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Consumer Response to TV Stock Recommendations: Merging Financial and Marketing Perspectives

Ekaterina V. Karniouchina, William L. Moore, and Kevin J. Cooney

"CONSUMER RESPONSE TO TV STOCK RECOMMENDATIONS: MERGING FINANCIAL AND MARKETING PERSPECTIVES"

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Ekaterina V. Karniouchina
Assistant Professor of Marketing, Argyros School of Business and Economics, Chapman University,
karniouc@chapman.edu

William L. Moore
David Eccles Professor of Marketing, David Eccles School of Business, University of Utah,
mktbm@business.utah.edu

Kevin J. Cooney
Innovative Options Management, LLC, *Miami, FL*

ABSTRACT: This paper relies on marketing theories to uncover persistent variations in consumer response to TV stock recommendations. Using an event analytical framework, we link the size of abnormal market reaction on the day following broadcasts of *Mad Money with Jim Cramer* to traditional advertising variables. We find that even though a substantial fraction of the audience is actively looking for recommendations, any individual recommendation is still subject to many of the same communication challenges as traditional advertisements. In particular we find evidence of recency and primacy effects, source credibility and information clutter effects. Implications for marketers, managers of public companies, and those interested in public policy aspects related to televised stock recommendations are discussed.

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INTRODUCTION AND PROJECT SUMMARY

> **“***I just want to make you money, because my job is not just to entertain you, but to educate you, so call me at 1-800-743-CNBC” –Jim Cramer*

The opening line of the *Mad Money with Jim Cramer* TV show sounds surprisingly like an advertisement. While Jim Cramer’s stock recommendations are technically not advertisements, they are persuasive messages delivered via mass media. Research in finance and economics has found that stock markets react to “buy” recommendations aired on *Mad Money* (e.g., Engelberg, Sasseville and Williams 2006, 2007; Lim and Rosario 2008). We expand these findings by using traditional advertising factors to examine *which* recommendations are likely to generate the greatest reaction. In spite of the fact that many of *Mad Money* viewers are actively seeking recommendations, we find that traditional advertising variables such as presentation order, information clutter, and source credibility influence the size of market reaction following a “buy” recommendation. In addition to uncovering potential arbitrage opportunities, this work also has implications for the emergent targeted advertising approaches (e.g., various forms of advertising based on consumer internet searches and browsing history or customized shopping portal recommendation lists) as it suggests that communication challenges associated with traditional ads, which may be perceived as nuisances, persist even when highly targeted messages are communicated to receptive and attentive audiences.

BACKGROUND AND MOTIVATION FOR THE STUDY

Every day consumers are bombarded with investment recommendations in newspaper and magazine articles, TV shows, and spam emails (Frieder and Zittrain 2007). Because no new information is typically embedded in these recommendations, the efficient market hypothesis (EMH) would suggest stock prices should not react to them. Nevertheless, the market does react to such recommendations in general (e.g., Elton, Gruber and Grossman 1986; Womack 1996; Barber, Lehavy, and McNichols 2001) and to Jim Cramer's recommendations on *Mad Money* in particular (e.g., Engelberg, Sasseville, and Williams 2006, 2007; Lim and Rosario 2008). It is believed that individual investors are highly susceptible to such recommendations because of the high search costs associated with a wide array of available options. Barber and Odean (2006) show that individual investors are net buyers of stocks that have recently been mentioned in the news, are experiencing abnormal volumes, and have extreme one-day returns. Frieder and Zittrain (2007) uncover short-term market fluctuations in reaction to spam emails suggesting that stock prices are being impacted by even the least credible forms of information.

Mad Money is clearly targeted at naïve investors. The host rarely uses complicated financial jargon. He favors clear cut "buy/sell" recommendations and does not resort to ambiguous statements common to this type of programming. He also incorporates a strong entertainment component into his show. Cramer resorts to a wide array of ostentatious tricks including dressing up in costumes, shouting, using, and sometimes, breaking props, throwing objects on the set and utilizing various sound effects. Regardless of one's personal stand in regard to the host's antics, it is hard to dispute the fact that Cramer succeeds in grabbing his audience's attention. *The Hollywood Reporter* (Gough 2006) attests that on average over a quarter million viewers watch *Mad Money* on *CNBC*.

Mad Money's overnight financial market impact is supported by academic research: for example, Engelberg, Sasseville, and Williams (2007) analyze a small sample (N=391) of initial "buy" recommendations that aired on *Mad Money* over a period of seven months and find that stock prices increased by an average of 2.86% on the day after the show aired but then fell back to their previous levels within several trading days. They also document the redistribution of wealth from uninformed to informed investors following such recommendations as the short sale volumes for recommended stocks increase on the day following the recommendations with the magnitude of the volume spike being proportional to the size of the arbitrage opportunity available.

As with any persuasive attempt, message intensity, presentation order and credibility could impact consumer decisions. In addition, various psychological and cognitive processes and biases may influence consumer judgment. Therefore, first we use an event study methodology to quantify individual stocks' reaction to Cramer's recommendations and then use regression analysis to uncover the factors that affect the size of resulting abnormalities. In particular, we explain the relative size of the next day market reaction by utilizing variables associated with a traditional advertising framework. In spirit, our investigation is similar to ones in the emerging field of behavioral finance (Barberis and Thaler 2003) and marketing that demonstrate how various heuristics and biases lead to irrational stock market behaviors (Johnson, Tellis, and MacInnis 2005).

We demonstrate that traditional marketing variables related to particular recommendations and broadcasts are informative in explaining some of the variance in the subsequent abnormal market returns. We also look at the overall short- and long-term impact of these stock recommendations on the stock prices of underlying securities. In addition to marketers using more targeted ads, the resulting analysis is of interest to investors, managers who are trying to gain insight into how the recommendations that appear on similar shows impact their companies' stock prices, executives who use appearances on stock recommendation shows in their PR strategy and to those interested in the public policy implications of providing stock recommendations to a large group of naïve investors.

CONCEPTUAL FRAMEWORK

Previous research on the impact of *Mad Money* recommendations documented the overall inefficiencies of the financial markets (Engelberg, Sasseville, and Williams 2006, 2007; Lim and Rosario 2008) and the resulting redistribution of wealth from uninformed to informed investors (Engelberg, Sasseville, and Williams 2006, 2007). The research has also outlined the fact that noise traders[1] are learning as the size of investor reaction diminishes over time. The literature also identified several factors associated with limits to arbitrage that were linked to stronger inefficiencies. For instance, small cap stocks and stocks with high turnover rates experience higher abnormal returns. Previous research only started to look at naïve investor-related factors as determinants of the stock market response to televised recommendations. For instance researchers addressed the viewer attention factor: some incorporated the TV ratings data into the analysis and distinguished between the highly condensed *Lightning Round* and

[1] The term *noise trader* (e.g. Kyle 1985) describes naïve investors who make investment decisions without the use of fundamental data, which often translates into poor transaction timing and overreaction to news.

other segments of the program (Engelberg, Sasseville and Williams 2007), while others looked at the differences between briefly covered caller-initiated vs. more elaborate host-initiated picks (Lim and Rosario 2008).

