EXPLORING THE RELATIONSHIP BETWEEN EFFICIENT SUPPLY CHAIN MANAGEMENT AND FIRM INNOVATION: AN ARCHIVAL SEARCH AND ANALYSIS

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This paper illustrates the use of secondary data for operations and supply chain management research by investigating the association between efficient supply chain management and innovation of firms. An empirical inquiry is conducted using archival financial statement information and patent citation data for firms in the manufacturing sector, over a 10-year period from 1987 to 1996. Longitudinal analysis, focusing on the influence of efficient supply chain management on a firm's innovation over time, is conducted. Results and limitations are discussed along with a summary of steps, which may be followed when using secondary data for operations and supply chain management research.

Keywords: *secondary data; econometric analysis; supply chain management; innovation; performance*

INTRODUCTION

Researchers in the area of operations and supply chain management have often highlighted the importance of multiple research methods for furthering knowledge (Fisher 2007; Craighead and Meredith 2008). In line with the objectives of this special issue and the call for using multiple methods in operations management investigations to triangulate academic evidence (Boyer and Swink 2008) and strengthen the empirical research base in operations (Fisher 2007), this study illustrates the use of secondary data which can complement theoretical research that uses primary data (e.g., Frohlich and Westbrook 2001; Thun 2010). To serve as an illustrative application, the association between efficient supply chain management and innovation performance is investigated in this research using secondary data.

Both innovation and efficient supply chain management provide firms with avenues to gain competitive advantage. The research literature confirms that the development of new, innovative products is a key source of competitive advantage (Dröge, Vickery and Markland 1994; Brown and Eisenhardt 1995). Many have alluded to the compelling operational and financial benefits which can accrue to firms from efficient and effective supply chain management (Fisher 1997; Vickery, Calantone and Dröge 1999). Efficiency is a core concept for operations and supply chain management that influences success. However, studies on the organizational determinants of innovation have shown that slack, not efficiency, can have a positive influence on innovation (e.g., Nohria and Gulati 1996). A focus on efficiency in supply chain management views slack as a sign of waste, an inefficiency that detracts from the firm's value. This represents a potential paradox and raises a question: What is the relationship between efficient supply chain management and a firm's innovation output — i.e., does a focus on efficiency in supply chain management reduce innovation output?

Using secondary data to investigate the above question, this research adds to the literature in multiple ways. First, it serves as an additional example of a broader set of tools available for operations and supply chain management research. Second, it demonstrates how the use of secondary data provides a longitudinal perspective to the existing literature in supply chain management, complementing cross-sectional evidence (e.g., Frohlich and Westbrook 2001; Thun 2010). Finally, existing supply chain management literature provides evidence that supply chain management influences firm performance primarily on the operational and financial performance metrics of organizations (e.g., Vickery, Jayaram, Dröge and Calantone 2003; McKone-Sweet and Lee 2009; Lao, Hong and Rao 2010). This research adds to that literature by illustrating how secondary data can be utilized to investigate the relationship of efficient supply chain management with innovation performance of organizations.

Secondary data research needs to start with a conceptual framework of the variables and relationships of interest. The following section presents a framework conceptualizing efficient supply chain management, the firm's innovation and the relationship between them. Next, it is critical to identify appropriate data sources, to develop operational measures, which are supported theoretically and choose appropriate analysis techniques. The research methodology, analysis and results are discussed in the methodology section. Finally, secondary data often provides proxy measures and one must be cognizant of its limitations in the context of the research question. The final section presents the limitations and conclusion.

CONCEPTUAL FRAMEWORK

Efficient Supply Chain Management

A central facet of supply chain management is the efficient flow of materials within the organization and across the firm's boundaries (Lee, Padamanabhan and Wang 1997; Frohlich and Westbrook 2001; Billington 2010). This research draws upon the principles which comprise the theory of swift and even flow (Schmenner and Swink 1998) for the conceptualization of efficient supply chain management. The theory states that the quicker and more even the flow of materials through any process, the higher the productive capability or efficiency of that process (Schmenner and Swink 1998) — "be it labor productivity, machine productivity, material productivity or total supply chain productivity" (Germain, Claycomb and Dröge 2008, p. 559). The efficiency rises with the speed of material flow and falls with the increase in variability of flow (Schmenner and Swink 1998).

The effort organizations expend to manage their supply chains — be it for managing their supply base through supplier development; managing their internal operations through lean, six sigma, etc.; or managing their distribution channels through practices such collaborative planning, etc. — often result in improvements in the swiftness and reduction in variability of material flow within and across organizational boundaries (Lee et al. 1997; Dooley, Yan, Mohan and Gopalakrishnan 2010; Lee 2010; Sheffi 2010; Sprague and Callarman 2010). As such, efficient supply chain management is conceptualized to manifest itself in the two dimensions of *swift* and *even* flow of materials for the firm.

The *firm's supply chain performance* refers to maintaining a swift flow of materials. The *firm's supply chain stability* refers to the lack of detrimental variability, noted by the even flow of materials.

A Firm's Innovation Output

The literature indicates that innovation reflects the stock of the firm's creative ideas, which are deemed implementable and have the potential to be commercialized by the organization (e.g., Amabile, Conti, Coon, Lazenby and Herron 1996). A firm's innovation is conceptualized as the innovative output of the firm. The multiple dimensions (volume, originality and generality) of innovation output are evaluated in this research. Innovation volume represents one important aspect of innovation output. Additionally, the value of innovations reflects the diversity of the knowledge base they build upon, i.e. originality, and the diversity of the knowledge base they influence, i.e., generality (Trajtenberg, Henderson and Jaffe 1997).

