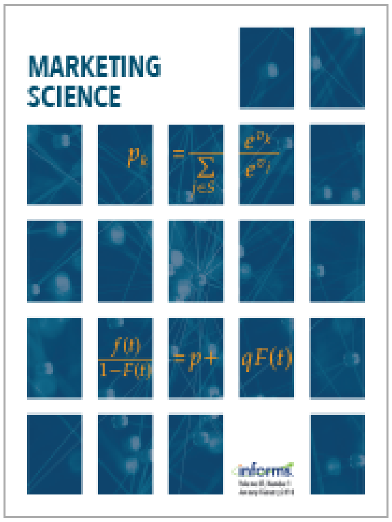

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Quantifying the Long-Term Impact of Negative Word of Mouth on Cash Flows and Stock Prices

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This paper seeks to quantify the long-term financial impact of negative word of mouth (NWOM), an issue that has long challenged extant research. We do so with real-world data on firm security prices. The developed time-series models innovatively uncover (1) short- and long-term effects of NWOM on cash flows, stock returns, and stock volatilities, and (2) NWOM's "wear-in" effects (i.e., it takes a number of months before the stock price impact of NWOM reaches the peak point) and "wear-out" effects (i.e., it takes several months after the peak before the stock price impact of NWOM dies out completely). In addition, the results related to endogeneity and feedback effects from the stock market are also interesting, supporting the idea that historical underperformance in stock prices may breed more harmful future buzz in a "vicious" cycle of NWOM. After controlling for competition, NWOM's long-term financial harm becomes more destructive in magnitude, kicks in more quickly, and haunts investors longer. Overall, these findings offer some unique implications for buzz management, time-series models quantifying the financial impact of word of mouth, and the marketing-finance interface.

Key words: word of mouth; customer experience; marketing strategy; stock price
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1. Introduction

Word of mouth (WOM), or the voice of the customer (Griffin and Hauser 1993), is one of the most effective tools for generating sales and future cash flows. Practitioners widely use WOM-based strategies such as buzz management, viral marketing, net promoter score, and referral programs. Researchers also suggest that WOM represents a low cost, trustworthy channel for acquiring and retaining customers (Villanueva et al. 2008), especially when used along with Internet blogs and feedback systems (Godes and Mayzlin 2004). Thus, the impact of WOM on firm stock value is often *implicitly* assumed among practitioners and academics.

Surprisingly, very little empirical research exists with respect to *explicitly* quantifying this impact with real-world data on firm security prices. Although Chevalier and Mayzlin (2006) find some significant impact of WOM on sales performance, the effects of negative word of mouth (NWOM) on important stock performance metrics like cash flows and stock prices are much less discussed in marketing science. One notable exception is the recent study by Luo (2007), which examined the impact of consumer negative voice on firm-idiosyncratic stock return. Using a random parameters modeling approach, Luo (2007) uncovers some short-term, immediate impact after controlling for latent heterogeneity and traditional fundamentals in finance. Here, we further investigate this void in the literature and comprehensively explore the dynamic[1] interactions among NWOM, cash flows, stock returns, and stock volatilities.

More precisely, our research offers significant incremental contributions beyond Luo (2007) as shown in a comparison table in the appendix. First, by extending Luo's (2007) work, which primarily modeled short-term, immediate effects, this research models the long-term, accumulative effects with a time-series approach: the vector autoregressive model (VAR). Long-term, accumulative effects are important because focusing solely on short-term effects would seriously underestimate the power of WOM. They also serve to meet one of the key challenges in WOM research, that is, "the [enduring and long-lasting] effect of WOM is notoriously hard to measure" (Rust et al. 2000, p. 46). VAR is a flexible time-series approach that can gauge the long-term, accumulative effects of an unexpected shock in NWOM and test whether such effects evolve nonmonotonically over time (Dekimpe and Hanssens 1999). Empowered by the VAR approach, our research is among the first to not only meet this challenge in the literature, but also

[1] By dynamic, we mean short-term, immediate (first-order autoregressive) and long-term, accumulative (higher-order autoregressive), wear-in, and wear-out effects of NWOM on cash flows, stock returns, and stock volatilities, as well as the *feedback* effects of historical cash flows, stock returns, and stock volatilities on future NWOM. These dynamics are modeled as they are because of the strength and advantages of the VAR modeling technique (see §3.1).

model how quickly or slowly NWOM[2] travels in the stock market, i.e., with wear-in and wear-out effects as discussed in §5.3.

Second, while Luo (2007) substantively examines the one-way impact running solely from NWOM to stock return, here we test the two-way influences with a *feedback loop*. That is, our framework captures not merely NWOM's direct impact on the stock market, but also the stock market's feedback impact on future NWOM over time. This feedback loop[3] matters because if supported it would suggest a vicious cycle of NWOM; i.e., historical shortfalls in cash flows and underperformance in the stock market breed more harmful buzz in the future. Because "it is difficult to draw clean inferences of reversed causality" (Keiningham et al. 2007, p. 47), the two-way dynamic influences with feedback effects would overcome this difficulty and contribute to the WOM literature on how to simultaneously model both direct and reversed feedback effects. To our knowledge, the dynamic influences with feedback effects between WOM and firm stock prices have not been examined in the extant literature.

Further, the study by Luo (2007) was not intended to uncover the role of market competition in the impact of WOM. What would be the changes in the short- and long-term effects of NWOM if market competition[4] is controlled for in the VAR models? Does NWOM matter more in the presence or without the presence of competition? These questions have not been resolved by Luo (2007), nor by Chevalier and Mayzlin (2006) and other WOM studies. Our work seeks to fill this gap. Addressing these questions will not only help uncover more realistic results of NWOM in today's competitive environments (Soberman and Gatignon 2005), it will also foster a more complete theory of the financial impact of WOM in the context of market competition (Chintagunta 2002, Hanssens 1980).

Finally, this research offers several data- and methodology-related advances. For example, beyond Luo (2007), we have collected new data on cash flows and many other firm-, industry-, and macroeconomic-level variables (see §4.1.1). In data analyses, we use various cutting-edge methodological techniques from econometrics to uncover novel and insightful results. Extending Luo's (2007) work valuing WOM with stock return (the *first* moment of stock prices' data), our research also investigates stock volatility (the *second* moment) as well as stock return. This makes another material contribution. While firm shareholder value is determined by both moments, stock volatility is a much underaddressed metric of stock performance in the marketing science literature. Yet stock volatility is a crucial variable because it is intimately related to a firm's cost of capital, corporate bankruptcy rates, and shareholder wealth (Ang et al. 2006). By simultaneously linking NWOM to both volatility and return (which has not been done before) our study innovatively divulges more mechanisms in the WOM effects on firm stock value, thus helping to advance data analyses and theories of the marketing-finance interface (Srinivasan and Hanssens 2007, Srivastava et al. 1998).

Overall, our research developed time-series econometric models to quantify the dynamic effects (short- and long-term, wear-in and wear-out, and feedback loop over time) of NWOM. The results also show that after modeling competition, NWOM's long-term financial damage may become more destructive in magnitude, kick in more quickly, and affect investors longer. As far as we know, this research is the first to reveal such fascinating dynamic effects of NWOM in a connected fashion, helping to cultivate a more exciting theory of the nuanced financial impact of WOM. Thus, we feel it makes material and significant contributions to the literature on WOM and to quantifying the financial value of marketing metrics, two nascent and growing research domains in marketing science (Gupta and Zeithaml 2006, Mayzlin 2006, Marketing Science Institute 2006).

The balance of this research presents theory background, model specification, an empirical study, and concluding remarks.

2. Theory Background

2.1. Concepts of WOM

WOM or buzz is an informal social networking-based communication channel among customers about consumption experience of products and services (Griffin and Hauser 1993, Liu 2006, Van den Bulte and Lilien 2001). While positive WOM often involves

[2] We are careful in the operationalization of NWOM. As detailed in §4, our measure is the *residual* NWOM, which is the portion unexplained by mean expectations. That is, it has parceled out a battery of confounding biases at the firm, industry, and macroeconomic levels based on Dixit and Chintagunta (2007).

[3] In a modeling sense, we estimate the feedback effects by allowing NWOM to be *endogenous*. NWOM may be affected by the other variables in the VAR system of equations.

[4] Market competition here is inferred with rival firms' NWOM and performance variables, similar to Chintagunta (2002) who infers market competition with rival retailers' store traffic. Because of data unavailability our VAR approach does not investigate competitive reactions (e.g., price wars); readers interesting in competitive reactions may consult Pauwels (2004). Instead, we study *competitive covariates* and model market competition between two rival segments, when testing the role of market competition in the financial impact of NWOM in §3.3. Further, our sample of firms has two rival segments in the airline industry: the non-low-cost segment of full-service airlines (like American Airlines) and the low-cost segment of limited-service airlines (like Southwest Airlines) as elaborated in §4.1.

favorable experience and recommendations of buying certain products, NWOM refers to unfavorable experience and recommendations of not buying certain products.[5]

Typically, NWOM consists of negative information such as brand-related belittlement, product denigration, and complaints of product failures and/or dissatisfying service experiences. If WOM is very effective in generating sales, awareness, and loyalty, then NWOM may be a significant detriment to achieving these goals (Fornell and Westbrook 1984, Singh 1988).

In this study, we develop a theoretical framework for the dynamic interactions among NWOM, cash flows, and stock prices. This framework captures (1) NWOM's direct impact on the stock market, (2) the stock market's feedback impact on NWOM, and (3) the role of market competition in the dynamic effects of NWOM. An important aspect of our framework is uncovering nuanced patterns of the dynamics of the impact of NWOM over time. We also seek to make a greater contribution to the WOM literature by revealing wear-in effects (i.e., the several months before the stock price impact of NWOM reaches the peak point) and wear-out effects (i.e., the number of months after the peak before the stock price impact of NWOM dies out) (e.g., Little 1979, Pauwels 2004). These effects would help track how soon the stock market reacts to the NWOM information, and how long the harmful effects last, as detailed in §5.

