Ties That Bind: The Impact of Multiple Types of Ties with a Customer on Sales Growth and Sales Volatility

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WEB APPENDIX

Measurement of Relationship Multiplexity

Weighted measure. Following Gulati and Gargiulo (1999) we use a weighting scheme that allocates different weights to different ties. This measure is suggested by the consideration that ties such as joint ventures involve greater investments and closer interaction compared to licensing agreements. As a result, these ties may lead to greater solidarity between partners and greater access to private information about a partner[1].

Grouped measure. It may be argued that a count of the number of different ties does not reflect multiplexity because ties such as R&D alliances and technology joint ventures are more similar to each other as compared to board interlocks and R&D alliances. We therefore construct a measure of multiplexity which categorizes ties into three groups, each with relatively similar types of ties: (i) Governance (i.e., board interlocks and equity ownership), (ii) Technology (i.e., R&D alliances, licensing agreements, and joint ventures) and (iii) Market ties (i.e., marketing alliances and customer as a supplier). Relationship multiplexity is measured by the number of groups represented by the ties between a supplier and a customer. Thus, a supplier and a customer having board interlock and equity ownership have a relationship multiplexity score of 1, while a supplier and a customer with a board interlock and an R&D alliance have a score of 2.

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[1] The following weights were used (see Gulati and Gargiulo 1999): Equity Investments = 6; Board Interlock = 5; Marketing Alliance = 4; Joint Venture = 4; R&D Alliance = 3; Customer as Supplier = 2; Licensing Agreement = 1.

Removal of a particular tie. Another potential concern with measurement of relationship multiplexity is that the results may be due to the presence of a specific type of tie. Thus, it may be argued that the results are driven by board interlocks, and if this tie is excluded from our measure of relationship multiplexity the results will change. To test for this possibility we formed a measure of multiplexity that does not include board interlocks, and tested the hypotheses with this measure. We also test our hypotheses by using a series of measures of relationship multiplexity, where each measure excludes a specific type of tie (e.g., marketing alliance, R&D alliance).

Alternative Estimators

Set of instruments. In estimating the growth and volatility models we use the first two lags of endogenous variables, the industry variables, and time dummies as instruments. However, recent work suggests that it is important to assess the sensitivity of conclusions to a reduction in the number of instruments (see Roodman 2006). Consequently, we estimate the growth and volatility models using only the first lags as instruments.

Clustering. Clustering of error terms is a plausible concern in the current study as the 200 relationships come from 126 unique suppliers. To test if results are sensitive to these concerns, we constructed a data-set that included only the 126 unique suppliers and their unique customers.

Sample Selection Bias

It is likely that firms that report their customer relationships and are therefore included in this study are systematically different from other firms that have single operating segments but are not included in this study. As such, the sample used in the current study may be biased. Failing to account for selection bias, therefore, could lead to a potentially misspecified model and biased results (Greene 2003). While the GMM methodology we utilize accounts for endogeneity, we also use the Heckman procedure to control for this potential bias. In order to execute this, we code the firms in our sample as 1 and all other firms (with a single operating segment) in the selected SIC population as zero. Following Shaver (1998), we estimate a Probit model using maximum likelihood estimation to assess the effects of risk (beta), profitability, financial slack, sales growth, sales volatility, intangible intensity, competitive intensity and the firm's competitive position (market share), all of which could be expected to influence likelihood of firms reporting their customer relationships. Selection bias is accounted for by creating a control variable 'the inverse mills ratio' (i.e., the non-selection hazard) using estimates obtained from this model. The inverse Mill's ratio (λ_i) is calculated as:

$$\hat{\lambda}_i = \phi\,(\hat{\gamma}_i\,w_i)/\Phi(\,\hat{\gamma}_i\,w_i),$$

Where, ϕ is the standard normal density function, w_i and $\hat{\gamma}_i$ are the vector of independent variables and coefficients from the probit model, and Φ is the standard normal distribution function (Greene 2003). The inverse mills ratio is used as an additional predictor in the model.

Alternate Specifications

Lagged effects of relationship multiplexity. We specify changes in relationship multiplexity to contemporaneously impact changes in sales and volatility. Unlike some investments such as R&D expenditures whose effect on performance may be discernable only after a time lag, our model posits that the effect of relationship multiplexity on sales growth and volatility is contemporaneous. We estimated an alternate specification using current as well as lagged values of relationship multiplexity as independent variables. We conducted χ^2 difference tests for both equations. In both cases, we do not find any support for including current as well as lagged values of relationship multiplexity[2]. The lagged effects of relationship multiplexity on sales growth (β = -.27, n.s.) and sales volatility (β = -2.27, n.s.) are not statistically significant.

