled for in the capacity and CU regressions. Moreover, sector-level fixed effects are included in all our regressions we report in our main results as described in our Econometric Adjustments above.

Nonetheless, in order to determine if there are industry-level differences that are not accounted for in our main results, we incorporate industry-level dummy variables in our FGLS estimation separate from our scale up of labor and intermediate inputs, dropping the sector-level fixed effects. We find that all of our qualitative results remain unchanged. In fact, the effects of IT capital are quantitatively consistent with the main results from our original FGLS estimation (i.e., without fixed effects) in terms of significance and magnitude. Non-IT capital is not significant in the output model in the earlier dataset. This is likely due to multicollinearity and the loss of degrees of freedom (Yaffee 2003; Han, Kauffman and Nault 2011). Historically, fixed-effects estimation has led to disappointing results with insignificant capital coefficients and implausibly low returns to scale (Griliches and Mairesse 1998, Stiroh 2010, Cheng and Nault 2012). Of course, we expect some level of multicollinearity in a production function estimation. However, the production function is a theoretical construct: output is a function of inputs. Therefore, one cannot throw out collinear variables such as labor or capital, and multicollinearity only affects the efficiency of the estimates.

Prior literature suggests that FGLS may underestimate the standard errors of the estimated coefficients, and that OLS with panel-corrected standard errors (OLS-PCSE) may perform better in estimating the standard errors (Beck and Katz 1995). As an additional robustness check, we estimate our models with OLS-PCSE, correcting for panel-level heteroskedasticity and autocorrelation. Our results remain highly consistent with our fixed-effects-based results. Results from fixed-effects and OLS-PCSE estimations for both datasets are provided in Tables 5 and 6.

3.2.1. Endogeneity Endogeneity of the independent variables arises from three sources: simultaneity, omitted variables, and measurement error (Wooldridge 2002). Simultaneity arises when one or more of the independent variables are determined with the dependent variable and are subject to shocks that affect both. In our context, this could happen when firms observe demand shocks in the market (not observable to researchers), and they choose output and input levels accordingly. Moreover, if these are productivity shocks (e.g., a new technology breakthrough) they could affect output, inputs and capacity, and could be correlated over time.

Table 5 Alternative Econometric Specifications for the Main Datasets - Output Elasticities

Sample Periods	Model	Coefficients	Main Results	Fixed Effects	OLS-PCSE
1987 - 1999	Output	IT Capital	0.077*** (0.019)	0.075*** (0.024)	0.089** (0.034)
		Non-IT Capital	0.101 *** (0.02)	0.024 (0.048)	0.137** (0.065)
	Capacity	IT Capital	0.133*** (0.024)	0.123*** (0.026)	0.151*** (0.035)
		Non-IT Capital	0.437*** (0.061)	0.385*** (0.067)	0.430*** (0.104)
	CU	IT Capital	0.036 (0.022)	0.009 (0.024)	0.012 (0.029)
		Non-IT Capital	-0.634*** (0.055)	-0.459*** (0.056)	-0.576*** (0.073)
1998 - 2013	Output	IT Capital	0.042* (0.022)	0.107*** (0.029)	0.065* (0.038)
		Non-IT Capital	0.355*** (0.065)	0.291*** (0.051)	0.295*** (0.052)
	Capacity	IT Capital	0.079*** (0.023)	0.099** (0.043)	0.094** (0.039)
		Non-IT Capital	0.450*** (0.061)	0.406*** (0.081)	0.465*** (0.144)
	CU	IT Capital	-0.042** (0.020)	-0.071** (0.035)	-0.049* (0.027)
		Non-IT Capital	-0.430*** (0.049)	-0.541*** (0.067)	-0.526*** (0.083)

Notes. Log dependent variable and input variables.
OLS-PCSE estimates are corrected for panel-level heteroskedasticity and autocorrelation.
∗p<0.10, ∗∗p<0.05, ∗∗∗p<0.01. Standard errors in parentheses.

