Producing Synergy: Innovation, IT and Productivity

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Abstract

Bringing innovations to market is critical to industrial progress and economic growth. We explore the potential for IT to enable innovations, and thus improve productivity. We hypothesize that a knowledge stock of process-oriented R&D increases total factor productivity growth by leveraging traditional forms of capital and labor, and further enhances the ability of IT capital to increase productivity. We estimate these relationships using two broad panels of US industries covering the periods 1987–1998 and 1998–2005. The results indicate qualified support for a synergistic effect of R&D and IT investment in both periods.

1 INTRODUCTION

The modern pursuit of innovation depends heavily upon information technology (IT). Most innovations we now encounter, if not entirely based upon IT, have been touched by it in some way. Advances in computing power and applications are not only evident in everything from smartphones to cars, but are inextricably involved in the development of new drugs, logistics services and mass customization processes. In its ubiquity, IT plays multiple roles. As an input to innovation, IT leads through automating, communicating and managing data, and enabling new methods of exploration (Thomke, 1998). This is the basis for some of the existing results in the literature (e.g., Kleis, Chwelos, Ramirez, and Cockburn (2012)). IT can also be an output of innovation as a class of innovative products, and as a form of capital that displaces labor and complements traditional capital (Chwelos, Ramirez, Kraemer, and Melville, 2010). Finally, IT can be the basis of, or an enabler of, innovation-driven changes in productivity.

Our focus is on the impact of efforts in innovation, which we measure as R&D, on IT as an input to production in a productivity-based model. As such, our approach is theoretically derived from production theory whereby output, measured as value-added, results from IT capital, non-IT capital and labor. The impact of innovation effort is on each of the inputs, and is combined with IT as an indirect effect on non-IT capital and labor, the latter effect being similar to that in Mittal and Nault (2009). Our model recognizes that firms continue to invest in established research and development (R&D) approaches to innovation with the goal of improving their processes and products. These investments in part allow IT to contribute to the firm's productivity. Consider a firm that develops an innovative production process: once implemented, it must reallocate some of its inputs (labor, non-IT capital, IT capital) to accommodate the new process. It has been shown that IT supports this reallocation by improving flexibility of production within an existing manufacturing setup (Bartel, Ichniowski, and Shaw, 2007), and enabling new possibilities for production scaling and new product introduction (Gao and Hitt, 2011) that could facilitate the successful implementation of a process innovation.

Working through the mechanisms of our model, the impact of R&D is related to the productivity of IT, and IT and R&D *together* have an indirect relationship with the other inputs. The indirect effects of IT and R&D both separately and together explain part of total factor productivity (TFP), and the presence of positive indirect effects of IT and R&D *together* is evidence of R&D/IT complementarities. To underscore our focus on R&D/IT complementarities we cite a broad base of current literature, from economics, business and fundamental sciences.

Recent research stresses the importance of synergy in various factors of business that will lead to greater competitiveness in the 21st century. Comin and Hobijn (2012) examined technological innovations dating from the late 18th century to today: from steam power to personal computers. They found technology adoption lags accounted for 25% of the differences in a country's per capita income. Most recently however, the adoption of modern IT in the form of cell phones and personal computers showed a much shortened time period for technology adoption between the advanced, industrial nations and the rapidly developing ones, e.g., the USA in 1980 and Pakistan following a few years later in 1987–88. Of all technologies, modern IT has the most rapid rate of adoption across nations. Pisano and Shih (2012) found that process-embedded and process-driven innovations require close connections between design and manufacturing. Design cannot be separated from manufacturing for products such as heat-treated metal fabrications, other advanced materials, and specialty chemicals. Further products such as biotech drugs, nano-materials and super-miniaturized assembly suffer large risks from separating design and manufacturing, highlighting the complementarities between R&D and IT. Porter and Rivkin (2012) studied seventeen macro and micro elements in the business environment that influence how productive the US is relative to other nations, surveying nearly 10,000 Harvard Business School alumni. Communications infrastructure based on IT (e.g., high quality and widely available telephony, Internet, and data access) and innovation infrastructure based on R&D (e.g., high-quality scientific research institutions and availability of scientists and engineers) are two factors identified as drivers of long run national productivity and prosperity differences amongst nations.

A major transformation of manufacturing is now underway, largely due to advances in R&D implemented through IT (Economist, 2012e). Driven by new manufacturing processes, three major changes have occurred: improved efficiency, increased flexibility, and new capabilities. First, factories are improving labor efficiency due to advances in robotics, materials handling and the use of less materials in production. For example, a Nissan factory in Sunderland, England, produced almost twice as many cars in 2011 as it did in 1999, with only one fifth more workers. Second, increased flexibility from digitized designs and computercontrolled custom manufacturing machinery vastly reduce the cost of producing a new or different design with the same machine. This has implications for economies of scope by reducing the risk of marketing a new design: testing and training can be done in the virtual realm, and physical prototypes can be produced far more quickly and easily. Moreover, changeover time is dramatically shortened. Third, these new, digitally driven, flexible manufacturing technologies are enabling new capabilities through entirely new manufacturing processes.

Collaborative manufacturing and additive manufacturing offer compelling examples of how the synergy between R&D and IT is transforming the manufacturing process. In collaborative manufacturing, the advent of digital designs being transmitted online to globally-dispersed 3D printing facilities reduces risk and cost due to the improved ease of creating prototypes (Economist, 2012c). Speed-to-market improves because 3D scanners and printers can produce instant copies of new objects. Further, the traditional model of in-house product development and commercialization may be challenged by an emerging web of individuals and small companies, connected through an online community. Individuals propose ideas, the community votes for their favourites, and a small shop creates prototypes with laser cutting and milling machines and a 3D printer. After further rounds of social-media test-marketing and refinement, the product is sent to a large-scale manufacturer.

Additive Manufacturing, also known as 3D printing, is a new approach to manufacturing that allows the production of designs and products previously considered too complex to be made economically (Economist, 2012a). The additive approach yields significant reductions in materials used to manufacture parts because nearly no waste is generated by creating objects using small particles layer-by-layer, versus cutting a shape from a solid block. Advanced designs of previously-infeasible complexity can be modeled with software and finished with

3D printing. One example from the aerospace industry is Rolls Royce's system of casting jet engine turbine blades in a unique production process that creates a continuous crystalline structure in the metal(Economist, 2012d). The IT-R&D complementarity is seen here in the electronically-controlled high-precision process required to produce ducts and ports that allow air to envelop the blade while in motion, preventing melting and enabling more efficient high-temperature combustion. In pharmaceuticals, the additive approach may enable new continuous manufacturing processes that are being tested at Novartis, which, if successful, will revolutionize the conventional batch-process approach to drug manufacturing (Economist, 2012b). Improvements in speed, testing, and flexibility are showing promise, and if successful, could make new treatments commercially viable.

IT Productivity Literature Existing productivity research has established IT as a distinct form of capital investment. These studies suggest IT contributes to productivity by substituting for less-efficient labor and, in some cases, capital (Dewan and Min, 1997; Mohammad, Zhang, Cheng, and Nault, 2009; Chwelos et al., 2010). Using industry-level data over a 30-year period, Hu and Quan (2005) found that IT leads to productivity growth (measured in GDP per employee) in most industries, and that feedback from these productivity gains leads to subsequent increases in IT spending.

IT's capacity for transforming business offers the greatest ongoing potential for productivity gains. David (1990) proposed that IT is a general purpose technology (GPT) which, like electricity or the steam engine, creates the conditions for widespread technological change due to its flexibility and stimulation of innovation. IT has enabled new organizational forms and improved the quality and variety of a firm's products (Brynjolfsson and Hitt, 2000; Brynjolfsson, Hitt, and Yang, 2002; Gao and Hitt, 2011). One way of measuring this transformative capacity is to consider the augmented productive capacity of the traditional labor and capital inputs owing to IT capital. Mittal and Nault (2009) found evidence of such IT augmentation in a study of US manufacturing industries from 1953–2000, with a greater effect over time and in the most IT-intensive industries. Other research has shown mixed results. Rapid price declines and quality improvements in IT lead to potential productivity mismeasurement across industries (Cheng and Nault, 2007; Han, Kauffman, and Nault, 2011).