Non-linear effects. The growth and volatility models in equation (2) and (4) assume that the effect of increasing relationship multiplexity on sales growth and volatility is linear. To test the assumption of linear effects, we include two spline measures of relationship multiplexity; low relationship multiplexity (below the median of observed values) and high relationship multiplexity (above the median) in the growth and volatility models. These models were estimated with the procedure followed in this study. We find that the coefficients of the spline measures are not significantly different in the sales growth model ($\beta_{M(low)} - \beta_{M(high)} = .07$; $\chi^2(1) = .23$, $p < .63$) and the sales volatility model ($\beta_{M(low)} - \beta_{M(high)} = .35$; $\chi^2(1) = .31$, $p < .58$). This suggests that the effect of relationship multiplexity on sales growth and volatility is linear.

Reverse causality. It may be argued that firms enter into multiplex relationships with a customer in response to growth in sales to the customer. In other words, growth in sales to a customer leads to relationship multiplexity and not the other way around. To assess this

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[2] The following equations were estimated using the GMM procedure,

Sales Growth Model 1: $\Delta S_{it} = \beta_1(\Delta S_{i(t-1)}) + \beta_2(\Delta M_{it}) + \ldots + \Delta\varepsilon_{it}$

Sales Growth Model 2: $\Delta S_{it} = \beta_1(\Delta S_{i(t-1)}) + \beta_2(\Delta M_{it}) + \beta_3(\Delta M_{i(t-1)}) + \ldots + \Delta\varepsilon_{it}$

with $\chi^2_{\text{difference Model(2) - Model(1)}} = -7.18$ (n.s.)

Sales Volatility Model 1: $\Delta V_{iz} = \beta_{v1}(\Delta V_{i(z-1)}) + \beta_{v2}(\Delta M_{iz}) + \ldots + \Delta\delta_{iz}$

Sales Volatility Model 2: $\Delta V_{iz} = \beta_{v1}(\Delta V_{i(z-1)}) + \beta_{v2}(\Delta M_{iz}) + \beta_{v3}(\Delta M_{i(z-1)}) + \ldots + \Delta\delta_{iz}$

with $\chi^2_{\text{difference Model(2) - Model(1)}} = -5.47$ (n.s.)

argument, we test three models with relationship multiplexity as the dependent variable. Model I explores contemporaneous effects of sales growth and volatility on relationship multiplexity. Model II explores the contemporaneous and lagged effects of sales growth and volatility on relationship multiplexity. Finally, Model III assesses the conjecture that multiplex relationships are formed with the expectation of higher sales growth and lower sales volatility. In other words, relationship multiplexity at time (t) is determined by sales growth at (t+1) and sales volatility at (z+1). In each model, we use all the control variables used in the sales growth and volatility model (see equation 2). Results show that sales growth and volatility are not significant predictors of relationship multiplexity[3]. In other words, the results fail to provide support for reverse causality.

[3] The following equations were estimated using the GMM procedure,

Model I: $\Delta M_{it} = \alpha + \beta_1 \Delta M_{i(t-1)} + \beta_2 \Delta S_{it} + \beta_3 \Delta V_{i(z)} + \beta_3 \Delta x_{it} + \ldots + \Delta\varepsilon_{it}$,
with $\beta_2 = .11$ ($p<.28$) and $\beta_3 = -.01$ ($p<.66$)

Model II: $\Delta M_{it} = \alpha + \beta_1 \Delta M_{i(t-1)} + \beta_2 \Delta S_{it} + \beta_3 \Delta S_{i(t-1)} + \beta_4 \Delta V_{iz} + \beta_5 \Delta V_{i(z-1)} + \ldots + \Delta\varepsilon_{iz}$
with $\beta_2 = .20$ ($p<.14$), $\beta_3 = .0001$ ($p<.20$), $\beta_4 = -.06$ ($p<.30$), $\beta_5 = .07$ ($p<.15$)

Model III: $\Delta M_{it} = \alpha + \beta_1 \Delta M_{i(t-1)} + \beta_2 \Delta S_{i(t+1)} + \beta_3 \Delta V_{i(z+1)} + \beta_3 \Delta x_{it} + \ldots + \Delta\varepsilon_{it}$,
with $\beta_2 = .19$ ($p<.23$) and $\beta_3 = -.04$ ($p<.44$)