IT Outsourcing and the Impact of Advisors on Clients and Vendors

Abstract

There is significant information asymmetry in the IT outsourcing market. Clients have uncertainty about vendors' capabilities and vendors' have uncertainty about clients' requirements. Prior literature has examined many devices to reduce such information asymmetry: vendor reputation, client-vendor prior relationship, CMM rating of the vendors, location of vendor, and technological diversity of the vendor. We examine the impact of a hitherto unconsidered device - the use of an advisor. In the context of global sourcing, third party advisors with their accumulated knowledge of client requirements and the vendor landscape can mitigate the information asymmetry between clients and vendors. However, in an extensive dataset of IT outsourcing contracts going back two decades we found the use of advisors to be rare (less than 5% of contracts go through an advisor). This motivates us to rigorously analyze their impact on clients and vendors as an open empirical question. Using a dataset of 753 large IT outsourcing contracts, and through a series of econometric specifications and robustness tests, we establish that the presence of advisor is associated with higher revenues for vendors and more positive contract outcomes. This analysis presents the first concrete evidence that third party advisors can mitigate the information asymmetry in the IT outsourcing market and lead to better matching that benefits clients as well as vendors.

Keywords: IT outsourcing, Advisor, Information Asymmetry, Propensity Score Matching, Coarsened Exact Matching

1. Introduction

IT outsourcing is a very large industry. Gartner's 2012 analysis sized the worldwide IT services market at 991 billion dollars per annum. However, different industry reports suggest that about half of the IT outsourcing contracts are renegotiated (Gartner, 2010; Computer Weekly, 2012). Similarly, other industry studies indicate that a very large proportion of outsourcing contracts are cancelled (Infosys 2011). Industry reports commonly blame poor customer service, lack of flexibility on the part of the vendor, and hidden costs for clients' inability to achieve the goals of outsourcing initiatives (Craig and Willmort 2005; McDougall, 2006). Poor service, lack of flexibility, and hidden costs can be attributed to the tension that exists in a typical outsourcing relationship where the client seeks a service at lower than the in-house cost and the vendor who wants to maximize its profits (Tadelis 2007). Given this natural tension between the client and the vendor, the IT outsourcing vendor must be selected carefully and the outsourcing contract must be designed assiduously. However, there is significant information asymmetry in the IT outsourcing market that makes the selection of vendors and contracting for IT projects especially challenging. For instance, clients' may understand their requirements (although this varies by the sophistication of their IT function and process maturity) but face significant uncertainty about the capabilities of different vendors to meet their requirements. Similarly, vendors may have an understanding about their capabilities, but face significant information asymmetry about the requirements, intentions, contexts, and motivations of different (potential) clients. If the vendor does not have the capabilities to satisfy client's requirements it may lead to cancellation or renegotiation of the contract. In this paper, we examine the hitherto unexplored role of third party advisors, a growing cottage industry, in mitigating such information asymmetry.

Prior to this research, different tools and devices have been studied to mitigate the information asymmetries in the IT outsourcing market. For example, prior relationship with a vendor, and experience and reputation of a vendor may mitigate a client's information asymmetry about a vendor's capabilities (Gao et. al. 2010). The vendor location/distance may also reduce information asymmetry. For example, US-based clients may have lower information asymmetry about US-based vendors compared to overseas vendors (Gao et. al. 2010). Similarly, third party certification of vendors e.g., CMM ratings (Gopal and Gao 2009) may mitigate the information asymmetry about the vendor's software development capabilities. The IT outsourcing literature has examined how vendors can use devices such as prior relationship with clients, vendors' experience and reputation, vendors' location, service diversification, and CMM certification to signal quality and reduce information asymmetry (Gao et al. 2010; Gopal and Gao 2009). We add to this stream of research by examining the role of third party advisors, such as TPI, Avasant and specific divisions of Ernst and Young and KPMG, to name a few[1], towards reducing information asymmetry in IT outsourcing.

The information asymmetry between clients and vendors and the difficulties in defining the scope and performance of outsourced work gives rise to opportunities for specialist third party advisors to intermediate between clients and vendors. Third party advisors can use their accumulated knowledge of the vendor space to match client requirements with vendor capabilities, help clients choose which global location matches their needs, help design appropriate outsourcing contracts, and get the best deal available in the market for both clients and vendors. If third party advisors, by virtue of their market knowledge, are able to match clients with the right vendors and design appropriate contracts, then even when advisors work on behalf of clients, advisors can help vendors secure more outsourcing contracts and help clients and vendors achieve more positive contracting outcomes. Yet, despite the presence of big-players (such as KPMG) in a rapidly growing IT outsourcing industry, the actual use of third-party advisors is in low single digit percentages over the last two decades. This suggests uncertainty in their value proposition and motivates us to address the issue of quantifying their impact as an open empirical question using a variety of econometric specifications. In particular, this paper investigates the impact of third party advisors on vendors' revenues and contract outcomes.

Our analysis, using 753 large IT outsourcing contracts from 1989-2009, suggests that the presence of advisor acts as a tool to reduce information asymmetry between clients and vendors and benefits both clients and vendors. The presence of advisor is associated with higher annual revenues for vendors. Furthermore, the presence of advisors is associated with higher likelihood of contract extension and expansion. The remainder of the paper is organized as follows. The second section details the institutional context and the various tensions

[1] See http://www.iaop.org/Content/19/165/3880 for an exhaustive list

that could drive outcomes for clients and vendors in different directions; section three discusses the data, empirical approach, and results; and section four discusses the implications of the findings.

2. Institutional Background

A large body of IT outsourcing literature (Han and Nault 2011; Koh et al. 2004; Susarla et al. 2010, 2012) recognizes the difficulties in writing IT outsourcing contracts and suggests that IT outsourcing contracts are inevitably incomplete. In many cases the agency issues in IT outsourcing contracts arise due to information asymmetry between clients and vendors. While clients lack the ability to judge vendors' capabilities, vendors too lack the ability to signal their capabilities to clients (Gopal and Gao, 2009; Spence 1973). The literature has examined how vendors could use devices such as their experience and reputation, prior relationship with clients, their location/distance from the client, and their CMM rating to signal quality (Gao et al. 2010; Gopal and Gao 2009). Given the information asymmetry between clients and vendors, and the difficulties in defining the scope and performance of outsourced work, specialist third party advisors, such as TPI, Everest and NeoIT are sometimes used by clients to set up outsourcing engagements. Third party advisors with knowledge of the IT outsourcing market can match clients' specific requirements with vendors with the right capabilities to meet those requirements (Chan 1983; Bailey and Bakos 1997). Table 1 summarizes the mechanisms through which advisors reduce information asymmetry and creates value in the IT outsourcing market.

