Effective Demand-Driven Supply Chain Management and Long-run Stock Performance

Xun Li
Nicholls State University

Qun Wu
University of Nevada

Clyde W. Holsapple
University of Kentucky

This paper examined the long-run stock price performance of firms with effective Demand-driven supply chain management (DDSCM). We used AMR's "Supply Chain Top 25" ranking to obtain a sample of firms independently identified as top performing DDSCM firms. The results show that investing in the portfolio of top DDSCM firms can generate significantly positive abnormal returns after controlling for a variety of factors to discount alternative explanations. We also investigated buy-and-sell abnormal returns and found that investors can earn significantly positive abnormal returns by simultaneously buying a portfolio of top DDSCM firms and selling a portfolio of matching firms.

INTRODUCTION

In today's turbulent and global environment, consumer demand has become far less predictable, product innovation is considerably more frequent, and many firms struggle to satisfy volatile demand, often on a transcontinental, just-in-time basis (Bode et al., 2011; Li et al., 2017). To cope with the challenges of more dynamic market places, leading firms such as Proctor & Gamble (P&G) began to adopt a management program termed as demand-driven supply chain management (DDSCM) since the early 2000s (Budd et al., 2012). Conceptually, DDSCM is referred to "a set of practices aimed at managing and co-coordinating the whole demand-driven supply chain, starting from the end customer and working backward to raw material suppliers" (Selen and Soliman, 2002). As an illustration, Keit Harrison, the global product supply officer for P&G says: "We start at the store shelf and work our way back through our supply network", "The point is that you design your supply network all the way back to your suppliers in ways that allow you to focus on winning at the shelf." (Supply Chain Brain, Feb. 1, 2006).

Multiple researchers argue that DDSCM has become a strategic weapon to create value and stay competitive over peers in the face of turbulent environment (Agrawal, 2012; Christopher and Ryals, 2014; Hines, 2004). It follows that tangible results, in terms of market valuations, may also be derived from effective DDSCM. Thus, from the contention that effective DDSCM is a key for value creation, the relationship between effective DDSCM and firms' stock value emerges as an important topic that deserves investigation (Ellinger et al., 2012). However, while the literature generally agrees that DDSCM is a key for value creation, that same literature contains little in the way of empirical support (Greer and Theuri, 2012). In the existing literature, Hendricks and Singhal (2003, 2005) and Hendricks et al. (2009) investigate stock market reaction to supply chain disruptions, which indicate that firms' poor DDSCM could negatively affect firm value. Direct empirical evidence for the linkage between DDSCM and firms' stock value is rare. As pioneer studies in establishing the linkage between supply chain excellence and economic values, Swink et al. (2010) provide descriptive statistics in comparing historical stock performances between top DDSCM firms and control firms. Ellinger et al. (2012) conducted paired t-tests comparing the shareholder value of top SCM performers with their respective industry average. In addition, recent studies adopt the theory of dynamic capabilities to explain that effective DDSCM can help firms sustain value creation over time (Gligor and Holcomb, 2012; Li et al., 2008). To the best of our knowledge, there is no empirical evidence for the effect of effective DDSCM on generating long-term economic earnings\stock performance.

To close the gap in the existing literature, our study investigates the relationship between effective DDSCM and value creation by examining the long-run stock performance of firms independently judged to have effective DDSCM. The research questions guiding this study are:

Does DDSCM have a long-term effect on stockholder value? If so, what is the magnitude of this value?

Being recognized in the American Marketing Association's "Supply Chain Top 25" is used as a proxy for effective DDSCM (Ellinger et al., 2012; Greer and Theuri, 2012; Swink et al., 2010). First, we examine whether or not investing in the portfolio of top DDSCM firms can generate abnormal stock returns, after controlling a variety of factors, over different holding periods. This is the most important and direct evidence for the long-run value creation through effective DDSCM. Second, we investigate whether or not the long-run performance of top DDSCM firms significantly outperforms that of matching firms. The results are robust with respect to different groups of matching firms. Our findings will provide new evidence for the relationship between effective DDSCM and long-term value creation for stockholders. Our finding will have widespread implications covering investors in financial market, supply chain managers, and researchers of supply chain management issues.

The remainder of this paper is organized as follows: Section 2 is comprised of literature review and statements of the hypotheses to be tested. Section 3 describes the sample collection and methods used for estimating the long-run stock performance. Section 4 presents our findings based on the empirical evidence. Section 5 concludes the study with discussion on findings and implications. In addition, Section 5 presents a further application and show that investors can earn significantly positive abnormal returns by simultaneously buying a portfolio of top DDSCM firms and selling a portfolio of matching firms.

LITERATURE REVIEW AND HYPOTHESES

Effective Demand-driven Supply Chain Management and Value Creation

With business environment becomes more turbulent, an ever-increasing number of companies have grown their interest in building up demand-driven supply chains as companies saw opportunities to create value/wealth through their managerial processes of matching supply and demand. Vollmann et al. (2000) suggest using the term "demand chain management" to emphasize the shift from efficient supply to meeting the needs of the customer. This new concept has been supported by many scholars. For example, Treville et al. (2004) state that differentiating from supply chain management that focus on efficient physical supply chains, demand-driven supply chain management (DDSCM) starts with the customers, working backward through the entire chain, to the suppliers of the suppliers (Baker, 2003; Heikkilä, 2002; Selen and Soliman, 2002). Hence, everything that is moved, handled or produced should ideally be in response to a known customer requirement (Jüttner et al., 2007).