Perhaps the most important aspect of IT's transformative power, as outlined above, is the potential for IT to shift productivity through technological innovation. Extant research has shown some evidence for IT's role as both an input to, and output of, innovation. The third role, wherein IT enables the commercialization and production of innovations, has not been addressed. Although the potential for IT to facilitate process innovations (and, by extension, productivity) has garnered much attention in the popular press, only a few researchers have investigated this relationship empirically. We could find only two papers that model the interaction between IT and innovation, Kleis et al. (2012) and Bardhan, Krishnan, and Lin (2010), and it is helpful to compare these papers to ours in order to better understand our contribution and how our contribution enhances theirs.

We use a traditional productivity model where the dependent variable is value-added, whereas the other works focus on innovations or intangibles: Kleis et al. (2012) use an innovation measure (citation-weighted patents) and Bardhan et al. (2010) use a market-to-accounting measure (Tobin's q). The data used in those papers is firm-level, and the dependent variable represents a theoretical construct (innovation or intangibles). In contrast, our data and analysis is industry-level and, consistent with productivity theory, the dependent variable is not a construct but rather an actual measure of output. Moreover, it is well known that R&D spills over within industries, and an industry-level measure of

R&D better captures these spillovers. Our work is consistent with these other papers as in our productivity model our indirect effects of IT and R&D both separately and together explain part of total factor productivity (TFP), and both innovation and intangibles are often understood to be generators of TFP. In terms of results, Kleis et al. (2012) find both IT and R&D separately have positive relationships with citation-weighted patents, but no significant interactions. Bardhan et al. (2010) find a positive main effect for R&D and IT, but when the interaction term is added the main effect of IT is no longer significant. However, more meaningful comparisons are not possible because the dependent variables are not comparable.

Innovation and Productivity Considerable prior research has modeled and measured the relationship between R&D and productivity. Griliches (1988, ch.15) summarized the general approach taken by researchers, extending the production function approach to include research and development activities. Using a three equation system,

$$Q = Tf(C, L); \quad T = g(I, O); \quad I = \sum w_j R_{t-j}$$

where in the first equation Q is output, T is total factor productivity, and C and L are capital and labor inputs, respectively. In the second equation I is a stock of productive research capital, or knowledge, and O represents other factors affecting productivity. The third equation relates the weighted sum of gross investment in research, R, to productive research capital, I, (Griliches, 1988, p.246).

The first equation concerns production and technological change: how does productivity advance beyond increased quantities of the inputs? The answer is through technology. In the growth accounting framework, the factor-neutral technology constant, in essence, sets an intercept for the firm's ability to efficiently transform inputs into outputs. It is a residual because it is not modeled explicitly; it is the leftover portion of productivity that cannot be explained by changes in input quantities.

In the foregoing framework, R&D enters the production function via a system of equations, and is not considered an input in the classical sense of capital and labor (the first equation). Some researchers have taken the approach that R&D should be treated as a stock of knowledge that is an input, beginning with Griliches (1979) and continuing to the present (Mairesse and Sassenou (1991); Hall, Mairesse, and Mohnen (2009)). Other researchers have included knowledge stock as part of the technology residual (Lichtenberg and Siegel, 1991; Siegel, 1997).

In the second equation, T (technology) originates from knowledge and "other factors." Knowledge and R&D spillovers, in particular, are of interest (Scherer, 1982; Griliches and Lichtenberg, 1984; Griliches, 1992). Although measurement of these spillover effects has proven difficult, researchers acknowledge the importance of industry concentration and R&D intensity is a primary factor (Acs and Audretsch, 1991, ch.1), and the fact that the flow of spillovers is proportional to the flow of trade between industries (Los and Verspagen, 2002). Addressing the latter, "borrowed R&D" comes from purchases, and can account for more of the return-to-R&D than the industry's own R&D (Nadiri, 1993), although other findings generally indicate firms need to spend on R&D in order to appropriate spillovers.

In the third equation, the genesis of knowledge is the R&D process. Many researchers have proposed measures of the knowledge stock and its rate of accretion/depreciation. Hall (2005) explores some of the difficulties in estimating the true rate of R&D depreciation. The R&D "knowledge production function" (Griliches, 1979) has featured prominently in this literature. However, even "private" R&D can be subject to external characteristics and influences, through contract R&D and government-funded research.

Drawing on the innovation-productivity literature and the IT productivity literature, our research opens a new area of IT productivity research by investigating the indirect effects of R&D and IT on output (via non-IT capital and labor) at the industry level. In doing so, we provide evidence of the presence and size of these effects and compare them to the estimates from traditional approaches to productivity analysis. We estimate whether these indirect effects exist, to what degree they vary over time and across industries, and to what extent they are salient. We distinguish between the indirect effects of R&D and IT, and estimate the interaction of the two, which represents the synergistic effect of R&D in concert with IT upon the traditional factor inputs. In addition to our analysis of this aspect of IT value, we offer new insights into the influence of innovation and how these translate to productivity at the industry level.

Our paper proceeds as follows. First we provide a model to guide our empirical analysis. We then describe the construction of our data sets: the first based upon the Standard Industrial Classification (SIC) codes, the second and third on the North American Industry Classification System (NAICS). We then present our empirical analyses, various econometric adjustments, and a discussion of the findings. We conclude by describing our study's limitations and suggestions for future research.

2 MODEL

We hypothesize that a knowledge stock of process-oriented R&D improves the efficiency of inputs by means of an indirect effect. This can be expressed in the following generalized form of a production function:

$$Y = f(h_1 K, h_2 L, h_3 Z),$$

where output, Y, is a function of non-IT capital K, labor L, and IT capital Z, and the terms h_1, h_2 and h_3 represent the indirect (augmenting) effects on the inputs. In other words, h_3, for instance, can be characterized as a scaling factor applied to Z, so that $h_3 Z$ represents the effective quantity available for production. Although we conceive of this relationship at the firm level, we will perform our analysis at the industry level. Prior research has shown such aggregation of firm-level production functions is feasible for an industry composed of similar firms. In our context, the industry level of analysis also allows us to better represent the returns to intra-industry R&D spillovers, as discussed above.

If we assume a standard Cobb-Douglas functional form, we have:

$$Y = A[h_1 K]^{\beta_1}[h_2 L]^{\beta_2}[h_3 Z]^{\beta_3}, \tag{1}$$

where A is the technological change parameter, also known as total factor productivity. Subscripts for industry and time are omitted for ease of exposition.

We hypothesize that h_3, the indirect effect on Z, is a function of the knowledge stock of process-oriented R&D, denoted R below. However, past research offers evidence that Z creates indirect effects on K and L. Building on this, we model the indirect effects on K and L (h_1 and h_2, respectively) as being driven by both R&D and the *R&D-augmented*-IT capital. This structure allows R&D stock to enter the production function in a novel way. Because it is not directly involved in production, modeling R&D as a factor input can be problematic. Rather, in this model we conceive of it as a parallel business endeavour in which the industry invests and receives a dividend in the form of a scaling factor on the industry's effective quantity of the factor inputs. Although some innovation may be applied directly to non-IT capital and labor, we propose that the capabilities of IT to improve input efficiencies also provide a mechanism by which process innovations may be implemented in production. Thus, the efficiency improvements from R&D on IT capital "flow through" to improve the efficiency of non-IT capital and labor, along with the conventional indirect effect of R&D on non-IT capital and labor. In so doing we reclaim some of the efficiency of the factors that would otherwise be lost to the total factor productivity term (i.e. the constant A).

Figure 1 presents this diagrammatically, with the dashed lines representing indirect effects (labeled α, α', α'', to be introduced below) and solid lines representing direct effects. The measured amounts of K, L, Z, R and Y are depicted in square boxes, and the effective amounts of K^*, L^* and Z^* in rounded boxes.

