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Corporate Quasi-Strategic Alliance via Outsourcing Transactions

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Abstract

This paper relates outsourcing parties together and tests whether the outsourcing contracts have any impact on the relationship of the two parties' performance. Both the *ex-anti* and the *ex-post* changes in stock and accounting related performance of the contract signatories are examined. We find that after the contract effective year, there is statistically significant cross-autocorrelation between client and vendor firms' stock returns. What's more, on average daily returns of the client stocks lead those of the vendor stocks. We also find that accounting performance changes between the two parties show significantly higher level of cross-correlation than pre-event. Our finding of an increase in cross-autocorrelation between the *ex-post* performance of client and vendor firms indicates that corporate outsourcing transactions result in a quasi-strategic alliance.

Keywords

Outsourcing, Cross-Autocorrelations, Stock Returns, Lead-Lag, Accounting Performance

1. Introduction

Outsourcing is generally defined as the transference to external parties the performance of functions otherwise administered in-house. In the past 20 years, with the growing interest of academics as well as other groups such as consultants and industry forums, outsourcing has developed to both an important business approach and a very popular strategic management initiative. Figure 1 is year-by-year graphs of the frequency and the value (in 2010 dollars) of outsourcing deals signed by firms listed on the US markets from 2002 to 2015. The figure suggests that both outsourcing frequency and contract value have grown substantially during this period, especially after 2009. There are some variations

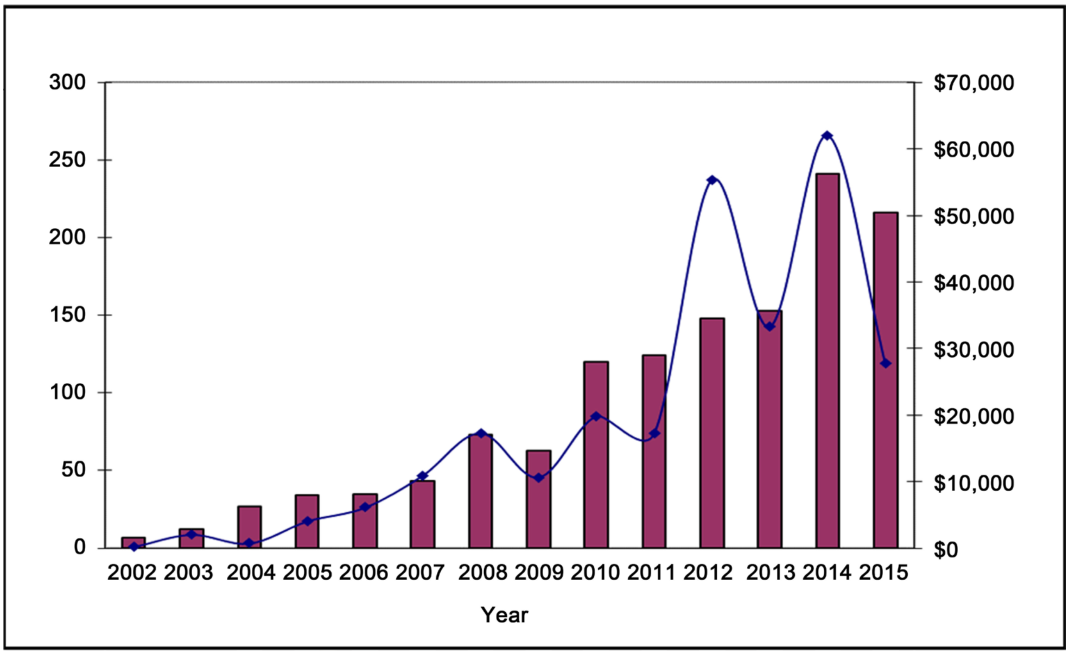

Figure 1. Outsourcing deals (this figure is a year-by-year graph of both the frequency and the value (in 2010 dollars) of outsourcing deals signed by firms listed on the US markets from 2002 to 2015. The columns represent the number of deals; the curve represents contract values).

for contract values in the recent past. But all in all, both variables follow increasing trend over time.

The major outsourcing discussions in the extant academic area focus on one party of the contract, either client or vendor firms. Since outsourcing contracts are the arrangements between two parties, both the firms purchasing services and the parties providing these services, one of the valuable theoretical frameworks for analyzing the relationship between client and vendor firms is agency theory. For example, Chaudhury, Nam, and Rao [1] focus on how the ideal contract should be negotiated, written, and enforced. Several other papers have also theoretically discussed the relationships between client and vendor firms. Gallivan and Oh [2] analyze information technology (IT) outsourcing relationships between clients and vendors. Specifically, they identify the taxonomy of four classes of outsourcing relationships based on how many clients and vendors are involved in the arrangements. Natovich [3] presents a case study of the relationship development of a Bezeq-AMS project.[1] By looking chronologically at the major events happened after Bezeq and AMS signed their contract, the author demonstrates some of the major vendor related risks and their contribution to system development failure. But until now, empirically investigating the relationship between the performances of contract signatories has been an untouched area. For example, Deavers [4] suggests that "because measurement problems are so difficult with outsourcing, it is only where a rigorous framework is established, and unique data are available, that any meaningful hypothesis testing is possi-

[1]Bezeq, the client firm, was a telecommunication company; the project vendor was the international software company AMS.

ble". This paper makes an initial attempt. Specifically, we ask the question, "what is the impact of outsourcing contracts on the relationship of the contract signatories' performance?"

