An Empirical Analysis of the Effect of Supply Chain Disruptions on Long-run Stock Price Performance and Equity Risk of the Firm

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November 2003

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Abstract

Supply chain disruptions are significant events for any firm. This paper investigates the long-term stock price effects and equity risk effects of supply chain disruptions based on a sample of 827 disruption announcements made during 1989-2000. We examine the stock price effects starting one year before through two years after the disruption announcement date. Over this time period the average abnormal stock returns of firms that experienced disruptions is nearly -40%. Much of this underperformance is observed in the year before the announcement, the day of the announcement, and the year after the announcement. Furthermore, the evidence indicates that firms do not quickly recover from the negative effects of disruptions.

We also find that equity risk (volatility) of the firm significantly increases around the announcement date. The equity risk in the year after the announcement is 13.50% higher when compared to the equity risk in the year before the announcement. Increases in the financial leverage (the ratio of the book value of debt to the sum of the book value of debt and the market value of equity) and asset risk are partly driving the increase in the equity risk. The increase in equity risk is not temporary as firms stay at the higher risk level for at least the next year.

Key Words: supply chain disruptions, long-run stock price, equity risk.

1. Introduction

The risk of supply chain disruptions – an indication of a firm's inability to match demand and supply – are receiving increased attention in the business as well as the academic press. Recent supply chain woes at Cisco (inventory write-off), Sony (shortage of critical components), Nike (inventory buildup) and Ericsson (parts shortages) and others have been written about in the Wall Street Journal and other business publications (Thurm (2001), Tran (2000), Latour (2001), and Engardio (2001)). There seems to be widespread recognition that such disruptions have the potential to cause significant negative economic impacts (Kilgore (2003), Radjou (2002), Lakenan et al. (2001), Billington et al (2001), Lee et al. (1997), and Fisher (1997)). However, research on the magnitude of the negative economic consequences of disruptions is just beginning to emerge. With few exceptions, most of what we have come across are anecdotes and case studies.

In a recent study, Hendricks and Singhal (2003a) use the event study methodology to estimate the economic impact of supply chain disruptions on shareholder wealth. Based on a sample of 519 publicly announced disruptions they find that after adjusting for normal market movements, shareholders on average lose about 10% of their stock value over a two-day period that spans the day of the announcement and the day before the announcement. Given that the underpinnings of event study methodology is that in an efficient capital market the shareholder wealth effect of an announcement will be immediately reflected in stock prices, one might conclude that the announcement effect of disruptions documented by Hendricks and Singhal measures the overall economic impact of disruptions. However, there are a couple of reasons why one must be cautious in making this interpretation.

First, the economic impact of an event and announcement effect will be equal only if the event was thought impossible prior to the announcement (Malatesta and Thompson (1984)) - that is the event was a complete surprise. If the event was partially anticipated then the economic impact of the event and the announcement effect will differ. With partial anticipation, the magnitude of the economic impact cannot be judged by simply looking at the announcement affect.

Second, under market efficiency one would expect that once the announcement of an event is made, there is no abnormal stock price behavior in the post-announcement period. However, recent empirical research suggests that the stock market reaction to new information is not fully reflected in stock prices at announcement (see Fama (1998) for a summary of these studies). Collectively these studies seem to suggest that the stock market adjusts slowly to new information resulting in abnormal stock price behavior after announcement. Although there is considerable debate whether post-announcement abnormal stock price performance is an artifact of the methodologies used to estimate abnormal performance or an indication of market inefficiency (Haugen (2002) and Fama (1998)), it does suggest that to get a more comprehensive estimate of the economic impact of an event, one must examine stock price performance in the post-announcement period.

Since partial anticipation and slow adjustment of stock prices to new information are likely in the case of supply chain disruptions (see section 2), one cannot yet equate the announcement effect documented by Hendricks and Singhal with the full economic impact of disruptions. To better understand the economic impact of disruptions, the long-run stock price effects of disruptions must be examined. A major objective of this paper is to carefully and rigorously examine the long-run stock price effects associated with disruptions.

Our analysis of the long-run stock price effects of disruptions is important for a number of reasons. First, managers and investors are likely to have more faith in estimates of economic impact that are based over long horizons as it provides them with a more complete picture of the economic implications of disruptions. By examining the long-run stock price effects of disruptions we are able to shed light on the time pattern of abnormal stock price behavior in terms of when it starts, how long does it lasts, and whether firms recover quickly from disruptions. These issues are important for setting realistic expectations of the likely consequences of disruptions.

Second, Kilgore (2003), Radjou (2002), and Kuper (2002) suggest that much of the supply chain management efforts in the recent past have focused on increasing the efficiency (lowering costs) of supply chain operations, and less on managing the risks of disruptions. Much of the recent academic literature on supply chain models also seems to focus on managing costs (see, for example, Barnes-Schuster et al. (2002), Cheung and Lee (2002), Milner and Kouvelis (2002), Aviv (2001), Corbett and DeCroix (2001), Cachon and Fischer (2000), and Lee et al. (2000)). This could partly be because improving efficiency is an ongoing activity at most firms, so managers have developed the necessary skills to deal with it, and they know how to justify and manage resources that improve efficiency. On the other hand, major supply chain disruptions are infrequent, they are hard to predict and manage, making it difficult to justify why resources should be devoted to proactively manage such risks. Evidence on the negative economic impact of disruptions can change a firm's perceptions on the importance of anticipating and managing the risk of disruptions.

In documenting the long-run stock price effects, the methodology and estimation techniques that we use are very different than those typically used in short time window event studies such as Hendricks and Singhal (2003a). The standard event study techniques used for measuring the stock price effects around announcements cannot be generally used to estimate long-run stock price effects as they often give biased estimates of both the overall economic impact as well as the test statistics (Barber and Lyon (1997) and Kothari and Warner (1997)).

Our results are based on more robust and reliable methodologies that have been recently developed and used extensively in the literature (Clark et al. (2003), Lyon et al. (1999), Lee and Loughran (1998)).

A second major issue addressed in this paper is the effect of supply chain disruptions on the risk of the firm. Stock price changes associated with disruptions can be a function of the both the changes in expected future cash flows as well as the risk or volatility of future cash flows. Hendricks and Singhal (2003b) examine how disruptions affect the profitability and hence the cash flows of the firm. To the best of our knowledge, the effect of disruptions on risk has not been addresses in the literature.

The risk effects of disruptions are important because changes in risk can have meaningful impact on the firm and its various stakeholders including investors, management, employees, suppliers, and customers. Increased risk may increase the rate of return required by investors, thereby increasing the cost of capital. It might make the firm's equity a less attractive currency for acquisitions as potential targets may be less willing to do deals that depends on volatile equity prices. It may also increase the probability of financial distress as the chances of the firm not being able to cover its fixed commitments increases as the risk increases. Increases in risk may also result in downgrading of debt by credit rating agencies, making it more expensive and difficult to raise capital.

Risk changes can also create conflicts between the various stakeholders. Galai and Masulis (1976) and Smith and Warner (1979) show that in increase in equity volatility transfers wealth from bondholders to shareholders, a potential source of conflict that may require management time and attention. Risk-averse employees may demand higher compensation to work for a firm that has high risk. Suppliers and customers may also be wary of dealing with the firm that has high risk and may demand some form of assurances and guarantees before doing business with the firm, thereby raising the cost of doing business for the firm. Since changes in risk have economic implications, it is important to understand how disruptions affect risk.

Our empirical results on long-run stock price effects and risk changes are based on a sample of 827 disruptions that are announced by publicly traded firms during 1989-2000. These disruptions resulted in some form of production and/or shipment delays. Section 2 elaborates on why it is important to examine both the long-run stock price effects and the risk of the firm. Section 3 describes the sample collection. Section 4 describes the methods used to estimate the long-run stock price effects of our sample firms. Section 5 presents the empirical evidence on the long-run stock price effects from disruptions. Section 6 discusses the effect of disruptions on risk. The final section summarizes the paper and discusses possible ways to mitigate and manage the risk of disruptions.

2. Issues examined

2.1 Supply chain disruption and the long-run stock price effects

Our results are based on a sample of publicly announced disruptions (see section 3). A review of these announcements indicates that most announcements refer to disruptions that have occurred in the recent past. Furthermore, disruption announcements are sometime made as part of earnings announcements and/or earnings pre-announcements. This suggests that firms typically delay the release of information about disruptions. This could be motivated by a number of factors. First, disclosing disruptions early may provide information to competitors, who can devise actions to take advantage of the situation. Early disclosure may also create uncertainty in the mind of the customers, which could affect sales of other products. Second, firms may have already taken corrective action and may be hopeful that they would quickly recover from the disruptions. Hence, there is no compelling need to announce the disruption as soon as it happens.