2.2. NWOM's Direct Impact on the Stock Market

Ceteris paribus, the stock market should react unfavorably to NWOM. That is, NWOM should lead to cash flow shortfalls and stock price vulnerability for the firm. Some studies have alluded to NWOM's impact on the stock market. For example, Richins (1983, p. 68) observes "if the number of consumers experiencing dissatisfaction is high enough, such responses may have lasting effects in terms of negative image and reduced sales for the firm." Based on customer equity theory (Rust et al. 2004) and customer lifetime value literature (Gupta and Zeithaml 2006), firms with higher NWOM would have diminished intangible assets (i.e., reduced customer repurchase intention, increased defection rates of existing customers, and inhibited new customer acquisition efforts), thus leading to less robust expected sum of cash flows in the future. Echoing this, Luo (2007, p. 78) suggests that "companies with more negative consumer voice would feel the pinch." To the extent that NWOM exerts a strong negative influence on consumer information processing and repurchase loyalty, NWOM may damage customer equity and customer lifetime value (Luo and Homburg 2007, Srivastava et al. 1998) and thus reduce the level of long-term future cash flows for the firm.

Furthermore, according to the brand equity theory (Keller 2003), as it may widely spread the unfavorable experience and negative recommendations, NWOM can result in denigrated corporate image, weaker institutional legitimacy, and harsher questioning from shareholders about damaged brand equity over time (Keller 2003, Luo and Bhattacharya 2006). All of these may limit the firm's capabilities to buffer against the vulnerability of the cash flow stream in the future. If so, then higher NWOM would induce more unstable cash flows (Gruca and Rego 2005), thus leading to higher volatilities in stock prices in the long run. Empirically, Pauwels et al. (2004) have established the long-run impact of new products and sales promotions. In the same spirit, we believe that NWOM may have a harmful long-term impact on cash flows and stock prices by damaging intangible assets like customer and brand equity (Srivastava et al. 1998).

In short NWOM has an impact on the stock market. More precisely, the higher (lower) *historical* NWOM of a firm, the more (fewer) shortfalls in the firm's *future* cash flows and stock returns and the higher (lower) the firm's *future* stock volatilities, all else being equal.

2.3. The Stock Market's Feedback Impact on NWOM

Stock prices may have a feedback impact on marketing actions and NWOM. According to prior theories (Rappaport 1987), stock market reactions triggered by firms' past marketing strategies can in turn influence firms' future responses and marketing tactics. For example, because "historical stock prices signal to managers and convey market intelligence and investor expectations" (Rappaport 1987, p. 57), these feedback signals from the stock market motivate managers to change their subsequent actions in advertising, product innovations, and branding (Benner 2007, Markovitch et al. 2005),[6] thus likely influencing customer experience and WOM in the future.

More specifically, finance researchers explicitly theorize that there is a "feedback from stock prices to cash flows" (Subrahmanyam and Titman 2001, p. 2,389). That is, lower returns can lead to cash flow shortfalls and constraints in subsequent periods. In addition, cash flow shortfalls are associated with "lower average levels of future investment in capital expenditures, R&D, and advertising" (Minton and Schrand 1999, p. 423). Current cash flow constraints may also

[5] As argued in prior research (Chevalier and Mayzlin 2006, Luo 2007, Mahajan et al. 1984, Mayzlin 2006), it seems reasonable to assume that NWOM is potentially more influential than the positive WOM that has received most of the academic interest to date.

[6] In parallel, Benner (2007, p. 712) suggests that "stock price decreases cause a reduction in future responsiveness and investment in capabilities in the new technology and commercialization of products incorporating the new technology."

limit the dynamics in future marketing investments (e.g., less advertising capital and customer relationship effort). This would lead to less customer service support and diminished customer care enhancement programs, inducing higher levels of NWOM in the future. Another factor supporting the feedback impact is that cash flow constraints may obstruct firms' capacity to invest in complaint handling management, which in turn can cause a firm to miss the opportunity to compensate for the negative experience, i.e., to correct the NWOM and regain customer confidence (Fornell and Westbrook 1984, Luo 2007). If so, then the reduced investments stemming from higher levels of cash flow shortfalls and stock volatilities in the past may lead to more dissatisfying customer service experiences, likely generating higher levels of NWOM in the future. Based on this line of research, there are reversed feedback effects from stock prices to NWOM in a vicious cycle: historical cash flow shortfalls may lead to under investment in marketing and customer service and thus further increase future NWOM. Conversely, lower levels of cash flow shortfalls and stock volatilities would generate less future NWOM.

In brief, the stock market has an impact on NWOM. More precisely, the more (fewer) shortfalls of a firm's historical cash flows and stock returns and the higher (lower) the firm's historical stock volatilities, the higher (lower) the firm's future NWOM, all else being equal.

2.4. The Role of Market Competition

Can market competition play a role in NWOM? In general, prior literature suggests that competition affects marketing mix responses (Chintagunta 2002; Hanssens 1980, 1998). For example, not unexpectedly, "advertising attacks are countered with advertising retaliations" (Steenkamp et al. 2005, p. 35). Soberman and Gatignon (2005) add that "there is a prevalence of competitive actions and reactions in the marketplace" (p. 165). Yet there is no published study that has explicitly controlled for competition in the long-term dynamic effects of WOM.

It is likely that NWOM's effects on the stock market may change after controlling for competition because firms may take advantage of their rivals' high level of NWOM for "a timelier launching of new product/service" and thus under cut the rivals in the competitive market segments (Soberman and Gatignon 2005, p. 169). Also, firms may promote targeted incentives to lure competing firms' customers to defect and switch[7] (Luo et al. 2007, Nijs et al. 2001, Pauwels et al. 2002). If so, then NWOM's harmful impact on future cash flows and stock prices may change after modeling competition.

By the same token, the stock market's feedback impact on future NWOM may change after controlling for competition. Possible attacks and counter attacks (Chintagunta 2002, Steenkamp et al. 2005) among rival firms may make it more likely for NWOM to become a vicious cycle over time. That is, when the role of competition is controlled for in time-series models (Hanssens 1980, Soberman and Gatignon 2005), it is more evident that historical cash flow shortfalls may cause under investments in marketing and customer service efforts that further increase future NWOM in a harmful loop.

In sum, controlling for competition may change the effects of NWOM dynamics. It is critical to model the role of competition when scientifically quantifying the financial value of WOM. Next, we present the model specifications.

3. Model Specifications

3.1. Dynamic Effects with VAR Models

We use an econometric VAR approach to model the dynamic interactions among NWOM, cash flows, and stock prices. VAR is a time-series method that can simultaneously estimate a system of equations. This method is quite flexible and powerful, accounting for many biases such as endogeneity, serial correlations, omitted variables, and reversed causality. Dekimpe and Hanssens (1999), Bronnenberg et al. (2000), and Nijs et al. (2007) provide outstanding examples of VAR applications in marketing, while Campbell and Shiller (1988) and Statman et al. (2006) offer exceptional examples of VAR studies in finance.

For this study, VAR has several advantages over alternative model specifications. First, it can estimate both short- and long-term effects of historical NWOM on firms' stock prices, as well as the changes of these effects over time. These are the direct effects in VAR. Second, the model allows for dynamic feedback loops from historical cash flows and stock prices to NWOM. These are the feedback, reversed effects in VAR. Third, it can capture not only carryover effects (i.e., past NWOM's impact on its own), but also the cross-effects (i.e., impact of historical cash flows on stock prices). These advantages suggest that VAR can fully investigate the dynamic interactions between the endogenous variables: NWOM, cash flows, stock return, and stock volatility.

[7] Because there are alternative explanations for the role of competition in the financial impact of NWOM (see §6.1), we do not subjectively limit the expected direction of this role a priori. Rather, based on past literature (Chintagunta 2002, Hanssens 1980), we are more flexible and expect that NWOM's effects may change after modeling competition.

Mathematically, we specify a four-variable VAR model as shown below

$$\begin{pmatrix} \mathrm{NWOM}_t \\ \mathrm{CAFL}_t \\ \mathrm{SPRE}_t \\ \mathrm{SPVO}_t \end{pmatrix} = \begin{pmatrix} \zeta_{10} \\ \zeta_{20} \\ \zeta_{30} \\ \zeta_{40} \end{pmatrix} + \sum_{j=1}^{J} \begin{pmatrix} \zeta_{11}^j & \zeta_{12}^j & \zeta_{13}^j & \zeta_{14}^j \\ \zeta_{21}^j & \zeta_{22}^j & \zeta_{23}^j & \zeta_{24}^j \\ \zeta_{31}^j & \zeta_{32}^j & \zeta_{33}^j & \zeta_{34}^j \\ \zeta_{41}^j & \zeta_{42}^j & \zeta_{43}^j & \zeta_{44}^j \end{pmatrix} \cdot \begin{pmatrix} \mathrm{NWOM}_{t-j} \\ \mathrm{CAFL}_{t-j} \\ \mathrm{SPRE}_{t-j} \\ \mathrm{SPVO}_{t-j} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{pmatrix}, \quad (1)$$

where NWOM = negative word of mouth, CAFL = cash flow, SPRE = stock return, SPVO = stock volatility, t = time, J = lag length, and ε = white-noise residual. The estimates of ζ_{10}, ζ_{20}, ζ_{30}, and ζ_{40} are intercepts. The direct effects of NWOM are ζ_{21}, ζ_{31}, and ζ_{41} for cash flow, stock return, and stock volatility, respectively. Feedback effects from cash flows to NWOM are ζ_{12}, and those from stock return and volatility to NWOM are ζ_{13} and ζ_{14}. The carryover effects are ζ_{11}, ζ_{22}, ζ_{33}, and ζ_{44}. Cross-effects between cash flows, stock return, and stock volatility are ζ_{32}, ζ_{23}, ζ_{42}, ζ_{24}, ζ_{34}, and ζ_{43}. Contemporaneous effects are modeled in the variance-covariance matrix of the white-noise residuals.

