Firms are increasingly sourcing internal information systems functions from external service providers. However, there is limited empirical evidence of the economic impact of this delivery option and, more specifically, of the productivity gains accruing to firms that have outsourced. Moreover, there is little evidence of the role and contributions of the individual mechanisms by which service providers create value for client firms. We are particularly interested in whether client firms benefit from the accumulated knowledge held by information technology (IT) service firms. In this paper, we examine the impact of IT outsourcing on the productivity of firms that choose this mode of services delivery; focusing on the role of IT-related knowledge. Since firms self-select into their optimal sourcing mode, we use a variety of econometric techniques including propensity score-based matching and switching regression to control for potential bias arising from endogenously determined sourcing modes. We demonstrate that IT outsourcing does lead to productivity gains for firms that select this mode of service delivery. Our results also suggest that IT-related knowledge held by IT services vendors enables these productivity gains, the magnitude of which is moderated by a firm’s IT intensity. Moreover, the value of outsourcing to a client firm increases with its propensity for outsourcing, which in turn depends on firm-specific attributes including efficiency level, financial leverage, and variability in business conditions. Our analyses also show that firms that outsource have been able to achieve additional productivity gains from contracting out compared with their counterfactuals.

Keywords: IT outsourcing, productivity, knowledge transfer

Introduction

In the last two decades, an increasing number of firms have sourced some or all of their information technology functions from external service providers in sharp contrast with their prior choice of internal delivery. As a result, worldwide spending on IT outsourcing grew to $821 billion in 2010 and continues to increase (Gartner Dataquest 2010). This shift recognizes that the full benefits of IT may accrue only when the production of information services is itself restructured. Executives at outsourcing companies cite many drivers of the outsourcing decision, including the benefits that accrue from vendors’ specialization and scale, learning that improves process performance with better IT systems, increased mana-
While the economic benefits of outsourcing can be measured in a variety of ways, we focus on productivity since it is the primary measure used both in studies on the economic impact of IT and in the industry-level studies of the impact of services outsourcing. This in turn is due to the fact that productivity is a measure that is appropriate to measure the impact of capital investment, is meaningful in all industries, and allows us to use the well-established production function approach.

Given the prevalence of IT outsourcing, it is important to examine the degree to which IT outsourcing pays off and what factors drive the benefits. Yet, while IT outsourcing is the subject of numerous studies in academia and in practice, there is surprisingly limited systematic empirical research on analyzing its payoffs. For a comprehensive review, see Dibbern et al. (2004). Of the small number of studies that have attempted to measure the economic impacts of IT outsourcing, only a few have examined its productivity impacts. At the firm level, Knittel and Stango (2007) examine the productivity impact of IT outsourcing in one specialized industry sector, credit unions. At the industry level, Han et al. (2011) focus on purchased IT services. These studies have found that purchased IT services contribute to productivity improvement while generally assuming that outsourcing firms or industries benefit equally. While these studies recognize the importance of disentangling the effects of individual sources of value, their focus is on demonstrating aggregate returns. None of the studies identify the mechanisms by which IT outsourcing confers productivity benefits on client firms or industries. As a result, we have a limited understanding of the sources and magnitude of the tangible economic benefits, such as productivity improvements, that client firms derive from outsourcing IT services.

This paper seeks to address this gap. We examine whether IT outsourcing leads to a productivity payoff for client firms, focusing on the role of vendors’ IT-related knowledge as a source of economic value, and consider the conditions that influence the magnitude of the payoff. While there may be multiple pathways to improvements in firm-level productivity improvement from outsourcing, we focus on IT-related knowledge since economies of specialization, which are an important source of advantage for vendor firms, arise from accumulated knowledge. Specifically, IT-related knowledge allows an external provider to achieve higher levels of efficiency in the delivery of IT services than their clients, while also enabling them to improve their business performance through the implementation of better systems. In addition, learning effects have been shown in other settings to be a critical element of productivity gains (Caselli and Coleman 2001; Coe and Helpman 1995). Hence, we argue that vendors’ IT-related knowledge is likely to be a key source of productivity improvement for client firms.

To this end, we examine the productivity impacts of IT outsourcing in a sample of large U.S. firms. Consistent with the widely accepted definition of IT outsourcing in academia and practice (Gurbaxani 2007; Young 2004), we consider only multiyear contractual arrangements in which a vendor manages part or all of a client’s IT operations. We begin our analysis with a matching technique based on propensity scores (Heckman et al. 1998; Rosenbaum and Rubin 1983) and examine the productivity gains for outsourcing firms relative to their counterfactuals (controlling for potential endogeneity). We complement this approach with switching regression which allows us to compare the productivity gains for firms that have outsourced with the hypothetical gains in the alternative sourcing mode. Since firms choose their mode of services delivery, we incorporate a firm’s self-selection process into the estimation procedure to control for potential bias. The resulting selection equation enables us to identify key factors that increase a firm’s propensity for outsourcing and helps to establish the direction of causality from outsourcing to productivity gains. These factors include a firm’s efficiency level, its financial leverage, variability in its business conditions, and its IT intensity.

To analyze the role of knowledge, we build a firm-level production function that includes a measure of service providers’ IT knowledge. We estimate the production function using data on IT outsourcing arrangements and assess both the overall returns and the impact of IT knowledge. Finally, we examine the heterogeneity in the magnitude of economic gains accruing from IT outsourcing by considering the role of firm-specific factors, including IT intensity and the types of services outsourced.

Our analyses show that IT outsourcing confers significant productivity gains on client firms. Importantly, our results

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3Han et al. (2011) do allow for limited variability in returns based on IT intensity.

4We provide a formal definition of IT outsourcing in the “Data” section of this paper.
suggest that IT knowledge transmitted from IT service providers is a major driver of these productivity gains. We find that firms with higher IT intensity accrue larger benefits from vendors’ IT knowledge. Interestingly, the magnitude of returns to in-house IT capital is higher for firms that outsource relative to those that do not. Accordingly, we infer that the reorganization of production from internal to external delivery is an important component of the value created by IT and that the knowledge-based capabilities of a vendor underpin its ability to generate value.

The factors included in the selection equation generally increase the likelihood of IT outsourcing. Our results also suggest that firms are not homogeneous in the economic gains they accrue from IT outsourcing. Firms with high propensity to outsource receive significant benefits, gaining a productivity improvement of as much as 6 percent. In contrast, firms with lower propensity for outsourcing receive few if any productivity benefits.

Our study builds on earlier research and makes several new contributions. To the best of our knowledge, this is one of a very few studies that has assessed the overall economic gains from IT outsourcing and the contribution of IT knowledge transmitted from IT services firms. In contrast with earlier research (e.g., Han et al. 2011; Knittel and Stango 2007), our firm-level study examines the mechanisms by which productivity gains are achieved, encompasses a variety of industries, and allows for heterogeneity in the value received by client firms. By accounting for firm-level differences, we are able to develop a deeper understanding of the sources of the payoffs, which, in turn, allows us to develop helpful insights for managers evaluating the outsourcing decision. Overall, our results shed light on the heterogeneous nature of the overall economic gains that accrue from IT outsourcing and highlight the critical role of the IT knowledge held by IT service providers.

This paper is organized as follows. In the next section, we address the relevant theoretical background. We then focus on the development of empirical models. The dataset is described next. The results of our empirical analysis are presented, followed by our conclusions.

**Theoretical Background**

The theoretical rationale for the productivity impact of IT outsourcing derives from the associated cost savings and from improvements in business performance. Firms can lower the costs of IT service delivery by relocating production processes for services in which they are relatively inefficient to a third party provider, resulting in productivity gains (Amiti and Wei 2006). Alternatively, when a vendor develops better systems as part of the outsourcing arrangement, a client firm may see improvements in performance, improving margins which in turn improve measured productivity (DiRomualdo and Gurbaxani 1998; Gorg et al 2008). Given the scope of our study, we focus here on research that addresses the economic impacts of outsourcing and the sources of these gains.

**IT Outsourcing: Economic Performance and its Determinants**

Researchers have investigated the relationship between IT outsourcing and resulting economic performance. Case study evidence (Lacity et al. 1996; Saunders et al. 1997) has documented cost savings of up to 40 percent. Other studies have examined its value using financial and accounting measures. For instance, Loh and Venkatraman (1995) show that increased levels of IT outsourcing lead to higher financial performance as captured in Tobin’s q and return on equity (ROE). Some studies have found a positive, but weak, impact of IT outsourcing arrangements on stock market returns (Farag and Krishnan 2003; Gurbaxani and Jorion 2005; Hayes et al. 2000), implying that investors expect IT service providers to improve client firm performance through a variety of means, including economies of specialization and scale.

A few studies have examined productivity improvement as the measure of economic performance. At the firm level, Knittel and Stango (2007) examine the impact of IT outsourcing on productivity in the specialized case of the credit union industry. They argue that IT drives productivity growth not just via capital deepening, but also through the reorganization of the production of IT services in favor of external provision. In turn, the benefits of external provision may stem from the vendor’s specialization, efficient scale, and can also be facilitated by complementary investments. To this end, they use a cost function approach, modeling IT outsourcing as a vector of indicator variables based on whether a firm uses in-house IT, a vendor supplied system run in-house, or a vendor supplied system run by the vendor at a remote location. They find that IT outsourcing confers significant benefits to credit unions primarily through cost savings.