At this point, it is critical to recognize the distinction between innovation output, which is the focus of this research, and innovation strategies that firms may choose to follow. Firms may choose to follow multiple innovation strategies. For example: Focusing on exploration of knowledge versus exploiting existing knowledge or a balance between the two strategies. Existing research indicates that a balance between exploration and exploitation enhances organizational learning and may be most conducive to innovation (Levinthal and March 1993). Additionally, some evidence exists indicating that firms valuing basic research, which requires exploration, may yield a higher volume of innovations (Peeters and Potterie 2006). Therefore, higher innovation output may indicate a firm's focus on exploration or a balance of exploration and exploitation. Recognizing innovation's multifaceted nature, this research takes into consideration the volume of the firm's innovations, the originality of the firm's innovations and the generality of the firm's innovations to assess its innovation output.

Efficient Supply Chain Management and a Firm's Innovation Output

Supply chain management involves managing material flows within and across organizational boundaries. Organizations typically improve the flow of materials in supply chains through a set of organizational routines developed by assembling organizational and interorganizational resources to perform distinctive activities (Teece, Pisano and Shuen 1997). Examples of such routines in the context of an organization's upstream supply chain are efforts to improve internal and supply side material flows by implementing practices such as JIT (e.g., Germain and Dröge 1998), supplier development (e.g., Krause and Scannell 2002) and relational purchasing (e.g., Terpend, Tyler, Krause and Handfield 2008). Such routines involve close communication, information sharing and joint problem solving. This increases the direct and indirect interaction that the organization has with its supply chain partners. This exposes the firm to different approaches and perspectives, influencing its ability to generate different alternatives and facilitate flexible thinking, which are critical for innovation (Granovetter 1982). As organizations endeavor to improve material flows, they increase their problem solving skills that lead to different alternatives (Perry-Smith and Shalley 2003), which could enhance innovation (Amabile et al. 1996). Efficient supply chain management may also lead to greater access to domain-relevant knowledge that can enhance innovation (Glynn 1996).

Additionally, efficient supply chain management is a result of more coordination with supply chain partners (Lee et al. 1997; Billington 2010; Lee 2010). Coordination efforts provide the firm with multiple interfaces across its organizational boundaries with firms, which are at different levels than itself in the value chain. Interfaces with firms across the value chain also provide organizations with access to an enhanced breadth of knowledge (Rindfleisch and Moorman 2001; Bustinza, Molina and Gutierrez-Gutierrez 2010), allowing knowledge integration for more diverse innovations (Kogut and Zander 1992).

Therefore, it is proposed that efficient supply chain management positively influences the volume, originality and generality of its innovations. Formally stated:

Proposition A: A firm's supply chain performance is positively associated with the firm's innovation output.

Proposition B: A firm's supply chain stability is positively associated with the firm's innovation output.

Figure 1 depicts the relationships between the variables, which are of interest in this study.

METHODOLOGY

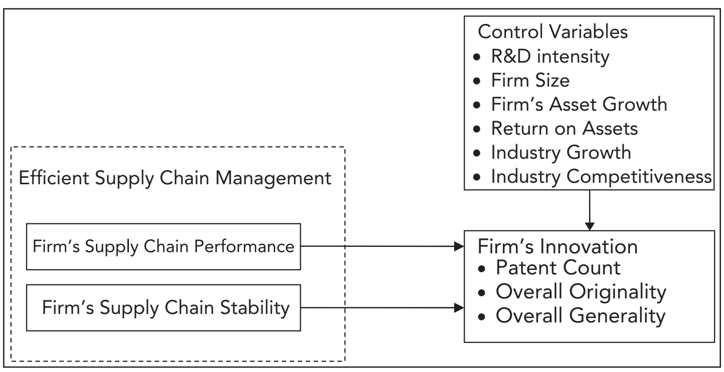
With the formal statement of the research focus complete, the next steps involve the development of operational measures, which are theoretically supported, the identification of appropriate data sources and choosing suitable analysis techniques. These are discussed below.

Variable Operationalization

Efficient Supply Chain Management. Given the direct impact of supply chain initiatives on inventories of an organization (Lee et al. 1997; Dong, Carter and Dresner 2001), inventory-based measures provide a good indication of a firm's supply chain efficiency. Similarly, manufacturing resources have a significant impact on a firm's performance (Fullerton, McWatters and Fawson 2003), as such manufacturing assets-based measures provide another indicator of the efficiency of the firm's supply chain management. This research follows an output–input approach to measure the efficiency of supply chain management of a firm — an approach often used in existing research in operations management (e.g., Hendricks, Singhal and Zang 2009) and strategic management (e.g., Bourgeois 1981) to capture efficiency.

Four financial ratios are used to create an index to assess a firm's supply chain performance and stability relative to other firms in the same four-digit SIC code. They are: *inventory days ratio*, *sales per dollar inventory ratio*, *inventory to assets ratio* and *sales per dollar plant, property and equipment ratio*. These indicators capture the key aspects of the firm's supply chain management. Similar measures have been used in past research (e.g., Hendricks et al. 2009). For the measures used in this research it is important to recognize the intraindustry environment of the firm: diverse industries traditionally have different levels of inventories and the assessment of performance needs to be done reflecting these differences. Therefore, the measures are normalized for the industry to assess how the individual (focal) organization performs in relation to others within the industry it operates. Since

FIGURE 1
Conceptual Model of the Influence of Efficient Supply Chain Management on a Firm's Innovation



a composite index is created using the four measures, normalization relative to industry helps ensure that the four measures are comparable across different industries and reflects the firm's performance on that particular measure relative to industry. The industry average and standard deviation used for normalization are calculated using financial information available for all firms within the same four-digit SIC code as the firm. It is important to note that the normalization based on industry was conducted using data of all firms, which were available in COMPUSTAT for the respective four-digit SIC code for that time period. These are discussed next.