*** Insert Figure 1 here ***

The structure of the scaling factors may be expressed as:

$$h_1 = f_1(R, Z(R)), \;\; h_2 = f_2(R, Z(R)), \;\; h_3 = f_3(R).$$

Now, let us define these terms with specific exponential forms:

$$h_1 = e^{(\alpha_1 R + (\alpha_1' + \alpha_1'' R)Z)}, \;\; h_2 = e^{(\alpha_2 R + (\alpha_2' + \alpha_2'' R)Z)}, \;\; h_3 = e^{\alpha_3 R}.$$

With these equations, we model the indirect effect of R&D through IT as a multiplicative effect. Although IT and R&D each drive productivity improvements in labor and non-IT capital, they produce an additional effect in combination.

We now adopt the assumption that the indirect effect of Z acts upon K and L in the same way; that is, for a given investment in IT capital, the effective amounts of non-IT capital and labor are changed by the same factor. This generalization allows us to estimate a general effect of Z (and, separately, ZR) on both K and L. Although the magnitudes of the indirect effects may be different, this is not essential to our research question. We impose the following constraints, based on the assumption that the indirect effects of $Z(R)$ and Z

are independent of K and L : $\alpha_1^{'} = \alpha_2^{'} = \alpha^{'}$ and $\alpha_1^{''} = \alpha_2^{''} = \alpha^{''}$. Now,

$$\begin{aligned} h_1 &= e^{(\alpha_1 R + (\alpha^{'} + \alpha^{''} R) Z)} \quad (2) \\ h_2 &= e^{(\alpha_2 R + (\alpha^{'} + \alpha^{''} R) Z)} \quad (3) \\ h_3 &= e^{\alpha_3 R}. \quad (4) \end{aligned}$$

Substituting the terms into the Cobb-Douglas production function (equation (1)), we have:

$$Y = A[e^{(\alpha_1 R + \alpha^{'} Z + \alpha^{''} ZR)} K]^{\beta_1} [e^{(\alpha_2 R + \alpha^{'} Z + \alpha^{''} ZR)} L]^{\beta_2} [e^{\alpha_3 R} Z]^{\beta_3}.$$

Taking the log of both sides and collecting the terms, we have:

$$\begin{aligned} y &= a + \beta_1 k + \beta_2 l + \beta_3 z + (\beta_1 \alpha_1 + \beta_2 \alpha_2 + \beta_3 \alpha_3) R \\ &\quad + \alpha^{'} (\beta_1 + \beta_2) Z + \alpha^{''} (\beta_1 + \beta_2) ZR \\ &= a + \beta_1 k + \beta_2 l + \beta_3 z + \theta_1 R + \theta_2 Z + \theta_3 ZR, \quad (5) \end{aligned}$$

where $\theta_1 = \beta_1 \alpha_1 + \beta_2 \alpha_2 + \beta_3 \alpha_3$, $\theta_2 = \alpha^{'} (\beta_1 + \beta_2)$, and $\theta_3 = \alpha^{''} (\beta_1 + \beta_2)$. Lowercase letters are used for variables where the natural log has been taken. Note the estimates of $\alpha^{'}$ and $\alpha^{''}$ are recoverable, but α_1, α_2 and α_3 are not separately recoverable. Thus we are able to estimate the indirect effect of R on K, L and Z collectively, and the indirect effect of Z and ZR on K and L, collectively. We may impose $\alpha_1 = \alpha_2 = \alpha_3 = \alpha$, such that the indirect effect of R&D is the same on non-IT capital, IT capital and labor. Under this restriction, we could identify all the parameters in the model, as $\theta_1 = \alpha(\beta_1 + \beta_2 + \beta_3)$. However, it is reasonable to expect that Z and R have differing indirect effects on K and L (i.e. $h_1 \neq h_2$).

2.1 Interpreting the Coefficients

In the Cobb-Douglas production function, the main-effect coefficients β_1 and β_2 are the output elasticities for each input. Thus, β_1 is the expected percentage change in Y for a percentage change in K, and β_2 is the equivalent for L. However, our main interest is whether the estimates of the indirect effects of IT capital and R&D, and their interaction, are positive and significant. By specifying the production function with both direct and indirect effects, we are able to separately estimate the direct contribution of IT capital to production, along with its indirect impact on labor and non-IT capital. We expect this to be positive in confirmation of the existing literature (Mittal and Nault, 2009). Likewise, we expect to find a positive indirect effect of R&D.

In order to interpret the overall impact of IT capital on productivity we must simultaneously account for the direct and indrect effects. The indirect effects deserve special attention due to the functional form and, in particular, the interaction. Although θ_1 and θ_2 represent a part of these effects, the overall indirect effect of R and Z also depends on ZR. Therefore we compute the estimate of the partial elasticity for R, and the output elasticity of Z (which includes all direct and indirect effects of IT capital).

The partial elasticity of R is derived from the production function (equation (5)), and is given by:

$$\partial \ln Y / \partial R = (\beta_1\alpha_1 + \beta_2\alpha_2 + \beta_3\alpha_3) + \alpha''(\beta_1 + \beta_2)Z = \theta_1 + \theta_3 Z. \tag{6}$$

Because R is not in log form, the partial elasticity expresses the percentage change in Y given a *unit* change in R (in our estimates, the unit is billions of dollars). As the elasticity is dependent on the level of Z, it would be evaluated at the mean or median value of Z.

We estimate the output elasticity of IT:

$$\partial \ln Y / \partial \ln Z = \beta_3 + \theta_2 Z + \theta_3 ZR, \tag{7}$$

which expresses the expected percentage change in Y given a percentage change in Z, including both direct and indirect effects. This may be compared to the output elasticity of

Z in the Cobb-Douglas specification to see the change induced by adding indirect effects to the estimation.

3 DATA

Using data from U.S. government agencies, we construct two datasets: 1987–1998 and 1998–2005, based on the Standard Industrial Classification (SIC) and North American Industry Classification System (NAICS) standards, respectively. Due to the change from SIC to NAICS in 1998, the data are not directly comparable across eras. While some industries are similarly-defined under both regimes, the aggregation of industries in our R&D data renders impossible any attempt to convert SIC to NAICS for much of our sample. We construct a third dataset, spanning the years 1998–2005, that draws R&D data from Standard and Poor's Compustat. All datasets are constructed in a similar manner from widely available sources. Summary statistics are reported in Table 1.

3.1 Dataset I: 1987–1998

Dataset I is a balanced panel of 276 observations (23 manufacturing industries) for the years 1987–1998. The following paragraphs explain the construction of this dataset.

Multifactor Productivity (MFP) Data The MFP data is the same as that used in Cheng and Nault (2007, 2012), which was originally collected by the Bureau of Labor Statistics (BLS). The BLS tracks gross output, capital, labor hours, and intermediate inputs (energy, materials and services) for all domestic industries. For the period 1987–1999, there are 140 industries in the data at the 3-digit SIC level. The variables consist of output and intermediate purchases in millions of nominal dollars. Capital equipment is in millions of nominal dollars, while labor is measured in millions of hours.

In order to prepare the data for analysis we perform several manipulations. First, we drop any observation where any data element is missing. Second, the published BLS data for this period is considered more reliable for manufacturing industries, so we drop non-manufacturing industries. Third, to create separate amounts of IT capital stock and non-IT capital stock, we identify five asset types that comprise IT and related equipment (computers & related equipment, office equipment, communication, instruments, photocopy & related equipment) in the capital stock data, which are expressed in constant 1987 dollars. The remaining 25 categories become non-IT capital stock. The BLS classifies productive capital into five classes: structures, equipment, land, rental residential capital and inventories. In our definition of capital and non-IT capital, the last three classes are excluded. Fourth, value added is calculated as gross output less intermediate inputs, each of which is deflated to constant 1987 dollars (using the output and intermediate input deflators, respectively).

