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SURGING VOLATILITY: AN INTERNET EFFECT?

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Abstract

This paper analyzes the impact of firms' adoption of online retailing on their stock price volatility. Given the nascency of the Web, firms moving online are faced with an increased uncertainty in their product markets in addition to fixed setup costs. A simple model illustrates how increased uncertainty in the product markets increases the volatility of the firm's profits and its stock price. Results consistent with the model are confirmed by an empirical analysis of the volatility of stock prices of traditional firms adopting online-retailing. Both the traditional event study methodology as well as the structural break analysis reveal a distinct surge in volatility of firms' stock prices around the date of announcement of their online-retailing operations, an effect that is absent in a matched sample of traditional firms. More interestingly, the volatility-surge is absent for the sample of firms that moved online prior to June 1998. Ongoing research examines possible drivers and the implications of these phenomena for investors, firms, and regulatory authorities.

Keywords: Electronic commerce, online retailing, volatility, structural break analysis.

INTRODUCTION AND MOTIVATION

Despite the recent slump in the stock prices of online start-ups, there has been a steady growth of traditional firms adopting emerging technology-driven channels such as the Web for commerce. The Web, as a channel for commerce, (1) provides firms direct access to consumers and new geographic markets and enables personalization and customization of product and services, (2) *increases competition* by reducing search costs and switching costs for consumers, creating new substitutes, lowering barriers to entry, increasing ease of imitation, increasing ease of entry into new product markets (due to increased demand-side economies of scale and positive externalities), blurring firm and industry boundaries (due to converging technologies, channels, and product markets), and (3) enables disintermediation, altering the bargaining power among channel members. In addition, new technologies trigger rampant experimentation, by both companies and customers, more so in the initial stages of adoption and growth. All this has lead to the creation of a new and uncertain environment, particularly for traditional firms that move online.

While it is widely believed that emerging technologies including the Web have contributed to the overall increase in market volatility in recent years, there has been no systematic study of this phenomenon. Our research aims to analyze some of these

important economic shifts and examine their implications for investors and firms. This paper focuses on the impact of increased uncertainty, particularly in a firm's product market, on its stock price volatility. The next section provides a brief review of related work and in the third section we derive a theoretical model that illustrates how increased uncertainty in *product markets* translates into a higher volatility of stock returns. The empirical methodologies that are used to examine the volatility of stock prices of traditional firms adopting online retailing are then described and conclusions presented.

A BRIEF REVIEW OF LITERATURE

Not much academic literature exists on the impact of online operations on the prices and price-volatility of firms' equity. An exception is the study by Subramani and Walden (2001), which looks at the impact of moving online on a firm's stock returns and finds a positive announcement effect on stock returns. Perotti and Rossetto (2000) study the impact of demand uncertainty in product markets on firms' profits. Their focus is on the valuation of Internet portals that are modeled as a portfolio of entry options. A number of studies in the finance literature examine the impact of various corporate events on firms' stock return volatility. For instance, Clayton et al. (2001) examine the impact of CEO turnover on return volatility. The event study methodology of this paper closely follows that in Clayton et al. The matched sample methodology for detecting abnormal performance follows the one suggested in Barber and Lyon (1996).

A SIMPLE MODEL OF DEMAND UNCERTAINTY

In this section we model the impact of increased uncertainty in the product markets for a traditional firm. Initially, the firm faces a stochastically varying inverse demand process θ_t in its traditional market, which is modeled as a diffusion process in continuous time. It maximizes its profit function $\pi_{lt} = (\theta_t - Q)Q$, where "Q" is the demand in its traditional channel. The optimal profit for a monopoly firm is given by $\pi_{lt} = 1/4(\theta_t^2)$. Let $x_t = 1/4(\theta_t^2)$. Its evolution can be expressed as a Geometric Brownian Motion (Merton, 1992), i.e.,

$$dx_t = x_t (\boldsymbol{\mu}_1 dt + \boldsymbol{\sigma}_1 dW_t)$$

so that

$$x_t = x_0 \exp\left(\left(\frac{2}{\mu_1 - \frac{\sigma_1}{2}}\right)t + \sigma_1 W_t\right)$$