5Our study is in the tradition of earlier studies that have demonstrated the productivity impacts of outsourcing in very different contexts. For instance, Girma and Gorg (2004) find that the outsourcing of industrial services, not including computer services, by manufacturing firms in the United Kingdom raises productivity.
At the industry level, studies have shown that purchased IT and business services have a positive influence on industry-level output growth. Han et al. (2011) use a production function framework to analyze the economic impact of purchased IT services in 61 private sector industries in the United States. They construct a measure of IT outsourcing by accounting for purchased services from the IT services industry, which is then included as an input factor in the production function. They find that purchased IT services make labor more productive and contribute significantly to the growth of industry output. Their results also suggest that the returns to IT outsourcing are higher when industry-level IT intensity is high, indicating potential variations in the payoffs from IT outsourcing across industries. They interpret this finding in terms of absorptive capacity or an organization’s ability to assess and use external knowledge (Cohen and Levinthal 1990).

In the related context of offshoring, Gorg et al. (2008) study the impact of services (including consultancy, maintenance, security, cleaning, and catering) and materials offshoring on manufacturing establishments in Ireland and find that services (but not materials) offshoring contributes to establishment-level productivity in the aggregate, but only for those establishments operating in the export market. At the industry level, Amiti and Wei (2006) similarly use a production function framework to examine the impact of services (including communication, computer, financial, insurance, and other business services) offshoring on labor productivity in the manufacturing sector. They compute purchased service inputs employing the input–output tables constructed by the U.S. Bureau of Labor Statistics. They estimate a production function that includes services offshoring as an input using instrument variables estimation to account for potential endogeneity. Their results show that purchased IT and business services are positively associated with higher labor productivity in the U.S. manufacturing sector between 1992 and 2000. Specifically, their findings suggest that business services outsourcing accounts for up to 13 percent of the growth in labor productivity.

While these studies provide evidence of the economic value of IT, and more broadly services, outsourcing, none addresses the heterogeneity in the value accruing from outsourced IT services, nor do they examine the sources of these gains. In contrast, Abraham and Taylor (1996) provide insights into the sources of potential gains in their examination of an establishment’s propensity to outsource. They argue that a decision to outsource may be influenced by wage and benefit savings, volatility in output demand, and a contractor’s specialized skills, which also results in heterogeneity in the value received by the establishments that outsource. They analyze the contracting decisions of establishments in the time period 1979–1986 for a range of services, including computer services. Interestingly, the only correlate for contracting out for computer services is economies of scale in the provision of specialized services based on the finding that smaller establishments show a greater propensity for contracting for this service. On the other hand, more recent evidence (Knittel and Stango 2007; Levina and Ross 2003) suggests that larger firms are more likely to engage in the outsourcing of IT services. Nevertheless, these studies highlight the importance of the specialized skills of the external service provider.

In summary, the fundamental sources of a vendor’s comparative advantage stem from economies of specialization and scale. Moreover, certain attributes of client firms and industries including their relative inefficiency, their current investments in IT, their ability to make complementary investments, and demand-side volatility are determinants of their propensity to outsource. Overall, while a few studies have shown its economic impact, there is a limited understanding of whether IT outsourcing results in productivity improvement for clients, which firms are likely to benefit, and the factors that enable IT service providers to create value for these firms.

Our focus on knowledge as an important source of value creation in IT outsourcing arrangements is based on knowledge-based theory, which argues that knowledge is a key competitive asset that can be created within and transmitted between organizations (Davenport and Prusak 1998; Grant 1996; Grant and Baden-Fuller 1995; Kogut and Zander 1992). Studies show that a firm’s knowledge allows it to improve its competitive position (King and Zethaml 2003) and is positively associated with performance (De Carolis and Deeds 1999). The theory also points to the importance of benefits accruing from the knowledge held by other firms, positing that a firm may not be able to efficiently create and apply knowledge in its production process due to a lack of resources and expertise (Grant 1996; Langlois and Foss 1999). In such cases, a firm may seek external partners to augment its knowledge assets and increase the efficiency with which knowledge is utilized (Grant and Baden-Fuller 1995; Takeishi 2002). As a result, firms can differentiate themselves from their competitors with the help of transmitted knowledge.

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6Abraham and Taylor’s definition of contracting out is fundamentally different from the industry standard definition used in Knittel and Stango and in our study, and includes any use of an external provider. In our assessment, their result is driven by the small size of the establishments in the dataset, the types of IT services delivered in the time period of the study, and their definition of outsourcing.
knowledge via interfirm agreements (Zander and Kogut 1995).

In our context, this perspective suggests that IT service providers can improve their competitive position by investing in research and development (R&D) activities that create knowledge related to developing and delivering better IT services. More importantly, while clients may benefit from their own investments in IT capabilities, they can also gain from their vendors’ knowledge assets through trading relationships. For instance, a client firm may hire an IT services firm to build systems which it is able to do more effectively due to its investments in software development methodologies and in acquiring domain expertise, and from its accumulated prior experience (Levina and Ross 2003; Ramasubbu et al. 2008). Moreover, a service firm’s solutions for a client (Keller and Chintu 1990) may embed improved business processes and routines generating value beyond efficiency improvements in systems delivery. To summarize, client firms can acquire the benefits of IT-related knowledge by hiring external service providers both through superior IT processes and through better solutions that can improve the performance of the client firm.

**IT Outsourcing: A Channel for Knowledge Transmission for Productivity Gains**

While knowledge-based theory points to the importance of IT knowledge in value creation in the context of IT outsourcing, we complement the theory by further developing the mechanism by which IT knowledge held by a services firm can translate into productivity gains for a client firm beyond those resulting from direct cost savings. Specifically, we focus on the spillover effects of knowledge transfer that can occur when firms trade with one another. Indeed, numerous studies have identified trade as a channel through which knowledge is transmitted (Caselli and Coleman 2001; Coe and Helpman 1995). Firms receive spillover benefits when the firm that invests in knowledge creation, say through R&D, cannot appropriate the full benefits from its investments because some part of the benefits diffuses (without proportionate compensation) to non-investing firms.

Prior studies have examined the productivity impact of spillovers, primarily in the context of R&D (Coe and Helpman 1995) and a few in the context of IT (Chang and Gurbaxani 2012; Cheng and Nault 2007). The primary transmission mechanism by which these benefits lead to spillovers is when an investing firm trades with other firms. In our context, this would occur when an IT services firm that has invested in R&D sells services related to its knowledge capital. Put differently, a firm may receive external benefits embodied in traded goods and services when suppliers cannot charge quality-adjusted prices for their output due to competition (Griliches 1979). As a result, a substantial portion of the benefits are transmitted from suppliers to their trading partners (Bresnahan 1986; Cheng and Nault 2007).

In the context of IT outsourcing, a firm that invests in R&D sells its know-how but frequently cannot fully appropriate rents because of competitive pressure. Clearly, the economic impact of this trade will manifest as a productivity gain for the outsourcing client since it acquires IT services and knowledge at a cost lower than its value. Moreover, formal trading relationships with IT services firms can also foster the diffusion of knowledge to a client firm due to its non-rival properties. That is, a firm may observe and learn from IT services firms while transacting with them, leading to performance improvement beyond the transaction. In this sense, we conjecture that IT outsourcing can be considered as both an explicit and an implicit channel through which IT service providers’ knowledge spills over to client firms (Lee 2001; Lin et al. 2005). This, in turn, will yield productivity gains for firms that have outsourced.

At this point, it is worthwhile to note that the magnitude of the gains that a firm receives will vary with its capacity to absorb knowledge, which, in turn, depends on its own capabilities (Cohen and Levinthal 1990). The IS literature often argues that a firm’s IT intensity is directly associated with its IT capabilities (Bharadwaj 2000; Bharadwaj et al. 1999). For instance, firms can foster organizational learning (Ayal and Seidmann 2009) and make use of other inputs more effectively (Mitra 2005) with intensive IT investments. In our context, firms with greater IT capabilities, which we proxy with IT intensity, may be in a better position to assimilate knowledge from IT services firms. For instance, Han and Mithas (2009) find that firms with higher investments in IT are able to achieve higher cost savings by outsourcing IT services.

In sum, we argue that formal outsourcing agreements with IT services firms can serve as a conduit for knowledge transmission. In turn, this transfer of knowledge will lead to gains in productivity for client firms due to the direct and spillover effects of the knowledge-based capabilities that a vendor possesses, while the impact of IT knowledge will vary with a firm’s ability to absorb this knowledge captured in its IT intensity.

In this paper, we focus on a vendor’s comparative advantage from specialization as the source of productivity improvements in client firms, which in turn may receive varying...
benefits based on their propensity to outsource. Specifically, we examine the value creating role of IT knowledge transmitted from IT service providers through formal arrangements with client firms since it is this knowledge that is the source of a vendor’s specialized capabilities that can generate value for client firms in several ways. These capabilities enable the vendor to use superior methodologies and know-how in service delivery. In turn, a client can reorganize the production of IT services by transferring inefficient services to more efficient external providers (Knittel and Stango 2007). A client firm may also benefit by having access to better information systems, which can improve business performance including productivity. Moreover, the vendor’s know-how and the related specialization can result in spillover effects for the client firm that absorbs this knowledge through the outsourcing transaction and improves its management practices, raising its productivity (Levina and Ross 2003).

**Econometric Models**

Our estimation strategy proceeds as follows: First, we examine the overall economic gains that accrue from IT outsourcing by assessing the productivity impacts for firms that have outsourced relative to a comparison set developed using a matching technique based on propensity scores. We then complement the analysis with the switching regression method. We also check the robustness of our results by conducting a sensitivity analysis to account for the possibility that we do not control for unobserved variables. Finally, we examine the sources of value derived from outsourced IT services via the production function approach.