Given that announcements are acknowledgement of disruptions that have already occurred and firms have an incentive to delay the acknowledgement, one can see why disruptions can be partially anticipated. Indication of disruptions could show up in many ways including difficulty in obtaining the firm's products, build-up of inventories at suppliers, the firm's inventory falling below critical levels, press releases by other supply chain partners, articles in business press, and analyst research reports. Accordingly, the market may have assigned a probability that the firm is likely to suffer from a disruption, and hence may have incorporated part of the economic impact of disruptions in stock prices even before the disruption announcement. Thus, our first hypothesis, stated in alternate form (as are all hypotheses in this paper), is:

H1: The abnormal stock price performance of firms that experience disruptions will be negative in the time period before the announcement of the disruption.

Since partial anticipation is probable, the next issue is what is the appropriate time horizon before the announcement that should be considered to capture the effect of partial anticipation. The existing literature provides little guidance on this issue. Although managers have an incentive to delay the acknowledgement of disruptions, they need to balance this against the fact that disruptions are significant events, and that too much delay in acknowledging disruptions could affect their credibility and reputation with the market as well as make them a possible target of shareholder lawsuits. Taking this into consideration, we chose to examine the stock price performance of our sample firms starting a year before the disruption announcement.

To get a full estimate of the economic impact of disruptions, it is also important to examine the stock price performance in the post-announcement period since recent research has documented statistically significant long-term stock price effects subsequent to event announcements. Examples of events where this has been observed include repurchase tender offers, spin-offs, dividend initiations and omissions, open market repurchases, stock splits, seasoned equity offerings, proxy contests, initial public offerings (see Fama (1998) for a summary of this evidence). This rapidly growing body of research suggests delayed stock market reaction to new information, which in itself is a sufficient reason for examining the post-announcement stock price effects of firms that have experienced disruptions.

Disruptions can also continue to affect financial performance even after the announcement as customer and suppliers react to the disruption. The ability of the firm to effectively deal with its customers and suppliers may continue to deteriorate more than anticipated, leading to worse financial performance than expected after the disruption announcement. Firms are also likely to take corrective actions to deal with disruptions. Depending on the effectiveness of these actions, firms may be able to recover some of the actual losses or avoid some of the anticipated losses due to disruptions. Since such effects should be part of any attempt to estimate the full economic impact of disruptions, one should examine the stock price performance over longer horizons after the announcement. Since both positive and negative stock price effects are possible in the post-announcement period, our hypothesis is:

H2: Firms that announce disruptions will experience abnormal stock price performance during the post-announcement period.

As was the case with partial anticipation, there is little guidance in the literature on what is the appropriate time period for examining post-announcement performance. Time periods used have ranged from anywhere from one year to five years. The choice of time period depends on the events being researched and rational choices made by researchers. We examine the stock price performance over two years after announcement. This should capture the post-announcement negative impacts of disruptions as well as any positive impacts due to corrective actions. Overall, we examine the stock price performance starting one year before through two years after the disruption announcement date.

2.2 Supply chain disruption and the risk of the firm

Another major issue that we examine in this paper is the effect of supply chain disruptions on the risk of the firm. A number of papers have considered the impact of corporate events on risk by focusing on equity risk (volatility), as measured by the variance of the rate of return of the firm's equity, σ_e^2 (see, for example, Clayton et. al (2002), Fargher and Wilkins (1998), Hertzel and Jain (1991), and Healey and Palepu (1990)). Equity risk depends on the risk of the underlying assets of the firm (the variance of the rate of return of the firm's assets, (σ_a^2)) as well as the financial leverage (ratio of the book value of debt to the sum of the book value of debt and the market value of equity). Assuming no taxes and risk-free debt, Hamada (1972) shows that equity risk is linked to asset risk and financial leverage as:

$$\sigma_e = \sigma_a * (1 + D/E) \tag{1}$$

where D is the book value of total debt, and E is the market value of equity.

Equation (1) shows that financial leverage amplifies the asset risk to give the equity risk. Holding asset risk constant, firms with higher financial leverage will have higher equity risk. It is common to use equation (1) to estimate the relation between equity risk, financial risk, and asset risk because corporate debt trades infrequently, data on the returns on debt are hard to obtain, and it is hard to estimate the future tax rate of the firm (see, for example, Fargher and Wilkins (1998), Hertzel and Jain (1991), and Healey and Palepu (1990)). Note that asset risk cannot be directly estimated. Instead, it is inferred from equation (1) by estimating the equity risk of the firm and the debt-equity ratio of the firm, variables that can directly estimated from stock price and balance sheet data.

The effect of supply chain disruptions on equity risk depends on how disruptions affect the financial leverage and asset risk. Disruptions have a negative impact on equity prices and the market value of the equity. Therefore, if a firm has debt in its capital structure and the level of debt is kept constant, disruption should increase the financial leverage (the debt-equity ratio) of the firm, resulting in an increase in the equity risk.

To highlight the effect of supply chain disruptions on the asset risk we use insights from the technology justification model by Lederer and Singhal (1988). They developed the model to more accurately determine the risk and hence the discount rate that ought to be used in net present value calculations of investments among technologies with different cost structures. Their model is based on the concept of operating leverage, defined as the ratio of variable profits (revenue minus variable costs) to operating profits (variable profits minus fixed costs). Lev (1974) and Gahlon and Gentry (1982) discuss the relation between operating leverage and the risk of the firm's asset. The higher the degree of operating leverage, the higher is the risk of a firm's assets.

With slight modifications, Lederer and Singhal's model indicates that under demand uncertainty and fixed selling price, the risk of a firm's assets is directly proportional to the coefficient of variation of demand (σ_d/D_e) and the breakeven point ($F/(P-C)$), where σ_d is the standard deviation of demand, D_e is the expected demand, F is the fixed operating cost per period, C is the variable cost per unit, and P is the selling price per unit. These results make intuitive sense as higher coefficient of variation demand suggests more volatile demand and firms with higher breakeven point are generally perceived to be riskier.

The Lederer-Singhal model together with the recent empirical results of Hendricks and Singhal (2003b) on the effect of disruptions on operating performance provides a rationale for why we expect supply chain disruptions to increase the asset risk. Hendricks and Singhal show that firms that suffer from disruptions experience lower growth rate in revenues. The drop in revenue growth rate could be due to lower prices and/or lower actual demand. Thus, the coefficient of variation of demand and the breakeven point of the firm's asset are likely to increase, resulting in higher asset risk. They also find that total costs increase due to disruptions. This increase could be due to an increase in fixed cost per period and/or variable cost per unit. In either case one would expect that the breakeven point of the firm's asset would increase, resulting in higher asset risk.

Overall, both the financial leverage and operating performance affects suggest that disruptions increase the equity risk of the firm. Accordingly our hypotheses with respect to risk changes are:

H3a: Firms that suffer from supply chain disruptions will experience an increase in their equity risk (σ_e^2*).*

H3b: Firms that suffer from supply chain disruptions will experience an increase in their financial leverage (measured by the ratio of the book value of debt to the sum of the book value of debt and the market value of equity).

H3a: Firms that suffer from supply chain disruptions will experience an increase in their asset risk (σ_a^2*).*

3. Sample selection procedure and data description

The Wall Street Journal and the Dow Jones News Service are our primary sources for collecting the sample of firms that experienced supply chain disruptions. The search covered the time period from 1989 to 2000, and looked for announcements that dealt with production or shipping delays. Key words used in the search include combinations of words such as delay, shortfall, shortage, manufacturing, production, shipment, delivery, parts, components, and other relevant phrases. To remain in our sample, an announcement must satisfy the following criteria:

1) The common stock is listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), or the NASDAQ exchange, and has returns information on the Center for Research on Security Prices (CRSP) database.

2) The firm has book value of equity available from COMPUSTAT for the second fiscal year end before the disruption announcement date and the book value of equity is non-negative.

3) The firms must have traded on at least 80% of the trading days during the time period that begins two years before and ends one year before the disruption announcement date.

4) The firm has not made an announcement of another disruption during the three years before this announcement date.

