The Journal of Behavioral Finance
2004, Vol. 5, No. 3, 154–169

Bubblelepsy: The Behavioral Wellspring of the Internet Stock Phenomenon

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This paper studies daily returns of Internet stocks before and after the Internet Crash of March 27, 2000. We find evidence of a bubble before the Crash. We argue that this bubble was propelled by overconfident investors suffering from biased self-attribution. Our analysis of subgroups of Internet firms finds the stocks that were perhaps the most salient in investors' minds drove the death spiral of Internet stocks and, although the evidence is at best marginal, the entire U.S. market.

Between 1998 and 2001, Internet stocks increased in market value by nearly 500%, before crashing to just 35% of their former peak value.[1] The financial press latched on to such seemingly irrational fluctuations and claimed that a speculative bubble drove Internet stock prices. At face value, there is much evidence that is consistent with these claims, such as the large premiums earned by companies who changed their names to incorporate dot-com (Cooper, Dimitrov, and Rau [2001]). Perhaps Internet stock prices were even controlled by "animal spirits" (Keynes [1936]). But why would investors have thrown away so much money investing in what appeared to be, even without hindsight, grossly overvalued companies?

The literature on psychology and finance provides potential answers. Specifically, it shows how, under certain conditions, people may succumb to systematic behavioral biases. For example, when making decisions, people seem to have a general tendency to overweight anecdotal and salient information (Klibanoff, Lamont, and Wizman [1998]), and underweight statistical base rate evidence (Griffin and Tversky [1992]). Perhaps the most robust finding, however, is that people are generally overconfident in their own abilities (see Barber and Odean [2001] for a recent example). People with limited abilities to perform specific tasks become overconfident about their ability to execute those tasks (Kruger and Dunning [1999]).

This paper examines the time-series of Internet stock returns. We outline literature salient to our discussion in the second section and discuss the sample period and data in the third section. The fourth section examines whether an Internet stock price bubble was present and, if we may preempt our findings, establishes a *prima facie* case for the presence of a bubble. The fifth section examines the contribution of behavioral biases to the Internet stock price bubble between 1998 and 2001. This enables us to use the Internet phenomenon to examine competing behavioral models of asset price behavior. The sixth section examines portfolios of Internet stocks to further explore our hypotheses about the wellspring of the bubble. The final section provides a conclusion.

Our paper contributes to the study of psychology and financial markets by using existing theoretical models to examine an intriguing and dramatic phenomenon. We take advantage of the Internet stock phenomenon to evaluate competing behavioral finance theories. We believe that our approach here may be used to examine other alleged bubble episodes. It would be of considerable interest if other alleged bubble episodes were driven by the same behavioral phenomena that appear to have driven the Internet stock phenomenon.

Literature

Hirshleifer [2001] provides a comprehensive review of the literature pertaining to investor psychology and asset pricing. In general, the literature shows that behavioral biases are common to novices and experts alike (Tversky and Kahneman [1971]). However, the extent of people's vulnerability to these biases seems to be affected by their personal characteristics and influenced by environmental conditions. Many of these conditions are common to the Internet stock market.

For example, Estrada and Blakely [1999] note that the most active investors in Internet stocks were individuals (reflected in the small average trade sizes for Internet stocks). Such investors can be overoptimistic about the future performance of their shares, and their perceived confidence intervals tend to be too narrow relative to the actual price variability (De Bondt [1998]). Similarly, the high exposure of Internet stocks in the fi-

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nancial press, the high volatility of Internet stock returns, and the lack of an accepted valuation model increased the likelihood of Internet investors succumbing to overconfidence (Alpert and Raiffa [1982], Tversky and Kahneman [1971], and Slovic [1982]), representativeness (Tversky and Kahneman [1974]), and self-attribution bias (Hirshleifer [2001], pp. 1548–1550). Barberis, Shleifer, and Vishny [1998] (henceforth BSV), Daniel, Hirshleifer, and Subrahmanyam [1998] (henceforth DHS), Odean [1998a], and De Long et al. [1990] (henceforth DSSW) all provide theoretical models of expected stock price behavior when representative investors in their model suffer from one or more of these cognitive biases.

In BSV's [1998] model, investors' decisions are guided by representativeness and conservatism, which causes them to incorrectly believe that earnings move between one of two "states" or "regimes," either mean-reverting or trend. In fact, earnings follow a random walk. Investor decisions about which regime is currently driving prices are determined by past information. For example, when consecutive shocks of the same sign are observed in the earnings stream, the representativeness bias causes investors to overweight the probability that they are in a regime where earnings follow trends. Investors then extrapolate the current trend too far into the future, causing stock prices to overreact.

DHS [1998] found that investors are overconfident about the precision of their private signals. They also suffer from biased self-attribution, where investors attribute their success to their own prowess and their failures to external factors. Biased self-attribution causes investors to become increasingly overconfident when public information seems to confirm their private information, but negative public signals do not commensurately reduce their confidence. Indeed, contradictory evidence may not affect their confidence at all. In the short term, such behavior implies a degree of return predictability, but over the long term, significant reversals in stock prices may occur as new information releases eventually overwhelm the trader's biases.

Odean [1998a] illustrates how overconfidence among price-taking traders affects trading volume. Odean shows that traders who are overconfident about their investing ability tend to weigh their own signals and their own interpretation of public signals more than the signals of others when calculating their posterior beliefs. This causes a greater divergence of beliefs about stocks' fundamental values, which, in turn, should cause investors to trade more and should increase aggregate trading volume.

Positive feedback trading may also cause similar stock price continuations and increased trading volume. In DSSW's [1990] model, positive feedback traders are assumed to be indifferent to current period prices; instead, they trade on past price trends. An interesting consequence of this model is that it implies that the optimal strategy for rational traders is to preempt future positive feedback trader demand. In this way, the combination of positive feedback trader demand and rational traders attempting to exploit their behavior should result in price destabilization, increased trading volume, and predictable future returns.

Sample Period and Data

The Sample Period

A visual examination of the data indicates that pre- and post-Crash relationships may be different. If the analysis is conducted without recognizing this possibility, any such differences may be averaged out. If our analysis finds no differences between the periods, however, little is lost by separate analyses. Therefore, we analyze pre- and post-Crash returns.

We define the pre-Crash period as October 12, 1998, until March 20, 2000. The October 12 commencement date is somewhat subjective, but visual inspection of a price index for the Goldman Sachs Internet index indicates that it marks the beginning of the first persistent upward trend in Internet stock prices. We focus on what sustained the bubble (if a bubble is found to have existed), and do not address why it may have begun.[2]

The market break of March 27, 2000, is a natural demarcation point for our study, as it is widely recognized as the "official" Internet Crash date. Our choice of this date is also supported by visual inspection of the Goldman Sachs Internet index. In the week following March 27, Internet stock prices lost nearly 10% of their value. Three weeks after, the slide was unrelenting: Internet stock prices had fallen nearly 40%.[3] *Prima facie*, this period appears to mark a significant adjustment stage in investor optimism about Internet stocks. In an effort to reduce noise associated with the Crash period, we end our pre-Crash period seven days prior to the Crash date. In total, the pre-Crash period spans seventeen months and includes 363 daily observations after deletion of non-trading days.

Internet stocks continued to crash until April 14, 2000. After April 14, stock prices appeared to steady for approximately the next three to five months. We commence our post-Crash period seven days after April 14, 2000, again in order to avoid noise, and end it at May 1, 2001. The post-Crash period spans just over twelve months and consists of 259 daily observations.

Internet Stocks: Definition

There is currently no standard industry code (SIC) or other classification system that properly identifies an Internet company. Defining a sample of Internet stocks can be problematic, as relatively few are pure plays. Most rely on multiple sources of income, such as software development, processing computer components, and so on.

The Goldman Sachs Internet Index (GSI) is comprised of seventeen stocks that are a subset of the stocks classified as Internet companies by Internet.com's 51% revenue criterion. The GSI was widely followed at the time, and was regularly reported in *The Economist* and *BusinessWeek*. Since share turnover data are unavailable for the GSI, we create an equal-weighted index using a list of the constituents of the GSI acquired from *PremierInvestor.Com*.[4, 5]

Table 1 gives descriptive statistics for the GSI index and the S&P 500 index (as well as for other control portfolios discussed later). Average returns for the GSI before the Crash were approximately seven times as large as those for the S&P. Standard deviations were more than three times as large. Shiller [1984] argues that noise trading causes excess volatility, and these initial statistics are consistent with that argument. In a similar vein, the order of magnitude of returns after the Crash is four times as great and three times as volatile as the S&P after the Crash.

Table 2 reports summary statistics for the number of shares traded (adjusted for capital changes). This table shows that trading volume in our sample of Internet stocks falls after the Crash. This is to be expected if investors behave in a way consistent with prospect theory and are reluctant to realize their losses (Shefrin and Statman [1985], Odean [1998b]).

Table 3 shows correlations between our main indexes for the pre- and post-Crash periods as well as for the aggregated period. Correlations between all the indexes become much stronger following the March 2000 Internet Crash, which suggests a change in behavior of Internet investors between the pre- and post-Crash periods and indicates that the markets became more alike after the Crash.

Was There An Internet Stock Bubble?

The literature discussed in the first section suggests that behavioral biases will result in predictable trading behavior. But whether this behavior will result in pre-

Table 1. *Descriptive Statistics (Returns)*

Summary statistics for the time-series of returns of the equal-weighted Goldman Sachs Internet index (GSI_R), four Internet subgroups [E-tailers (ETAIL_R), Content and Communities (CONT_R), Search and Portals (SEAR_R), and Security firms (SEC_R)], and the S&P 500 index. The three time periods are the pre-crash period (October 12, 1998–March 20, 2000) (Panel A), the post-crash period (April 20, 2000–May 1, 2001) (Panel B), and the whole period (October 12, 1998–May 1, 2001) (Panel C). The Jarque-Bera statistic tests the null hypothesis that the distribution conforms to a Gaussian normal distribution.

