MEASURING SPILLOVERS FROM INFORMATION TECHNOLOGY INVESTMENTS

Valuing IT Opportunities

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Abstract

Intra-industry spillovers from information technology investments have been cited as a potentially important driver of productivity growth. Using firm-level data to measure the sizes of these spillovers, however, can be challenging because of biases caused by 1) measurement error and 2) the difficulty in separating the effects of spillovers from the effects of shared technological opportunity. In this analysis, we employ two separate approaches to develop more accurate estimates of the contributions of information technology driven spillovers to economic output. First, we use an instrumental variables approach to correct biases caused by measurement errors in IT capital, and second, we use technological variation from establishment level data to create richer models of knowledge spillover pools that are less vulnerable to the econometric problems identified above. We report estimates from both of these approaches and compare them with estimates from methods relying on conventional firm-level models of spillover. Our results suggest that existing estimates of within-industry spillovers from information technology investments may be considerably overstated. The estimates produced by our different approaches are internally consistent, and suggest that the contribution of within-industry information technology spillovers may actually be smaller than previously reported.

Keywords: spillovers, knowledge flows, organizational complements, information technology

Introduction

Researchers have suggested that an important part of the way in which information technologies create economic value is through spillovers between firms within the same industry (Dedrick, et al. 2003; Van Ark, 2002). These spillovers can take a variety of forms. Firm level investments in communication technologies can create benefits for business partners. Alternatively, investments in information technologies can produce knowledge that can spill over between firms. For example, much of the value generated by investments in information technologies has been attributed to the organizational complements that accompany firm investment, and knowledge of these organizational technologies can be transferred between firms through worker mobility, consulting, or other mechanisms (Brynolfsson and Hitt, 2000).

Within-industry spillovers produced by information technology investments, therefore, are likely to be substantial. The most well-known and widely used approach to measuring these spillovers is to estimate a 'knowledge production function', pioneered by Griliches (1979). Through this approach, the contribution of the knowledge pool available to a firm is estimated by including it along with other conventional inputs in a production framework. The few studies that have attempted to measure within-industry information technology spillovers using these methods have produced large estimates of the contribution of spillovers to output, on the same order or larger than the contribution of a firm's internal IT investment. If information technology spillovers really do play such an important role in production, than these results have important implications for policy makers.

Measuring the contribution of knowledge spillovers in this way, however, presents at least two econometric difficulties. The first is that because firms face the same technological opportunities and factor costs, they will invest similarly, making it impossible to determine whether covariation in the data between output and the investments of other firms in the same industry is a result of knowledge spillovers, or the result of exogenous technological shocks that cause firms in the same industry to all make similar investments (Griliches, 1998). A second problem is that when estimating the knowledge production function using conventional measures of spillover capital, measurement error in a firm's own investments are likely to result in an upward bias on the estimated contribution of spillovers (Hitt and Tambe, 2006). For information technologies, where measurement error in existing data is especially severe, these biases can be large. Taken together, these problems make it difficult to meaningfully interpret estimates of within-industry spillovers derived from firm-level analyses.

Solutions to the above problems, however, do exist, and in this analysis, we exploit two of them to develop more accurate estimates of the contributions of information technology externalities to production. Our first approach is to use an instrumental variable to correct for the measurement error in IT capital. This approach produces estimates that are considerably smaller than estimates that do not account for measurement error problems. We also take a second approach drawing on establishment level data to create richer models of the spillover paths. Creating better models of spillover paths breaks the correlation between a firm's technological position and its spillover pool, reducing or eliminating the effects of the problems discussed above (Hitt and Tambe, 2006). This approach also produces smaller estimates of the importance of spillovers than comparable firm-level analyses.

This paper contributes to the existing literature on information technology spillovers in several ways. We use two separate approaches to estimate the importance of within-industry spillovers from information technology investments, both of which improve on conventional firm level analyses. In both cases, our estimates are smaller than comparable estimates using conventional methods. In the next section, we begin with a brief review of the existing literature on spillovers, including a discussion of the econometric difficulties presented by conducting firm-level analyses of within-industry spillovers. We then describe our approach to addressing these problems, our data sets, and the models that we estimate. After reporting our estimates, we compare them with estimates that use only firm-level data. We conclude the paper with a discussion of the importance of accurate spillover estimates, and the benefits of using more detailed models of spillover paths.

