Dynamic relationships of knowledge creation activities in supply chains: Evidence from patent data in the US auto industry

Yan Lin*, Jian Chen2 and Yan Chen1

1School of Transportation Management, Dalian Maritime University, 1st Ling Hai Road, Dalian, 116026, P. R. China. 
2School of Economics and Management, Tsinghua University, Beijing, 100084, P. R. China.

Accepted 18 August, 2011

To examine the coordination of knowledge creation activities (KCAs) in the supply chain, this paper used time series analyses to study the dynamic relationships of KCAs between buyers and suppliers in the auto industry. Using patent data a stationary relationship, it had been disclosed between both parties even if KCAs of either side were non-stationary over the long run. Furthermore, it was disclosed by phenomenon that, in comparison with suppliers, auto makers adjust more actively back to the equilibrium while deviation occurs. Finally, one side’s fluctuation is not triggered by the other side’s previous fluctuations; whereas both sides’ fluctuations are positively correlated and occur simultaneously.

Key words: supply chain, knowledge creation activities, dynamic relationship, time series analysis, auto industry.

INTRODUCTION

Knowledge recently emphasized by both managers and scholars has been treated as one of the most important resources of companies in a turbulent business environment (Bhatti et al., 2011; Hitt et al., 2010; Nonaka, 1998). Researchers have paid increasing attention to the effects of knowledge creation activities (KCAs), which include innovation, research and development (R and D), and other activities that create new knowledge for firms. For example, Alipour et al. (2011) used an Iranian example to verified that the knowledge creation is significantly related with the firm competitive advantage. Nowadays, outsourcing has arisen because of environmental changes in the business world. Large firms have been inclined to trim their tasks and outsource some previously in-house task to suppliers (Clark and Fujimoto, 1991; Fine and Whitney, 1996; Fine, 1998; Lynch, 2004; McIvor et al., 2006; Stanko and Calantone, 2011). Because of the ubiquity of outsourcing, issues related to supply chain partners have become important to firms.

In environments with frequent changes in technology, and the bulk emergence of new knowledge, a firm needs to plan strategically for successive product introductions and improvements. Following this process, the firm not only needs to endeavor in KCAs, but also has to pay attention to supply chain partners’ KCAs because his KCAs may be shaped by the adjoining participants. In other words, there may be quantitative relationships between buyers and suppliers in terms of their KCAs. Hua and Wemmerlöv (2006) examined this issue in the personal computer industry with a questionnaire survey, and verified that there was a significant positive relationship of KCAs between buyers and suppliers. However, their results were limited to a short time span.

Another angle, that is, the temporal dimension, also needs to be emphasized. Firms need some time to plan and implement KCAs. Therefore, from the long term point of view the dynamic relationships of KCAs between
buyers and suppliers should be studied: Whether the KCAs relationship between buyers and suppliers can be maintained over a long run? What is the attitude of each side towards their long term relationship? And whether the fluctuations of one side’s quantity of KCAs are triggered by the other side’s previous fluctuations, or if they occur simultaneously?

In this paper, we employ the time series analyses to discuss the long run dynamic relationship in KCAs between auto makers and suppliers. Using cointegration analysis, we examine whether there exists a stationary relationship in KCAs between both parties over the long term. Then, based on an error correction model we analyze each side’s attitude to this relationship, and the temporal relationships between both sides’ fluctuations.

Theory and hypotheses development

To build a conceptual model of the KCAs dynamic relationship in the supply chain context, we first review the literature on partition and interdependence, collaboration and KCAs interaction between buyers and suppliers. Based on relevant studies we present the research hypotheses for this paper.

LITERATURE REVIEW

Early research pointed out the importance of task partitioning, that is, how a project is divided into tasks that can then be distributed among actors (Von Hippel, 1990). Traditional organization theory relied on vertical integration that nearly all related tasks to produce a product were carried out by a single firm, and the task partitioning was done among sectors within the firm. However, over the past several decades the world has become an international market, while demand has become increasingly unpredictable. To be responsive to rapid market changes, outsourcing has become increasingly popular as firms focus on their core competencies while shifting many non-core tasks to their suppliers. As Achrol (1997) suggested, vertical integration lacked the speed and flexibility necessary to keep up with fast-paced environmental and technological changes. Instead, “it is increasingly apparent that the giant, vertically integrated, multidivisional firm, so successful in the 20th century is likely to be the dinosaur of the 21st century. Replacing it, are smaller, more focused, vertically disaggregated firms.” Thus, tasks are partitioned among supply chain members.

However, between the upstream and the downstream supply chain members tasks are not only partitioned, but also related, which can be interpreted by the theory of interdependence. Three types of system-level interdependence have been categorized (Bailey et al., 2010; Gattiker and Goodhue, 2005; Thompson, 1967): pooled, sequential and reciprocal. In pooled interdependence, each participant makes a discrete contribution to the whole but does not necessarily depend upon every other participant directly. In sequential interdependence, the output of a participant becomes the input of another participant. In reciprocal interdependence, the output of each participant becomes an input for the other, and each interdependent member is penetrated by the other. This traditional concept of interdependence can be used to describe the relationship between the upstream and the downstream participants in supply chains (Nirmalya et al., 1995). Furthermore, Hult et al. (2004) and Ketchen and Hult (2011) described supply chains as being characterized by reciprocal interdependence, meaning that each supply chain member depended on adjoining participants to perform its tasks.

During the 1980s, researchers shifted their viewpoint on supply chain members’ roles. Earlier research drew contradictions between buyers and suppliers and described the search for competitive advantage as a distributive game (Porter, 1980). Later research found that there were not only contractual trading relationships, but also more intimate embeddedness between a firm and its suppliers. Porter (1985) suggested that between successive stages of the industry chain there were complementarities in their resources. Wernerfelt (1985) emphasized the role of inputs as a source of competitive advantage and suggested that a firm could benefit from long established links, allowing effective interaction of resources with its suppliers.

Collaboration is the centerpiece of product development processes. Firms not only require their suppliers to perform better in operations activities, but also involve them in more knowledge-based innovations (Handfield et al., 1999; Petersen et al., 2005). Suppliers’ knowledge creation capabilities are pivotal for buyers. Thus, collaborations in the supply chain can involve not only material flow, but also knowledge flow and collaborative creation activities (Choi and Hong, 2002; Samaddar and Kadiyala, 2006).