We estimate Equation (1) with the simultaneous generalized method of moments (GMM) approach (Hamilton 1994, Hansen 1982), which does not require full density, but rather moment conditions. It can accommodate unobserved random effects and time-series biases such as heteroskedasticity and autocorrelation. Simultaneous GMM not only provides heteroskedasticity-consistent and asymptotically correct standard errors, but also allows for testing joint significance with respect to the full set of coefficient estimates. Mathematically, when computing coefficient estimates, GMM minimizes the quadratic form (Chintagunta and Desiraju 2005, Hansen 1982, Kim et al. 2002)

$$\arg\min q = \left\{ \bar{m}' W^{-1} \bar{m},\ \bar{m} = \frac{1}{N} \sum_{i-1}^{N} m_i(\zeta, Y) \right\}, \quad (2)$$

where W = an efficient weighting matrix specifying moment conditions, and Y is a vector of endogenous variables in VAR system of equations. In controlling for random unobserved biases, GMM uses the White heteroskedasticity and autocorrelation consistent covariance matrix $\mathbf{\Phi}_{\mathrm{HAC}}$

$$\hat{\Phi}_{\mathrm{HAC}} = \hat{\Gamma}(0) + \left(\sum_{j=1}^{T-1} k(j, q)\big(\hat{\Gamma}(j) + \hat{\Gamma}'(j)\big) \right),$$
$$\hat{\Gamma}(j) = \frac{1}{T-K} \left(\sum_{t=j+1}^{T} Z'_{t-j} u_t u'_{t-j} Z_t \right), \quad (3)$$

where u = vector of White errors, k = the kernel, q = the bandwidth, and Z_t = a $k \times p$ matrix in GMM time-series models (Hamilton 1994).

3.2. Long-Term Accumulated Effects with Impulse Response Functions

Based on VAR model estimates, impulse-response functions (IRF) can capture the long-term, accumulative effects of an unexpected shock in NWOM on other endogenous variables in the VAR system. For example, we can simulate a shock (i.e., a unit unexpected shock in NWOM), and use IRF to track the present and long-term responses of cash flows and stock prices. Mathematically, IRF model is specified as follows (Hamilton 1994):

$$(\mathrm{NWOM}, \mathrm{CAFL}, \mathrm{SPRE}, \mathrm{SPVO})'_t = (\overline{\mathrm{NWOM}}, \overline{\mathrm{CAFL}}, \overline{\mathrm{SPRE}}, \overline{\mathrm{STVO}})'_t + \sum_{k=0}^{+\infty} \Theta_k \zeta_{t-k}, \quad (4)$$

where the coefficient in the matrix of Θ_k is the impulse response (or impact multiplier) of the ith endogenous variable to one standard deviation of random shock in the jth variable after k time periods. Note that because the white-noise residuals can still be contemporaneously correlated and thus generate misleading results, we apply an orthogonolising transformation to correct this bias (Hamilton 1994, Villanueva et al. 2008). We then rely on Monte Carlo simulations (1,000 runs in each case) of the impulse responses from the IRF model to assess the long-term, cumulative effects of NWOM on cash flows, stock returns, and stock volatilities.

3.3. Modeling the Role of Market Competition in VAR and IRF

Following Steenkamp et al. (2005, p. 41), we introduce segment-level competitive covariates in the VAR and IRF models.[8] In modeling firms' dynamic interrelationships between NWOM, CAFL, SPRE, and SPVO under market competition, we enter their rivals' $\mathrm{NWOM}_{\mathrm{rival}}$, $\mathrm{CAFL}_{\mathrm{rival}}$, $\mathrm{STRE}_{\mathrm{rival}}$, and $\mathrm{STVO}_{\mathrm{rival}}$ as additional exogenous variables in the system of equations. Thus, for these rival $\mathrm{VAR}_{\mathrm{rivalry}}$ and $\mathrm{IRF}_{\mathrm{rivalry}}$ models, we can estimate the direct effects of NWOM (ζ_{21}, ζ_{31}, and ζ_{41}), feedback effects (ζ_{12}, ζ_{13}, and ζ_{14}), carryover effects (ζ_{11}, ζ_{22}, ζ_{33}, and ζ_{44}), and cross-effects (ζ_{32}, ζ_{23}, ζ_{42}, ζ_{24}, ζ_{34}, and ζ_{43}) with competition.

Then, we calculate the changes (in percentages) of these effects in the $\mathrm{VAR}_{\mathrm{rivalry}}$ and $\mathrm{IRF}_{\mathrm{rivalry}}$ models with the possible segment-level competitive covariates, relative to those in the $\mathrm{VAR}_{\mathrm{nonrivalry}}$ and $\mathrm{IRF}_{\mathrm{nonrivalry}}$

[8] As discussed subsequently, our sample of firms has two rival segments. Section 5.5 reports the findings about the role of the possible segment-level competition in the dynamic effects of NWOM.

Table 1 Measures and Data Sources

Conceptual variables	Operationalization	Data sources	Time frequencies
NWOM	Negative customer voice in response to dissatisfaction of consumption experience in the airline industry, publicly filed with the U.S. Department of Transportation (USDT); the more precise measure of residual NWOM was used in VAR and IRF analyses; *residual* NWOM is the portion of NWOM unexplained by mean expectations. That is, it has parceled out a battery of confounding biases at the firm, industry, and macroeconomic levels	USDT	Monthly (January 1999–December 2005)
Cash flow	Measured as net operating income before depreciation adjusted for working capital accruals	BTS COMPUSTAT	Quarterly, same for the three months in a given quarter
Stock return	Measured as the firm's abnormal, excessive stock price changes unexplained by the average market portfolio returns in AMEX/NYSE/NASDAQ exchanges	CRSP and French's database	Monthly (January 1999–December 2005)
Stock volatility	Measured as the volatile fluctuations of the firm's abnormal, excessive stock price changes unexplained by the average market portfolio returns in AMEX/NYSE/NASDAQ exchanges	CRSP and French's database	Monthly (January 1999–December 2005)
Service quality	Based on flight arrival delays, departure delays, flight cancellations, mishandled baggages, and oversales as voluntarily reported by each airline company	BTS	Monthly (January 1999–December 2005)
Seat-mile load factor	The percentage of available seat-miles that are sold by the airlines	BTS	Monthly (January 1999–December 2005)
Air time	The reported airline companies' airborne time	BTS	Monthly (January 1999–December 2005)
Ramp-to-ramp time	The reported airline companies' time spent from ramp to ramp	BTS	Monthly (January 1999–December 2005)
Passengers	Number of passengers transported	BTS	Monthly (January 1999–December 2005)
Freight	Amount of freight transported	BTS	Monthly (January 1999–December 2005)
Mail	Amount of mail transported	BTS	Monthly (January 1999–December 2005)
GNP	Gross national product	DATASTREAM	Quarterly, same for the three months in a given quarter
Unemployment	The reported unemployment rate	DATASTREAM	Monthly (January 1999–December 2005)
CPI	Consumer price index	DATASTREAM	Monthly (January 1999–December 2005)

models without the competition (where rival firms' $NWOM_{rival}$, $CAFL_{rival}$, $STRE_{rival}$, and $STVO_{rival}$ are not included as exogenous variables) (Pauwels 2004). In doing so, we can model the role of market competition in the dynamic effects of NWOM, i.e., the short- and long-term, wear-in, and wear-out effects over time.

4. An Empirical Study

4.1. Data and Measure for NWOM

The data for NWOM are based on the communicated negative customer voice in response to dissatisfaction of consumption experience in the airline industry, collected from the U.S. Department of Transportation (USDT). According to USDT, consumers have been able to voice their complaints against airline companies in writing, by telephone, via e-mail, or in person since 1999. Because this data set is objective and not self-reported by airline companies, it provides a reliable measure that can reasonably infer NWOM (Godes and Mayzlin 2004).

The NWOM data source also appears to be quite comprehensive (Lapré and Tsikriktsis 2006, Luo 2007). It covers the voiced complaints (rates per 100,000 passengers) ranging from flight, oversales, advertising, discrimination, baggage, customer service, refund, to animal-related problems with the airline companies.[9] Table 1 summarizes the conceptual variables, operationalization, and data sources for the data set assembled in this study.

The data descriptive statistics for NWOM are summarized in Table 2. Our time-series data set of NWOM covers 84 months from January 1999 to December 2005 for nine airline companies.[10] The airline companies are Alaska Airlines, American Airlines, Continental Airlines, Delta Air Lines, Mesa Airlines, Northwest Airlines, Skywest Airlines, Southwest Airlines, and United Airlines, representing 95% of the industry sales revenue. Figure 1 presents the time-series movements of NWOM. Figure 2 plots the time series of

[9] Airline data have been used in accounting (Riley et al. 2003), marketing (Dixit and Chintagunta 2007, Luo 2007, Rust et al. 2004), management science (Lapré and Tsikriktsis 2006), and political economy (Rose 1990).

[10] We also check result robustness by testing the dynamic effects of NWOM over 78 months and using the last 6 months as a holdout sample. This procedure produces quantitatively similar results.

Table 2 Descriptive Statistics

	Mean	Median	Std. dev.	Observations
All airlines				
NWOM	53.362	36.389	38.586	84 months
Low-cost airlines segment				
NWOM	13.190	12.250	7.172	84 months
Non-low-cost airlines segment				
NWOM	85.500	57.600	64.699	84 months

a macroeconomic variable of consumer price index (CPI). Figure 3 offers the time series of NWOM for different segments of the airline companies (low-cost airlines and non-low-cost airlines).

Though not impeccably, following prior studies (Lapré and Tsikriktsis 2006) we segregate airline companies into low-cost airlines (Airtran, Alaska, Mesa, and Southwest Airlines) and non-low-cost airlines (American, Continental, Delta, Northwest, and United Airlines). This uncovers more nuanced results (i.e., segment-level competition in §5.5 and segment-level heterogeneity in §5.7) with respect to the dynamic impact of NWOM. It is reasonable to believe that there is intense competition between the two segments, given that non-low-cost segment full-service airlines like American or United are facing fierce competition from low-cost segment limited-service discount airlines like Southwest or Mesa. In fact, a publicly available article, http://en.wikipedia.org/wiki/Airline, clearly explains why the competition between these two segments significantly matters both for the non-low-cost segment of full-service airlines *and* the low-cost segment of limited-service airlines, from the perspective of operating costs, asset efficiencies, and policy regulations.