	GSI_R	ETAIL_R	CONT_R	SEAR_R	SEC_R	SP500_R
Panel A: Pre-crash						
Mean	0.007031	0.004831	0.006127	0.008177	0.008185	0.001024
Median	0.007805	0.002442	0.00163	0.007654	0.007141	0.001115
Maximum	0.139671	0.262808	0.364386	0.193761	0.177086	0.047482
Minimum	–0.157484	–0.141893	–0.209629	–0.179836	–0.135554	–0.038489
Std. Dev.	0.038907	0.042138	0.049703	0.049336	0.031005	0.012184
Skewness	–0.034416	1.05043	1.321798	0.361805	0.515201	0.070667
Kurtosis	3.91466	9.326083	12.23077	4.180387	7.401977	3.646061
Jarque-Bera	12.72526	672.0483	1394.461	28.9935	309.1419	6.615222
p-value	0.001725	0	0	0.000001	0	0.036604
Panel B: Post-crash						
Mean	–0.002002	–0.000905	–0.002299	–0.003511	–0.001358	–0.000517
Median	–0.004572	–0.002666	–0.002264	–0.009029	–0.002468	–0.001401
Maximum	0.202458	0.124137	0.095711	0.179821	0.108338	0.049945
Minimum	–0.150758	–0.078247	–0.09693	–0.135577	–0.106983	–0.043306
Std. Dev.	0.050809	0.031927	0.031115	0.046323	0.037638	0.013911
Skewness	0.615143	0.688218	0.207026	0.638253	0.249378	0.354691
Kurtosis	3.990238	4.096947	3.472339	4.40517	3.152154	3.898064
Jarque-Bera	26.91628	33.43117	4.257775	38.89284	2.934339	14.13430
p-value	0.000001	0	0.11897	0	0.230577	0.000853
Panel C: Whole period						
Mean	0.002694	0.001638	0.001726	0.002485	0.003511	0.000339
Median	0.003645	–0.000682	–0.000566	–0.001096	0.003188	8.77E–05
Maximum	0.202458	0.262808	0.364386	0.193761	0.177086	0.049945
Minimum	–0.157484	–0.141893	–0.209629	–0.179836	–0.181178	–0.058435
Std. Dev.	0.04515	0.039346	0.044172	0.049019	0.036475	0.013197
Skewness	0.296277	0.957512	1.159331	0.423102	0.08237	0.085541
Kurtosis	4.059621	8.550197	12.43125	4.146612	5.951298	4.150958
Jarque-Bera	39.55009	924.9988	2531.044	54.49261	234.4509	36.33160
p-value	0	0	0	0	0	0

Table 2. *Descriptive Statistics (Volume)*

Summary statistics for the time-series of daily volume of shares traded (expressed in thousands of shares and adjusted for capital changes) of the equal-weighted Goldman Sachs Internet index (GSI_R), four Internet subgroups [E-tailers (ETAIL_R), Content and Communities (CONT_R), Search and Portals (SEAR_R), and Security firms (SEC_R)], and the S&P500 index. The three time periods are the pre-crash period (October 12, 1998–March 20, 2000) (Panel A), the post-crash period (April 20, 2000–May 1, 2001) (Panel B), and the whole period (October 12, 1998–May 1, 2001) (Panel C). The Jarque-Bera statistic tests the null hypothesis that the distribution conforms to a Gaussian normal distribution.

	GSI_VOL	ETAIL_VOL	CONT_VOL	SEAR_VOL	SEC_VOL	SP500_VOL
Panel A: Pre-crash						
Mean	9261.969	2976.639	993.1368	20406.44	841.6931	883142.3
Median	8525.869	2233.15	710.6846	12936.36	698.9538	828243.0
Maximum	21877.42	19994.67	6881.243	89014.6	4975.893	1711143
Minimum	3272.044	605.4172	224.2238	1915.322	242.2786	217191.0
Std. Dev.	3392.407	2436.099	860.3161	17976.9	501.114	224358.1
Skewness	1.104542	2.663863	3.433667	1.315779	3.285916	0.708396
Kurtosis	4.088801	13.3058	18.75026	4.197791	20.42351	3.627353
Jarque-Bera	91.74132	2035.738	4465.37	126.442	5244.862	36.31317
p-value	0	0	0	0	0	0
Panel B: Post-crash						
Mean	6335.224	782.0347	334.1563	2871.911	890.8957	1509778
Median	5843.3	732.0688	305.1485	2627.331	758.4	1496052
Maximum	17093.53	2392.034	1246.257	7581.733	3125.657	2923679
Minimum	1510.533	181.1687	109.4636	935.4727	246.7267	501370.0
Std. Dev.	2330.529	294.0347	146.7545	1053.964	463.9247	398392.2
Skewness	1.138852	1.412584	2.09364	1.52851	1.386679	0.606563
Kurtosis	4.722675	7.056788	11.27315	6.287758	5.202213	3.579299
Jarque-Bera	88.01196	263.7387	927.85	217.5031	135.3411	19.50338
p-value	0	0	0	0	0	0.000058
Panel C: Whole period						
Mean	8027.551	2025.101	712.0559	12819.7	867.7301	1151053
Median	7305.656	1222.958	501.5606	5396.773	724.1536	1067166
Maximum	21877.42	19994.67	6881.243	89014.6	4975.893	2923679
Minimum	1510.533	181.1687	109.4636	935.4727	242.2786	217191.0
Std. Dev.	3289.43	2133.366	727.5127	16031.49	482.8903	433066.3
Skewness	1.186122	3.168125	4.064144	2.00559	2.541136	0.926983
Kurtosis	4.648602	17.66865	26.32792	6.756618	14.81315	3.722004
Jarque-Bera	223.9356	6851.013	16375.33	810.4134	4437.698	106.2191
p-value	0	0	0	0	0	0

Table 3. Pairwise Correlations

Pearson's product moment correlations between the equal-weighted Goldman Sachs Internet index (GSI_R), the S&P 500 index (S&P500_R), and the four Internet subgroup indexes (SEC_R, CONT_R, ETAIL_R, and SEAR_R). Panel A shows Pearson's product moment correlations for the pre-crash period (October 12, 1998-March 20, 2000). Panel B shows Pearson's product moment correlations for the post-crash period (April 20, 2000-May 1, 2001). Panel C shows Pearson's product moment correlations for the whole period (October 12, 1998-May 1, 2001).

	SP500_R	ETAIL_R	CONT_R	SEAR_R	SEC_R
Panel A. Pre-Crash					
GSI_R	0.574065	0.652756	0.563979	0.777472	0.392238
SP500_R		0.383192	0.400730	0.475358	0.266789
ETAIL_R			0.543772	0.564632	0.368409
CONT_R				0.532562	0.291202
SEAR_R					0.316039
Panel B. Post-Crash					
GSI_R	0.757233	0.645453	0.649604	0.806752	0.753804
SP500_R		0.513801	0.527450	0.702019	0.718380
ETAIL_R			0.694966	0.634512	0.622025
CONT_R				0.660151	0.658135
SEAR_R					0.730259
Panel C. Whole period					
GSI_R	0.670234	0.638395	0.578304	0.789330	0.612479
SP500_R		0.431447	0.436291	0.576900	0.509624
ETAIL_R			0.614427	0.606317	0.503138
CONT_R				0.587705	0.459274
SEAR_R					0.538636

dictable price patterns depends on the effectiveness of arbitrage. If arbitrage is ineffective,[6] prices should be predictable and weak form market efficiency (Fama [1970]) will be violated. We examine whether there is a *prima facie* case that market efficiency was violated during the bubble period by examining whether Internet returns followed a first-order autoregressive process.[7]

An autoregressive process is consistent with the theoretical models discussed in the first section. For example, DSSW [1990] illustrate that positive feedback traders cause price movements in one period to be followed by similar movements in the next period. Similarly, DHS [1998] demonstrate that overconfidence causes investors to overreact to information releases, which implies subsequent price reversals and an autoregressive relationship between future returns and past price movements. Autocorrelation implies that price changes are predictable, so trading strategies based on past price information can be profitable, which is a clear violation of weak form market efficiency and the fair game model.

In contrast to DHS [1998], Fisher [1966] argues that positive serial correlation in portfolio returns is a manifestation of the portfolio construction process. If portfolios consist of infrequently traded firms, reactions to price-sensitive events will occur on multiple days because news will only be reflected in the component stocks as they are traded. This implies positive autocorrelation but not necessarily market inefficiency.

Chowdhury and Lin [1993] develop a methodology to differentiate between the two competing causes of serial correlation by examining changes in the time-series structure of returns following the 1987 U.S. market Crash. Specifically, they argue that a change in the time-series structure of returns from a serially correlated process before the Crash to a moving average process afterward can only be plausibly explained as a rational response to pre-Crash irrational forces. A rational explanation would need to explain why non-synchronous trading, or any other microstructure-induced phenomenon, affects portfolio autocorrelation in the pre-Crash period but not in the post-Crash period, or why investors suddenly changed their risk preferences after the Crash. Chowdhury and Lin [1993] anticipate and address concerns recently articulated by Ahn et al. [2002], who have suggested there is a problem with using a behavioral story to explain autocorrelation in an index.