To the extent that different industries have distinct yet time-invariant responses to the demand or productivity shocks, we have shown that simultaneity is not an issue in our models by generating largely consistent results using industry-level fixed-effects estimation. Furthermore, if the industries respond to the demand or productivity shocks similarly within a time interval (i.e., industry-invariant), we mitigate simultaneity by incorporating year fixed effects in our models assuming that industries' responses are consistent within the same year but different across years. What is more, in our main results we use sector fixed effects to replace industry fixed effects in order to mitigate simultaneity that results when industries that belong to the same sector have similar responses to demand shocks that determine the level of output before the inputs. As we can see from our tables using the alternative econometric specifications (Tables 5 and 6) the results are consistent using these specifications.

Table 6 Alternative Econometric Specifications for the Main Datasets - Marginal Products

Sample Periods	Model	Coefficients	Main Results	Fixed Effects	OLS-PCSE
1987 - 1999	Output	IT Capital	2.51*** (0.619)	2.445*** (0.782)	2.900** (1.108)
		Non-IT Capital	0.156*** (0.031)	0.037 (0.074)	0.211** (0.100)
	Capacity	IT Capital	5.224*** (0.943)	4.831*** (1.021)	5.931*** (1.374)
		Non-IT Capital	0.817*** (0.114)	0.72*** (0.125)	0.804*** (0.194)
	CU	IT Capital	4.788% (2.926)	1.197% (3.192)	1.596% (3.857)
		Non-IT Capital	-2.999%*** (0.26)	-2.171%*** (0.265)	-2.725%*** (0.345)
1998 - 2013	Output	IT Capital	2.61* (1.184)	5.761*** (1.56)	3.500* (2.046)
		Non-IT Capital	0.731*** (0.134)	0.599*** (0.11)	0.608*** (0.107)
	Capacity	IT Capital	5.611*** (1.633)	7.031** (3.05)	6.676** (2.769)
		Non-IT Capital	1.233*** (0.167)	1.112*** (0.22)	1.274*** (0.394)
	CU	IT Capital	-1.07% ** (0.005)	-1.85%** (0.011)	-1.27%* (0.007)
		Non-IT Capital	-0.45%*** (0.001)	-0.56%*** (0.001)	-0.55% (0.001)

Notes. Log dependent variable and input variables.
$*$p<0.10, $**$p<0.05, $***$p<0.01. Standard errors in parentheses.

Even though we have mitigated the simultaneity concern by using fixed effects models, our results still face the threat of simultaneity because of time- and industry- variant responses to demand shocks. In addition, there may be measurement errors and omitted variables that might affect both the output and the inputs. Any variables that are not included in the model and that may cause a productivity shock (e.g., droughts, change in exchange rate, fluctuations in inflation rate, structural change or disruptive technology in an industry) may result in endogeneity. Moreover, these productivity shocks may be correlated over time, in which case lagged inputs as instruments might be invalid.

We recognize at the outset that to the extent that these omitted variables are serially correlated, our adjustments with panel-specific/common autocorrelation help relieve this problem. To more fully address this issue, we conduct two-stage least squares (2SLS) estimation, using one-year lags of the four input variables and their interactions with the industry dummies as excluded instruments. For IT capital in particular, we also use the two-year lag as an excluded instrument. All our qualitative results remain unchanged, except that IT capital now has a negative and significant association with CU in the earlier dataset. The average F-statistic from the first stage is 1243.61 ($Prob > F = 0.00$), rejecting the null hypothesis that the excluded instruments are weakly associated with the endogenous variables. The 2SLS results are presented in Table A4 in our Appendix.

A precondition for 2SLS estimation is that our instrumental variables are indeed exogenous. That is, they are not correlated with the error terms in our models. The canonical test for instrument exogeneity in over-identified models is the Sargan Test (Sargan 1958). We conducted Sargan tests for all our models in the two datasets and sample splits. The results are summarized in Table A5 in our Appendix. All of the test results indicate that we cannot reject the null hypothesis that our instrumental variables are exogenous. In fact, lagged input variables have been accepted as valid instrumental variables in industry-level production function contexts in prior research (e.g., Mittal and Nault 2009; Han et al. 2011; Cheng and Nault 2012). Finding other appropriate instruments is challenging. Stiroh (2010) compared the lagged independent variables with demand side instruments such as oil prices and defense spending shocks, and concluded that the approach with the best performance is a system GMM estimator (Blundell and Bond 1998).