Typically, supply chain members are not branches of the same organization, so they cannot be governed by a headquarters. Knowledge has been an important source of coordination and thus has become central to supply chain functions. The whole supply chain will increase operational performance when members advance their level of knowledge acquisition and information distribution activities (Hult et al., 2004). Malhotra et al. (2005) focused on the downstream member’s viewpoint; their research paid attention to the buyer’s “absorptive capability,” which explains how he smoothly acquires his suppliers’ knowledge. Their core concept was that, efficient knowledge acquisition from suppliers could lead to the buyer’s benefit, such as operational efficiency and partner-enabled market KCAs. On the other hand, Kotabe et al. (2003) revealed that, the supplier could also gain benefits from collaboration with buyers. They verified that in Japanese auto manufacturing industry, the
quantity of technology transfer from an auto maker is positively associated with the supplier’s performance improvement. Because knowledge sharing is mutually beneficial, it can be accepted by both sides. Dyer and Hatch (2004) found that some leading companies, such as Toyota, Microsoft, and Dell, embraced their suppliers and encouraged knowledge sharing with them by establishing networks through which to facilitate the exchange of information. Furthermore, Dyer and Hatch (2006) empirically found that, in contrast with US auto makers, Toyota shared more knowledge with suppliers, and created more value for both Toyota and its suppliers.

Recent research focuses on the new type of supply chain performance, that is, green management performances, such as reduction of air emission, reduction of waste water, reduction of solid wastes, and so on. Wu et al. (2010) verified that efficient information sharing and knowledge transfer can improve these “green” performances. Though all the above research concerns knowledge transfer in the supply chain context, these studies are also related to KCAs, because knowledge transfer and KCAs are inseparable concepts. Bresman, Birkinshaw, and Nobel (1999) pointed out that “a literature search reveals that what some call knowledge transfer typically results in KCAs. Birkinshaw and Nobel (1999) emphasized that KCAs are the natural result of knowledge transfer, and knowledge transfer typically results in KCAs.

These studies make it clear that firms can gain benefits from their supply chain partners’ knowledge. These benefits include not only task efficiency, but also improvements in KCAs. Are these KCAs are also related in the supply chain context? Hua et al. (2006) examined this question in the personal computer industry. They tested the relationship between the rates of changes in suppliers’ component innovations (regarded as a measure of suppliers’ KCAs) and the rates of changes in buyers’ product innovations (regarded as a measure of buyers’ KCAs). Their results show that the buyers’ rate of product changes were positively related with their key suppliers’ rate of component changes. They analyzed this issue with a questionnaire survey. However, their study only examined a short period of time. Therefore, although they obtained interesting results, the method they used could only reflect the KCAs relationship at a certain time point. Aimed to reveal the dynamic relationship of KCAs between buyers and suppliers, we used time series analysis in this paper. The time series data give us another perspective that views the relationship along the temporal dimension.

**Hypotheses development**

The auto manufacturing industry is a good example for the study of KCAs coordination in the supply chain context. A motor vehicle is typical of a complex product, for example, a passenger car consists of more than 30,000 components and many suppliers are heavily involved in the development of new vehicles (Takeishi, 2002). The production process of automobiles integrates many KCAs which not only emerge within auto makers, but also spill over to and take advantage of suppliers. Therefore, in this industry, firms may be related with their supply chain partners in KCAs.

Concerning the time dimension, studies on technology life cycle theory (Utterback, 1996; Nelson, 1996) have suggested that technologies change and evolve continually over the long term. Thus, the quantity of KCAs evolves over time. When radical innovation occurs, more KCAs are needed to solve difficulties both in product design and in process improvement. Comparatively, during periods of incremental innovation, fewer KCAs are needed to deal with problems in products or processes. Therefore, the evolution of the KCAs displays non-stationary over the long time.

When confronting complex technology, it is not a single company, but a network, including many companies and a shared body of knowledge, that deals with difficulties. The units of a network constitute a ‘technological community’ (Kash and Rycroft, 2000). Automobile manufacturing is a typical complex technology sector that needs cooperation between the upstream and the downstream members, thus technological communities are formed between auto makers and suppliers (Kash et al., 2000). When the entire task of the supply chain is technically changed or improved, KCAs of both auto makers and suppliers are initiated at the same time, thus the quantity of KCAs of both sides may keep a stationary and positive relationship over long periods of time.

Research on architectural innovation suggested that some effective innovations are executed through changes in product architecture rather than through radical changes in core components (Henderson and Clark, 1990). However, even in architectural innovations, some key components may also need to be reinforced technically to fit the new architectural scheme. Therefore, the KCAs between auto makers and suppliers may be positively related. Generally, over the long term, there is a positive correlation in the quantity of KCAs between auto makers and suppliers. The concept of equilibrium can be used to express this relationship¹. We describe the equilibrium in the KCAs between auto makers and suppliers as a linear combination of both sides evolving stationarily over the long term, even though each side may change turbulently. Thus, we can predict as follows:

H₀: There is equilibrium in the KCAs between auto makers and suppliers, that is, there is a stationary and positive relationship in the quantity of KCAs between them over the long term.

¹ Kouassi et al. (2004) argued that statistically long term equilibrium was said to exist when a linear combination of two non-stationary time series was stationary, and the two time series had the tendency to move together over the long time.
While both sides have long term equilibrium in their KCAs, a convergent trend may arise: each side may make adjustments to their KCAs reacting to the departure from the equilibrium, and through these adjustments the equilibrium can be maintained for the long term. Thus, we predict:

\( H_{0.1} \): Auto makers react to a deviation from long term equilibrium by adjusting towards the equilibrium during the subsequent period.

\( H_{0.2} \): Suppliers react to a deviation from long term equilibrium by adjusting towards the equilibrium during the subsequent period.

While technical changes occur in some product parts which are produced by suppliers, fluctuations (increases or decreases) may be displayed in the quantity of suppliers' KCAs. Because there are intrinsic technological interactions between the product parts produced by suppliers and other parts, auto makers' KCAs may be influenced by suppliers, and the quantity of their KCAs may fluctuate correspondingly.