Engelberg, Sasseville, and Williams (2007) also looked at message intensity by incorporating the overall number of competing recommendations as one of the variables explaining the size of next day price abnormality. We extend this analysis by distinguishing between the overall recommendation clutter and competition from similar stocks, incorporating the effects associated with viewer information processing (presentation order and memory decay), information uniqueness (new vs. repeat recommendations) and information credence (accuracy of host's previous picks for particular security, and factors related to recommendation reversals). Figure 1 gives a high-level conceptual framework behind our analysis.

----- Insert FIGURE 1 about Here -----

In this study we (1) look at an extended sample of Cramer's recommendations across different segments of the program[2], and (2) take on a marketing perspective to examine the differences and similarities between the effects of stock recommendations and effects of traditional advertising.

RESEARCH QUESTIONS AND HYPOTHESES

Anecdotal evidence and prior research suggest that contrary to the efficient market hypothesis, consumers do respond to *Mad Money* recommendations (Engelberg, Sasseville and Williams 2006; 2007; Lim and Rosario 2008). We go beyond simply documenting the resulting inefficiencies by examining the impact of traditional advertising variables. Advertising effectiveness has been found to be susceptible to "threshold" (Blair 1987, Pechmann and Stewart 1989) and "wearout" effects (Haley 1978; Simon 1982; Winter 1973), leading to an inverted-U relationship between number of exposures and advertising effectiveness (see Anand and Sternthal 1990 for summary of this research stream).

Jim Cramer's recommendations to buy certain stocks are similar to traditional TV ads in that both are impersonal broadcast messages persuading consumers to make a particular purchase. At the same time

[2] We look at the *Opening, Closing, Lightning Round*, *Sudden Death,* and *Executive Interview* segments that are described in Table 1. We use *Discussion* or *Main* segment as a reference category.

there are some critical differences. For instance, stock recommendations operate in a high involvement environment: viewers are actually looking for recommendations rather than having to endure an ad to watch a show. [3] If viewers are actively looking for unique stock recommendations, we would not expect any threshold effect, just a rapid "wearout" effect. For example, Busse and Green (2002) show that investors incorporate TV stock recommendations from CNBC's *Opening Call* and *Midday Call* almost instantly. Moreover, research repeatedly finds that starting with day two, the security prices start drifting toward their original levels (e.g., Engelberg, Sasseville, and Williams 2006, 2007):

H1: Consumer reaction to an initial stock recommendation is stronger than it is to subsequent recommendations.

H2: Positive price abnormalities occur on the trading day that follows the Mad Money broadcast. Stocks prices start gravitating to their original levels on the second trading day.

In addition, we examine the possible existence of presentation order effects corresponding to the order in which the stocks are recommended during a particular show segment. Pieters and Bijmolt (1997) find that in a block of television commercials there are modest recall advantages associated with first (last) commercial indicating presence of primacy (recency) effects.

H3: Recency effect of stock pick order is associated with stronger consumer response.

H4: Primacy effect of stock pick order is associated with stronger consumer response.

Next, we consider the effects of competition. It is possible that similar (e.g., in terms of industry/market segment) stocks compete for individual investor attention because of consumer industry knowledge or expectations regarding sector performance. Presence of competing stock picks in general (regardless of sector membership) is likely to reduce the chances of individual stocks being purchased by the viewers (here we draw the connection with the work by Burke and Srull (1988) that shows that presence of competitive advertising impacts consumer memory). Advertising clutter can create consumer overload, decrease viewer attention span and interfere with cognitive responses (Webb 1979; Zhao 1997;

[3] Another difference is that traditionally, a message must have an identifiable sponsor to be considered an advertisement (e.g., American Marketing Association 1960). However, this demarcation is growing less relevant today as companies attempt to fly under the radar of skeptical consumers by devising advertisements that are less identifiable and at times completely covert (e.g., Dahlén and Edenius 2007).

Keller 1987, 1991). Anand and Sternthal (1990) find support for a general notion that time available for the message processing influences the effectiveness of the message while Pieters and Bijmolt (1997) find that both the duration of the commercial and the competition from other commercials in the same block influence recall. In a context of *Mad Money* stock picks there are three reasons to expect that the more elaborate segments of the program should be associated with stronger consumer reaction. First, the message is longer, giving greater time for information processing. Second, there are fewer stocks, and therefore, less clutter. Finally, these are stocks that Cramer has thought about in more detail and has decided they are worthy of a recommendation.

> *H5: An increase in the number of total recommendations in the same show decreases the response to a recommendation.*

> *H6: An increase in the number of similar (i.e., same industry) recommendations in the same show decreases the response to a recommendation.*

> *H7: Consumer response to more (less) elaborate recommendations is stronger (weaker).*

While Cramer is not explicitly trying to sell anything, his brand and credibility are dependent on the correctness of his picks, the strength of his persuasive power, and on the consequent consumer following. Therefore, we examine the effects of information credence on consumer response to his recommendations. According to the learning theory perspective, consumers would react based on the success of previous recommendations. If price movements are exploited by institutional players, and individual investors learn that price shifts are temporary, they will be less likely to follow future recommendations. As first suggested by Engelberg, Sasseville, and Williams (2006 and 2007), we hypothesize that large price jumps which followed the earlier broadcasts subside over time due to the influence of informed arbitrage players and gradual consumer learning evoked by such strategies.

> *H8: The magnitude of stock price fluctuations induced by the show declines over time.*

We also look at the impact of past prediction accuracy and recommendation reversals. One needs to consider whether or not Cramer's previous recommendation on this stock was correct and if the reversal is the admittance of a mistake or if it is just an acknowledgement of a changing environment.

When future price movements contradict one of Jim Cramer's previous recommendations, a subsequent recommendation reversal could either lead to strong consumer reaction or to the loss of credibility on the part of the host.[4]

H9: When the host reverses his recommendation on a stock, the resulting stock price change is greater than the one that would have taken place on a repeated recommendation.

H10: Accuracy of host's previous pick for a given stock influences the strength of consumer response.

H11: Accuracy of previous prediction moderates consumer response to recommendation reversals.

CONTROL VARIABLES

The general level of awareness of a stock may influence the level of post-recommendation response regardless of the number of previous exposures. Financial literature points out that familiarity fuels investment (Huberman 2001), therefore, investors may have more confidence in buying stock in a company that they are already familiar with when it is recommended by Cramer. On the other hand, it is more likely that if the stock is well-known, investors may see fewer opportunities to beat the market. If noise traders search for "unique" information, they would be more likely to respond to recommendations of relatively unknown stocks. It is also possible that recommendations for unknown stocks would be more effective due to the lack of preconceived notions regarding these stocks. If true, these findings would echo Winter (1973), who found that advertising can produce significant attitude change only in individuals initially unfamiliar with the brand.