Consistent with Chowdhury and Lin's [1993] analytical framework, we separately fit an ARMA(1, 2) process to the Goldman Sachs Internet portfolio and the S&P 500 index for the pre- and post-Crash periods. The results are reported in Table 4. In sum, Panel A shows a significant positive autocorrelation in Internet returns in the pre-Crash period, which suggests that Internet stocks were affected by irrational influences prior to the Crash. Similarly, changes in the S&P are autocorrelated. Thus, it appears that the main market may also have been infected with "bubblelepsy."[8]

For all the indexes, the autoregressive component disappears in the post-Crash period (Table 4, Panel B). This finding supports the view that the Internet Crash was a rational response to irrational prices that prevailed prior to the Crash. This, along with the fall in volume after the Crash reported in Table 2, belies the argument that the autoregressive component before the Crash is

Table 4. *ARMA Results*

Results from fitting an autoregressive moving average model to the data, using a least squares regression technique, for both the pre-crash period (October 12, 1998–March 20, 2000) and the post-crash period (April 20, 2000–May 1, 2001). Specifically,

$$\phi(L^{p=1})X_t = \theta(L^{q=2})\varepsilon_t$$

where L is the lag operator, ε_t is white noise, the t subscript is time, and X_t denotes returns. We fit this equation to the equal-weighted Goldman Sachs Internet indexes (GSI_R) and the S&P 500 index (S&P500_R). *T*-statistics are in parentheses and are adjusted for heteroscedasticity using White's correction procedure (White [1980]).

	Panel A: Pre-Crash		**Panel B: Post-Crash**	
Variable	**GSI_R**	**SP500_R**	**GSI_R**	**SP500_R**
Intercept	0.007	0.001	−0.002	−0.001
t-statistic	(3.762)***	(3.362)***	(−0.641)	(−0.727)
AR(1)	0.680	0.929	−0.138	0.055
t-statistic	(3.903)***	(54.748)***	(−0.334)	(0.086)
MA(1)	−0.634	−0.958	0.258	−0.110
t-statistic	(−3.559)***	(−18.690)***	(0.599)	(−0.172)
MA(2)	−0.097	−0.032	−0.124	−0.090
t-statistic	(−1.585)	(−0.623)	(−1.115)	(−1.085)
R-squared	0.020654	0.044953	0.034708	0.011706
Adjusted R-squared	0.012470	0.036972	0.023351	0.000079
F-statistic	2.523743	5.632613	3.056238	1.006816
p-value	0.057484	0.000881	0.028956	0.390306

Note: *, **, and ***denote significance at the 10%, 5%, and 1% significance levels, respectively.

due to infrequent trading. We also find that non-Internet stock returns exhibit similar autoregressive qualities to Internet stocks in the pre- and post-Crash periods. We examine this issue further in the next section by using vector autoregression (VAR).

What Sustained the Bubble? The Behavioral Wellspring

To differentiate between alternate behavioral explanations for the Internet bubble, we examine the dynamic relationship between market index returns and Internet stock returns. Specifically, we use VAR[9] to determine the relationship between excess returns and number of stocks traded[10] for the GSI and the S&P. The models discussed earlier provide testable hypotheses on the wellspring of the Internet stock phenomenon (BSV [1998], DHS [1998], Odean [1998a], and DSSW [1990]).

Following DSSW, if positive feedback trading drove the bubble, we would expect past Internet returns to predict future Internet returns. Such price autocorrelation would also be consistent with BSV, although with overreaction we might expect positive autocorrelation to be followed by negative autocorrelation as the market corrects for its initial response.

In contrast, DHS present a broader model where information, such as movements in the broad market index or other publicly available information, reinforces investors' views of themselves and motivates their faith-based trading. If overconfidence is the driver of the phenomenon, however, Odean [1998a] suggests we would also expect a volume-return relationship.

The behavior of returns in the pre-Crash period appears consistent with DHS [1998]. Table 5 presents results for the VAR in the pre-Crash period using the equal-weighted GSI portfolio. Perhaps the most striking results here are the positive and significant coeffi-

Table 5. *Goldman Sachs Equal-Weighted Pre-Crash VAR*

Results for the vector autoregressions(VAR) of return(_R) and volume(_VOL) data for the equal-weighted Goldman Sachs Internet index(GSI) with the S&P500(SP500) during the pre-crash period: October12,1998–March20,2000. Volume is the number of shares traded on a particular day(expressed in thousands and adjusted for capital changes); returns are daily simple excess returns, using the three-month U.S. T-bill rate as a proxy for the risk-free rate. MONDAY is a dichotomous variable taking the value of1 if the observation occurs on a Monday and zero otherwise. *T*-statistics are in parentheses and represent White's heteroscedasticity-adjusted two-tailed test of the null hypothesis that the coefficient is equal to zero.

	GSI_R	GSI_VOL	SP500_R	SP500_VOL
GSI_R(−1)	−0.074921	−4471.551	−0.056807	−69997.50
	(−0.95795)	(−0.7911)	(−2.2402)**	(−0.34665)
GSI_R(−2)	−0.216579	−43.20168	−0.020430	198191.1
	(−2.9547)***	(−0.00806)	(−0.97292)	(0.84144)
GSI_R(−3)	0.041754	−1508.581	−0.014349	14064.99
	(0.54705)	(−0.30349)	(−0.62916)	(0.064266)
GSI_VOL(−1)	−3.00E−07	0.586894	−7.02E−09	−0.694634
	(−0.30032)	(8.3783)***	(−0.02550)	(−0.26617)
GSI_VOL(−2)	1.65E−06	−0.085435	2.96E−07	−7.391067
	(1.3722)	(−0.90618)	(0.93119)	(−2.0388)**
GSI_VOL(−3)	4.02E−07	0.153310	1.75E−07	−0.913370
	(0.41374)	(2.3818)**	(0.63921)	(−0.30947)
SP500_R(−1)	0.530045	−533.4361	0.106470	−251225.9
	(2.8232)***	(−0.03859)	(1.4491)	(−0.36913)
SP500_R(−2)	0.621166	12166.17	0.072934	−1012813
	(2.6973)***	(0.88823)	(1.1453)	(−1.5962)
SP500_R(−3)	0.175394	3106.888	−0.075319	−1277198
	(0.82109)	(0.23360)	(−1.1654)	(−1.8696)*
SP500_VOL(−1)	7.00E−09	−0.001566	3.83E−09	0.518082
	(0.41997)	(−1.6114)	(0.55280)	(6.7693)***
SP500_VOL(−2)	6.18E−10	−0.000111	2.76E−09	0.232923
	(0.030893)	(−0.09350)	(0.39247)	(3.0041)***
SP500_VOL(−3)	−1.22E−09	−0.001277	−3.81E−09	0.091839
	(−0.07631)	(−1.0828)	(−0.75147)	(1.3570)
INTERCEPT	−0.015092	5714.155	−0.005137	240048.0
	(−0.9475) ·	(5.8227)***	(−1.2155)	(4.3741)***
MONDAY	0.003065	523.6794	−0.000514	−79701.77
	(0.4780)	(1.6329)*	(−0.32323)	(−4.0853)***
R-squared	0.084445	0.451121	0.055383	0.720153
Adj. R-squared	0.050341	0.430676	0.020196	0.709729
F-statistic	2.476118	22.06473	1.573983	69.08533
(*p*-value)	(0.003)	(0.000)	(0.09)	(0.000)

Note: *, **, and ***denote significance at the10%,5%, and1% significance levels, respectively.

cients on lagged market movements in the Internet returns equation. *T*-statistics of 2.8 and 2.7, respectively, for the first and second lags are statistically significant at the 1% level. This implies that in the pre-Crash period positive returns on the market index were followed by two days of positive Internet stock index returns.

In contrast, the statistically significant negative autoregressive relationship for Internet returns two days earlier implies that, in the pre-Crash period, positive Internet stock returns were followed by negative returns two days later. Investors may in some way be compensating for their overreaction to signals from the wider market; the coefficient, however, is relatively small (-0.22) compared to lags on the market (0.53 and 0.63, respectively, for the first and second lags).

In addition, *F*-statistics for three of the four equations are significant at the 1% level, implying rejection of the null hypothesis that all coefficients simultaneously equal zero for these equations. The market index returns equation is marginal, with an *F*-statistic (*p*-value) of 1.57 (0.09). For the market as a whole, this provides, at best, only marginal evidence against the violation of weak efficiency postulated by behavioral models. It is not clear if the broader market was caught up in the "irrational exuberance" of the period.

The R-squared values in Table 5 show that the analyses explain much more of the variation in Internet volume (45%) than Internet returns (8.5%). Trading in the GSI is positively autocorrelated. This is consistent with overconfidence, which postulates that as individuals become more confident in an activity, they are likely to continue it or increase their exposure to it.

The models of overconfidence and self-attribution bias developed by Odean [1998a] and DHS [1998], however, imply that current period returns should be predictive of future trading activity because changes in price affect the level of confidence, which determines investors' willingness to trade. But there is no indication that GSI returns are related to GSI volume and vice versa, so the data do not support these models.

In the DSSW [1990] positive feedback trader model, traders implement their trades following persistent trends in stock prices. Thus, lagged returns should be predictive of current period trading volume and this lagged relationship should be positively correlated. The DSSW [1990] model also illustrates that positive feedback traders cause stock price overreactions (predictable changes in prices). Thus, current period volume should be predictive of future period returns.

But once again, the data are not consistent with this model. Trading in the S&P is autocorrelated. We find, however, a negative impact with the two-day lagged GSI volume, and a marginal relationship with three-day lagged returns in the S&P. Furthermore, there is no evidence of a "joy of trading" effect, as noted in Durand and Scott [2003]. In other words, there is no evidence that trading in one area of the market affects trading in another.