Literature and Background

Information Technology Spillovers

While researchers have cited spillovers as an important source of value created by information technology investments (Van Ark, 2002), most existing empirical research has focused on rent spillovers between industries (Mun and Nadiri, 2002; Cheng and Nault, 2005). Spillovers within industries, however, are also likely to be substantial. Much of the value attributed to information technology investments, for example, is created by organizational complements (Brynjolfsson and Hitt, 2000). As workers and managers move between firms, they are likely to take any knowledge of organizational technologies with them and transfer them to new environments. Furthermore, innovations taking advantage of the computer as a 'general purpose technology' are likely to be built upon existing innovations from other technologically similar firms, leading to important spillover effects. The importance of industry-specific knowledge communities for knowledge transfer has also been recognized by ethnographic studies of knowledge communities (Saxenian, 1984). These communities and trade associations may foster the flow of knowledge between firms through informal social interaction. Finally, as firms invest in communication technologies, benefits flow to all other firms with which the firm interacts. To the extent that interaction occurs primarily between firms in the same technological space, investments in technologies that lower communication costs will also produce externalities. Spillovers within industries, therefore, while empirically difficult to examine, deserve attention.

Knowledge Production Framework

A widely used approach to estimating returns to these types of spillovers comes from the 'knowledge production function' which expresses firm level output as a function of conventional inputs, knowledge capital, and the weighted knowledge capital of other firms that share knowledge with firm *i*, where the weights represent the strength of the transmission path between firms (Griliches, 1979). Two firms that exchange a great deal of knowledge, for example, will have higher weights than two unrelated firms. While this model has been most widely used to explore spillovers of knowledge capital created from R & D investment, researchers have recently started to explore similar knowledge spillovers associated with information technology investments. Using this approach, firm output is represented by a Cobb-Douglas technology

$$VA_{it} = AK_{it}^{\alpha}L_{it}^{\beta}F(C)_{it}$$

where VA is value-added, K is capital, L is labor inputs, and F(C) includes information technology investments and associated organizational investments, both internal and external to the firm. When using firm-level data, the external knowledge pool available to a firm is often modeled as the weighted sum of the investments of other firms in the same industry. In logs, a simple version of this model used for information technology spillovers can be written as

$$y_i = \beta_0 + \beta_1 l_i + \beta_2 k_i + \beta_3 c_i + \beta_4 \sum_{j \neq i}^{j \in I(i)} w_j c_j + controls + \varepsilon_{it}$$

where l is labor, k is non-IT capital, c is IT capital, and w is the spillover weighting measure. Because data on knowledge flows between firms can be difficult to come by, w is often proxied by the technological distance between firms using SIC codes, under the assumption that firms that are more technologically proximate (i.e., in the same or a closely related industry) have more in common, and are therefore more likely to exchange knowledge than firms that are technologically distant.

Technological Opportunity and Measurement Error

While this specification has been widely used in the literature, it is subject to two important criticisms, both of which are worse in the IT context than in the R & D context. The first problem is one of identification. It is impossible to distinguish positive spillover effects from the effects of common technological shocks, largely because spillover models use technological proximity to model knowledge transmission paths. Given covariation in the data between economic output and the knowledge pool of a firm, it is impossible to distinguish whether productivity increases experienced by a firm are caused by spillovers from this knowledge pool, or whether common technological opportunity, such as industry-specific increases in the returns to coordination, drive increases in productivity and simultaneously cause other firms in the same industry to invest in the knowledge-generating asset because they are optimizing across the same economic landscape (Manski, 1993). The R & D literature addresses this issue by controlling for technological opportunity through patent positioning, but studies of information technology spillovers do not have the benefits of similarly descriptive data to describe shared technological opportunity.