"Popular"[5] stocks have the highest following by analysts and the highest percentage ownership by institutional investors and market makers. These informed investors will be the most likely candidates to

[4] We see similarities to a political candidate's policy changes. Political science literature finds that, among other things, policy changes increase voter uncertainty (Alvarez and Nagler 2002). Tavits (2007) differentiates between different political domains and argues that policy reversals could be rewarded (punished) by the voters when the underlying issue is pragmatic (ideological). Policy reversals on pragmatic issues are perceived as signs of flexibility and adaptation to changing economic conditions while reversals that strike a voter's ideological cord are perceived as signs of inconsistency undermining candidates' credibility and voter rapport. If viewers take on a pragmatic perspective, they could see reversals as necessary adaptations to changing conditions. Thus reversals will be taken very seriously by investors because they may infer that the new information that became available to Cramer was persuasive enough to make him change his previous recommendation. Alternatively, if viewers do not take on a pragmatic stance, the recommendation reversals could undermine host's credibility and make investors doubt his expertise when it comes to a particular security (which could later on spill onto their distrust to the show in general).

[5] In this study we use market capitalization as a measure of stock popularity.

exploit the market inefficiencies created by individual investors. These more liquid and widely traded stocks also have very low limits to arbitrage. Therefore, we should expect these stocks to be less susceptible to recommendations. At the same time "speculative" stocks (e.g., stocks with higher turnover) are more susceptible to recommendations because of the low institutional ownership and higher overall volatility. Therefore, we control for pre-event market capitalization and turnover rates. We also control for possible day of the week effects and/or memory decay by creating a set of week day dummies and a variable that captures the number of days between the recommendation and market open.

Security prices could influence the size of inefficiencies produced by the show. Consumers may see "cheaper" stocks as bargains. Even after controlling for market cap which would capture the potentially higher limits to arbitrage and reduced liquidity associated with "cheaper" stocks, we expect these stocks to be associated with higher inefficiencies. In addition we also control for whether or not Jim Cramer owns[6] the security in question as this factor may raise some trust issues on the part of investors. Finally, since trading mechanisms, volatility and spreads differ across exchanges, we consider the exchange on which a given security is traded as a factor in determining the size of market abnormality.

DATA

We have obtained the recommendations data from one of the subscription-based *Mad Money* recap providers. Utilized data source has a number of advantages: (1) it operates independently from the *Mad Money* show, (2) it recaps recommendations in the order in which they appear on the program (where many other recap providers disseminate segment information in alphabetical order), (3) the provider creates special designations for some stocks which eliminates the need for the use of researcher's judgment in classifying the recommendations (for instance "*Special Mention*" [7] designation indicates that Jim Cramer discussed the stock in detail).

[6] As a part of Jim Cramer's charitable trust.

[7] These stocks are not the same as *special discussion* stocks mentioned in Engelberg, Sasseville, and Williams (2007). They use this term to describe non-*Lightning Round* stocks. In our sample *SM* is the designation given by the third party. These are the stocks recognized by the recap provider as those receiving special attention/endorsement from the host (they appear across all segments of the show including the *Lightning Round* and *Sudden Death*, however they are underrepresented in these segments).

Table 1 presents various show segments while Table 2 covers website recommendation designations utilized in this study and summarizes the average depth of recommendations associated with these groupings. We do not include all the segments. For instance, we exclude "*Am I diversified*?" segment of the program since the recommendations provided in this segment are specific to the caller portfolio.

----- Insert Tables 1 & 2 about Here-----

This study utilizes 8,269 unambiguous "buy" recommendations for stocks trading on NASDAQ, AMEX, or NYSE that aired between November 1, 2005 and July 31, 2007. "Sell" recommendations that aired during the same time period were used to estimate the variables pertaining to coverage intensity, accuracy of previous recommendations, and recommendation reversals for "buy" recommendations. Of the initial 8,269 "buy" recommendations **8,160** observations had enough data for the estimation period specified in the *Event Study* section of this paper. Therefore, our regression analysis was carried out on the final sample of 8,160 observations.

With monetary support from the *Marketing Science Institute* and the *Emory Marketing Institute* we have also purchased daily TV ratings data for the show from *Nielsen Media Research.* All financial data are obtained from *The Center for Research in Security Prices (CRSP).* The event study related portion of the analysis is carried out using *EVENTUS*® software. Both financial data and *EVENTUS*® software were made available to us through *Wharton Research Data Services*.

EVENT STUDY

Event studies have become a popular tool in a number of fields beyond finance (Kalaignanam, Shankar and Varadarajan 2007; Balasubramanian, Mathur, Thakur 2005). It has been previously used to enhance our understanding of various marketing domains such as brand equity (Simon and Sullivan 1993), product quality (Tellis and Johnson 2007), product innovation (e.g., Chaney, Devinney, and Winer 1991; Sood and Tellis 2004; Sharma and Lacey 2004; Eliashberg and Robertson 1988; Chan, Lakonishok and Sougiannis 2001), celebrity endorsements (Agarwal and Kamakura 1995), and customer service (Balasubramanian, Mathur, Thakur 2005).

This approach uses the returns of the market portfolio as a benchmark for normal returns and then detects any deviations from it. We assume that the event (or recommendation) takes place at $t = 0$ and use (-30, 30)[8] as our broad event window. We use the default estimation window in EVENRUS® (between days -300 and -46) to estimate the normal or expected return. Since Cramer first makes his recommendations after the close of the market at 6:00 PM, we are particularly interested in the abnormal return over the (0, 1) event window.

----- Insert Figure 2 about Here -----

To evaluate the event's impact, we require a measure of the abnormal return. Following Campbell, Lo, and MacKinlay (1997), the abnormal return is defined as the actual *ex post* return of the security over the event window minus the normal return of the firm over the event window. The normal return is the return that would be expected if the event (recommendation) did not take place. For each firm *i* and event date *τ*:

$$AR^{*}_{it} = R_{it} - E[R_{it} \mid X_t] \qquad (1)$$

Where AR^{*}_{it}, R_{it}, and $E[R_{it}]$ are the abnormal, actual, and normal returns, respectively. X_t is the conditioning information to determine normal performance. We start with the most common variation of the normal return model known as the *Market Model* (see Srinivasan and Bharadwaj (2004) for the detailed description and applications within marketing domain). In this model we detect the influence of an "event" by isolating the movements associated with the overall market fluctuations:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \qquad (2)$$

where

R_{it}	is return of stock *i* at time *t*
R_{mt}	monthly return on CRSP value-weighted index
β_i	is a measure of stock *i*'s sensitivity to market changes
ε_{it}	is a random variable, E[ε_{it}]=0, corr(ε_{it}, R_{mt})=0, corr(ε_{it}, R_{jt})=0, for $i \neq j$

[8] Where "-30" indicates 30 days before the event and "30" indicates 30 days after the event.