Table 6 shows the results of the VAR analysis in the post-Crash period for the equal-weighted index. In contrast to the pre-Crash results, the *F*-statistics indicate that we cannot reject the hypothesis that the coefficients jointly equal zero (although some individual *t*-statistics are present in the return equations).[11]

Like Carvalho, Durand, and Ng [2002], we draw some comfort from the "failure" of our model after the Crash. Perhaps the atheoretical nature of VAR leaves our analysis vulnerable to criticisms based on the joint hypothesis problem (Fama [1970, 1991]). Yet the return to the status quo of weak form efficiency, as seen after the 1987 Crash (Chowdhury and Lin [1993]), supports the argument that our findings are not due to a "bad model." The period before the Crash was unusual, both for the GSI and the S&P 500. The Crash is the jolt that brought investors back to their senses and drove the market back to its expected unpredictability. The level of confidence that, in aggregate, would be needed to sustain investor participation in an informationally efficient market replaced the overconfidence that drove the bubble.

Representativeness and Overconfidence: An Examination of the Market Sub-Groups

People's overconfidence tends to increase as their familiarity with the decision-making process grows. So if the relationship between past market prices and future Internet prices in the pre-Crash period is due to overconfidence, and if this overconfidence is caused by market movements confirming investors' previously acquired information, Internet stocks that investors are more familiar with should have a stronger relationship with past movements. This follows simply because investors are more likely to have acquired information about them.

We next explore the hypothesis that overconfidence, engendered by familiarity, was the mechanism behind pre-Crash returns by examining the dynamic relationships between market returns and Internet stock returns based on sub-industry type. We follow Trueman, Wong, and Zhang [2000], who stratify their sample of Internet stocks into three groups: E-tailers, content and community (henceforth C&C), and Search and Portals.[12]

We examine portfolios of these subgroups using VAR analysis and we use the same companies as Trueman, Wong, and Zhang [2000] to define Internet subgroups. We also define a portfolio of Internet security firms,[13] which should rely less than the other subgroups on Internet usage for revenues.

Table 6. *Goldman Sachs Equal-Weighted Post-Crash VAR*

Results of vector autoregressions(VAR) of return(_R) and volume(_VOL) data for the equal-weighted Goldman Sachs Internet index(GSI) with the S&P500 index(SP500) for the post-crash period: April20,2000–May1,2001. Volume is the number of shares traded on a particular day(expressed in thousands and adjusted for capital changes); returns are daily simple excess returns, using the three-month U.S. T-bill rate as a proxy for the risk-free rate. MONDAY is a dichotomous variable taking the value of1 if the observation occurs on a Monday and zero otherwise. *T*-statistics are in parentheses and represent White's heteroscedasticity-adjusted two-tailed test of the null hypothesis that the coefficient is equal to zero.

	GSI_R	**GSI_VOL**	**SP500_R**	**SP500_VOL**
GSI_R(−1)	0.185681	−4956.247	0.035852	−441416.4
	(1.4627)	(−1.3411)	(1.2300)	(−0.81408)
GSI_R(−2)	−0.259868	−2029.284	−0.029075	−559462.7
	(−2.5001)***	(−0.47555)	(−1.0172)	(−1.0302)
GSI_R(−3)	0.064098	−2516.635	−0.006987	153568.6
	(0.61446)	(−0.68161)	(−0.24808)	(0.34889)
GSI_VOL(−1)	−1.76E−06	0.501969	−7.41E−07	−7.694565
	(−0.75057)	(5.9669)***	(−1.1632)	(−0.72815)
GSI_VOL(−2)	5.79E−06	0.078449	1.38E−06	−2.165394
	(2.0917)**	(0.81546)	(1.6539)*	(−0.17640)
GSI_VOL(−3)	−2.54E−07	0.094945	−4.35E−08	16.48322
	(−0.11498)	(1.0784)	(−0.06217)	(1.4052)
SP500_R(−1)	−0.332911	6755.271	−0.142516	577425.5
	(−0.79978)	(0.59639)	(−1.3451)	(0.31607)
SP500_R(−2)	0.381603	11525.74	−0.032120	−1943063
	(1.0037)	(0.86446)	(−0.30891)	(−1.1189)
SP500_R(−3)	0.024548	12131.35	0.013824	781622.0
	(0.066212)	(0.87455)	(0.13308)	(0.46532)
SP500_VOL(−1)	1.04E−08	0.000381	1.99E−09	0.633109
	(0.68632)	(0.76296)	(0.47478)	(6.8425)***
SP500_VOL(−2)	−2.30E−08	−0.000557	−5.59E−09	0.012197
	(−1.3632)	(−1.0331)	(−1.1507)	(0.14371)
SP500_VOL(−3)	3.97E−09	0.001049	1.58E−09	0.169355
	(0.24765)	(1.9973)**	(0.33955)	(2.4132)**
INTERCEPT	−0.012830	871.3150	−0.001648	282389.0
	(−1.0097)	(2.2284)**	(−0.47109)	(4.7194)***
MONDAY	−0.000455	−758.1345	0.001685	−246651.3
	(−0.061301)	(−3.2183)***	(0.77494)	(−6.2186)***
R-squared	0.073111	0.523394	0.044767	0.650557
Adj. R-squared	0.023929	0.498104	−0.005919	0.632015
F-statistic	1.486537	20.69623	0.883231	35.08578
(*p*-value)	(0.123)	(0.000)	(0.571)	(0.000)

Note: *, **, and ***denote significance at the10%,5%, and1% significance levels, respectively.

Trueman, Wong, and Zhang [2000] argue that a metric for a company's "Internet visibility," or web usage, should be more important for E-tailers and C&C firms because they rely more on visitors spending time on their company's web pages than the other subgroups. Their findings generally confirmed their hypothesis.

Shiller [2000] argues that the Internet bubble was largely attributable to investors being able to easily recall examples of Internet companies due to time spent on the Internet. Such analyses suggest that E-tailers should be more affected by quasi-rational trading behavior than the other subgroups. The effect should be progressively weaker for C&C, Search and Portals, and Security firms, respectively.

In addition to descriptive statistics for the GSI and S&P indexes, Table 1 gives summary statistics for the returns of the four Internet stock subgroups. Table 2 gives them for the subgroup volumes. Like the GSI, average returns for the subgroups before the Crash were much larger (four to eight times larger) than the S&P. Standard deviations for the subgroups were also greater than the S&P standard deviation before the Crash. Using these standard deviations as a benchmark, however, it is not as clear if noise traders were more prevalent in one group or another.

The orders of magnitude of returns after the Crash are much larger and more volatile than those for the S&P. Table 2 shows that volume fell after the Crash, most notably for the Search and Portals subgroup. Table 3 shows that correlations between all the indexes tended to become much stronger following the Crash, suggesting a change in behavior between periods.

Tables 7, 8, 9, and 10 show results for the E-tailers, C&C, Search and Portals, and Security subgroups, re-

Table 7. *E-Tailers–Pre-Crash VAR*

Results for the vector autoregressions (VAR) of return (_R) and volume (_VOL) data for the equal-weighted E-tailers index (ETAIL) with the S&P500 index (SP500) during the pre-crash period: October 12, 1998–March 20, 2000. Volume is the number of shares traded on a particular day (expressed in thousands and adjusted for capital changes); returns are daily simple excess returns, using the three-month U.S. T-bill rate as a proxy for the risk-free rate. MONDAY is a dichotomous variable taking the value of 1 if the observation occurs on a Monday and zero otherwise. *T*-statistics are in parentheses and represent White's heteroscedasticity-adjusted two-tailed test of the null hypothesis that the coefficient is equal to zero.

	ETAIL_R	ETAIL_VOL	SP500_R	SP500_VOL
ETAIL_R(−1)	0.066001	5823.837	−0.045509	−105736.5
	(.82048)	(1.5285)	(−2.2338)**	(−0.54653)
ETAIL_R(−2)	−0.014428	−1108.616	−0.020330	294591.9
	(−0.14880)	(−0.33042)	(−1.0122)	(1.5237)
ETAIL_R(−3)	0.038268	−4389.043	−0.000744	204965.9
	(0.52496)	(−1.4134)	(−0.040359)	(1.1284)
ETAIL_VOL(−1)	5.89E−06	0.649964	6.96E−07	−10.67069
	(2.9231)***	(7.0434)***	(1.7655)*	(−2.1008)**
ETAIL_VOL(−2)	−1.98E−06	−0.099340	−1.86E−07	−3.805533
	(−.75562)	(−1.1646)	(−0.38075)	(−0.70373)
ETAIL_VOL(−3)	1.88E−06	0.236641	6.27E−07	2.464438
	(1.3089)	(4.1430)***	(1.3701)	(0.78052)
SP500_R(−1)	0.342706	−10190.38	0.034831	−767413.2
	(2.1194)**	(−1.5140)	(0.53729)	(−1.3611)
SP500_R(−2)	0.331028	−4099.374	0.034492	−902792.4
	(1.6949)*	(−0.51380)	(0.50166)	(−1.8149)*
SP500_R(−3)	0.396216	6238.577	−0.065372	−1403905
	(2.3295)**	(1.0216)	(−1..1278)	(−2.8635)***
SP500_VOL(−1)	1.20E−08	0.002301	2.79E−09	0.506681
	(0.81178)	(3.8698)***	(0.45189)	(7.2289)***
SP500_VOL(−2)	−7.90E−09	−0.001572	7.65E−10	0.217949
	(−0.48562)	(−2.5333)***	(0.10781)	(3.1857)***
SP500_VOL(−3)	9.94E−09	−0.001960	3.76E−09	0.101502
	(0.63514)	(−3.1679)***	(0.66568)	(1.7368)*
INTERCEPT	−0.027402	1810.951	−0.008972	207679.4
	(−2.2011)**	(3.5460)***	(−2.1256)**	(4.3525)***
MONDAY	−0.002457	−414.6502	−0.000507	−79420.58
	(−0.42764)	(−2.3154)**	(−0.28579)	(−4.3752)***
R-squared	0.164968	0.642446	0.042755	0.710133
Adj. R-squared	0.136772	0.630372	0.010432	0.700345
F-stat	5.851	53.217	1.3227	72.5534
(*p*-value)	(0.000)	(0.000)	(0.197)	(0.000)

Note: *, **, and ***denote significance at the 10%, 5%, and 1% significance levels, respectively.