A second problem in using a knowledge production function approach to estimate returns to spillover is caused by measurement error. Measurement errors in IT capital can result in significant upward biases on estimates of the contribution of spillover capital (Hitt and Tambe, 2006). These biases become considerably worse in the information technology context, because, among other problems, rapid quality changes in information technology make measurement a difficult issue. Taken together, these issues complicate the interpretation of spillover estimates from firm level analyses. In the next sections, we take two approaches to reduce or eliminate these problems and produce estimates of the contributions of IT spillovers that are free from these biases.

Instrumental Variables and Measurement Error

The second problem described above derives from a measurement error problem in capital measurement. IT capital has been notoriously difficult to accurately measure for several reasons. First, because of the widespread use of information technologies within the firm, a large fraction of IT hardware purchases may be transacted without the knowledge of IT personnel, making it difficult for an IS manager to estimate the total value of computer capital stock in the firm. A second source of error is that the rapid change in quality-adjusted prices in recent years makes it difficult to accurately estimate the value of information technologies within the firm. This is aggravated because IT assets can differ on many intangible dimensions, and assigning values to all of these can be difficult. Finally, a considerable portion of the value created by IT, such as the creation of software or databases, is not recorded by conventional measurements of IT capital stock, but may represent a large fraction of a firm's IT investment.

Our approach to addressing measurement error induced biases is to use an instrumental variable to correct the error.[1] Our strategy is to follow conventional methods for estimating the returns to spillovers, and then to explore whether correcting for measurement error in IT capital significantly changes our results. For our modeling approach, we rely on the knowledge production function approach described above, where the knowledge spillover pool accessible by a firm is proxied by the average of the IT investment of other firms that share the same two digit SIC code.

Data

Our IT dataset is constructed using the same procedures as in Brynjolfsson and Hitt (2000). We combine computer stock data from Computer Intelligence InfoCorp (CII) with public financial information from Compustat. Price data and related measures are provided by the Bureau of Labor Statistics (BLS) other government sources. Our panel consists of 1183 firm-year observations ranging over the period 1987-1993. Finally, we use value-added instead of total sales as our dependent variable because value-added reduces biases caused by heterogeneity between firms at different stages of the supply chain, and is more resistant to problems caused by the endogeneity of materials expenditures. While we use a similar panel in the next section, the size of this panel is limited by the availability of our instrumental variable, described below. Composition of the sample used in this section is described in Table 1.

Table 1: Sample Composition

Industry	**Observations**	**Sample %**
Non-Durable Manufacturing	161	13.61

[1] See Johnston and Dinardo (pp. 153-156) for a concise treatment of the use of instrumental variables for correction of measurement error.

Durable Manufacturing	176	14.88
Process Manufacturing	229	19.36
High-Tech Manufacturing	181	15.30
Trade	62	5.24
Utilities	155	13.10
Transport	99	8.37
Finance	120	10.14
Total	1324	100.0

To test our hypothesis regarding the effects of measurement error on spillover estimation, we correct for measurement error using an alternative measure of IT capital stock from the marketing research firm IDG as an instrumental variable. To act as an effective instrument, the instrumental variable must be uncorrelated with the measurement error in our primary IT capital stock variable from CII. The independence of the error terms of these two different measures is derived from the different methods through which these two market research firms value IT capital stock. CII conducts surveys to track specific pieces of computer equipment at the site level for the 1000 largest firms in the United States, and interviews information systems managers to obtain detailed information on a site's IT hardware assets, ranging from monthly to annually. The interview process includes checking on hardware that was reported in previous interviews to make accurate time-series comparisons. Each piece of hardware is market-valued and aggregated to form a measure of total hardware use at the firm. These data omit software, information system staff, and telecommunications equipment. Market valuation is performed by a proprietary algorithm developed by CII that takes into account current rental prices and machine configurations in determining an estimate.

IDG uses very different methods to gather their data. IDG gathers data from a single officer in the firm and looks only at mainframes and PC components. They use survey methods through which the officer reports the number of mainframes, PCs and terminals in the firm. The number of PCs and terminals is multiplied by an estimated value, determined by the average nominal PC price over 1989-1991.