R&D Data We construct a measure of industry R&D stock based on data obtained from the National Science Foundation (NSF) Survey of Industrial Research and Development ((National Science Foundation, 2009)). The survey is an ongoing project, since the late 1950s, to provide data about corporate R&D for policymakers, researchers and industry. The survey is based on a sample that seeks to include all for-profit companies that perform R&D, and automatically includes all companies with 1000 or more employees (the 1987 sample size was 154,000 companies). The NSF updates the sample annually to ensure that firms previously excluded on the basis of not having R&D activity are included if they begin to undertake R&D. The survey is administered by the Bureau of the Census and firms are required by law to respond. Individual surveys are sent to establishments (i.e. prominent research labs or manufacturing installations), but the data is aggregated by company, and the company is categorized into the SIC designation based on the type of business which had the highest dollar share of payroll. Additional details of the NSF's sampling technique are available on its website (`http://www.nsf.gov/statistics/srvyindustry/`). For the purposes of measuring company and federally-funded R&D, the data covers the period 1967–1998. It is organized by SIC; however, individual SIC codes at the 2-digit and 3-digit level are sometimes combined into aggregated categories. The NSF table H-3 reports company-funded R&D spending at U.S. locations. The amount of R&D is reported in millions of nominal dollars. We use the GDP deflator to convert these amounts to constant 1987 dollars. The Bureau of Economic Analysis (BEA) has produced an R&D input price index for the years 1987–1999, and its correlation to the GDP index is 0.9995.

The NSF data reports annual expenditure on R&D at the industry level. However, the concept of a *stock* of R&D-related knowledge is more useful when modeling the innovation process and its relationship with productivity (as in the aforementioned system of equations owed to Griliches (1988)). There are three main reasons why it is appropriate to construct such a measure. First, stock is the more appropriate concept in production because the innovation process exploits an accumulated stock of knowledge. This knowledge stock changes over time in response to many internal and external factors, of which R&D investments are the most directly observable. Second, the knowledge stock concept facilitates the lag structure linking R&D spending with innovation output and accommodates heterogeneity in the lag structure across industries. Finally, the knowledge stock concept better represents intra-industry knowledge spillovers that could further obscure the relationship between innovation investment and output due to delays in innovations finding their best economic use within an industry. In addition, research suggests the receiving firm's R&D expenditure is complementary to spillovers by creating absorptive capacity (Cohen and Levinthal, 1990; Cockburn and Henderson, 1998).

To generate R&D stock using annual expenditures, we use the perpetual inventory method with a depreciation rate (δ) of 15%. The initial amount of R&D stock is calculated as:

$$Stock_{t_0} = \frac{Expenditure_{t_0}}{(1-\delta)},$$

where $Expenditure_{t_0}$ is the expenditure in a base year. For each subsequent year, the stock is computed:

$$Stock_t = (1-\delta)Stock_{t-1} + Expenditure_t.$$

Ideally, one should begin calculating the stock several years prior to the first year for which the measure is used in analysis in order to smooth out any unusual movements in the annual R&D expense. For Dataset I, we begin with the R&D data for 1982 and apply this formula to compute a stock for 1983–1998.

As the R&D data are aggregated at different SIC levels, some adjustments are required in order to merge with the MFP and other data from BLS. Of the 31 NSF industry groups, 4 are at the 2-digit level, 5 are combinations of 2-digit industries, 6 are at the 3-digit level, and 10 are combinations of 3-digit industries. To preserve the largest number of observations, we use this scheme as the basis for aggregating MFP data. Wherever possible, we match 3-digit industries from both sources. Where one source aggregates several 3-digit industries, or reports only the 2-digit industry, we replicate this aggregation in the other source. Finally, we drop any industries missing an observation in either the first or last year. When combined with MFP data, this yields an integrated data set of 276 observations with 23 industries over the years 1987–1998. Some industries do not have R&D data for certain years due to NSF confidentiality policies. One industry is missing an observation for 1989, and 5 industries are missing observations in 1991. We use linear interpolation to generate these observations. Table 2 lists the industry groups by which the dataset is organized.

3.2 Dataset II: 1998–2005

Dataset II consists of a balanced panel of 200 observations (25 industries). It is a continuation of the first dataset, but differs in two material ways. The industries, although comparable in number, are aggregated into larger groups. It also includes non-manufacturing industries, such as Information and Finance, Insurance and Real Estate.

MFP Data Other than being organized by NAICS, the MFP data is comparable to the first dataset. Labor hours, IT and non-IT capital stock are obtained from the BLS. One notable difference in the NAICS-based data is that the BLS includes software in IT capital stock, which was not available in the SIC-based data. Thus, our measure of Z better reflects the actual investment in IT in Dataset II. To calculate value added, we subtract intermediate inputs from gross output by 3-digit NAICS industry. These amounts, expressed in constant 2005 dollars, are obtained from the BEA.

R&D Data As with Dataset I, we obtain R&D data from the NSF's annual R&D in Industry reports that present the results of their Survey of Industrial Research and Development. Beginning with 1999, the industries are grouped by NAICS. In order to facilitate the transition to NAICS, the NSF also provides bridge tables for 1997 and 1998. Thus, NAICS-based data are available from 1997 to 2008. We are unable to use the years 2006–2008 due to changes made by the NSF to the industry aggregations in 2006 and again in 2008, which result in the data not being comparable to earlier years. We use 1997 as the base year for our R&D stock calculation, which we create as before, with the standard 15% rate and perpetual inventory method.

As with the earlier SIC-based reports, the NSF does not report R&D on a consistent level of NAICS industry aggregation. Some industries are aggregated to the 2-digit level, while others are broken down to the 4-digit level. To facilitate matching to the MFP data, we choose the 3-digit level where available, using the 2-digit level where necessary. Table 3 lists the industry groups by which the dataset is organized.

We obtain the amount of company- and non-federally-funded R&D from NSF table A-7 for 1998, NSF table 12 for 1999–2003, and NSF table 1 for 2004–2005. These tables report R&D performed within the company's U.S. facilities, funded (predominantly) by the company or outside organizations excluding the federal government. Because company-funded R&D is unavailable for two industries (NAICS 312 and 324) in 1999, the missing observations are generated by linear interpolation. Two major industries, wholesale trade and retail trade, are unavailable prior to 2002 so we exclude these industries. In all cases, the amount of R&D is reported in millions of nominal dollars. We use the BEA GDP deflator (as published August 20, 2009) to convert these amounts to constant 2005 dollars.

3.3 Dataset III: 1998–2005 Compustat

In order to further test the robustness of our results from Dataset II, we construct a third dataset at the industry level using an alternative source of R&D data that provides a more consistent level of industry aggregation. As with Dataset II, this dataset covers the 1998–2005 period and uses NAICS industries. Further, the labor, non-IT capital and IT capital data is identical to the source data used in the construction of Dataset II. The main difference between the two datasets is that we are able to retain the 3-digit NAICS industry aggregation found in the MFP source data. We obtain R&D data from Standard and Poor's Compustat Industrial Annual, which captures firm-level data from the annual reports of publicly-traded companies listed on all US exchanges. The total number of firms reporting R&D Expense was 13,277 during the sample period (plus a 5-year lead period). We sum the

R&D expenditures by industry and match this with the MFP data, dropping any industry that does not report R&D expense in any of the sample years. The resulting total number of industries is 38, in a balanced panel over 8 years. We compute R&D stock as before, using a 5-year lead to reduce the influence of an usual observation on initial values of the R&D stock.

We recognize that our datasets are aggregations over firms in a given industry. As suggested by Cheng and Nault (2012), the use of industry-level datasets at different levels of aggregation and with different measures of IT capital yielding consistent results mitigates the chances that the results are due to aggregation. In addition, as we know from Kundisch, Mittal, and Nault (2013), as well as some prior work in economics, aggregation from firm-level to industry-level poses few problems with Cobb-Douglas-related forms. Finally, as we describe below, we do control for industry-level effects through our econometric adjustments.