4.1.1. Residual NWOM. To be more precise in the operationalization of NWOM, we build a model and derive the *residual* NWOM, i.e., the portion unexplained by mean expectations. Residual NWOM has corrected a battery of confounding biases at the firm, industry, and macroeconomic levels. We focus on this portion of NWOM that deviates from some mean expectations (which can be associated with poor service quality, operations, macroeconomic conditions, or an event like 9/11, for example).[11] Following Dixit and Chintagunta (2007), we develop a multilevel model of NWOM, in which the total number of NWOM correlates with various *firm characteristics* (service quality, seat-mile load factor, air time, ramp-to-ramp time, passengers, mail, freight transported, and hub-based full-service airlines or not), *industry factors* (industry-level service quality, seat-mile load factor, air time, ramp-to-ramp time, passengers, mail, and freight transported), and *macroeconomic indicators* (a 9/11 dummy, fuel price, gross national product, CPI, unemployment rate). Given the cross-section, time-series nature of the data set, we specify the following random mixed model of NWOM to account for two-way (firm and year) unobserved random effects

$$\begin{aligned}\mathrm{NWOM}_{it} = \chi_0 &+ \chi_{\text{firm-level}}(\textit{Firm characteristics})\\ &+ \chi_{\text{industry-level}}(\textit{Industry factors})\\ &+ \chi_{\text{macro-level}}(\textit{Macroeconomic indicators})\\ &+ \delta_i[\text{as unobserved random firm effects}]\\ &+ \xi_t[\text{as unobserved random time effects}]\\ &+ \varepsilon_{it}[\text{as residual NWOM}], \qquad (5)\end{aligned}$$

Figure 1 Time-Series Plot of NWOM

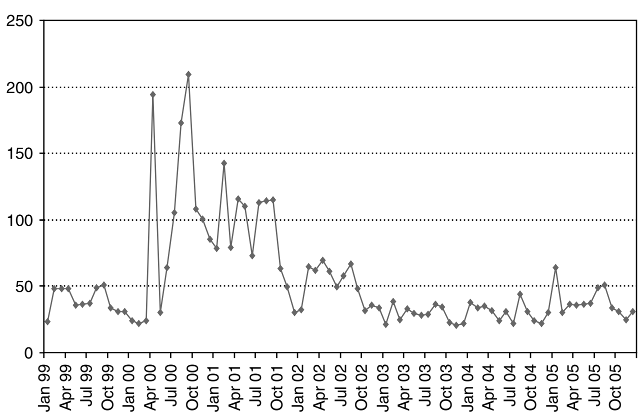
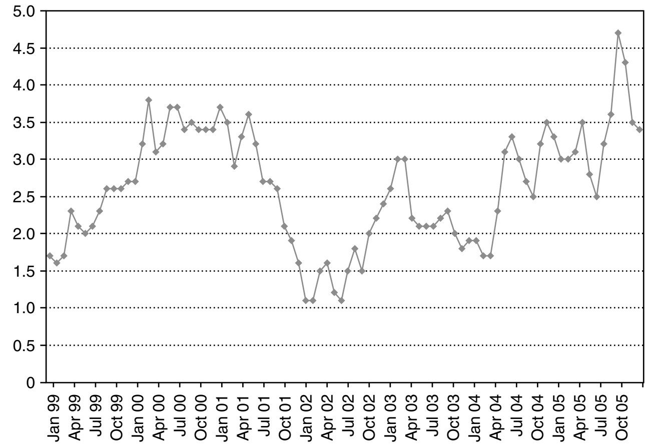
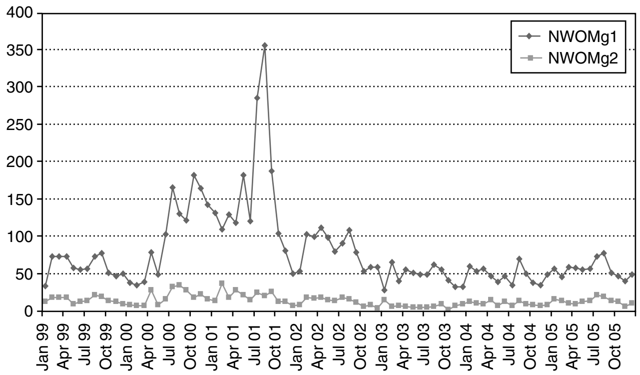


Figure 2 Time-Series Plot of Consumer Price Index



[11] For example, at the firm level, if service quality of airline companies deteriorates, then cash flows tend to decrease as well. Thus, it is important to tease out the effects of service quality with the residual approach. We measured service quality based on flight arrival delays, departure delays, flight cancellations, mishandled baggage, and oversales as voluntarily reported by each airline. These data are from USDT. We also check the construct validity by linking the USDT-based NWOM data to Internet WOM data from www.planebuzz.com, www.planetravel.blogspot.com, and other sources.

Figure 3 Time-Series Plot of NWOM Across Market Segments



Notes. NWOMg1 = non-low-cost airlines segment; NWOMg2 = low-cost airlines segment.

where χ_0 = the grand intercept; δ_i = the random disturbance of ith firm, which varies across firms but is constant across time periods with a variance σ_δ^2; ξ_t = the random disturbance of tth year, which varies across years but is constant across firms with a variance σ_ξ^2; and ε_{it} = the residual term in this model of NWOM.

The residual from Equation (5), or *residual NWOM*, is then used as proxy for the NWOM that deviates from some mean expectations. In other words, it is the unexpected portion of NWOM, relative to what is predicted by known determinants. Therefore, the residual NWOM is deemed as a clean and more precise measure of NWOM for subsequent VAR and IRF analyses. We use this residual approach to disentangle NWOM from poor service and other firm-, industry-, and macroeconomic-level factors, thus more precisely assessing the dynamic effects uniquely attributable to NWOM. For each company-month observation, we matched the residual NWOM with data for cash flows, stock returns, and stock volatilities.

4.2. Data for Cash Flows

Data for cash flows are obtained from COMPUSTAT and company financial reports filed with the Securities and Exchange Commission (SEC), and the Bureau of Transportation Statistics (BTS). Following Minton et al. (2002, p. 199), we measured firm operating cash flow as net operating income before depreciation adjusted for working capital accruals, based on BTS and COMPUSTAT.[12] This measure is also adjusted for expenditures that are expensed as part of operating income by adding back advertising and publicity expenses. If measured annually it is Data 308 in COMPUSTAT (Gruca and Rego 2005, Minton and Schrand 1999). We also checked the results by scaling cash flows with the firm's total assets.

In matching the monthly NWOM data to quarterly cash flows data, we follow Pauwels et al. (2004) data-coding scheme, which assigned the same number for all 12 weeks in a given quarter in the data coding for earning forecasts. Similarly, we assigned the same number for all three months in a given quarter in the data coding for cash flows. We also check result robustness by using VAR-bootstrapping specifications with 5,000 simulated databases (Hamilton 1994, Statman et al. 2006), and find no evidence that our results are sensitive to the temporal aggregation in this study.

4.3. Data Description for Stock Returns and Stock Volatilities

Using the Center for Research in Security Prices (CRSP) database, we measure stock return as the firm's abnormal, excessive stock price changes unexplained by the average market portfolio returns in stock exchanges (or after adjusting for common, market wide risk factors). In addition, we measured stock volatility as the fluctuations of the firm's stock price changes unexplained by the average market portfolio returns in AMEX/NYSE/NASDAQ exchanges (Campbell et al. 2001, Ferreira and Laux 2007).

Following prior finance literature (Ang et al. 2006), we model stock return and volatility on the basis of the Fama-French (FF) approach to asset pricing. The FF momentum momentum multirisk market model[13] is specified below (Fama and French 1993, 2006):

$$SR_{it} = \gamma_i + \beta_{iMKT} MKT_t + \beta_{iHML} HML_t + \beta_{iSMB} SMB_t + \beta_{iUMD} UMD_t + \omega_{it}, \tag{6}$$

where SR_{it} = stock return excessive to Treasury bill risk-free rate for firm i at time t, MKT = the excess market return, SMB = size-based risk premium factor, HML = book-to-market-based risk premium factor, UMD = return momentum factor, and ω = the residual.

The level of this residual ω in Equation (6) is then used as the final measure of stock return, which has teased out the expected portion of stock return that can be explained by the average market portfolio returns (via the common market-wide risk factors of *SMB*, *HML*, and *UMD*).

The variance of this residual is then stock volatility, which precisely captures the fluctuations of the firm's

[12] Note that the cash flows in question are the net of cash inflows (revenues) and outflows (costs) of the firm, which is consistent with prior marketing literature (Gruca and Rego 2005) and finance literature (Fama and French 1993).

[13] We also checked the validity of our result by modeling two-way (firm and year) unobserved random effects as we did in Equation (5). The conclusion does not change. Yet here we reported the market model as shown in Equation (6) because this version (without considering two-way unobserved random effects) is the standard form in the finance literature (Fama and French 1993).

stock prices unexplained by average market portfolio returns (Brown and Kapadia 2007). Furthermore, because there may be time-serial correlation in the residual, we use the conditional FF approach to tease out this bias as follows:

$$\omega_{it} = \rho\omega_{it-1} + \gamma_{it}, \tag{7}$$

where $\gamma_{t,i}$ is a white noise (McAlister et al. 2007).