Criteria 2 and 3 are imposed because the methodology that we use requires that sample firms be matched to benchmark firms on market value of equity to book value of equity (market-to-book ratio) as well as prior performance outside of the time period that is of interest to us. Since negative market-to-book ratio is meaningless we drop such firms from our sample. We also drop firms that do not have sufficient return history to compute prior performance. Criterion 4 is imposed to avoid overlapping time periods. For each disruption we examine the performance starting one year before through two years after the disruption announcement date. Thus, including disruptions that occurred within three years of each other would cause overlapping time periods, with the performance during the overlapping period being counted more than once in the overall averages, which could potentially bias our results.

The final sample consists of 827 announcements. Examples of some announcements are.

- *"Sony Sees Shortage of Playstation 2s for Holiday Season"*, <u>*The Wall Street Journal*</u>*, September 28, 2000*. The article indicated that because of component shortages, the company has cut in half the number of PlayStation 2 machines it can manufacture for delivery.

- *"Motorola 4th Quarter Wireless Sales Growth Lower Than Order Growth",* The Dow Jones News Service*, November 18, 1999.* In this case Motorola announced that its inability to meet demand was due to the shortage of certain types of components and that the supply of these components is not expected to match demand sometime till 2000.
- "*Boeing Pushing for Record Production, Finds Parts Shortages, Delivery Delay,"* The Wall Street Journal*, June 26, 1997*. The article discusses reasons for the parts shortages, the severity of the problems, and the possible implications.

Nearly 45% (374 out of 827) of the disruption announcements convey information about other firm-specific events besides supply chain disruptions. Although the main results of the paper are based on the full sample, we will present results that exclude these 374 announcements to test whether announcements with other firm-specific events drive our overall results.

Panel A of Table 1 presents statistics on the sample based on the most recent fiscal year completed before the date of the supply chain disruption announcement. The mean (median) observation represents a firm with annual sales of nearly \$2047 million (\$116.8 million), total assets of \$2437 million (\$102.3 million), and operating income of \$56.3 million (\$3.7 million). Panel B presents the number of announcements by year. Nearly 60% of the announcements in our sample are made during 1996-2000 and the rest during 1989-1995.

4.0 Methodology for estimating the long-term stock price effects

The basic idea in long-term stock price effect studies is to estimate abnormal returns for a sample of firms that have experienced the same kind of event, and then test the null hypothesis that the abnormal returns over the period of interest are equal to zero. An abnormal return is the difference between the return on a stock and the return on an appropriate benchmark, where the benchmark is chosen to control for factors that are known to explain stock returns. The idea is that after controlling for the known factors, whatever remains unexplained is deemed as abnormal and can be attributed to the event under consideration.

Our focus in this paper is on estimating the buy-and-hold abnormal returns (BHARs) using daily return data. To compute BHARs the raw returns of the sample firm and its benchmark are first compounded across the period of interest. The abnormal return is then the difference between the compounded returns of the sample firm and its benchmark. More specifically, BHARs are calculated as

$$BHAR_i = \prod_{t=1}^{T}(1 + R_{it}) - \prod_{t=1}^{T}(1 + R_{bt}), \quad (2)$$

where $BHAR_i$ is the buy-and-hold abnormal return for stock i, R_{it} is the rate of return for stock i on day t, R_{bt} is the rate of return for the benchmark for stock i, and T is the number of days in the period of interest.

There is considerable debate in the literature on what is the appropriate methodology for computing long-run abnormal returns (Lyon et al. (1999), Fama (1998), Barber and Lyon (1997) and Kothari and Warner (1997)). This debate has centered on two issues. The first issue is the appropriate factors that one should control for in computing long-run abnormal returns. Earlier long-run abnormal stock price studies mainly controlled for the systematic risk (or beta) of a firm's stock. Recent research indicates that size and market-to-book ratio (Fama and French (1996)) as well as prior performance (Cahart (1997) and Jegadeesh and Titman (1993)) are important predictors of stock returns. The current consensus seems to be that abnormal returns should be computed after controlling for size, market-to-book ratio, and prior performance (Lyon et al. (1999)).

The second issue is the interpretation of the statistical significance of the observed long-run abnormal returns. Barber and Lyon (1997) and Kothari and Warner (1997) report that the test statistics from many commonly used methods are severely mis-specified making it hard to judge the true significance of observed abnormal returns. A primary source of misspecification is the presence of cross-sectional dependency that arises because of overlapping time period among sample firms that usually exists in long-run stock price studies. Cross-sectional dependency (positive or negative) leads to biased test statistics. Recent simulation results suggest that abnormal returns computed using matching portfolios or one-to-one matching give well-specified tests (Barber and Lyon (1997) and Lyon et al. (1999)). Since we use both these approaches in this paper, we briefly describe these approaches.

4.1 Buy-and-hold abnormal returns (BHARS) using matching portfolios

The matching portfolio approach computes abnormal returns using as benchmarks portfolios of firms that are similar in size, market-to-book ratio of equity, and prior performance. We implement this approach using the following five-step procedure (see, for example, Byun and Rozeff (2003), Clark et al. (2003), Lyon at al (1999), and Lee (1997)).

Step1: In each month, all eligible NYSE firms are sorted into deciles according to their market value of equity. Next all AMEX and NASDAQ firms are placed into the appropriate size portfolio. The smallest size decile portfolio is further divided into quintiles, resulting in 14 size portfolios. Each portfolio is further divided into quintiles according to their market-to-book ratio of equity, resulting in 70 portfolios. Each portfolio is further divided into three portfolios based on the stock price performance of firms in that portfolio over the previous year, resulting in 210 portfolios for each month where firms in each portfolio are similar in terms of size, market-to-book ratio, and prior performance.

Step 2: In step 1, each sample firm has been assigned to a portfolio. We identify the portfolio that a sample firm is assigned to 12 months before the month of the announcement date (the beginning of our measurement period). Since all other firms in this portfolio are similar to the sample firm on size, market-to-book ratio, and prior performance, all these firms can be considered as matched to the sample firm. The portfolio assignment and hence the set of matched firms for a sample firm remains the same over the three-year time period that we use in our study.

Step 3. We compute the buy-and-hold return for each sample firm. If the sample firm is delisted before the end of a time period, the buy-and-hold return stops on the delisting date of the sample firm. The buy-and-hold return of each matched firm in the portfolio that the sample firm is assigned to is also computed over the same time period. If a matching firm delists prior to the end of the period or before the sample firm's delisting date, whichever is earlier, the CRSP value-weighted return is spliced into the calculation from the day after the matched firm's delisting date. This assures that the buy-and-hold return of the sample and matched firms are computed over the same time period. The benchmark return for each sample firm is then the average of the buy-and-hold returns of all its matched firms in its assigned portfolio. Abnormal performance is the difference between the return of the sample firm and the return to its assigned portfolio.

Step 4. Statistical inference is based on a simulation approach first advocated by Ikenberry et al (1995), and more recently confirmed by Lyon et al. (1999) as yielding well-specified test-statistics. The idea is to compute an empirical distribution of abnormal returns for a portfolio that is similar in characteristics as that of the sample portfolio, and compare where the abnormal return of the sample portfolio falls on this distribution. The procedure for doing this is as follows. We first create a pseudo-sample where for each sample firm we randomly select with replacement a firm that belongs to the portfolio assigned to the sample firm, and assign it the same announcement date as that of the sample firm. Next we calculate the mean abnormal performance for this pseudo-sample using the portfolio approach discussed in Step 3. This results in one observation of the mean abnormal performance from a pseudo-sample with the same size, market-to-book ratio of equity, and prior performance as the sample portfolio. We repeat this 1000 times to obtain 1000 mean abnormal return observations.

Step 5. Under the null, the mean abnormal return of the sample portfolio equals the mean for the 1000 pseudo-portfolios. To test whether the mean abnormal return for the sample portfolio is significantly less than the mean abnormal returns from the 1000 pseudo-portfolios, we use the empirical distribution to compute the p-value as the fraction of pseudo-samples with mean abnormal return less than the mean abnormal return of the sample portfolio. Using the empirical distribution to compute p-values enables us to take into consideration the effect of cross-sectional dependencies, which has been a major source of concern about the validity of p-values from conventional test-statistics.

4.2 Buy-and-hold abnormal returns (BHARS) using one-to-one match samples

Even under the null hypotheses of no abnormal performance, the portfolio matching approach can result in positively skewed long-term abnormal returns (Cowan and Sergeant (2001)), which can inflate the mean abnormal returns and negatively bias some test statistics. This happens because long-run buy-and-hold returns of individual stocks show substantial positive skewness, while long-run buy-and-hold returns of portfolios are less skewed since they represent averages of many stocks. Furthermore, since the distribution of BHARs in the portfolio approach is not symmetric under the null hypothesis, non-parametric tests such as the Wilcoxon signed-rank test cannot be used to test the statistical significance of the abnormal returns.