4 RESULTS

We present our analysis in three parts. We first describe the estimation strategies and econometric adjustments appropriate to industry-level panel data. Next, we estimate several variations of our research model using panel regression. Finally, we explore an alternative model specification, and check if our results are robust to the inclusion of software in IT capital in Dataset I.

The dependent variable in all estimations is the natural log of value added. Where variables are shown in lowercase, the natural log has been taken. The variables are rescaled to billions of dollars to improve the readability of the estimates. In all estimations, we assume a multiplicative error structure on the production function (in its log form).

4.1 Econometric Adjustments

Ordinary least-squares (OLS) regression techniques are sensitive to a number of violations of underlying assumptions with respect to error structure, which can bias the estimation results. There are three main concerns with cross-sectional time-series data: autocorrelation in the time series due to repeated measures of the same industries and common economic cycles, industry-level heterogeneity due to industry differences, and heteroskedastic errors.

To test for first-order autocorrelation of errors (AR(1)), we use the Wooldridge test. We find that AR(1) is clearly present in all datasets. Since the test is a post-estimation procedure we run it following our estimation of both the Cobb-Douglas and full model specifications using GLS. Under the null hypothesis, there is no first-order autocorrelation. The test rejects the null hypothesis for both Cobb-Douglas and our full model, on all three datasets, with p-values well below 0.001. Thus we may reject the null hypothesis of no autocorrelation. To address industry-level heterogeneity we considered that the AR(1) process may differ by industry. We test for whether panel-specific AR(1), or PSAR(1), adjustment is warranted using a Likelihood Ratio (LR) test with the Cobb-Douglas specification. We found significant evidence that using PSAR(1) was warranted for all datasets. This tests whether, under H_0, $\rho_1 = \ldots = \rho_{25}$; under H_1, the correlations are not equal. The difference in likelihoods (PSAR1-AR1) for the indirect effects model in equation (5) is significant at the 1% level of significance. As an additional confirmation, we test the Cobb-Douglas specification and find the difference in likelihoods is significant. Therefore we reject the null hypothesis that the ρ coefficients are equal to one another, and conclude that there is evidence to support using a panel-specific autocorrelation parameter. Finally, we use an LR test to check whether heteroskedasticity is present in the error terms, and find evidence of it in all three datasets. The null hypothesis is that a nonhetereoskedastic model is nested in a heteroskedastic model. The test statistics are highly significant, so we reject the null hypothesis. An alternative test is the modified Wald test for groupwise heteroskedasticity in time-series feasible GLS model (implemented in the Stata 11 software as `xttest3`). Under the null hypothesis, $\sigma_i^2 = \sigma^2$ for all i. The test statistics for all datasets are highly significant at any reasonable level. Thus we conclude there is strong evidence for heteroskedasticity in the sample and we must correct for it. Consequently, we use cross-sectional time series Generalized Least Squares, and control for PSAR(1) and for heteroskedasticity (hereafter labeled He+PSAR1). In the appendix, we compare these estimates to those from a random-effects estimation with first-order autoregressive errors (labeled AR1). We control for cross-sectional temporal unobservables by adding a dummy variable for each year to all regressions (for brevity, we omit these coefficient estimates from the results tables).

In addition to the foregoing tests related to error structure, we assess the conformity of the data to the assumption that it is normally-distributed. Although the skewness for R&D stock in Datasets I and II is mild to moderate, it is substantially more pronounced in Dataset III. We therefore use the Box-Cox transformation on R&D stock in Dataset III to mitigate the effect of this skew on our regression estimates.

4.2 Estimation Results

The results for our three datasets are presented in Tables 5 and 6, and 7, respectively. Starting with Table 5, we obtain a reasonable result from the Cobb-Douglas specification in column (1): all three inputs are positive and significant, with magnitudes relatively close to the findings of other researchers on similar samples, although the output elasticity for IT, at 0.246, is unusually high compared to prior studies (e.g., in Mittal and Nault (2009) the Cobb-Douglas IT output elasticity is 0.12 for their most comparable sample period). For our full model in column (2), the estimated coefficients are positive and significant for k, l, and z, while the indirect effect of Z is negative and significant. The indirect effect of R is not significant, but the interaction term ZR is positive and significant. This suggests that the while the indirect effect of IT on the other inputs may not be positive, there is a positive indirect effect when combined with R&D. Because of the interaction (and, in the case of Z, the overall direct effect), the net effects need to be evaluated according to the elasticities in equations (6) and (7), while the indirect effects may be evaluated in the context of the scaling factors in equations (2) and (3). We further discuss these elasticities in subsection 4.2.1 below.

With Datasets II and III (Tables 6 and 7), the Cobb-Douglas parameter estimates are qualitatively similar to those in Dataset I, although for Dataset II the output elasticity for IT is closer to the results found in prior studies. In the full model in column (2), all coefficient estimates are significant. The estimates for Z and R are negative, while the interaction term ZR is positive. It is worth noting that for all our datasets in the full model the direct effect of IT through z is substantially higher than the corresponding estimate from the Cobb-Douglas, while the indirect effect of IT through Z is negative, and the indirect effect of IT through ZR is positive. The indirect effect of IT through Z being negative is in contrast to that found in the augmented Cobb-Douglas used in Mittal and Nault (2009), but in their study this is offset by the direct effect of IT through z being smaller than the corresponding estimate from the Cobb-Douglas. Consequently, except for Dataset I where there is an unusually high IT output elasticity in the Cobb-Douglas, our finding of an increased total effect of IT, when incorporating the indirect effects, is consistent with Mittal and Nault (2009).

4.2.1 Elasticities

The output elasticities of labor and non-IT capital are straightforward to calculate and interpret in our model. For IT capital, the total effect captured by the output elasticity η_Z includes both the direct and indirect effects of IT (including its interaction with R&D). However, since we introduce R&D through an indirect effect in our model, we calculate a partial elasticity that has a slightly different interpretation. We evaluate three aspects of the direct and indirect effects in our model. First, we evaluate the output elasticity of Z and compare this with the earlier estimates. Second, we compute the Z and $Z(R)$ components of the scaling factors ($\alpha^{'}$ and $\alpha^{''}$), to the extent made possible by our model. Third, we compute the partial elasticity of R to estimate the influence of the indirect effect of R&D on the factor inputs.

In Dataset I, for the full model (Table 5, column (2)), the estimated output elasticity η_Z is 0.169 when evaluated at the mean (.168 at the median), with a standard error of 0.035. This does not suggest an improvement over the estimated direct effect of 0.322. Rather, we infer that once the indirect effects of R&D and IT capital are included in the model, the total elasticity of IT capital is lower than the estimated Cobb-Douglas elasticity with this dataset – which as we noted earlier is unusually high relative to prior studies. This follows from the estimates of the scaling factor components $\alpha^{'}$ (-.0573) and $\alpha^{''}$ (0.00138); the indirect effect of Z is negative, while for ZR it is positive. Thus it appears that IT capital has a small, negative indirect effect on K and L, which is not entirely mitigated by the positive effect of the interaction of IT with R&D. However, R&D appears to have the expected positive marginal effect on output through its collective indirect effects on the factor inputs (α). The partial elasticity estimate for R is 0.101 with a standard error of 0.044 (t=2.29), although the model specification does not allow us to decompose this effect into specific amounts for the scaling factors on K, L, and Z.

In Dataset II, for the full model (Table 6, column (2)), the estimated output elasticity η_Z is 0.221 when evaluated at the mean (.254 at the median), with a standard error of 0.0279. This exceeds the estimated Cobb-Douglas IT output elasticity of 0.172, indicating that the full impact of IT capital is larger than first estimated, once the indirect effects are included in the model. The estimate of α' is -0.0040075, and the estimate of α'' is 0.00003095. Thus, the indirect effect of Z is negative, but the interaction ZR (along with the larger direct effect of Z) results in a larger net output elasticity. In contrast, the partial elasticity estimate for R is -0.00242, with standard error of 0.000797 (t=-3.04). Thus, it seems that R&D has, at the margin, a net negative effect on output.