When auto makers develop new architectural designs for vehicles, the relevant key components, some of which are produced by suppliers, should be changed technically. Further, the assignment of tasks in a supply chain is complex; auto makers often retain tasks of a lot of important components. When auto makers change the technical scheme for these components, some other components, which are produced by suppliers, should also be changed technically. Thus, auto makers' KCAs fluctuation may lead to suppliers' similar fluctuation.

The question should be answered of whether the technological changes of both sides occur simultaneously, or if one side is triggered by the other side (here, "trigger" means A's fluctuation occurs previously and B's fluctuation occurs latter correspondingly, in other words, B's technological changes are affected by A's previous technological changes)? We argue that in the supply chain context each side's KCAs would rather change simultaneously with than wait for triggers from the other side.

Nowadays, collaboration between buyers and suppliers has been emphasized. For example, the importance of and benefits from involving suppliers in buyers' new product development have been demonstrated. Several studies have highlighted that supplier participation in buyers' product development projects could help reduce costs and the concept-to-customer development time, at the same time providing innovative technologies, which could eventually help capture market share (Handfield et al., 1999). The selection criteria for supplier integration were also investigated. The two highest scoring items in responses by buyers were supplier's product knowledge/capability and supplier's process knowledge/capability (Handfield et al., 1999), revealing that collaborations between buyers and suppliers are often knowledge-based. Belderbos et al. (2004) also confirmed that supplier cooperation projects often focus on incremental innovations, which can improve buyers' productivity. With the rapid rate of technological changes, shortened product life cycles and globalizations of markets, suppliers are involved early in buyers' new product development (Bennet, 1994), and more new knowledge can be created in cooperation between buyers and suppliers. Thus, the quantity of their KCAs may fluctuate toward the same direction at the same time.

The interactive relationship between auto makers and suppliers also determines the simultaneous technological changing in their KCAs. The sourced product parts often possess complex interfaces with other parts, influencing auto maker-supplier interactions in product development (Laseter and Ramdas, 2002). It is necessary for either side to adjust their own designs according to the interests and needs of the other side. Broad communication and reciprocal adjustment are needed when auto makers and suppliers initiate KCAs. Thus, KCAs of both sides may fluctuate simultaneously and toward the same direction.

Waiting for supply chain partners to accomplish their KCAs often means a firm dragging their feet in their own business. This is especially true in an environment of rapid developments and short product life cycles that any firm's delay may lead to him being defeated by rivals. We can conclude as follows:

\( H_{1} \): Fluctuation of one side's KCAs occurs simultaneously with, rather than being triggered by, fluctuation of the other side's KCAs toward the same direction.

**METHODOLOGY**

We chose the USA auto manufacturing industry as the study subject. Further, like previous research in innovation and knowledge management, we use patent counts as proxies for KCAs. To study the principal issues of this paper, we should construct two time series variables: the quantity of auto makers' KCAs and the quantity of suppliers' KCAs. We take advantage of time series analytical methods, such as tests for cointegration and the error correction model (ECM) to test above hypotheses.

**Sample and data**

The USA currently possesses the largest auto market, and almost all of the world's largest auto makers and suppliers operate in the market. Indeed, the number of participants in the US auto market makes it sufficiently large to represent all aspects of the world auto industry.

Patent data have received much attention because they provide detailed information, are systematically compiled, and are available continuously over long time. Much research in innovation and knowledge management has adopted patent data as a measure of KCAs (Scherer, 1965; Acs and Audretsch, 1989; Arora and Gambardella, 1990; Mowery et al., 1996; Jaffe and Trajtenberg, 2002), and significant relationships have been found between the quantity of KCAs and some indicators constructed from patent data.

As the method of using patent data as a proxy for KCAs is sensitive across different industries (Levin et al., 1997), suspicions may arise as to whether patent data can measure KCAs in this paper's
research context.

The first suspicion may be that patents can only represent explicit technological knowledge, but not tacit knowledge. Although patent documents may represent codified knowledge themselves, more importantly, they also indicate the result of many KCAs that comprise volumes of new knowledge, including tacit knowledge embedded in the brains of staff or hidden in the routines of organizations. Furthermore, Mowery et al. (1996) pointed out that codified knowledge and tacit knowledge flows are closely linked and are quantitatively complementary.

The second suspicion could be that many KCAs do not result in patents (Almeida et al., 2002), especially in cases where patents are not especially effective in protecting innovations from imitation. However, Levin et al. (1987) showed the effectiveness of patents in preventing duplication in 18 industries, and demonstrated that motor vehicle parts manufacturing ranked quite highly among these industries. In fact, it was only inferior to chemical industries, and was superior to some industries that have been sampled using patent data as a proxy for KCAs in many studies, such as semiconductors and communications equipment, implying that auto makers and suppliers have strong incentives to patent their innovations.

Finally, some patents are sought not only with the aim of protecting new knowledge, but also targeting strategies, such as entering and occupying new markets. However, looking across many industries, Acs and Audretsch (1989) found a high degree of similarity between patent counts and innovative activities, thus the situation of strategically applied was only noise and could not bias the test results. Among indicators constructed from patent data, a basic and convenient one is the patent count, which is measured by the number of successfully applied patents. Many studies in the field of knowledge management have used patent counts as a proxy for KCAs (Deng et al., 1999; Penner-Hahn and Shaver, 2005; Hoetker, 2005) and Tseng and Wu (2007) showed that the patent count was a significant indicator for measuring KCAs in the auto industry. Because the USA auto manufacturing industry was chosen as the study subject and patent count is used as a proxy for KCAs in this paper, the USPTO’s (United States Patent and Trademark Office) online patents database facilitated our study. Our data were collected from this database.

To guarantee a sufficiently populated data series to provide a viable sample set, a data set over 24 years, from January 1980 to December 2003 is adopted. We collected monthly data, resulting in 288 periods. We collected the count of successfully applied patents rather than the granted patent count in every period, because applications typically spend several years in the USPTO from the filing date until they are granted, so counts of granted patents may not reflect the current KCAs.