3.1 Impact of Advisor on Vendors

Prior work has examined how rating information such as CMM ratings, vendor's location, service diversification, prior relationship with the client, and reputation can mitigate information asymmetry. As summarized in Table 1 the presence of advisor can also acts as a tool to reduce information asymmetry between client and vendor. This information asymmetry reducing impact of advisors may benefit vendors in two distinct ways. First, in the presence of advisors, high quality vendors may receive contracts from clients that they do not receive in markets with no advisors. In this way, advisors may enable vendors to receive "new matches" that increase vendors' revenues. Second, in the presence of advisors, vendors may receive larger contracts as advisors may find clients who have higher value for a vendor's capabilities. In this way advisors may be able to secure “better matches” for the vendor that increase vendors’ revenues. Advisors, thus, may be associated with higher revenues for vendors.

Clients often want to reduce their costs by outsourcing IT work. Thus, one goal of advisors is to help clients assess the in-house cost of IT work and use the information to secure a good deal for the client. Advisors may strive to secure a good deal for the client by making the bidding process more competitive by attracting a large number of vendors to the bidding process. Conversations with executives at leading vendors suggest that “bidding wars” are often associated with deals that materialize through advisors. If advisors make the bidding process overly competitive, then vendors may receive lower revenue from contracts than when no advisors are used by clients. Thus, advisors can also reduce vendors’ revenues. Whether advisors have a positive or negative impact on vendor revenues is thus an open empirical question.

3.2 Impact of Advisor on Contract Outcome

The IT outsourcing literature has examined the drivers of outsourcing success, specifically the impact of and the balance between formal/structural controls such as reporting arrangements and penalty clauses, and informal controls such as trust and interpersonal relationships (Choudhury and Sabherwal 2003; Gopal and Gosain 2010; Kirsch 2004; Levina 2005; Levina and Vaast 2005). Sabherwal (1999) argues that both structural and informal controls are vital for performance of contacts. Further, the balance between formal and informal control improves outcomes and too much focus on either can hurt performance. The IT outsourcing literature has also examined customer satisfaction with IT outsourcing (e.g., Mani et al. 2012) and profitability of the project for the vendor (e.g., Gopal et al. 2003). However, while contracting has been studied at the point of signing the contract, large IT outsourcing contracts are not transactional, rather they are long-term relationships. Outcomes that are realized over longer time horizons are important to study in the context of complex inter-organizational relationships. Thus, in this paper we study the outcomes of large contracts (average size ~350 Million) in the long-term.

It is believed that the likelihood of contract success depends on a number of project, client, and vendor characteristics. Controlling for project, client, and vendor characteristics, the presence of advisor may also influence project success. Again, the reader is referred to Table 1 which discusses the specific mechanisms by which advisors create value and affect contract outcomes. For example, by selecting a vendor with the technological capabilities to meet the client's requirements; by designing an appropriate contract that takes into account project, client, vendor, and market characteristics; and by monitoring vendor behavior, advisors may improve contract outcome. However, as discussed above clients often want to reduce their costs by outsourcing IT work and thus advisors may strive to make the bidding process more competitive in order to secure a good deal for their client. Nevertheless, there is a fine line between securing a good deal for the client and achieving a win-win project outcome for the client and the vendor. If high quality vendors are not the most cost effective vendors, they may be dissuaded from entering into the bidding process when advisors are involved in vendor selection. If advisors discourage high quality vendors from participating in the bidding process, advisors may negatively impact contract outcome. Thus, whether an advisor has a positive or negative impact on contract outcome is ultimately an open empirical question.

3. Data and Measures

We primarily rely on IDC's services contract database (SCD) for our data. Additional data about CMM certifications and vendor age are obtained from public sources such as company websites. The IDC database includes over twenty two thousand large IT outsourcing contracts signed from 1989-2009. Our analysis includes seven hundred and fifty-three contracts where the outcome of the outsourcing contract i.e., whether the contract was extended, expanded, renegotiated or cancelled is indicated. We measure **Contract Outcome** as a binary variable. A contract is coded as one if it was extended or expanded and is coded as zero if it was renegotiated or cancelled. It is believed that if a project/contract is going well and the vendor is performing, the contract is likely to be extended or expanded and that is a good outcome for the client and the vendor. However, if a contract is not going well for the client and or the vendor, the contract is likely to be cancelled or renegotiated, and this is not a good outcome for the client or the vendor. We exclude contracts from the dataset if the contract status is unknown. The database indicates the name of the advisor, if an advisor was used in the contract.

Project/Contract Variables: The size of the project is measured as the dollar value of the contract **(ContractValue**). **EngagementTypeComplexity** is a categorical variable that measures the complexity of the project. This variable takes a value of three for Application Development, Business Consulting, IT consulting, and Systems Integration engagements; a value of two for Learning and Education, IT Education and Training, and Business Outsourcing; and a value of one for Deploy and Support, Contract Labor and Capacity Engagement, and Business Support Engagements. This classification follows Susarla et al (2010). **NumberofSubsegments** is the number of distinct IT tasks/activities that are involved in the outsourcing project. The presence of an advisor (**Advisor Y/N**) is a binary variable that takes the value of one, if an advisor was used in the contract. The strength of the client and vendor relationship prior to signing the contract **(ExistingRelationshipStrength)** is measured as the count of the number of different projects the vendor had done for the client, before signing the contract under consideration. **CompetitiveY/N** measures the competitive intensity of the bidding process. This is a binary variable that is coded as one if the bidding process for the contract was competitive bidding, and is coded as zero if the contract was awarded to the incumbent or if the contract was sole-sourced. The database indicates whether the contract was more like a fixed price contract (**FixedPriceY/N**) or more like a time and material contract. The number of outsourcing partners (**NumberofMultisourcingPartners**) is the number of primary contractors on the project.

Client Variables: The client's experience with IT outsourcing (**CustomerOutsourcingExperience**) is measured as the dollar value of all the projects outsourced by the client, before signing the contract under consideration. The resources a client can bring to a project are likely to be influenced by the size of the client. Thus, firm size measured as customer revenue (**CustomerRevenue**) is used as a proxy for the resources of the client that can brought to bear on the project.