However, it is recommended that one finds a model that best fits the market in order to make the event study more efficient (Srinivasan and Bharadwaj 2004). Fama and French (1996) use a multifactor model that explains several asset pricing anomalies which exist in the market. This more elaborate model has been previously used in finance, as well as, marketing studies (e.g., Sood and Tellis 2007).

$$R_{it} = \alpha_i + \beta_i R_{mt} + s_i SMB_t + h_i HML_t + \varepsilon_{it} \qquad (3)$$

Where the two additional factors relate to market anomalies with respect to stocks of different market capitalization and value vs. growth stocks, namely:

SMB_t is the difference between average returns of small and large cap portfolios
HML_t is the difference between average returns on high vs. low B/M[9] portfolios

The Fama-French three factor model captures the majority of market inefficiencies but it fails to capture momentum (Carhart, 1997). Therefore, we incorporate Carhart's (1997) momentum factor. The resulting equation is what is known as the four-factor model:

$$R_{it} = \alpha_i + \beta_i R_{mt} + s_i SMB_t + h_i HML_t + u_i UMD_t + \varepsilon_{it} \qquad (4)$$

where UMD_t is the average return on high performing portfolios minus the average return on low return portfolios. Using four-factor model, abnormal returns are defined as:

$$AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt} + \hat{s}_i SMB_t + \hat{h}_i HML_t + \hat{u}_i UMD_t) \qquad (5)$$

where $\hat{\alpha}_i, \hat{\beta}_i, \hat{s}_i, \hat{h}_i$, and $\hat{u}_i$ are GARCH (1,1) estimates of $\alpha_i, \beta_i, s_i, h_i$, and u_i.

We use GARCH (1, 1) model (as suggested by Bollerslev, 1986) because it allows the conditional variance to change as a function of the past-realized residuals and past variances. Boehmer, Musumeci, and Poulsen (1991) and Corhay and Tourani Rad (1996) provide evidence that event-study regression models that account for time-varying conditional variance properties and stochastic parameters generate more efficient estimators of regression parameters and thus lead to a more robust conclusion than traditional event-study methodology.

[9] Portfolios are formed based on Book-to-Market ratios.

We estimate abnormal returns (5); aggregate them over respective event windows and test their significance. We use the following event windows: (-30,-10) to estimate the mid range pre-show price buildup, and (-10,-2) to estimate immediate pre-show price buildup. We also look at the day preceding the show (-1,-1), event day (0, 0), and the day following the show (1, 1) which is of the central importance to our study. We evaluate post reaction price drift by studying post event windows (2, 10) and (10, 30).

We also conduct a volume-based event study with daily volume data centered on a single date for each firm (see Campbell and Wasley 1996 for details). Volume event studies are similar to the market model event studies described in equation (2) except we use log-transformed relative volume data in place of the returns.

TESTS

We use a number of tests to identify the significance of resulting inefficiencies. *Time series standard deviation* t-test (Brown and Warner 1985) is used to detect the significance of abnormal returns over a specified time frame. In addition, a more sophisticated *jackknife test* (Giaccotto and Sfiridis 1996) was used due to its robustness in situations where events cause transient changes in return variation. The *generalized sign* test uses normal approximation to the binomial distribution and determines whether the differences in the number of positive and negative returns are significant at the desired confidence level (for details of generalized sign test see Sprent 1989 and Cowan, 1992).

RESULTS OF EVENT STUDY

First, we replicated previous research by looking at the abnormal price and volume fluctuations associated with all "buy" recommendations that appear on the show. We find that stocks recommended during the show are stocks that are experiencing abnormal returns prior to recommendation (See Figure 3). This is not surprising since callers often ask Cramer whether he thinks that a stock "on the move" has "peaked." We find a significant abnormal return of .50% on the day following "buy" recommendations (see Appendix A for details), however these gains quickly disappear. As shown in Figure 3, starting with day two, there is a significant drop in security prices as the unwarranted sharp price increases trigger the profit taking sell-off by the informed investors.

----- Insert Figure 3 Here -----

Note that prices continue to fall far below the pre-recommendation levels; they actually fall back to their pre-run up values. This suggests that pre-show run up is not driven by fundamentals either and that Cramer's endorsement (which possibly brings more scrutiny to the stocks) drives stock prices down closer to their intrinsic values. Appendix A summarizes average daily stock price abnormalities within the event window.

In summary, the host's "buy" recommendations are associated with positive momentum prior to recommendation, indicating a possible tendency on the part of the host to recommend momentum-based trades. After the recommendation, however, the stocks experience a large one day abnormal return on the day following the recommendation and then start retreating creating losses for those who traded based on recommendations. The decline does not stop at the pre-show levels. The pre-show momentum reverses and the stocks lose the ground gained in pre-show price build up. The bulk of the significant pre-show build up in prices is taking place between days -8 and 0. Then we register a sharp uptick in prices (.50%) on the day following a recommendation (1, 1), which is followed by a gradual decline. Securities come back to their pre-show price levels during the next six to seven trading sessions.

Appendix A also presents a summary for the event related daily transaction volume reaction. We register an abnormal increase in trading volume on the trading day following the "buy" recommendations. Recommended stocks are already experiencing abnormal activity prior to the show, but the show further stimulates trading activity. Note that for every day in the event window [-30, 30], the mean abnormal relative volume (MARV) is positive and significant with *p*-value <.0001. The day after the show airs; stocks experience a significant ($p<.0001$) abnormal trading volume increase of 73.34% (Figure 4 depicts daily abnormal trading volume).

----- Insert Figure 4 about Here -----

"Buy" Recommendations across Different Segments. Table 3 summarizes event study results across different show segments and special designations. The *Main, Opening,* and *Closing* segments are associated with abnormal returns of 1.06%, 1.21%, and .57%, respectively, on the day following the show. The *Main* and *Opening* segments have greater impact compared to the *Closing* segment, which indicates a possible presence of primacy effects or the fact that viewers do not stick around until the end of the program. Stocks in these elaborate segments are associated with higher next day abnormal returns compared to those stocks in the less elaborate *Lightning Round* and *Sudden Death* segments.

Surprisingly, the stocks featured in the *CEO Interview* segment experience abnormal returns of about .74% *on* the day of the show, which is followed by the 1% abnormal return on the day following the show indicating that Cramer either contacts the CEOs of companies on the move, or what is more likely given the CEOs' busy schedules, evidence of information leakage (show appearances require advanced scheduling and the information about the CEO's visit gets leaked).

As expected *SM* (i.e., stocks that the data provider has classified as *Special Mention*) stocks get the biggest boost the day after the show airs (1.27%). '*Mon Back* stocks also receive a relatively large boost (.83%), however investors are a bit cautious despite host's strong endorsement, since these are often the stocks that Cramer suggests have bottomed out (indicating that some investors are too conservative to utilize a "catching the falling knife" strategy).

----- Insert Table 3 about Here -----

Initial vs. Repeat Recommendations. We could not obtain a sample of initial recommendations only since the show started airing in March 2005 and our sample starts in November 2005. However, we separated our sample into the first observation for a particular security in our sample vs. the repeat recommendations for the same security. The first sub-sample would, by design contain all first time recommendations that aired during the observed period (we refer to this sub-sample as "initial" recommendations).