Following this process, we calculated the stock return and stock volatility based on daily securities price data from CRSP and the common market risk factors from French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). As a result, we have extracted a total of 24,696 data points ($24{,}696 = 9$ firms $\times$ 7 years $\times$ 252 trading days $+$ 5 market-wide factors $\times$ 7 years $\times$ 252 trading days). We calculated the resulting monthly series of stock return and stock volatility data (Ferreira and Laux 2007), then matched them with the monthly NWOM, cash flows, and controls data. We also checked our results by adding market liquidity, a hot research issue in the recent asset-pricing literature in finance, as another market-wide risk on top of the four FF risk factors in Equation (6). The data for market liquidity are available at Sadka's website, http://faculty.washington.edu/rsadka (also available in CRSP).

5. Results

5.1. VAR Model Estimation

The process of estimating VAR models starts with unit-root tests to check if the variables are evolving or stationary. Thus, we conducted augmented Dickey-Fuller (ADF)[14] and Kwiatkowski-Phillips-Schmidt-Shin (KPS) tests, following Dekimpe and Hanssens (1999) research. The results are reported in Table 3. The ADF test results show that the values range from −3.512 to −5.647, all of which are significant ($p < 0.05$). Thus, the null hypothesis of a unit root can be rejected with a 95% confidence level. Furthermore, KPS values range from 0.211 to 0.343, which are all less than the 5% level critical value. Thus, the null hypothesis of stationary (or no unit root) in KPS cannot be rejected at a 95% confidence level. Overall, these tests show that the series are stationary at the level and do not cointegrate in equilibrium (Hamilton 1994). We estimate VAR model with levels of these endogenous variables.

The optimal lag length of the VAR model is 2 according to Schwartz's Bayesian Information Criterion (SBC)[15] and final prediction error (FPE). We also tested various assumptions of the VAR residuals (multivariate normality, omission-of-variables bias, White heteroskedasticity tests, and Portmanteau autocorrelation). We found no violations of these assumptions at the 95% confidence level.

Table 3 Unit-Root Test Results

	ADF test statistics	5% level C.V.	KPS test statistic	5% level C.V.	Test conclusion
NWOM	−4.543	−2.897	0.252	0.463	Stationary and no unit root at the 5% confidence level
Cash flows	−3.512	−2.897	0.343	0.463	Stationary and no unit root at the 5% confidence level
Stock returns	−5.028	−2.897	0.235	0.463	Stationary and no unit root at the 5% confidence level
Stock volatilities	−5.647	−2.897	0.211	0.463	Stationary and no unit root at the 5% confidence level

Note. ADF = Augmented Dickey-Fuller test; KPS = Kwiatkowski-Phillips-Schmidt-Shin test; C.V. = critical value.

5.2. NWOM's Short- and Long-Term Impact on the Stock Market: Direct Effects

Table 4 indicates the short-term and long-term effects of NWOM on cash flows and stock prices (in averages across VARs for each firm). Overall, for the whole sample, NWOM has a negative short-term, immediate (one month) impact on firm cash flows ($b = -0.799$, $p < 0.01$). In addition, the IRF results show that NWOM has a negative long-term, accumulated (20 months) impact on cash flows ($b = -3.425$, $p < 0.01$). Thus, the higher (lower) historical NWOM of a firm, the more (fewer) shortfalls of the firm's future cash flows. Economically, these effects are substantial: on average, a unit unexpected shock in NWOM may lead to a drop of \$1.882 million for the airline companies in the following month. Furthermore, on average, a unit unexpected shock in NWOM may lead to an accumulated loss of \$8.169 million for the airline companies in the next 20 months, other things being constant.

As reported in Table 4, NWOM has a short-term, immediate negative impact on stock returns and positive impact on stock volatilities (both $p < 0.01$). In addition, the IRF results show that NWOM has a long-term, accumulated (20 months) negative impact on stock returns and positive impact on stock volatilities (both $p < 0.01$). Thus, the higher (lower) historical NWOM of a firm, the lower (higher) the firm's future stock returns and the higher (lower) future

[14] The general form for the ADF test is given by: $\Delta y_t = \alpha y_{t-1} + \sum_{t=1}^{k} \beta_t \Delta y_{t-1} + \gamma x_t + \varepsilon_t$, where x can be a constant, trend, and exogenous variable (Fok et al. 2006; Nijts et al. 2001, p. 18). From the ADF test statistics $t_\alpha = \hat{\alpha}/se(\hat{\alpha})$.

[15] SBC is calculated as $\text{SBC} = -2l/T + (k \log T)/T$.

Table 4 Short- and Long-Term Effects of NWOM on Cash Flows and Stock Prices

	Cash flows		Stock returns		Stock volatilities	
	Short-term	Long-term	Short-term	Long-term	Short-term	Long-term
All airlines						
NWOM	−0.799	−3.425	−0.0003	−0.0012	0.006	0.0229
Low-cost airlines segment						
NWOM	−2.351	−5.657	−0.0007	−0.0025	0.011	0.0233
Non-low-cost airlines segment						
NWOM	−0.627	−3.092	−0.0002	−0.0011	0.004	0.036

stock volatilities, all else being equal. Compared to its impact on cash flows, the effect of NWOM's impact on stock prices is weaker. This suggests that investors may have incorporated some of the NWOM news in asset pricing (Pauwels et al. 2004). In addition, because NWOM's impact on stock prices is significant after controlling for cash flows, these results lend more support to additional information content of customer equity information (Keller 2003, Rust et al. 2004), or the harmful financial effects of NWOM (Luo 2007) in the stock market.

5.3. How Quickly Does Bad News Travel in the Stock Market?

We explore how quickly or slowly bad news of NWOM travels in the stock market. We do so because Pauwels (2004, p. 603) theorizes some "wear-in" and "wear-out" effects of marketing actions like advertising. Indeed, prior theories suggest "buildup and decay effects" (Little 1979, p. 635), "dynamic erosion effects" (Bronnenberg et al. 2000, p. 18), and an "adjusting period" (Pauwels et al. 2002, p. 423) or a "dust settling period" (Nijs et al. 2001, p. 6). In a similar spirit, Godes and Mayzlin (2004, p. 533) also explore the differential effects of early versus late WOM over time.

As reported in Table 5, the results on the wear-in and wear-out effects of NWOM are interesting. Regarding the wear-in effects, on average it takes three months before the impact of NWOM on cash flows reaches its peak. In addition, it takes about four months before the impact of NWOM on stock returns and volatilities reaches the peak, other things being constant. With respect to the wear-out effects, on average the impact of NWOM on cash flows dies out in about six months. Moreover, the impact of NWOM on stock returns and volatilities dies out in about seven months, other things being constant.

Table 5 Wear-In and Wear-Out Effects of NWOM on Cash Flows and Stock Prices

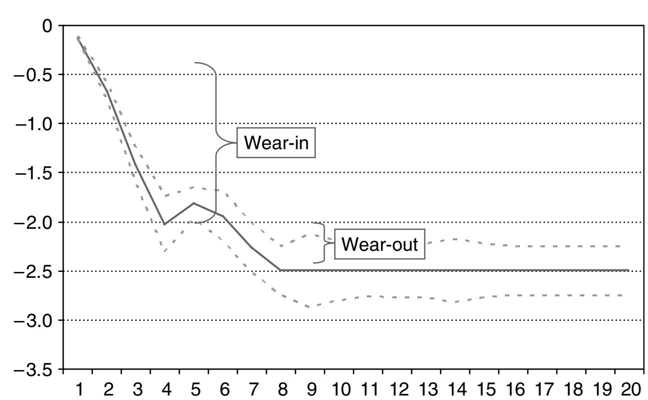
	Cash flows		Stock returns		Stock volatilities	
	Wear-in	Wear-out	Wear-in	Wear-out	Wear-in	Wear-out
All airlines						
NWOM	3	6	4.2	6.7	4	6.3
Low-cost airlines segment						
NWOM	2.1	7.8	4	7.1	3.8	6.4
Non-low-cost airlines segment						
NWOM	3.5	4.7	5	6	5.2	6.1

Collectively, these findings are important because they explicitly show that the stock market does not instantaneously react to NWOM. Rather, investors' reactions may grow over time, as the effects of NWOM unfold. In addition, the harmful effects of NWOM do not vanish overnight. After the peak point, the damaging impact of NWOM may affect investors for a while. These results extend the literature by revealing more nuanced patterns with respect to the dynamics of NWOM effects.

Figure 4 plots the accumulated impact of NWOM on cash flows for Continental Airline over time, based on IRF Monte Carlo simulations (1,000 runs). As explained previously, IRF use VAR estimates to trace the effects of a unit unexpected shock in NWOM with Monte Carlo one-standard-deviation confidence band. As shown in Figure 4, the first-period impulse-response suggests that a one standard-deviation unexpected shock in NWOM results in \$0.2 million loss in the next month's cash flows. The peak loss of \$2.08 million is reached at the fourth month (wear-in) after the shock in NWOM. Interestingly, the shape of the IRF is not monotonic. Rather, it increases much faster for the first four months. The damaging impact of NWOM decays slowly but is persistent and stabilizes with a \$2.49 million loss in about eight months (wear-out). The loss is statistically and economically significant.

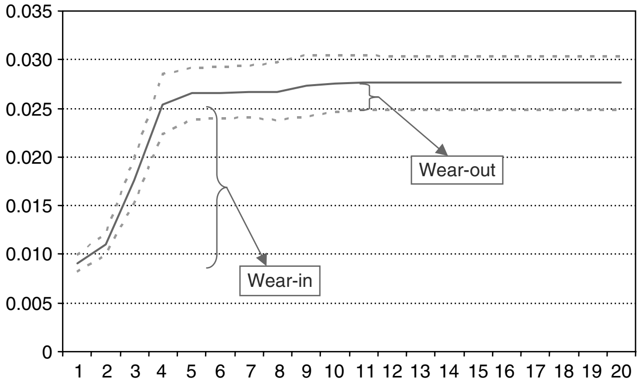
Figure 5 plots the accumulated impact of NWOM on stock volatilities for Southwest Airlines over time, based on IRF Monte Carlo simulations with 1,000 runs. Again, the shape of the IRF is not linear. It increases

Figure 4 Accumulated Response of Cash Flows to NWOM (Continental Airlines)



Note. Vertical is cash flow loss in \$ millions, horizontal is time in months. Based on Monte Carlo simulations (1,000).