The *Inventory Days* ratio represents the efficiency of material flow. The fewer days that units stay in inventory, the quicker they will move through an organization's processes to its customers. High inventory is an indicator of the asynchronization for an organization's supply chain. This variable is labeled $\text{InventoryDays}_{fit}$ and is calculated as follows:

$$\text{InventoryDays}_{fit} = \frac{\left(\frac{AI_{fit} \times 365\ \text{days}}{COGS_{fit}}\right) - \mu_{it}^{\text{InventoryDays}}}{\sigma_{it}^{\text{InventoryDays}}} \tag{1}$$

where AI_{fit} is the average inventory for firm f, in industry i, in years t and $t-1$, $COGS_{fit}$ is the cost of goods sold for firm f, in industry i, in year t, $\mu_{it}^{\text{InventoryDays}}$ is average inventory days for all firms in industry i in year t, $\sigma_{it}^{\text{InventoryDays}}$ is standard deviation of inventory days for all firms in industry i in year t. A lower inventory-days ratio is more desirable, with a negative value of $\text{InventoryDays}_{fit}$ indicating that a firm has fewer inventories compared with industry counterparts. This measure was reverse coded for the analysis.

The *Sales per dollar of inventory* ratio allows one to account for the efficiency of inventory keeping in mind the sales. This is important as inventory turns alone may often be increased by compromising on sales as lower inventories can lead to higher stockouts (Gaur et al. 2005). Firms, which manage their supply chains more efficiently, will be able to lower inventories without losing sales and therefore generate higher sales per dollar of inventory compared with their industry counterparts. This is labeled $SalesInventory_{fit}$ and is calculated as follows:

$$\text{SalesInventory}_{fit} = \frac{\left(\frac{\text{Sales}_{fit}}{AI_{fit} \times 365}\right) - \mu_{it}^{\text{SalesInventory}}}{\sigma_{it}^{\text{SalesInventory}}} \tag{2}$$

where Sales_{fit} is the total sales of firm f, in industry i, in year t, AI_{fit} is average inventory for firm f, in industry i, in year t and $t-1$, $\mu_{it}^{\text{SalesInventory}}$ is average sales per dollar inventory for all firms in industry i in year t and $\sigma_{it}^{\text{SalesInventory}}$ is standard deviation of sales per dollar inventory for all firms in industry i in year t.

The *Inventory to Asset* ratio allows one to capture the efficiency of material flow with respect to firm assets. Inventory represents tied-up financial assets, which a firm cannot use for other purposes (Fullerton et al. 2003). Organizations that manage their supply chains more efficiently will have less inventory and hence a lower inventory-to-asset ratio. This is labeled as $InventoryAsset_{fit}$ and calculated as follows:

$$\text{InventoryAsset}_{fit} = \frac{\left(\frac{TI_{fit}}{\text{Total Assets}_{fit}}\right) - \mu_{it}^{\text{InventoryAsset}}}{\sigma_{it}^{\text{InventoryAsset}}} \tag{3}$$

where TI_{fit} is the total inventory for firm f, in industry i, in year t, Total Assests_{fit} is the total assets for firm f, in industry i, in year t. $\mu_{it}^{\text{SalesInventory}}$ is average inventory asset ratio for all firms in industry i in year t and $\sigma_{it}^{\text{InventoryAsset}}$ is standard deviation of inventory asset ratio for all firms in industry i in year t. A lower inventory to asset ratio is more desirable, with a negative value of $\text{InventoryAsset}_{fit}$ indicating that a firm has a lower inventory-to-asset ratio compared with industry counterparts. This measure was reverse coded for the analysis.

The *Sales per dollar plant, property and equipment investments* ratio is used to capture the efficiency of production assets to generate revenues for the firm. The productivity of the firm's facilities reflects its ability to manage its operations effectively, with less nonvalue added activities and less waste in its operations. Firms that manage their supply chains more efficiently should be able to generate higher sales per dollar invested in manufacturing assets compared with their industry counterparts. This is labeled $SalesPPE_{fit}$ and is calculated as follows:

$$SalesPPE_{fit} = \frac{\left(\frac{\text{Sales}_{fit}}{PPE_{fit}}\right) - \mu_{it}^{SalesPPE}}{\sigma_{it}^{SalesPPE}} \tag{4}$$

where Sales_{fit} is total sales of firm f, in industry i, in year t, PPE_{fit} is plant, property and equipment investments for firm f, in industry i, in year t, $\mu_{it}^{\text{SalesInventory}}$ is average sales per dollar inventory for all firms in industry i in year t and $\sigma_{it}^{\text{SalesInventory}}$ is standard deviation of sales per dollar inventory for all firms in industry i in year t.

Using the above four measures, two indices are constructed to capture the two dimensions of efficient supply chain management. One index measures the firm's supply chain stability, while the other reflects the firm's supply chain performance.