While both of these approaches include potential error sources, instrumental variable estimation requires only that the error sources be uncorrelated. The CII data is collected at the site level from a number of managers, while the IDG data is collected from a single officer through survey questions. CII's more rigorous methods suggest that the CII estimates will be more accurate, and we use it as our primary variable. Given the two different data collection methods, the only reason that the error across estimates from the two firms may be correlated is if there is a decision bias causing managers to misreport IT stock in a systematic way. Since we are unaware of any such systematic biases, however, we assume for this study that the errors in IT capital stock estimates are uncorrelated, and that IDG measurements can be used as an effective instrument to correct for measurement error in CII data.

Results

Table 2 shows the results of estimating a model similar to a Cobb-Douglas specification in logarithms using firm-level data on information technology. Columns 1 and 2 show estimates with and without including measures of within-industry spillover, where industry is determined by 2-digit SIC codes. Regressions are pooled in levels, and significance levels are computed using Huber-White robust standard errors (clustered by firm) to account for repeated observations of the same firm over time. The results in Column 2 suggest that spillovers are significant and almost as large in size as the effects of own IT investment. Column 3, for comparison purposes, shows the regression results for a limited sample for which the instrumental variable is available. While the coefficient on information technology is smaller, the coefficient on spillover is nearly identical. Column 4 shows the results of using our instrumental variable to correct for measurement error problems in IT capital. After correcting the measurement error, the estimate of the contribution of spillovers becomes considerably smaller, and is no longer significant. These numbers suggest that a significant portion of the estimated contribution of spillovers in typical firm-level analyses may be attributable to measurement error problems. Even after this correction, however, this approach still ignores the confounding influences of common technological shocks that result from modeling spillover pools arising from measuring technological proximity by two-digit SIC industry designations. In the next section, we use establishment level data to develop richer models of transmission paths that simultaneously address this problem and the measurement error problem.

Table 2: Measurement Error in Firm-Level Analyses

Production Function Estimates, Dependent Variable: Log(Value Added)				
	(1)	**(2)**	**(3)**	**(4)**
Specification (Sample)	**OLS (Full Sample)**	**OLS (Full Sample)**	**OLS (IV Sample)**	**OLS, IV (IV Sample)**
Log(Labor)	0.719 (0.028)**	0.721 (0.028)**	0.773 (.020)**	0.757 (0.028)**
Log(Non-IT Capital)	0.196 (0.018)**	0.194 (0.018)**	0.178 (.016)**	0.171 (0.018)**
Log(IT Capital)	0.048 (0.011)**	0.046 (0.011)**	.023 (.011)**	0.049 (0.031)
Log(Within Industry Spillover)		0.040 (0.020)*	.039 (.020)*	0.029 (0.024)
Controls	Industry Year	Industry Year	Industry Year	Industry Year
Constant	0.852 (0.162)**	0.75 (0.177)**	0.879 (.200)**	1.08 (0.272)**
Observations	4097	4058	1324	1324
R-squared	0.95	0.95	0.96	0.96
Robust standard errors in parentheses * significant at 5%; ** significant at 1%				

Establishment Level Data

The problems discussed above are driven by the correlations between firm and industry investment in specifications that use technological proximity to model the transmission paths for spillovers. When only firm-level data are available, estimates of the contribution of the spillover pool to economic output rely on variation between industries, because firms within the same industry choose similar inputs, and by construction, have nearly identical spillover pools. What is needed is a way to decouple the technological position of a firm from its spillover pool. This is a data problem, not an economic one, because technological proximity is often used for convenience, and firms in practice exchange knowledge with an array of firms across many different industries. A solution to this problem, therefore, is to use richer models that go beyond a simple two digit characterization of the firm. In this study, we explore the use of establishment level data to build these models.

Data

The data used in this part of the study come from the same sources described above, Computer Intelligence Infocorp (CII) data describing information technology investments at the establishment level, and other financial measures at the firm level that come from the Compustat databases. Because we are not limited by the availability of our instrumental variable, however, in this section we use a larger panel that spans the years 1987 to 2001. Furthermore, while in the above section, the CII data is aggregated to the firm level, in this section we exploit elements of the data at the establishment level. Specifically, we take advantage of the fact that the establishment level data assigns SIC codings to each different establishment. Through establishment data, therefore, firms are essentially mapped to a variety of different technological areas.