Variables

We examined relationships between two factors: the auto makers’ quantity of KCAs (denoted by the time series variable $AUT_i$) and the suppliers’ quantity of KCAs (denoted by the time series variable $SUP_j$). We chose the six auto makers with the highest market share in the US (GM, Ford, Chrysler/DaimlerChrysler, Toyota, Honda, and Nissan) as the samples of the US auto makers. At the end of 2005 these six corporations accounted for almost 90% of car sales in the US. We measure their summed counts of successfully applied patents as proxies of $AUT_i$.

Definition 1: The time series variable $AUT_i$ is the summed counts of patent applications of the six auto makers in period $t$, as a measure of the quantity of the auto makers’ KCAs.

$$AUT_i = \sum_{j=1}^{6} AUT_{i,j}$$

where $t = 1, 2, ..., 288$, indicating a period among the 288 time periods, $i = 1, 2, ..., 6$, indicating one of the six auto makers, and $AUT_{i,j}$ is the count of successfully applied patents of auto maker $i$ in period $t$.

Candidate suppliers were identified from the motor vehicle suppliers in the Fortune 500 companies and the US Ward’s auto suppliers’ directory (www.wardsauto.com). To guarantee the integrity of the samples, we chose all suppliers who had applied successfully for patents through the years from 1980 to 2003, so that 30 suppliers are included in this study. Similar to the definition of $AUT_i$, we define the time series variable $SUP_j$, as:

Definition 2: The time series variable $SUP_j$ is the summed total of patent (relevant to auto technology) applications by the 30 suppliers in period $t$, as a measure of the quantity of the suppliers’ KCAs.

$$SUP_j = \sum_{i=1}^{30} SUP_{i,j}$$

where $t = 1, 2, ..., 288$, indicating a period among the 288 time periods, $j = 1, 2, ..., 30$, indicating one of the 30 suppliers, and $SUP_{i,j}$ is the count of patent (relevant to auto technology) applications by supplier $j$ in period $t$.

Our objective is to reveal dynamic relationships of KCAs between auto makers and suppliers. Over the 24-year study period, some auto makers and suppliers had made radical transformations in their tasks, some actors may have changed their business model or diverted their technology trajectory, and some auto makers changed their suppliers frequently. If we focus on peer to peer (one auto maker versus one supplier) samples, the individual transformations will bias the overall long term trend. The effect of the summed values of $AUT_i$ and $SUP_j$ can pool such transformations and remove the bias. We took the natural logarithms of the two time series variables $AUT_i$ and $SUP_j$, providing $LNAUT_i$ and $LNSUP_j$, respectively. A graph and descriptive statistics of $LNAUT_i$ and $LNSUP_j$ are shown in Figure 1 and Table 1.

The correlation of these two variables is quite high, equal to 0.82 and significant at 0.001 level. A factor analysis is done, and the result shows that both variables belong to a single factor with the same loading value 0.95.

Research methods

When examining relationships between two variables, one convenient method is regression analysis. However, these two time series variables may be non-stationary which can lead to ordinary least squares (OLS) regression being inappropriate. In an analysis of relationships between a pair of non-stationary time series variables, the concept of “cointegration” is useful. When a linear combination of two non-stationary time series is stationary, the OLS method is appropriate for the two series and they are said to be cointegrated. The significance of cointegration means there is long term equilibrium between these two series (Engle and Granger, 1987; Kouassi et al., 2004), through which we can test Hypothesis 1. This method has been introduced into the dynamic studies on strategic management, for example, Nair and Filer (2003) used cointegration analyses to verify that there was long term equilibrium of strategic behaviors among firms in groups.

As many suppliers diversify their business fields, some of which have no relation with automobiles, for example, the top 500 firm Johnson Controls not only produces auto parts but also supplies building automation and control systems for construct enterprises. To guarantee all patents we include are related with auto technologies, we limit the patents with Current International Class on auto manufacturing technology.
According to classical time series analytical methods (Engle et al., 1987), cointegrated variables must have an ECM representation. Using extended ECM-based models we can analyze how actively one side adjusts towards the long run equilibrium when deviation occurred, by which we can test the Hypothesis 2.1 and 2.2. Further, using the extended ECM-based models, we can analyze whether two variables fluctuate simultaneously or one triggers the other, by which we test the Hypothesis 3.

RESULTS

Because the variables, LNAUT\textsubscript{t} and LNSUP\textsubscript{t}, are both time series variables, which may be non-stationary, we first check whether they are stationary and then ascertain the order of integration for both variables. Then, we test the hypotheses using the cointegrative and the ECM-based analyses.

**Order of integration**

Before testing the cointegration of LNAUT\textsubscript{t} and LNSUP\textsubscript{t}, we first ascertain the integration order for each. Only if both are non-stationary and have the same integration order may cointegration exist between them. Augmented Dickey Fuller (ADF) tests\(^3\) are adopted to ascertain the integration order of these two series. Here, we denote the first difference of LNAUT\textsubscript{t} as:

\[
\Delta \text{LNAUT}\textsubscript{t} = \text{LNAUT}\textsubscript{t} - \text{LNAUT}\textsubscript{t-1}.
\]

\(^3\) The ADF tests whether a given series is stationary; if the null hypothesis is rejected, then the series is stationary. If the series are non-stationary, then the first order difference of the series is tested, and so on, until the \(d\) order difference is stationary; it is said the series is integrated of order \(d\) (Dickey and Fuller, 1981; Engle and Granger, 1987).
Table 2. ADF test of series.