Vendor/Advisor Variables: The capabilities, revenue and, reputation of the vendor is measured as the annual dollar value (**VendorRevenue**) of all the IT contracts signed by the vendor, in the signing year of the contract under consideration. The claim here is that vendors with lower information asymmetry about their capabilities will have higher annual value of contracts signed by the vendor. **Age** is the numerical age of the vendor in years at the time of signing the contract. The process maturity of the vendor is assessed as the CMM rating of the vendor (**CMMRating**). Most clients in the data are US-based clients. The cultural and physical distance of the vendor is a binary variable that takes a value of 1 for US-based vendors and a value of 0 for non-US-based vendors. **Diversity** is a measure of the different kinds of projects or tasks executed by a vendor (Gao et al. 2010). It is computed every year based on the number of subsegments a vendor has worked on in that year. It is the average of **NumberofSubsegments** (which is a proxy for distinct IT tasks involved in the outsourcing project) of all the projects executed by the vendor in the year of the project under consideration. Table 2 presents the summary statistics and correlations between the key variables.

4.1 Econometric Model and Results

We first examine the relationship between the presence of advisor in project *k* ($AdvisorY/N_{k,t}$) and vendor *j*'s revenue ($VendorRevenue_{j,t}$) in period *t* defined as the year in which the contract was signed. We treat advisor selection as endogenous and use a two-stage-least-squares (2SLS) model to predict vendor revenue.

(1) $$AdvisorY/N_{k,t} = \beta_0 + \beta_1 CustomerOutsourcingExperience_{i,t} + \beta_2 ContractValue_{k,t} + \beta_3 EngagementTypeComplexity_{k,t} + \beta_4 NumberofSubsegments_{k,t} + \varepsilon_1$$

(2) $$VendorRevenue_{j,t} = \beta_0 + \beta_1 Advisor\,Y/N_{k,t} + \beta_2 ExistingRelationshipStrength_{k,t} + \beta_3 CMM_{j,t} + \beta_4 USY/N_{j,t} + \beta_5 Diversity_{j,t} + \beta_6 Age_{\ j,t} + \varepsilon_2$$

Equation (1) is the advisor selection model. This model suggests that a client *i* may choose an advisor based on how experienced they are at IT outsourcing at time *t* ($CustomerOutsourcingExperience_{i,t}$), how large ($ContractValue_{k,t}$) and complex ($EngagementTypeComplexity_{k,t}$) the project is, and how many different tasks and activities are involved in the project ($NumberofSubsegments_{k,t}$). We expect clients to use advisors when they lack IT outsourcing experience and thus are not very familiar with the vendor landscape. We also expect clients to use advisors for large and complex projects, and projects that involve a number of distinct tasks and activities.

Equation (2) is the vendor revenue model. A vendor *j*'s revenue is a function of different devices available to reduce information asymmetry about the vendor. Thus, we predict vendor revenue based on how long the vendor has been in business ($Age_{\ j,t}$), the technological capabilities of the vendor ($Diversity_{j,t}$), the maturity of the vendor's software development process ($CMM_{j,t}$), whether the vendor is a US-based vendor ($USY/N_{j,t}$), and the strength of the client-vendor prior relationship ($ExistingRelationshipStrength_{k,t}$), if any. We expect the information asymmetry about the vendor to be lower (and vendor revenue to be higher) when the vendor is older and has been in business for longer, the vendor has the experience to execute projects that include different types of tasks and activities, the vendor is a US-based vendor, and the client and vendor have worked with each other in the past such that the client is aware of the vendor's capabilities and the vendor understands the client's requirements. We are most interested in the relationship between the presence of advisor in a project and vendor revenue.

Results from the 2SLS model (see Table 3) indicate that larger contracts (**ContractValue**) and contracts with higher number of distinct IT tasks and activities (**NumberofSubsegments**) are more likely to use an advisor. The vendor revenue model indicates that the presence of advisor (**Advisor Y/N**) is associated with an increase in vendor revenues. Consistent with prior research (Gao et al. 2010) this analysis also indicates that CMM rating (**CMM**), location and physical and cultural distance of the vendor (**USY/N**) and task diversity (**Diversity**) are also positively associated with vendor revenue.

We next examine the relationship between the presence of advisor in project *k* and project outcome. We again treat advisor selection as endogenous and use a bivariate probit model (see equation (3) and (4)) to predict the project outcome. Equation (3) is the advisor selection model. It is the same model as equation (1).

(3) $AdvisorY/N_{k,t} = \beta_0 + \beta_1 CustomerOutsourcingExperience_{i,t} + \beta_2 ContractValue_{k,t} + \beta_3 EngagementTypeComplexity_{k,t} + \beta_4 NumberofSubsegments_{k,t} + \varepsilon_3$

(4) $Outcome_{k,t} = \beta_0 + \beta_1 ContractValue_{k,t} + \beta_2 EngagementTypeComplexity_{k,t} + \beta_3 NumberofMultisourcingPartners_{k,t} + \beta_4 AdvisorY/N_{k,t} + \beta_5 CompetitiveY/N_{k,t} + \beta_6 FixedPriceY/N_{k,t} + \beta_7 ExistingRelationshipStrength_{k,t} + \beta_8 CustomerOutsourcingExperience_{i,t} + + \beta_9 CustomerRevenue_{i,t} + + \beta_{10} VendorRevenue_{j,t} + \beta_{11} CMM_{j,t} + \beta_{12} USY/N_{j,t} + \beta_{13} Diversity_{j,t} + \beta_{14} Age_{\ j,t} + \varepsilon_4$

Equation (4) is the project outcome model. This model suggests that the likelihood of a contract success depends on a number of project, client, and vendor characteristics. In this regard it is believed that larger

($ContractValue_{k,t}$) and more complex ($EngagementTypeComplexity_{k,t}$) projects are less likely to be successful. Similarly, if a project has a large number of vendors involved in the project ($NumberofMultisourcingPartners_{k,t}$) then the project is less likely to be successful. On the other hand, prior relationship between the client and the vendor ($ExistingRelationshipStrength_{k,t}$) gives the vendor a better understanding of what the new project entails and is likely to be associated with contract success. However, if the project contract had been won after a competitive bidding process ($CompetitiveY/N_{k,t}$), it is likely that the competitive bidding process may have reduced a vendor's profit margin, thereby negatively affecting the particular project's likelihood of success. Similarly, vendors face less risk in Time and Material contracts, so a Fixed Price ($FixedPriceY/N_{k,t}$) contract is less likely to be successful.