Thus, expected profit is

$$\boldsymbol{\pi}_1 = E\left[\int_0^\infty x_t \exp(-rt)dt\right] = \frac{x_0}{r - \boldsymbol{\mu}_1}$$

and variance of the profit is

$$Var(\boldsymbol{\pi}_{1}) = E\left[\boldsymbol{\pi}_{1}^{2}\right] - \left[E\left[\boldsymbol{\pi}_{1}\right]\right]^{2} = x_{0}\left(\frac{\frac{1}{2}\left(\boldsymbol{\sigma}_{1}^{2}\right)}{\left(r-\boldsymbol{\mu}_{1}\right)^{2}\left(r-\boldsymbol{\mu}_{1}-\frac{1}{2}\left(\boldsymbol{\sigma}_{1}^{2}\right)\right)}\right)$$

When the traditional firm adopts online retailing it incurs a fixed set-up cost, indicated by *I* and is also faced with an increased uncertainty in its demand, which is captured by a stochastically evolving multiplier γ . The firm therefore maximizes the objective function $\gamma_t(\theta_t - Q)Q_t$ and the maximized profit process is $\pi_{2t} = \gamma_t x_t - I$. The evolution of γ_t is assumed to be given by the process

$$d\boldsymbol{\gamma}_t = \boldsymbol{\gamma}_t (\boldsymbol{\mu}_2 dt + \boldsymbol{\sigma}_2 dB_t)$$

where corr $(B_t, W_t) = 0$.

This implies that

$$\boldsymbol{\gamma}_t = \boldsymbol{\gamma}_0 \exp\left(\left(\boldsymbol{\mu}_2 - \frac{\boldsymbol{\sigma}_2}{2}\right)t + \boldsymbol{\sigma}_2 B_t\right)$$

The expected profit and the variance of the profit are then given by

$$\boldsymbol{\pi}_{2} = E \begin{bmatrix} \boldsymbol{\alpha} \\ \boldsymbol{\beta} \\ \boldsymbol{\gamma}_{t} x_{t} \exp(-rt) dt \end{bmatrix} - I = \frac{\boldsymbol{\gamma}_{0} x_{0}}{r - \boldsymbol{\mu}_{1} - \boldsymbol{\mu}_{2}} - I$$

$$Var(\boldsymbol{\pi}_{2}) = \boldsymbol{\gamma}_{0} x_{0} \left(\frac{\frac{1}{2} \left(\boldsymbol{\sigma}_{1}^{2} + \boldsymbol{\sigma}_{2}^{2}\right)}{\left(r - \boldsymbol{\mu}_{1} - \boldsymbol{\mu}_{2}^{2}\right)^{2} \left(r - \boldsymbol{\mu}_{1} - \frac{1}{2} \left(\boldsymbol{\sigma}_{1}^{2}\right) - \boldsymbol{\mu}_{2}^{2} - \frac{1}{2} \left(\boldsymbol{\sigma}_{2}^{2}\right) \right)} \right) + 2I^{2}$$

The ratio of the two variances $Var(\pi_2)/Var(\pi_l)$ is always greater than 1,¹ implying that the effects of higher demand uncertainty and fixed-cost of entry due to moving online would always lead to an increase in the volatility of the firm's profit or net cash flow in each period, which translates into higher price volatility.

EMPIRICAL ANALYSIS

Data: An event in the context of this study is defined as the announcement of a traditional firm's online retailing initiative and the level of analysis is the individual firm. The data set consists of announcements by traditional firms that are publicly traded on the NYSE or Nasdaq, and for which the stock prices are available for a substantial period before and after the event. There are 166 firms in our sample with event dates between 1995 and 2000, after dropping firms that lack an adequate trading history or firms whose announcements are confounded by announcements of earnings or alliances and mergers. This data set is compiled primarily from leading new sources—PR Newswire, Business Wire, Hoover's Online, and the Lexis/Nexis database. The focus is primarily on B2C commerce, and hence firm announcements concerning B2B initiatives are neglected. Since the focus is on online retailing, we disregard firms that only have an informational Web site without any transaction capabilities. Daily stock-return data and market data are collected from CRSP files.