<table>
<thead>
<tr>
<th>Series</th>
<th>Models</th>
<th>ADF values</th>
<th>10% level</th>
<th>5% level</th>
<th>1% level</th>
<th>Null hypothesis: the series are non-stationary</th>
</tr>
</thead>
<tbody>
<tr>
<td>LNAUT</td>
<td>Model 3</td>
<td>-1.787365</td>
<td>-3.136301</td>
<td>-3.426191</td>
<td>-3.991656</td>
<td>Accept null hypothesis</td>
</tr>
<tr>
<td></td>
<td>Model 2</td>
<td>-1.043765</td>
<td>-2.572313</td>
<td>-2.871806</td>
<td>-3.453910</td>
<td>Reject null hypothesis</td>
</tr>
<tr>
<td></td>
<td>Model 1</td>
<td>0.928325</td>
<td>-1.615931</td>
<td>-1.941978</td>
<td>-2.573367</td>
<td></td>
</tr>
<tr>
<td>∆LNAUT</td>
<td>Model 3</td>
<td>-9.457831</td>
<td>-3.136301</td>
<td>-3.426191</td>
<td>-3.991656</td>
<td>Accept null hypothesis</td>
</tr>
<tr>
<td></td>
<td>Model 2</td>
<td>-9.476795</td>
<td>-3.453910</td>
<td>-2.871806</td>
<td>-2.572313</td>
<td>Reject null hypothesis</td>
</tr>
<tr>
<td></td>
<td>Model 1</td>
<td>-9.428646</td>
<td>-1.615931</td>
<td>-1.941978</td>
<td>-2.573367</td>
<td></td>
</tr>
<tr>
<td>LNSUP</td>
<td>Model 3</td>
<td>-1.738807</td>
<td>-3.136301</td>
<td>-3.426191</td>
<td>-3.991656</td>
<td>Accept null hypothesis</td>
</tr>
<tr>
<td></td>
<td>Model 2</td>
<td>-0.146344</td>
<td>-2.572313</td>
<td>-2.871806</td>
<td>-3.453910</td>
<td>Reject null hypothesis</td>
</tr>
<tr>
<td></td>
<td>Model 1</td>
<td>2.389196</td>
<td>-1.615931</td>
<td>-1.941978</td>
<td>-2.573367</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Model 2</td>
<td>-9.799100</td>
<td>-2.572313</td>
<td>-2.871806</td>
<td>-3.453910</td>
<td>Reject null hypothesis</td>
</tr>
<tr>
<td></td>
<td>Model 1</td>
<td>-5.847537</td>
<td>-1.615926</td>
<td>-1.941986</td>
<td>-2.573429</td>
<td></td>
</tr>
</tbody>
</table>

and the first difference of \(LNSUP_t\) as

\[ \Delta LNSUP_t = LNSUP_t - LNSUP_{t-1} \]

Three typical models\(^4\) of ADF are employed to test the null hypothesis that the corresponding series are non-stationary. The results are shown in Table 2. From Table 2, both \(LNAUT_t\) and \(LNSUP_t\) are non-stationary, but their first order difference series are stationary, verifying that \(LNAUT_t\) and \(LNSUP_t\) are both integrated of order 1.

Test of cointegration

Because both time series variables have the same integration order, cointegration possibly exists between them. The first step in testing cointegration is performing OLS estimation for the series \(LNAUT_t\) and \(LNSUP_t\). Let:

\[ LNAUT_t = \alpha_0 + \alpha_1 \times LNSUP_t + ec_t \]  \hspace{1cm} (1)

where \(ec_t\) is a random error term which is the residual series of the OLS. The actual, fitted, and residual series of \(LNAUT_t\), after OLS are shown in Figure 2. The residual series is the error correction term \(ec_t\), and the stationarity test of \(ec_t\) is shown in Table 3.

As shown in Table 3, series \(ec_t\) are stationary, indicating that the OLS estimate is appropriate and gives a stationary linear combination for \(LNAUT_t\) and \(LNSUP_t\). This result verifies that \(LNAUT_t\) and \(LNSUP_t\) are cointegrated, implying that there is equilibrium in the quantity of KCAs between auto makers and suppliers. That is, there is a stationary positive relationship in the quantity of KCAs between them in the long term. Thus, the \(H_1\) is verified. Finally, the relationship between \(LNAUT_t\) and \(LNSUP_t\) is:

\[ LNAUT_t = 3.216 + 0.4286LNSUP_t \]  \hspace{1cm} (2)

Error correction model (ECM)-based analysis

Because \(LNAUT_t\) and \(LNSUP_t\) are cointegrated, referring to Baussola (2000) and Kouassi et al. (2004), we can construct ECM-based representation to test \(H_{2.1}\), \(H_{2.2}\) and \(H_3\). Using the ECM-based model, we test whether one variable’s current fluctuation is affected by both its own deviation from the equilibrium in the last period and the other variable’s past fluctuation. Moreover, to test whether one variable’s current fluctuation is affected by the other variable’s simultaneous fluctuation, we refer to Lütkepohl (1991), who discussed instantaneous causality, based on Granger causality (Granger, 1969), and added the term of the other variable’s simultaneous fluctuation to the models. Therefore, our ECM-based regression models are constructed as follows:

\[^4\] Using the typical ADF method, a researcher should test 3 models: a model that includes both intercept and time trend terms (model 3), a model that includes the intercept term (model 2), and a model that includes neither the intercept nor time trend terms (model 1). The testing sequence is first model 3, then model 2, and finally model 1, until rejection of the null hypothesis that the series are non-stationary, and then the series is stationary. If all three models cannot reject the null hypothesis, then the series is non-stationary (for details see Hamilton, 1994, Chapter 17).
Figure 2. Actual, fitted, and residual series of $LNAUT_t$ after OLS.

Table 3. ADF test of the series $ec_t$.

<table>
<thead>
<tr>
<th>Augmented Dickey-Fuller test statistic</th>
<th>t-Statistic</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-9.180115</td>
<td>0.0000</td>
</tr>
<tr>
<td>Test critical values ($%$ level)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-2.573073</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>-1.941937</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>-1.615958</td>
<td></td>
</tr>
</tbody>
</table>


\[
\Delta LNAUT_t = \alpha_1 + \sum_{i=1}^{n} A_i \Delta LNAUT_{t-i} + \beta_1 \Delta LNSUP_t + \sum_{i=1}^{n} B_i \Delta LNSUP_{t-i} + \rho_1 ec_{t-1} + \mu_t
\]  
\[
\Delta LNSUP_t = \alpha_2 + \sum_{i=1}^{m} C_i \Delta LNSUP_{t-i} + \beta_2 \Delta LNAUT_t + \sum_{i=1}^{m} D_i \Delta LNAUT_{t-i} + \rho_2 ec_{t-1} + \nu_t
\]

where, $A_i, B_i, C_i, D_i, \rho_1, \rho_2, \beta_1, \text{ and } \beta_2$ are coefficients, $n$ and $m$ are optimal lags of the series (method to ascertain both of them will be described latter), $\mu_t$ and $\nu_t$ are serially independent random error terms, and $ec_{t-1}$ are the 1-period lagged values of the error-correction terms ($ec_t$), derived from the long run cointegrating in Equation 1. Using these two equations, we can explore whether either side is willing to keep the equilibrium for a long time, that is, whether one side's current fluctuation is a reaction and correction to his earlier departure from the equilibrium. We construct the null hypotheses as follows:

$\rho_1 = 0$ in Equation 3, that is, auto makers' fluctuation in the quantity of KCAs is not affected by the deviation from equilibrium in the last period.