**Overall Economic Gains from IT Outsourcing**

Our main objective is to assess the economic gains resulting from IT outsourcing. An obvious way to do this is to compare the productivity gains for a firm $i$ that has outsourced with those for a firm $j$ that has not outsourced, which can be specified as follows:

\[
\text{Economic gains from IT outsourcing} = E(\Delta \ln Y_i|\text{out} = 1) - E(\Delta \ln Y_i|\text{out} = 0)
\]  

(1)

where $Y_i$ and $Y_j$ are the outputs of firm $i$ and $j$ respectively, and superscripts 1 and 0 refer to the sourcing mode, 1 for outsourcing and 0 for non-outsourcing. The symbol $\Delta$ denotes the first difference in the value in two consecutive periods.

In social experiments that randomly assign treatment and control groups, we can assess the effect of the treatment (IT outsourcing in our context) by comparing the treatment group’s outcome with the control group’s outcome (Dehejia and Wahba 2002). However, in nonexperimental settings like ours, firms are not randomly assigned to either the treatment or the control group, but instead select their own group. For instance, firm $i$ (the outsourcing firm) may be better positioned to create value by outsourcing IT services relative to firm $j$ (the non-outsourcing firm). Therefore, if we were to use equation (1) as the basis of gauging the value of IT outsourcing, the resulting estimates would be biased since the difference in productivity gains may result from the inherited heterogeneity between the two groups. In such cases, a better approach is to compare the productivity gains for firms that have outsourced with those for the same firms in the alternative regime (for applications of this approach in other contexts, see Mithas and Krishnan 2009; Shaver 1998).

Recall that in estimating equation (1), we cannot use the productivity gains of non-outsourcing firms since outsourcing and non-outsourcing firms may react to outsourcing differently. The essence of the matching technique is to sort and divide data into homogeneous groups on the basis of propensity scores by identifying a set of control firms that are similar to the treated firms (Heckman et al. 1998; Heckman and Smith 1995). Each set should consist of firms that are homogenous in their attributes, but that differ in their sourcing mode. Then, we can assess the value of IT outsourcing by comparing the two homogenous groups (Imbens 2004). That is, we construct counterfactuals for outsourcing firms by identifying a set of

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7The lower costs of a vendor to deliver services may manifest as a joint productivity increase for both client and vendor or as lower input cost to the client.

8See Mithas and Krishnan (2009) for more detail and an excellent application of the method in the IS context.
non-outsourcing firms that are similar to outsourcing firms. This yields

\[ \text{Economic gains of IT outsourcing} = E(\Delta \ln Y_i | out = 1) - E(\Delta \ln Y_i | out = 0) \]  

(2)

where firms \( i \) and \( j \) are homogenous in terms of their firm attributes. The matching technique requires the conditional independence assumption (CIA), which implies that treatment assignment conditional on observed attributes is independent of potential productivity gains (Rosenbaum and Rubin 1983) and is formally represented as

\[ (\Delta \ln Y_i, \Delta \ln Y_j) \perp D | Z \]  

(3a)

where \( D \) is treatment status and \( Z \) is the set of observed attributes which we discuss later.

Equation (3a) justifies the use of the productivity gains of non-outsourcing firms as counterfactuals for outsourcing firms. The underlying logic is that once we control for observed attributes \( (Z) \), the productivity gains for outsourcing firms \( (\Delta \ln Y_i) \) and non-outsourcing firms \( (\Delta \ln Y_j) \) should be the same. Therefore, a difference in productivity gains between firm \( i \) and \( j \) can be solely attributed to their sourcing choice. In practice, it is difficult to find matched non-outsourcing firms conditioning on a high-dimensional vector of attributes \( (Z) \). Rosenbaum and Rubin (1983) suggest the use of propensity scores to alleviate the dimension problem specified as:

\[ (\Delta \ln Y_i, \Delta \ln Y_j) \perp D | P(Z) \]  

(3b)

where the propensity score, \( P(Z) \), is the probability that firms with attributes \( Z \) will be in the treatment (outsourcing) group.

Then, we can identify (matched) control firms for outsourcing firms on the basis of their propensity scores and assess the value of IT outsourcing by comparing productivity gains for outsourcing firms with those for control firms (which do not outsource) but have the same propensity scores, \( P(Z) \). In addition, the matching method requires the assumption of \( 0 < P(D = 1 | Z) < 1 \), which implies the existence of both outsourcing and non-outsourcing firms for the same attribute \( (Z) \). For instance, if \( P(D = 1 | Z = z) = 1 \) for \( z \), we cannot identify control firms with the same attributes since firms with these attributes always outsource.

Under these assumptions, we take several steps to assess the value of IT outsourcing. First, we obtain propensity scores using a probit model. Based on these scores, we identify a set of control firms using a kernel-based matching technique (for details, see Heckman et al. 1998).\(^\text{10}\) This allows us to divide the sample into several strata in which the means of attributes \( (Z) \) do not differ between the outsourcing and non-outsourcing firms. Finally, we can obtain the treatment effect by computing the differences in productivity gains between outsourcing firms and their counterfactuals for each stratum.

Switching regression can also be used to estimate economic gains resulting from IT outsourcing by constructing assumption productivity gains under the alternative sourcing mode. This yields

\[ \text{Economic gains from IT outsourcing} = E(\Delta \ln Y_i | out = 1) - E(\Delta \ln Y_i | out = 0) \]  

(4)

Unlike the matching technique, switching regression computes the productivity gains for firms that have outsourced in the two different regimes under the normality assumption of error terms (see Gopal and Sivaramakrishnan 2008; Maddala 1983). However, this approach also uses a probit model to control for selection bias in estimating equation (4) by introducing a selection equation.\(^\text{11}\)

While the above discussion allows us to gauge the overall value of IT outsourcing, we cannot rule out the possibility that not all outsourcing firms receive similar benefits by outsourcing IT services. We construct several strata based on propensity scores to classify outsourcing firms by their tendency to outsource. Then, we can assess the heterogeneous effects of IT outsourcing by examining productivity gains computed from the matching technique and switching regression in each stratum.\(^\text{12}\)

\(^9\)Note that while equation 2 appears to be the same as equation 1, the two are fundamentally different in that they compare the productivity gains of the two groups before and after matching.

\(^10\)The basic idea of kernel-based matching is that we use weighted average of all control firms to obtain counterfactuals while assigning the greatest weight for control firms that are closest to treatment firms. In our context, the weight is constructed on the basis of the difference in propensity scores between outsourcing and non-outsourcing firms.

\(^11\)A more detailed discussion on the switching regression method is provided in a following subsection on sources of economic payoff.

\(^12\)We also estimate the overall gains using OLS, which does not account for selection bias, for the purpose of comparison with our matching technique and with switching regression.
Sensitivity Analysis

As discussed above, the primary issue in evaluating the economic gains of IT outsourcing is that we observe only one of the two alternatives in a firm’s sourcing choice. While the matching method does so under the conditional independence assumption (CIA), switching regression addresses this issue under the normality assumption of error terms. The latter is well-established and widely used (see Gopal and Sivaramakrishnan 2008). However, it is difficult to empirically test and validate the underlying normality assumption and the estimated results may be sensitive to distributional misspecification (Lalonde 1986, Mithas and Krishnan 2009). Therefore, it is worthwhile to check whether the two methods provide similar estimates. Further, the CIA assumption may also be problematic in the presence of unobserved heterogeneity for which we cannot control. Therefore, we conduct a sensitivity analysis for the results from the matching method by checking the extent to which inference about the treatment effect is altered by unobserved attributes (Mithas and Krishnan 2009).13

Sources of Economic Payoff from IT Outsourcing

So far, we have focused on measurement of the overall value of IT outsourcing by employing both a matching technique and switching regression. We now focus on switching regression under the production function framework to examine the mechanism by which outsourcing firms can achieve economic gains from external service provision. We do so since the matching technique does not allow us to specify a production function. As discussed above, IT knowledge transmitted from IT services providers has been identified as a key source of productivity gains for firms that have outsourced. Consistent with the IT productivity literature, we assume that a firm’s production process follows Cobb-Douglas technology (Brynjolfsson and Hitt 1995; Dewan and Min 1997). We then extend the production function by including a measure of IT knowledge transmitted from IT services firms. Next, we take first differences to control for unobserved firm-specific effects. We refine our model by including the possibility that firms with higher IT intensity may be better positioned to absorb knowledge transmitted from outsourced IT services. To this end, we include an interaction term between a firm’s IT intensity and the knowledge held by services vendors. To allow for the possibility that IT knowledge may be more valuable for certain service offerings, we also examine the potential interplay between a service provider’s IT knowledge and the types of services outsourced. Specifically, we classify IT services using dummy variables into two categories, software (SW) and hardware (HW) focused, and include them individually and as interaction (with IT knowledge) terms. Finally, we include a dummy variable to distinguish firms that have outsourced from those that have not. This yields

\[
\Delta \ln Y_i = \Delta A_i + \alpha \Delta \ln L_i + \beta \Delta \ln K_i + \gamma \Delta \ln N_i + \delta D_i \Delta \ln K_n + \eta \Delta ITINT_i + \theta \Delta NINT_i + \Delta \ln K_n + \phi_1 H W_i + \phi_2 H W_i + \Delta \ln K_n + \phi_3 S W_i + \phi_4 S W_i \times \Delta \ln K_n + \text{controls}
\]

where \( \Delta Y_i \) is value added of firm \( i \) measured as sales less material expenses, \( L_i \) is labor, \( K_i \) is capital, \( N_i \) is in-house IT capital, \( K_n \) is the IT knowledge transmitted from IT services providers, and \( D_i \) is a dummy variable denoted as 1 if firm \( i \) outsources and 0 otherwise. ITINT is IT intensity measured as IT capital per unit of labor. HW\(_i\) is a dummy variable denoted as 1 if firm \( i \) outsources datacenter, desktop, or network services and 0 otherwise. Similarly, SW\(_i\) is a dummy variable denoted as 1 if firm \( i \) outsources application development or maintenance and 0 otherwise. \( \Delta \) denotes the first difference between the year after and the year in which firm \( i \) outsources IT services and controls include year dummies to capture any unobserved time-varying effect and industry dummies at the two-digit SIC levels to incorporate potential heterogeneity in productivity across industries.