Project success is likely to be influenced by client characteristics. Larger clients ($CustomerRevenue_{i,t}$) may have more resources to devote to projects that may increase the likelihood of project success. Similarly, client's with significant IT outsourcing experience ($CustomerOutsourcingExperience_{i,t}$) may have developed routines to contract for and monitor IT projects executed in partnership with external vendors, and thus are likely to achieve higher rates of project success.

It is also natural to expect that vendor capabilities influence contract success. For example, larger vendors ($VendorRevenue_{j,t}$) may have reputation and future business to protect. Larger vendors may also have more slack resources to devote to contracts until they are successful. Similarly, process maturity ($CMM_{j,t}$) of the vendor is likely to be positively associated with contract success. Likewise, the diversity of other projects ($Diversity_{j,t}$) signifies the technological capabilities of the vendor and is likely to be positively associated with the contract success. Finally, it is likely that physical and cultural proximity of the vendor from the client ($USY/N_{j,t}$) may influence contract success. However, the key variable of interest is the advisor ($AdvisorY/N_{k,t}$). We are interested in the relationship between the presence of an advisor and contract outcome.

Equations (3) and (4) are estimated as a bivariate probit model and the results are presented in Table 4. The analysis indicates that larger contracts (ContractValue) with distinct IT tasks (NumberofSubsegments) are more likely to use an advisor. The outcome model indicates that the presence of advisor is associated with contract extension or expansion. The outcome model also indicates that projects with larger vendors (VendorRevenue) improve project outcomes. However larger (ContractValue), competitively intense (CompetitiveY/N), more complex (EngagementTypeComplexity) and projects with higher CMM rating of the vendor are more likely to get renegotiated or cancelled. Customer experience (CustomerOutsourcingExperience) is also negatively associated with contract outcome.

In the dataset an advisor is used in about 5% of the contracts. The small number of contracts with advisors may (potentially) bias the results of the analysis examining the relationship between presence of advisor and contract outcome. According to King and Zheng (1999a, 1999b, 2001) when faced with rare events (e.g., wars, senate confirmation denials etc.) standard logit models face the issue of prediction bias and underestimate the probability of rare events. To mitigate this concern a rare event logit model is proposed by King and Zheng (1999a, 1999b, 2001). In this approach data collection involves collecting data on all possible occurrences of 1 as well as a random selection of 0's from the sample. This approach is called choice based sampling. That is, first collect all 1's from the sample and then randomly collect about an equal number of 0's from the sample. In our case we first collected all 1's from the sample and then randomly collected 5% of 0's from the 0's sample. We then apply the relogit procedure (Tomz et al. 1999) on the choice based sample to correct for the prediction bias issue faced by standard logit models. Column 1 in Table 5 shows the results with the basic logit procedure and column 2 shows the results with the rare event logit procedure applied to correct the bias. Results of rare event logit model (column2) are consistent with the bivariate probit analysis. This analysis indicates that though around 5% of the contracts in the dataset used an advisor, advisors have a positive impact on contract outcome.

4.2 Robustness Analyses

We conduct a series of robustness analysis using alternative approaches and find consistency in the direction and significance of our main results[2]. We begin by using a 3SLS specification and follow that by showing the same results using a propensity score matching framework as well as a coarsened exact matching (CEM)

[2] While direction and significance are consistent, specific effect size may vary by specification for instance due to varying coverage that is afforded by various matching schemes in estimating treatment effects.

procedure that has attractive statistical properties. Further, we repeat all our analysis by dropping contract renegotiation as a negative outcome as it can be argued that some contracts are better off by getting renegotiated (say to account for technological change).

We are motivated to consider the 3SLS specification as it can be argued that advisor selection, vendor revenues, and project outcomes are determined simultaneously. Thus, we treat advisor selection (equation 1), vendor revenue (equation 2) and contract outcome (equation 4) as endogenous and use a three-stage-least-squares (3SLS) model to examine the impact of advisor on vendor revenues and contract outcomes. The 3SLS procedure is used to derive the parameters of the full system because endogenous variables in some equations of the model are used as explanatory variables in other equations. In such systems of equations it is likely that the error terms across the equations are correlated. Thus, predicted or instrumented values of the endogenous variables are generated using all exogenous variables in the system. Second, a cross-equation covariance matrix is estimated. Third, the equation with the contract outcome as the dependent variable is estimated with generalized least squares using the exogenous variables as well as the estimated covariance matrix. In summary, three stage least squares combines two stage least squares and seemingly unrelated regression (SUR) to account for both endogenous regressors and cross-equation correlation of errors.

Table A1 included in the online appendix presents the results of the empirical analysis. The advisor selection model (model (1)) indicates that larger contracts (ContractValue), and experienced customers (CustomerOutsourcingExperience) are positively associated with use of advisors. The vendor revenue model (model (2)) indicates that advisors are associated with increased vendor revenues.[3] CMM rating (CMM), vendor location and physical and cultural distance of the vendor (USY/N) and task diversity (Diversity) are also positively associated with vendor revenue. The outcome model (model (3)) indicates that the presence of advisor improves project outcomes. The findings of the 3SLS analysis are thus broadly consistent with the findings of the 2SLS analysis, the bivariate probit analysis, and the rare event logit model.

[3] We also calculate vendor revenue by excluding the value of the contract under consideration from vendor revenue and re-run the 2SLS and 3SLS analysis. These analyses produce very consistent results.

In the next subsection we test the robustness of our findings using an alternative 'counter-factual' based approach that compares the 'treatment' effect of working with an advisor versus not for statistically, observably[4] similar IT outsourcing contracts.

4.2.1 Propensity Score Matching

To further demonstrate robustness of our results we use propensity score matching, a technique that allows the researcher to reduce model dependence in making inference about treatment effects (Ho et al 2007). Propensity score matching is a way to correct the estimation of treatment effect after controlling for the existence of other confounding factors, based on the idea that the bias is reduced when the comparison of outcomes is performed using similar treated and controlled observations (Roseanbaum and Rubin 1983, Dehejia and Wahba 2002). The propensity score is the probability of receiving treatment (in our case advisor), conditional on the observable covariates, X. The idea is to compare entities, who based on observables have a very similar probability of receiving treatment (similar propensity score), but one of them received the treatment and the other did not. Technically, our preprocessed propensity scored dataset will be a subset of the observed sample for which the treatment group and control group will have the same background characteristics, or:

$\tilde{p}(X|T = 1) = \tilde{p}(X|T = 0)$.