Initial recommendations cause stronger market reaction vis-à-vis repeat recommendations. Next day stock market increase for the initial recommendations is 1.43%, which is significantly higher than the overall average of .50% and the .36% average for the repeat recommendations. Furthermore the 1.43% estimate is conservative as some of the recommendations in our "initial" recommendation sample are repeat recommendations (Engelberg, Sasseville, and Williams (2007) estimate for initial recommendations only was twice as large). Pre-show price buildup is more pronounced for initial recommendation stocks (price increases are probably the reason the stocks catch viewers' and host's attention). In addition to the next day price increase differences, the price decrease that follows is much slower (faster) for initial (repeat) recommendations. In (2, 30) event window, initial (repeat) coverage stocks lose 1.50 (2.2) %. It takes initial recommendation stocks much longer (around 27 trading sessions) to bounce back to the pre-show levels (it takes repeat recommendation stocks only five sessions).

----- Insert Table 4 about Here -----

REGRESSION ANALYSIS

Next, we looked at the abnormal returns on the first market day following the "buy" recommendation, AR_{i1}. For all **initial "buy" recommendations** we specify the model:

$$\begin{aligned}
AR_{i1} &= \beta_{TIME} EVENT_DATE_{i0} + \beta_{VIEWERS} VIEWERS_{0} + \beta_{Clutter} CLUTTER_OVERALL_{i0} \\
&+ \beta_{SIC_Clutter} CLUTTER_SIC_{i0} + \beta_{NYSE} NYSE_{i1} + \beta_{AMEX} AMEX_{i1} \\
&+ \beta_{price} SHARE_PRICE_{i(-1)} + \beta_{Turn} TURNOVER_{i(-1)} + \sum_j \beta_j SEGMENT_{ij0} \\
&+ \beta_{SM} SPECIAL_MENTION_{i0} + \beta_{MB} MON_BACK_{i0} + \beta_{own} CRAMER_OWNS_{i0} \\
&+ \beta_{Cap} LN(MARKET_CAP_{i(t-1)}) + \beta_{MD} MEMORY_DECAY_{i1} \\
&+ \beta_{rec} RECENCY_{i0} + \beta_{pr} PRIMACY_{i0} + \eta_{it}
\end{aligned} \tag{6}$$

For all **repeat "buy" recommendations** separately we run:

$$\begin{aligned}
AR_{i1} &= \beta_{TIME} EVENT_DATE_{i0} + \beta_{VIEWERS} VIEWERS_{0} + \beta_{Clutter} CLUTTER_OVERALL_{i0} \\
&+ \beta_{SIC_Clutter} CLUTTER_SIC_{i0} + \beta_{NYSE} NYSE_{i1} + \beta_{AMEX} AMEX_{i1} \\
&+ \beta_{price} SHARE_PRICE_{i(t-1)} + \beta_{Turn} TURNOVER_{i(t-1)} + \sum_j \beta_j SEGMENT_{ij0} \\
&+ \beta_{SM} SPECIAL_MENTION_{i0} + \beta_{MB} MON_BACK_{i0} + \beta_{own} CRAMER_OWNS_{i0} \\
&+ \beta_{Cap} LN(MARKET_CAP_{i(t-1)}) + \beta_{MD} MEMORY_DECAY_{i1} \\
&+ \beta_{rec} RECENCY_{i0} + \beta_{pr} PRIMACY_{i0} + \beta_{CI} COVERAGE_INTENSITY_{i0} \\
&+ \beta_{CA} RETURN_SINCE_LAST_{i0} + \beta_{flip} RECOMMENDATION_FLIP_{i0} \\
&+ \beta_{int} RECOMMENDATION_FLIP_{i0} * RETURN_SINCE_LAST_{i0} + \eta_{it}
\end{aligned} \tag{7}$$

Appendix B presents the summary of all the variables used in this study. Correlation table for model 6(7) is in Appendix C (D). Descriptive statistics are in Appendix E.

RESULTS OF REGRESSION ANALYSIS

Regression results for models 6 and 7 are summarized in Tables 5 and 6. In addition to the specified model we run the models omitting *Special Mention* designation as an explanatory variable in order to establish if the between-segment differences are driven by the amount of host's attention given to individual stocks.

----- Insert Tables 5 and 6 about Here-----

Information Intensity Effects: Recommendations that air during more elaborate segments are associated with bigger inefficiencies. Our analysis shows that between segment differences are primarily attributable to the amount of attention each stock receives. When we incorporate the special mention designation into the analysis, segment specific dummy variables lose their significance in initial recommendation equation. Some of the coefficients reverse their signs in the repeat recommendation model. After incorporating "*SM*" designation, we get a positive coefficient for *LR* and *SD* segments (which consumers tend to favor) and negative for the closing comments segment.[10] Therefore, after controlling for the amount of the attention received by each stock we start picking up the signs of viewer preference for different segment formats.

Overall information clutter marginally contributes to reducing the size of market inefficiency that follows "buy" recommendations. Clutter seems to be less relevant for initial recommendations than repeat ones. Overall clutter is not significant for initial recommendations. For initial recommendations, clutter from similar (same SIC header code) picks is positively associated with the size of inefficiency. This finding is surprising from the information processing stand point, however it could be explained by host's tendency to talk about potentially attractive segments and bringing up several stocks he finds particularly promising. These positive remarks about the industry may influence investor decisions. We also find

[10] Which is not surprising given that SD is a new segment that was designed to stop the viewers from changing the channel before the end of the program.

some evidence of size of audience effects. The number of VIEWERS variable is marginally significant in the repeat recommendation model that includes *SM* designation.[11]

Information Processing Effects: To our knowledge no prior study examined presentation order effects within stock recommendations domain. This paper contributes to the literature by finding very convincing evidence for the existence of primacy effects in this setting as they are significant ($p<.05$) for initial as well as repeat recommendations. We also find evidence of significant ($p<.05$) recency effects in the repeat recommendations sample. Similar to the previously mentioned advertising research (Pieters and Bijmolt 1997), we find primacy effects to be stronger than recency effects.

Information Credence Effects: Recommendation reversals are associated with larger abnormal returns indicating that viewers respond to such reversals very strongly. Investor return from last recommendation for a particular equity and its interaction with recommendation reversal variable are also significant. These results indicate that investors do pay attention to Cramer's track record as the response to recommendation is contingent upon the accuracy of his previous prediction for the same security. If his track record for a particular security is strong (i.e., larger positive returns on recommended "buys" or steeper stock price declines for recommended "sells"), investors are more likely to pay attention to his subsequent recommendations especially when he reverses his opinion.

There is also mixed evidence of global "learning" taking place. Similar to previous research, we find a general negative trend in market response to Cramer's recommendations over time. We find that the time variable is significant in the initial recommendation model. However, we find that time effect loses its significance in the repeat recommendation model once we introduce the "*SM*" designation variable into the equation. As the number of stocks recommended by Cramer on a single show increases over time and individual stocks receive less attention. There is some collinearity between the *SM*, time, and individual segment variables but none of the VIFs exceed 10 (the cutoff point suggested by

[11] One possible explanation for only a marginal effect could be the fact that *Mad Money* has a group of hard core followers who are responsible for the bulk of the price movements. The size of the occasional viewer segment (that fluctuates in response to other programming available) may not have a very strong effect on stock prices. This matter requires further investigation.

Marguardt (1970) for identifying serious collinearity problems). Overall, model comparison tests favor using *SM* designation in both initial and repeat recommendation cases (See Appendix F).