In the literature, the theories proposed as a suitable theoretically foundations for DDSCM effectiveness primarily include the customer value based theory of the firm (Slater, 1997) and the theory of dynamic capabilities (Teece et al., 1997). The customer value-based theory of the firm suggests that effective DDSCM creates value through providing effective customer value. Firms need to organize themselves around understanding customer needs and customer value delivery processes. The demand-driven supply chain can be seen as an organization which brings a variety of participants together for the specific purpose of facilitating customer value creating processes (Jüttner et al., 2007; Ketchen and Guinipero, 2004).

The theory of dynamic capabilities provides a framework for understanding how a firm sustains wealth creation by achieving new forms of competitive advantages in a rapidly changing environment (Teece et al., 1997). Dynamic capability is referred to the firm's capability to scan the environment, to evaluate markets and to quickly integrate, build, and reconfigure internal and external competences to match the requirements of a changing environment (Eisenhardt and Martin, 2000; Teece et al., 1997). Organizational practices/routines are critical sources of dynymaic capabilities (Teece et al., 1997). Effective DDSCM builds up dynamic capabilities in supply chain practices\routines to detect and respond to changes (Ketchen and Hult, 2007; Lee, 2004). For example, Simchi-Levi et al. (2013) illustrates how effective DDSCM enables Dell to create four supply chains, Build-to-Order, Build-to-Plan, Build-to-Stock, and Build-to-Spec, each has different supply chain practices / routines and is dedicated to a different customer segment, addressing different dimensions of demand uncertainty and customer relationship. As a result, Dell has experienced a substantial business transformation and kept its leading position in its industry.

Previous Studies

Research on the long-term effect of DDSCM on value creation is just beginning to emerge. DDSCM research has theorized that DDSCM built upon dynamic capabilities are effective or effective in value creation and sustain (e.g., Christopher et al., 2004; Ketchen and Hult, 2007; Lee, 2004; Li et al., 2008). According to the theory of dynamic capabilities, the existence of dynamic capabilities can only be examined by changes over time (Teece et al., 1997). Among the existing few studies, Greer and Theuri (2012) focus on accounting-based measures of firm performance including cost ratios, activity ratios, and liquidity ratios. In contrast to accounting-based measures of firms' competitive performance, a couple of studies provoke research on long-run stock performance because such analysis can provide an estimate of the economic impact of a management program, reflecting not only the magnitude of market value created for shareholders, but also whether the value/performance can be sustained in the face of challenges over time (e.g., Hendricks et al., 2009). However, so far, these studies have focused on proving that firms' market value erodes if failing to manage supply chains effectively. For example, supply chain disruptions, indicators of a firm's poor DDSCM, cause significant negative economic impacts (Hendricks and Sinhal, 2003, 2005; Hendricks et al., 2009). Whether or not effective DDSCM contributes directly to long-term stock performance has not been examined yet.

We recognize that there are multiple ways that can be used to measure the value of DDSCM, such as management perceptions, accounting-based performance measures (ROA, ROE), and stock-market-based performance. Each of the methods is subject to particular biases.

Melnyk et al. (2004) point out that individual perceptions about financial impact of their respective firms' management decisions and actions are not particularly reliable. Accounting-based measures tap only historical aspects of performance (McGuire et al., 1986). Moreover, they are subject to bias from managerial manipulation and differences in accounting procedures (Brilloff, 1972, 1976). Compared with accounting-based measures, stock performance measures are less susceptible to differential accounting procedures and managerial manipulation, and represent investors' evaluations of a firm's ability to generate future economic earnings rather than past performance (McGuire et al., 1988).

Research Hypotheses

Given the debate over the proper measure of firm performance, this study uses long-run stock performance to investigate the value of effective DDSCM. Following finance literature, we examine long-run stock performance using different benchmarks and controlling for different factors. By doing so, we can not only overcome the limitations as discussed above, but also provide a more comprehensive estimate of the economic impact of effective DDSCM, reflecting not only the magnitude of market value that effective DDSCM can create for shareholders, but also whether the value can be sustained in the face of challenges over time. Building upon the theory of dynamic capabilities and the existing literature as discussed in previous sections, we advance the following hypotheses:

H1: Firms with effective DDSCM have significant and positive long-run abnormal stock returns.

More specifically, we compare a portfolio of top supply chain management firms as designated by AMR versus that of matching firms in terms of risk-adjusted performance. Reasons for using AMR's ranking for top DDSCM firms are discussed in next section for methodology. In this study, we mainly use the calendar time portfolio approach to measure risk-adjusted performance. The calendar time portfolio approach is well accepted in finance studies on long-run performance because it provides more reliable test statistics, especially at the presence of cross-sectional dependence (see Brav and Gompers, 1997; Fama, 1998; Mitchell and Stafford, 2000).

Stock price changes can be a function of the changes in expected future cash flows as well as the risk or volatility of future cash flows (Hendricks et al., 2009). After the portfolios of top supply chain management firms and matching firms are built, we first look into the Sharpe Ratio--a measure of performance adjusted for total risks (Sharpe, 1966). Then, the Treynor Ratio is used to measure performance adjusted for systematic risks (Treynor, 1965). According to the theory of dynamic capabilities, firms with effective DDSCM have better capabilities in dealing with risks/changes. Therefore, we expect that:

H1a: The portfolio of effective DDSCM firms outperforms that of matching firms in terms of stock performance adjusted for total risks (the Sharpe Ratio is the measure of performance adjusted for total risk).

H1b: The portfolio of effective DDSCM firms outperforms that of matching firms in terms of stock performance adjusted for systematic risks (the Treynor Ratio is the measure of performance adjusted for systematic risks).