A firm's *supply chain stability* refers to the evenness of flow and is assessed through the assessment of variability using the indicators discussed above. When a firm's supply chain has higher variability in delivery times, then production lead times or throughput rates fluctuate (Schmenner and Swink 1998). Variability is represented in the variance or standard deviation of the measures. Often the standard deviation or variance of a measure must be understood in the context of its mean; as such, we use the coefficient of variation as a measure of variability. The coefficient of variation for the above four indicators is calculated over a 5-year period, following Morgan and Rego's (2009) approach. Because the coefficient of variation is unitless, it allows for comparison across multiple units and the addition of the measure for the formation of an index. A summated index is used to measure of a firm's supply chain stability relative to other organizations and is calculated as

$$\begin{aligned} SC\,\text{Stability}_{fit} = {} & SCCV_{fit}^{\text{InventoryDays}} \\ & + SCCV_{fit}^{\text{SalesInventory}} \\ & + SCCV_{fit}^{\text{InventoryAsset}} \\ & + SCCV_{fit}^{\text{Sales}PPE} \end{aligned} \tag{5}$$

where $SCCV_{fit}^{\text{InventoryDays}}$, $SCCV_{fit}^{\text{SalesInventory}}$, $SCCV_{fit}^{\text{InventoryAsset}}$ and $SCCV_{fit}^{\text{Sales}PPE}$ represent 5-year coefficient of variations in their respective measures. The coefficients of variations were reverse coded so that a higher value indicated more stability.

A firm's *supply chain performance* refers to the swiftness of flow. Given that supply chain initiatives often extend over multiple years for full implementation, and to ensure that the performance and stability indices are over the same time period, we calculate a summated index of the measures discussed above aggregated over a 5-year period. It measures the firm's supply chain performance relative to other organizations and this is calculated as

$$\begin{aligned} SC\,\text{Performance}_{fit} = {} & SCP_{fit}^{\text{InventoryDays}} \\ & + SCP_{fit}^{\text{SalesInventory}} \\ & + SCP_{fit}^{\text{InventoryAsset}} \\ & + SCP_{fit}^{\text{Sales}PPE} \end{aligned} \tag{6}$$

where $SCP_{fit}^{\text{InventoryDays}}$, $SCP_{fit}^{\text{SalesInventory}}$, $SCP_{fit}^{\text{InventoryAsset}}$ and $SCP_{fit}^{\text{Sales}PPE}$ represent aggregate 5-year performance in their respective measures.

Firm's Innovation Output. Patent counts, citation information and metrics developed by Trajtenberg et al. (1997) are used to measure a firm's innovation output. One limitation of using patent data as an indicator of innovation performance is that not all innovations are patented (Pakes 1985; Trajtenberg et al. 1997), with firms resorting to secrecy to protect their intellectual property. The United States Patent and Trademarks Office (USPTO) grants patents with a life of 20 years. It is legally binding to disclose and cite any prior knowledge on which the innovation is built. The responsibility to ensure the validity and correctness of citations rests on the patent examiner who is an area expert. Given the process of patenting and the legal significance of citations, it is less likely that patent citations are contaminated by inventor or examiner bias. Further, the widespread use of patent and patent citation data in research on innovation also points to the validity of this measure across firms as an indicator of innovation (Pakes 1985; Ziedonis 2004). Three distinct facets of innovation are measured: volume of the firm's innovations, overall originality of the firm's innovation and overall generality of the firm's innovation.

Volume of a Firm's Innovation. This is measured by using patent count as a proxy. It is important to note that this count was developed based on the application year of the patent, indicating the time when the innovation was completed as opposed to the grant year. This ensures that an innovation that was deemed as not new during the patent examination process is excluded. This measure is calculated as follows:

$$\begin{aligned} \text{Patent Count} &= N_{pft} \\ &= \text{Number of patents } p \text{ applied for} \\ &\quad \text{by firm } f \text{ in year } t \text{ which were granted} \end{aligned} \tag{7}$$

Overall Originality of a Firm's Innovations. Original innovations tend to be significantly different from what has been developed in the past and build on patents from innovations in a wide range of fields (Trajtenberg et al. 1997). A backward-looking measure of innovation originality proposed by Trajtenberg et al. (1997) is used to measure the overall originality of the organization's innovations. It is labeled Originality_{ft} and is calculated as

$$\text{Originality}_{ft} = \sum_{p=1}^{N_{ft}} \left[1 - \sum_{k=1}^{Nc} \left(\frac{NCITED_{pk}}{NCITED_{p}} \right)^2 \right]_{fp} \tag{8}$$

where NCITED_{pk} is the number of patents cited by patent p in patent class k, NCITED_{p} is total number of patents cited by patent p, N_c is number of patent classes and N_{ft} is total number of patents applied for by firm f in year t that were granted.

Overall Generality of a Firm's Innovations. If an innovation has high impact, future innovation in diverse fields will build on that innovation. Similarly, the forward-looking measure of generality indicating the range of areas the patent has impacted developed by Trajtenberg et al. (1997) will be used to measure the overall generality of the firm's innovations. It is labeled Generality_{ft} and is calculated as

$$\text{Generality}_{ft} = \sum_{p=1}^{N_{ft}} \left[1 - \sum_{k=1}^{Nc} \left(\frac{NCITING_{pk}}{NCITING_{p}} \right)^2 \right]_{fp} \tag{9}$$

where NCITING_{pk} is the number of patents citing patent p in patent class k, NCITING_{p} is total number of patents citing patent p, N_c is number of patent classes and N_{ft} is total number of patents received by firm f in year t that were granted.

Control Variables. To reduce confounding from certain exogenous factors, the following discusses the measurement of firm and industry level control variables: (1) R&D intensity, (2) firm size, (3) asset growth, (4) return on assets (ROA), (5) industry growth and (6) industry competitiveness.

A firm's *R&D intensity* may influence its innovation output (Ziedonis 2004; King, Slotegraaf and Kenser

2008). R&D intensity is measured as the ratio of R&D expenditure to total sales for the firm (Ziedonis 2004; King et al. 2008). R&D intensity was normalized within industry to account for industry differences.