Figure 5 **Accumulated Response of Stock Volatility to NWOM (Southwest Airlines)**



Note. Vertical is stock price volatilities, horizontal is time in months. Based on Monte Carlo simulations (1,000).

much faster for the initial four months (wear-in), then gradually diminishes and dies out (wear-out) in about 10 months, confirming the nonmonotonic effects of NWOM over time.

Overall, it seems that NWOM goes a long way in the stock market, according to these VAR and IRF results. The impact of NWOM on stock prices generally evolves nonmonotonically over time. The dynamic effects of NWOM grow quickly before the peak, then erode slowly after the peak, while still persistently influencing cash flows and stock prices.

5.4. Stock Market's Impact on NWOM: Feedback, Reversed Effects

VAR results also indicate that firms' historical cash flows have a negative, marginally significant impact ($b = -0.022$, $p < 0.10$) on NWOM for the short-term (i.e., the following month). IRF simulations show that the long-term impact of cash flows on NWOM is negative ($b = -0.0706$, $p < 0.05$). Thus, the more (fewer) shortfalls of a firm's historical cash flows, the higher (lower) the firm's future NWOM, all else being equal. These findings imply that if an unhealthy cash flow stream in the past induces a firm to permanently forgo future investments in marketing and customer service, then it can lead to more damaging NWOM in the future, thus creating a vicious cycle. This adds more empirical evidence for stock market's feedback effects reported in the extant literature (Benner 2007, Markovitch et al. 2005, Rappaport 1987). Conversely, this implies that a healthy stream of cash flows in the past would reduce the chances of underinvestment in future marketing and customer service programs (Minton and Schrand 1999) and thus may help to reduce future NWOM.

Regarding the feedback from stock prices, VAR results suggest that firms' historical stock returns and volatilities have a marginally significant impact (both $p < 0.10$) on NWOM for the short term (i.e., the following month). However, although there is a long-term feedback impact of stock returns on NWOM, IRF results show that the impact of stock volatilities on NWOM is not statistically significant ($p > 0.10$). This long-term result is not totally unexpected because cash flows were controlled for as another endogenous variable in the VAR system of equations. As such, there is limited support for the notion that the more (fewer) shortfalls of a firm's historical stock returns and the higher (lower) the firm's historical stock volatilities, the higher (lower) the firm's future NWOM. Overall, we find some evidence for the feedback effects from the stock market to NWOM, an issue that has escaped research attention in the extant WOM literature.

5.5. The Role of Segment-Level Competition in the Dynamic Effects of NWOM

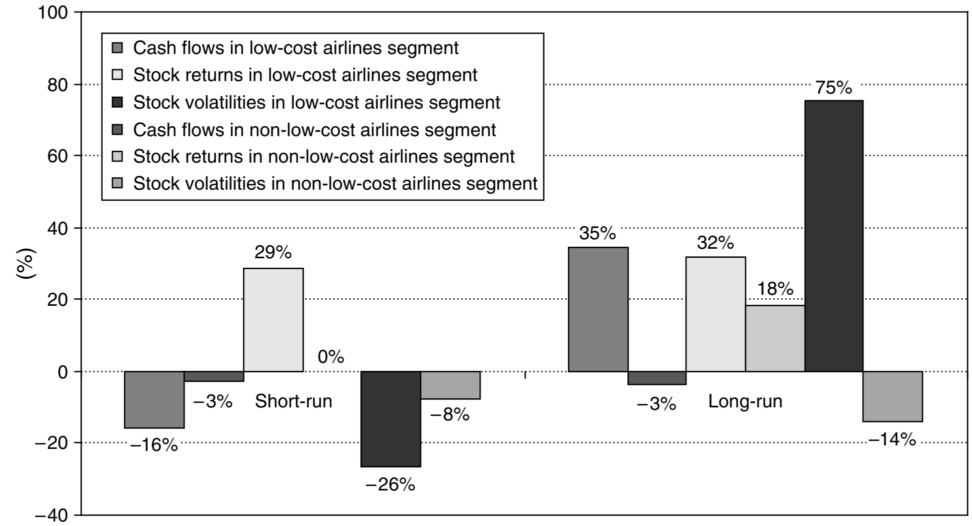
5.5.1. The Role of Competition in the Short- and Long-Term Effects of NWOM. Table 6 and Figure 6 present the changes (in percentages) of the short- and long-term effects of NWOM after controlling for possible competition from the rival segment with competitive covariates. VAR results show that for the low-cost airlines, NWOM's negative short-term impact on cash flows reduces in magnitude (from $b = -2.351$ to $b = -1.978$ with 16% decrease). In addition, IRF results show that NWOM's negative long-term impact on cash flows becomes more damaging and increases in magnitude (from $b = -5.657$ to $b = -7.613$), an additional sizeable (35% increase) long-term loss after controlling for competition.

Regarding the non-low-cost airlines, NWOM's negative short-term impact on firm cash flows decreases

Table 6 **The Role of Competition in the Short- and Long-Term Effects of NWOM (VAR Model)**

	With competition		Without competition		% change	
	Short-term	Long-term	Short-term	Long-term	Short-term	Long-term
			Cash flows			
Low-cost airlines segment						
NWOM	−1.978	−7.613	−2.351	−5.657	−16	35
Non-low-cost airlines segment						
NWOM	−0.609	−2.985	−0.627	−3.092	−3	−3
			Stock returns			
Low-cost airlines segment						
NWOM	−0.009	−0.0033	−0.007	−0.0025	29	32
Non-low-cost airlines segment						
NWOM	−0.002	−0.0013	−0.002	−0.0011	0	18
			Stock volatilities			
Low-cost airlines segment						
NWOM	0.0081	0.0408	0.011	0.0233	−26	**75**
Non-low-cost airlines segment						
NWOM	0.0037	0.031	0.004	0.036	−8	−14

Figure 6 Changes (%) of Short- and Long-Term Effects of NWOM After Modeling Possible Segment-Level Competition in VAR



a bit (from $b = -0.627$ to $b = -0.609$ with 3% decrease) after controlling for possible competition from the rival segment. In addition, IRF results show that NWOM's negative long-term impact on cash flows also decreases (from $b = -3.092$ to $b = -2.985$ with 3% decrease) after controlling for competition.

Furthermore, VAR results show that for the low-cost airlines, NWOM's short-term, immediate impact on firms' stock returns is more harmful (29% increase) after controlling for the possible competition from the rival segment. IRF results also show that NWOM's long-term impact on stock returns becomes more damaging (32% increase). Yet NWOM's short-term, immediate impact on stock volatilities drops (26% decrease), after controlling for possible competition from the rival segment. Interestingly, IRF results show that NWOM's long-term impact on stock volatilities becomes very detrimental (75% increase), inducing more instability in stock prices, and thus greater long-term loss in shareholder value.

With respect to the non-low-cost airlines, NWOM's short-term impact on firms' stock returns (0% change) and stock volatilities (8% decrease) does not change substantially, after modeling possible competition from the rival segment. However, IRF results show that NWOM's long-term impact on stock returns is more detrimental (18% increase), suggesting more damage after controlling for competition.

Overall, these results suggest that after controlling for competition, the long-term harmful effects of NWOM's may become more severe, hurting cash flows and stock prices more seriously. Yet the changes of short-term effects of NWOM due to competition seem rather mixed across the low-cost and non-low-cost airlines, suggesting some heterogeneity in results. Nevertheless, market competition appears to play an important role in the long-term financial effects of NWOM.

5.5.2. The Role of Competition in the Wear-In and Wear-Out Effects of NWOM. Figure 7 shows the changes of the wear-in and wear-out effects of NWOM on cash flows and stock prices after controlling for possible competition from the rival segment. VAR results show that for the low-cost airlines, NWOM's wear-in effect on firm cash flows significantly reduces (i.e., 33%). Thus, the financial damage from NWOM kicks in much faster after modeling competition. In addition, IRF results show that NWOM's wear-out effect drops (i.e., 19%) for the low-cost airlines after controlling for competition.

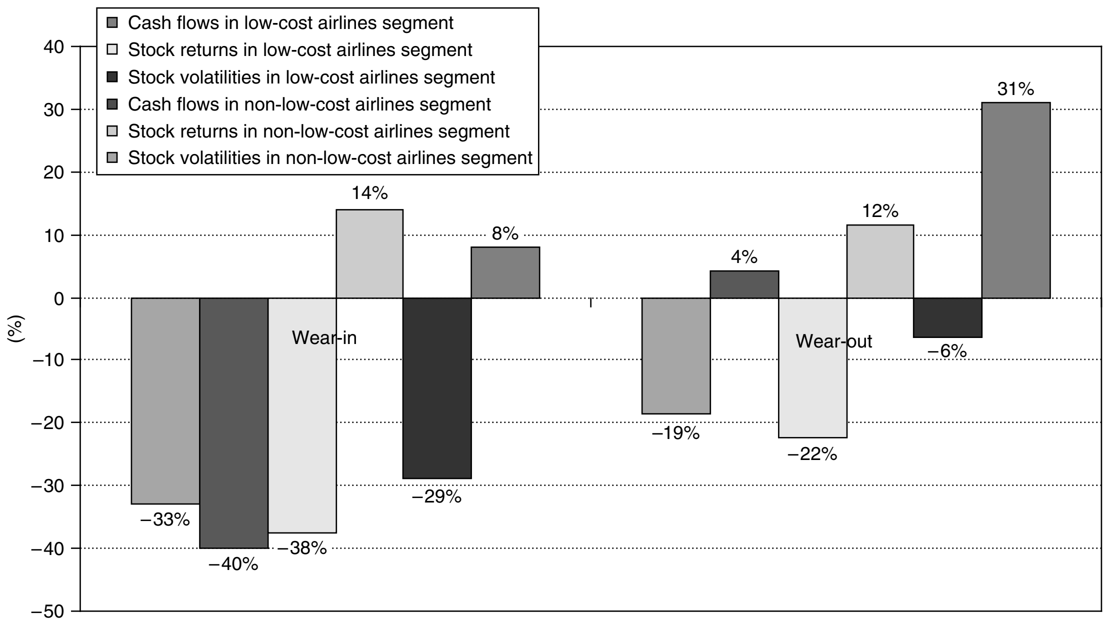
Regarding the non-low-cost airlines, NWOM's wear-in effect on firm cash flows decreases significantly (40%) after controlling for the possible competition from the rival segment. Again, after modeling competition, the financial damage is realized faster as well.