The literature on cross-autocorrelations was initiated by Lo and MacKinlay [5]. In their seminal paper, Lo and MacKinlay have documented that the profitability of contrarian strategies may not be due to stock market overreaction, but mainly due to a systematic lead-lag relation among returns of size-sorted portfolios. Using weekly US stock market data for five equally-weighted size-sorted portfolios, they found evidence of positive cross-autocorrelation between lagged returns of portfolios of large capitalization stocks (large-firm portfolios) and the returns of portfolios of small capitalization stocks (small-firm portfolios), indicating that large portfolio returns lead small portfolio returns.

Different cross-autocorrelation patterns have then been discussed by several authors. Brennan, Jegadeesh, and Swaminathan [6] investigate the effect of the number of investment analysts following a firm on the speed of adjustment of the firm's stock price to new information that has common effects across firms. They find that returns on portfolios of firms that are followed by many analysts tend to lead those of firms that are followed by fewer analysts. Badrinath, Kale, and Noe [7] document that the returns on the portfolio of stocks with the highest level of institutional ownership lead the returns on the portfolios of stocks with lower level of institutional ownership. Chordia and Swaminathan [8] find that trading volume is a significant determinant of the lead-lag patterns observed in stock returns. Daily and weekly returns on high volume portfolios lead returns on low volume portfolio. Higgins, Howton, and Perfect [9] report that there are cross-correlations between their IPO samples and the CRSP equally-weighted index.

The above papers have documented different patterns of cross-autocorrelations among portfolio groups. But will there be cross-autocorrelation patterns among different groups associated with a specific event? This test has stricter requirement, which is, all parties involved need to remain independent both *ex-anti* and *ex-post*. For example, mergers do not meet this criterion, in that the previous independent firms become one company after a merger successfully accomplishes. Since the parties involved in an outsourcing contract still perform their own operations after the contract taking effect, outsourcing provides a natural experiment for testing the post-event cross-autocorrelation patterns.

In this paper, we examine both the *pre*- and the *post*-changes in relationship of the stock and accounting performance of the outsourcing client and vendor firms. We find that the *ex-post* stock returns of client and vendor firms have significantly higher level of cross-correlation than *ex-anti*. What's more, on average daily returns of client stocks lead those of vendor stocks, controlling for firm size. We also find that after the contract effective year, there is statistically significant cross-autocorrelation between client and vendor firms' accounting performance changes. The operating performance is proxied by three measures: return on assets (ROA), which is the ratio of operating income to assets; leverage (LEV), which is the total debt divided by assets; and asset turnover (AT), which is sales divided by assets. Collectively, our findings suggest that outsourcing contracts impact contract signatories in the sense that their performances affect each other after the contract effectiveness.

This article extends extant finance literature at least in two directions. First, it brings outsourcing client and vendor firms together and investigates the relationships of their performance changes associated with the contracts. Our second extension is to focus on cross-autocorrelation patterns associated with a specific event. The extant literature only documents patterns of cross-autocorrelations among portfolio groups with different characteristics.

The authors do recognize that a lot of outsourcing deals are between a domestic client and an international vendor. Due to the difficulty involved with data collection, this is not accomplished in the current paper.

The remainder of the paper is organized as follows. Section 2 describes the sample and the methodologies used in the analysis of the impact of outsourcing. Empirical results and the interpretation of the results are reported in Section 3. Section 4 offers some robustness tests while Section 5 concludes.

2. Data and Methodologies

2.1. Sample Construction

A total sample of 1058 outsourcing contracts for the period 2002-2015 was drawn from Factiva, a Dow Jones & Reuters Company, which provides world-class global content, including Dow Jones and Reuters newswires and The Wall Street Journal. We focus on investigating the stock and accounting performance relationship of client and vendor firms in this paper.

In our original sample, client and vendor firms can be public, private firms or non-profit organizations. Sometimes client firms are governmental entities such as US army. Then we restrict our sample to 333 contracts with only publicly traded client and vendor firms. Both client and vendor firms have to meet the following criteria: 1) they are NYSE, AMEX or Nasdaq listed firms with data from the Center for Research in Security Prices (CRSP) to calculate their stock returns; 2) they have data available in Compustat on a consolidated basis;[2] Since the same client firm can outsource in different years and the same vendor can contract with several different client firms in a given year, the client and vendor firm relationship is not one-on-one. In order to avoid the influences of multiple contracts when we perform stock and accounting performance change tests, we require that the contract client and vendor firms not sign another contract in three years surrounding that specific contract. And the final number of unique outsourcing contracts is 216.