Table 8. *Content and Community–Pre-Crash VAR*

Results for the vector autoregressions (VAR) of return (_R) and volume (_VOL) data for the equal-weighted Content and Community index (CONT) with the S&P 500 index (SP500) during the pre-crash period: October 12, 1998–March 20, 2000. Volume is the number of shares traded on a particular day (expressed in thousands and adjusted for capital changes); returns are daily simple excess returns, using the three-month U.S. T-bill rate as a proxy for the risk-free rate. MONDAY is a dichotomous variable taking the value of 1 if the observation occurs on a Monday and zero otherwise. *T*-statistics are in parentheses and represent White's heteroscedasticity-adjusted two-tailed test of the null hypothesis that the coefficient is equal to zero.

	CONT_R	CONT_VOL	SP500_R	SP500_VOL
CONT_R(−1)	0.111041	1632.502	−0.009835	−236247.3
	(1.2825)	(1.4530)	(−0.53789)	(−1.5577)
CONT_R(−2)	−0.123393	−491.1305	−0.025500	473673.0
	(−1.7452)*	(−0.38942)	(−1.4393)	(3.2642)***
CONT_R(−3)	−0.034659	−2814.230	−0.007267	42188.93
	(−0.45550)	(−3.1061)***	(−0.40953)	(0.28238)
CONT_VOL(−1)	2.90E−06	0.465277	−8.21E−07	3.032455
	(0.51674)	(3.6175)***	(−0.68392)	(0.34977)
CONT_VOL(−2)	2.10E−06	0.057207	1.92E−06	−20.55423
	(0.43028)	(0.71403)	(1.8194)	(−2.3836)**

(continued)

Table 8. *(continued)*

	CONT_R	CONT_VOL	SP500_R	SP500_VOL
CONT_VOL(−3)	−1.25E–06	0.207997	−5.73E–08	−5.139978
	(−0.17751)	(2.0015)**	(−0.05803)	(−0.53212)
SP500_R(−1)	0.067496	−664.3633	0.004142	−699923.5
	(0.31148)	(−0.24856)	(0.05953)	(−1.3775)
SP500_R(−2)	0.213068	1517.166	0.029653	−1175370
	(0.96677)	(0.69381)	(0.44607)	(−2.3225)**
SP500_R(−3)	0.354038	5167.604	−0.080799	−1023904
	(1.8596)*	(2.2363)**	(−1.3413)	(−2.1089)**
SP500_VOL(−1)	1.03E–08	−0.000267	2.76E–09	0.529549
	(0.66279)	(−1.5266)	(0.39833)	(7.3021)***
SP500_VOL(−2)	−6.66E–09	4.41E–05	−1.83E–09	0.217501
	(−0.33355)	(0.21652)	(−0.24708)	(3.0867)***
SP500_VOL(−3)	−2.14E–09	−1.67E–05	2.68E–09	0.112065
	(−0.11789)	(−0.087507)	(0.50561)	(1.8901)*
INTERCEPT	0.000494	484.1097	−0.003177	163236.4
	(0.04329)	(3.7971)***	(−0.86810)	(4.3007)***
MONDAY	−0.003568	−57.58924	−0.000237	−82747.29
	(−0.54602)	(−0.75262)	(−0.13778)	(−4.5688)***
R-squared	0.036191	0.427384	0.024665	0.705578
Adj. R-squared	0.003647	0.408048	−0.008268	0.695636
F-stat	1.1121	22.104	0.74895	70.973
(*p*-value)	(0.347)	(0.000)	(0.714)	(0.000)

Note: *, **, and ***denote significance at the 10%, 5%, and 1% significance levels, respectively.

Table 9. *Search and Portals–Pre-Crash VAR*

Results for the vector autoregressions (VAR) of return (_R) and volume (_VOL) data for the equal-weighted Search and Portals index (SEAR) with the S&P 500 index (SP500) during the pre-crash period: October 12, 1998–March 20, 2000. Volume is the number of shares traded on a particular day (expressed in thousands and adjusted for capital changes); returns are daily simple excess returns, using the three-month U.S. T-bill rate as a proxy for the risk-free rate. MONDAY is a dichotomous variable taking the value of 1 if the observation occurs on a Monday and zero otherwise. *T*-statistics are in parentheses and represent White's heteroscedasticity-adjusted two-tailed test of the null hypothesis that the coefficient is equal to zero.

	SEAR_R	SEAR_VOL	SP500_R	SP500_VOL
SEAR_R(−1)	0.168077	2383.502	−0.017878	−20239.16
	(2.4594)***	(0.20210)	(−0.91316)	(−0.13364)
SEAR_R(−2)	−0.130964	−7581.721	−0.012988	−5478.132
	(−1.7478)*	(−0.53775)	(−0.81879)	(−0.031076)
SEAR_R(−3)	−0.001844	13989.34	−0.005126	−12164.85
	(−0.0332)	(0.97440)	(−0.34397)	(−0.08849)
SEAR_VOL(−1)	−3.65E–07	0.747677	−1.23E–07	−0.198246
	(−1.0762)	(8.5790)***	(−1.1549)	(−0.24535)
SEAR_VOL(−2)	2.58E–07	−0.084997	1.09E–07	−0.685440
	(0.66499)	(−0.80293)	(1.0318)	(−0.79022)
SEAR_VOL(−3)	2.36E–07	0.215608	8.07E–08	−0.282939
	(0.72143)	(2.5552)***	(0.86935)	(−0.34289)
SP500_R(−1)	−0.006935	−88447.77	0.006382	−1000640
	(−0.31423)	(−1.5975)	(0.08949)	(−1.6176)
SP500_R(−2)	0.442409	48104.00	0.019870	−606148.1
	(1.7542)*	(1.1780)	(0.29836)	(−1.1036)
SP500_R(−3)	0.198703	−37850.02	−0.061501	−1021847
	(0.96301)	(−0.77719)	(−1.0302)	−2.0342**
SP500_VOL(−1)	1.15E–09	−0.004389	6.51E–09	0.515368
	(0.051979)	(−1.2470)	(0.93042)	(7.1664)***
SP500_VOL(−2)	1.02E–08	−0.001720	−1.65E–09	0.193788
	(0.40636)	(−0.46345)	(−0.21306)	(2.7279)***
SP500_VOL(−3)	−1.48E–08	−0.003087	3.97E–10	0.115475
	(−0.85495)	(−0.78061)	(0.072943)	(1.7792)*
INTERCEPT	0.006262	10277.36	−0.004957	200143.4
	(0.40265)	(3.7754)***	(−1.2833)	4.4979***

(continued)

Table 9. *(continued)*

	SEAR_R	SEAR_VOL	SP500_R	SP500_VOL
MONDAY	0.002614	2436.662	–0.001265	–82152.67
	(0.33608)	(2.0010)**	(–0.65772)	(–4.4069)***
R-squared	0.054736	0.799542	0.035857	0.702421
Adj. R-squared	0.022818	0.792773	0.003302	0.692373
F-stat	1.7149	118.1230	1.1014	69.9056
(*p*-value)	(0.056)	(0.000)	(0.356)	(0.000)

Note: *, **, and ***denote significance at the 10%, 5%, and 1% significance levels, respectively.

Table 10. *Security Firms–Pre-Crash VAR*

Results for the vector autoregressions (VAR) of return (_R) and volume (_VOL) data for the equal-weighted Security index (SEC) with the S&P 500 index (SP500) during the pre-crash period: October 12, 1998-March 20, 2000. Volume is the number of shares traded on a particular day (expressed in thousands and adjusted for capital changes); returns are daily simple excess returns, using the three-month U.S. T-bill rate as a proxy for the risk-free rate. MONDAY is a dichotomous variable taking the value of 1 if the observation occurs on a Monday and zero otherwise. *T*-statistics are in parentheses and represent White's heteroscedasticity-adjusted two-tailed test of the null hypothesis that the coefficient is equal to zero.