Impact of the Event on Stock Price Volatility: Following the standard event study methodology, we realign the stock returns of the sample firms in event time. Using pre-event and post-event windows of six months to two years, we estimate a market model for volatility for each window. This model essentially controls for the changes in market volatility and allows us to compute excess volatility, λ , which is defined to be the ratio of stock return volatility and the market return volatility over a particular period. The volatilities are all estimated by the sample variances of daily returns over the relevant period. We compute the pre-event and post-event λ s of each stock in calendar time and then take a cross-sectional average of individual λ s in event time (see Table 1, Panel A). It is interesting to note that except for the three-month windows, the average λ jumps significantly from pre-

¹Detailed proofs are available upon request.

event to post-event period. The ratio of post-event to pre-event average λ varies between 1.32 and 1.95. The jump is statistically significant as well, using a standard t-test. This indicates that moving online is associated with a volatility increase. We then split the sample into two parts, part one with event dates prior to June 1998 and part two with event dates after June 1998 (see Table 1, Panels B and C). We find that firms with event dates before June 1998 show almost no jump in volatility associated with the event and most of the effect noted above for the overall sample can be attributed to firms that moved online after June 1998, a period that coincides with the surging popularity of the Web.

Table 1. Pre- and Post-Event Excess Volatility

	Test Sample				Matched-Sample			
Window Length	Pre-event Average λ	Post-event Average λ	Ratio Post/Pre	t-stat	Pre-event Average λ	Post-event Average λ	Ratio Post/Pre	t-stat
1 year	30.97	60.24	1.95	6.07	31.08	51.21	1.65	2.51
6 months	44.14	58.48	1.32	2.73	36.34	50.70	1.39	1.73
3 months	62.41	62.61	1.00	0.02	42.17	46.10	1.09	0.55
2 years	34.11	60.07	1.76	5.72	32.88	51.32	1.56	2.44

Panel A. Full Sample Results (166 firms)

Panel B. Sub-sample I (Pre-June 1998) Results (56 firms)

	Test Sample				Matched-Sample			
Window Length	Pre-event Average λ	Post-event Average λ	Ratio Post/Pre	t-stat	Pre-event Average λ	Post-event Average λ	Ratio Post/Pre	t-stat
1 year	37.49	37.84	1.01	0.06	32.76	34.02	1.04	0.12
6 months	44.84	42.31	0.94	-0.33	32.50	37.71	1.16	0.51
3 months	53.34	57.26	1.07	0.26	38.13	29.97	0.79	-1.03
2 years	39.18	35.60	0.91	-1.12	32.09	33.60	1.05	0.16

Panel-C: Sub-sample II (Post-June 1998) Results (110 firms)

	Test Sample				Matched-Sample			
Window Length	Pre-event Average λ	Post-event Average λ	Ratio Post/Pre	t-stat	Pre-event Average λ	Post-event Average λ	Ratio Post/Pre	t-stat
1 year	27.65	71.65	2.59	6.98	30.22	59.96	1.98	2.73
6 months	43.79	66.71	1.52	3.40	38.30	57.31	1.50	1.67
3 months	67.03	65.34	0.97	-0.17	44.22	54.31	1.23	1.00
2 years	31.52	72.53	2.30	6.63	33.29	60.34	1.81	2.62

Figures 1(A), 1(B), and 1(C) illustrate the changes in excess volatility around the event date. The λ of each stock each month (using daily returns) for 24 months before and after the event was computed and the individual λ s for each month were then averaged cross-sectionally in the event time. The time-series of average λ are plotted in Figure 1. The notable result is the spike in λ at the event date, which can be seen in Figure 1(A). This is consistent with the results in Table 1 that the event is associated with a volatility increase. Figures 1(B) and 1(C) illustrate the results of the analysis with the two sub-samples, confirming that firms moving online after June 1998 had a strong surge in volatility unlike those that moved prior to June 1998.