The results from our analysis of Dataset III are similar to those found with Dataset II. For the full model (Table 7, column (2)), we find the estimated output elasticity for η_Z is 0.308 when evaluated at the mean (0.283 at the median), with a standard error of 0.027. As with dataset II, this output elasticity, which includes the indirect effects of IT and its interaction with R&D, exceeds that of IT in the Cobb-Douglas model. We note, however, that as with Dataset I, the estimated IT output elasticity from the Cobb-Douglas is higher than in prior studies. The estimated partial elasticity of R&D is -1.012e-08 (evaluated at the mean) (SE = -3.671e-09), which again corroborates the results from Dataset II.

4.3 Robustness: A Model of Product-Oriented R&D

In contrast to the model of process-oriented R&D developed in Section 2, a model of product-oriented R&D would have the impact of IT on R&D. Consequently, the effects of h_1, h_2 and h_3 on our equation (1) are different:

$$h_1^\dagger = f_1^\dagger(R(Z)), \;\; h_2^\dagger = f_2^\dagger(R(Z)), \;\; h_3^\dagger = f_3^\dagger(R),$$

where the superscript † refers to this alternative model. Here we have IT impacting R&D through $R(Z)$ and notice that $h_3^\dagger = h_3$ as we do not model IT having an effect on itself through R&D. Following the same steps as we established in Section 2, we arrive at an estimation form

$$y = a + \beta_1 k + \beta_2 l + \beta_3 z + \theta_1^\dagger R + \theta_3 ZR, \tag{8}$$

where $\theta_1^\dagger = \beta_1\alpha_1 + \beta_2\alpha_2 + \beta_3\alpha_3$, $\theta_3 = \alpha''(\beta_1 + \beta_2)$ as in equation (5), and there is no longer the indirect effect of IT capital term as per Mittal and Nault (2009). The estimation results, shown in column (3) of tables 5, 6, and 7, suggest the alternative model of product-oriented R&D is less robust than our process R&D model. In Dataset I neither the R&D nor the IT-R&D interaction are significant. In Dataset II R&D is significant and negative while the IT-R&D interaction is not significant, and in Dataset III the estimates are almost exactly the same as those from our process R&D full model.

4.4 Robustness of Software in IT Capital

We recognize that software makes up a significant proportion of IT capital, and that this component is not captured by our Dataset I. Some data on the relative prominence of software is available at higher levels of aggregation. According to the BLS Information Capital data for the *MN* manufacturing sector (equivalent to NAICS 31–33), the software proportion of total information capital productive stock rose from 0.212 in 1987 to 0.272 in 1992. The proportion then increased more rapidly in the second six-year period, from 0.289 in 1993 to 0.426 in 1998 (using constant 2005 dollars). The industries in our analysis are generally comparable to the manufacturing sector but, as noted elsewhere, we are unable to represent all industrial classifications due to missing NSF data on R&D for some industries.

To determine if our results for the IT-R&D interaction are robust to the increase in the relative software component of IT capital, we split the sample and ran our analysis for comparison. Our results are shown in Table 8. The Cobb-Douglas results for the IT capital coefficient (z) are reasonably stable across the sub-samples and the whole sample (columns 1, 3, and 5 below). This encouraging outcome indicates that, despite the probable increase in software's share of IT Capital, the relationship between IT and R&D holds.

5 DISCUSSION

In this research, we propose a model of the indirect effects of IT and R&D on production. The results of our analyses shed some light on the relationship between innovation and IT, and how they combine to influence production efficiencies at the industry level.

In the first analysis, covering the years 1987–1998, the elasticity of IT capital in the indirect effects model is lower than that of the Cobb-Douglas model, but we note that the Cobb-Douglas estimate is unusually high relative to prior studies. Decomposing this net effect, we find that IT capital has a slightly deleterious indirect effect on non-IT capital and labor that outweighs the positive indirect effect of the interaction of R&D and IT. Nevertheless, the estimated net marginal contribution of IT capital to productivity remains positive. We find the net effect of R&D knowledge stock is positive, indicating R&D investments enable the factor inputs to perform more efficiently. Furthermore, part of this net effect arises from the interaction of R&D with IT.

In the analysis of Dataset II (1998–2005), the net marginal contribution of IT capital is larger in the full model than in the Cobb-Douglas model, suggesting that the production efficiencies are enhanced by the indirect effects of IT. More specifically, since the indirect effect of IT alone is negative, it is the interaction of IT with R&D that creates the overall increase in net effect. However, for R&D, the estimated net effect is negative. Thus it appears that, for our second sample, IT drives productivity enhancements in the presence of R&D, but R&D on its own does not. We are unable to determine if this is due to differences in the nature of the sample in comparison to Dataset I (such as addition of software to IT capital, inclusion of non-manufacturing industries, and grouping by NAICS) or other factors, such as a shift in the way that industries use IT and R&D to improve production efficiency. There is reason to believe that widespread improvements in productivity in the late 1990s and early 2000s arose from IT and complementary organizational investments and practices that helped firms and industries capitalize on earlier IT capital investments (Brynjolfsson and Hitt, 2003; Jorgenson, Ho, and Stiroh, 2008). Thus, part of this effect may owe to process innovation efficiencies captured by the indirect effects in our model.

In the third set of results, based on Dataset III, we examine the same years as Dataset II but with a more consistently-aggregated and finer set of industries, and find the estimates corroborate the results from Dataset II. Once again we find the estimated net marginal contribution of IT is greater in our model than in the Cobb-Douglas model, resulting from the positive interaction of IT and R&D that outweighs the negative indirect effect of IT. The agreement between the estimates from Dataset II and III make it unlikely that the results for the 1998–2005 period are an artifact of the NSF R&D data or industry aggregation scheme.

To better understand the effects of using the NSF industry aggregation scheme (required to match the R&D data) on Dataset I, we ran the Cobb-Douglas model using the 85 industries in the source data. For the Cobb-Douglas we found an IT output elasticity of 0.195, substantially lower than the 0.246 in our aggregated data. However, similar to our results above, the 85-industry dataset had a higher output elasticity estimate for IT capital than for non-IT capital. This inflated value of the output elasticity of IT capital appears to be due to confounding with TFP: after accounting for additional effects such as supplier spillovers

(Cheng and Nault, 2007) and customer spillovers (Cheng and Nault, 2012) the 85-industry dataset and another closely related dataset finds the output elasticity of non-IT capital to be higher than IT capital. Consequently, there is evidence that the anomaly we find in Dataset I—an inflated value of the output elasticity of IT capital in the basic Cobb-Douglas—is due to unmeasured effects from TFP.

One potential concern is with the negative coefficient on R&D in our empirical results, which is clearly an empirical regularity within our models. However, it is important to recognize that our models are production models, and they include non-IT capital, labor and IT capital as inputs. In our view it is a misspecification to simply add R&D to a production model because it is not an input—or alternatively it has been counted in one of the other three inputs already if it has been converted to real capital (non-IT or IT) or some form of knowledge capital embedded in labor. Consequently, our theoretical model has R&D increasing the effectiveness of all three inputs, and following Mittal and Nault (2009) has IT augmenting the other two inputs. The theoretical model leads to the empirical specification, and in that context the empirical results must be mapped back to the theoretical model to interpret the results. Therefore interpreting the individual estimates in isolation, such as a negative coefficient on the R&D term, can be misleading.