The sample includes announced outsourcing contracts between 2002 and 2015 that are collected from Factiva and also meet the following criteria: Client firms

[2]We double check firms' SEC 10K filings to verify the existence of these events.

and vendors are both NYSE, AMEX or Nasdaq traded firms with sufficient data from the Center for Research in Security Prices (CRSP) to calculate their stock returns. They have data available in Compustat on a consolidated basis. All accounting data are obtained from Compustat one year before the contract effective year. All values are reported in 2010 dollars. MVE is market value of equity. CGS is the costs of goods sold. A minimum cutoff point of 0.01 is set for the relative deal size measures (contract size per year divided by CGS, sales or MVE).

Sample summary statistics are presented in Table 1. Panel A and B show that the average size of client and vendor firms is similar, with mean sales and market value of equity (MVE) of vendors bigger than those of client firms, whereas the median sales and MVE of client firm are larger than those of vendors. The relative deal size as denoted by contract size per year divided either by MVE or by costs of goods sold (CGS) measures the cash outflow of the client firms because of their outsourcing deals.[3] We also report similar relative deal size measures for vendor firms in Panel B to measure the cash inflow of vendors because of the deals. The mean cash inflow of vendors is much bigger than that of client firms. Panel C describes characteristics of the deals in our sample. The average contract spans 6 years. The mean contract value is $889.67 million, and the maximum contract value is $30 billion.

2.2. Methodology-Stock Returns Cross-Autocorrelations

For all the outsourcing contracts in the sample, we define the contract effective

Table 1. Sample description.

Specifications	# obs.	Mean	Median	Maximum	Minimum	Std. dev.
Panel A: Client firm characteristics						
Sales ($ millions)	216	15,617.00	7522.36	168,920.00	0.13	22,542.43
MVE ($ millions)	216	19,999.97	5622.63	229,918.03	2.75	34,878.21
Contract size per year/CGS	88	0.04	0.01	1.10	0.01	0.11
Contract size per year/MVE	75	0.03	0.02	0.89	0.01	0.09
Panel B: Vendor characteristics						
Sales ($ millions)	216	15,962.15	3062.13	88,346.00	0.02	26,212.35
MVE ($ millions)	216	24,211.56	4573.13	208,433.55	2.84	47,266.43
Contract size per year/sales	88	46.07	0.02	2425.56	0.01	320.98
Contract size per year/MVE	75	0.12	0.02	2.24	0.01	0.44
Panel C: Deal characteristics						
Contract years	216	6.09	5.00	11.00	1.00	2.65
Contract value ($ millions)	216	889.67	165.00	30,000.00	1.15	2561.58
Contract value per year ($ millions)	216	121.52	29.13	6000.00	0.50	515.72

[3]The minimum cutoff point for the relative deal size is 0.01. This is to ensure that the contracts have at least some impact on client firms' cash outflows.

day as event day zero. Trading dates before event day zero are denoted with a negative sign and those after are denoted with a positive sign (for example, 5 trading days before day zero is referred to day −5). With our unique contract sample, two time series of daily common stock returns for 3 years (756 trading days) centered on the effective day are taken from CRSP Daily Stock Return File for each client and vendor pair. In order to minimize the effect of non-synchronous trading on cross-autocorrelation, for each pair of contract firms, if either client or vendor stocks did not trade on date t, both returns of client and vendor firms on that day are excluded from the computation. This ensures controlling of the different trading frequency of client and vendor pairs. Cross-autocorrelation coefficients are calculated by Pearson product-moment correlation method.

2.2.1. Daily Returns Cross-Correlations

When estimating cross-correlations, previous papers transform panel data into time series data for analysis. For example, in Chordia and Swaminathan, daily equal-weighted portfolio returns are computed by averaging the non-missing daily returns of all the stocks in the portfolio. Portfolios in their paper are classified by size and trading volume. But we believe our client (vendor) firms express more heterogeneity from one another.[4] For example, each client firm may have both different size and different covariation with the stock market. Price movements of stocks reflect not only marketwise information, but also firm-specific information. For the reasons above, we do not take client (vendor) firms as one portfolio and average daily returns across different client (vendor) firms. Instead, we treat each client firm (vendor) independently. For example, we have one pair of client and vendor firms for 3 years surrounding day 0. And for that pair of client and vendor firms, we include two time series (one for client firm and the other for vendor) of daily common stock returns for 756 trading days centered on the same contract effective day. Since we have 216 unique pairs of client and vendor firms, panel data are generated. By treating each client firm (vendor) independently, we hope that the heterogeneity across stocks will not become an issue that can cause dramatic increases in the induced spurious relationship.