Tables 3 and 4 provide summary statistics of the sample for both the firm and establishment level data. Firms in the sample have an average of almost 140 establishments per firm. In constructing the key variables we followed the standard methodology for calculating production outputs and inputs used in R&D and IT productivity studies (see e.g., Brynjolfsson and Hitt, 2003). In addition, and most importantly for this study, each firm, through its establishments, occupies a variety of technological positions. On average, firms inhabit ten different four digit SIC categories, and more than four different two digit SIC categories. Thus, firms that look similar at the aggregate firm level, where firms are generally assigned to a single SIC category, can be quite different when compared at the establishment level. If technological proximity does play an important role in knowledge spillovers, then the firm may be best described as a collection of establishments, each of which operate in different technological areas, and have access to a variety of different spillover pools. The firm's access to knowledge, therefore, may best be modeled by accounting for the diversity in its establishments. In the next section, we explain how we integrate these establishment data into a firm-level analysis.

Table 3: Sample Composition

Industry	**Firm-year Observations**	**Sample %**
Transport, Utilities, Telecommunications	1808	17.18
Non-durable manufacturing	1096	10.42
Durable manufacturing	1313	12.48
Process manufacturing	1286	12.22
High-tech manufacturing	1227	11.66
Trade	1375	13.07
Finance	1743	16.56
Non-Financial services	675	6.41
	10,523	100

Table 4: Establishment-Level Statistics

Variable	**Mean**	**N**	**Std. Dev.**
Number of Sites per Firm	138.28	328,425	300.7
PCs per Site	103.4	364,986	598.2
Mainframes per Site	0.177	364,986	1.02
4 digit SIC per Firm	7.67	328,425	8.69
2 Digit SIC per Firm	4.29	328,425	3.66

Model

The conventional knowledge production function approach, repeated below for convenience, relies on estimation of the following model

$$y_i = \beta_0 + \beta_1 l_i + \beta_2 k_i + \beta_3 c_i + \beta_4 \sum_{j \neq i}^{j \in I(i)} w_j c_j + controls + \varepsilon_{it}$$

where lowercase letters represent variables in logs, *l* is labor, *k* is non-IT capital, *c* represents IT capital, the summation term represents the knowledge pool available to the firm, and *i* and *t* index industry and time. While firm-level analyses generally use the weighted sum of the investments of other firms to model the knowledge capital external to a firm, we use establishment level data to model spillover pools available to a firm, where the spillover available to a firm is the weighted sum of the spillover pools available to each of its establishments, and lowercase and uppercase indices represent establishments and firms, respectively.

$$s_I = \sum_{i \in I} \left(\frac{c_i}{c_I} \right) s_i$$

The weights are determined by the ratio of IT capital at the establishment level to total IT capital at the firm level. To justify these weights, we rely on an 'absorptive capacity' argument. (Cohen and Levinthal, 1990) Establishments within the firm that are more heavily invested in information technologies will generally have more capacity to absorb spillovers. Thus, conditional on the size of the spillover pool, corporate sites that are larger and more invested in information technologies will do a better job transferring knowledge from these spillover pools into the firm. The spillover pool of each establishment *i* is computed as the average of the information technology investments of all other establishments that occupy the same SIC industry *I(i)*, not including other establishments that are in the same Firm *F(i)*.

$$s_i = \frac{1}{N} \sum_{j \notin F(i)}^{j \in I(i)} c_j$$

Therefore, the spillover pool of each establishment is driven by the SIC code in which it operates, independent of the technological position of the parent firm. Our spillover measure, therefore, differs from traditional firm level measures because use of establishment level data provides a richer description of spillover channels, and because the variation produced by these richer models allows separation between spillover pools and a firm's technological position.