To overcome the limitation of improperly specified non-parametric tests when using portfolios as benchmark, and to check for the robustness of our portfolio results, we use the one-to-one matching approach where each sample firm is matched to an appropriately chosen control firm. The potential candidates for matching to a sample firm are those firms that belong to the portfolio that the sample firm is assigned to in the portfolio matching approach. This ensures that the matched firm will at least be similar to the sample firm on size, market-to-book ratio, and prior performance. We then create three different one-to-one control samples as follows:

1. Select the firm that is closest in size to the sample firm from the sample firm's assigned portfolio (Size Matched).
2. Select the firm that is closest in terms of prior performance to the sample firm from the sample firm's assigned portfolio (Performance Matched).
3. Select the firm that has the best matching on SIC code to the sample firm from the sample firm's assigned portfolio. If at least a one-digit match is not possible, the sample firm is dropped from the analysis (Industry Matched).

The abnormal return for a sample firm is the difference between its buy-and-hold return and that of the control firm thus providing for symmetry under the null hypothesis. Statistical inference can then be based on both parametric as well as non-parametric tests.

To pool observations across time, for each firm in our sample, we translate calendar time to event time as follows. The announcement date is day 0 in event time, the next trading date is day 1, and trading day preceding the announcement day is day -1, and so on. Since a year typically has 250 trading days, we examine the stock price performance of our sample firms starting from day –251 through day 500, which spans three years in calendar time. We also report results for the year before the announcement (days –251 to –2), announcement period (days –1 and 0), the year after the announcement (days 1 to 250), and the second year after the announcement (days 251 to 500).

5.0 The long-term stock price effects

5.1 Results using matching portfolios

Table 2 presents the abnormal return results from the matched portfolio approach. Here and in all subsequent abnormal return results and tests, we winsorize abnormal returns at the 1% and 99% levels to remove the influence of outliers that can distort the mean values. Specifically, we identify the 1st and 99th percentile observations of our sample firms, and for all sample firms having returns greater than (less than) the 99th (1st) percentile, we replace that return with the 99th (1st) percentile observation. We report the mean and median abnormal returns. In addition, we report a simple non-parametric sign test based on the % of sample firms whose return is below the median return of all other firms that belong to the portfolio assigned to the sample firm.

During the year before the disruption announcement, the stock price performance of the sample firms fared poorly relative to the performance of the benchmark portfolios. The mean (median) abnormal return during this time period is -13.68% (-18.92%). A p-value of 0.001 indicates that the mean abnormal return of the sample firm is lower than mean abnormal returns of all the 1000 pseudo-portfolios abnormal returns. Of the 827 sample firms, nearly 60% of the sample firms do worse than the median return of the firms that belong to their assigned portfolios. If for a given sample firm the probability of its return being below the portfolio median return equals 0.5, then the probability of observing nearly 60% or more negative changes out of a sample of 827 is less than 1% (Binomial sign test Z-statistic is -5.53). The abnormal stock price performance during the year before the disruption announcement is negative and statistically significant. This suggests that the market partially anticipates disruptions and reflects part of the economic impact of the disruptions before the formal announcement of the disruptions.

As expected the stock price performance during the announcement period (days -1 and 0) is negative and statistically significant. The mean (median) abnormal return is -7.18% (-5.64%) and nearly 73% of the sample do worse than the median of their assigned portfolio. Although we use a different methodology than Hendricks and Singhal (2003a) and our sample is larger than that study employed, these results are consistent with their event study on a sample of 517 firms.

Even after the announcement of disruptions, firms continue to experience worsening stock price performance. In the year after the announcement sample firms on average lose another 10.45% relative to their benchmark portfolios. The median abnormal return is -20.91%. Nearly 56% of the sample firms do worse than the median return of the firms that belong to their assigned portfolios, significantly different from 50% at the 1% level. This suggests that the market has not fully capitalized the negative impact of the disruptions. The post-announcement negative abnormal performance may be because customers and suppliers who did not know about the supply chain problems are now reconsidering their relationships with the firm in terms of the amount of business they decide to do with the firm. In any event, the negative abnormal performance persists even after the announcement. The market underreacts to disruption announcements over the short term.

Although the mean abnormal return during the second year after the announcement is negative, it is not statistically significant. A p-value of 0.25 indicates that the mean abnormal returns of 250 pseudo portfolios are below the mean abnormal of –1.77% for the sample firms. 55% of the sample firms do worse than the median of their portfolio returns, significant different from 50% at the 1% level. Thus, the results for the second year after the announcement are mixed with the parametric test indicating insignificant abnormal performance and the non-parametric test indicating significant performance. Alternative methods of estimating abnormal performance as well as analysis of abnormal performance of various subsamples (discussed later) seem to support the view that during the second year the abnormal performance is statistically insignificant. More importantly, all of our results show that firms do not recover during this time period from the negative stock price performance that they experienced in the prior two years, indicating that the loss associated with disruptions is not short term.

Over the three-year time period that begins a year before the disruption announcement through two years after the announcement the mean abnormal return is -40.66% (p-value = 0.001). The median abnormal return is -59.94%. Nearly 67% of the sample firms do worse than the median return of the firms that belong to their assigned portfolios, significantly different than 50% at the 1% level. Note that the mean abnormal return of -41% over three years is nearly five to six times in magnitude when compared to the abnormal returns observed at announcement. Supply chain disruptions devastate stock prices over time and firms do not quickly recover from this devastation.

5.2 Results using one-to-one match samples

To check for the robustness of our portfolio results, we next report the results from the one-to-one matching approach where each sample is matched to an appropriately chosen control firm. As discussed earlier, we use three different control samples where each sample firm is matched to a control firm taken from its matched portfolio based either on closeness in size, performance, or industry. Table 3 presents these results. The sample size for the industry matched control sample is lower than the size or performance matched control samples since for some sample firms we could not find at least a one-digit match SIC code. Since the results across the three control samples are very similar, we focus our discussion on the size matched control sample.

The results from the one-to-one match sample approach are very consistent with the portfolio approach. When samples firms are matched on size, the mean and median abnormal returns during the year before the disruption are –13.51% and –11.29%, respectively, significantly different from zero at the 1% level. Nearly 58% of the sample firms experience negative abnormal performance, significantly different from 50% at the 1% level. Consistent with the portfolio results the stock price performance during the announcement period (days -1 and 0) is negative and statistically significant. The mean (median) abnormal return is -7.17% (-5.36%) and nearly 73% of the sample firms experienced negative abnormal performance. The negative abnormal stock price performance persists even after the disruption announcement. In the year after the announcement, the mean (median) abnormal return is –8.88% (-14.16%), with nearly 59% of the sample firms experiencing negative abnormal returns. These performance levels are highly significant.

Although the mean and median abnormal returns during the second year after the announcement are negative, they are not statistically significant. Nearly 54% of the sample firms experience negative abnormal returns, significantly different from 50% at the 1% level. Overall two out of three performance statistics are not statistically significant suggesting weak evidence of negative abnormal performance during the second year after announcement. As is the case with the portfolio results, the important thing to note is that there is no recovery from the negative abnormal performance observed in the prior two years.

Overall during the three-year time period, the mean abnormal return is –34.77%, the median abnormal return is –31.99%, and nearly 63% of the sample firms experience negative abnormal returns. These levels of negative performance are highly significant and similar to those from the portfolio method of estimating abnormal returns. Since the results from the two approaches are very similar, we focus the rest of our discussion using the results from the portfolio approach.

5.3 Sensitivity analysis using results from the matching portfolio

As mentioned earlier 374 (nearly 45%) of our sample announcements conveyed information about other firm-specific events besides supply chain disruptions. To examine whether these 374 announcements are driving the overall results, we estimate the abnormal stock price performance by excluding these announcements. Statistically significant negative abnormal stock price performance is observed during the year before the announcement, announcement period, and year after the announcement. Over the three-year time period the mean abnormal return is -37.36% (p-value = 0.001), median abnormal return is -53.04%, and over 65% of the sample firms do worse than the median return of the firms that belong to their assigned portfolios. These results are very similar to the results for the full sample. Thus, our results are not driven by systematic announcements that convey information about other firm-specific events.