A natural way to investigate the serial correlation properties of individual security returns would be to separately examine their time-series correlation behavior. And then use the parameter estimates aggregated across securities for statistical inference. From a panel data set which has both cross-sectional client and vendor firms and different time periods, we first calculate pair-wise stock cross-correlation coefficients between each client and vendor pair for the negative periods. Next we calculate pair-wise stock cross-correlation coefficients between each client and vendor pair for the positive periods. Then correlation coefficient change of each pair is calculated by using the same pair's positive period correlation coefficient minus that of its negative period correlation. Mathematically this can be expressed as,

[4]In Boudoukh, Richardson and Whitelaw (1994), they mention: "Another issue that has received little attention in the literature is the effect of the heterogeneity of stocks within portfolios".

$$\rho\left(r_{C_i,t}, r_{V_i,t}\right) - \rho\left(r_{C_i,-t}, r_{V_i,-t}\right) \tag{1}$$

where ρ is the stock cross-correlation coefficient, $r_{C_i,t}$ ($r_{C_i,-t}$) represents the daily stock return of the client firm for contract *i* during the positive (negative) periods, similarly $r_{V_i,t}$ ($r_{V_i,-t}$) represents the daily stock return of the vendor for the same contract *i* during the positive (negative) periods. Finally, we combine the above correlation coefficient change of every contract to see whether that change is different from zero on average. A statistically significantly positive change implies that for each client and vendor pair, their stock performance becomes more related after their contract takes place.

2.2.2. Daily Stock Lead-Lag Relations

We also try to investigate whether there is a lead-lag relationship between daily return series of client and vendor pairs *ex-post*. We use vector autoregressions (VARs). The VAR tests are designed to address two questions: 1) Do cross-autocorrelations have information independent from own autocorrelations? 2) Is the ability of returns on client firm stocks to predict returns on vendor stocks better than the ability of returns on vendor stocks to predict returns on client stocks? To understand the VAR tests, let us suppose that we want to test whether returns of stock B lead returns of stock A. The lead-lag effects between the returns of these two stocks can be tested using a bivariate vector autoregression,[5]

$$r_{A,t} = a_0 + \sum_{k=1}^{K} a_k r_{A,t-k} + \sum_{k=1}^{K} b_k r_{B,t-k} + \mu_t \tag{2a}$$

$$r_{B,t} = c_0 + \sum_{k=1}^{K} c_k r_{A,t-k} + \sum_{k=1}^{K} d_k r_{B,t-k} + \nu_t . \tag{2b}$$

In regressions (2a) and (2b), if lagged returns of stock B can predict current returns of stock A, controlling for the predictive power of lagged returns of stock A, returns of stock B are said to *granger cause* returns of stock A.

First, the granger causality test is to examine whether the sum of the slope coefficients corresponding to return B in Equation (2a) is greater than zero, which allows us to determine if cross-autocorrelations are independent of stock own autocorrelations. Next, we are interested in testing formally whether the ability of lagged returns of B to predict current returns of A is better than the ability of lagged returns of A to predict current returns of B. This hypothesis can be tested by examining if $\sum_{k=1}^{K} b_k$ in Equation (2a) is greater than $\sum_{k=1}^{K} c_k$ in Equation (2b). This test is crucial to establishing that returns of stock B lead returns of stock A and is a formal test of any asymmetry in cross-autocorrelations between client and vendor stocks for our purpose.

We use a modified version of VAR with lead-lag of one day to test whether there is a lead-lag relation between client and vendor stock returns.[6] The specific

[5]Since the regressors are the same for both regressions, the VAR can be efficiently estimated by running ordinary least squares (OLS) on each equation individually.

[6]The order of VAR model is selected by using several information criteria: Akaike information criterion (AIC); Bayes information criterion (BIC). For both criteria, the smallest number is when the order is 1: AIC = −13.45298; BIC = −13.45094.

equations are given as below,

$$r_{V_i,t} = \alpha_{i,0} + a_{i,1} r_{V_i,t-1} + a_{i,2} r_{C_i,t-1} + v_{i,t} \tag{3a}$$

$$r_{C_i,t} = \beta_{i,0} + b_{i,1} r_{V_i,t-1} + b_{i,2} r_{C_i,t-1} + \mu_{i,t} \tag{3b}$$

where r_{V_i} represents the returns of vendor firms, r_{C_i} denotes the returns of client firms, both for contract *i*. We test two sets of hypotheses: 1) If daily stock returns of client firms lead those of vendor firms, we expect $a_{i,2} > 0$ and $a_{i,2} - b_{i,1} > 0$. 2) If daily stock returns of vendor firms lead those of client firms, we expect $b_{i,1} > 0$ and $b_{i,1} - a_{i,2} > 0$. For each contract, a separate VAR regression is run for positive periods from day 0 to 756. The final coefficients are calculated by averaging the coefficients across different contracts.

Lo and MacKinlay show that returns of large stocks lead those of smaller stocks. In order to control for size effect documented in the literature, we stratify our client (vendor) firms into 5 different size quartiles using the Fama and French ME_breakpoints.[7] Next we compare size quartiles of each client and vendor pair. According to their size quartiles, we group client and vendor pairs into three groupings: 1) client firms have bigger sizes than vendors (for example, client firm in quartile 4 and vendor in quartile 2); 2) client firms and vendors belong to the same size quartiles; 3) client firms are smaller than vendor firms. These three different groupings will provide us further information of the lead and lag relationships.