Results

Results from our model are shown in Table 5. All regressions are pooled in levels, with controls for industry and year. The full dataset, ranging from 1987 through 2001, consists of almost 8000 firm-year observations, with errors clustered by firm. For comparison, we also estimate the contributions of spillover using conventional models at the two and four digit SIC level. Specifically, spillover pools for the comparison set are modeled as

$$s_I = \frac{1}{N} \sum_{J \notin I}^{J \in I(I)} c_J$$

where the knowledge pool available to a firm is the average investment of all other firms in the same industry. Column 1 shows estimates using the conventional firm-level measures at the four digit level, and Column 2 shows the equivalent estimate using spillover pools derived from establishment level numbers. The second estimate is considerably smaller, although magnitudes are comparable. Columns 3 and 4 show the equivalent estimates at the two digit SIC level. At the two digit level, the level at which most firm-level spillover studies are conducted, the estimates are dramatically different. Estimates from the establishment level are nearly four times smaller than firm-level estimates, and are consistent with our estimates in the previous section.

Table 5: Establishment-Level Spillover Estimates

Production Function Estimates, Dependent Variable: Log(Value Added)				
	(1)	**(2)**	**(3)**	**(4)**
Specification (Spillover Linkages)	**OLS (SIC)**	**OLS (Establishment)**	**OLS (SIC)**	**OLS (Establishment)**
Log(Capital)	0.28 (0.014)**	0.269 (0.013)**	0.271 (0.013)**	0.27 (0.013)**
Log(Labor)	0.65 (0.019)**	0.66 (0.018)**	0.655 (0.018)**	0.66 (0.018)**
Log(IT Capital)	0.030 (0.011)**	0.035 (0.010)**	0.034 (0.010)**	0.036 (0.010)**
Log(Spillovers) (4 digit)	0.024 (0.011)*	0.016 (0.006)**		
Log(Spillovers) (2 digit)			0.086 (0.018)**	0.022 (0.009)*
Controls	Industry Year	Industry Year	Industry Year	Industry Year
Constant	0.274 (0.121)*	0.356 (0.094)**	-0.104 (0.13)	0.345 (0.094)**
Observations	7572	8837	8747	8837
R-squared	0.82	0.82	0.82	0.82
Robust standard errors in parentheses * significant at 5%; ** significant at 1%				

Discussion and Conclusions

Our estimates of the importance of information technology spillovers place their value at about half that of investment in information technology capital. Estimates using the establishment level data to create more detailed models of spillover paths are broadly in line with our estimates that use instrumental variables to correct for measurement error. While estimates from the establishment level models are slightly lower, this may reflect the fact that this approach mitigates problems caused by measurement error as well as the confounding influences of common technological opportunity, whereas the instrumental variable approach only addressed the measurement error problem. The internal consistency of the estimates, therefore, offers evidence in support of our findings.

Through this paper, we make the following contributions :

(1) We demonstrate that firm-level analyses of spillovers that use simple models of knowledge pools may produce estimates that are too large.

(2) We uses two different approaches to address the most common problems with firm-level approaches. Specifically, we use (a) an instrumental variable to correct for problems caused by measurement error, and (b) establishment level data to create richer models of spillover paths.

(3) We report internally consistent estimates that suggest the contribution of within-industry spillover effects is significant, but smaller than reported in some earlier studies.

This study also demonstrates the value that can be added by creating richer models of spillover transmission paths. Unlike the literature on R & D spillover, studies of IT spillover do not have the benefit of observable linkages such as shared patent citations that provide a clear indicator of spillover between firms. In the absence of these links, researchers are sometimes forced to use broader brush strokes to compute spillover. These limitations, however, are subject only to the availability of data, and attempts to model spillover will benefit greatly from a better understanding externality transmission paths, and the availability of data with which to estimate the effects of these paths.

Getting increasingly accurate estimates of the contributions of information technology spillover to economic output is important for several reasons. Understanding the nature of spillovers generated by these investments sheds light on the relationships between IT investment and economic growth, and may serve to inform policy makers about the potential impacts of subsidies. If for example, estimates suggest that spillovers are larger than they actually are, subsidies may not produce the desired effects, and may be better spent elsewhere. Future research will go further towards untangling the different ways in which information technologies generate externalities, and building richer and more accurate models through which to estimate these effects.

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