We then have reason to believe that we obtain an accurate causal effect that is relatively model free (Ho et al 2007).

To implement this, we first compute the propensity score (see Table A2 in the online appendix) using the same variables we used earlier in equation 1 for advisor selection, as we expect clients to use advisors when they lack IT outsourcing experience, for large and complex projects, and projects that involve a number of distinct tasks and activities. Next we use the Kernel matching estimator (Heckman et al 1997, 1998; Mithas and Krishnan 2009) that uses multiple control contracts to construct each of the matched contracts leading to reduced variance of the estimator. The idea of Kernel matching is to obtain counterfactuals by weighted average of all control contracts where weights are inversely proportional to the distance between the propensity scores of treatment and control contracts. We compare the average treatment effect of contracts with advisor, to

[4] It is a well-known limitation of matching based treatment effect methodologies that they cannot handle unobservables.

contracts without advisor but within the common support region. The results suggest that contract success is 24% more likely with the presence of advisor and the vendor revenue is likely to be higher by approximately \$6B with the presence of advisor (see Table A3 in the online appendix). Note that this estimate is based on the average treatment effect representing the total vendor revenue that can be attributed to advisors for all matched contracts where the average contract size is over \$358M. While our inference does not extend to smaller contracts, it is likely that for such contracts the role of the advisor is not pertinent.

4.2.2 Treatment Effect Heterogeneity

An added advantage of the propensity score pre-processing that we did is that it allows us to assess the treatment effect heterogeneity (Dahejia and Wahba 2002). Specifically, we answer the following two questions, 1) do all contracts benefit equally by the presence of advisor and 2) do advisors impact the revenue of all vendors equally. To do this, we classified the sample into three strata within which the propensity score for contracts with and without advisor are not significantly different. Intuitively, the differences among strata are in terms of number of subsegments. Strata 1 has few, about 2 subsegments, strata 2 has about 3 subsegments and strata 3 has more, about 5 subsegments. Table A4 in the online appendix presents the mean of treatment (with advisor) and control group (without advisor) before matching and Table A5 in the online appendix presents the mean of treatment (with advisor) and control group (without advisor) after matching. Means reported in Table A5 shows that contracts with and without advisor are similar in terms of their characteristics after matching. This similarity allows us to directly compare the impact of advisor on contract outcome as well as vendor revenue. Table A6 in the online appendix shows the impact of advisor on outcome and vendor revenue for each stratum. Our results suggest that in stratum 1, contract success is 22% more likely and the vendor revenue is higher by 6.23B with advisor. In stratum 2, contract success is 26% more likely and vendor revenue is higher by 5.87B with advisor and in stratum 3, contract success is 34% more likely and vendor revenue is higher by 5.43B with the advisor. It seems that as the number of subsegments increases, the treatment effect of advisor increases the likelihood of contract success, though as the number of subsegment increases the presence of an advisor results in vendor revenue increases by lower amounts.

4.2.3 Sensitivity Analysis

To examine the impact of unobserved factors on the probability that a contract is in treatment group we conduct sensitivity analysis (Rosenbaum 1999). This analysis measures how strongly an unobservable impacts the selection process. We construct the log odds ratio Γ to check the extent to which unobserved factors influence advisor selection. Γ measures the level of selection bias from unobservable factors. If there are no unobserved variables that impact the advisor selection Γ equals 1. However, in reality we do not know the true value of Γ. Thus, we conduct a sensitivity analysis by changing the values of Γ and examine how advisor selection is impacted. Based on Rosenbaum (1999) analysis we conduct Wilcoxon sign-rank test. The test statistics suggest (please see Table A7 in the online appendix) that our estimates for contract outcome become sensitive when Γ =1.75 (i.e., contracts with the same observed factors differ in the propensity for advisor selection by 75%) and for vendor revenue become sensitive when Γ =2 (i.e., contracts with the same observed factors differ in the propensity for advisor selection by 100%). Thus, we believe that we have captured most key variables which drive advisor selection and our results are not driven by unobserved variables.

4.2.4 Coarsened Exact Matching

Next, we apply **Coarsened Exact Matching** (CEM) procedure (Iacus et al 2011,2012). CEM coarsens the observed covariates in order to perform an exact match on the coarsened data. In the next step the original uncoarsened but matched data is used to perform the analysis (Blackwell 2009). CEM (Iacus et al 2012) is a part of general class of methods known as the "monotonic imbalance bounding" (MIB) and has beneficial statistical properties compared to methods under the umbrella of "equal percent bias reducing" (EPBR) models (Rubin 1976), of which Propensity Score Matching (PSM) is an example. CEM generates solutions that are better balanced and have lower estimation error compared to propensity score based matching method. CEM works differently than PSM as it chooses a fixed level of imbalance ex ante and hope that the number of observations left as a result of the procedure is sufficiently large. On the other hand PSM chooses a fixed number of observations ex ante and hope for imbalance reduction as part of the procedure. Table A8 in the online appendix summarizes the output after CEM procedure. Here we focus of four key variables which impact the Advisor selection: EngagementTypeComplexity, ContractValue, NumberofSegments and CustomerOutsourcing Experience. Next, we repeat the 2SLS, Bivariate Probit and 3SLS analyses on the CEM sample. The results are included in tables A9, A10 and A11 in the online appendix. The results are consistent with the primary analysis, suggesting that use of advisors is associated with positive contract outcome and higher vendor revenue.

4.2.5. Renegotiation: The analysis in section 4.1 and section 4.2 above consider contract extension and expansion as positive project outcomes and contract cancellation and contract renegotiation as negative project outcomes. It may be argued that contract renegotiation is not a necessarily bad outcome, if the client and vendor renegotiate the contract as technologies or client requirements change during the contract (Susarala 2012). Thus, as a robustness check we repeat all the 2SLS, bivariate probit, rare event logit, and the 3SLS analysis by considering contract extension and expansion as positive project outcomes and contract cancellation as negative project outcome. These analyses again suggest that the presence of advisor has a positive relationship with vendor revenues and that the presence of advisor has a positive impact on contract outcome. These results are available from authors.