The impact of IT knowledge transmitted from IT services providers to firms that have outsourced is captured by the estimate of the coefficient, \( \delta \). As discussed, it is likely that firms choose their sourcing mode on the basis of expected returns and are not homogenous in the value received from IT outsourcing. As a result, it is somewhat restrictive to assume that the parameter estimates are the same for both sourcing modes given the likely heterogeneities between the two groups of firms (see Shaver 1998). In this case, a traditional regression technique, such as OLS, cannot provide consistent estimates. To address the self-selected nature of a sourcing decision and to examine the factor that leads to productivity gains for outsourcing firms, we use endogenous switching regression (Gopal and Sivaramakrishnan 2008; Heckman 1976; Lee 1978).14

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13We thank an anonymous reviewer for suggesting this.

14The switching model is commonly used in this type of situation. For instance, Lee (1978) examines the effect of unions on wage rates under the assumption that union membership and wage rates are simultaneously determined. Bertschek and Kaiser (2004) investigate how organizational changes affect productivity in the German service sector. In the context of offshore software projects, Gopal and Sivaramakrishnan (2008) model a vendor’s profit and contract choice functions where contract choice is assumed to depend on potential profits.
As in the case of the matching technique, we use a probit model to control for selection bias (Heckman 1976; Lee 1978; Maddala 1983). To this end, we model a firm’s sourcing choice with a latent variable

\[ D_i^* = \theta Z_i + \epsilon_i \]  

(6)

where \( D_i^* \) is a latent variable which depends on firm \( i \)'s preference for outsourcing. \( Z_i \) are variables that affect firm \( i \)'s sourcing choice operationalized one year before the year in which firm \( i \) outsources,\(^{15}\) and \( \epsilon \) follows a normal distribution, \( N(0, \sigma) \).

In equation (6), the latent variable \( D_i^* \) is not observable. However, we do observe firm \( i \)'s sourcing mode. The observed sourcing choice for firm \( i \) is specified as \( D_i = 1 \) (i.e., \( D_i^* > 0 \)) if it chooses to outsource or \( D_i = 0 \) (i.e., \( D_i^* < 0 \)) otherwise.

Once we estimate equation (6) using a probit model, we specify the two production functions by separating firms into different productivity regimes based on their outsourcing decisions and removing the dummy variable that indicates the sourcing mode (see Gopal and Sivaramakrishnan 2008; Shaver 1998) as

\[ \Delta \ln Y_{i1} = \Delta A_{01} + \alpha_1 \Delta \ln L_{i1,j} + \beta_1 \Delta \ln K_{i1,j} + \gamma_1 \Delta \ln h_{i1,j} + \\
\delta_1 \Delta \ln K_{n1,j} + \eta_1 \Delta \ln m_{i1,j} \times \Delta \ln d_{i1,j} + \\
\varphi_1 \Delta h_{i1,j} + \varphi_2 \Delta h_{i1,j} \times \Delta \ln K_{n1,j} + \varphi_3 \Delta w_{i1,j} + \varphi_4 \Delta w_{i1,j} \times \\
\Delta \ln K_{u1,j} + \sigma_{11} \lambda_{1,i} + u_{1,i} \]  

(7a)

\[ \Delta \ln Y_{i0} = \Delta A_{00} + \alpha_0 \Delta \ln L_{i0,j} + \beta_0 \Delta \ln K_{i0,j} + \gamma_0 \Delta \ln h_{i0,j} + \\
\delta_0 \Delta \ln K_{n0,j} + \eta_0 \Delta \ln m_{i0,j} \times \Delta \ln d_{i0,j} + \\
\varphi_0 \Delta h_{i0,j} + \varphi_2 \Delta h_{i0,j} \times \Delta \ln K_{n0,j} + \varphi_3 \Delta w_{i0,j} + \varphi_4 \Delta w_{i0,j} \times \\
\Delta \ln K_{u0,j} + \sigma_{10} \lambda_{1,i} + u_{0,i} \]  

(8a)

if \( \theta Z_i + \epsilon_i > 0 \)

\[ \Delta \ln Y_{i1} = \Delta A_{11} + \alpha_1 \Delta \ln L_{i1,j} + \beta_1 \Delta \ln K_{i1,j} + \gamma_1 \Delta \ln h_{i1,j} + \\
\delta_1 \Delta \ln K_{n1,j} + \eta_1 \Delta \ln m_{i1,j} \times \Delta \ln d_{i1,j} + \\
\varphi_1 \Delta h_{i1,j} + \varphi_2 \Delta h_{i1,j} \times \Delta \ln K_{n1,j} + \varphi_3 \Delta w_{i1,j} + \varphi_4 \Delta w_{i1,j} \times \\
\Delta \ln K_{u1,j} + \lambda_{1,i} + u_{1,i} \]  

(7b)

\[ \Delta \ln Y_{i0} = \Delta A_{01} + \alpha_0 \Delta \ln L_{i0,j} + \beta_0 \Delta \ln K_{i0,j} + \gamma_0 \Delta \ln h_{i0,j} + \\
\delta_0 \Delta \ln K_{n0,j} + \eta_0 \Delta \ln m_{i0,j} \times \Delta \ln d_{i0,j} + \\
\varphi_0 \Delta h_{i0,j} + \varphi_2 \Delta h_{i0,j} \times \Delta \ln K_{n0,j} + \varphi_3 \Delta w_{i0,j} + \varphi_4 \Delta w_{i0,j} \times \\
\Delta \ln K_{u0,j} + \lambda_{0,i} + u_{0,i} \]  

(8b)

where \( \lambda_{1,i} \) is a latent variable which depends on firm \( i \)'s preference for outsourcing. As in the case of the matching technique, we use a probit model to estimate \( \lambda_{1,i} \) and \( \lambda_{0,i} \) using a traditional regression technique such as OLS (Gopal and Sivaramakrishnan 2008; Heckman 1976). That is, we can assess the impact of IT knowledge transmitted from IT services firms by estimating the parameter, \( \delta_i \). Finally, it should be noted that the inverse Mills ratios capture the covariance between error terms in the selection equation and the production functions (for details, see Maddala 1983). Therefore, the statistical significance of inverse Mills ratios informs us about the extent to which sourcing choices and productivity gains are interrelated.

Data

Description of Data

Our empirical analysis requires data on a firm’s capital and IT investments, its labor pool, and its financials. For IT related variables, we use the Harte Hanks Computer Intelligence Technology (CII) database, which includes data on IT capital and provides the numbers of a variety of technologies in Fortune 1000 firms spanning the years 1987 to 1999. We use Compustat to obtain data on capital stock, labor expense, and industry classification at the two-digit SIC level. The data are constructed and deflated using standard procedures (for details, see Brynjolfsson and Hitt 2003).

To learn whether firms have engaged in IT outsourcing, we collected IT outsourcing announcements from two primary sources, Business Wire and PR Newswire, beginning in 1991.\(^{16}\) We do not consider outsourcing deals before 1991.

\(^{15}\)We conjecture that there are many variables that influence a firm’s sourcing decisions. Further details will be discussed in the next section.

\(^{16}\)Up to 1994, IT capital encompassed all information systems within a firm. In 1995, it was redefined to capture only the value of computer processing units. Therefore, we reconstructed the IT stock variable starting in 1995 by estimating it using ordinary least squares (OLS). Specifically, we regress IT capital on the number of mainframes, minicomputers, PCs, and local area networks (LAN) using the data from the years 1987 to 1994. The estimated coefficients are used to estimate IT capital for 1995 and later years. The OLS results explain 75 percent of the total variation, which is reasonably high.
since the absolute number of deals was small then and media did not report IT outsourcing arrangements as frequently as they do now. Since the term *IT outsourcing* is used to describe a variety of delivery options, it is useful to begin by describing our use of this term. Here, consistent with industry and academic usage of the term (Young 2004), IT outsourcing is defined as "a long-term contractual arrangement in which one or more service providers are assigned the responsibility of managing all or part of a client’s information systems (IS) infrastructure and operations" (Gurbaxani 2007).\(^\text{17}\)

To ensure that we capture as many deals as possible, we use various combinations of keywords such as outsourcing, contract, information technology, and so on. We matched the IT outsourcing deals with the IT investment data in the CII database and with financial data for the years in which the IT outsourcing arrangement occurs, resulting in 97 IT outsourcing arrangements for the set of firms in our database.\(^\text{18}\) Then, we identify a set of firms that have not outsourced from the CII database. We do not allow for repeating firms in the sample given that our estimation strategy is best suited to a cross-sectional context. This provides us with 520 non-outsourcing firms. Taken together, our data set consists of a total of 617 unique firms classified as outsourcing and non-outsourcing firms.\(^\text{19}\)

We construct a measure of the IT knowledge accumulated by IT services providers. We begin with the R&D capital of an IT services provider as a proxy for IT knowledge since their investment is likely to be associated with the creation of IT knowledge. We obtain data on R&D expenditures from Compustat. Like other forms of capital, we calculate R&D capital as the sum of R&D expenditures for the past four years after taking depreciation into account (Griliches 1984, 1998).\(^\text{20}\) Service providers have an inherent advantage in engaging in R&D activities since they can recover their costs by serving multiple customers (Lacity and Willcocks 1995). To estimate the flow of this knowledge to an outsourcing firm, we consider the annualized IT outsourcing contract value, and the provider’s R&D capital and its revenues. Our IT knowledge index assumes that IT knowledge transmitted from an IT service provider is proportional to the relative size of the firm’s transaction with it and its R&D capital. We construct the IT knowledge variable as follows:

\[
\text{IT Knowledge}_j = \frac{x_i}{R_D} j
\]

where \(x_i\) is the annualized value of an outsourcing contract between firm \(i\) and IT service provider \(j\), \(x_j\) is the annual revenue of IT services provider \(j\), and \(R_D\) is the R&D capital of IT services provider \(j\) (as a proxy for IT-related knowledge).