	SEC_R	SEC_VOL	SP500_R	SP500_VOL
SEC_R(–1)	0.088841	441.0126	–0.047417	–104922.3
	(1.4516)	(0.49127)	(–1.8255)*	(–0.44165)
SEC_R(–2)	0.001078	–606.0063	–0.030980	315323.4
	(0.01533)	(–0.5366)	(–1.2687)	(1.1716)
SEC_R(–3)	0.085307	11.51765	0.026804	301935.2
	(1.2449)	(0.02122)	(0.88713)	(1.3731)
SEC_VOL(–1)	–4.54E–06	0.489454	–7.64E–07	14.64656
	(–1.0962)	(9.4759)***	(–0.38972)	(1.0710)
SEC_VOL(–2)	5.78E–07	0.135307	1.56E–06	–23.67173
	(0.12409)	(1.8387)*	(0.95218)	(–1.2864)
SEC_VOL(–3)	–4.92E–08	–0.072378	–1.12E–06	–9.300444
	(–0.01127)	(–1.2900)	(–0.67689)	(–0.55049)
SP500_RF(–1)	0.310680	284.7297	0.030787	–928094.8
	(2.2364)**	(0.18044)	(0.48262)	(–1.7908)*
SP500_RF(–2)	0.101679	1647.599	0.044604	–822300.7
	(0.65185)	(0.99865)	(0.72366)	(–1.6157)
SP500_RF(–3)	0.072892	–765.3551	–0.099802	–1371969
	(0.46801)	(–0.53821)	(–1.7811)*	(–2.6714)***
SP500_VOL(–1)	7.23E–09	0.000109	1.04E–09	0.514043
	(0.39797)	(0.35631)	(0.15848)	(7.2065)***
SP500_VOL(–2)	–1.75E–08	–0.000636	–7.27E–10	0.221634
	(–0.73504)	(–1.3988)	(–0.09942)	(3.0542)***
SP500_VOL(–3)	2.71E–08	0.000429	3.39E–09	0.138645
	(1.8506)*	(2.0705)**	(0.57812)	(2.1519)**
INTERCEPT	–0.006037	452.0345	–0.001878	141065.6
	(–0.72694)	(4.8910)***	(–0.55750)	(4.0702)***
MONDAY	–0.003020	6.141542	–0.000429	–79730.64
	(–0.68513)	(0.10629)	(–0.24762)	(–4.4345)***
R-squared	0.067834	0.302844	0.031871	0.699538
Adj. R-squared	0.036359	0.279304	-0.000819	0.689393
F-stat	2.1551	12.8649	0.9749	68.951
(*p*-value)	(0.011)	(0.000)	(0.475)	(0.000)

Note: *, **, and ***denote significance at the 10%, 5%, and 1% significance levels, respectively.

spectively, for the pre-Crash period. The findings support the overconfidence arguments we described in the previous paragraph.

Table 7 reveals that the lagged values of public information have a positive and significant impact on E-tailer returns. This is consistent with DHS [1998], and even stronger than the relationship seen in Table 5. In comparison with the return regressions we discuss elsewhere, the analysis of E-tailer returns in Table 7 reports a surprisingly high R-squared, approximately 16%. The *t*-statistics for the S&P provide a *prima facie* case that E-tailers influence the broader market in a similar way to GSI in Table 5. But the *F*-statistic for this equation indicates that we cannot reject the null hypothesis that

E-tailers had no effect on the market. Once again, we cannot find a relationship of volume to returns consistent with overconfidence arguments.

Contrary to our expectations, Table 8 reveals that C&C returns are not explicable using our VAR framework (the p-value of the F-statistic is 0.347). Tables 9 and 10, however, provide mixed support for DSSW [1990]. Table 10 shows that security firms have a positive correlation with the previous day's change in the S&P 500. In Table 9, we see that, like the GSI, Search and Portal firms have a marginally significant and positive relationship to S&P returns two days earlier (the p-value is 0.08). The Search and Portal subgroup also appears to have significant positive first-order autocorrelation consistent with positive feedback trading (its p-value is 0.014). Tables 8, 9, and 10 provide no evidence that these subgroups drive the S&P 500.

Overall, the examination of the four subgroups in the pre-Crash period is consistent with our overconfidence hypotheses and with our conclusions from the fourth section. E-tailers seem to have the strongest relationship with marketwide movements, but the lack of success of the C&C analysis clouds our story that the pre-Crash phenomenon was driven by overconfidence.

Tables 11, 12, 13, and 14 repeat the analysis for the E-tailers, C&C, Search and Portal, and Security subgroups, respectively, in the post-Crash period. Consistent with the analysis of GSI in Table 6, Tables 13 and 14 report insignificant F-statistics in the equations for Portals and Security returns, suggesting a return to the weak form *status quo* after the Crash consistent with a market not stricken with bubblelepsy.

Surprisingly, Tables 11 and 12 reveal that both E-tailers and C&C firms have significant positive autocorrelation up to two lags following the Crash.

Table 11. *E-Tailers–Post-Crash VAR*

Results of vector autoregressions (VAR) of return (_R) and volume (_VOL) data for the equal-weighted E-tailers index (ETAIL) with the S&P 500 index (SP500) for the post-crash period: April 20, 2000- May 1, 2001. Volume is the number of shares traded on a particular day (expressed in thousands and adjusted for capital changes); returns are daily simple excess returns, using the three-month U.S. T-bill rate as a proxy for the risk-free rate. MONDAY is a dichotomous variable taking the value of 1 if the observation occurs on a Monday and zero otherwise. T-statistics are in parentheses and represent White's heteroscedasticity-adjusted two-tailed test of the null hypothesis that the coefficient is equal to zero.

	ETAIL_R	ETAIL_VOL	SP500_R	SP500_VOL
ETAIL_R(−1)	0.220378	742.8061	−0.026569	−428192.5
	(2.7277)***	(1.0222)	(−0.68756)	(−0.67749)
ETAIL_R(−2)	0.127883	281.0762	0.081141	199130.4
	(1.4954)	(0.45340)	(1.9557)**	(0.23556)
ETAIL_R(−3)	0.076202	−668.7356	−0.006005	299647.5
	(1.0215)	(−1.1335)	(−0.19729)	(0.48497)
ETAIL_VOL(−1)	7.23E−07	0.443305	1.21E−06	−77.28607
	(0.09278)	(5.8499)***	(0.38154)	(−1.3889)
ETAIL_VOL(−2)	2.13E−06	0.042634	−4.17E−07	43.40613
	(0.28770)	(0.54753)	(−0.12236)	(0.71126)
ETAIL_VOL(−3)	2.66E−06	0.040827	1.89E−06	61.18613
	(0.41766)	(0.79366)	(0.54470)	(1.2837)
SP500_R(−1)	0.006337	−285.7191	−0.007805	28838.12
	(0.03509)	(−0.21392)	(−0.0926)	(0.01867)
SP500_R(−2)	−0.115713	−1269.975	−0.201129	−3590904
	(−0.61183)	(−0.92285)	(−2.2732)**	(−2.2627)**
SP500_R(−3)	0.237061	2409.521	−0.026407	1027433
	(1.4466)	(1.8585)*	(−0.32104)	(0.71723)
SP500_VOL(−1)	4.45E−09	0.000190	1.08E−11	0.607751
	(0.60612)	(3.1255)***	(0.00314)	(8.5434)***
SP500_VOL(−2)	6.24E−09	−0.000120	−8.66E−10	0.006323
	(0.69571)	(−1.8311)*	(−0.21421)	(0.08684)
SP500_VOL(−3)	−4.36E−11	4.75E−05	1.29E−10	0.219094
	(−0.00611)	(1.0305)	(0.03184)	(3.9260)***
INTERCEPT	−0.020668	192.5601	−0.002033	279518.3
	(−2.1355)**	(2.4950)***	(−0.52377)	(4.3339)***
MONDAY	−0.001925	0.839401	0.002532	−250188.0
	(−0.39299)	(0.0151)	(1.1675)	(−5.7800)***
R-squared	0.154259	0.317417	0.041237	0.645749
Adj. R-squared	0.107671	0.279817	-0.011576	0.626235
F-stat	3.3112	8.442	0.78081	33.0918
(p-value)	(0.000)	(0.000)	(0.680)	(0.000)

Note: *, **, and ***denote significance at the 10%, 5%, and 1% significance levels, respectively.

Table 12. *Content and Community–Post-Crash VAR*

Results of vector autoregressions (VAR) of return (_R) and volume (_VOL) data for the equal-weighted Community and Content index (CONT) with the S&P 500 index (SP500) for the post-crash period: April 20, 2000–May 1, 2001. Volume is the number of shares traded on a particular day (expressed in thousands and adjusted for capital changes); returns are daily simple excess returns, using the three-month U.S. T-bill rate as a proxy for the risk-free rate. MONDAY is a dichotomous variable taking the value of 1 if the observation occurs on a Monday and zero otherwise. *T*-statistics are in parentheses and represent White's heteroscedasticity-adjusted two-tailed test of the null hypothesis that the coefficient is equal to zero.

	CONT_R	CONT_VOL	SP500_R	SP500_VOL
CONT_R(−1)	0.312606	−318.2583	0.060790	−447552.2
	(4.4825)***	(−1.0207)	(1.2727)	(−0.51880)
CONT_R(−2)	0.258738	27.92846	0.095239	822977.2
	(2.8617)***	(0.08085)	(2.1363)**	(0.85147)
CONT_R(−3)	−0.052654	72.61427	−0.087068	725887.1
	(−0.70740)	(0.27396)	(−2.3484)**	(0.91636)
CONT_VOL(−1)	3.66E–05	0.463453	−8.17E–06	−360.9031
	(2.2407)**	(6.3277)***	(−1.1293)	−2.0438**
CONT_VOL(−2)	−7.22E–06	0.114019	1.78E–06	231.8637
	(−0.24886)	(1.5708)	(0.18818)	(1.3115)
CONT_VOL(−3)	−1.87E–05	0.076030	−3.94E–09	−105.0928
	(−1.1075)	(1.2585)	(−0.00052)	(−0.67612)
SP500_R(−1)	−0.025048	244.5193	−0.103567	53822.39
	(−0.15909)	(0.39619)	(−1.1894)	(0.03031)
SP500_R(−2)	−0.421205	637.7872	−0.238475	−4530201
	(−2.4046)**	(0.89108)	(−2.7246)***	(−2.5673)***
SP500_R(−3)	0.258861	514.2873	0.051285	595487.4
	(1.6112)	(1.0278)	(0.57358)	(0.38161)
SP500_VOL(−1)	1.79E–09	−2.87E–05	1.82E–09	0.621182
	(0.23626)	(−1.3489)	(0.51192)	(8.7980)***
SP500_VOL(−2)	6.83E–09	−5.62E–06	−1.60E–09	−0.036719
	(0.72707)	(−0.19183)	(−0.41375)	(−0.49364)
SP500_VOL(−3)	−9.16E–10	1.14E–05	−6.98E–10	0.238758
	(−0.11145)	(0.36594)	(−0.18258)	(4.1611)***
INTERCEPT	−0.015686	152.1706	0.001913	394718.4
	(−1.3516)	(4.0743)***	(0.39178)	(4.4555)***
MONDAY	−0.004290	−28.04956	0.002168	−256344.5
	(−0.87041)	−1.6111	(1.0435)	(−6.1038)***
R-squared	0.219940	0.363205	0.073574	0.656456
Adj. R-squared	0.176971	0.328127	0.022542	0.637532
F-stat	5.1185	10.3543	1.4417	34.681
(*p*-value)	(0.000)	(0.000)	(0.141)	(0.000)

Note: *, **, and ***denote significance at the 10%, 5%, and 1% significance levels, respectively.