4. Discussion and Conclusion

There exist significant information asymmetries in IT outsourcing between clients and vendors. IT outsourcing projects are also hard to scope. This gives rise to opportunities for third party advisors to intermediate between clients and vendors. Such third party advisors can help clients by using their knowledge of the vendor space to match client requirements with vendor capabilities and design appropriate contracts. However, whether and how advisors create value in IT outsourcing was hitherto unaddressed in the literature. Our empirical analysis suggests that advisors can reduce information asymmetry between clients and vendors. We find evidence that supports the expectation that by appropriately matching client requirements with vendor capabilities, advisors are associated with higher revenue for vendors and higher likelihood of contract success. A number of devices have been discussed in the literature about how to mitigate information asymmetry: CMM ratings, vendor location, vendor reputation, technological diversity, etc. The key contribution of this paper is to examine the presence of advisor, in mitigating this information asymmetry.

In the models examining the impact of advisor on contract outcome, the competitive intensity of the bidding process has a negative impact on contract outcome. This suggests that if advisors make the bidding process more competitive in order to secure a good deal for the client, the client may pay the price at the back end of the project. In other words, advisors have to balance between finding a vendor to satisfy the client's technical requirements, helping the client specify an appropriate contract, and monitoring vendor behavior; with the goal of securing a good financial deal for the client with a competitive bidding process.

This study has certain limitations that suggest avenues for future research. The study is limited in that we do not have access to contract outcomes for all the contracts in the Services Contract Database (SCD). The mean contract value for the data used in this analysis is $359 million, whereas the mean contract value for the entire dataset excluding the ones used in the analysis is $71.4 million. Thus, caution may be used when extending the findings of the current analysis to small and mid-size projects. It is likely that our findings hold only for larger projects where advisors are more likely to be used. However, we find evidence that link contract value and contract failure, thus it is reasonable to assume that these high value contracts would have been under greater scrutiny at the time of signing and would have attracted higher managerial attention as compared to the average contract in the SCD data. The same factor furthers the salience of the analysis; observe that the practice of restricting attention to high stakes contracts has been prevalent in the IT outsourcing literature (Barua, Mani and Whinston 2011 restrict their attention to the 100 top IT and BPO deals over the period 1995 and 2006). At the expense of generalizability, our analysis provides a more virile petri-dish to examine an interesting phenomenon that has not examined by the prior literature.

This study examines the impact of advisors on vendor revenue and contract outcomes. However, many other questions remain unanswered. There is an issue of allegiance: who hires and pays the advisor: the client or the vendor. It is likely that advisors strive to meet the goals of the party that hires and pays them, typically the client. The analysis seems to suggest that if the advisor focuses on a good match between client requirements and vendor capabilities, advisors are associated with higher revenues for vendors, and better contract outcomes which benefit clients and vendors. However, if advisors make the bidding process more competitive, it may hurt vendor revenues as well as project outcomes that do not benefit the client or the vendor. Table 1 summarizes the advisor activities that help in mitigating information asymmetry. However, the empirical analysis does not disentangle the contribution of individual force/mechanisms. It is important to examine the specific force/mechanisms through which advisors affect vendor revenue and contract outcome. It is likely that the vendor capability assessment and client-vendor matching influences vendor revenues; whereas client-vendor matching and moral hazard reduction influence contract outcome. The issue of what affects vendor revenue and what influences contract outcome deserves further research.

Two of the findings of this research also raise questions for future research. The analysis suggests that CMM ratings are positively associated with vendor revenues. This is consistent with prior research that CMM ratings reduce information asymmetry about the maturity of vendors' software development methodology and thus are positively related with vendor revenues. However, CMM rating has a negative impact on contract outcome. Though prior research suggests that CMM ratings are associated with lower error rates, CMM ratings are also associated with longer development time and effort (Harter et al. 2000). It is plausible that a longer development time and effort may sometimes lead to contract cancellation or renegotiation. Nevertheless, this finding requires further investigation.

In the contract outcome models, the outsourcing experience of the client has a negative impact on contract outcome. Our prior expectation was that clients with significant outsourcing experience would have developed routines to monitor projects executed in partnership with vendors and therefore would be more likely to achieve positive contract outcome. However, the results indicate that outsourcing experience of the client has a negative impact on contract outcome. One possible explanation is that since clients with more IT outsourcing experience are more likely to use an advisor such clients have less experience with IT projects. Thus, IT outsourcing experience has a negative relationship with contract outcome. However, this finding requires further investigation.

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Table 1: Summary of Mechanisms through which Advisors Reduce Information Asymmetry and Create Value

Dimension of Value Creation by Advisors	**References**
A. Vendor capability assessment a. Third party advisors, by being in close proximity to vendors and through company visits, can reduce uncertainty about vendors' capabilities such as specific technological capabilities, business continuity plans, human capital development strategies, attrition management strategies, management skills to manage geographically apart projects, and financial stability.	Vashistha and Vashistha 2006
B. Client-vendor matching and contracting a. Advisors screen vendors and match client requirements with vendors' with appropriate capabilities. They use their market knowledge to reduce the transaction space and match clients and vendors at lower transaction costs. b. Further, given the role contract alignment in achieving desirables outcomes, they use their knowledge of client (such as in-house costs), vendor and market characteristics to design optimal contracts	Susarla et al. 2010, 2012
C. Moral hazard reduction a. Advisors help clients with monitoring the vendors as the contract gets underway, reducing opportunistic behavior and shirking b. Advisors cast a shadow of the future on the vendors affecting their behavior, as vendors know that in the presence of advisors it's more likely that higher quality vendors will get chosen in future	Bailey and Bakos 1997
D. Economies of scale a. Since the information about each vendor is useful for multiple clients, there are economies of scale in advisors' operations, even when the information search and evaluation cost is same for clients and advisors	Chan 1983, Bailey and Bakos 1997

Table 2: Summary Statistics and Correlations.