Matched-Sample Analysis: It is possible that the volatility increase that we observe could be caused by unobservable factors unrelated to the firms' adoption of online retailing. To rule out this possibility, we repeat the above event study in a matched-sample of firms. We construct a matched-sample of firms as follows. For each firm in the test sample, we find a matching firm

which satisfies two criteria viz., (1) it is in the same market capitalization decile as the firm in the test sample and (2) within this size decile, its compounded return in the two years prior to the event date is the closest to that of the test firm. This methodology closely follows that recommended by Barber and Lyon (1996). If the matching firm happens to be an Internet pure-play or an Internet-related firm, we select the next-best match. Size and past returns are well known to be among the most important influences on the volatility of individual stocks, and hence a control for size and past returns should account for volatility changes not related to the event under consideration.





We repeat the event study described in the previous section on the matched-sample of firms and the results are shown in Table 1. For the six-month window lengths, the values of post-event to pre-event ratio of λ s are similar in the test sample and the matched-sample. However, for longer windows of one and two years, the volatility increase is statistically and economically much more significant for the test sample compared to the matched-sample. The hypothesis of no change in abnormal volatility even for the matched-sample is rejected, albeit with much smaller t-statistics. This could be attributable to a general increase in volatility of individual stocks compared to the market in the latter periods of the sample. Figures 2(A), 2(B), and 2(C) depict the monthly average λ s for the matched-sample. No spike in average λ is seen at the event date, though the general level of average λ is higher in the post-event period than in the pre-event period.



Figure 2. Event Study Analysis—Matched Sample

Structural Break Analysis: We study the effects of the event on volatility in a new setting as well. We postulate that the return volatility of these firms undergoes a fundamental change when they adopt online retailing. We thus expect a *structural break* in the volatility process around the event date. We adopt the methodology used by Banerjee et al. (1992) (BLS1) and Bai et al. (1998) (BLS2). These papers contain two key observations viz. (1) that tests can be constructed to determine whether or not a structural break occurred in the data and (2) that confidence intervals can be computed enabling inference about the break date. Finite sample properties of these test statistics are investigated in BLS2. The tests are shown to have good size and power properties under the null hypothesis of no break and the alternative of a breaking mean, respectively.

This methodology is used to detect the breaks in the average λ series computed as the ratio of 12-month rolling stock volatility to market volatility (see Merton 1980; Officer 1973). The average λ series is used instead of individual λ series to gain power. The average rolling λ series for the full sample, pre-June 1998 sample and post-June 1998 sample are shown in Figures 3(A), 3(B), and 3(C) respectively. The formal test for structural break using a Wald statistic confirms this result. The pattern here is similar to the one seen in Figure 1 with non-smoothed λ series. In the overall sample, as in the post-June 1998 sample, we see a sharp spike in λ (and the Wald statistic) around the event date. The 1% confidence band of the break date includes the event date and is quite narrow, covering a period of only about four months. This is a very clear evidence of a break at the event date for the average λ series. From Figure 3(B), it can be seen that the pre-1998 sample does not show a structural break in average λ at the event date. These results are consistent with those of the event study.



Figure 3. Structural Break Analysis

SUMMARY AND ONGOING RESEARCH

This paper examines the impact of increased uncertainty in a firm's demand as a consequence of adopting a new distribution channel. Two independent empirical methodologies show that the stock prices of traditional firms that adopt online retailing become systematically more volatile around the time of adoption, consistent with the results of the analytical model, and a matched sample analysis confirms the robustness of the findings. While the model highlights the impact of increased product-market-related uncertainty, other possible causes for the increased volatility are being examined to weed out any market microstructure effects such as a change in the volume of trades, size, and mix of trades (retail vs. institutional trades). The analytical model is also being extended to a dynamic competitive setting.

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