2.2.3. Cross-Sectional Regression of Daily Returns Cross-Correlation Changes

To figure out which items are mostly related to the stock cross-correlation changes, a cross-sectional regression is run for each contract *i*,

$$\begin{aligned}&\rho\left(r_{C_i,t}, r_{V_i,t}\right) - \rho\left(r_{C_i,-t}, r_{V_i,-t}\right)\\&= \alpha_i + \beta CSize_i + \chi VSize_i + AnnualContractSize_i\\&\quad + CRelativeDealSize_i + VRelativeDealSize_i + \sigma_i\end{aligned} \tag{4}$$

where ρ is the stock cross-correlation coefficient, $r_{C_i,t}$ ($r_{C_i,-t}$) represents the daily stock return of the client firm for contract *i* during the positive (negative) periods, similarly r_{V,t_i} ($r_{V_i,-t}$) represents the daily stock return of the vendor for the same contract *i* during the positive (negative) periods. $CSize_i$ is the log of client firm sales or MVE. $VSize_i$ is the log of vendor firm sales or MVE. $AnnualContractSize_i$ is the log of contract value per year. $CRelativeDealSize_i$ is the log of contract value per year divided either by client firm's costs of goods sold or by MVE. $VRelativeDealSize_i$ is the log of contract value per year divided either by vendor's sales or by MVE.

2.3. Methodology-Accounting Performance Change Cross-Autocorrelations

To examine whether client and vendor firms' operating performance changes

[7]They compute ME breakpoints for each month. ME is price times shares outstanding (divided by 1000) at month end ... See French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

after outsourcing transactions are correlated, we obtain financial data for the seven-year period centered on the contract effective year (defined as year 0) from Compustat files. Specifically, operating performance is proxied by three main measures: return on assets (ROA), leverage (LEV) and asset turnover (AT). Return on assets is the ratio of operating income to assets (Compustat data item 13 divided by item 6); leverage is total debt to assets (sum of Compustat data item 9 and 34 divided by item 6); asset turnover is sales divided by assets (Compustat data item 12 divided by item 6).

2.3.1. Unadjusted Accounting Performance Change Cross-Correlations

Since we use Compustat annual file, for each pair of client and vendor firms, we have 7 observations representing each of the 7 years from −3 to +3. As in the stock return tests, Pearson product-moment correlation method is used to calculate cross-autocorrelations in accounting performance change.

For negative periods, we first calculate changes of accounting performance for client firm and vendor pairs from negative years −3, −2 and −1 to year 0, from that we calculate whether that change is correlated cross-sectionally. For example, in the case of ROA, it is expressed as,

$$\rho\left(\left(ROA_{C,0}-ROA_{C,-t}\right),\left(ROA_{V,0}-ROA_{V,-t}\right)\right). \tag{5a}$$

Next, we perform the same tests for positive periods 3, 2, 1 to 0 changes to see whether the positive period performance changes are correlated. For ROA again, it is expressed as,

$$\rho\left(\left(ROA_{C,t}-ROA_{C,0}\right),\left(ROA_{V,t}-ROA_{V,0}\right)\right). \tag{5b}$$

If *ex-post* changes are statistically significantly correlated, that means accounting performances of client and vendor firms are more related *ex-post*.

2.3.2. Control Industry Effects

To control for industry effects, the raw operating performance measures are adjusted by subtracting the median value of the corresponding measures for all firms in the primary two-digit SIC industry in every event year, and then perform the above test procedures. A two-digit industry definition is used because Clarke [10] has shown that the two-digit definition captures similarities among firms as effectively as industry definitions based on three- or four- digit SIC groupings.

2.3.3. Cross-Sectional Regression of Industry-Adjusted Accounting Cross-Correlation Changes

A cross-sectional regression is run for each contract *i* to see which items are closely related to the accounting performance change cross-correlation,

$$\begin{aligned}&\rho\left(\left(IndACC_{C,t}-IndACC_{C,0}\right),\left(IndACC_{V,t}-IndACC_{V,0}\right)\right)\\&=\alpha_i+\beta CSize_i+\chi VSIze_i+AnnualContractSize_i\\&\quad+CRelativeDealSize_i+VRelativeDealSize_i+\sigma_i\end{aligned} \tag{6}$$

where $\rho\left(\left(IndACC_{C,t}-IndACC_{C,0}\right),\left(IndACC_{V,t}-IndACC_{V,0}\right)\right)$ represented the correlation between client and vendor with their industry-adjusted accounting performance change *ex-post*. The accounting performance can be any of the three measures that we defined earlier, return on assets (ROA), leverage (LEV) and asset turnover (AT). $CSize_i$ is the log of client firm sales or MVE. $VSize_i$ is the log of vendor firm sales or MVE. $AnnualContractSize_i$ is the log of contract value per year. $CRelativeDealSize_i$ is the log of contract value per year divided either by client firm's costs of goods sold or by MVE. $VRelativeDealSize_i$ is the log of contract value per year divided either by vendor's sales or by MVE.