Table 1 provides descriptive statistics for the key variables. The average value added for a firm is $1.9 billion, indicating that our sample is drawn from large firms, but ranges from $18.7 million to $31 billion. In general, however, most of the variables display large variation, leading to higher explanatory power in empirical analysis.

### Variables for the Selection Equation

As discussed earlier, firms self-select into their sourcing mode on the basis of their expected returns. To address the issue of self-selection, we adopt both the matching method and switching regression. Both approaches require us to estimate a selection equation by choosing observable variables that influence a firm’s outsourcing decision.

We conducted a comprehensive review of the outsourcing literature focused on identifying determinants of outsourcing. Based on theoretical considerations of a firm’s propensity to outsource (Smith et al. 1998), we focus on variables that serve as indicators of business performance, of cash flow, of variability in business conditions, and of the performance of the internal IT organization, all of which have been found to be drivers of IT outsourcing. Ultimately, we included six variables in the selection equation.\(^\text{21}\) These are sales efficiency, cost inefficiency, leverage, sales fluctuation, volatility of the labor-IT ratio and internal IT intensity (see Table 2 for a detailed description of these variables).

Generally speaking, we argue that more efficient firms are less likely to outsource IT services since they are more likely

\(^{17}\)This definition focuses on outsourcing arrangements where a provider manages functions for a prespecified duration (which may be extended), and excludes project-based arrangements in which a client hires the provider to execute a specific task such as the delivery of a software solution.

\(^{18}\)On average, IT outsourcing intensity, measured as the ratio of annual contract value to sales, is 0.76 percent in our sample and 0.64 percent in the industry level sample in Han et al. (2011). This supports the notion that our sample of firms is representative of the population.

\(^{20}\)Following Griliches (1984), we assume an annual depreciation rate (\(\eta\)) of 0.85 for the past four years.
Table 1. Descriptive Statistics for Key Variables

<table>
<thead>
<tr>
<th>Variable (N = 617)</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value added (VA)</td>
<td>1,836.7</td>
<td>18.7</td>
<td>31,240</td>
<td>3,090</td>
</tr>
<tr>
<td>Ordinary capital (K)</td>
<td>1,849.6</td>
<td>0.7</td>
<td>71,285</td>
<td>4,602</td>
</tr>
<tr>
<td>Labor (L)</td>
<td>865.2</td>
<td>10.1</td>
<td>16,944.6</td>
<td>1,371</td>
</tr>
<tr>
<td>IT capital (IT)</td>
<td>48.3</td>
<td>0.8</td>
<td>819.9</td>
<td>74.3</td>
</tr>
<tr>
<td>Dlnva</td>
<td>0.042</td>
<td>-0.930</td>
<td>1.260</td>
<td>0.177</td>
</tr>
<tr>
<td>Dlnk</td>
<td>0.056</td>
<td>-2.680</td>
<td>1.860</td>
<td>0.276</td>
</tr>
<tr>
<td>Dlnl</td>
<td>0.040</td>
<td>-1.360</td>
<td>1.130</td>
<td>0.204</td>
</tr>
<tr>
<td>Dlnit</td>
<td>0.276</td>
<td>-1.904</td>
<td>2.545</td>
<td>0.433</td>
</tr>
<tr>
<td>IT knowledge</td>
<td>2.1</td>
<td>0.0</td>
<td>23.6</td>
<td>4.2</td>
</tr>
<tr>
<td>Total asset</td>
<td>4,683</td>
<td>109</td>
<td>91,496</td>
<td>13,133</td>
</tr>
</tbody>
</table>

Table 2. Variables for Adjusting for Selection Bias

<table>
<thead>
<tr>
<th>Variable</th>
<th>Construct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales efficiency</td>
<td>Sales/employee</td>
</tr>
<tr>
<td>Cost inefficiency</td>
<td>SGA/Sales</td>
</tr>
<tr>
<td>Leverage</td>
<td>(long term debt+ debt in current liability)/(total assets)</td>
</tr>
<tr>
<td>Sales fluctuation</td>
<td>Regression of sales on constant and time trend. Then, divide the resulting standard errors by the average sales of a firm</td>
</tr>
<tr>
<td>Std (L/IT)</td>
<td>standard deviation of (labor/IT)</td>
</tr>
</tbody>
</table>

A firm’s sourcing decision may also be associated with financial ratios that are indicative of its cash flow, such as its leverage (Hall and Liedtka 2005). An important motivation for firms to outsource is the generation of cash through the sale of IT assets (Lacity and Hirschheim 1993; Smith et al. 1998). Firms with higher leverage have the incentive to engage in IT outsourcing to increase internal cash equivalence.

Next, we consider variation in the demand for a firm’s output, measured as fluctuation in sales. Outsourcing is seen as a way to achieve flexibility in the level of input resources to allow a firm to match the demand for its output without a fixed investment in resources that are needed only for periods of high demand (Abraham and Taylor 1996). A related measure of fluctuation in capacity is the variance of the labor–IT capital ratio. We conjecture that firms respond to external shocks by changing their labor pool, while fixed investments are more difficult to change, resulting in higher variance of the labor–capital ratio (Lane et al. 1998). Given our interest in IT outsourcing, we focus on the labor–IT capital ratio. Since outsourcing has a significant impact on a firm’s labor composition (Hsieh and Woo 2005), IT outsourcing may help firms respond to external shocks better by providing the ability to more easily adjust their input mix (i.e., the ratio of labor to IT capital). Greater variations in this ratio may indicate that firms are already flexible in adapting to a volatile external environment. Therefore, we expect to see that firms with high volatility of the labor–IT capital ratio are less likely to rely on external services providers. Alternatively put, firms may be more likely to outsource IT functions when the firm or its IT organization is not efficient enough to respond to environmental changes (Apte and Mason 1995; Slaughter and Ang 1996).

We include a firm’s internal IT intensity in the selection equation as a proxy for internal IT capability. The IS literature often suggests that IT intensity can serve as an important factor in determining IT capability (Bharadwaj 2000; Bharadwaj et al. 1999; Chang and Gurbaxani 2012). As a result, firms with larger IT scale may be better able to leverage the skills and capabilities of IT services firms (DiRomualdo and
correlated with the output variable, input variables in the production equation including IT are (see Table 4). In general, Table 4 shows that the traditional key input variables in the production and selection equations.

Finally, we also present the correlation coefficients among the variables including leverage, sales fluctuation, variability in the ratio of labor to IT, and IT intensity encompass a wide range of values (see Table 3). In general, all variables indicate that outsourcing firms are less efficient, more leveraged, face more variability, and invest more in IT.

Table 3 presents descriptive statistics of the key variables used in the selection equation. The average sales efficiency is 6.67 for outsourcing firms and 7.08 for non-outsourcing firms, while their cost inefficiency scores are 0.373 and 0.230 respectively. This indicates that outsourcing firms are relatively less efficient than their counterparts. The other variables including leverage, sales fluctuation, variability in the ratio of labor to IT, and IT intensity encompass a wide range of values (see Table 3). In general, all variables indicate that outsourcing firms are less efficient, more leveraged, face more variability, and invest more in IT.

Finally, we also present the correlation coefficients among the key input variables in the production and selection equations (see Table 4). In general, Table 4 shows that the traditional input variables in the production equation including IT are correlated with the output variable, $\Delta \ln Y^*_i$, while the independent variables used in the selection equation are not. This suggests that we have appropriately chosen a set of variables that influence a firm’s sourcing choice but do not directly affect productivity.

**Empirical Analyses**

**Results for Overall Gains from IT Outsourcing**

We begin with the matching technique to compute the overall economic gains resulting from IT outsourcing. Recall that we must first run a probit model to control for selection bias.

Since the probit model does not provide consistent estimates in the presence of heteroscedasticity (Greene 2000), we first check for heteroscedasticity by conducting the Lagrange multiplier (LM) test (Davidson and MacKinnon 1993, Donald 1995). Our test result suggests that we are not able to reject the null hypothesis of homogeneous variance. Accordingly, we present the estimates from the probit model for the selection equation (see Table 5). All of the coefficients in the probit model are statistically significant at the 5 percent or 1 percent levels with the expected signs. The predicted power of our sourcing choice model is 80.2 percent, which implies that a substantial portion of the firms in our sample are correctly classified into the appropriate sourcing regime. We conclude that our probit model adequately controls for selection bias.