5.1 Limitations

We recognize several limitations arising from our data. First, the aggregation of industries in Datasets I and II is not at a consistent level, due to the availability of the NSF R&D data. However, we have found the results from Dataset II are comparable to those from Dataset III, which is aggregated on a consistent 3-digit NAICS basis. Second, the lack of a long history of NAICS-based R&D data limits the generation of the R&D stock variable in Dataset II to a shorter smoothing period, though this is again mitigated by the similar results from Dataset

III, for which historical data is not so restricted. Third, we are unable to isolate the portion of the factor inputs that are dedicated to R&D from those dedicated to production, so the R&D inputs are to some extent double-counted. As a result the interpretation of the interaction term ZR does not precisely fit the standard approach, since some portion of R overlaps with a portion of Z. Fourth, our measure of R&D does not distinguish between process- and product-related innovation. Although our hypotheses focus on production efficiencies arising from process innovation, product innovation commands a significant share of R&D spending in many industries (Cohen and Klepper, 1996). Thus our use of R&D is a rough proxy for the resources dedicated to innovations which aim to affect efficiency, while an unknown proportion is devoted to product improvement. As detailed in section 4.3, we propose and estimate an alternative theoretical model in which IT drives *product* innovation, but this approach is nonetheless unable to account for a mixture of product and process innovation activity in an industry. Finally, we note that we exclude a number of industries from our datasets I and II due to the NSF's intentional withholding of R&D survey data. Although it is possible that this may bias our results, it occurs only where a very small number of firms perform R&D within an industry. As such, these industries may be unusual in structure and therefore unsuitable for inclusion in our sample.

Our conclusions regarding the different nature of indirect effects between the samples from 1987–1998 and 1998–2005 must be taken cautiously. Although it is tempting to conclude that a change has taken place in the way industries implement process innovations, the direct comparison of results from the two eras is hindered by differences in the makeup of the samples. As is clear from the summary statistics in Table 1, the industries are much larger in the second sample due to the higher level of NAICS aggregation. Further, the inclusion of non-manufacturing industries, such as finance and information, introduces different characteristics with respect to the measurement of outputs and their methods of production compared to manufacturing industries.

5.2 Future research

Extensions to this research could explore different dimensions of the R&D knowledge stock, which the NSF identifies as internal, contract research, and government-funded research. In addition, the NSF R&D survey is continually refined and expanded to include additional data on the breakdown of spending on different R&D activities. This may make it possible to estimate the impact of the components of R&D (labor, IT capital and non-IT capital), facilitating a more nuanced model. With the more detailed data collected by the NSF beginning with the 2008 survey of innovation, the separate impacts of process innovations and product innovations could also be investigated.

Another area for further exploration is the effect of R&D spillovers on innovation and the indirect effect of IT. The scaling effect of R&D and IT may not be isolated within firms but extend across an industry and between industries. Economists have found empirical support for R&D spillovers (Griliches and Lichtenberg, 1984; Griliches, 1992), and more recently, spillover phenomena have also captured the attention of Information Systems researchers (Stiroh, 2002; Hitt and Tambe, 2006). Such industry-level effects are worth investigating given the nature of IT, which lends itself to rapid communication, replication and discovery.

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APPENDIX A: AR1 RESULTS

As an alternative approach to handling autocorrelation and industry-level heterogeneity, we also report random effects regressions controlling for AR(1) for both datasets I and II. In Table 9, column (1) reports the standard Cobb-Douglas production function as a base model to check for reasonableness. For both the Cobb-Douglas and the full model, the sign, significance and magnitude of the direct and indirect effect estimates are very similar to those found using the He+PSAR1 estimator, with the exception of the estimate for k which is not significant, while R is negative and significant. In Dataset II, Table 10 shows both model variations have positive and significant estimates for k and l (again similar to the He+PSAR1 estimates) but z is not significant. The indirect effects Z and R have non-significant coefficient estimates, while the interaction term in column (2) remains significant and positive. In sum, the AR1 estimator produces similar estimates with somewhat larger standard errors, perhaps due to the coarser treatment of autocorrelation error structures compared with He+PSAR1 or the lack of adjustment for heteroskedasticity.

Table 1: Summary statistics

	N	Mean	Std. Dev.	Min	Max
Dataset I: 1987–1998 (millions of 1987 dollars)					
Value added	276	44,944.83	48,406.65	1,674.66	505,614.00
Non-IT capital	276	74,960.50	57,521.65	2,897.80	223,860.90
Labor (millions of hours)	276	1,509.49	1,048.20	119.80	3,972.50
IT capital	276	6,073.78	5,932.29	258.50	39,195.20
R&D stock	276	14,648.24	14,443.52	915.41	60,509.25
R&D expense	276	2,526.91	2,656.55	51.90	11,330.51
Dataset II: 1998–2005 (millions of 2005 dollars)					
Value added	200	342,022.70	524,093.70	30,097.00	2,606,450.00
Non-IT capital	200	473,052.90	605,868.20	20,340.00	2,584,289.00
Labor (hours)	200	7,262.45	11,839.93	259.30	60,110.00
IT capital	200	56,754.75	82,130.94	832.00	381,533.00
R&D stock	200	39,927.73	62,945.78	238.57	241,671.90
Dataset III: 1998–2005 (millions of 2000 dollars)					
Value added	304	180,783.10	222,282.20	17,697.00	1,273,933.00
Non-IT capital	304	205,784.90	264,850.30	15,552.00	1,449,984.00
Labor (hours)	304	3,795.42	4,761.86	240.00	25,773.00
IT capital	304	28,103.16	33,329.54	795.00	154,685.00
R&D stock	304	37,822.55	100,917.00	14.25	517,134.30

Table 2: Dataset I industries

Industry	SIC Codes	Major Industry	Subordinate Industry
2	13, 29	Petroleum refining and extraction	
4	20, 21	Food, kindred, and tobacco products	
5	22, 23	Textiles and apparel	
6	24, 25	Lumber, wood products, and furniture	
7	26	Paper and allied products	
8	27, 31, 39	Other manufacturing industries	
10	281–82, 286	Chemicals and allied products	Industrial chemicals
11	283		Drugs and medicines
12	284–85, 287–89		Other chemicals
13	30	Rubber products	
14	32	Stone, clay, and glass products	
99[a]	331–32, 3398–99	Primary metals	Ferrous metals and products
99[a]	333–36		Nonferrous metals and products
18	34	Fabricated metal products	
20	351–56, 358–59	Machinery	Other machinery, except electrical
21	357		Office, computing, and accounting machines
23	361–64, 369	Electrical equipment	Other electrical equipment
24	365		Radio and TV receiving equipment
25	366		Communication equipment
26	367		Electronic components
28	371	Transportation equipment	Motor vehicles and motor vehicles equipment
30	373–75, 379		Other transportation equipment
32	381–82	Professional and scientific instruments	Scientific and mechanical measuring instruments

Continued on next page

Table 2 – continued from previous page

Industry	SIC Codes	Major Industry	Subordinate Industry
33	384–87		Optical, surgical, photographic, and other instruments

[a] The two Primary Metals industries are combined into a single industry to facilitate matching to the MFP industry aggregation

Table 3: Dataset II industries

Industry	Sector[a]	NAICS Codes	Description
1	NM	21	Mining, extraction, and support activities
2	NM	22	Utilities
3	NM	23	Construction
5	M	311–312	Food, beverage and tobacco products
7	M	313–316	Textiles, apparel, and leather
8	M	321	Wood products
9	M	322–323	Paper, printing, and support activities
10	M	324	Petroleum and coal products
11	M	325	Chemicals
12	M	326	Plastics and rubber products
13	M	327	Nonmetallic mineral products
14	M	331	Primary metals
15	M	332	Fabricated metal products
16	M	333	Machinery
17	M	334	Computer and electronic products
18	M	335	Electrical equipment, appliances, and components
19	M	336	Transportation equipment
20	M	337	Furniture and related products
21	M	339	Miscellaneous manufacturing
24	NM	48–49	Transportation and warehousing
25	NM	51	Information
26	NM	52–53	Finance, insurance, and real estate
27	NM	54	Professional, scientific, and technical services
28	NM	621–623	Health care services
29	NM	55, 56, 61, 624, 71, 72, 81	Other non-manufacturing