C&C firms also develop a significant relationship with two- and three-day lags of the market.[14] It would appear that the most visible, or salient, Internet shares were those most affected by quasi-rational pessimism in the post-Crash shakedown. Indeed, in the post-Crash period, C&C firms behave more like E-tailers did in the pre-Crash period.

One explanation is that C&C firms may have grown in "Internet visibility" after the Crash. The autocorrelation may be consistent with BSV [1998] and DSSW [1990], although, contrary to the latter, our analysis does not detect changes in volume that might be expected if rational traders were exploiting positive feedback traders' reaction to negative returns. Once again, while the *t*-statistics for the subgroups in the equations for the S&P (reported in Tables 11 and 12) are significant, the *F*-statistics for these analyses preclude us from making a link between the wider post-Crash bear market and the infectious pessimism of these two most visible subgroups.

Conclusion

In discussing the Crash of 1929, Galbraith [1975] proffers that the collapse in the stock market in the autumn of 1929 was implicit in the speculation that went before...sooner or later, confidence in the short-run reality of increasing common stock values would weaken. When this happened, some people would sell...there would be a rush, pell-mell, to unload. This was the way past speculative orgies had ended. It was the way the end came in 1929. It is the way speculation will end in the future (p. 187).

Table 13. *Search and Portals–Post-Crash VAR*

Results of vector autoregressions (VAR) of return (_R) and volume (_VOL) data for the equal-weighted Search and Portals index (SEAR) with the S&P 500 index (SP500) for the post-crash period: April 20, 2000–May 1, 2001. Volume is the number of shares traded on a particular day (expressed in thousands and adjusted for capital changes); returns are daily simple excess returns, using the three-month U.S. T-bill rate as a proxy for the risk-free rate. MONDAY is a dichotomous variable taking the value of 1 if the observation occurs on a Monday and zero otherwise. *T*-statistics are in parentheses and represent White's heteroscedasticity-adjusted two-tailed test of the null hypothesis that the coefficient is equal to zero.

	SEAR_R	SEAR_VOL	SP500_R	SP500_VOL
SEAR_R(−1)	0.096088	−5085.904	0.041551	−687053.8
	(0.90050)	(−2.6881)***	(1.6403)*	(−1.6053)
SEAR_R(−2)	−0.091941	−806.8872	−0.040035	−709094.4
	(−0.89008)	(−0.43679)	(−1.1651)	(−1.3815)
SEAR_R(−3)	0.069347	91.69665	0.005914	603924.1
	(0.71264)	(0.05845)	(0.21331)	(1.0766)
SEAR_VOL(−1)	−1.14E−06	0.338488	−1.41E−06	−14.91567
	(−0.29375)	(3.4821)***	(−1.1305)	(−0.82274)
SEAR_VOL(−2)	6.79E−06	0.219755	8.08E−07	4.680770
	(1.4219)	(2.4147)**	(0.34435)	(0.17291)
SEAR_VOL(−3)	2.12E−06	0.075975	1.33E−06	7.363802
	(0.67687)	(1.0666)	(1.0507)	(0.31842)
SP500_R(−1)	0.014512	13841.79	−0.122710	1514501
	(0.04483)	(2.3678)**	(−1.4085)	(0.91841)
SP500_R(−2)	−0.095045	1299.577	−0.024159	−1689440
	(−0.30742)	(0.22080)	(−0.23391)	(−1.2110)
SP500_R(−3)	0.211379	8216.117	−0.024261	306081.9
	(0.61563)	(1.4309)	(−0.25848)	(0.18784)
SP500_VOL(−1)	7.67E−09	0.000424	1.77E−09	0.635836
	(0.58245)	(1.7114)*	(0.43621)	(7.6918)***
SP500_VOL(−2)	−8.20E−09	−0.000555	−1.30E−09	−0.002273
	(−0.49238)	(−2.0639)**	(−0.23510)	(−0.02682)
SP500_VOL(−3)	7.32E−10	0.000292	−1.23E−09	0.214808
	(0.048793)	(1.2573)	(−0.27876)	(3.4634)***
INTERCEPT	−0.025082	860.7823	−0.001723	284401.2
	(−2.1658)**	(4.0499)***	(−0.46213)	(4.4006)***
MONDAY	−0.006866	−346.3890	0.000980	−254763.5
	(−1.0748)	(−2.8569)***	(0.43297)	(−5.9010)***
R-squared	0.064759	0.355650	0.044475	0.648334
Adj. R-squared	0.013241	0.320156	-0.008160	0.628963
F-stat	1.2570	10.020	0.89498	33.4686
(p-value)	(0.240)	(0.000)	(0.612)	(0.000)

Note: *, **, and ***denote significance at the 10%, 5%, and 1% significance levels, respectively.

This paper has studied the last great speculative episode of the twentieth century – the Internet stock bubble. Unlike Galbraith [1975], we are fortunate in having a range of analytical models to use in empirical tests of bubble episodes.

In the fourth section, we found evidence of autocorrelation in GSI and S&P 500 returns that are the "smoking guns" of a bubble. In the fifth section, we used VAR analysis to capture the *pas de deux* of the Internet and main markets. We found that, of the theories outlined in the second section, the model of Daniel, Hirshleifer, and Subrahmanyam [1998] (DHS) is the most consistent with the interrelationships of returns. Prices appear to have been driven by investor overconfidence as well as investors' mistaken understanding of their own abilities.

We did not, however, see the relationship of returns to volume predicted by other theories based on overconfidence. Overconfident behavior carries with it the seeds of its own destruction. Investors will try to drown out cognitive dissonance, but eventually reality will overcome cognitive bias and a correction must occur. Following the Crash, both the GSI and the S&P returned to "normality" in that price behavior was consistent with weak form efficiency. We look forward to further research on bubbles that may empirically capture such a collective return to sense.

In the sixth section, we extended our analysis by examining four subgroups of Internet stocks. We expected investors to be most confident about things they are most familiar with. Our analysis of pre-Crash returns finds that E-tailers, perhaps the most visible and familiar of Internet stocks, appear to be the wellspring of the GSI role found in the fifth section. Following the Crash, however, E-tailers and C&C firms have autocorrelated and, on average, negative returns. The

Table 14. *Security Firms–Post-Crash VAR*

Results of vector autoregressions (VAR) of return (_R) and volume (_VOL) data for the equal-weighted Security index (SEC) with the S&P 500 index (SP500) for the post-crash period: April 20, 2000–May 1, 2001. Volume is the number of shares traded on a particular day (expressed in thousands and adjusted for capital changes); returns are daily simple excess returns, using the three-month U.S. T-bill rate as a proxy for the risk-free rate. MONDAY is a dichotomous variable taking the value of 1 if the observation occurs on a Monday and zero otherwise. *T*-statistics are in parentheses and represent White's heteroscedasticity-adjusted two-tailed test of the null hypothesis that the coefficient is equal to zero.

	SEC_R	SEC_VOL	SP500_R	SP500_VOL
SEC_R(−1)	0.102700	−1970.206	−0.047688	−800518.6
	(0.84285)	(−2.4705)**	(−1.1520)	(−1.1906)
SEC_R(−2)	0.107547	−157.0832	0.034212	111577.1
	(1.0441)	(−0.16042)	(0.85098)	(0.13446)
SEC_R(−3)	0.093979	1593.898	0.010318	347210.9
	(1.0157)	(1.5727)	(0.30835)	(0.49607)
SEC_VOL(−1)	2.10E−05	0.414021	4.36E−06	−17.68273
	(2.2392)**	(4.6464)***	(1.0668)	(−0.23497)
SEC_VOL(−2)	−6.82E−06	0.170576	3.94E−06	103.7080
	(−0.65625)	(1.8026)*	(0.93847)	(1.7422)*
SEC_VOL(−3)	−9.43E−06	0.172783	−5.61E−06	−22.84058
	(−0.92261)	(1.6940)*	(−1.5055)	(−0.43994)
SP500_R(−1)	0.079651	1327.708	0.063799	928515.8
	(0.25560)	(0.58264)	(0.57790)	(0.50796)
SP500_R(−2)	−0.285485	−439.1397	−0.135836	−3288334
	(−1.1022)	(−0.17920)	(−1.3292)	(−1.7500)*
SP500_R(−3)	−0.028177	389.6316	−0.036486	1028462
	(−0.10825)	(0.15444)	(−0.38426)	(0.56795)
SP500_VOL(−1)	−6.97E−09	1.97E−05	−2.93E−09	0.614631
	(−0.59354)	(0.16862)	(−0.65277)	(7.1086)***
SP500_VOL(−2)	6.87E−09	−8.02E−06	−2.52E−09	−0.078904
	(0.49807)	(−0.07614)	(−0.48286)	(−0.81032)
SP500_VOL(−3)	6.43E−10	0.000113	3.73E−09	0.250553
	(0.05389)	(1.1581)	(0.83946)	(3.5925)***
INTERCEPT	−0.005252	55.69600	−0.000729	315256.9
	(−0.52249)	(0.63642)	(−0.20032)	(4.7188)***
MONDAY	−0.006960	−134.6935	0.001962	−248262.7
	(−1.2922)	(−2.4901)***	(0.91762)	(−5.7215)***
R-squared	0.063178	0.572250	0.043547	0.646747
Adj. R-squared	0.011573	0.548687	−0.009139	0.627288
F-stat	1.2243	24.2865	0.82654	33.2367
(p-value)	(0.263)	(0.000)	(0.632)	(0.000)

Note: *, **, and ***denote significance at the 10%, 5%, and 1% significance levels, respectively.

firms that were perhaps the most salient in investors' minds are the ones that drove the death spiral of Internet stocks, and, although the evidence is marginal, possibly the market itself too. The analysis suggests that bear markets might also be a bubble-like phenomenon; this may be another fruitful area for research.