With this, we test Hypothesis 2.1.

$\rho_2 = 0$ in Equation 4, that is, suppliers' fluctuation in the quantity of KCAs is not affected by the deviation from equilibrium in the last period.

With this, we test $H_{2.2}$.

Using Equation 3, we can analyze the effect of either simultaneous or past fluctuation of suppliers' KCAs on auto makers' current fluctuation of KCAs. We construct the null hypotheses as follows:

$\beta_1 = 0$ in Equation 3, that is, auto makers' fluctuation in the quantity of KCAs is not affected by suppliers' simultaneous fluctuation in the quantity of KCAs.
\[ B_i = 0, \forall i \] in Equation 3, that is, auto makers’ fluctuation in the quantity of KCAs is not affected by suppliers’ past fluctuation in the quantity of KCAs.

Similarly, using Equation 4, we can also analyze the impact of either simultaneous or past fluctuation of auto makers’ KCAs on suppliers’ current fluctuation. Therefore, we test the null hypotheses as follows:

\[ D_i = 0, \forall i \] in Equation 4, that is, suppliers’ fluctuation in the quantity of KCAs is not affected by auto makers’ simultaneous fluctuation in the quantity of KCAs.

We used the \( F \)-test to model changes to test these null hypotheses. To establish ECM-based models, we have to choose appropriate lag lengths of independent variables \( n \) in Equation 3 and \( m \) in Equation 4 according to information criteria. We use the Akaike information criterion (AIC) to ascertain the optimal lag length of explanatory variables (Akaike, 1973). The results are shown in Table 4.

According to AIC, the appropriate lag length of explanatory variables (that is, \( \Delta LNAUT_i \) and \( \Delta LNSUP_i \)) in the regression model of \( \Delta LNAUT_i \) (Equation 3) is 11 \( (n=11) \), and the appropriate lag length of explanatory variables in the regression model of \( \Delta LNSUP_i \) (Equation 4) is 12 \( (m=12) \).

Results of the \( F \)-test for the six null hypotheses are shown in Table 5.

Different attitudes toward the equilibrium between auto makers and suppliers can be found by the analyses of the coefficients \( \rho_1 \) in Equation 3 and \( \rho_2 \) in Equation 4. In the regression model of \( \Delta LNAUT_i \) (that is, Equation 3), the null hypothesis of \( \rho_1 = 0 \) was rejected, as the \( F \)-value is close to 5 and significant at the 0.05 level, and the estimate of \( \rho_1 \) is negative (-0.37). This implies that, while the auto makers’ quantities of KCAs deviated from the long run equilibrium in period \( t-1 \) (expressed by \( e_{D_i} \), being unequal to 0), they actively and largely correct this deviation by adjusting their own quantity of KCAs in period \( t \). This result verifies \( H_{3.1} \). However, in the regression model of \( \Delta LNSUP_i \) (that is, Equation 4), the null hypothesis of \( \rho_2 = 0 \) could not be rejected as the \( F \)-value was small and not significant. This means that the suppliers’ fluctuation of KCAs in period \( t \) is not related to their deviation from equilibrium in period \( t-1 \). Thus, \( H_{3.2} \) cannot be verified.

From the regression model of \( \Delta LNAUT_i \) (that is, Equation 3), we also find that the null hypothesis of \( \beta_1 = 0 \) is strictly rejected, as the \( F \)-value is higher than 15 and significant at the 0.001 level, and the estimate of \( \beta_1 \) is positive (0.33), meaning that auto makers’ current fluctuation in the quantity of KCAs is positively affected by suppliers’ simultaneous fluctuation. However, the null hypothesis of \( \beta_2 = 0 \) cannot be rejected as the \( F \)-value is very small and not significant. This result shows that, auto makers’ current fluctuation in the quantity of KCAs cannot be explained by the suppliers’ past fluctuations.

Similar results are found from the regression model of \( \Delta LNSUP_i \) (that is, Equation 4), where the null hypothesis of \( \beta_2 = 0 \) is also strictly rejected, as the \( F \)-value is high, close to 40, and significant at the 0.001 level, and the estimate of \( \beta_2 \) is positive (0.40). Furthermore, the null hypothesis of \( D_i = 0 \) cannot be rejected as the \( F \)-value is very small. This result shows that, suppliers’ current fluctuation in the quantity of KCAs is positively related with auto makers’ simultaneous fluctuation, but it cannot be explained by past ones. Integrating above two results, \( H_5 \) is verified.

\[ LNAUT_i = 0.6210 + 0.2209 LNSUP_i + 0.3755 LNTOT_i \] \( (5) \)

Control the patenting trend

To guarantee the robustness of these results, we should...
The regression coefficients of both influenced by the patent application trend, but is still influenced by the OLS estimate for the series real relationship between and . We use the time series , to denote the patent application trend, which is the USPTO's total number of patent applications in period . Some factors, such as macroeconomics, policies, and USPTO work patterns, are able to cause changes in the trend of , further may influence both and and then cause them to display a positive relationship. However, because these factors are independent of our research purpose, we should control the impacting factor to guarantee real relationship between and .

We introduce the natural logarithm of , , to the OLS estimate for the series . The regression result is as follows: The regression coefficients of both , and , are significant at the 0.001 level. Compared with Equation 2, the regression coefficient of , in Equation 5 is much smaller. However, even after controlling for the influence of , , is significantly correlated with . This result reveals that although , is influenced by the patent application trend, , has a positive correlation with , over the long run even control the influence of the patent application trend. A similar situation is found in the regression equation of . That is, , is influenced by the patent application trend, but is still influenced by even control the influence of the patent application trend.