It is often posited that *firm size* can influence innovation output (e.g., Chandy and Tellis 2000). Therefore, to control for the effects of firm size, the log of total assets is used as a variable in the analysis (Ziedonis 2004).

Growth in firm size can affect its innovation performance and may be due to the acquisition of smaller firms which are R&D intensive (e.g., King et al. 2008). To control for the effects of growth in firm size over time, the percentage *growth in assets* over a 5-year period is used as a proxy.

It is plausible that firms, which in general demonstrate higher performance, may have more efficient supply chain management and higher innovation output. Existing research often uses ROA as a typical measure of overall firm performance (e.g., Fairfield, Sweeney and Yohn 1996). Therefore, ROA for the firm is used as an indicator of general management ability of the firm. It is important to note that ROA may penalize older firms and aid contract manufacturers. However, given its widespread use in research (e.g., Fullerton et al. 2003) as an indicator of overall firm performance, it should provide a reasonable proxy.

New products are likely to be introduced more often in industries which experience faster growth (e.g., Hendricks and Singhal 1997). To control for this, the *industry sales growth* measured over a 5-year period for industries specified at a four-digit SIC level are used.

Highly competitive markets may have higher rates of product development and introductions (e.g., Aboulnasr, Narasimhan, Blair and Chandy 2008). Therefore, *industry competitiveness* is used as a control variable, with the Herfindahl index employed as a proxy (Hendricks and Singhal 1997). A higher index is indicative of lower competition. The measure was reverse coded for the analysis.

Data Collection

For computing the indicators of a firm's supply chain stability, supply chain performance and control variables, extensive use was made of company financial statement reports through the COMPUSTAT database. Data included firms which fell under the SIC codes from 2,000 to 3,999 inclusive, representing the manufacturing sector. To ensure that the developed measures are comparable across firms, all ratios were calculated by requiring firms using Last-In, First-Out (LIFO) inventory evaluation be comparable to those using First In, First Out (FIFO) inventory evaluation. This was done by using the process outlined in Kieso, Weygandt and Warfield (2004, p. 385). It is important to note that at this stage, data from all available firms for the specific four-digit SIC codes were used to calculate the values for normalization of the respective measures. This allowed for an accurate assessment of the measures compared with the firm's industry counterparts.

Following this step, the patent data for the measurement of the firm's innovation were drawn from the database developed by Hall, Jaffe and Trajtenberg (2001), available through the National Bureau of Economic Research (NBER). This database contains citation data from 1975 to 1999. Data over one decade, from 1987 to 1996 for publicly traded for-profit U.S. organizations within the manufacturing sector of SIC codes 20–39 inclusive, were used for the analysis. The objective of this research is to assess the influence of efficient supply chain management on innovation over time. Therefore, an additional constraint that the firms in the final sample should have at least one patent every year over the period of analysis was placed in the generation of the final sample, allowing for the generation of a balanced panel for analysis. With this constraint, 148 firms were identified. These 148 firms had at least one patent in each year over the years 1987–96. Corresponding data required for calculating the dependent variables for these firms was available in the NBER database, and the data required for calculating the independent variables was available in the COMPUSTAT database. This matching constrained on the use of firms, which have at least one patent every year to achieve a balanced panel led to the elimination of a large number of firms. While limiting the generalizability of the research, it is important to note that it helps control for methodological concerns, which can arise due to the use of fixed effects models for very sparse unbalanced panels or with zero inflated panels. Hence, the results of this study are not generalizable to firms, which innovate sporadically: the implications to generalizability are discussed in the next section.

The overall sample consists of 1,480 observations across the 10-year period. The fact that the data used for this study are over a period of 1987–96 merits some discussion. It is important to note that academic studies in the past have used data of similar age, especially when using archival data. For example, D'Aveni and Ravenscraft (1994) use data over a decade old, starting from 1976, to study the relationship between vertical integration and performance. Hendricks et al. (2009) use data over a period of 1987–98 to study the relationship between operational slack, vertical relatedness and the stock market's reaction to supply chain disruptions.

Table I presents the distribution of firms across the industry sectors (at a two-digit SIC level) represented in the sample. Of the 148 firms in the sample, 126 are in the two-digit SIC codes of 28, 35, 36, 37 and 38. This research uses patent based indicators of innovation output that can be sensitive to the choice of mechanism used by various industries for intellectual property protection (Hall et al. 1986). Therefore, patent based measures

TABLE I

Distribution of Firms Across Industry Sectors

SIC	# Firms
20 Food and kindred products	1
24 Lumber and wood products	1
25 Furniture and fixtures	1
26 Paper and allied products	1
27 Printing, publishing and allied industries	1
28 Chemicals and allied products	33
29 Petroleum refining and allied industries	3
30 Rubber and miscellaneous plastic products	1
32 Stone clay glass and concrete products	1
33 Primary metal industries	6
34 Fabricated metal products, except machinery and transportation products	5
35 Industrial and commercial machinery and computer equipment	31
36 Electronics and other electrical components, except computer equipment	25
37 Transportation equipment	17
38 Measuring analyzing and controlling equipment	20
39 Miscellaneous manufacturing industries	1
	148

may be a better representation of innovation output in industries which exhibit higher patenting propensity such as chemical, pharmaceutical, and high-tech industries (Hagedoorn and Cloodt 2003). In line with this, most firms in our sample fall in industry sectors represented by SIC codes 28, 35, 36, 37 and 38, indicating that patenting behavior in these industry sectors is much higher. Hence, the measures of innovation output used in this research should be more reflective for these industries and this research may be most relevant to them. To investigate this point further, a subsample of 126 firms (1,260 observations) representing SIC codes 28, 35, 36, 37 and 38 in our data was subjected to analysis.