Construct	Mean	Std. Dev	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. AdvisorY/N	.03585	.1860	1														
2. CompetitiveY/N	.5905	.4920	0.03	1													
3. VendorRevenue	29.5b	49.1b	0.01	0.03	1												
4. Contractvalue	358m	823m	0.12*	0.09	0.19*	1											
5. EngagementTypecomplexity	1.291	.5537	-.01	0.02	-.11	-.11*	1										
6. ExistingRelationshipStrength	1.4023	.9792	-.01	-.25*	0.08	0	0.01	1									
7. CustomerRevenue	22.1b	65.7b	-.01	0.05	0	0.19*	-.02	0.03	1								
8. NumofMultisourcingPartners	.0066	.0812	0.08	0.06	-.04	0	-.01	0	0.10	1							
9. NumberofSubSegments	2.3358	1.4232	0.10*	-.03	0.14*	0.14*	-.31*	0.06	-.11*	-.03	1						
10. CustomerOutsourcingExperie	114m	466m	0.05	-.20*	0.19*	0.12*	-.02	0.46*	0.03	-.02	0.07	1					
11. CMMRating	1.79	1.51	0.08	0.02	0.34*	0.03	0	0.02	-.02	-.04	-.03	0.04	1				
12. USY/N	0.64	0.47	0.08	-.09	0.35*	0.09	-.05	0.11*	-.04	-.07	0.17*	0.08	0.15*	1			
13. FixedPriceY/N	0.39	0.48	0	0.03	-.07	-.15*	-.05	0.09*	0.02	0	0.01	-.06	0.02	-.08	1		
14. Diversity	2.34	1.09	0.05	-0.04	0.22*	0.09*	-0.30*	0.04	-0.12*	-0.06	0.76*	0.03	-0.04	0.22*	0.01	1	
15. VendorAge	31.64	27.96	0.05	0.03	0.01	0.07	-0.08	0.04	0.02	0.06	0.08	0.07	-0.04	-0.06	0.01	0.11*	1
16. Outcome	0. .787	0. .409	-0.09	-0.17*	-0.01	-0.12*	-0.07	0.04	-0.01	-0.03	0.06	0.01	-0.11*	0.03	0.04	0.05	-0.01

*correlation coefficients significant at the 10% level or better

Table 3: 2SLS Model to study the impact of advisor on vendor revenue

	(1)	(2)
VARIABLES	AdvisorY/N	VendorRevenue
AdvisorY/N		0.803**
		(0.320)
ExistingRelationshipStrength		0.045
		(0.045)
EngagementTypeComplexity	0.033	
	(0.038)	
ContractValue	0.109***	
	(0.037)	
NumberofSubsegments	0.087**	
	(0.039)	
CustomerOutsourcingExperience	0.036	
	(0.036)	
USY/N		0.210***
		(0.051)
CMMRating		0.246***
		(0.051)
Diversity		0.148***
		(0.047)
VendorAge		-0.024
		(0.048)
Constant	0.001	-0.001
	(0.036)	(0.044)
Observations	753	753

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Adjusted R^2 = 0.531

Table 4: Bivariate probit model to study the impact of advisor on contract outcome

	(1)	(2)
VARIABLES	AdvisorY/N	Outcome
AdvisorY/N		1.513***
		(0.142)
ExistingRelationshipStrength		0.030
		(0.060)
EngagementTypeComplexity	0.005	-0.178*
	(0.179)	(0.099)
ContractValue	0.001***	-0.001***
	(0.001)	(0.001)
NumberofSubsegments	0.130***	
	(0.047)	
NumberofMultisourcingPartners		0.529
		(0.410)
CompetitiveY/N		-0.450***
		(0.109)
FixedPriceY/N		0.114
		(0.097)
CustomerRevenue		0.001
		(0.001)
CustomerOutsourcingExperience	0.001	-0.001*
	(0.001)	(0.001)
USY/N		0.161
		(0.112)
CMMRating		-0.094***
		(0.032)
Diversity		-0.017
		(0.050)
VendorAge		-0.001
		(0.002)
VendorRevenue		0.002*
		(0.001)
Constant	-2.281***	1.332***
	(0.294)	(0.254)
Observations	753	753

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Pseudo R^2 =0.436

Table 5: Logit and rare event logit models to study the impact of advisor on contract outcome

VARIABLES	Outcome (Logit Model)	Outcome (Rare-events Logit model)
AdvisorY/N	0.367	0.779***
	(0.356)	(0.449)
ExistingRelationshipStrength	0.005	0.065
	(0.034)	(0.128)
EngagementTypeComplexity	-0.037*	-0.389*
	(0.176)	(0.189)
ContractValue	-0.004*	-0.098**
	(0.035)	(0.121)
NumberofMultisourcingPartners	0.158	0.374
	(0.037)	(0.328)
CompetitiveY/N	-0.916**	-0.939***
	(0.132)	(0.276)
FixedPrice Y/N	0.024	0.671
	(0.047)	(0.891)
CustomerRevenue	0.073	0.891
	(0.002)	(0.780)
CustomerOutsourcingExperienc**e**	0.058	0.090
	(0.003)	(0.430)
USY/N	0.039	0.391
	(0.037)	(0.224)
CMMRating	0.068	0.181
	(0.024)	(0.678)
Diversity	0.018	0.027
	(0.036)	(0.100)
VendorAge	0.001	0.008
	(0.027)	(0.090)
VendorRevenue	0.004**	0.008***
	(0.003)	(0.700)
Constant	0.002	0.487
	(0.001)	(0.497)
Observations	753	64
	Standard errors in parentheses	Robust Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Pseudo R^2 (of the Logit Model) =0.381[5]

[5] The purpose of relogit is to minimize the bias and not to obtain the best fit of the model. Thus the fit statistic of relogit is worse than that of the logit model. For the same reason, it's not reported or compared with the fit statistic of the logit model (King and Zheng 1999a, 1999b, 2

Online Appendix

Table A1: 3SLS Model

	(1)	(2)	(3)
VARIABLES	AdvisorY/N	VendorRevenue	Outcome
AdvisorY/N		0.517***	0.928**
		(0.186)	(0.457)
ExistingRelationshipStrength		0.014	0.032
		(0.033)	(0.048)
EngagementTypeComplexity	0.014		-0.091**
	(0.036)		(0.044)
ContractValue	0.142***		-0.224***
	(0.036)		(0.068)
NumberofSubsegments	0.049		
	(0.039)		
NumberofMultisourcingPartners			-0.037
			(0.063)
CompetitiveY/N			-0.169***
			(0.040)
FixedPriceY/N			0.021
			(0.042)
CustomerRevenue			0.032
			(0.040)
CustomerOutsourcingExperience	0.082**		-0.106**
	(0.034)		(0.053)
USY/N		0.244***	0.050
		(0.036)	(0.050)
CMMRating		0.293***	-0.128**
		(0.037)	(0.053)
Diversity		0.157***	-0.019
		(0.036)	(0.045)
VendorAge		0.001	-0.021
		(0.034)	(0.041)
Constant	0.004	-0.023	0.013
	(0.038)	(0.037)	(0.042)
Observations	753	753	753