***Other Significant Findings*:** The magnitude of share price is negatively associated with abnormal returns indicating that consumers are "bargain hunting" while watching the show. This finding persists even after we control for other variables such as market cap. Similar to previous research we find that market cap is inversely related to the abnormal return. In addition, we find that different markets are associated with different sizes of inefficiencies. For stocks traded on *NYSE* inefficiencies are marginally lower than those associated with *NASDAQ* stocks. These differences could be potentially linked to the differences in the security types listed on these exchanges, levels of idiosyncratic volatility associated with these stocks, differences in effective spread sizes, and short sales rules governing different exchanges. However, finding the exact sources of this variation is beyond the scope of this project.

SUMMARY

Table 7 summarizes the findings in regard to original hypotheses:

----- Insert Table 7 about Here -----

MANAGERIAL IMPLICATIONS

First, we document a number of inefficiencies/arbitrage opportunities that that are created by televised stock recommendations. These inefficiencies are of interest to the managers of publicly traded companies affected by *Mad Money* recommendations as they may influence stock repurchase decisions. In addition (while not a managerial recommendation), virtually all of *MSI*'s active participants are also stock holders. This study offers an insight into the behavior of their personal portfolios and a cautionary note for following the recommendations of any stock selection strategy that is divorced from company fundamentals.

We assumed that the response to Jim Cramer's recommendations might differ from the response to advertisements because many viewers are actively looking for recommendations instead of passively watching commercials. We do find considerable evidence that viewers are actively looking for recommendations. First, rather than a threshold or inverted-U shaped response curve to the number of ads, initial recommendations generated stronger reactions than subsequent recommendations for the same stock. Second, this seems to be a high involvement purchase. For initial recommendations, it appears that rather than focusing on better known stocks with large capitalizations consumers are looking for niche/small cap stocks as the size of the next day stock price abnormality is inversely related to the size of the pre-event market capitalization. However, this larger inefficiency could also be explained by the higher limits to arbitrage associated with small cap stocks. Additionally, stocks with higher turnover rates generated higher next day price increases compared to stocks with low turnover/higher institutional ownership.

In spite of these differences, we find numerous similarities between consumer response to traditional advertising and Cramer's recommendations. Even though a substantial fraction of the audience is looking for recommendations, any individual recommendation is still subject to many of the same communication obstacles in terms of getting heard as advertisements. We found strong evidence of both recency and primacy effects in consumer response to stock recommendations. Primacy had a greater impact than recency (and affected both initial and repeat recommendations while only repeat recommendations were affected by the recency effect) possibly indicating that search is active and that once a satisfactory recommendation is found, the search ends. We found that overall clutter had a marginally negative impact on the reaction to repeat recommendations while having no effect for initial recommendations. This indicates that initial recommendations can cut through the clutter. The clutter due to other recommendations in the same industry had no impact. This indicates that viewers are looking for stocks in general and not within particular industries. Finally, recommendations that were given greater emphasis had a greater response than others.

When consumers are looking for recommendations, but not a specific stock recommendation, the situation could be similar to the case where a person has an interest in a product or service class, but does not have a specific brand in mind. This similarity should make the findings of this study relevant to well-targeted ads (i.e., ads that are served to consumers who have expressed some interest in a particular product category) of the future. Our findings suggest that it is not enough to appropriately target a message to a certain viewer, its chances of being attended to and acted upon are significantly greater with proper placement, reduced clutter and better execution. For instance in targeted online advertising campaigns, marketers need to make sure that the message is not only going to the right people but that it is also appropriately positioned among the competitive entries and designed in a way that is capable of grabbing consumer attention and cutting through the clutter.

The findings are also relevant to the domain of search engine marketing (e.g., Google's AdWords), browsing history based advertising (e.g., FrontPorch, NebuAd, Phorm) and to the effectiveness of recommendation lists and advice columns (e.g., Amazon Daily Blog) that are becoming integral parts of Internet shopping portals. Even in such high involvement environments where consumers are presented with information relevant to their needs, information processing related effects could influence consumer purchasing decisions.

We find that information credence has an impact as response to subsequent recommendations on a particular stock are significantly impacted the success of past recommendations on the same stock. At the same time there is also some evidence of global learning taking place. The decrease in response to Cramer's recommendations over time is consistent with viewers learning the general pattern of abnormal returns shown in Figure 3. However, at least for repeat recommendations, a part of the overall decrease in recommendation impact can be attributed to the fact that the number of *Special Mention* stocks declined over time as program's format shifted toward favoring *Lightning Round* and *Sudden Death* formats.

Previous research indicates that repeated exploitation by informed investors results in the loss of consumer following, especially if individual investors become aware of this exploitation through the dissemination of the related research through the mass media. However this research does not explore the possibility of the positive (negative) brand equity impact associated with accurate (inaccurate) longer term predictions. In this study we looked at accuracy of Cramer's predictions and found that consumers do track the host's performance for particular securities when making purchase decisions. Therefore, if the host did possess accurate information on longer-term price movements, this could offset some of the loss in consumer following due to short-term arbitrage plays.

We also find that the per share price is informative in explaining the size of abnormal return following initial recommendations even after we control for variables traditionally associated with limits to arbitrage indicating that naïve investors could be "bargain hunting." This finding outlines irrationality of naïve investor actions and suggests that pricing related considerations could inform finance models of investor behavior.

It is instructive to compare the results of this study with those of Tellis and Johnson (2007) in their event analysis of abnormal returns to stock prices of firms whose products were reviewed by the *Wall Street Journal*. A positive product review by Walter Mossberg of the *WSJ* provided a bigger abnormal next day return that was sustained in the following days. This suggests that if CEOs introduce credible, positive, new information, its impact on stock returns might be similar to that of an objective product review. If an appearance does not provide any new information, (similar to most appearances on *Mad Money*), its effects would dissipate quickly.

It is possible that it would be better to restrict PR activities to general business shows and communication with analysts and not shows, like *Mad Money,* where viewers are looking for stock picks. In order to create a sustainable stock price increase, the appearances should concentrate on the new developments that are material (i.e., affect company's long-term potential and future cash flows) since the market does not reward the PR efforts that are not based on fundamentals. At the same time there could be some positive side effects associated with *Mad Money* appearances as increased scrutiny may reduce the cost of management/market information asymmetry which, in efficient markets, is ultimately borne by the firm (Myers and Majluf, 1984). In addition, it is possible that these appearances create additional brand equity especially when it comes to relatively unknown consumer goods (viewers could be inclined to try the brands marketed by the companies mentioned on the show) but this aspect needs further investigation.

ROBUSTNESS CHECKS

We estimated the results based on several different event study configurations. In total twelve models varying in model configuration (four factor, three-factor and market model), estimation method

(OLS or GARCH (1, 1)) and weighting scheme (value vs. equal weighting index) were estimated and compared. The following graph represents the different CAR estimates for all "buy" recommendations produced by the different models estimated by these two techniques.

----- Insert FIGURE 5 about Here -----

Given the results, we are confident that this study's findings are robust across different model specifications as the directionality and significance levels are similar across all twelve methods.