Tables IIA–IIC provide the descriptive statistics and correlations for the complete sample (n=1,480) and the subsample of firms in SIC codes 28, 35, 36, 37 (n=1,260). It is important to keep in mind that the descriptive statistics and the correlations in the Tables IIA–IIC are across firms and time. Therefore, they need to be interpreted with caution.

Analysis

Two estimation approaches were used to analyze the data. Using patent counts as the dependent variable, a negative binomial fixed effects panel regression model (Cameron and Trivedi 1998) was employed. The general form for the negative binomial fixed effects model estimated is

$$\log \lambda_{ft} = \mu_t + \beta x_{ft} + \alpha_i \quad (10)$$

where λ_{ft} is the expected value of y_{ft}, i.e., the dependent variable patent count for firm f at time t, μ_t is time intercepts, x_{ft} is the vector of time-varying predictor variables that are a firm's supply chain performance, supply chain stability, R&D intensity, firm size, asset growth, ROA, industry growth and industry competitiveness and α_i is the unobserved fixed effects.

TABLE IIA

Descriptive Statistics for the Complete Sample

Variable	*N*	Minimum	Maximum	Mean	SD	10th percentile	50th percentile	90th percentile
Patent count	1,480	1.0000	985.0000	58.9534	112.7533	3.0000	20.0000	128.5000
Originality	1,480	0.0000	402.9288	24.5353	45.8128	1.1279	8.5881	53.3415
Generality	1,480	0.0000	318.5249	18.9932	38.6009	0.5306	5.7822	42.8310
SC performance	1,480	−3.2002	7.5533	2.1859	1.7175	0.0065	2.2025	4.3455
SC stability	1,480	134.2059	462.2821	315.3055	67.8331	239.7005	298.5423	415.6903
R&D intensity	1,480	−1.4754	2.3554	−0.0039	0.5314	−0.4473	−0.1722	0.7821
Firm size (in US$10 million)	1,480	0.2324	2628.6700	69.8142	223.3678	1.9627	18.1959	138.3170
Asset growth	1,480	−0.6499	13.6155	0.5343	0.9294	−0.0843	0.3712	1.1892
Return on assets	1,480	−0.4657	0.3619	0.0539	0.0666	−0.0110	0.0592	0.1224
Industry growth	1,480	−0.8851	4.2190	0.4209	0.5217	−0.0409	0.3604	0.8810
Industry competitiveness	1,480	0.0487	0.9998	0.2442	0.1698	0.0700	0.2025	0.4611

TABLE IIB

Descriptive Statistics for the Sample of Firms in SICS 28, 35, 36, 37 and 38

Variable	*N*	Minimum	Maximum	Mean	SD	10th percentile	50th percentile	90th percentile
Patent count	1,260	1.0000	985.0000	64.8349	120.4458	3.0000	24.0000	142.5000
Originality	1,260	0.0000	402.9288	26.9973	48.9352	1.1596	10.5838	63.1785
Generality	1,260	0.0000	318.5249	20.9531	41.2708	0.6250	6.6991	48.4820
SC performance	1,260	−3.2002	6.8783	2.1744	1.7047	−0.0222	2.2298	4.2761
SC stability	1,260	134.2059	462.2821	314.9778	67.7552	239.7625	298.5423	415.4597
R&D intensity	1,260	−1.4754	1.5301	−0.0644	0.4504	−0.4390	−0.1844	0.6523
Firm size (in US$10 millions)	1,260	0.2324	2,628.6700	70.5233	239.2879	1.8638	16.7774	119.6200
Asset growth	1,260	−0.6496	13.6155	0.5730	0.9674	−0.0765	0.4046	1.2693
Return on assets	1,260	−0.4657	0.3619	0.0550	0.0681	−0.0107	0.0596	0.1264
Industry growth	1,260	−0.8851	4.2190	0.4487	0.5353	−0.0162	0.3881	0.9323
Industry competitiveness	1,260	0.0487	0.9998	0.2454	0.1707	0.0786	0.2002	0.4607

To analyze the data for overall originality and generality as dependent variables, a fixed effects regression model was used. Fixed effects models allow one to estimate only within firm variation over time and control for time invariant characteristics of the firm. Additionally, a Hausman's test indicated that the fixed effects model was preferable. The general form of the model used for analysis is

$$y_{ft} = \mu_t + \beta x_{ft} + \alpha_i + \varepsilon_{ft} \quad (11)$$

where y_{ft} is the dependent variable (originality or generality) for firm f at time t, μ_t is time intercepts, x_{ft} is the vector of time-varying predictor variables, α_i is the unobserved fixed effects and ε_{ft} is a random disturbance term.

Interpreting Results

Two models are evaluated with the data, Model 1 — representing the 148 firms across all the SICs (shown in Table I) and Model 2 — representing 126 firms only within SICs 28, 35, 36 and 38 (shown in Table I). Tables IIIA and IIIB present the results with patent count as the dependent variable, with Tables IV and V presenting results with originality and generality as the dependent variable, respectively. Time and firm effects are suppressed in the output.

With respect to volume of innovations represented by the patent count measure, the results of Model 1 and Model 2 are similar with the exception of the significance for R&D intensity. The results for Model 1 and Model 2 presented in Table IIIA indicate a good fit because the value/*df* is close to 1. In support of research propositions A and B, the results support the hypothesized positive association of a firm's supply chain performance and stability with the volume of innovation (p value < 0.0001). This provides evidence that a firm's supply chain performance and stability positively influence the volume of innovation, which is measured through patent count. The control variables (firm size, industry growth and industry competitiveness) are all highly significant (p value ≤ 0.001) indicating that larger firms develop more innovations, with industry growth and competition driving firms to innovate more. The influence of R&D intensity on volume of innovation may not be generalized across all industries. The coefficient is significant for Model 2, which represents SIC codes 28, 35, 36 and 38. These SIC codes may represent industries where firms patent more aggressively for intellectual property protection. It is plausible that in other industries firms rely on secrecy leading to a lack of significance of the relationship of R&D intensity and volume of innovation in the complete sample of 148 firms (Model 1).