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
System Weighted R^2 =0.608

Table A2: Propensity score logit model for AdvisorY/N

VARIABLES	AdvisorY/N
EngagementTypeComplexity	0.145
	(0.176)
ContractValue	0.003***
	(0.001)
NumberofSubsegments	0.130**
	(0.059)
CustomerOutsourcingExperience	0.003**
	(0.002)
Constant	0.062
	(0.328)
Observations	753

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Pseudo R^2 =0.625

Table A3: Propensity score matching using Kernal Matching

	Outcome (after matching)	Vendor Revenue (after matching)
Number of Matched Cases	618	618
Treated	27	27
Control	591	591
Difference	0.24**	5.93B***

Table A4: Mean Comparison of Treatment and Control groups before matching

	Treatment (A=1)	Control (A=0)
EngagementTypeComplexity	1.32	1.29
ContractValue	879M	338M
NumberofSegments	3.03	2.31
CustomerOutsourcingExperience	254M	109M
Observations	27	726

*A means Advisor

Table A5: Mean Comparison of Treatment and Control groups after matching

	Stratum 1		Stratum 2		Stratum 3	
	A=1	A=0	A=1	A=0	A=1	A=0
EngagementTypeComplexity	1.34	1.32	1.30	1.29	1.31	1.28
ContractValue	847M	364M	980M	461M	791M	267M
NumberofSegments	1.9	1.2	3.2	2.5	5.1	4.6
CustomerOutsourcingExperience	169M	68M	341M	205M	293M	167M
Observations	12	386	9	175	6	30

*A means Advisor

Table A6: Propensity score stratification and Treatment effect heterogeneity

Treatment effect (of Advisor) by Strata	Treated (A=1)	Control (A=0)	Outcome (Average treatment Effect	Vendor Revenue (Average treatment Effect
Stratum 1	12	386	0.22**	6.23B**
Stratum 2	9	175	0.26**	5.87B***
Stratum 3	6	30	0.34*	5.43B*

* Significance at 10%, ** Significance at 5%, *** Significance at 1%

Table A7: Sensitivity Analysis

Γ	Significance Level (Outcome)	Significance Level (Vendor Revenue)
1	0.000	0.000
1.25	0.008	0.003
1.50	0.038	0.014
1.75	**0.069**	0.023
2	0.189	**0.085**

Γ: Log odds of differential assignment due to unobserved factors

Table A8: Mean comparison before and after Coarsened Exact Matching Procedure

	Pre-CEM Treatment (Advisor=1)	Pre-CEM Control (Advisor=0)	Post CEM Treatment Advisor=1)	Post CEM Control (Advisor=0)
EngagementTypeComplexity	1.32	1.29	1.32	1.30
ContractValue	879M	338M	804M	358M
NumberofSegments	3.03	2.31	3.04	2.34
CustomerOutsourcingExperience	254M	109M	267M	150M
Observations	27	726	24	565

Table A9: A 2SLS Model after CEM to study the impact of advisor on vendor revenue

	(1)	(2)
VARIABLES	AdvisorY/N	VendorRevenue
AdvisorY/N		0.128**
		(0.102)
ExistingRelationshipStrength		-0.029
		(0.042)
EngagementTypeComplexity	0.094	
	(0.055)	
ContractValue	0.629***	
	(0.080)	
NumberofSubsegments	0.074*	
	(0.045)	
CustomerOutsourcingExperience	0.130	
	(0.130)	
USY/N		0.231***
		(0.037)
CMMRating		0.278***
		(0.036)
Diversity		0.174***
		(0.036)
VendorAge		0.004
		(0.035)
Constant	0.180	-0.062
	(0.050)	(0.035)
Observations	589	589

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Adjusted R^2 =0.573

Table A10: A Bivariate Probit Model after CEM to study the impact of advisor on contract outcome

	(1)	(2)
VARIABLES	AdvisorY/N	Outcome
AdvisorY/N		1.476***
		(0.140)
ExistingRelationshipStrength		0.106
		(0.084))
EngagementTypeComplexity	0.004	-0.082*
	(0.181)	(0.142)
ContractValue	0.003*	-0.006**
	(0.001)	(0.003)
NumberofSubsegments	0.107**	
	(0.051)	
NumberofMultisourcingPartners		0.386
		(0.565)
CompetitiveY/N		-0.510***
		(0.141)
FixedPriceY/N		0.087
		(0.104)
CustomerRevenue		0.003
		(0.001)
CustomerOutsourcingExperience	0.001	-0.005
	(0.002)	(0.000)
USY/N		0.104
		(0.120)
CMMRating		-0.064
		(0.018)
Diversity		-0.005
		(0.054)
VendorAge		-0.002
		(0.002)
VendorRevenue		0.001*
		(0.001)
Constant	0.062	0.137
	(0.328)	(0.301)
Observations	589	589

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Pseudo R^2 =0.458

Table A11: 3SLS Model after CEM

	(1)	(2)	(3)
VARIABLES	AdvisorY/N	VendorRevenue	Outcome
AdvisorY/N		0.043*	0.933**
		(0.092)	(0.558)
ExistingRelationshipStrength		-0.029	0.002
		(0.040)	(0.065)
EngagementTypeComplexity	0.080		-0.123*
	(0.054)		(0.077)
ContractValue	0.636***		-0.820**
	(0.080)		(0.380)
NumberofSubsegments	0.070		
	(0.043)		
NumberofMultisourcingPartners			-0.024
			(0.065)
CompetitiveY/N			-0.171***
			(0.042)
FixedPriceY/N			0.024
			(0.051)
CustomerRevenue			0.078
			(0.062)
CustomerOutsourcingExperience	0.140*		-0.249
	(0.125)		(0.202)
USY/N		0.235***	0.055
		(0.036)	(0.058)
CMMRating		0.294***	-0.084
		(0.035)	(0.049)
Diversity		0.167***	-0.010
		(0.034)	(0.046)
VendorAge		0.004	-0.022
		(0.033)	(0.044)
Constant	0.178	-0.071	-0.173
	(0.049)	(0.034)	(0.119)
Observations	589	589	589

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
System Weighted R^2 =0.649