3. Empirical Results

3.1. Stock Relation

3.1.1. Daily Returns Cross-Correlations

Table 2 shows that there is statistically significantly positive change in stock return cross-correlation between client and vendor firms *ex-post*. For each of the three different periods, the cross-correlation change all shows statistical significance at high degrees. For example, 756 days afterwards compared to 756 days before, the client and vendor firm stock returns on average are more positively correlated, with a positive change of 2.87%, which is statistically significant at 1% level. For 252 days afterwards compared to 252 days before, the client and vendor firm stock returns on average are also more positively correlated, with a positive change of 2.66%, which is statistically significant at 1% level.

3.1.2. Daily Returns Lead-Lag Relations

Since our evidence implies a significant increase in cross-autocorrelation between stock returns of client firms and their non-serial winning vendors after their outsourcing contracts taking effect. We investigate whether there is a lead-lag relationship between their stock price movements *ex-post*. With daily returns, the VAR is estimated. Table 3 summarizes the results from VAR regressions. a_1 or b_1 and a_2 or b_2 represent the slope coefficients of the one-lag returns of the vendor firms and the client firms. For the whole sample, the mean value of a_2 is

Table 2. Daily stock return cross-correlation change.

Negative period (days) correlation	Positive period (days) correlation	Cross-correlation change $Mean\left(\rho\left(r_{C_i,t},r_{V_i,t}\right)-\rho\left(r_{C_i,-t},r_{V_i,-t}\right)\right)$
	Period 1: (−756, −1) and (1, 756)	
0.1628	0.1918	0.0287 (0.0010)***
	Period 2: (−504, −1) and (1, 504)	
0.1481	0.1949	0.0419 (0.0005)***
	Period 3: (−252, −1) and (1, 252)	
0.1556	0.1871	0.0266 (0.0488)**

Cross-correlation coefficients are Pearson correlation coefficients. The correlation change of each contract is calculated by using the same client and vendor pair's positive period stock correlation coefficient minus its negative period correlation coefficient. Mean change of stock cross-correlation coefficients are reported in column three (P-values in parentheses). *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Table 3. Granger causality tests.

VCS	a_1 or b_1	a_2 or b_2	$a_2 - b_1$
Panel A: whole sample (Nobs. = 216)			
$r_{V_i,t}$	0.0391 (0.0009)**	0.0352 (<0.0001)***	
$r_{C_i,t}$	0.0085 (0.1276)	0.0979 (<0.0001)***	0.0266 (0.0067)***
Panel B: Client firm size > vendor firm size (Nobs. = 70)			
$r_{V_i,t}$	0.0192 (0.3543)	0.0354 (0.0519)**	
$r_{C_i,t}$	−0.0027 (0.7857)	0.0851 (0.0027)***	0.0381 (0.0802)*
Panel C: Client firm and vendor firm belong to the same size quartile (Nobs.=90)			
$r_{V_i,t}$	0.0881 (0.0005)***	0.0366 (0.0004)***	
$r_{C_i,t}$	−0.0053 (0.4447)	0.1387 (<0.0001)***	0.0423 (0.0011)***
Panel D: Client firm size < vendor firm size (Nobs. = 56)			
$r_{V_i,t}$	0.0472 (0.0154)**	0.0235 (0.0024)***	
$r_{C_i,t}$	0.0354 (0.0007)***	0.0343 (0.2018)	−0.0114 (0.3992)

For each contract, a separate VAR regression is run for positive periods 0 to 756. The final coefficients are calculated by averaging the coefficients across different contracts. The VCS variable is the return on vendor or client firms. Nobs. refers to the number of pairs of client and vendor firms used in the test. Panel A include the test for the whole sample; Panel B include sub-sample in which client firms' sizes are bigger than those of vendor firms'; Panel C is when they belong to the same size quartiles; Panel D is when client firms are smaller than vendors. P-values are based on tests that the mean difference equals to zero and are reported in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively.

0.0352 and the mean value of $a_2 - b_1$ is 0.0266, both are statistically significantly positive at 1% level. The above results suggest not only that the lagged returns of client firms can predict current returns of vendor firms, controlling for the predictive power of lagged returns of vendors themselves, but also the ability of lagged returns of client firms to predict current returns of vendors is better than the ability of lagged returns of vendors to predict current returns of client firms. The one-day lead-lag period is calculated by several information criteria. The rapid development of the communication networks provides quick and easy ways to transform information. Therefore, the lead-lag relation between client and vendor firms should hold for only short period.

Panel B to Panel D report three different classifications according to the relevance of the sizes of client and vendor firms. In Panel B, when client firms are in bigger size quartiles than vendor firms, the mean value of a_2 is 0.0354, which is significant at 5% level. The coefficient $a_2 - b_1$ is 0.0381, which is weakly significant at 10% level. In Panel C, when both client and vendor firms are in the same size quartiles, the value of a_2 is 0.0366 and the coefficient $a_2 - b_1$ is 0.0423, both are statistically significant at 1% level. Panel D reports the results when client firms are smaller than vendor firms, this time the corresponding coefficients are 0.0235 and −0.0114 and $a_2 - b_1$ is not significant at conventional level. The finding that bigger sized client firms lead smaller vendors is consistent with the extant literature with respect to size effect. But the most significant results are from similar size client and vendor firms. So controlling for the size effect, our sub-sample tests imply that stock returns of client firms lead those of vendors.