The results for Model 1 and Model 2 with overall originality and generality of patents as a measure of innovation are presented in Tables IV and V. The R^2 values indicate that a significant variance in the dependent variable is explained by the models. However, the results for the association between a firm's supply chain performance and supply chain stability and originality of innovation remain nonconclusive with p values > 0.05 for both models. The firm size and industry growth control variables are significant (p value ≤ 0.01) for both models, indicating that larger firms develop more original innovations and the industry growth rate positively influences originality of innovations. For the generality measure, only the firm size control variable is significant (p value < 0.0001) for both models.

TABLE IIC

Sample Correlations

	Patent Count	Originality	Generality	SC Performance	SC Stability	R&D Intensity	Firm Size	Asset Growth	Return on Assets	Industry Growth	Industry Competitiveness
Patent count	1.0000	0.9934	0.9617	0.1684	0.0605	0.1342	0.4807	0.0328	0.0112	0.0389	0.1094
		<.0001	<.0001	<.0001	0.0319	<.0001	<.0001	0.2450	0.6920	0.1679	0.0001
Originality	0.9930	1.0000	0.9578	0.1640	0.0696	0.1341	0.4771	0.0295	0.0115	0.0355	0.1362
	<.0001		<.0001	<.0001	0.0135	<.0001	<.0001	0.2951	0.6836	0.2082	<.0001
Generality	0.9622	0.9583	1.0000	0.1572	0.0062	0.1271	0.4235	0.0475	0.0006	0.0448	0.1243
	<.0001	<.0001		<.0001	0.8267	<.0001	<.0001	0.0918	0.9818	0.1124	<.0001
SC performance	0.1542	0.1506	0.1416	1.0000	0.1627	−0.0559	0.1339	0.1449	0.0347	0.0647	0.0027
	<.0001	<.0001	<.0001		<.0001	0.0471	<.0001	<.0001	0.2184	0.0217	0.9239
SC stability	0.0509	0.0617	−0.0009	0.1731	1.0000	0.0309	0.0254	−0.1706	0.0862	−0.0853	−0.0233
	0.0503	0.0176	0.9729	<.0001		0.2735	0.3680	<.0001	0.0022	0.0024	0.4088
R&D intensity	0.0877	0.0893	0.0870	−0.0218	0.0340	1.0000	0.1993	−0.0496	−0.0676	−0.0947	0.0493
	0.0007	0.0006	0.0008	0.4027	0.1905		<.0001	0.0786	0.0163	0.0008	0.0802
Firm size	0.4813	0.4761	0.4236	0.1304	0.0206	0.1535	1.0000	0.0795	−0.0549	−0.0195	−0.0489
	<.0001	<.0001	<.0001	<.0001	0.4284	<.0001		0.0047	0.0512	0.4887	0.0827
Asset growth	0.0392	0.0372	0.0541	0.1262	−0.1685	−0.0421	0.0707	1.0000	0.1270	0.1913	−0.0400
	0.1315	0.1530	0.0373	<.0001	<.0001	0.1057	0.0065		<.0001	<.0001	0.1559
Return on assets	0.0157	0.0159	0.0062	0.0272	0.0861	−0.0387	−0.0521	0.1319	1.0000	0.0644	−0.1761
	0.5466	0.5413	0.8104	0.2960	0.0009	0.1372	0.0451	<.0001		0.0222	<.0001
Industry growth	0.0491	0.0471	0.0548	0.0590	−0.0726	−0.1053	−0.0232	0.2113	0.0828	1.0000	−0.0409
	0.0591	0.0704	0.0351	0.0232	0.0052	<.0001	0.3728	<.0001	0.0014		0.1473
Industry competitiveness	0.0939	0.1187	0.1076	−0.0089	0.0011	0.0667	−0.0618	−0.0216	−0.1404	−0.0526	1.0000
	0.0003	<.0001	<.0001	0.7312	0.9664	0.0103	0.0174	0.4054	<.0001	0.0431	

Correlations between the variables of the complete sample (N=1,480) are below diagonal. Correlations between the variables for the sample of firms in SICS 28, 35, 36, 37 and 38 (N=1,260). p values shown below estimates

TABLE IIIA

Fit Statistics for Patent Count for Model 1 (All SICS) and Model 2 (SICS 28, 35, 36, 37 and 38)

	Model 1			Model 2		
Criterion	*df*	Value	Value/*df*	*df*	Value	Value/*df*
Deviance	1,462	1,592.0347	1.0889	1,242	1,343.1765	1.0815
Scaled deviance	1,462	1,592.0347	1.0889	1,242	1,343.1765	1.0815
Pearson's χ^2	1,462	1,918.777	1.3124	1,242	1,609.1615	1.2956
Scaled Pearson's χ^2	1,462	1,918.777	1.3124	1,242	1,609.1615	1.2956
Log likelihood		347,406.3632			331,795.3612	

CONCLUSION AND LIMITATIONS

This paper had two objectives: To investigate the association between efficient supply chain management and innovation output of firms and to demonstrate an archival data analysis methodology. The results of the research indicate that over time a firm's supply chain performance and supply chain stability positively influence the volume of its innovations. However, the association of supply chain performance and stability with the originality and generality of innovations are inconclusive.