The two efficiency variables, sales efficiency and cost inefficiency, are negatively and positively associated with IT outsourcing at the 1 percent and 5 percent significance levels, respectively. Accordingly, our results support the notion that firms seek to improve internal efficiency via IT outsourcing. Consistent with prior work, our results also indicate that firms tend to outsource more when they are more leveraged (Smith et al. 1998). We also find that firms are more likely to outsource IT services when there is higher fluctuation in sales. On the other hand, firms with higher volatility in the labor–IT capital ratio, which we interpret as more flexible firms, are less likely to outsource. Finally, our results also suggest that firms with higher IT intensity are more likely to outsource, implying that these firms may be better positioned to benefit from outsourcing IT services. This is consistent with the industry-level finding that industries with higher IT intensity outsource more IT services (Han et al. 2011).

The coefficient of firm size is also positive, implying that larger firms are more likely to outsource. We observe that many large and successful firms have entered into long-term and large outsourcing deals (McDougall 2002). As mentioned earlier, firms may outsource for strategic purposes (DiRomualdo and Gurbaxani 1998) and vendors provide complementary assets that internal IS departments cannot provide (Levina and Ross 2003). Larger clients may also be able to better exploit their bargaining power with vendors, or be better positioned to find the right partner (Grossman and Helpman 2002). Therefore, greater benefits from outsourcing may accrue to large client firms, consistent with the observed frequency of outsourcing arrangements by these firms.

Next, we matched firms on the basis of their propensity scores, which allows us to classify the sample into several strata in which the propensity scores for outsourcing and non-
### Table 3. Descriptive Statistics for Key Variables in the Selection Equation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Outsourcing Firms (N = 97)</th>
<th></th>
<th></th>
<th>Std. Dev.</th>
<th>Non-Outsourcing Firms (N = 520)</th>
<th></th>
<th></th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Min</td>
<td>Max</td>
<td></td>
<td>Mean</td>
<td>Min</td>
<td>Max</td>
<td></td>
</tr>
<tr>
<td>Sales efficiency</td>
<td>6.671</td>
<td>1.524</td>
<td>29.35</td>
<td>5.201</td>
<td>7.081</td>
<td>0.085</td>
<td>103.9</td>
<td>9.57</td>
</tr>
<tr>
<td>Cost inefficiency</td>
<td>0.373</td>
<td>0.002</td>
<td>5.16</td>
<td>0.637</td>
<td>0.230</td>
<td>0.001</td>
<td>11.15</td>
<td>0.533</td>
</tr>
<tr>
<td>Leverage</td>
<td>0.382</td>
<td>0.002</td>
<td>3.473</td>
<td>0.236</td>
<td>0.274</td>
<td>0.002</td>
<td>5.59</td>
<td>0.286</td>
</tr>
<tr>
<td>Sales fluctuation</td>
<td>0.045</td>
<td>0.005</td>
<td>10.95</td>
<td>0.087</td>
<td>0.023</td>
<td>0.005</td>
<td>7.035</td>
<td>0.036</td>
</tr>
<tr>
<td>Std(L/IT)</td>
<td>15.428</td>
<td>0.001</td>
<td>52.74</td>
<td>23.41</td>
<td>24.096</td>
<td>0.052</td>
<td>52.4</td>
<td>26.23</td>
</tr>
<tr>
<td>IT intensity</td>
<td>0.039</td>
<td>0.001</td>
<td>0.736</td>
<td>0.012</td>
<td>0.033</td>
<td>0.002</td>
<td>0.544</td>
<td>0.009</td>
</tr>
</tbody>
</table>

### Table 4. Correlation for Key Variables

<table>
<thead>
<tr>
<th></th>
<th>(i)</th>
<th>(ii)</th>
<th>(iii)</th>
<th>(iv)</th>
<th>(v)</th>
<th>(vi)</th>
<th>(vii)</th>
<th>(viii)</th>
<th>(ix)</th>
</tr>
</thead>
<tbody>
<tr>
<td>dlnva (i)</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dlink (ii)</td>
<td>0.23</td>
<td></td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dlnit (iii)</td>
<td>0.13</td>
<td></td>
<td>0.44</td>
<td>1</td>
<td></td>
<td>0.17</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dln (iv)</td>
<td>0.47</td>
<td></td>
<td>0.44</td>
<td>0.17</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales efficiency (v)</td>
<td>0.02</td>
<td></td>
<td>0.17</td>
<td></td>
<td></td>
<td>0.47</td>
<td>0.18</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Cost inefficiency (vi)</td>
<td>0.02</td>
<td></td>
<td>0.02</td>
<td></td>
<td></td>
<td>0.17</td>
<td>0.02</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Leverage (vii)</td>
<td>0.02</td>
<td></td>
<td>0.02</td>
<td></td>
<td></td>
<td>0.09</td>
<td>0.08</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Sales fluctuations (viii)</td>
<td>0.02</td>
<td></td>
<td>0.02</td>
<td></td>
<td></td>
<td>0.03</td>
<td>0.05</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Variance of labor-IT ratio (ix)</td>
<td>0.02</td>
<td></td>
<td>0.02</td>
<td></td>
<td></td>
<td>0.04</td>
<td>0.06</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

### Table 5. Estimation Results for Selection Equation

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Marginal Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales efficiency</td>
<td>-0.036***</td>
<td>-0.006***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Cost inefficiency</td>
<td>0.205**</td>
<td>0.036**</td>
</tr>
<tr>
<td></td>
<td>(0.094)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Leverage</td>
<td>0.425***</td>
<td>0.075***</td>
</tr>
<tr>
<td></td>
<td>(0.155)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Std (L/IT)</td>
<td>-0.004**</td>
<td>-0.0007**</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.0003)</td>
</tr>
<tr>
<td>Sales fluctuations</td>
<td>0.201*</td>
<td>0.038*</td>
</tr>
<tr>
<td></td>
<td>(0.114)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>IT intensity</td>
<td>0.877*</td>
<td>0.096*</td>
</tr>
<tr>
<td></td>
<td>(0.452)</td>
<td>(0.050)</td>
</tr>
<tr>
<td>Firm size</td>
<td>0.84***</td>
<td>0.068***</td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Chi-square</td>
<td>158.24***</td>
<td>158.24***</td>
</tr>
</tbody>
</table>

*p < 0.1, **p < 0.05, ***p < 0.01; Year and industry dummies are reported for expositional brevity.
outsourcing firms are not significantly different.\textsuperscript{22} In our context, stratum 1 consists of a set of firms that are the least likely to outsource, while firms in stratum 5 include those that are most likely to outsource. The summary statistics in Table 6 show that outsourcing and non-outsourcing firms within each stratum are similar in terms of their characteristics after matching. This similarity allows us to directly compare the productivity of outsourcing firms with that of non-outsourcing firms, which are used as counterfactuals in a matching technique. We also compare the productivity of these two groups of firms using switching regression.

Overall, our results suggest that outsourcing firms have achieved significant gains from their sourcing choice independent of the methodology (see row 1 in Table 7). This, by itself, is not surprising given that firms self-select their sourcing mode on the basis of expected returns. In general, the estimates obtained from the matching technique and switching regression are not significantly different. However, it is worthwhile to compare the magnitude of our estimates from the matching technique and from switching regression with those using OLS. In general, Table 7 provides evidence that OLS results in overestimates of the returns. The reason for the difference is that the matching model and switching regression allow for the sample to be drawn from self-selected firms that are more likely to benefit from IT outsourcing while OLS does not.

Finally, it is worthwhile to examine the heterogeneity in the magnitude of the economic gains resulting from variation in the propensity to outsource. Our matching technique also allows us to classify outsourcing firms into several strata based on propensity scores and to assess the heterogeneous effects of IT outsourcing. Our results provide evidence of heterogeneity in the value of IT outsourcing. In general, firms that are less likely to outsource (i.e., low propensity score), but did so anyway, benefit less from their decision to outsource (see rows 2 and 3 in Table 7). However, IT outsourcing confers significant productivity benefits to firms with higher propensity scores. Firms in the high propensity score stratum achieve significant productivity gains ranging from 3 percent to 6 percent depending on the method used.

\textsuperscript{22}To stratify the sample, we start with five equal-sized strata based on propensity scores (Dehejia and Wahba 2002). We then check the propensity scores of outsourcing and non-outsourcing firms in each stratum. If there is a difference in the propensity scores of the two groups, we reconstruct the strata and recheck the scores. We repeat the process until we obtain groups where the non-outsourcing and outsourcing firms in each stratum have similar propensity scores and attributes (for details, see Dehejia and Wahba 2002). Since there are only six outsourcing firms in the fifth stratum due to limited sample size, we combine the fourth and fifth strata to ensure a reasonable number of firms in each stratum.

In sum, our results suggest that that firms that outsource gain additional productivity improvements by contracting out. However, there is significant heterogeneity in the magnitude of value accruing from IT outsourcing.

\textbf{Sensitivity Analysis}

The results from the matching method are built on the assumption that we can assess the productivity effects of IT outsourcing once we control for all observed attributes (the CIA assumption). In practice, however, it is not highly likely that we have identified all attributes that influence a firm’s sourcing decision. For instance, firms may outsource to exploit a services vendor’s scale economies or may choose not to outsource due to the potential risks associated with transaction costs that are not observable to us. In such cases we may not obtain unbiased estimates due to the unobserved variables (Caliendo and Kopeinig 2008) that also influence a firm’s sourcing mode. Therefore, it is important to assess the sensitivity of our results in the presence of unobserved factors (see Table 8).