One of the most important assumptions of the system GMM is that the number of time periods is smaller than the number of panels. This is exactly what we have in our datasets where we have 39 industries and 13 years in our first dataset; and 22 industries and 16 years in the second dataset. Another crucial assumption of system GMM is that the estimators are designed for general purpose so they assume the only available instruments are internal, which are based on lags of the instrumented variables (Roodman 2009). In our analysis we have taken advantage of this feature and have used lags of our independent variables as IVs. The GMM estimators also consider the potential fixed effects and problems with the error structures such as heterosketasticity and autocorrelation. This again fits our data well because we have detected both heterosketasticity and autocorrelation. We adopt the system GMM estimator in our models across both datasets, and find that the results are highly consistent from our main results based on FGLS. The results are presented in Table 7 below that can be compared with our earlier Tables 1 and 2.

Table 7 Results for the System GMM Estimation

	1987-1999			1998-2013		
	Output	Capacity	CU	Output	Capacity	CU
	Output Elasticities					
IT Capital	0.354 ***	0.176 ***	0.026	0.118 ***	0.112 ***	-0.043 **
	(0.01)	(0.025)	(0.02)	(0.015)	(0.027)	(0.021)
Non-IT Capital	0.007 *	0.332 ***	-0.579 ***	0.228 ***	0.375 ***	-0.513 ***
	(0.004)	(0.068)	(0.055)	(0.029)	(0.063)	(0.049)
	Marginal Products					
IT Capital	11.529 ***	6.905 ***	3.42%	6.353 ***	7.954 ***	-1.12% **
	(0.337)	(0.985)	(2.715)	(0.808)	(1.917)	(0.005)
Non-IT Capital	0.011 *	0.620 ***	-2.74% ***	0.470 ***	1.028 ***	-0.53% ***
	(0.006)	(0.127)	(0.261)	(0.059)	(0.172)	(0.001)

Notes. Log dependent variable and input variables.
∗p<0.10, ∗∗p<0.05, ∗∗∗p<0.01. Standard errors in parentheses.

As capacity and CU levels may be related to the competitiveness of an industry which may also determine the input levels, we have downloaded the industry concentration data from the Census Bureau, and merged it with our main dataset. We re-ran all our analyses with industry concentration as an additional control variable, and all of our main findings remain qualitatively the same. The results from these analyses are available from the authors. To further verify that our results are not driven by the correlation between the independent variables and the error term, we investigate the correlations between the residuals and our independent variables. We find that the correlations are consistently low and not significant as we show in Table A6 in our Appendix.

4. Discussion and Conclusion

Adopting the FRB's definition of productive capacity, we examine how IT and non-IT capital constrain the short-run production expansion from actual output to sustainable maximum output, that is, capacity. We find first that IT capital has a significant contribution to capacity, and it is substantially different in magnitude compared with its contribution to output. This provides empirical evidence that IT, as the emerging general-purpose technology, has a substantial impact on capacity besides its well-documented impact on output. Second, and more importantly, when examining the impact on capacity we find that IT capital has a greater MP than non-IT capital. This is consistent with our results and other results in the related literature for actual output. Because both types of capital are fixed in the short-run, they are constraints on capacity. Therefore, the MPs represent the shadow prices of the two types of capital, and our results imply that investing in IT to relax the IT capital constraint yields a greater increase in capacity than investing in non-IT capital.

Over the 27 years covered by our two datasets IT's role has changed from automation and substitution towards enabling organizational changes and making labor and non-IT capital more productive (Brynjolfsson and Hitt 2003, Mittal and Nault 2009). Thus, IT capital's contribution to capacity gradually outweighs that to output as this transition of role deepens over time.