As with all research, this study has limitations that provide opportunities for future enquiry. First, it is important to recognize some limitations of using patent data: (a) It is plausible that firms with efficient supply chains rely on cross licensing to leverage their supply chain expertise without developing patentable innovations. Further, firms may choose to rely on the exploration of new knowledge or exploitation of existing knowledge or a balance strategy in developing competitive advantage (Levinthal and March 1993). Secondary measures of innovation output such as patent counts and diversity measures (originality and generality) do not directly shed light on these aspects of innovation. (b) Not all innovations are patentable because they may not satisfy the three conditions of nonobviousness, inventive step and industrial application simultaneously (Griliches 1990). Additionally, firms may be less likely to patent process innovations since they are more difficult to replicate (Peeters and Potterie 2006), underestimating the innovation output of some firms. (c) Patent based measures are sensitive to mechanisms typically used in different industries for intellectual property protection. Therefore, the results of this research may be more relevant to industries with higher propensity to use patenting as a mode of intellectual property protection. Second, this study assesses the firm's supply chain performance and supply chain stability over a 5-year period. Efforts for improving a firm's supply chain performance and stability tend to be multiyear in practice. However, no

TABLE IIIB

Parameter Estimates for Patent Count for Model 1 (All SICS) and Model 2 (SICS 28, 35, 36, 37 and 38)

	Patent Count					
	Model 1			Model 2		
Parameter	*df*	Estimate	$p>\chi^2$	*df*	Estimate	$p>\chi^2$
Intercept	1	−4.2166	<0.0001	1	−4.0760	<0.0001
SC performance	1	0.0675	<0.0001	1	0.0746	<0.0001
SC stability	1	0.0052	<0.0001	1	0.0046	<0.0001
R&D intensity	1	0.0173	0.7283	1	0.2117	0.0005
Firm size	1	0.6618	<0.0001	1	0.6875	<0.0001
Asset growth	1	0.0135	0.6335	1	0.0054	0.8424
Return on assets	1	0.6519	0.0753	1	0.5092	0.1656
Industry growth	1	0.3515	<0.0001	1	0.2937	<0.0001
Industry competitiveness	1	0.5466	0.0001	1	0.4728	0.0011
Dispersion	1	0.6845		1	0.6003	

TABLE IV

Parameter Estimates for Originality for Model 1 (All SICS) and Model 2 (SICS 28, 35, 36, 37 and 38)

	Originality			
R-Square	Model 1 0.879572		Model 2 0.880036	
Parameter	Estimate	$p > \|t\|$	Estimate	$p > \|t\|$
SC performance	1.4388	0.0561	1.6197	0.0831
SC stability	0.0411	0.1202	0.0526	0.0832
R&D intensity	− 2.2231	0.3543	− 3.7576	0.2178
Firm size	19.4923	< 0.0001	21.4906	< 0.0001
Asset growth	− 0.5195	0.4501	− 0.3812	0.619
Return on assets	8.1645	0.3694	11.3167	0.2745
Industry growth	2.9414	0.0076	3.0225	0.0145
Industry competitiveness	12.3456	0.158	16.7575	0.1019

benchmark is available in the current research literature regarding the appropriate period length, which can be used to assess returns of a firm's supply chain management initiatives. Future research in this regard would be beneficial. And third, this research uses measures of efficient supply chain management with the firm as a unit of analysis. It may be beneficial to develop measures of efficient supply chain management considering dyadic (focal firm with supplier/customer) or triadic (supplier–focal firm–customer) relationships to develop more accurate measures.

Finally, archival research is an important option for supply chain management researchers and the following summarizes the methodology for other investigators. *First*, as with any research endeavor, the conceptual framework was developed for the research project. *Second*, based on theoretical literature, appropriate measures for the variables of interest were identified and limitations of the data recognized. *Third*, related data sources were used to collect data and develop the panel for analysis. It is important to note that the dependent and independent variable measurements for this research are from different data sources, reducing potential confounding. *Fourth*, given the panel nature of the data, fixed effects models were used for analysis. Keeping in mind the nature of the dependent variables, a negative binomial fixed effects model was used for analysis of count data and a fixed effects regression model was utilized to analyze other dependent variables. Results were interpreted with a significance level of $p \leq 0.01$. *Finally*, the main limitations of the research and the use of secondary data were discussed. These steps present guidelines that

TABLE V

Parameter Estimates for Generality for Model 1 (All SICS) and Model 2 (SICS 28, 35, 36, 37 and 38)

	Generality			
R-Square	Model 1 0.843599		Model 2 0.84518	
Parameter	Estimate	$p > \|t\|$	Estimate	$p > \|t\|$
SC performance	0.9119	0.2072	1.1255	0.2087
SC stability	0.0389	0.1252	0.046	0.1136
R&D intensity	− 1.3092	0.57	− 1.0253	0.7255
Firm size	12.9205	< 0.0001	15.3979	< 0.0001
Asset growth	0.2051	0.7561	0.3458	0.6377
Return on assets	6.4888	0.4575	8.2087	0.408
Industry growth	2.0346	0.0544	1.9095	0.1066
Industry competitiveness	10.7884	0.1988	18.7729	0.0559

may be followed while using secondary data and are not intended as rigid rules. The use of secondary data for research in supply chain management is important, as it allows for triangulation of results across primary and secondary data collection studies, while also providing a number of unique opportunities. For example, it allows for a longitudinal analysis, which is very difficult with primary data collection processes. We hope that the detailed discussion of methodological steps for our analysis will prove useful to others interested in using archival data from secondary sources.

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