All in all, **Table 3** implies that on average, there is a lead-lag relation between returns of client firms and vendors after their contracts taking effect. Specifically, client firms' stock returns are leading those of vendors on average. And this result holds still when we control the size effect often documented in the literature.

3.1.3. Cross-Sectional Regression of Daily Returns Cross-Correlation Changes

The regression results of Equation (4) are reported in **Table 4**. The most interesting result is that vendor sales are significantly negatively related to the changes of daily stock correlation between client and vendor firms. While vendor relative deal size calculated by sales is significantly positively related to the changes of

Table 4. Cross-sectional regression of daily returns cross-correlation changes.

Specifications	1	2	3	4	5	6
Constant	−0.2117 (0.16)	−0.1222 (0.39)	−0.1828 (0.12)	−0.0419 (0.29)	−0.2122 (0.15)	−0.1251 (0.38)
Csales	−0.0170 (0.30)				−0.0177 (0.24)	
Cmve		−0.0135 (0.34)				−0.0100 (0.43)
Vsales	−0.0170 (0.10)*		−0.0169 (0.09)*			
Vmve		−0.0117 ((0.32)		−0.0098 (0.37)		
Annual Contract Size	0.0155 (0.33)	0.0204 (0.21)				
CRDSCGS			0.0141 (0.28)			
CRDSMVE				0.0158 (0.22)		
VRDSSales					0.0168 (0.10)*	
VRDSMVE						0.0134 (0.24)
R^2	0.0597	0.0494	0.0578	0.0488	0.0495	0.0572

A cross-sectional regression is run for each contract *i*, P-values are reported in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively.

daily stock correlation between client and vendor firms. The bigger the vendor's relative deal size compared to entire sales, the more related their relationship is afterwards.

3.2. Accounting Relation

3.2.1. Unadjusted Accounting Performance Change Cross-Autocorrelation Test

Table 5 shows the results of cross-autocorrelation change for our accounting measures of performance. For all three different accounting performance measures, *ex-anti* changes of performance of client and vendor firms are not correlated at conventional levels. But *ex-post*, the cross-correlation coefficients of changes of all three accounting measures are statistically significantly positive at different levels. For example, in each of the three years after the contract effectiveness, ROA changes of client and vendor firms are all highly correlated at 1% significance level with correlation coefficients of 0.8259, 0.9844, and 0.2976, respectively. LEV and AT follow the same patterns.

3.2.2. Industry-Median Adjusted Accounting Performance Change Cross-Autocorrelation Test

Table 6 further reports industry-median adjusted correlation of accounting

Table 5. Unadjusted accounting performance change cross-autocorrelation test.

Correlation/Year	(−3, 0)	(−2, 0)	(−1, 0)	(0, 1)	(0, 2)	(0, 3)
ROA	0.0433 (0.1322)	0.0692 (0.1529)	0.0696 (0.1471)	0.8259 (<0.0001)***	0.9844 (<0.0001)***	0.2976 (0.0006)***
LEV	0.0446 (0.3621)	0.0708 (0.1406)	−0.0611 (0.1997)	0.80402 (<0.0001)***	0.9690 (<0.0001)***	0.7186 (<0.0001)***
AT	0.0314 (0.5215)	0.0299 (0.5341)	0.0130 (0.7858)	0.1345 (0.0133)***	0.1237 (0.0709)*	0.2661 (0.0018)***

Pearson Correlation Coefficients are reported. We denote contract effective year as year 0. For negative years, we first calculate changes of accounting performance for every pair of client and vendor firms from negative years −3, −2 and −1 to year 0, from that we calculate whether that change is correlated cross-sectionally. Next, we perform the same tests for positive periods 3, 2, 1 to 0 changes to see whether the positive period changes are correlated. P-values are reported in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Table 6. Industry-median adjusted accounting performance change cross-autocorrelation tests.

Correlation/Year	(−3, 0)	(−2, 0)	(−1, 0)	(0, 1)	(0, 2)	(0, 3)
IndROA	0.0303 (0.5277)	0.0581 (0.2306)	0.0669 (0.1635)	0.8176 (<0.0001)***	0.9640 (<0.0001)***	0.1909 (0.0296)**
IndLEV	0.0427 (0.3832)	0.0628 (0.1911)	−0.0570 (0.2319)	0.8096 (<0.0001)***	0.96382 (<0.0001)***	0.7090 (<0.0001)***
IndAT	0.0658 (0.1785)	0.0381 (0.4273)	0.0393 (0.4095)	0.2107 (<0.0001)***	0.2165 (0.0014)***	0.3365 (<0.0001)***

Pearson Correlation Coefficients are reported. All accounting measures are adjusted by industry median measures. We denote contract effective year as year 0. For negative years, we first calculate industry-median adjusted changes of accounting performance for every pair of client and vendor firms from negative years −3, −2 and −1 to year 0, from that we calculate whether that change is correlated cross-sectionally. Next, we perform the same tests for positive periods 3, 2, 1 to 0 changes to see whether the positive period changes are correlated. P-values are reported in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively.

performance changes. Same results can be concluded from this table. Table 6 provides further evidence that the post-event accounting performance changes of client and vendor firms following the same direction is not an industry related effect.