Our results also show that additional non-IT capital helps to reduce CU. More importantly, IT capital also does so in the more recent dataset (1998-2013), and to even a greater degree that non-IT capital, consistent with our capacity results. However, IT capital does not have a significant effect on CU in the earlier dataset (1987-1999). Dividing the earlier dataset into pre-and post-Internet periods, we find that non-IT capital continues to reduce CU, and in contrast IT capital increases CU in both sub-periods, although substantially more pre-Internet. We suspect this decline in IT capital's impact on CU in the post-Internet period is evidence of a regime change as well as the lack of software in the measure of IT capital in the earlier dataset. These pre-2000 results are consistent with other studies we cite that examine the effect of IT on CU through specific examples mostly pre-2000 (Koltai and Stecke 2008, Barua et al. 1995, Nightingale et al 2003, and Hubbard 2003). In contrast, Bansak et al. (2007) find small increases in CU from IT from 1974-2000 on a subset of manufacturing industries, perhaps due to the selection of industries and the many changes in IT from pre-personal computer to post-Internet over that period.

Contributions and Implications: The objective of this work has been to examine the potential of IT capital, relative to non-IT capital, to contribute to a strategy of holding excess capacity in the short-run. This excess capacity can be used to deter entry and/or respond to short-term fluctuations in demand cost-efficiently. In our production theory-based analysis, investments in IT and non-IT capital are both long-run decisions. Once the capital in place is fixed, the maximum amount of variable inputs (i.e., labor and intermediate inputs) that can be used for production and sustainable maximum output (i.e., capacity) is determined. However, quasi-fixed inputs determine not only capacity but minimum efficient scale – the lowest level of output where average costs are minimized – is also determined. Consequently, our results on capacity whereby IT capital has a positive impact on capacity and a higher MP than non-IT capital strongly suggests IT capital is more effective in increasing capacity. This makes IT capital a more effective investment to increase capacity in order to deter entry and to manage demand uncertainty.

In addition, the results with our more recent dataset show that IT capital reduces CU – in contrast with most other studies that examine a single IT application or group of applications. Taken together with these other studies, and consistent with Bansak et al. (2007), IT increases both efficiency and capacity where the latter is a larger effect. Indeed, this provides more evidence that the impacts of IT go beyond individual applications and extend to organization and business processes, enhancing the productivity of other inputs, and various spillovers of value. This further supports the argument that IT capital is more valuable for a strategy of holding excess capacity.

More broadly, CU has long been a policy-related variable because of its relationship to demand pressure, and its consequent predictive power for inflation, unemployment, etc. The impact of IT capital on productivity has often been touted as a reason for relatively low inflation since the mid-1990s. Most results that support this conjecture come from the relatively large impact of IT capital on output. Although we do not examine this directly, we provide a possible alternative explanation whereby it has been the relatively larger impact of IT capital on capacity than on output, and the reduction of CU that has reduced demand pressure in industries and hence inflation in the economy.

Limitations and Future Research: Our first limitation is that our analysis is done at the industry level. Industry-level analyses are more likely to suffer from aggregation error in measurement than firm-level analyses, although such aggregation errors in measurement also exist when moving from product level to firm level. Despite the fact that our industry-level datasets are at different levels of aggregation and with different measures of IT capital, that we still obtain consistent results mitigates the chance that our results are driven by aggregation errors versus real effects between IT and capacity. Moreover, as an industry-level production function can be understood as the production function of an average firm in the industry, our results can be interpreted at the firm-level (Aigner and Chu 1968). Although the majority of IS studies are conducted at the firm level, prior research has indicated that information systems research at the industry level not only is necessary but also has significant importance to improving both information systems theories and their practical relevance (Chiasson and Davidson 2005, Ren and Dewan 2015).