[a] Sector M = Manufacturing, NM = Non-manufacturing

Table 4: Dataset III industries

Industry	NAICS Codes	Description
5	22	Utilities
7	311,312 (311FT)	Food and beverage and tobacco products
8	313,314 (313TT)	Textile mills and textile product mills
9	315,316 (315AL)	Apparel and leather and allied products
10	321	Wood products
11	322	Paper products
12	323	Printing and related support activities
13	324	Petroleum and coal products
14	325	Chemical products
15	326	Plastics and rubber products
16	327	Nonmetallic mineral products
17	331	Primary metals
18	332	Fabricated metal products
19	333	Machinery
20	334	Computer and electronic products
21	335	Electrical equipment, appliances, and components
22	336	Transportation Equipment
23	337	Furniture and related products
24	339	Miscellaneous manufacturing
25	42	Wholesale trade
26	44,45 (44RT)	Retail trade
33	487,488,492 (487OS)	Other transportation and support activities
35	511	Publishing industries (includes software)
36	512	Motion picture and sound recording industries
39	521,522 (521CI)	Federal Reserve banks, credit intermediation, and related activities
40	523	Securities, commodity contracts, and investments
41	524	Insurance carriers and related activities
43	531	Real estate

Continued on next page

Table 4 – continued from previous page

Industry	NAICS Codes	Description
44	532,533 (532RL)	Rental and leasing services and lessors of intangible assets
46	5412-5414,5416-5419 (5412OP)	Miscellaneous professional, scientific and technical services
47	5415	Computer systems design and related services
49	561	Administrative and support services
50	562	Waste management and remediation services
52	621	Ambulatory health care services
56	713	Amusements, gambling, and recreation industries
57	721	Accommodation
58	722	Food services and drinking places
59	81	Other services, except government

Table 5: GLS He+PSAR1 regression results

Dataset I: 1987–1998

VARIABLES	(1) Cobb-Douglas	(2) Process R&D Full Model	(3) Alternative Product R&D Full Model
k	0.135***	0.178***	0.0814**
	(0.0516)	(0.0431)	(0.0384)
l	0.710***	0.650***	0.750***
	(0.0542)	(0.0474)	(0.0422)
z	0.246***	0.322***	0.268***
	(0.0330)	(0.0549)	(0.0329)
Z		-0.0474***	
		(0.0153)	
R		-0.00231	0.00395
		(0.00357)	(0.00295)
ZR		0.00114**	-0.000237
		(0.000475)	(0.000313)
Constant	2.468***	2.383***	2.592***
	(0.178)	(0.155)	(0.134)
Observations	276	276	276
η_Z (mean)	0.246	0.169	0.240
η_Z (median)	0.246	0.168	0.250
$\eta_K + \eta_L + \eta_Z$ (mean)	1.091	0.997	1.071

[a] Standard errors in parentheses.
[b] *** p<0.01, ** p<0.05, * p<0.1
[c] Dependent variable: Value Added.
[d] Year dummies omitted from results.

Table 6: GLS He+PSAR1 regression results

Dataset II: 1998–2005			
	(1)	(2)	(3)
VARIABLES	Cobb-Douglas	Process R&D Full Model	Alternative Product R&D Full Model
k	0.338***	0.275***	0.317***
	(0.0380)	(0.0455)	(0.0499)
l	0.520***	0.504***	0.482***
	(0.0279)	(0.0320)	(0.0365)
z	0.172***	0.314***	0.230***
	(0.0330)	(0.0432)	(0.0472)
Z		-0.00312***	
		(0.000655)	
R		-0.00383***	-0.00247***
		(0.000931)	(0.000918)
ZR		2.14e-05***	1.55e-06
		(5.57e-06)	(3.91e-06)
Constant	2.155***	2.190***	2.091***
	(0.139)	(0.166)	(0.178)
Observations	200	200	200
η_Z (mean)	0.172	0.221	0.235
η_Z (median)	0.172	0.254	0.230
$\eta_K + \eta_L + \eta_Z$ (mean)	1.03	1.000	1.034

[a] Standard errors in parentheses.
[b] *** p<0.01, ** p<0.05, * p<0.1
[c] Dependent variable: Value Added.
[d] Year dummies omitted from results.

Table 7: GLS He+PSAR1 regression results

	Dataset III: 1998-2005		
	(1)	(2)	(3)
VARIABLES	Cobb-Douglas	Process R&D Full Model	Alternative Product R&D Full Model
k	0.253***	0.233***	0.243***
	(0.0121)	(0.0120)	(0.0135)
l	0.542***	0.532***	0.544***
	(0.0141)	(0.0147)	(0.0141)
z	0.259***	0.299***	0.270***
	(0.0102)	(0.0153)	(0.0111)
Z		-1.482***	
		(0.538)	
R		-2.01e-08**	-2.01e-08**
		(8.48e-09)	(7.85e-09)
ZR		3.55e-07**	3.50e-07**
		(1.81e-07)	(1.75e-07)
Constant	5.871***	6.046***	5.906***
	(0.0410)	(0.0767)	(0.0460)
Observations	304	304	304
η_Z (mean)	0.259	0.308	0.320
η_Z (median)	0.259	0.283	0.270

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Dependent variable: Value Added.
Year dummies omitted from results.

Table 8: Dataset I: Split Sample

Dataset I: 1987-1998

	(1)	(2)	(3)	(4)	(5)	(6)
	1987-92		1993-98		All Years	
VARIABLES	Cobb-Douglas	Full Model	Cobb-Douglas	Full Model	Cobb-Douglas	Full Model
k	0.0370	0.0324	0.0877	0.205***	0.135***	0.178***
	(0.0510)	(0.0602)	(0.0656)	(0.0350)	(0.0516)	(0.0431)
l	0.839***	0.835***	0.614***	0.589***	0.710***	0.650***
	(0.0513)	(0.0612)	(0.0545)	(0.0346)	(0.0542)	(0.0474)
z	0.269***	0.347***	0.242***	0.277***	0.246***	0.322***
	(0.0284)	(0.0661)	(0.0398)	(0.0723)	(0.0330)	(0.0549)
Z		-0.0296		-0.0466***		-0.0474***
		(0.0199)		(0.0159)		(0.0153)
Rstock15		0.00477		0.000429		-0.00231
		(0.00314)		(0.00361)		(0.00357)
ZRstock15		0.000384		0.00110**		0.00114**
		(0.000636)		(0.000459)		(0.000475)
Constant	2.804***	2.810***	2.814***	2.376***	2.468***	2.383***
	(0.175)	(0.219)	(0.247)	(0.126)	(0.178)	(0.155)
Observations	138	138	138	138	276	276
η_Z (mean)	0.269	0.240	0.242	0.0981	0.246	0.169
η_Z (median)	0.269	0.245	0.242	0.0717	0.246	0.168

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Dependent variable: Value Added.
Year dummies omitted from results.

Table 9: Random effects AR(1) regression results

Dataset I: 1987–1998		
	(1)	(2)
VARIABLES	Cobb-Douglas	Full Model
k	0.113	0.0944
	(0.113)	(0.0937)
l	0.604***	0.614***
	(0.120)	(0.100)
z	0.386***	0.561***
	(0.0884)	(0.118)
Z		-0.0940***
		(0.0240)
R		-0.0180***
		(0.00673)
ZR		0.00318***
		(0.000671)
Constant	2.392***	2.683***
	(0.395)	(0.338)
Observations	276	276
η_Z (mean)	0.386	0.366
η_Z (median)	0.386	0.310

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Dependent variable: Value Added.
Year dummies omitted from results.

Table 10: Random effects AR(1) regression results

Dataset II: 1998–2005		
	(1)	(2)
VARIABLES	Cobb-Douglas	Full Model
k	0.449***	0.418***
	(0.108)	(0.105)
l	0.417***	0.442***
	(0.0901)	(0.0866)
z	0.105	0.155
	(0.0958)	(0.113)
Z		-0.00138
		(0.00113)
R		-0.00110
		(0.00143)
ZR		1.48e-05*
		(8.58e-06)
Constant	1.782***	1.836***
	(0.437)	(0.411)
Observations	200	200
η_Z (mean)	0.105	0.128
η_Z (median)	0.105	0.129

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Dependent variable: Value Added.
Year dummies omitted from results.

Figure 1: Indirect effects model of R&D