The observed abnormal returns for the full sample are also not driven by disruptions that happened during certain time periods. Panel A of Table 4 presents abnormal returns for four different three-year subperiods: 1989-1991, 1992-1994, 1995-1997, and 1998-2000. Sample firms are assigned to a subperiod based on the announcement dates. Over the three-year time period, the mean abnormal returns are highly significant (p-value = 0.001) and range from -30% to -51%. The median abnormal returns are also negative and range from -48% to -67%. The percent of the sample firms that do worse than the median return of the firms that belong to their assigned portfolios are significantly higher than 50% in all four subperiods.. It does not matter when disruptions happen – they have a negative affect on stock prices.

Panel B of Table 4 gives the abnormal returns by size quintiles formed using CRSP's assignment of firm to size deciles based on the market value of equity. The results indicate that disruptions have a negative impact on stock prices across all size quintiles. Over the three-year time period, the mean (median) abnormal returns are highly significant and range from -20% to -65% (-34% to -78%). The percent of the sample firms that do worse than the median return of the firms that belong to their assigned portfolios are significantly higher than 50% in all size subsamples.. Although there is some evidence to suggest that mean abnormal returns for smaller firms are more negative than larger firms, the abnormal returns for larger firms are still economically significant. A -20% abnormal return for the largest firm (size deciles 9 and 10) and -33% for the next largest group (size deciles 7 and 8), suggest that the dollar impact on shareholder value is likely to be quite significant for larger firms. Overall, supply chain disruptions are bad news irrespective of the size of the firm.

We also note that for the various subperiods as well as the various size quintiles, statistically significant negative abnormal returns are observed during the year before the announcement, announcement period, and year after the announcement. There is no consistent evidence of statistical significant abnormal performance (positive or negative) during the second year after the disruption announcement.

5.4 Descriptive results

We next present some descriptive results on the abnormal returns by responsibility for disruptions, reasons for disruptions, and by various industry groups. Out of the 827 announcements, nearly 70% of the announcements gave information on who was responsible for the disruptions as well as the reasons for disruptions. Panel A of Table 5 indicates that the mean abnormal return over the three-year period is -35.69% for disruptions due to internal failures, -24.93% for supplier caused disruptions, and -52.88% for customer caused disruptions. All these changes are statistically significant at the 1% level or better. The percent of the sample firms that do worse than the median return of the firms that belong to their assigned portfolios are significantly higher than 50% in all three subsamples. Since we have not presented any specific hypotheses on the relation between responsibility and the extent of abnormal returns, we do not test whether the effects of internal, supplier, and customer caused disruptions are significantly different from each other. The important thing to observe is that it does not matter who caused the disruption: the firm that experiences the disruption pays a steep price. The results underscore the need to ensure that the various links in the supply chain (internal or external) are operating in a robust and reliable manner. The significant loss in share price could provide sufficient incentive for various links in the supply chain to work together to reduce the probability of disruptions in supply chains.

Of the more than 20 reasons that we are able to identify as the causes of disruptions, the four top ones with at least a sample size of 40 are part shortages, ramp-up and rollout problems, customer order changes, and various production problems. Panel B of Table 5 presents the three-year abnormal return statistics for these reasons. Parts shortages are associated with a statistically significant mean abnormal return of -25.48% (p-value = 0.003), with nearly 64% of the sample firms doing worse than the median return of the firms that belong to their assigned portfolios. Disruptions in ramping and rollout of new products and processes are associated with a mean abnormal return of –52.79% (p-value = 0.001), underscoring the importance that the market places on timely introduction of products and processes. Order changes by customers are associated with a mean abnormal return of –46.59% (p-value = 0.005), whereas disruptions caused by production problems are associated with a mean abnormal return of -41.67% (p-value = 0.001). Basically, the evidence indicates that it does not matter what caused the disruptions, the stock price effects are quite devastating.

We also estimated the abnormal returns by various industry groups. We define eight broad industry groups and assigne the sample firms to these groups based on their primary SIC codes. Table 6 reports results for five of these eight industry groups, as the remaining three had sample sizes less than 40. These five industry groups are:

Process Industry - primary SIC code between 2000-2999 (food, tobacco, textiles, lumber, wood, furniture, paper, and chemicals).

Batch manufacturing - primary SIC code between 3000-3569 or 3580-3659 or 3800-3999 (rubber, leather, stone, metals, machinery, equipment).

High Technology - primary SIC code between 3570-3579, 3660-3699 or 3760-3789 (computers, electronics, communications, defense).

Wholesale and retailing - primary SIC code between 5000-5999 (wholesaling, retailing).

Services - primary SIC between 6000-6999 (services, financial services, government).

The results indicate that disruptions have a negative impact across all industry groups. The mean abnormal returns range from -27% in the case of the high technology industry to -51% in the case of process industry. All these mean abnormal returns are significantly different from zero. The median abnormal returns range from -49% in the case of process industry to -77% in the case of wholesale and retailing. The percent of sample firms that do worse than the median return of the firms that belong to their assigned portfolios are significantly higher than 50% in all the five industry groups.

Finally, for the subsamples on responsibility, reasons, and industry, statistically significant negative abnormal returns are observed during the year before the announcement, announcement period, and year after the announcement. There is no consistent evidence of statistical significant abnormal performance (positive or negative) during the second year after the disruption announcement.

6.0 The effect of supply disruptions on risk

We next examine the effect of supply chain disruptions on risk by comparing the equity standard deviations before and after the disruption announcement date. We estimate equity standard deviations for four years, starting two years before (year -2 and year -1) through two years after the disruption announcement (year 1 and year 2). Each year consists of 250 trading days. To preclude the possibility of our risk estimates being unduly influenced from the unusual trading activity that may happen around the announcement date, we exclude a two-week interval (10 trading days) around both side of the announcement date in computing the standard deviations. We estimate the standard deviations using daily stock returns over the following four time periods:

Year -2: trading days -509 to -260

Year -1: trading days -259 to -10

Year 1: trading days 10 to 259

Year 2: trading days 260 to 509

Many of the papers that consider the impact of corporate events on risk changes perform their analysis based on a comparison of the risk levels of sample firms before and after the announcement date (see, for example, Fargher and Wilkins (1998), Dann et al. (1991), Hertzel and Jain (1991), and Bhagat et al. (1987)). This approach could misestimate the true risk changes as risk can be influenced by certain macro factors that may have nothing to do with the event under consideration. Such factors could include interest rates, investor sentiments, consumer confidence, market expectations, and global business environments etc. To control for such factors, we compare the percent changes in the equity standard deviations of our sample firms with that of a matched control sample. In other words we estimate the abnormal change in equity standard deviations. For this purpose, we use the same three control samples that we used to estimate the buy-and-hold abnormal returns calculation using one-to-one matching approach (see section 4.2). We refer to these controls as size matched, performance matched, and industry matched control samples.

6.1 Evidence on changes in equity standard deviation

Table 7 reports the summary statistics for abnormal changes in equity standard deviations, σ_e, for the sample firms computed using the three different control samples as benchmark. Year to year changes as well as the overall change from year -2 through year 2 are reported. Statistical inference is based on parametric as well as non-parametric tests. Since the results across the three control samples are very similar, we focus our discussion on the results from the size matched control sample.

From year -2 to year -1, the mean and median changes in abnormal equity standard deviations are negative, with less than 50% of the sample firms experiencing a positive abnormal change in equity standard deviations. However, none of these changes are statistically significant at the conventional five percent levels. Relative to the controls, there is not much change in the equity standard deviations of the sample firms from year -2 to year -1.

The results are quite different when we examine the changes from year -1 to year 1. The mean abnormal change in equity standard deviation is 13.50%, significant at the 1% level (t-statistic is 7.54). The median abnormal change in equity standard deviation is 9.81%, significant at the 1% level ((Z-statistic of the Wilcoxon signed rank test is 6.93). 58.82% of the abnormal changes are positive, significantly different from 50% at the 1% level (Z-statistic of the Binomial sign test is 5.03). Thus, both the parametric and non-parametric tests indicate that equity risk has significantly increased between year -1 and year 1. The increased risk during this time period could have partly contributed to the negative abnormal returns that we observe over this period.

Although the mean and median changes from year 1 to year 2 are positive, they are insignificantly different from zero. This is an important result for a number of reasons. First, it indicates that much of the risk increase is centered around the time that occurrence of disruptions are publicly announced. Second, the increase in equity standard deviations between year -1 and year 1 is not due to non-stationarity of standard deviations as changes in standard deviations between year -2 and year -1, and year 1 and year 2 are not statistically significant. Finally, the risk increase between year -1 and year 1 is not temporary, as the risk does not decrease in the subsequent years. Firms have a lower level of risk before they experience disruptions, disruptions increase the risk of the firm, and the risk of the firm stays at the higher level during the subsequent years.