Another limitation is that we have a small sample size and relatively large numbers of parameters especially in the model of capacity and CU. This may affect the power of our analysis. However, the fact that we consistently obtain significance for our main results despite the relatively small sample size makes our findings even more convincing. In addition, our IT capital measure in the earlier dataset does not contain software, which underestimates IT capital in that dataset. We realize that the inclusion of software in IT in our earlier dataset could make IT capital more significant. We also realize that some granularity is lost in not having disaggregated measures of IT. On the other hand, many types of IT are complements in production, such as hardware and software, and examining them in isolation may not capture their full effect.

We recognize that there is much to learn about how IT capital affects capacity and CU differentially among industries and applications, and how IT capital impacts capacity as compared with non-IT capital. As mentioned in the Introduction, IT has been found to have a myriad of effects on CU. It would be interesting for future research to explore IT's heterogeneous impact on CU across different types of industries. Following our contributions based on industry-level data, important contributions are possible in understanding why IT capital has different and relatively larger effects than non-IT capital, and what drives these effects. Future research should also take into consideration that the scale-up of labor and intermediate inputs for a particular industry may be time-varying.

Acknowledgments

We thank the Social Sciences and Humanities Research Council of Canada, National Natural Science Foundation of China (Project 71272077, 71490721, 71490723 and 71402031) and the E-Commerce Research Center at the School of Management of Fudan University for support. We also thank the participants of the 2011 INFORMS Conference on Information Systems and Technology, and of the University of Connecticut, the University of Kentucky, University of Maryland, and Dalian University of Technology research seminars who provided feedback on various earlier drafts. Finally, we thank Jeanette Burman for helpful editing support.

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6. Appendix

Table A1 Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Dataset I (1987-1999)				
Output (in millions of 1987 dollars)	63714.56	75386.87	2926.97	738130.80
Intermediate inputs (in millions of 1987 dollars)	36670.75	43113.01	1425.65	245896.60
Labor (in millions of hours)	913.60	899.73	27.10	3599.50
Non-IT capital stock (in millions of 1987 dollars)	43662.16	42219.60	3877.70	202606.40
IT capital stock (in millions of 1987 dollars)	3979.03	5086.10	82.60	29408.60
Capacity utilization (in percentage*100)	83.28	7.00	55.34	98.98
Capacity (in millions of 1987 dollars)	77834.01	92029.29	3078.72	885654.20
Dataset II (1998-2013)				
Output (in millions of 2009 dollars)	277205.10	284703.00	30286.68	1501812.00
Intermediate inputs (in millions of 2009 dollars)	151846.50	135729.20	4132.50	546358.30
Labor (in thousands of full-time equivalent employees)	660.49	438.77	109.00	1807.00
Non-IT capital stock (in millions of 2009 dollars)	188455.80	248737.20	12908.95	1260947.00
IT capital stock (in millions of 2009 dollars)	8483.67	14011.04	630.00	84878.00
Capacity utilization (percentage*100)	76.34	8.60	43.59	96.92
Capacity (in millions of 2009 dollars)	363035.10	377640.40	39162.56	1931607.00

Notes. Dataset I has 507 observations; Dataset II has 352 observations.

Table A2 1987 - 1999 Dataset - Three-Digit SIC Industry Description

1987 SIC Code	Industry Description
20	Food and kindred products
21	Tobacco products
221-4	Broadwoven fabric mills, cotton, wool, silk, and manmade fiber
225-7,9	Knitting mills, carpets and rugs, dyeing, finishing and miscellaneous textile goods
228	Yarn and thread mills
23	Apparel and other finished products made from fabrics and similar material
243-5,9	Millwork, plywood, and structural members, Wood containers and misc. wood products, Wood buildings and mobile homes
25	Furniture and fixtures
261	Pulp mills
262	Paper mills
263	Paperboard mills
265,7	Paperboard containers and boxes Converted paper products except containers
27	Printing, publishing, and allied industries
281	Industrial inorganic chemicals
282	Plastics materials and synthetics
283-5,9	Drugs, soap, cleaners, and toilet goods, Paints and allied products, Miscellaneous chemical products
286	Industrial organic chemicals
287	Agricultural chemicals
29	Petroleum refining and related industries
301	Tires and inner tubes
302,5,6	Rubber products, plastic hose and footwear
308	Miscellaneous plastics products, nec
31	Leather and leather products
321-3	Glass and glass products
324	Hydraulic cement
325-9	Stone, clay, and misc mineral products, Concrete, gypsum, and plaster products
331,2	Blast furnaces and basic steel products; Iron and steel foundries
34	Fabricated metal products, except machinery and transportation equipment
351-3	Engines and turbines, Farm and garden machinery; Construction and related machinery