While Treynor ratio attempts to control for the systematic risk (i.e., stock's covariance with the overall stock market), more recent finance studies show that to detect abnormal long-run returns, factors including market, size, book-to-market ratio, and momentum should be taken into account (see Carhart, 1997; Fama and French, 1993). These factors need to be controlled as potential confounding correlates. For example, in the finance literature, market is used as the indicator for the stock market performance; while book-to-market ratio is typically used as a proxy for firms' quality and growth potential (e.g., Larker et al., 2011). Firm size is a direct measure of firm resources (i.e., larger firms typically control more resources). Momentum in a stock is described as the tendency for the stock price to continue rising if it is going up and to continue declining if it is going down. Therefore, to control alternate explanations on the effect of effective DDSCM on long-term stock performance, we also look into abnormal returns after adjustment for the Fama-French three factors (market, size and book-to-market ratio are controlled) and Carhart four factors (market, size, book-to-market ratio, and momentum are controlled). Putting all of this together, we expect that:

H1c: The portfolio of effective DDSCM firms outperforms that of matching firms in terms of abnormal returns adjusted for market, size, and book-to-market factors (i.e., the Fama-French three factors).

H1d: The portfolio of effective DDSCM firms outperforms that of matching firms in terms of abnormal returns adjusted for market, size, book-to-market, and momentum factors (i.e., the Carhart four factors).

METHODOLOGY

Data

Data on effective DDSCM are obtained from American Market Research's yearly study on the "Supply Chain Top 25." AMR, a Gartner, Inc. company, focuses on the global supply chain and is well known among supply chain practitioners and researchers. Since 2004, AMR has annually conducted a "Supply Chain Top 25" study. In 2008, AMR extended the top list to 50 firms.[1]

We view inclusion in AMR's "Supply Chain Top 25" as a proxy for effective DDSCM for the following reasons. First, it is well-accepted in the literature that recognition by independent expert evaluators as being a top performer serves to indicate that the firm has effectively implemented the management program of interest (e.g., Hendricks and Sinhal, 2003, 2005). Second, evidence for the validity of AMR's evaluations comes from empirical studies regarding AMR ranking results as a reliable source to identify top supply chain firms (e.g., Ellinger et al., 2011; Greer and Theuri, 2012; Swink et al., 2010). Third, the criteria that AMR study has used to rank top supply chains match with the conceptualization of DDSCM in this study. AMR requires the voting panelists to rank top supply chains based on the supply chains management routines/practices classified as the "orchestral level" in AMR's Demand-Driven Supply Network (DDSN) model. AMR's comment on Apple furnishes an illustration. Apple has been ranked No. 1 for three consecutive years in the Supply Chain Top 25 research. AMR analysts attribute Apple's success to its ability to break new ground in transforming a supply chain into a value chain by starting with the consumer experience and designing its network to serve that master first and foremost. Forth, it provides comparable data over an extended period.

The methodology for AMR Research to determine "Supply Chain Top 25" firms is as follows: First, AMR Research analysts derive a master list of firms from a combination of sources, including the Fortune Global 500, the Fortune 1000, and the Forbes 2000. The primary source is the Fortune Global 500, which is pared down to the manufacturing and retail sectors. Analysts then supplement this group with companies from the Fortune 1000 that fall between $10 billion in revenue and the smallest revenue on the Global 500 list, as well as select companies from the Forbes 2000. Second, a composite score is created for the firm to determine its ranking. There are three components that make up the composite score. The first component is publicly available financial data. The second component is an AMR Research Opinion from an AMR Research voting panel. The third component is a Peer Opinion Panel comprised supply chain professionals. Public financial data gives a view into how companies have performed in the past, while the opinion component provides an eye to future potential and reflects future expected leadership, a crucial characteristic. These three components are combined to create a weighted average score for overall supply chain leadership.

The AMR Research voting panelists represent a variety of industry and functional specialties. Each draws on his or her primary field research and continuous work with companies. The goal of the peer panel is to draw on the extensive knowledge of the professionals that, as customers and/or suppliers, interact and have direct experience with the companies being ranked. Any supply chain professional working for a manufacturer or retailer is eligible to be on the panel, and only one panelist per company is accepted. Excluded from the panel are consultants, technology vendors, and people not working in supply chain roles (e.g., PR, marketing, finance, and the like).

Each voter from both the AMR Research Panel and the Peer Opinion Panel goes through a four-page system to get to her/his final selection of firms that come closest to the DDSN ideal (i.e., DDSN Level 4) as defined in AMR Research Reports. The first page provides instructions and the DDSN model against which voters are later asked to create their rankings. The second page asks for some demographic information. The third page provides the complete list of the firms to be considered. Voters are asked to choose 30 to 50 that, in their opinion, most closely fit the ideal. This is done by checking off the boxes next to those firms. The fourth page automatically brings up just those chosen firms. Panelists are asked to rank the firms from 1 through 25, with 1 being the firm most closely fitting the ideal in their opinion. AMR Research then tallies all the individual votes across the entire panel, with 25 points earned for a No. 1 ranking, 24 points for a No. 2 ranking, and so on.

Sample Construction

This study includes the "Supply Chain Top" firms in the AMR annual announcement from 2004 to 2008. We start at the year of 2004 because 2004 is the first year of AMR publication of "Supply Chain Top 25" firms. We stop at the year of 2008 for three major reasons: first, AMR was sold to Gartner in

2009; second, leading consumer products companies, such as Proctor & Gamble, begin to adopt DDSC strategies to overcome market challenges in the period of 2000-2009 (Budd et al., 2012); third, we want to investigate the long-run stock performance, i.e., 12 months and longer. Given the special situation of year 2008 (i.e., global financial crisis), it's a good time to test the effectiveness of a firm's DDSCM to respond to the crisis.