The final column in Table 4 gives the magnitude of risk changes between year -2 and year 2 (a three-year period). The mean and median abnormal changes in equity standard deviations are 15.16% and 9.09%, respectively, both significant at the 1% level. 57.31% of the abnormal changes are positive, significantly different from 50% at the 1% level. Much of this change is due to the statistically significant risk increases observed between year -1 and year 1. Overall, we find strong evidence that disruptions cause a significant increase in equity risk.

6.2 Evidence on changes in financial leverage

As discussed in section 2.2, an increase in equity risk can be due to an increase in financial leverage and/or an increase in asset risk. To understand what caused the increase in equity risk, we next examine the changes in financial leverage as well as asset risk. As we did with equity risk, we estimate the abnormal change in financial leverage and asset risk by comparing the changes in the sample firms against the changes in firms that belong to the size matched, performance matched, and industry matched control samples.

Table 8 reports the abnormal changes in financial leverage for the sample firms. Financial leverage is expressed as the % of debt (measured by the book-value of total debt) to total value of the firm (measured as the sum of the book value of debt and the market value of equity). Financial leverage is computed using data from the most recent fiscal year completed before the beginning of a particular time period. The changes reported are the change in the level of financial leverage. For example, if the financial leverage of the firm increased from 10% to 20%, we report the change in the level that is 10% and not the percent change of 100%. The reason for doing this is that we cannot compute the percent change in financial leverage since the starting financial leverage for some of our sample firms is zero (no debt in the capital structure).

The evidence presented in Table 8 indicates that when the size matched and performance matched control samples are used, financial leverage increases from year -1 to year 1 are statistically significant, while changes are insignificantly different from zero from year -2 to year -1, and year 1 to year 2. With the size matched control sample, the mean and median increases in financial leverage are 3.50% and 2.16%, respectively, both significant at the 1% level. Nearly 59% of the sample firms experienced an increase in their financial leverage, which is significantly different from 50%. The pattern of changes is somewhat different when the industry matched control sample is used. In this case statistically significant increases in financial leverage are observed for all time periods, with the changes from year -1 to year 1 associated with the highest value of the test statistics. Overall, the results indicate that firms that experience supply chain disruptions experience a statistically significant abnormal change in financial leverage from year -2 to year 2. Thus, part of the increase in equity risk documented in Table 7 is because of the increase in financial leverage of the sample firms.

6.3 Evidence on changes in asset risk

Summary statistics for abnormal changes in asset standard deviations, σ_a, are reported in Table 9. We use equation (1) to estimate the asset standard deviations for both the sample and controls firms, and then compute the abnormal change as the difference between sample and control firms. The results depend on the control sample used. The abnormal change in asset risk from year -2 to year -1 is negative across all the three control samples, but only the changes using the industry matched control sample are statistically significant at typical levels.

The abnormal changes from year -1 to year 1 are positive, with the results based on size matched and performance matched control samples statistically significant. Thus, we see some evidence of asset risk increases during this time period. The asset risk changes from year 1 to year 2 are insignificant across all the three control samples. Over the three-year period from year –2 to year 2 the changes in asset risk are not significantly different from zero.

The results on asset risk changes are somewhat mixed but seem to suggest that the asset risk does increase as indicated by two of the three control samples used from year -1 to year 1. The results however are not as strong as that of the changes in equity risk (Table 7) and financial leverage (Table 8).

To summarize, the evidence on risk changes show that sample firms experience a significant increase in equity risk relative to the controls. Part of this increase is because the financial leverage of the sample firms increases more than that of the controls. The evidence although not as conclusive, indicates that the asset risk of sample firms also increases relative to the controls. Finally, it is important to note that the increases in equity and asset risk are not temporary. Once the risk level increases, it remains at that level for the next year or so.

7. Summary and discussion

This paper investigates the long-run stock price effects and risk effects due to supply chain disruptions. Based on a sample of 827 disruptions announced by publicly traded firms during 1989-2000, we find that over a three year time period starting one year before through two years after the disruption announcement date, the mean abnormal return of our sample firms is a nearly -40%. Some of this negative abnormal performance is observed during the year before the announcement, indicating that the market partially anticipates the disruption. Consistent with Hendricks and Singhal (2003a), the abnormal return during the announcement period is negative and statistically significant. We also observe statistically significant negative abnormal stock price performance in the year after the announcement, indicating that the market underreacts to announcement of disruptions. There is no evidence to indicate the stock price performance of disruption experiencing firms recovers anytime soon after the disruption.

Our investigation of the risk effects finds that disruptions are associated with increases in financial leverage and to a lesser extent asset risk, the net effect of which is to increase equity risk. We observe statistically significant increases in equity risk from the year before the announcement to the year after the announcement. Furthermore, we find that the equity risk increase is not temporary as firms stay at the higher risk level for at least the next year.

The significant negative economic consequences of disruptions and the lack of any evidence of quick recovery underscore the need to pay close attention to the risk of disruptions. Supply chains are perhaps more susceptible to disruptions today than a few years ago. Some of this is due to the structural changes in the product market itself. Many product markets are characterized by intense and increased competition, volatile demand, increased product variety, rapid changes in product technology, and short product life cycles, making it very challenging to match demand with supply. This increased risk of disruptions has been further exacerbated by recent trend and practices in managing supply chains including 1) increased complexity due to global sourcing, the large number of supply chain partners, the need to coordinate many tiers of supply chains, and long lead times; 2) increased reliance on outsourcing and partnering that has heightened the interdependencies of different nodes of the global supply network, making it more likely that a disruption or problem in one link of the supply chain will quickly ripple through the rest of the chain, bringing the whole supply chain to a halt; 3) single-sourcing strategies may have reduced purchase prices and the administrative costs of managing the supplier base but may have increased the vulnerability of supply chains if a single supplier is unable to deliver on time; and 4) focusing on reducing inventory, excess capacity, and slack in the supply chain has more tightly coupled the various links, leaving little room for errors.

There is no doubt that these trends and practices have led to improvements in supply chain performance particularly in reducing costs. However, they may have also contributed to supply chains becoming more vulnerable and susceptible to disruptions. At the minimum firms must carefully analyze the trade-offs between lower costs and negative economic consequences associated with higher risk of disruptions.

Even if major disruptions are infrequent, it can severely hamper a firm's stock price performance for years to come. Firms must anticipate and do whatever possible to avoid major disruptions. Better forecasting and better planning can go a long way to reduce the frequency of disruptions. Firms also need to develop the ability to predict disruptions, which involves selecting, defining, and tracking leading predictors of future performance and providing visibility into the extended supply chain that includes internal operations, suppliers, and customers. Since the negative consequences of disruptions are amplified when disruptions go undetected, firms need to develop the capability to learn about disruptions sooner rather than later, and aim for a lag time of zero between occurrence and detection. Real-time visibility within their extended supply chains can help on this dimension. Finally, firms must be able to resolve the problem quickly and prevent escalation and worsening of the situation. This requires developing a systematic process for dealing with and responding to disruptions, with clear identification of responsibilities and allocation of resources, and learning from past disruptions

Although the specific focus area will vary across firms, developing real-time visibility capability into the performance of the extended supply chain would be very critical in anticipating disruptions and mitigating the adverse economic effects of disruptions. Both practitioners and academics have argued that this would require organizational changes and investments in initiatives such as integrated planning across various functions; collaboration and information sharing with other partners in the supply chain; as well as investments in information technology.

Our results underscore why firms need to focus on improving the reliability and responsiveness of their supply chains. Unlike efficiency improving or cost reduction activities, where return on investment is easy to compute, it is much harder to make a business case for investments that improve the reliability and responsiveness of supply chains. The evidence presented in this paper can help with the business case. Investments in increasing reliability and responsiveness of supply chains could be viewed as buying insurance against the economic loss from disruptions.

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Table 1: Description of the sample of 827 announcements of supply chain disruptions

Panel A: Descriptive statistics for the sample of 827 announcements of supply chain disruptions.

Measure	Mean	Median	Std. Dev.	Maximum	Minimum
Sales ($million)	2047.6	116.8	11438	160121	0.01
Equity Market value ($million)	1849.1	117.6	9702	145227	0.92
Total Assets ($million)	2437.8	102.3	17269	279097	0.93
Operating Income ($million)	56.3	3.7	286.2	6845	-23498
Employment (thousands)	9.6	0.7	47.86	750	0.01

Panel B: Distribution of the announcement year for the sample of 827 announcements of supply chain disruptions.