The role of overconfidence before the Crash should not be surprising. Investors without adequate levels of confidence probably wouldn't have been in the market. The Internet episode provided a fertile field for investor overconfidence to grow, as the ever-growing returns reinforced investors' beliefs in their own abilities.

We used markets that were more or less bubble-driven to explore the role of overconfidence in sustaining a bubble episode. Our approach could be used as an important tool to analyze other alleged bubble episodes, as we believe it is those who do not understand the past who are condemned to repeat it.

Notes

1. As measured by Internet.com's Internet index (an index of fifty Internet stocks representing 90% of the universe of pure Internet companies).
2. Shleifer [2000, pp. 169–174] provides a narrative outlining general patterns of famous bubbles. We have no information, however, on scenarios where the conditions he outlines were present and bubbles did not occur. Given this, meaningful modeling of the beginning of bubbles does not appear possible.
3. "Monopoly Money" (*The Economist*, April 8, 2000, pp. 85–87) and "After the Gold Rush" (*The Economist*, April 22, 2000, pp. 75–76) capture the *zeitgeist*.
4. Constituent lists are available from http://www.premier-investor.com /indexes/internetindices.asp, accessed on October 21, 2001.
5. We also conducted our analysis using a value-weighted index. As it did not alter our conclusions, we do not report this analysis.
6. For example, in the way proposed by Shleifer and Vishny [1997].

7. Summers [1986] suggests a first-order autoregressive process as an alternate hypothesis to that of market efficiency.
8. Since the autocorrelation for the S&P 500 is close to unity, we performed "augmented" Dickey-Fuller tests, which reject the hypothesis that the data follow a unit root process.
9. Hamilton [1994] describes this technique.
10. Chordia, Roll, and Subrahmanyam [2001] show that few meaningful differences result from using alternate measures of trading activity.
11. There is marginal evidence of a negative relationship of the GSI to its two-day lagged returns (which we interpreted in the pre-Crash period as a correction for overreaction), although the F-statistic is not significant. There is also a small positive relationship of lagged Internet volume to Internet returns, which is significantly positive in the post-crash period (p-value = 0.037).
12. E-tailers are companies that sell goods online to consumers, businesses, or both, such as toys, books, or computers, as well as services like downloadable music, plane tickets, and hotel rooms. Consumer auction sites are also considered e-tailers.

    Content and Communities companies run websites and networks organized around specific content (sports, politics, stocks, etc.) and personal or professional interests. Some are B2B-oriented (Vertical Net, Internet.com), others are geared toward consumers or a mix. A few charge membership fees for premium content – and, like Search and Portals, all are trying to increase e-commerce revenue – but most live and die by advertising revenue.

    Search and Portal companies run websites designed to be gateways to the Internet. Most feature news and information gathered by category, and all offer Internet search capabilities. With the exception of AOL and GoTo.com, most Search/Portals rely primarily on advertising revenue, although all are seeking to increase e-commerce revenue.
13. Security companies sell firewalls and e-commerce security software (digital certificates) and provide outsourced services.
14. The second lag of the market is significantly negative (p-value = 0.017), and the third lag is marginally significantly positive (p-value = 0.108).

References

Alpert, M., and H. Raiffa, "A Progress Report on the Training of Probability Assessors", in Daniel Kahneman, Paul Slovic, and Amos Tversky, eds., *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge: Cambridge University Press, 1982.

Anh, D., J. Boudouck, M. Richardson and R. Whitelaw. "Partial Adjustment or Stale Prices? Implications from Stock Index and Futures Return Autocorrelations." *Review of Financial Studies*, 15, (2002), pp. 655–689.

Barber, B.M. & T. Odean. "Boys Will Be Boys: Gender, Overconfidence and Common Stock Investment." *Quarterly Journal of Economics*, (2001) pp. 261–292.

Barberis, N., A. Shleifer, and R. Vishny. "A Model of Investor Sentiment." *Journal of Financial Economics*, 49, (1998), pp. 307–343.

Carvalho, J.P., R. B. Durand and Hock Guan Ng. "Australian Internet Stocks: Were They Special?" University of Western Australia Department of Accounting and Finance Working Paper #2002-151, (2002).

Chordia, T., R. Roll and A. Subrahmanyam. "Market Liquidity and Trading Activity." *Journal of Finance*, 56, (2001), pp. 501–530.

Chowdhury, M., and J. Lin. "Fads and the Crash of '87." *The Financial Review*, 28, (1983) pp. 385–401.

Cooper, M., O. Dimitrov and P.R. Rau. "A Rose.com By Any Other Name." *Journal of Finance*, 56, (2001), pp. 2371–2388.

Daniel, K. D., D. Hirshleifer, and A. Subrahmanyam. "Investor Psychology and Security Market Under- and Over-reactions." *Journal of Finance*, 53, (1998), pp. 1839–1886.

De Bondt, W. F. M. "A Portrait of the Individual Investor." *European Economic Review*, 42, (1998), pp.831–844.

De Long, J. B., A. Shleifer, L. Summers, and R. J. Waldmann. "Positive Feedback Investment Strategies and Destabilizing Rational Speculation." Journal of Finance 45, (1990), pp. 375–395.

Durand, R.B. and D. Scott. "iShares Australia: A Clinical Study in International Behavioral Finance." *International Review of Financial Analysis*, 12, (2003), pp. 223–239.

Estrada, J., and B. Blakely. The Pricing of Internet Stocks. Working Paper, International Graduate School of Management, 1999.

Fama, E. F. "Efficient Capital Markets: A Review of Empirical Work." *Journal of Finance*, 25, (1970), pp. 383 – 417.

Fama, E. F. "Efficient Capital Markets II." *Journal of Finance*, 46, (1991) pp. 1575–1643.

Fisher, L." Some New Stock Market Indexes." Journal of Business, 39, (1966), pp. 91–225

Gailbraith, J.K. The Great Crash 1929. London: Penguin, 1975.

Griffin, D., and A. Tversky. "The Weighing of Evidence and the Determinants of Overconfidence." *Cognitive Psychology*, 24, (1992), pp. 411–435.

Hamilton, J. D., Time Series Analysis, Princeton: Princeton University Press, 1994.

Hirshleifer, D. "Investor Psychology and Asset Pricing." *The Journal of Finance*, 56, (2001), pp. 1533 – 1597.

Keynes, J. M. The General Theory of Employment, Interest and Money. London: Macmillan, London, 1936.

Klibanoff, P., O. Lamont and T. A. Wizman. "Investor Reaction to Salient News in Closed-End Country Funds." *Journal of Finance*, 53, (1998), pp. 673–699.

Kruger, J., and D. Dunning. "Unskilled and Unaware of It: How Difficulties in Recognizing One's Own Incompetence Lead to Inflated Self Assessments." *Journal of Personality and Social Psychology*, 77, (1999), pp. 1121–1134.

Odean, T. "Volume, Volatility, Price and Profit When all Traders are Above Average." *Journal of Finance*, 53, (1998a), pp. 1887–1934.

Odean, T. "Are Investors Reluctant to Realize Their Losses?" *Journal of Finance*, 53, (1998b), pp. 1775–1798.

Shefrin, Hersh, and M. Statman. "The Disposition to Sell Winners Too Early and Ride Losers Too Long." *Journal of Finance*, 40, (1985), pp. 777–790.

Shiller, R. J. "Stock Prices and Social Dynamics." Brooking Papers on Economic Activity, 2, (1984), pp. 457–498.

Shiller, R. J. Irrational Exuberance. Princeton: Princeton University Press, 2000.

Shleifer, A. Inefficient Markets. Oxford: Oxford University Press, 2000.

Shleifer, A. and R. Vishny. "The Limits to Arbitrage." *Journal of Finance*, 52, (1997), pp. 35–55.

Slovic, P. Facts Versus Fears: "Understanding Perceived Risk." in Daniel Kahneman, Paul Slovic, and Amos Tversky, eds., *Judgment under Uncertainty: Heuristics and Biases*, Cambridge: Cambridge University Press, 1982.

Summers, L.H. "Does the Stock Market Rationally Reflect Fundamental Values?" *Journal of Finance*, 41, (1986), pp. 591–602.

Trueman, B., M.H.F. Wong, and X.J. Zhang. "The Eyeballs Have It: Searching For The Value In Internet Stocks." *Journal of Accounting Research*, 38, (2000), pp. 137–162.

Tversky, A., and D. Kahneman. "Belief in the Law of Small Numbers." *Psychological Bulletin* 76, (1971), pp. 105–110.

Tversky, A., and D. Kahneman. "Judgment Under Uncertainty: Heuristics and Biases." Science, 185, (1974), pp. 1124–1131.

White, H. "A Heteroscedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroscedasticity." Econometrica, 48, (1980), pp. 817–838.