For the purpose of our research on firms with effective DDSCM, the firms in our sample must meet the following criteria: 1) The companies go into our sample on the month of their first appearance in AMR's "Supply Chain Top 25" list; 2) The companies must have return records on the CRSP monthly data; 3) The company must have complete data on Compustat provided by Standard and Poor's Research Insight. Our empirical results are based on a sample of 44 firms from 19 different industry sectors based on the 48 Fama-French industry classifications, which are well accepted in finance studies (see Fama and French, 1997). The multi-industry context of our sample firms suggests that the results are more likely to be applicable and generalizable across organizations as well as industries (Zacharia and Mentzer, 2004).

Method for identifying long-run abnormal return

In the finance literature, calendar-time portfolio approach is widely used in identifying long-run abnormal returns. Fama (1998) point out that calendar-time portfolio approach is more appropriate in research on long-run performance because it provides more reliable test statistics, especially at the presence of cross-sectional dependence. Thus, our hypothesis testing is based on the calendar-time portfolio approach.

The calendar-time portfolio approach is conducted in two steps. The first step is to create portfolios. The portfolio of top DDSCM firms is formed as follows: Following the announcement of top supply chain firms by AMR, stocks newly appearing in the top list are formed into a portfolio. We consider holding periods of 12, 15, 18 months, meaning that a stock is held in the portfolio for these lengths of time and then dropped. The portfolio of matching firms is formed similarly. The second step is to estimate the long-run abnormal returns based on the time-series of monthly portfolio returns.

As mentioned above, we find matching firms and use the portfolio of matching firms as a benchmark. Matching sample firms to firms of similar industry, size and BE/ME ratio is well accepted in the finance literature (e.g., Chemannur et al., 2010; Loughran and Ritter, 1995). In this study, we create two groups of matching firms. The first group of matching firms is identified based on industry (Fama-French 48 Industry Classification) and firm size. The second group of matching firms is identified based on industry (Fama-French 48 Industry Classification), firm size, and book-to-market ratio (BM). To generate the industry-size-matched firms, we pair each sample firm with a control firm that has the same industry and is the closest in terms of market capitalization. To generate the industry-size-BM-matching firms, we pair each sample firm with a control firm that has the same industry and is the closest in terms of matching score calculated from market capitalization and the book-to-market (BE/ME) ratio (see Filbeck et al., 2009). Formula for calculating matching score is listed in equation (1) as follows:

$$MS = \left[\frac{X_1^T - X_1^M}{(X_1^T + X_1^M)/2} \right]^2 + \left[\frac{X_2^T - X_2^M}{(X_2^T + X_2^M)/2} \right]^2 \tag{1}$$

Where

$X1$ represents firm size (market capitalization), obtained from CRSP monthly data;

$X2$ represents Book-to-market ratio (B/M), defined as the book value of common equity (data item 60) from Comustat, divided by the year-end market value of common equity;

T refers to the *Top Demand-driven supply chain Management* sample; and

M refers to the whole CRSP-Compustat sample.

Validity Test: Halo Effect Test

It has been noted that most supply chain ranking systems including AMR study either explicitly or implicitly use accounting ratios of firms (e.g., inventory ratio), which is based on accounting numbers (or book values) at time t. Our test on long-run stock performance is based on market value (specifically, stock price change) after time t (i.e., 12 months, 15 months, and 18 months after the announcement).

In addition, we conducted halo effect test to exclude the alternative explanation that AMR panel experts rank supply chain performance simply based on prior financial performance (i.e., halo effect) rather than their effective DDSCM. We follow Brown and Perry (1994) and examine halo effect with a logistic regression model.

In the logistic regression model, we set up a binary variable (1 for Top DDSCM firms and 0 for control firms) as the dependent variable and five financial performance measures as independent variables.[2]

Corresponding to our two groups of control firms (Industry-Size matching, and Industry-Size-BM matching), we do halo tests twice. In the first test, we put Top DDSCM firms and Industry-Size matching together and run a logistic regression. From Panel A of Table 1 we see none of the finance performance variables has statistical significant effect. The *p*-value (0.46) for the model's chi-square of 4.63 is not statistically significant, either. Based on the test, we conclude that our TOP DDSCM sample does not appear to suffer from a halo effect emanating from prior financial performance results.

In the second test, we put Top DDSCM firms and Industry-Size-BM matching firms together and run logistic regression. Like the first test, as shown in Panel B of Table 1, there is no evidence that AMR panel experts rank firms based on halo effect. Therefore, the conclusion is: the use of these financial metrics in the original selection of the top demand-driven supply chain management companies does not appear to have systematically biased our results.

TABLE 1
HALO EFFECT TEST

Panel A: Top DDSCM firms vs. Industry-Size matching firms

Statistic	ROA	RMBV	Sales	Growth	Risk
Coefficient	-5.468	0.023	-0.024	3.888	-3.690
p-Value	0.25	0.77	0.90	0.18	0.14
Chi-Square *p*- Value	4.63 0.46				

Panel B: Top DDSCM firms vs. Industry-Size-BM matching firms

Statistic	ROA	RMBV	Sales	Growth	Risk
Coefficient	-2.116	0.008	0.183	-0.739	-0.545
p-Value	0.39	0.91	0.27	0.72	0.79
Chi-Square *p*- Value	2.06 0.84				

Note: RMBV = (market/book $value_{firm}$)/(market/book $value_{industry}$) at year t ;
Sales = logarithm of sales at year t;
$Growth_t$ = (%change in sales $_{t-1}$ + … + %change in $sales_{t-3}$)/3;
Risk = debt/equity at year t; where t is year in which a firm is recognized as Top DDSCM.