VAR results show that for the low-cost airlines, NWOM's wear-in effects on firm stock prices drop (38% for stock returns and 29% for stock volatilities) after modeling the possible competition from the rival segment. In addition, IRF results show that NWOM's wear-out effects on firm stock prices drop as well (22% for stock returns and 6% for stock volatilities), albeit to a lesser degree.

With respect to the non-low-cost airlines, the changes in NWOM's wear-in and wear-out effects on firm stock prices seem to be mixed, with both decreases and increases, after controlling for competition. As shown in Figure 7, after modeling competition, the wear-out effects of NWOM on stock volatilities increase significantly (31%) for non-low-cost airlines, showing more persistent financial harm for firms' future stock prices.

Overall, these results show that after controlling for competition, NWOM's damage seems to accelerate,

Figure 7 Changes (%) of Wear-In and Wear-Out Effects of NWOM After Modeling Possible Segment-Level Competition in VAR



i.e., with shorter wear-in effects. Also, the financial damage of NWOM can become more persistent and long-lasting, i.e., with longer wear-out effects. This strongly indicates the power of WOM and the damaging effects of NWOM in our context.

5.6. Additional Results of NWOM Impact with Stochastic Volatilities Model

Recall that VAR approach models stock volatilities in a nonstochastic, homoskedastic fashion. Thus, it would be desirable to complement the results with stochastic, heteroskedastic models of stock volatilities. Following finance literature (Bollerslev 1986, Hamilton 1994, Li and Zhao 2005), we use the generalized autoregressive conditional heteroskedasticity (GARCH) model. Mathematically, the GARCH model for the impact of NWOM on stochastic volatilities is specified as follows:

$$SR_t = \rho SRs_{t-1} + \varepsilon_t; \quad \varepsilon_t \sim (0, \sigma_t^2),$$
$$\sigma_t^2 = \eta_0 + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \sum_i^I \psi_i \mathrm{NWOM}_{t-i} + \sum_k^K \varphi_k \mathrm{CAFL}_{t-k} + \Sigma\gamma_{\mathrm{exogenous}} \mathit{Exogenous}, \tag{8}$$

where σ_t^2 = the stochastic estimate of stock volatilities, SR = stock return excessive to Treasury bill risk-free rate, ρ = the estimate of first-order autoregressive AR(1), η_0 = constant, ε_{t-1}^2 = the lag of the squared residual, ψ_i = parameters for the impact of NWOM on the stochastic estimate of stock volatilities, and φ_k = parameters for the impact of CAFL on stochastic estimate of stock volatilities. Upon analysis, the GARCH results indicate that past periods of NWOM significantly affect the stochastic estimates of stock volatilities ($\sum_i^I \psi_i = 0.0338$ with $I = 10$ past months) in this data set. Therefore, these additional analyses with stochastic volatility models add more credibility to the significant impact of NWOM, thus helping to establish the robustness of our results.

5.7. Additional Results of Segment-Level Heterogeneity

We checked result sensitivity with different segments of airline companies. As reported in Table 4 in the rows of low-cost airlines and non low-cost airlines, the results consistently support NWOM's direct impact and the feedback impact across the different segments. That is, VAR results show that for the low-cost airlines only, NWOM's short-term impact is more salient for not only firm cash flows (from $b = -0.799$ in the whole sample to $b = -2.351$ in the low-cost airlines segment), but also for stock returns (from $b = -0.0003$ to -0.0007) and stock volatilities (from $b = 0.006$ to 0.011). In addition, IRF results show that NWOM's negative long-term impact on cash flows (from $b = -3.425$ to $b = -5.657$) and stock returns is more harmful (from $b = -0.0012$ to $b = -0.0025$), although its long-term, accumulated impact on stock volatility stays about the same for the low-cost airlines segment.

For the non-low-cost airlines segment, NWOM's short-term impact is less salient for firm cash flows (from $b = -0.799$ in the whole sample to $b = -0.627$ in the non-low-cost airlines segment), stock returns (from $b = -0.0003$ to $b = -0.0002$), and stock volatilities (from $b = 0.006$ to $b = 0.004$) in magnitude. IRF results also show little change in NWOM's long-term impact on cash flows and stock returns, whereas its long-term, accumulated impact on stock volatilities increases (from $b = 0.0229$ to 0.036) for non-low-cost airlines.

Overall, these results confirm that (1) NWOM can be both a driver of future cash flows and stock prices (direct effects) and a consequence of historical cash flows and stock prices (feedback effects), and (2) this conclusion is robust to segment-level heterogeneity.[16]

6. Concluding Remarks

6.1. Summary of the Findings

Our goal for this paper was to quantify the financial impact of NWOM. To summarize:

(1) NWOM has significant direct short- and long-term effects on firm cash flows and stock prices. The higher (lower) historical NWOM of a firm, the more (fewer) shortfalls in the firm's future cash flows and stock returns and the higher (lower) the firm's future stock volatilities. On average a unit unexpected shock in NWOM may lead to a drop of \$1.882 million in cash flows for the airlines in the following month, and an accumulated loss of \$8.169 million in the next 20 months, other things being constant. Our results show that these findings can be justified by at least two lines of reasoning. First, assuming that customer equity theory (Rust et al. 2004) and customer lifetime value literature (Gupta and Zeithaml 2006) are reliable, higher NWOM would diminish firms' intangible assets (which would have a long-term impact on stock prices) and thus generate long-term damaging effects on shareholder value. Second, to the extent that widespread negative customer experience can tarnish corporate image, institutional legitimacy, and brand equity (Keller 2003), NWOM would induce more unstable firm cash flows and higher volatilities in stock prices.

(2) NWOM does not travel linearly in the stock market, but rather creates both wear-in and wear-out effects. Regarding wear-in effects, on average it takes three to four months for the impact of NWOM on cash flows and stock prices to reach its peak. With respect to the wear-out effects, on average the financial impact of NWOM remains persistent and significant for six to seven months after the peak, *ceteris paribus.* Thus, the damaging effects of NWOM are long-term for the firm and for investors. These wear-in and wear-out effects can be explained by Little's (1979, p. 635) theory, which holds that advertising response models should capture the dynamic effects of forgetting (i.e., wear-out or the decay in adverting quality with diminishing impact over time). In addition, the advertising effects vary over time and, generally speaking, do not build up instantaneously (i.e., wear-in) in the initial time periods. Based on this theory, Pauwels (2004, p. 596) suggests that marketing actions like "product-line extension has both wear-in, i.e., it takes a number of weeks before the peak sales impact is reached, and wear-out, i.e., it takes several weeks after the peak impact before sales effects die out." Therefore, based on Little's (1979) theory and Pauwels' (2004) empirical evidence on sales impact, we show that NWOM may also have buildup (wear-in) and decay (wear-out) impact on cash flows and stock prices over time.

(3) There are significant feedback effects from the stock market to NWOM over time. The more (fewer) shortfalls of a firm's historical cash flows and stock returns and the higher (lower) the firm's historical stock volatilities, the higher (lower) the firm's future NWOM. To the extent that an unhealthy cash flow stream in the past may cause a firm to permanently forgo future investments in marketing and customer service, shortfalls of cash flows and historical underperformance in the stock market may breed more damaging future buzz, creating a "vicious" cycle of NWOM. We believe there are two reasons for these feedback effects. If higher levels of cash flow shortfalls and stock volatilities in the past lead to current cash flow constraints that (1) likely cause under investment in future marketing and customer relationship efforts, and (2) obstruct firms' capacity to invest in complaint handling management (Fornell and Westbrook 1984, Markovitch et al. 2005), then no wonder historical underperformance of firm stock prices may breed more harmful future NWOM.

(4) Market competition plays a significant role in the dynamic effects of NWOM. After controlling for competition among rival segments with competitive covariates, the long-term harmful effects of NWOM hurt firm cash flows and stock prices more seriously (over 35%). In addition, the damaging effects of NWOM seem not merely to kick in sooner, i.e., with shorter wear-in effects (time-to-peak drops from 29% to 40%), but can also become more persistent and long-lasting, i.e., with longer wear-out effects (i.e., diminishing-time after peak increases 31%). These

[16] We checked Granger causality to further explore the dynamic interactions among NWOM, cash flows, and stock prices. The Granger causality test results with the whole sample and the holdout sample consistently confirm the direct effects and feedback effects. Moreover, in line with prior finance research (Subrahmanyam and Titman 2001), we find that historical stock returns and volatilities have a cross-feedback impact on cash flows ($p < 0.05$). Also, historical cash flows affect stock returns and volatilities ($p < 0.01$). Interestingly, consistent with Minton and Schrand (1999), we do find that past periods of cash flows significantly induced more damaging NWOM ($p < 0.01$) more so than historical stock volatilities ($p < 0.10$). As expected, we find that the carryover effects exist for all endogenous variables in the VAR model ($p < 0.01$).

results suggest doubly significant damage of NWOM in the presence of competition. Because prior studies have pointed out that competition matters for marketing mix responses (Chintagunta 2002, Hanssens 1980, Luo et al. 2007), the long-term dynamic effects of WOM in the presence of competition should not be the same as those without the presence of competition. Although in some cases rivals may collude (even though price collusion among competitors can be illegal), rivals often take advantage of one another in competitive market segments (Soberman and Gatignon 2005). Thus, based on prior marketing literature (Hanssens 1980), we show that when the role of competition is controlled for, it is more clear that NWOM's long-term financial damage becomes more destructive in magnitude, kicks in more quickly, and creates longer-term damaging effects for investors.