We address this issue by examining the impact of unobserved attributes on the probability that a firm is in a treatment group, IT outsourcing in our context (Rosenbaum 1999). To this end, we construct the odds ratio (Γ) which measures the extent to which firms with the same observed attributes differ in their sourcing mode. If two firms have the same attributes and Γ equals 1.5, they differ in their propensity to outsource by a factor of 1.5, or 50 percent. If there are no unobserved variables that influence a firm’s sourcing mode, the ratio equals 1. In practice, however, we do not know the true value of Γ. Therefore, we conduct a sensitivity analysis by changing the values of Γ and examine how our inference about the outsourcing effect is altered. Following Rosenbaum (1999), we conduct Wilcoxon sign--rank tests and our test statistics suggest that our estimates become sensitive due to unobserved variables when Γ = 2 (i.e., firms with the same observed attributes differ in the propensity to outsource by 100 percent due to unobserved attributes). Given that we capture a large portion of variations in the sourcing decision with several key variables, we believe that this is a large difference. In sum, we can conclude that our results are not driven by unobserved variables.

\textbf{Estimation Results for the Impact of IT Knowledge}

Now, we examine the role of IT knowledge as a source of productivity gains for firms that have outsourced. We have already estimated the selection equation to control for selec-
Table 6. Characteristics of Outsourcing and Non-Outsourcing Firms*

<table>
<thead>
<tr>
<th></th>
<th>Stratum 1</th>
<th>Stratum 2</th>
<th>Stratum 3</th>
<th>Stratum 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>out (n = 18)</td>
<td>non (n = 227)</td>
<td>out (n = 30)</td>
<td>non (n = 205)</td>
</tr>
<tr>
<td>Sales efficiency</td>
<td>8.11</td>
<td>8.33</td>
<td>7.25</td>
<td>6.45</td>
</tr>
<tr>
<td>Cost inefficiency</td>
<td>0.117</td>
<td>0.13</td>
<td>0.169</td>
<td>0.172</td>
</tr>
<tr>
<td>Leverage</td>
<td>0.345</td>
<td>0.259</td>
<td>0.267</td>
<td>0.26</td>
</tr>
<tr>
<td>Sales fluctuation</td>
<td>0.019</td>
<td>0.011</td>
<td>0.018</td>
<td>0.02</td>
</tr>
<tr>
<td>Std(L/IT)</td>
<td>31.12</td>
<td>36.94</td>
<td>10.93</td>
<td>14.66</td>
</tr>
</tbody>
</table>

*out and non indicate outsourcing and non-outsourcing.

Table 7. Productivity Gains for Outsourcing

<table>
<thead>
<tr>
<th></th>
<th>Kernel Matching</th>
<th>Switching Regression</th>
<th>OLS</th>
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<tr>
<td></td>
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</tr>
<tr>
<td>All</td>
<td>0.032***</td>
<td>0.029***</td>
<td>0.037**</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.008)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Stratum 1</td>
<td>0.002</td>
<td>0.017</td>
<td>0.024</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.017)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Stratum 2</td>
<td>0.023</td>
<td>0.019</td>
<td>0.027</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.015)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Stratum 3</td>
<td>0.059***</td>
<td>0.046**</td>
<td>0.066**</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.013)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Stratum 4</td>
<td>0.056**</td>
<td>0.035***</td>
<td>0.059***</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.012)</td>
<td>(0.018)</td>
</tr>
</tbody>
</table>

*p < 0.1, **p < 0.05, ***p < 0.01; Year and industry dummies are reported for expositional brevity.

Table 8. Sensitivity Analysis

<table>
<thead>
<tr>
<th>Gamma</th>
<th>Significance Level</th>
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</thead>
<tbody>
<tr>
<td>1</td>
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<tr>
<td>1.25</td>
<td>0.017</td>
</tr>
<tr>
<td>1.75</td>
<td>0.075</td>
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<tr>
<td>1.8</td>
<td>0.094</td>
</tr>
<tr>
<td>2</td>
<td>0.195</td>
</tr>
</tbody>
</table>

Gamma: log odds of differential assignment due to unobserved factors.

tion bias using a probit model. Recall that this model is reasonably specified and shows high predictive power (around 80 percent), which suggests that we adequately control for selection bias. Before we estimate the two production functions in equations (7b) and (8b) with and without the correction for selection bias, we check for heteroscedasticity using the Breusch-Pagen test (Greene 2000). Our test results lead us to reject the null hypothesis that the errors are homoscedastic. Therefore, we adjust for standard errors in our estimates using the White heteroscedasticity-consistent estimator (White 1980). Table 9 presents the estimation results for the production function approach for the cases of the two productivity regimes.23 Columns (i) through (viii) display the results for outsourcing firms with no interaction terms and with different combinations of interaction terms. Columns
Table 9. Estimation Results for Production Function Under Two Productivity Regimes

<table>
<thead>
<tr>
<th></th>
<th>With Outsourcing</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Without Outsourcing</th>
<th></th>
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<tr>
<td></td>
<td>Switching</td>
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<td>Switching</td>
<td>OLS</td>
<td>OLS</td>
<td>OLS</td>
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<td>OLS</td>
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<td>OLS</td>
<td>OLS</td>
</tr>
<tr>
<td></td>
<td>Regression (i)</td>
<td>Regression (ii)</td>
<td>Regression (iii)</td>
<td>Regression (iv)</td>
<td>Regression (v)</td>
<td>Regression (vi)</td>
<td>Regression (vii)</td>
<td>Regression (ix)</td>
<td>Regression (x)</td>
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<tr>
<td>Dlnk</td>
<td>0.232*</td>
<td>0.246*</td>
<td>0.243*</td>
<td>0.243*</td>
<td>0.279*</td>
<td>0.293**</td>
<td>0.274*</td>
<td>0.278*</td>
<td>0.092***</td>
<td>0.094**</td>
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<tr>
<td></td>
<td>(0.122)</td>
<td>(0.142)</td>
<td>(0.143)</td>
<td>(0.144)</td>
<td>(0.146)</td>
<td>(0.143)</td>
<td>(0.147)</td>
<td>(0.144)</td>
<td>(0.033)</td>
<td>(0.003)</td>
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<tr>
<td>Dlnl</td>
<td>0.565*</td>
<td>0.553*</td>
<td>0.50*</td>
<td>0.591*</td>
<td>0.550*</td>
<td>0.537*</td>
<td>0.556*</td>
<td>0.588*</td>
<td>0.753***</td>
<td>0.758***</td>
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<tr>
<td></td>
<td>(0.333)</td>
<td>(0.326)</td>
<td>(0.341)</td>
<td>(0.336)</td>
<td>(0.331)</td>
<td>(0.320)</td>
<td>(0.332)</td>
<td>(0.323)</td>
<td>(0.064)</td>
<td>(0.064)</td>
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</tr>
<tr>
<td>Dlnlt</td>
<td>0.077**</td>
<td>0.079**</td>
<td>0.077**</td>
<td>0.072**</td>
<td>0.070**</td>
<td>0.073**</td>
<td>0.072**</td>
<td>0.074**</td>
<td>0.018*</td>
<td>0.017*</td>
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<tr>
<td></td>
<td>(0.030)</td>
<td>(0.034)</td>
<td>(0.036)</td>
<td>(0.035)</td>
<td>(0.035)</td>
<td>(0.035)</td>
<td>(0.036)</td>
<td>(0.035)</td>
<td>(0.010)</td>
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<tr>
<td>IT intensity</td>
<td>0.054</td>
<td>0.035</td>
<td>0.017</td>
<td>0.015</td>
<td>0.089</td>
<td>0.032</td>
<td>0.018</td>
<td>0.023</td>
<td>0.046</td>
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<tr>
<td></td>
<td>(0.034)</td>
<td>(0.030)</td>
<td>(0.029)</td>
<td>(0.029)</td>
<td>(0.029)</td>
<td>(0.030)</td>
<td>(0.030)</td>
<td>(0.029)</td>
<td>(0.115)</td>
<td>(0.115)</td>
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<tr>
<td>IT knowledge</td>
<td>0.051*</td>
<td>0.047*</td>
<td>0.052*</td>
<td>0.051*</td>
<td>0.069**</td>
<td>0.065**</td>
<td>0.069**</td>
<td>0.068**</td>
<td>0.016</td>
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<tr>
<td></td>
<td>(0.028)</td>
<td>(0.027)</td>
<td>(0.031)</td>
<td>(0.029)</td>
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<td>(0.027)</td>
<td>(0.030)</td>
<td>(0.028)</td>
<td>(0.008)</td>
<td>(0.008)</td>
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<tr>
<td>HW</td>
<td>0.020*</td>
<td>0.012</td>
<td>0.004</td>
<td>0.006</td>
<td>0.003</td>
<td>0.003</td>
<td>0.003</td>
<td>0.006</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td></td>
<td>(0.007)</td>
<td></td>
<td>(0.007)</td>
<td></td>
<td>(0.007)</td>
<td></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>SW</td>
<td>-0.018</td>
<td></td>
<td></td>
<td></td>
<td>-0.010</td>
<td></td>
<td></td>
<td>-0.126*</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.012)</td>
<td></td>
<td></td>
<td></td>
<td>(0.019)</td>
<td></td>
<td></td>
<td>(0.071)</td>
<td></td>
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</tr>
<tr>
<td>IT intensity × IT</td>
<td>0.011**</td>
<td></td>
<td></td>
<td></td>
<td>0.011**</td>
<td></td>
<td></td>
<td>0.012*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>knowledge</td>
<td>(0.005)</td>
<td></td>
<td></td>
<td></td>
<td>(0.005)</td>
<td></td>
<td></td>
<td>(0.007)</td>
<td></td>
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</tr>
<tr>
<td>HW × IT knowledge</td>
<td>0.004</td>
<td></td>
<td></td>
<td></td>
<td>0.003</td>
<td></td>
<td></td>
<td>0.003</td>
<td></td>
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<tr>
<td></td>
<td>(0.006)</td>
<td></td>
<td></td>
<td></td>
<td>(0.006)</td>
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<td></td>
<td>(0.006)</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>SW × IT knowledge</td>
<td>0.013*</td>
<td></td>
<td></td>
<td></td>
<td>0.012*</td>
<td></td>
<td></td>
<td>0.012*</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td></td>
<td></td>
<td></td>
<td>(0.007)</td>
<td></td>
<td></td>
<td>(0.007)</td>
<td></td>
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</tr>
<tr>
<td>Inverse Mill’s ratio</td>
<td>0.152*</td>
<td>0.154**</td>
<td>0.145*</td>
<td>0.150*</td>
<td>0.105</td>
<td>0.144</td>
<td>0.024</td>
<td>0.023</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.078)</td>
<td>(0.076)</td>
<td>(0.084)</td>
<td>(0.083)</td>
<td>(0.135)</td>
<td>(0.191)</td>
<td>(0.099)</td>
<td>(0.099)</td>
<td></td>
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<tr>
<td>Constant</td>
<td>0.423</td>
<td>0.144</td>
<td>0.141</td>
<td>0.168</td>
<td>0.267</td>
<td>0.105</td>
<td>0.144</td>
<td>0.024</td>
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<tr>
<td></td>
<td>(0.425)</td>
<td>(0.133)</td>
<td>(0.135)</td>
<td>(0.125)</td>
<td>(0.433)</td>
<td>(0.135)</td>
<td>(0.191)</td>
<td>(0.099)</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Adj R square</td>
<td>0.396</td>
<td>0.424</td>
<td>0.381</td>
<td>0.400</td>
<td>0.375</td>
<td>0.402</td>
<td>0.365</td>
<td>0.381</td>
<td>0.321</td>
<td>0.315</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*p < 0.01, **p < 0.05, ***p < 0.01; Year and industry dummies are reported for expositional brevity.
When selection bias is controlled for, the coefficient of IT knowledge in equation (7b) ranges from 0.047 to 0.052 depending on the empirical specification, and is statistically significant at the 10 percent level. This result implies that outsourcing firms receive additional benefit from the IT knowledge accumulated by their IT services vendors. While the coefficient of IT intensity is not significant in all specifications, its interaction term with IT knowledge is significant at the 5 percent level (see column (ii)). This implies that firms with higher IT intensity receive greater benefits from the IT knowledge transmitted from IT services firms, perhaps because they are better equipped to absorb external knowledge. We also include interaction terms for IT knowledge with the types of IT services that a firm outsources, whether hardware or software focused, to see if there is any systematic difference in value creation depending on the type of service outsourced. In this specification, we consider one service type at a time and drop the interaction term for IT knowledge with IT intensity due to multicollinearity between the interaction terms. The results suggest that hardware has a main effect on productivity gains but its interaction effect is not statistically significant. In the case of software we find that the main effect is not significant, while its interaction with IT knowledge becomes statistically significant at the 10 percent level.  