354-6,8,9	Metalworking machinery and equipment; Special industry machinery; General industrial machinery and equipment; Refrigeration and service industry machinery; Industrial machinery nec.
357	Computer and office equipment
363,5	Household appliances, Household audio and video equipment
366	Communication equipment
371	Motor vehicles and equipment
372	Aircraft and parts
373	Ship and boat building and repairing
374-6,9	Railroad equipment, motorcycles, bicycles, Guided missiles and space vehicles, Miscellaneous Trans. Equipment
38	Measuring, analyzing and controlling instruments; photographic, medical and optical goods; watches and clocks
39	Misc. manufacturing industries

Table A3 1998–2013 Dataset - Three-Digit NAICS Industry Description

2007 NAICS Code	Industry Title
211	Oil and Gas Extraction
212	Mining (except Oil and Gas)
213	Support Activities for Mining
22	Utilities
311,312 (311FT)	Food and beverage and tobacco products
313,314 (313TT)	Textile mills and textile product mills
315,316 (315AL)	Apparel and leather and allied products
321	Wood products
322	Paper products
323	Printing and related support activities
324	Petroleum and coal products
325	Chemical products
326	Plastics and rubber products
327	Nonmetallic mineral products
331	Primary metals
332	Fabricated metal products
333	Machinery
334	Computer and electronic products
335	Electrical equipment, appliances, and components
336	Transportation Equipment
337	Furniture and related products
339	Miscellaneous manufacturing

Table A4 Results for 2SLS Estimation

	1987-1999			1998-2013		
	Output	Capacity	CU	Output	Capacity	CU
	Output Elasticities					
IT Capital	0.206 ***	0.211 ***	-0.037 **	0.154 ***	0.181 ***	-0.020 **
	(0.019)	(0.022)	(0.016)	(0.021)	(0.041)	(0.011)
Non-IT Capital	0.032 ***	0.348 ***	-0.500 ***	0.096 ***	0.454 ***	-0.391 ***
	(0.013)	(0.095)	(0.069)	(0.035)	(0.136)	(0.085)
	Marginal Products					
IT Capital	6.713 ***	8.269 ***	-4.92% **	8.291 ***	12.855 ***	-0.52% **
	(0.619)	(0.857)	(2.111)	(1.131)	(2.912)	(0.003)
Non-IT Capital	0.049 ***	0.651 ***	-2.36% ***	0.198 ***	1.244 ***	-0.41% ***
	(0.02)	(0.179)	(0.329)	(0.072)	(0.373)	(0.001)

Notes. Log dependent variable and input variables.
∗p<0.10, ∗∗p<0.05, ∗∗∗p<0.01. Standard errors in parentheses.

Table A5 Results for the Sargan Tests

	Output	Capacity	CU
1987 - 1999	0.484	0.565	0.114
1998 - 2013	0.181	0.282	0.291

Notes. The numbers are p-values of the Sargan tests.
∗p<0.10, ∗∗p<0.05, ∗∗∗p<0.01.

Table A6 Correlations between the Residuals and the Independent Variables

	1987 - 1999			1998-2013		
	Output	Capacity	CU	Output	Capacity	CU
IT Capital	0.129	-0.088	-0.008	0.067	0.030	0.107
Non-IT Capital	-0.036	-0.036	-0.001	0.066	0.172	0.069
Labor	-0.063	-0.035	-0.022	0.163	-0.155	0.041
Intermediate Inputs	0.056	-0.031	-0.026	0.196	0.185	0.067