6.2. Implications for Marketing Research and Buzz Management

These findings contribute to the theory of WOM and the voice of the customer (Griffin and Hauser 1993, Richins 1983). One of the key challenges in prior WOM research is that "the effect of WOM is notoriously hard to measure" (Rust et al. 2000, p. 46) because this impact may be enduring and long-lasting. Indeed, yielding to this challenge by focusing solely on the short-term effects would seriously underestimate the power of WOM. Our developed time-series econometric models overcome this by quantifying the dynamic effects NWOM with new and valuable insights (short- and long-term, wear-in, and wear-out effects over time). Our results also show that after modeling competition, the long-term financial damage of NWOM changes substantially, becoming more destructive in magnitude, kicking in more quickly, and affecting investors longer. To our knowledge, this is the first study to examine, model, and analyze the various factors, in a connected manner, thus cultivating a more exciting theory of the nuanced dynamic effects of WOM.

This work also contributes to the theory of the marketing-finance interface. Few, if any, studies link marketing variables such as WOM to shareholder value (let alone marketing's long-term financial effects). By analyzing the impact on stock prices, this study constitutes an important effort to respond to the recent calls in marketing literature for a paradigm shift in assessing the value of marketing activities (Gupta and Zeithaml 2006, Luo 2008, Marketing Science Institute 2006, Srinivasan and Hanssens 2007). It is true that the stock market does not instantaneously react to marketing information content (Pauwel et al. 2004). We add that the damage to stock prices from negative customer experience does not vanish overnight. In addition, we shed new light on the connection between marketing and shareholder value with important financial metrics, i.e., unhealthy cash flows and volatile stock prices. This connection has not been substantially addressed in marketing science to date. The direct and feedback results we uncovered help extend theory on the marketing-finance interface by mapping a two-way street: There are mutual, bidirectional influences, i.e., from historical marketing policies to finance metrics and from finance metrics to future marketing policies.

From a modeling perspective, we contribute to the methodologies of systematic models in marketing. Chintagunta et al. (2006, p. 610) call for research in marketing science to "resolve potential bias due to endogeneity, heterogeneity, and competition" in misspecified models. Our VAR and IRF methods not only accommodate these issues, but also simultaneously estimate the long-term financial effects. Our systematic models acknowledge the possible role of competition in the wear-in and wear-out dynamic effects. These methodological strengths of VAR are important because they show support for the theory of hysteresis (Little 1979) and expand this theory with the role of competition (Chintagunta 2002). Furthermore, we contribute to literature on how to model direct and reversed feedback effects because in non-VAR models "it is difficult to draw clean inferences of reversed causality" (Keiningham et al. 2007, p. 47). Finally, agreeing with Bronnenberg et al. (2005, p. 22) argument that "the primary goal of structural modeling is to recommend optional marketing policy," we add that it is critical to build systematic models in the context of market competition and long-term dynamics.

For buzz management and marketing policy simulation, our results offer some relevant implications. For example, firms should allocate marketing and customer service resources not only to promote positive WOM, but also to reduce NWOM. Managing negative buzz carefully and efficiently helps to assure that the revenue of WOM investment exceeds the related cost in today's competitive marketplace. Companies that fail to manage negative buzz risk learning how quickly and tremendously, in this Internet era, product denigration, scandals, and complaints of service failures can hurt the bottom line, top line, and stock performance. Companies like Dell, KFC, JetBlue, Pepsi, etc., are excellent examples (*BusinessWeek* 2006, Richheld 2003, Ward and Ostrom 2006). In fact, "Thanks to Blogs, no industry can escape from the critical mass ranging from planebuzz.com for airlines, corante.com for Pharma, to wallstreetfolly.com for finance" (*Fortune* 2007, p. 144).

On the other hand, companies with smart buzz management can integrate "the voice of the customer to engineering, manufacturing, and R&D decisions"

(Griffin and Hauser 1993, p. 3) and enjoy better brand equity and financial superiority. For instance, the popular trade press writes "Build the buzz: Johnson & Johnson is ramping up makeover parties, book readings, concerts, and other indirect sales tools that amplify the brand and generate double digit sales increases" (*BusinessWeek* 2007, p. 53).

Prudent buzz managers should also eye stock prices for market intelligence: After all, "managers who ignore important signals from stock prices do so at their peril" (Rappaport 1987, p. 62). Underperforming firms should proactively diagnose the powerful signals from the stock market, analyzing the shortfall in past marketing and customer service strategies and then reshaping these strategies to curtail the shortfall in the future and avoid the vicious cycle of NWOM over time.

6.3. Future Research Opportunities

With respect to future research, there are plenty of opportunities. First, we agree with Godes and Mayzlin's (2004, p. 545) call for more work on WOM in general because "WOM may have more potential impact than any other communication channel." We would add that NWOM may deserve extra research attention if it is asymmetrically more influential as predicted by prospect theory. Indeed, given the tremendous potential in social networks and virtual communities such as MySpace, Facebook, and Xanga, more research is needed to value NWOM, especially in the context of "a free customer" (Gupta et al. 2007, p. 1).

Second, we expect that marketing modelers may uncover more insights if empowered by VAR econometrics (Pauwels and Hanssens 2007) and time-series data sets on pricing, advertising, and other marketing phenomena (Bronnenberg 1998, Chintagunta 2001, Luo and Homburg 2008, Mitra and Golder 2006, Van den Bulte and Joshi 2007). For example, in line with Chevalier and Mayzlin (2006) and Luo (2007), marketing scientists may use data on book reviews, movie, and newsgroup blogs to further explore the dynamic effects of WOM on hot-button but less-researched financial metrics such as stock recommendations, financial analyst forecasting, and investor trading activities.

In conclusion, we strongly encourage future research efforts to follow these exciting paths to quantify the long-term financial impact of NWOM.

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Appendix

Table A.1 A Summarization of the Significant Incremental Contributions

Criterion	Luo (2007)	The present study	Specific incremental contributions
Short-term, immediate effects of NWOM on stock returns	✓	✓	Extending Luo's (2007) work mainly modeling the short-term, immediate effects, this research models the *long-term*, accumulative effects with a time-series approach, namely VAR. These long-term, accumulative effects are important because focusing solely on the short-term effects would seriously underestimate the power of WOM.
Short-term, immediate effects of NWOM on cash flows	X	✓	
Short-term, immediate effects of NWOM on stock volatilities	X	✓	
Long-term, accumulative effects of NWOM on stock returns	X	✓	Empowered by VAR approach this research is among the first to be able to model how quickly or slowly bad news of NWOM travels in the stock market. These findings are important because they explicitly show that the stock market does not instantaneously react to NWOM information content. Rather, investors' reactions may grow over time, as the effects of NWOM keep unfolding. In addition, the harm of NWOM does not vanish overnight. After the peak point, the damaging impact of NWOM may still keep haunting investors for a while. Thus, our results help extend the literature by revealing more nuanced patterns of the dynamic effects of NWOM.
Long-term, accumulative effects of NWOM on cash flows	X	✓	
Long-term, accumulative effects of NWOM on stock volatilities	X	✓	
Wear-in effects of NWOM	X	✓	
Wear-out effects of NWOM	X	✓	
Feedback effects of historical cash flows on *future* NWOM	X	✓	This feedback loop extends Luo's (2007) work and makes an important contribution because if supported it would suggest a "vicious" cycle of NWOM: i.e., historical shortfalls in cash flows and underperformance in the stock market breed more harmful buzz in the future.
Feedback effects of historical stock returns on *future* NWOM	X	✓	
Feedback effects of historical stock volatilities on *future* NWOM	X	✓	Indeed, the two-way dynamic influences with feedback effects would (1) overcome the difficulty of drawing clean inferences of reversed causality and (2) contribute to WOM literature on how to model direct and reversed feedback effects simultaneously. To our best knowledge, the dynamic influences with feedback effects between WOM and firm stock prices have not been examined in the extant literature.

Table A.1 (Cont'd.)

Criterion	Luo (2007)	The present study	Specific incremental contributions
The role of *market competition*	X	✓	The study by Luo (2007) was not intended to uncover the role of market competition in the impact of WOM. What would be the changes in the dynamic effects of NWOM if competition is controlled for in the VAR models? Does bad news of NWOM matter more in the presence or without the presence of competition? This study by addressing these questions is an important effort because doing so would help uncover more realistic results and foster a more complete theory of the financial impact of WOM with market competition.
Monte Carlo simulation or bootstrapping specifications	✓	✓	The diverse modeling techniques used here not only accommodate latent heterogeneity, unobserved random effects, and time-series biases like heteroskedasticity and autocorrelation, but also uncover fascinating results: 1. Economically, on average, a unit unexpected shock in NWOM may lead to a drop of \$1.882 million cash flows for the airline companies in the following month, and an accumulated loss of \$8.169 million for the airline companies in the next 20 months, other things being constant. 2. On average it takes 3 to 4 months for the impact of NWOM on cash flows and stock prices to reach the peak point. The financial impact of NWOM remains significant for 6 to 7 months after the peak, *ceteris paribus*. Thus, the bad news of NWOM goes a long way and keeps haunting investors for a while in the stock market. 3. After modeling competition, the long-term harmful effects of NWOM hurt firm cash flows and stock prices more seriously (over 35%). In addition, the harm of NWOM seems to not merely kick in quicker, i.e., with shorter wear-in effects (time-to-peak drops 29% to 40%), but also becomes more persistent and long-lasting, i.e., with more salient wear-out effects (decaying-time after the peak increases 31%).
Random parameters modeling	✓	X	
Vector autoregressive model (VAR)	X	✓	
Impulse response functions (IRF)	X	✓	
Simultaneous estimation via generalized method of moments (GMM)	X	✓	
Generalized autoregressive conditional heteroskedasticity (GARCH)	X	✓	

Note. X = not addressed, ✓ = addressed.

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