Because , positively influences both and , the above tests regarding the relations of fluctuations between and may be biased by the patent application trend. We control for this by introducing lags of the first difference of into above ECM-based regression models (Equations 3 and 4). The results are listed in Table 6, showing that there are no distinct differences with the results in Table 5.

**DISCUSSION**

The tests of cointegration for the time series variables support the hypothesis that, over the long term, between auto makers and suppliers, there is a positive relationship in their quantity of KCAs. Although both time series variables are non-stationary, a linear combination of them is stationary along the temporal dimension, meaning that there is equilibrium between them. The existence of this equilibrium suggests that, there are similar trends in KCAs between auto makers and suppliers. That is, when the quantity of auto makers’ KCAs is higher in a period, the quantity of suppliers’ KCAs is also higher in the same period.

The test results of also verify that both sides’ KCAs fluctuate synchronously (with similar direction and at the same time). Generally, when one side increases its KCAs, the other side also increases its KCAs; when one side decreases its KCAs, the other side also decreases its KCAs.

The existence of the similar evolution process (equilibrium) and synchronous fluctuation accounts for the KCAs of each side being shaped by the KCAs of the other side. One reason for the forming of this relationship is that there are technical interactions between them. The automobile is a typical complex product, and some parts of a vehicle have complex interfaces with other vehicle components. For example, an axle and suspension module with high interface complexity, because it has many physical interfaces and many system interactions that make key vehicle performance characteristics, such as steering and handling, which are difficult to predict (Laseter et al., 2002). These parts are tightly related with the entire vehicle technologically and functionally. When auto makers initiate innovations in vehicles, these important product parts, some of which are produced by suppliers, will be changed in design or production processes, thus, in this case, innovations are initiated by the suppliers.

When suppliers initiate innovations, relevant technological adjustments are also initiated in auto makers. Even some parts with simple interfaces with other vehicle components can not be ignored on their technological influence on the vehicle. A case reported by Mikkola (2003) showed a mistake made by Chrysler who ignored the corresponding adjustment when one of their suppliers initiated innovation. In the early 1990s, Chrysler used a supplier to produce a new type of windshield wiper controller for their new Jeep Grand Cherokee, resulting in two technological solutions, solid-state and silent-relay. Because the controller used by older Jeep families applied relay-based technology which made noise when switching from ON to OFF, the supplier was asked to
develop a ‘quiet’ wiper controller. One technical solution was to create a solid-state module which was simple for the supplier’s electrical engineers and there were no radical innovations involved in the process, so Chrysler paid less attention to this part and neglected the technological changes to the components related with this new type wipers controller. Furthermore, the supplier also neglected how this part would function as an integrated wiper system in relation to the rest of the vehicle. The result was nearly catastrophic because the solid-state wipers would catch fire when tested under certain conditions, even though the modules worked well in lab simulations and tests. Eventually, the development of solid-state wiper was halted.

Another example is the introduction and development of antilock braking system (ABS) into the auto industry (Veloso and Fixson, 2001). ABS, as a modular part to automobiles, was first introduced and dominated by suppliers (mainly Bosch and ITT-Teves). Because it kept the modular characteristic of the braking system, the solution just described was clearly independent from the vehicle where it was applied. Suppliers developed this system over years and dramatically enhanced its reliability and decreased its cost. ABS benefited auto makers who actively accepted this system. In 1984, less than 1% of the cars produced were equipped with ABS, but by 2003 about 95% new cars came equipped with ABS. However, auto makers had to do more than merely buy ABS components and install them in their vehicles; they also needed to make technological changes to make the ABS fit. These changes were mainly complementary adjustments needed to incorporate the ABS in the vehicle, so some patents related with ABS are also applied by auto makers. For a long time, Veloso and Fixson (2001) illustrated that ABS-related patents of auto makers and suppliers followed a similar pattern. Therefore, when one side initiates innovation, the other side must also initiate innovation; thus, there is an intimate relationship in KCAs between auto makers and suppliers over the long term.

Furthermore, the KCAs of each side may be subject to constraints caused by the other side. An example comes from Carlile (2004), who showed the importance for a supplier to adequately take care of his partner’s real needs. At an anonymous US auto corporation, in 1990, the engine group, which can be regarded as an internal supplier of the auto maker, had developed a new, more powerful engine, which was the outcome of a sustained effort over several years. However, the size and the shape of the engine caused the hood to be higher than the auto maker wanted; the style of hood was settled in the market in the 1990s. The unfortunate result of this engine design was that it could not be used, and worse, it generated costly design changes and delays downstream. The reasons for such a mistake include one side not being able to develop corresponding innovation to suit to the other side’s designs, or the design not meeting the interests of the other side. A smart firm will avoid initiating redundant KCAs which exceed their supply chain partner’s capabilities or interests to cooperate with them. Thus, technical interaction between auto makers and suppliers leads to the formation of intimately relationship in KCAs between auto makers and suppliers for the long run.

Viewing the whole supply chain, auto makers and suppliers execute their respective tasks, which are parts of the entire task for the supply chain (creating and making new motor vehicles to match market needs). The entire task includes all tasks assigned among the supply chain members, and all R and D and innovations of the entire task can be considered as the collective of all members’ KCAs. Auto makers’ and suppliers’ KCAs are both branches of this collective, and they maintain equilibrium over the long term because both branches have a close technological relationship. Either side’s fluctuations may be influenced by this long term relationship. For example, when deviation from the equilibrium occurs, each side should adjust quickly back to the equilibrium to guarantee the successful implementation of the entire supply chain’s task. However, among supply chain members, different attitudes to the equilibrium have been found through the analyses of the ECM-based model (that is, tests of the coefficient \( \rho_1 \) in Equation 3 and \( \rho_2 \) in Equation 4). Different expressions in the test reflect different attitudes to the needs of the entire task’s KCAs. An auto maker, who dominates the entire task and lies at the downstream side of the supply chain, is directly influenced by achievements of the entire task. The auto maker cares more about the entire task’s needs, and adjusts their KCA quantity to reverse the past period’s departures from equilibrium. In contrast, suppliers’ performances are indirectly affected by the results of the entire task, and many suppliers operate with guidance from auto makers’ specifications. Therefore, they may not be sensitive to the needs of the entire task, and they then have less motivation to actively adjust their KCAs to correct previous departures from equilibrium.