Note that our matching firm methodology also minimizes any possibility that experts' perceptions of past stock performance have a substantial effect on the ultimate identification of AMR's top DDSCM firms. We select the matching firms based on book-to-market ratio right before the AMR announcement.

If a top DDSCM firm had done abnormally well or poorly in past stock movements, then its book-to-market ratio should be very low or high. By selecting matching firms on the characteristic of the book-to-market ratio, we control for the effect (if any were to exist). Even if one were to assume that we have not completely controlled for such an effect, we do an analysis with the Carhart four-factor model, which accounts for any book-to-market effect and momentum effect. For example, if stock of a top DDSCM firm has performed very well in the past, then there could be some continuing momentum or reversal in later movement. In our results based on the Carhart four-factor model, we use book-to-market and momentum factors to control for such an effect. If later abnormal returns are driven by book-to-market or momentum effects, they should not be particularly important after controlling for the two factors.

RESULTS

In this section, we examine the long-run performance of top DDSCM firms. As discussed in previous section, we present our main results based on the calendar-time portfolio approach.

Results from Sharpe Ratio

Table 2 presents Sharpe ratio results for the portfolios of top DDSCM firms, matching firms, and stock market based on CRSP market index. For the definition and formula of the Sharpe ratio, please see Appendix.

From Table 2, we can see that for the 12-month portfolio, the top DDSCM firms have a positive Sharpe ratio, indicating that on average, investment in the top supply chain portfolio earns a positive risk premium of .0935 each month after adjusting for total risks. In contrast, the investments in the matching firm portfolio and CRSP market index have negative Sharpe ratios. The Sharpe ratios for the 15-month and 18-month portfolio show similar patterns, except that the values become positive for industry-size matching firms and market for the 18-month portfolio. Overall, based on the Sharpe ratio, it is clear that the portfolios of top DDSCM firms perform better than both groups of matching firms and market. Thus, our results from the Sharpe Ratio investigation support our hypothesis H1a.

TABLE 2
SHARPE RATIOS

	12-month	15-month	18-month
Top DDSCM	0.0935	0.1139	0.1254
Industry-Size-Matching	-0.0666	-0.0292	0.0048
Industry-Size-BM-Matching	-0.1251	-0.0765	-0.0363
CRSP Market Index	-0.1007	-0.0224	0.0044

Results from Treynor Ratio

Table 3 presents the Treynor ratios for the portfolios of top DDSCM firms, matching firms, and stock market based on CRSP market index. For the definition and formula of the Treynor ratio, please see Appendix.

TABLE 3
TREYNOR RATIOS

	12-month	15-month	18-month
Top DDSCM	0.0060	0.0073	0.0078
Industry-Size-Matching	-0.0042	-0.0018	0.0003
Industry-Size-BM-Matching	-0.0079	-0.0047	-0.0022
CRSP Market Index	-0.0052	-0.0011	0.0002

Consistent with results for the Sharpe ratio, the portfolios of top DDSCM firms perform better than matching firms and the market for all three holding periods (12-month, 15-month, and 18-month). Take the 18-month portfolio as an example. The top supply chain portfolio has a Treynor ratio of .0078, indicating that, on average, investment in the top supply chain portfolio earns a positive risk premium of .0078 per month after adjusted for systematic risks. In contrast, the investments in industry-size-matching firms, industry-size-BM-matching firms, and the CRSP market index have much lower Treynor ratios, 0.0003, -0.0022 and 0.0002, respectively. Thus, results from the Treynor Ratio support our hypothesis H1b.

Abnormal returns after controlling for 3-factors

Table 4 shows the abnormal returns after controlling for Fama-French 3-factors for the portfolios of top DDSCM firms and matching firms. The second row of Table 4 reports the abnormal returns for the portfolio of top DDSCM firms. The third row reports the abnormal returns for the portfolio of matching firms.

We run the following Fama-French Three-factor regression:

$$R_p - R_f = \alpha + \beta_1 * (R_m - R_f) + \beta_2 * SMB + \beta_3 * HML + \varepsilon \qquad (2)$$

where $R_p - R_f$ is the monthly excess return on a portfolio, $R_m - R_f$ is the CRPS value weighted market return minus the risk-free rate in month, and *SMB* and *HML* are monthly returns on zero-investment portfolios based on size and book-to market (see Fama and French 1993). The estimated intercept or "alpha" is interpreted as the monthly abnormal return in excess of what could have been achieved by passive investments in the three factors.

As indicated in Table 4, for the 12-month holding period, the top supply chain portfolio generates positive and significant monthly excess return (i.e., Alpha) of 1.64 percent (p-value=.0194), which is equivalent to about 21.55 percent as an annual return. For the15-month holding period, the monthly excess return is 1.21 percent (p-value=.0592) and the equivalent annualized return is about 15.39 percent. When the holding period extends to 18 months, the monthly excess return is 1.07 percent and equivalent to 13.62 annualized returns. This is important evidence that DDSCM do create value for shareholders after controlling for the Fama-French three factors. In contrast, the portfolios of both groups of matching firms produce no significant excess returns.

TABLE 4
ABNORMAL RETURNS AFTER CONTROLLING FOR FAMA-FRENCH 3-FACTORS

	12-month	15-month	18-month
Top DDSCM	0.0164 (0.0194)	0.0121 (0.0592)	0.0107 (0.0675)
Industry-Size-Matching	0.0007 (0.9206)	-0.0008 (0.8907)	0.0006 (0.9163)
Industry-Size-BM-Matching	-0.0035 (0.5424)	-0.0040 (0.4459)	-0.0022 (0.6677)

Our results so far show that, after controlling for three-factors, the portfolio of top DDSCM firms provides investors with more significant abnormal long-term returns than matching firms. Our hypothesis H1c is supported.