Year	Number of Announcements	% of Announcements
1989	43	5.12%
1990	30	3.63%
1991	30	3.63%
1992	43	5.12%
1993	50	6.05%
1994	61	7.38%
1995	77	9.31%
1996	92	11.12%
1997	99	11.97%
1998	117	14.14%
1999	97	11.73%
2000	88	10.64%
1989-1999	827	100.00%

Table 2: Buy-and-hold abnormal returns of firms experiencing supply chain disruptions using the matching portfolio approach where each sample firm is assigned to one of the 210 benchmark portfolios formed on the basis of size, market-to-book ratio, and prior performance. Abnormal performance is calculated as the difference between the buy-and-hold return for the sample firm and the average buy-and-hold return of the firms in the matching portfolio. The p-values are calculated using the empirical distribution created from 1000 replications of pseudo portfolios. The Binomial sign test is used to test whether the % of sample firm returns less than the median return of the firms that belong to their assigned benchmark portfolios is different from 50%.

Performance Statistics	Time period				
	Year before announcement (days -251 to -2)	Announcement period (days -1 to 0)	1st year after announcement (days 1 to 250)	2nd year after announcement (days 251 to 500)	one year before thorough two years after announcement (days -251 to 500)
Number of observations	827	826	827	826	827
Mean abnormal returns (%)	-13.68%	-7.18%	-10.45%	-1.77%	-40.66%
p-value based on the rank in the empirical distribution	0.001	0.001	0.001	0.25	0.001
Median abnormal returns (%)	-18.92%	-5.64%	-20.91%	-9.70%	-59.94%
% of abnormal returns less than the portfolio median	59.62%	72.64%	62.91%	55.45	66.39%
Binomial sign test Z-statistic for % of abnormal returns less than the portfolio median	-5.53 a	-12.91 a	-7.43 a	-3.13 a	-9.43 a

a denotes significantly different from 50% at the 1% level in two-tailed tests.

Table 3: Buy-and-hold abnormal returns of firms experiencing supply chain disruptions using the one-to-one matching approach where each sample firm is matched to a firm from its assigned portfolio out of 210 portfolios formed on the basis of size, market-to-book ratio, and prior performance. Abnormal performance is calculated as the difference between the buy-and-hold return for the sample firm and its matched firm. Size (performance) matched control sample picks as control the firm that is closest in size (performance) to the sample firm from the sample firm's assigned portfolio. Industry matched control sample picks as control the firm that is closest on SIC code to the sample firm from the sample firm's assigned portfolio with at least a one-digit matching. T-statistics for the mean, Wilcoxon signed-rank test Z-statistic for the median, and Binomial sign test Z-statistic for the % negative are reported in parentheses.

	Obs	Mean	Median	%Neg.	Obs	Mean	Median	%Neg.	Obs	Mean	Median	%Neg.
Year before announcement	827	-13.51%	-11.29%	57.68%	827	-11.86%	-11.76%	58.17%	773	-14.01%	-10.97%	57.18%
(days -251 to -2)		(-4.70) a	(-4.83) a	(-4.42) a		(-4.53) a	(-5.02) a	(-4.70) a		(-4.89) a	(-4.31) a	(-4.13) a
Announcement period	826	-7.17%	-5.36%	73.17%	826	-6.81%	-4.98%	71.31%	772	-7.81%	-6.15%	72.93%
(days -1 to 0)		(-15.72) a	(-14.67) a	(-13.32) a		(-14.51) a	(-13.69) a	(-12.25) a		(-15.64) a	(-14.24) a	(-13.18) a
1st year after announcement	827	-8.88%	-14.16%	58.77%	827	-7.10%	-11.09%	55.87%	773	-9.21%	-7.44%	56.67%
(days 1 to 250)		(-4.65) a	(-4.65) a	(-5.04) a		(-2.43) b	(-3.91) a	(-3.38) a		(-2.81) a	(-3.16) a	(-3.84) a
2nd year after announcement	826	2.38%	-2.67%	54.12%	826	0.13%	-2.81%	54.12%	772	-2.55%	-3.01%	54.67%
(days 251 to 500)		(0.85)	(-1.12)	(-2.37) b		(0.04)	(-1.39)	(-2.37) b		(-0.86)	(-1.85)	(-2.60) a
One year before thorough two years after announcement	827	-34.77%	-31.99%	62.88%	827	-32.21%	-22.83%	62.04%	773	-38.40%	-25.97%	61.97%
(days -251 to 500)		(-6.77) a	(-7.94) a	(-7.41) a		(-6.05) a	(-7.21) a	(-6.92) a		(-6.89) a	(-7.46) a	(-6.88) a

a and b denote significantly different from zero (50% in the case of % negative) at the 1% and 2.5% levels, respectively, for two-tailed tests.

Table 4: Buy-and-hold abnormal returns of firms experiencing supply chain disruptions segmented by time period and size. Abnormal returns computed using the matching portfolio approach where each sample firm is assigned to one of the 210 benchmark portfolios formed on the basis of size, market-to-book ratio, and prior performance. Performance numbers are reported for the time period that begins one year before and ends two years after the disruption announcement. The p-values in parentheses for the mean abnormal returns are calculated using the empirical distribution created from 1000 replications of pseudo portfolios. The Binomial sign test is used to test whether the % of sample firm returns less than the median return of the firms that belong to their assigned benchmark portfolios is different from 50%.

Subsamples	Number of Observations	Mean Abnormal Returns	Median Abnormal Returns	% of sample returns less than its portfolio median
Panel A - Time period				
1989-1991	103	-33.62% (0.001)	-47.54%	61.17% b
1992-1994	154	-29.38% (0.001)	-58.40%	64.94% a
1995-1997	268	-51.37% (0.001)	-66.72%	70.15% a
1998-2000	302	-37.79% (0.001)	-58.25%	65.57% a
Panel B - Firm Size				
Size deciles 1 and 2 - smallest firms	132	-47%.05 (0.001)	-70.49%	65.16% a
Size deciles 3 and 4	158	-64.28% (0.001)	-78.24%	70.89% a
Size deciles 5 and 6	163	-46.68% (0.001)	-68.25%	66.26% a
Size deciles 7 and 8	182	-32.35% (0.001)	-56.83%	63.39% a
Size deciles 9 and 10 - largest firms	190	-19.6% (0.009)	-34.19%	64.22% a

a and b denotes significantly different from 50% at the 1% and 2.5% level, respectively in two-tailed tests

Table 5: Buy-and-hold abnormal returns of firms experiencing supply chain disruptions segmented by responsibility and reasons for disruptions. Abnormal returns computed using the matching portfolio approach where each sample firm is assigned to one of the 210 benchmark portfolios formed on the basis of size, market-to-book ratio, and prior performance. Performance numbers are reported for the time period that begins one year before and ends two years after the disruption announcement date. The p-values in parentheses for the mean abnormal returns are calculated using the empirical distribution created from 1000 replications of pseudo portfolios. The Binomial sign test is used to test whether the % of sample firm returns less than the median return of the firms that belong to their assigned benchmark portfolios is different from 50%.

Subsamples	Number of Observations	Mean Abnormal Returns	Median Abnormal Returns	% of sample returns less than its portfolio median
Panel A - Responsibility for disruptions				
Internal failure	278	-35.69% (0.001)	-47.51%	64.75% a
Supplier	120	-24.93% (0.013)	-41.97%	62.66% a
Customer	106	-52.88%(0.001)	-71.62%	72.65% a
Panel B - Reasons for disruptions				
Parts Shortages	179	-25.48% (0.003)	-47.96%	63.69% a
Rampup & rollout	74	-52.79% (0.001)	-72.68%	74.33% a
Customer order changes	73	-46.59% (0.005)	59.94%	69.87% a
Various production problems	70	-41.67% (0.001)	-37.18%	64.29% b

a and b denotes significantly different from 50% at the 1% and 2.5% level, respectively in two-tailed tests

Table 6: Buy-and-hold abnormal returns of firms experiencing supply chain disruptions segmented by industry. Abnormal returns computed using the matching portfolio approach where each sample firm is assigned to one of the 210 benchmark portfolios formed on the basis of size, market-to-book ratio, and prior performance. Performance numbers are reported for the time period that begins one year before and ends two years after the disruption announcement. The p-values in parentheses for the mean abnormal returns are calculated using the empirical distribution created from 1000 replications of pseudo portfolios. The Binomial sign test is used to test whether the % of sample firm returns less than the median return of the firms that belong to their assigned benchmark portfolios is different from 50%.