For auto makers the first step of product innovation is determining the market requirements, and then steadily breaking them down into sub-requirements, associating these lower levels with the physical things which can fulfill them. The succeeding steps include converting customers’ needs to engineering specification, converting engineering specification to process specification, converting process specification to process, making item, and verifying if that item meets specifications. Following this course, auto makers make the decision if and when an item should be outsourced to suppliers. For example, some items are outsourced relatively early after determining the market requirements and auto makers should offer suppliers with detail request for quotation (RFQ) based on market needs. Some items are later outsourced later, after the step of converting engineering specification into process specifications, while auto makers should offer suppliers with detail RFQ based on the process specification (Fine and Whitney, 1996). Suppliers’ KCAs are initiated by auto makers’ requirement, thus they have
less willingness to actively adjust their KCAs according to the needs of the entire task.

Our analysis suggests that auto makers actively adjust their activities according to the equilibrium because they are directly influenced by the achievements of the entire task. When the suppliers' quantities of KCAs are greater than the corresponding amount of the equilibrium, the entire task's requirements force auto makers to initiate more KCAs in the next period to match their suppliers' level and regain the equilibrium. When the suppliers' quantity of KCAs is lower than the corresponding equilibrium amount, suppliers' capabilities cannot match the entire task's needs. The auto makers' quantity of KCAs is not a bottleneck and extra innovation activities only induce higher costs but little improvement for the product development. Thus, auto makers initiate fewer KCAs in the next period.

Results of the ECM-based analysis support our hypothesis that fluctuation in the quantity of one side's KCAs occurs simultaneously with, rather than is triggered by, fluctuation in the quantity of the other side's KCAs. The cooperation between the European auto maker IVECO and one of their first-tier suppliers provide evidence that their KCAs would fluctuate simultaneously. When IVECO started the S-2000 project, which aimed at launching the renewal of their light vehicle range, a certain supplier was selected for the development of a new component. This supplier was to start co-design activities with IVECO and supply a complete module rather than only the component. The IVECO-supplier design relationship is arranged such that product development activities are conducted together by staff from both sides at the same time, even at the same location (Zagnoli and Pagano, 2001). This type of early supplier involvement in new product development is ubiquitous in the auto manufacturing industry. Some suppliers might cooperate with auto makers as early as the step of idea generation based on the requirement of consumers (Handfield et al., 1999), and during the cooperation period, auto makers and suppliers could improve own designs according to the other side. Therefore, KCAs of both sides fluctuate at the same time.

An instructional point emerges from these test results. In the supply chain context we found that there is a very intimate relationship between supply chain partners in their KCAs, so that a company should be careful of their partners' KCAs because their own innovation performance is not only caused by their own actions, but is also related to their supply chain partners' KCAs. A powerful manufacturer aiming to increase their own performance can do more than adjusting their KCAs according to the equilibrium; they can actively improve their suppliers' capabilities and then increase their suppliers' KCAs. Similarly, a powerful supplier can increase their own performance by improving their downstream partners' capabilities to increase their KCAs. These points should be studied in future research, focusing on whether firms' involvement in knowledge diffusion and knowledge transferring with their supply chain partners can lead to important gains.

Conclusions

We examined the dynamic relationships of KCAs between buyers and suppliers in the supply chain context. Using patent application counts in the US auto manufacturing industry we verify that there is long term equilibrium in the quantity of KCAs between auto makers and suppliers. This result extends the analysis of Hua et al. (2006), that is, the short run relationship they verified can be maintained for long periods of time. Taking advantage of the ECM-based regression model, we found that auto makers, contrasting with suppliers, are more active in correcting past period's deviations from the equilibrium, revealing that auto makers (the buyer) are more sensitive to the needs of the supply chain's entire task and express more inclination to attain the supply chain's mission. We analyzed the effects of both simultaneous and past fluctuations in one side's KCAs on the other side's current fluctuation in KCAs, and determined that both sides would rather initiate KCAs simultaneously with the other side.

Based on the aforementioned analyses, our policy suggestions include the following points:

1. A company should be familiar with both the advantages and limitations of their supply chain partners' KCAs because the quantity of their own KCAs is often shaped by that of their suppliers or customers.
2. Buyers and suppliers should develop broad collaboration with each other when they initiate KCAs because there is tight interdependence between them and they need to create knowledge simultaneously.
3. Because there is equilibrium in KCAs between auto makers and suppliers, the powerful side (whoever owns the higher level knowledge-creating capability, comparatively) is often limited by the weakness of their partners' KCAs. Therefore, a powerful company, aiming to increase their own performance, should actively improve their supply chain partners' capabilities.

LIMITATIONS AND FUTURE RESEARCH

The results of this paper build a basic foundation for future research. This paper verifies that there are dynamic relationships of KCAs in the supply chain context. However, it is lack of the direct empirical evidence for partners' collaborations. Further research should investigate "knowledge transfer" or "knowledge sharing" between supply chain members, which could directly account for interdependence in KCAs: does one side acquires the other's knowledge to support his own KCAs? To obtain a general view, we use pooled samples, including many auto makers and many suppliers. Further
research should compare the nature of endogenous and exogenous factors, such as suppliers’ capabilities, relationship among members, and performance, by introducing samples that include many separate companies.

In this paper we only discuss the behaviors of the automaker and the supplier, such as holding the equilibrium, reacting to the deviation. Future research should analyze the specific actions of automakers and suppliers: which methods they use respectively.

Finally, if the patent data include specialty classifications, further research could analyze the relationships between architectural knowledge and component-specific knowledge, or architectural innovation and component-specific innovation. The results of such research could guide strategic choices in practical business activities, such as which types of supplies, which types of supply chain relationships, and which types of knowledge transfer tactics should be chosen under different conditions.

ACKNOWLEDGEMENTS

This paper was supported by the National Science Foundation of China under grant No. 71072124, Research Foundation of Liao Ning Educational Committee under grant No. W2010075, and the Fundamental Research Funds for the Central Universities under grant No. 2011JC008.

REFERENCES