Abnormal returns after controlling for 4-factor

As an extension of the Fama-French three-factor model, Carhart (1997) proposed an additional factor—Momentum (*MOM*). Incorporating *MOM* shows whether the portfolios rely on momentum investing to earn abnormal returns. For the purpose of robustness checks and dealing with the possibility that the abnormal returns in our study result from momentum trading, we run the four-factor regression as follows (See Carhart 1997 for more details):

$$R_p - R_f = \alpha + \beta_1 * (R_m - R_f) + \beta_2 * SMB + \beta_3 * HML + \beta_4 * MOM + \varepsilon \qquad (3)$$

TABLE 5
ABNORMAL RETURNS AFTER CONTROLLING FOR CARHART 4-FACTORS

	12-month	15-month	18-month
Top DDSCM	0.0164 (0.0210)	0.0121 (0.0624)	0.0106 (0.0718)
Industry-Size-Matching	0.0004 (0.9450)	-0.0012 (0.8235)	0.0000 (0.9983)
Industry-Size-BM-Matching	-0.0036 (0.5354)	-0.0041 (0.4333)	-0.0024 (0.6359)

The results for abnormal returns after controlling for the Carhart four factors are presented in Table 5. We can see that the results here are very consistent with those results in Table 4. For example, for the 12-month holding period, after controlling for four factors, the top supply chain portfolio generates a positive and significant monthly excess return (i.e., Alpha) of 1.64 percent (p-value=.0210) and it is equivalent to an annual return about 21.55 percent. In sum, our results are robust even after controlling for the additional factor of momentum (*MOM*). That is, our hypothesis H1d is supported.

CONCLUSION

Our study examines the long-run stock price performance of firms recognized as having highly effective DDSCM. We find statistically significant difference in the long run performance of top DDSCM firms versus the matched control firms. Based on a sample of 44 top DDSCM firms announced by AMR Research during 2004-2008, and applying various ways to measure risk-adjusted long-run abnormal stock returns, we find that the portfolio of top DDSCM firms provide investors with statistically significant abnormal long-term returns. Specifically, the abnormal return of our sample firm portfolio after controlling for four-factors (market, size, book-to-market ratio, and momentum are controlled) is nearly 21.55 percent for annual return if holding sample firms for 12 months after the announcement date; 15.39 percent if holding for 15 months; 13.62 percent if holding period extends to 18 months.

Implications

Our results have several of key implications. We provide evidence for the effect of DDSCM on firms' market value based on an overall evaluation of DDSCM practices by an independent party (AMR). Hendricks and Singhal (2001) point out that ranking systems play important roles in spreading out best managerial practices. We have similar comments on the value of AMR's top supply chain ranking system, which recognizes firms that have implemented effective DDSCM, promotes DDSCM awareness and practices, motivates and challenges firms to improve DDSCM, and provides a bench-mark and goal against which a firm can evaluate the progress of its DDSCM. In addition, winning recognition as being a top DDSCM firm can be viewed as a credible and low-cost mechanism to signal to the market and customers that the firm has implemented an effective DDSCM program.

In contrast to the anecdotal and perceptual evidence used by many to pass judgment on DDSCM's value-creation potential, we provide a more factual and statistically valid assessment of the value. Effective implementation of DDSCM leads to significant improvement in long-term market value performance. Our results also indicate that DDSCM effectiveness stands the examination of changes over time. Especially, the evidence suggests that the market retains strong confidence in the competitiveness of firms with effective DDSCM in turbulent environment caused by global financial crisis in 2008. This confidence is revealed through the superior stock returns that effective DDSCM can create over an extended period (12, 15, 18 months).

Our results should be interesting and useful to those who are seeking new investment opportunities. Like such factors as brand reputation and risk management, DDSCM effectiveness can be an excellent indicator for stock purchase and holding decisions. Building on effective DDSCM, the best value supply chains are emerging as means to create competitive advantages and market performance (Ketchen and Hult, 2007; Lee, 2004).

Our results underscore why firm strategies need to focus on effective DDSCM. Successful firms understand that the right supply chain strategy is to meet specific needs of the end customers (Lee, 2002). The “Supply Chain Top 25” firms have consumer-driven supply chain systems, which build up dynamic capabilities across supply chains so that customized supply chains can be created for every customer need (Lee, 2004; Magretta, 1998). However, as Hendricks and Singhal (2005) have pointed out, unlike efficiency-improving or cost-reduction activities, where return on investment is easy to compute, it is much harder to make business decisions for investments that improve the reliability and responsiveness of supply chains. The evidence presented in this paper can help with business decisions in this regard. Investments in supply chain practices enhancing DDSCM could be viewed as buying insurance against unexpected changes in business environment.

Further Application: Buy-and-Sell Abnormal Returns

To provide further evidence regarding the practical application of our findings, we conducted additional analysis as shown in Table 6. This additional test investigates whether investors can earn significantly positive abnormal returns by simultaneously buying a portfolio of top SCM firms and selling a portfolio of matching firms.