Subsamples	Number of Observations	Mean Abnormal Returns	Median Abnormal Returns	% of sample returns less than its portfolio median
Process Industry	95	-51.12% (0.001)	-48.81%	63.16% a
Batch Manufacturing	256	-47.65% (0.001)	-58.26%	66.80% a
High Technology	243	-27.31 % (0.001)	-64.77%	65.44% a
Wholesale and Retailing	72	-42.21% (0.001)	-77.26%	70.84% a
Services and others	72	-35.84 (0.030)	-58.67%	64.39% a

a denotes significantly different from 50% at the 1% in two-tailed tests

Table 7: Summary statistics on abnormal changes in equity standard deviations, σ_e, for firms announcing supply chain disruptions in years surrounding the announcement date. Abnormal performance is calculated as the difference between the percent change for the sample firm and its matched firm. Size (performance) matched control sample picks as control the firm that is closest in size (performance) to the sample firm from the sample firm's assigned portfolio. Industry matched control sample picks as control the firm that is closest on SIC code to the sample firm from the sample firm's assigned portfolio with at least a one-digit matching. Equity standard deviations are estimated using daily stock returns for days -509 to –260 (year –2), -259 to –10 (year –1) 10 to 259 (year 1), and 260 to 509 (year 2). T-statistics for the mean, Wilcoxon signed-rank test Z-statistic for the median, and Binomial sign test Z-statistic for the % positive are reported in parentheses.

	Time period			
Performance statistics of changes in equity standard deviation (σ_e)	Year -2 to Year -1	Year -1 to Year 1	Year 1 to Year 2	Year -2 to Year 2
Relative to size matched control sample				
Number of Observations	827	816	752	752
Mean abnormal change in standard deviation	-1.74% (-1.08)	13.50% (7.54) a	2.82% (1.50)	15.16% (4.84) a
Median abnormal change in standard deviation	-0.95% (-1.67)	9.81% (6.93) a	1.88% (1.09)	9.09% (4.60) a
% of abnormal changes that are positive	48.12% (-1.08)	58.82% (5.03) a	51.72% (0.94)	57.31% (4.01) a
Relative to performance matched control sample				
Number of Observations	827	816	752	752
Mean abnormal change in standard deviation	-2.22% (-1.15)	12.78% (6.47) a	2.46% (1.61)	14.81% (4.29) a
Median abnormal change in standard deviation	0.40% (-0.59)	10.20% (6.84) a	2.01% (1.83)	7.66% (4.56) a
% of abnormal changes that are positive	50.66% (0.38)	59.68% (5.53) a	52.52% (1.38)	56.64% (3.64) a
Relative to industry matched control sample				
Number of Observations	757	747	688	688
Mean abnormal change in standard deviation	-2.07% (-1.17)	9.50% (4.30) a	3.36% (1.67)	9.55% (2.20) c
Median abnormal change in standard deviation	-1.06% (-1.60)	7.84% (4.96) a	1.21% (1.49)	5.1% (3.04) a
% of abnormal changes that are positive	47.69% (-1.29)	58.50% (4.65) a	51.01% (0.53)	53.05% (1.60)

a, b, and c denote significantly different from zero (50% in the case of % positive) at the 1%, 2.5%, and 5% levels, respectively, for two-tailed tests.

Table 8: Summary statistics on abnormal changes in financial leverage for firms announcing supply chain disruptions in years surrounding the announcement date. Abnormal performance is calculated as the difference between the percent change for the sample firm and its matched firm. Size (performance) matched control sample picks as control the firm that is closest in size (performance) to the sample firm from the sample firm's assigned portfolio. Industry matched control sample picks as control the firm that is closest on SIC code to the sample firm from the sample firm's assigned portfolio with at least a one-digit matching. Financial leverage is expressed as the % of debt (measured by the book-value of total debt) to total value of the firm (measured as the sum of the book value of debt and the market value of equity). Financial leverage is computed using data from the most recent fiscal year completed before the beginning of a particular time period. T-statistics for the mean, Wilcoxon signed-rank test Z-statistic for the median, and Binomial sign test Z-statistic for the % positive are reported in parentheses.

Performance statistics of changes in financial leverage	Year -2 to Year -1	Year -1 to Year 1	Year 1 to Year 2	Year -2 to Year 2
Relative to size matched control sample				
Number of Observations	816	785	727	722
Mean abnormal change in level of financial leverage	0.31% (0.57)	3.50% (5.61) a	0.10% (0.16)	3.82% (3.89) a
Median abnormal change in level of financial leverage	0.01% (0.65)	2.16% (6.07) a	0.04% (1.33)	2.47% (4.08) a
% of abnormal changes that are positive	50.61% (0.35)	58.98% (5.03) a	51.23% (0.67)	58.03% (4.32) a
Relative to performance matched control sample				
Number of Observations	815	783	731	726
Mean abnormal change in level of financial leverage	0.59% (1.04)	3.82% (5.71) a	0.39% (0.59)	4.64% (4.62) a
Median abnormal change in level of financial leverage	0.18% (1.27)	2.41% (6.54) a	-0.01% (0.10)	1.69% (4.31) a
% of abnormal changes that are positive	51.90% (1.09)	61.11% (6.22) a	49.18% (-0.44)	53.93% (2.11) c
Relative to industry matched control sample				
Number of Observations	750	717	673	670
Mean abnormal change in level of financial leverage	1.36% (2.45) b	2.99% (4.50) a	1.39% (1.98) c	5.22% (5.13) a
Median abnormal change in level of financial leverage	0.33% (2.78) a	1.64% (4.96) a	0.88% (2.57) a	4.01% (5.49) a
% of abnormal changes that are positive	53.60% (1.97) c	59.62% (5.15) a	54.83% (2.51) b	59.02% (4.67) a

a, b, and c denote significantly different from zero (50% in the case of % positive) at the 1%, 2.5%, and 5% levels, respectively, for two-tailed tests.

Table 9: Summary statistics on abnormal changes in asset risk, σ_a, for firms announcing supply chain disruptions in years surrounding the announcement date. Abnormal performance is calculated as the difference between the percent change for the sample firm and its matched firm. Size (performance) matched control sample picks as control the firm that is closest in size (performance) to the sample firm from the sample firm's assigned portfolio. Industry matched control sample picks as control the firm that is closest on SIC code to the sample firm from the sample firm's assigned portfolio with at least a one-digit matching. Asset risk, σ_a, is computed as $\sigma_a = \sigma_e*(E/(D+E))$ where D is the book value of total debt, and E is the market value of equity. T-statistics for the mean, Wilcoxon signed-rank test Z-statistic for the median, and Binomial sign test Z-statistic for the % positive are reported in parentheses.

Performance statistics of changes in asset standard deviation (σ_a)	Time period			
	Year -2 to Year -1	Year -1 to Year 1	Year 1 to Year 2	Year -2 to Year 2
Relative to size matched control sample				
Number of Observations	816	780	709	705
Mean abnormal change in standard deviation	-3.04% (-1.62)	6.31% (2.51) b	0.01% (0.004)	3.48% (1.10)
Median abnormal change in standard deviation	-2.57% (1.88)	4.30% (2.44) b	2.06% (0.26)	3.36% (0.99)
% of abnormal changes that are positive	47.18% (-1.61)	53.97% (2.21) c	51.90% (1.01)	52.91% (1.54)
Relative to performance matched control sample				
Number of Observations	815	779	711	707
Mean abnormal change in standard deviation	-3.38% (-1.53)	1.25% (0.26)	0.25% (0.11)	2.88% (0.87)
Median abnormal change in standard deviation	-0.33% (-0.73)	5.43% (2.28) b	0.90% (0.546)	1.60% (0.80)
% of abnormal changes that are positive	49.57% (-0.25)	54.17% (2.33) b	50.77% (0.41)	51.49% (0.79)
Relative to industry matched control sample				
Number of Observations	750	717	655	652
Mean abnormal change in standard deviation	-4.17% (-2.26) b	4.59% (1.53)	-1.37% (-0.61)	-2.90% (-0.81)
Median abnormal change in standard deviation	-3.94% (-3.31) a	2.22% (1.35)	-1.58% (-1.09)	-3.37% (-1.01)
% of abnormal changes that are positive	45.2% (-2.63) a	53.13% (1.68)	48.09% (-0.98)	47.85% (-1.10)

a, b, and c denote significantly different from zero (50% in the case of % positive) at the 1%, 2.5%, and 5% levels, respectively, for two-tailed tests.