The coefficients of ordinary capital, labor, and IT capital are significant in both productivity regimes. The magnitude of the coefficient of an input factor captures the percent change in productivity when the level of the input factor increases by 1 percent. Here, a 1 percent marginal increase in IT capital will raise productivity under the two regimes of outsourcing and no outsourcing by 0.077 percent and 0.018 percent, respectively (see columns (i) and (vii)). The results show that firms that outsource experience substantially higher returns to IT capital. Moreover, the marginal product of IT capital is also higher in firms that outsource relative to those served by internal IS departments.

Overall, we conclude that these findings are consistent with the theory. The interaction term for IT knowledge and IT intensity indicate that the knowledge held by vendors is an important determinant of productivity. Moreover, when service type is considered, the interaction of knowledge with software-focused services is significant, while its counterpart with hardware-focused services is not, indicating that knowledge seems to matter mainly for the types of tasks embodied in software. This is not surprising since software services require considerable expertise in software development and maintenance processes as well as in industry and process domains. To the extent that firms outsource more inefficient IT processes (over efficient ones) which may involve a transfer of less efficient assets to the vendor, we expect the coefficient of IT capital to be higher for the IT capital that is retained in outsourcing client companies. Moreover, in that outsourcing results in new or better IT systems and that knowledge spillovers from the vendor can lead to improvement in a client’s own IT management processes, the returns on a client’s IT capital may increase. This finding is consistent with Han and Mithas (2009) who show that internal IT investments and IT outsourcing are complements. On the other hand, in that our measure for internal IT capital may be correlated with transferred IT assets, the magnitude of the IT coefficient for outsourcing firms could be higher.

Next, we find that the production functions are correlated with the selection equation (the inverse Mills ratios: 0.152 for outsourcing firms and -0.126 for non-outsourcing firms, see columns (i) and (vii) in Table 9). The positive and negative signs of $\lambda_i$ and $\lambda_d$ suggest that firms choose the sourcing mode that leads them to achieve higher productivity gains (see Lee 1978). This supports our view that firms self-select into a particular productivity regime on the basis of their own characteristics.

### Concluding Remarks

We examine the overall economic gains from IT outsourcing for large U.S. firms focusing on the role of IT knowledge.

---

24 The marginal product of IT is output elasticity of IT times (output/IT). For comparison between the two groups, we use average output (value added) and IT capital.
transmitted from IT services firms. We first estimate a probit model to control for the self-selection issue in sourcing decisions. In general, our probit analysis shows high explanatory power, around 80 percent, providing an understanding of the determinants of the mode of service delivery. Consistent with our expectation, efficient firms are less likely to outsource. On the other hand, more leveraged firms are more likely to outsource. Similarly, firms that experience variation in demand, or in their input mix, are more likely to outsource. Interestingly, larger firms are also more likely to outsource. This finding reflects current trends in IT outsourcing deals that frequently involve large clients and are often long-term and large. Firms with higher IT intensity, which the literature typically interprets as absorptive capacity, pursue IT outsourcing more aggressively.

The productivity gains from IT outsourcing are substantial. Specifically, firms achieve additional productivity gains from IT outsourcing of up to 6 percent. The accumulated IT knowledge held by IT services providers is a key contributor of value. In particular, firms with higher IT intensity accrue greater benefit from transmitted IT knowledge. The role of IT knowledge appears to be more pronounced in software services rather than in hardware intensive tasks, perhaps reflecting the underlying knowledge requirements of software activities. Client firms receive higher returns on internal IT capital, a finding that is consistent with the contracting out of inefficient processes. While firms have achieved productivity gains from contracting out, these gains are heterogeneous in that they do not accrue to firms evenly. Firms that are more likely to outsource, as seen in their propensity scores, receive significantly higher benefits from IT outsourcing.

Our study makes several contributions. First, by focusing on productivity impacts, we are able to develop a better understanding of the economic value of IT outsourcing and the key role of IT knowledge. Specifically, our results improve our understanding of why firms outsource and whether and how outsourced IT services can enhance the productivity of client firms. We show that the returns to IT investment result not just from reductions in the prices of IT capital, but also from the reorganization of production. Moreover, to the extent that the IT knowledge held by a vendor reflects economies of specialization, we argue that these economies are an essential factor in achieving the benefits of IT outsourcing. Methodologically, we introduce a selection equation to reflect the outsourcing decision process, which allows us to estimate the productivity effects of IT knowledge while controlling for potential endogeneity arising from self-selection, resulting in more robust findings.

Our study has important implications for practice. We show that IT outsourcing is a valuable delivery option, but not for all firms. Managers considering IT outsourcing will benefit from our insights into which firms are likely to benefit from outsourcing. Client firms must assess potential service providers not just using the traditional criteria of price and service levels, but also their knowledge capabilities. In addition, client firms must focus on building in-house assets that complement the provider’s capabilities. Since IT vendors may become better positioned to deliver IT services as they accumulate knowledge over time, all firms, but especially those that have not outsourced, should periodically evaluate their sourcing strategy.

While we provide an integrative framework to analyze the productivity impact of IT outsourcing, our study is not without limitations. The sample data for IT outsourcing contracts is limited to large Fortune 1000 firms. These firms are survivors in competitive business environments (perhaps by exploiting IT better than others). Therefore, we need to be cautious in generalizing our results to smaller firms. Similarly, the data on outsourcing arrangements is collected from press releases, which may favor larger IT outsourcing deals as these often get more attention from the media. Since data on some determinants of the sourcing decision are not available, we use proxy variables where appropriate. For example, we use IT intensity as a proxy for internal IT capability. In general, the proxy variables are reasonably specified and have the expected signs. Still, we are not able to include factors such as transaction costs and resource relocation costs in the selection equation.

Our matching analysis requires the identification of non-outsourcing firms with attributes similar to outsourcing firms. However, since the analysis requires IT data for all firms, the set of non-outsourcing firms is also limited to those in the CII database. The matching analysis is based on the assumption that all of the firm-specific attributes that lead to heterogeneity in value creation from IT outsourcing are observed. However, several diagnostic statistics give us confidence that our results are not driven by unobserved heterogeneity. While switching regression explicitly assumes normality in the error terms that cannot be tested, it does allow us to account for unobserved heterogeneity in choosing the mode of service delivery. Although the matching technique and switching regression require different assumptions, our results from both methods are consistent, increasing our confidence in the results. In our analysis of the effect of spillovers, we ignore the possibility of other forms of knowledge transfer, such as employee turnover. Finally, we acknowledge that we reconstructed the IT stock variable starting in 1995 due to a redefinition of IT capital in the dataset during the sample period. Further research would benefit from a richer dataset. Despite these limitations, our study provides robust evidence and insights into whether and how IT outsourcing benefits client firms.
References


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