TABLE 6
ABNORMAL RETURNS FROM BUY AND SELL PORTFOLIO

Panel A:	12-month	15-month	18-month
Fama-French 3 factors: Buy Top DDSCM and Sell Industry-Size-Matching	0.0157 (0.0298)	0.0129 (0.0496)	0.0010 (0.1013)
Fama-French 3 factors: Buy Top DDSCM and Sell Industry-Size-BM-Matching	0.0200 (0.0029)	0.0161 (0.0095)	0.0128 (0.0261)
Panel B:	12-month	15-month	18-month
Carhart 4 factor: Buy Top DDSCM and Sell Industry-Size-Matching	0.0160 (0.0219)	0.0133 (0.0344)	0.0106 (0.0735)
Carhart 4 factor: Buy Top DDSCM and Sell Industry-Size-BM-Matching	0.0200 (0.0031)	0.0162 (0.0095)	0.0129 (0.0254)

As presented in Table 6, we create a portfolio of simultaneously taking a long position for top DDSCM firms and a short position for matching firms. We still control Fama-French three factors and Carhart four factors for this analysis. The results indicate that investors can earn significantly positive abnormal returns by simultaneously buying a portfolio of top DDSCM firms and selling a portfolio of matching firms. Take the 12-month period portfolio of buying top DDSCM firms and selling industry-size-BM-matching firms as an example. As shown in Panel A of Table 6, on average, after three factors are controlled, investors can make 2.00 percent (p-value=.0029) abnormal returns each month. Results from the 12-month period portfolio of buying top DDSCM firms and selling industry-size-matching firms are qualitatively similar and statistically significant. Panel B of Table 6 shows that we have consistent findings after we control for Carhart four factors.

ENDNOTES

1. For the year of 2008, we include those firms ranked from 26th to 50th as long as it is their first appearance on top list. Our results are also robust if excluding the firms from the study (i.e., firms ranked from 26^{th} to 50^{th}).
2. The logistic regression model is as follows:
   $Y = B_0 + B_1ROA + B_2RMBV + B_3SALES + B_4GROWTH + B_5RISK + e$
   ROA = net income/total assets at year t;

REFERENCES

Agrawal, D. K. (2012). Demand chain management: factors enhancing market responsiveness capabilities. *Journal of Marketing Channels*, 19, (2), 101-119.

Baker, S. (2003). *New consumer marketing*. Chicester: John Wiley & Sons.

Bode, C., Wagner, S.M., Petersen, K.J. and Ellram, L.M. (2011). Understanding responses to supply chain disruptions: insights from information processing and resource dependence perspectives. *Academy of Management Journal*, 54, (4), 833-856.

Briloff, R. (1972). *Unaccountable accounting*. New York: Harper and Row.

Briloff, R. (1976). *The truth about corporate accounting*. New York: Harper and Row.

Brown, B. & Perry, S. (1994). Removing the financial performance halo from Fortune's most admired companies. *Academy of Management Journal,* 37, (5), 1347-1359.

Brav, A. & Paul, G. (1997). Myth or reality? The long-run underperformance of initial public offerings: Evidence from venture and non-venture-backed companies. *Journal of Finance,* 52, 1791–1821.

Budd, J., Knizek, C. & Tevelson. B. (2012). The Demand-Driven Supply Chain. In M. Deimler, R. Lesser, D. Rhodes and J. Sinha (Eds.), *Own the Future: 50 Ways to Win from the Boston Consulting Group*), Hoboken, NJ: John Wiley & Sons.

Carhart, M. (1997). On persistence in mutual fund performance. *Journal of Finance,* 52, 57-82.

Chemmanur, T., Jordan, B., Liu, M. & Wu, Q. (2010). Anti-takeover provisions in corporate spin-offs. *Journal of Banking and Finance,* 34, 813-824.

Christopher, M., Lowson, R. & Peck, H. (2004). Creating agile supply chains in the fashion industry. *International Journal of Retail & Distribution Management,* 32, (8), 367-376.

Christopher, M., & Ryals, L.J. (2014). The supply chain becomes the demand chain. *Journal of Business Logistics*, 35, (1), 29–35.

Eisenhardt, K. & Martin, J. (2000). Dynamic capabilities: What are they? *Strategic Management Journal,* 21, 1105-1122.

Ellinger, A., Shin, H., Northington, W.M., Adams, F.G., Hofman, D. & O'Marah, K. (2012). The influence of supply chain management competency on customer satisfaction and shareholder value. *Supply Chain Management: An International Journal,* 17(3), 249 – 262.

Fama, E. F. (1998). Market efficiency, long-term returns and behavioral finance. *Journal of Financial Economics,* 49, 283–307.

Fama, E. & French, F. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics,* 33, 3–56.

Fama, E. & French, F. (1997). Industry costs of equity. *Journal of Financial Economics,* 153–194.

Filbeck, G., Gorman, R. & Zhao, X. (2009). The "Best Corporate Citizens": Are they good for their shareholders? *Financial Review,* 44, 239-262.

Gligor, D.M. & Holcomb, M.C. (2012). Antecedents and consequences of supply chain agility: Establishing the link to firm performance. *Journal of Business Logistics*, 33, (4), 295-308.