3.2.3. Cross-Sectional Regression of Accounting Performance Change Cross-Correlation

The regression results of Equation (6) are reported in Table 7. We have similar results compared to the stock related regressions. The most interesting result is that vendor sales are significantly negatively related to all three industry-median adjusted accounting cross-correlation changes between client and vendor firms. While vendor relative deal size calculated by sales is significantly positively related to these industry-median adjusted accounting cross-correlation changes between client and vendor firms. The bigger the vendor's relative deal size compared to entire sales, the more related their relationship is afterwards.

4. Robustness of Results

Throughout this paper, we report the Pearson product-moment cross-autocorrelation

Table 7. Cross-sectional regression of industry-median adjusted accounting cross-correlation changes.

Specifications	1 IndROA	2 IndROA	3 IndLEV	4 IndLEV	5 IndAT	6 IndAT
Constant	−0.3125 (0.44)	−0.3044 (0.28)	−0.3822 (0.22)	−0.3442 (0.34)	−0.3401 (0.36)	−0.3302 (0.45)
Csales	−0.0255 (0.33)				−0.0225 (0.47)	
Cmve		−0.0213 (0.32)				−0.200 (0.37)
Vsales	−0.0288 (0.10)*		−0.0213 (0.07)*			
Vmve		−0.0137 (0.45)		−0.0155 (0.38)		
Annual Contract Size	0.0188 (0.45)	0.0193 (0.26)				
CRDSCGS			0.0242 (0.32)			
CRDSMVE				0.0026 (0.27)		
VRDSSales					0.0112 (0.09)*	
VRDSMVE						0.0222 (0.24)
R^2	0.0694	0.0390	0.0552	0.0458	0.0512	0.0622

For a contract *i*, all the accounting variables are taken from Compustat one year before the contract effective year. P-values are reported in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively.

coefficient, which is a parametric measure of association for two variables. Though not reported in the paper, we also perform our tests by using the Spearman rank-order correlation, which is a nonparametric measure of association based on the ranks of the data values. Out main results are not affected by different methods to calculate correlations.

4.1. Stock Relation

Size effect related with lead-lag relationship is widely documented in the literature. We control size effect by performing our tests on three different groupings: 1) client firms are bigger than vendors; 2) they belong to the same size quartile; 3) client firms are smaller than vendors. And our results are robust to those different classifications.

Positive cross-autocorrelation and lead-lag effects are also a symptom of the so-called "nonsynchronous trading" or "thin trading" problem, in which the prices of distinct securities are mistakenly assumed to be sampled simultaneously. Perhaps the first to show that nonsynchronous sampling of prices induces auto-correlated portfolio returns was Fisher [11]; hence the nonsynchronous trading problem is also known as the "Fisher effect".[8] Lead-lag effects are also a natural consequence of thin trading, as the models of Lo and MacKinlay show. We also controlled nonsynchronous trading problem when we perform our tests.

4.2. Accounting Relation

Up to now, when we test the cross-autocorrelation in accounting performance measure changes, we use the difference of two years' accounting measures to denote the accounting performance change. We also use the change ratio. For example, change of ROA from year −3 to year 0 is calculated as $\left(ROA_0 - ROA_{-3}\right)/ROA_{-3}$. Our main results are not changed when we are using accounting ratio changes to define performance change. The ratio change of accounting measures of client and vendor firms are not correlated before their contracts taking effect, while in each year afterwards, that measures are significantly positively correlated.

5. Conclusion

This paper relates outsourcing signatories together and tests whether the outsourcing contracts have any impact on the two parties' performance relationship. Both the pre- and the post-event changes in stock and accounting related performance of the contract signatories are examined. We find that after the contract effective year, client and vendor stock returns have significantly higher levels of correlation than pre-event. What's more, on average daily returns of client stocks lead those of vendor stocks. We also find that there is statistically significant cross-autocorrelation between client and vendor firms' accounting performance changes. Our finding of an increase in cross-autocorrelation between the *ex-post*

[8]We refrain from this usage since the more common usage of the Fisher effect (that of Irving Fisher) is the one-for-one change in nominal interest rates with changes in expected inflation.

performance of client and vendor firms indicates that corporate outsourcing transaction results in a quasi-strategic alliance. Our final thoughts on this topic are: maybe outsourcing is an efficient yet inexpensive way to bridge the performance of contract parties without dramatic changes of firms' organizations and expensive bidding process. Further work needs to be done to investigate this question, which is beyond the scope of our current paper. We also would like to pursue more deals related to domestic clients and international vendors when data permit.

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