Greer, B.M. & Theuri, P. (2012). Linking supply chain management superiority to multifaceted firm financial performance. *Journal of Supply Chain Management,* 48, (3), 97-106.
Heikkilä, J. (2002). From supply to demand chain management: efficiency and customer satisfaction. *Journal of Operations Management,* 20, 747-767.
Hendricks, K.B. & Singhal, V.R. (2001). The long-run stock price performance of firms with effective TQM programs. *Management Science,* 47, (3), 359-368.
Hendricks, K.B. & Singhal, V.R. (2003). The effect of supply chain glitches on shareholder wealth. *Journal of Operations Management,* 21, (5), 501-522.
Hendricks, K.B. & Singhal, V.R. (2005). An empirical analysis of the effect of supply chain disruptions on long-run stock price performance and equity risk of the firm. *Production and Operations Management,* 14, (1), 35-52.
Hendricks, K.B., Singhal, V.R. & Zhang, R. (2009). The effect of operational slack, diversification, and vertical relatedness on the stock market reaction to supply chain disruptions. *Journal of Operations Management,* 27, (3), 233-246.
Hines, T. (2004). *Supply chain strategies: Customer driven and customer focused*. Oxford: Elsevier.
Jüttner, U., Christopher, M & Baker, S. (2007). Demand chain management-integrating marketing and supply chain management. *Industrial Marketing Management,* 36, (3), 377-392.
Ketchen Jr., G. & Guinipero, L. (2004). The intersection of strategic management and supply chain management. *Industrial Marketing Management,* 33, (1), 51-56.
Ketchen Jr., G. & Hult, T.M. (2007). Bridging organization theory and supply chain management: The case of best value supply chains. *Journal of Operations Management,* 25, (2), 573-580.
Larcker, D. F., Ormazabal, G. & Taylor, D.J. (2011). The Market Reaction to Corporate Governance Regulation. *Journal of Financial Economics,* 101, 431–48.
Lee, H.L. (2002). Aligning supply chain strategies with product uncertainties. *California Management Review,* 44, (3), 105-119.
Lee, H.L. (2004). The triple-a supply chain. *Harvard Business Review,* 83, 102-112.
Li, X., Wu, Q., Holsapple, C.W. & Goldsby, T. (2017). An empirical examination of firm financial performance along dimensions of supply chain resilience. *Management Research Review*, 40, (3), 254-269.
Li, X., Chung, C., Goldsby, T. & Holsapple, C.W. (2008). A unified model of supply chain agility: The work-design perspective. *International Journal of Logistics Management,* 19, (3), 408-435.
Loughran, T. & Ritter, J.R. (1995). The new issues puzzle. *Journal of Finance,* 50: 23–51.
Magretta, J. (1998). Fast, global, and entrepreneurial: Supply chain management, Hong Kong Style. An interview with Victor Fung. *Harvard Business Review,* 76, (5), 102-114.
Melnyk, S.A., Stewart, D.M. & Swink, M. (2004). Metrics and performance management in operations management: dealing with the metrics maze. *Journal of Operations Management,* 22, (3), 209-217.
McGuire, J.B., Schneeweis, T. & Hill, J. (1986). *A comparison of alternative measures of strategic performance*. In R. Lamb & P. Stravastava(Eds.), Advances in strategic management. 4: 107-153. Greenwich, Conn.; JAI Press.
McGuire, J.B., Sundgren, A. & Schneeweis, T. (1988). Corporate social responsibility and firm financial performance. *Academy of Management Journal,* 31, (4), 854-872.
Mitchell, M. L. & Stafford, E. (2000). Managerial decisions and long-term stock price performance. *Journal of Business,* 73, 287–329.
Selen, W. & Soliman, F. (2002). Operations in today's demand chain management framework. *Journal of Operations Management,* 20, 667-673.
Sharpe, W. (1966). Mutual fund performance. *Journal of Business,* 39, (1), 119–138.

SimChi-Levi, D., Clayton, A. & Raven, B. (2013). When One Size Does Not Fit All. *Sloan Management Review*, 54, (2), 14-17.
Slater, S. (1997). Developing a customer value-based theory of the firm. *Journal of the Academy of Marketing Science,* 25, 162-167.
Swink, M.L., Golecha, R. & Richardson, T. (2010). Does supply chain excellence really pay off? *Supply Chain Management Review*, March/April, 14-21.
Teece, D. J., Pisano, G. & Shuen, A. (1997). Dynamic capability and strategic management. *Strategic Management Journal,* 18, (7), 509-533.
Treville, S.D., Shapiro, R.D. & Hameri, A.P. (2004). From supply chain to demand chain: the role of lead time reduction in improving demand chain performance. *Journal of Operations Management,* 21, 613-627.
Treynor, J. (1965). How to rate management of investment funds. *Harvard Business Review,* 43, (1), 63–75.
Vollmann, T., Cordon, C. & Heikkilä, J. (2000). Teaching supply chain management to business executives. *Production and Operations Management*, 9, (1), 81-90.
Zacharia, Z.G. & Mentzer, J.T. (2004). Logistics salience in a changing environment. *Journal of Business Logistics*, 25, (1), 187-210.

APPENDIX

Formulas for Portfolio Performance Measures

1. <u>Sharpe Ratio:</u> $SRp = (Rp - Rf) / \sigma$

Where: SRp = Sharpe's Ratio for portfolio p,
Rp = average monthly return on portfolio p,
Rf =average monthly return on risk-free asset,
σ = standard deviation of returns of portfolio p

2. <u>Treynor Ratio:</u> $TRp = (Rp - Rf) / \beta p$

Where: TRp = Treynor Ratio for portfolio p,
Rp = average monthly return on portfolio p,
Rf =average monthly return on risk-free asset,
βp = beta for portfolio p

3. <u>Fama-French Three-Factor Model:</u>

$$R_p - R_f = \alpha + \beta_1 * (R_m - R_f) + \beta_2 * SMB + \beta_3 * HML + \varepsilon$$

Where: α = Abnormal return of a portfolio after controlling for the Fama-French factors
Rp = monthly return on portfolio p,
Rf = monthly return on risk-free asset,
Rm= monthly market return
SMB=Small minus big stocks
HML= High minus low stocks
ε = residual

4. <u>Carhart Four-Factor Model:</u>

$$R_p - R_f = \alpha + \beta_1 * (R_m - R_f) + \beta_2 * SMB + \beta_3 * HML + \beta_4 * MOM + \varepsilon$$

Where: α = Abnormal return of a portfolio after controlling for the Carhart factors

Rp = monthly return on portfolio p,
Rf = monthly return on risk-free asset,
Rm= monthly market return
SMB=Small minus big stocks
HML= High minus low stocks
MOM=Momentum factor
ε = residual