DISCLAIMER

By no means are we trying to suggest that *Mad Money* show is misleading or unethical, we are simply documenting the market response that follows stock picks being provided to a large group of uninformed investors. While some will undoubtedly see the resulting redistribution of wealth as "abuse" of the naïve investors, classic theories of market microstructure (Kyle (1985) and Admati and Pfleiderer (1988)) suggest that in order for the markets to be efficient, the informed investors (i.e. those who participate in price discovery and improve market efficiency) need to be "compensated" for collecting the information. In addition, the dissemination of this study's findings may actually prevent some individual investors from trading based on TV recommendations.

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FIGURE 1: CONCEPTUAL FRAMEWORK (Shaded Areas Represent This Study's Contribution)

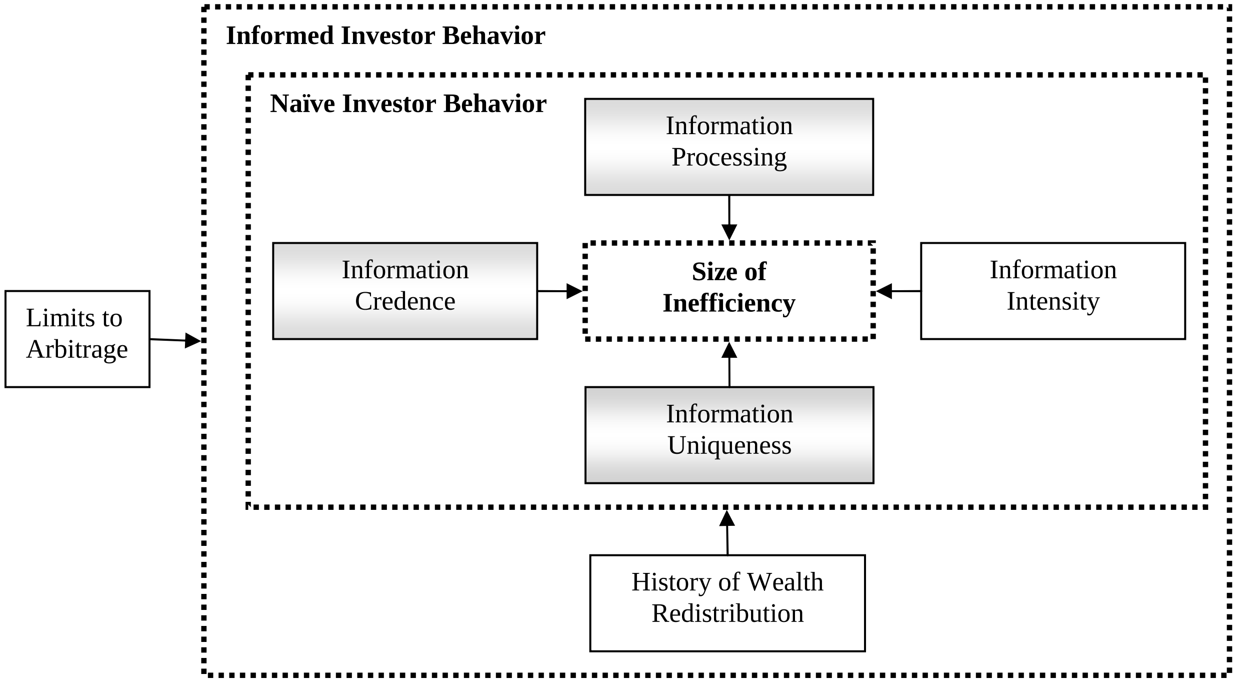

FIGURE 2: Event Study Timeline

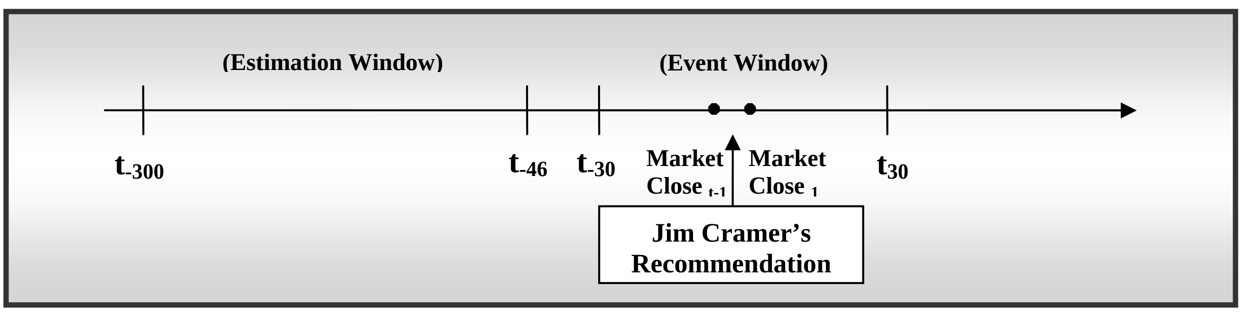

FIGURE 3: Cumulative Abnormal Returns Following "Buy" Recommendations

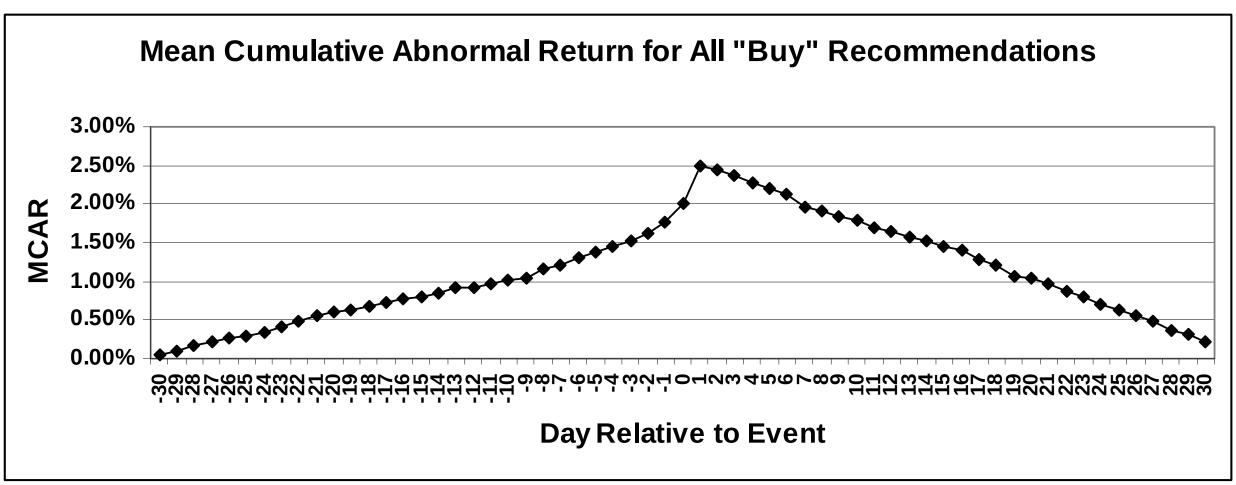

FIGURE 4: Abnormal Volume Following "Buy" Recommendations

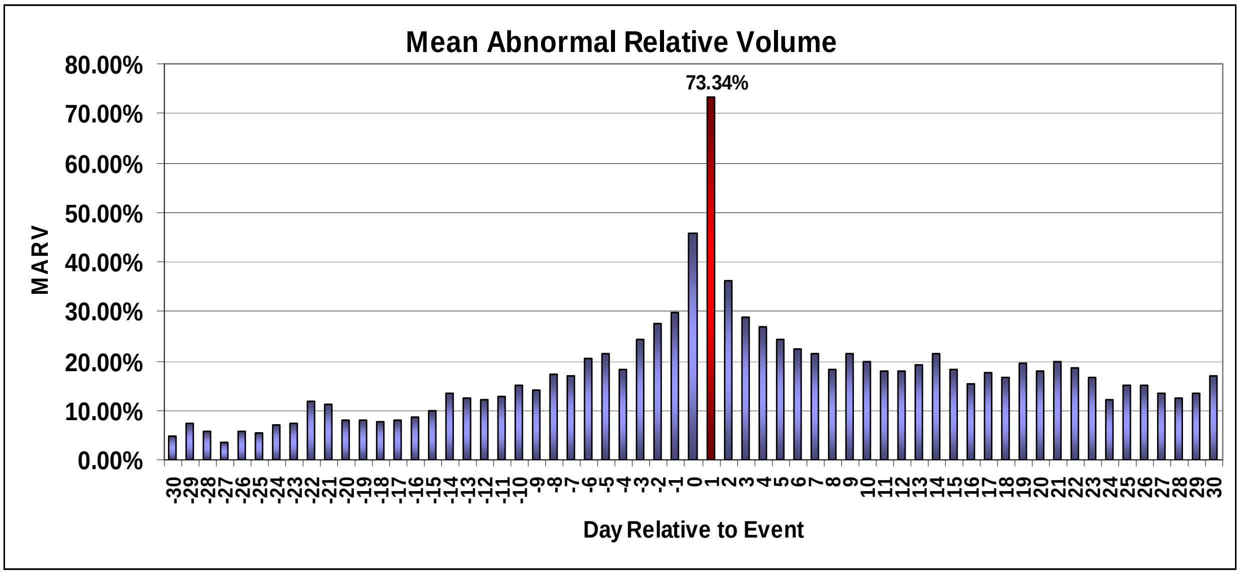

FIGURE 5: Robustness Check

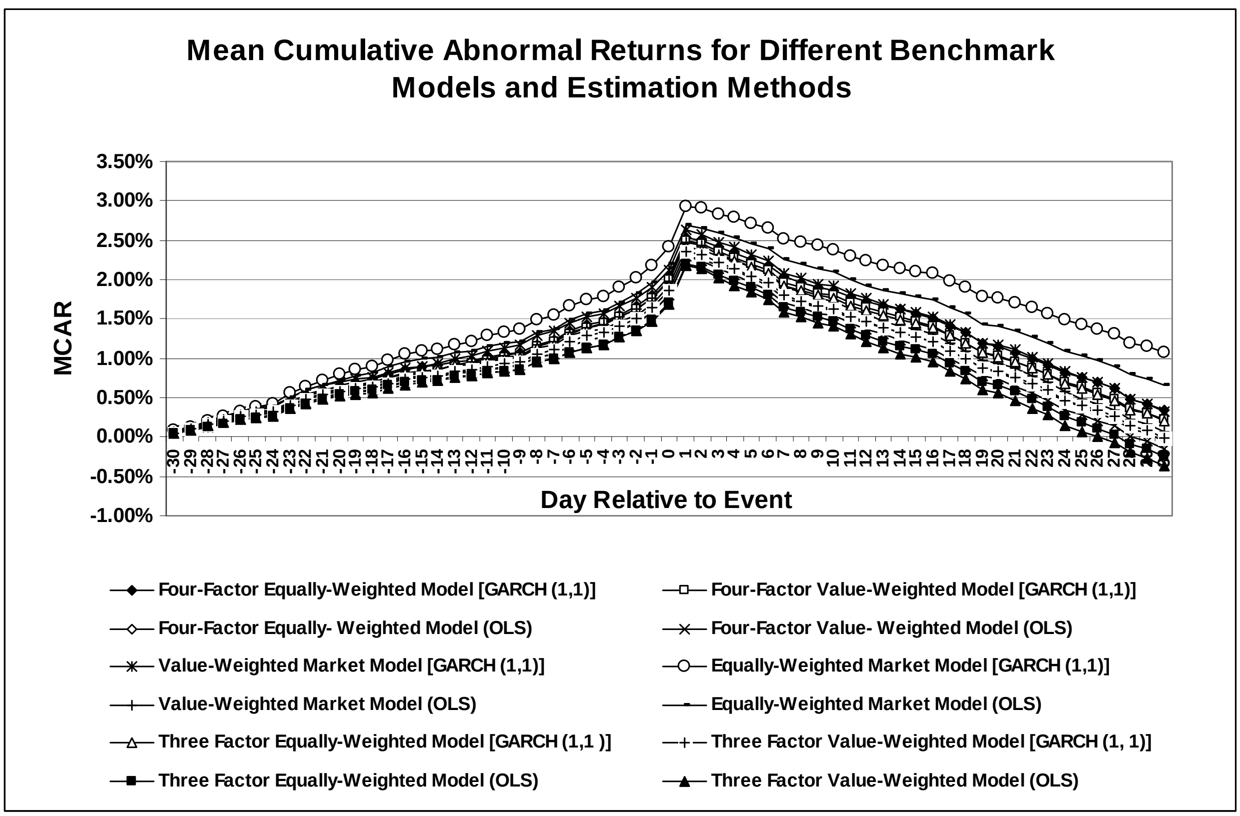

TABLE 1: Segment Description and Information Intensity across Different Segments

Amount of Attention	**Segment**	**Description**
HIGH	***CEO Interview***	The most detailed segment. With rare exceptions (which are excluded from our dataset since these instances do not translate into "buy" recommendations), CEO's provide very upbeat view of the market and very positive company outlook.
	Opening and Closing Segments	Cramer opens the show with fairly detailed discussion of select stocks. The segment is also commonly labeled as "first" segment. Host tends to wrap the show with fairly detailed recommendations.
MEDIUM	***Main or Discussion Segment***	The segment with average amount of attention, in this study we use it as the base category.
LOW	***Lightning and Sudden Death Rounds***	In both of these segments, the host provides a fast-paced series of stock picks (many of them are in response to viewers' calls where they call in for a recommendation on a specific security and Cramer quickly responds with his opinion). Sometimes he also mentions related stocks/provides his opinion on the entire sector. In rare event when the pick is more elaborate, it is also designated as a *Special Mention*. The difference between the two segments is that the LR takes place in the beginning of the show and SD appears at the end.

TABLE 2: Special Designations

Special Designation	**Description**
'Mon Back	Some stocks are designated as "*'Mon Back*" stocks [Jim Cramer's term for "C'mon back," suggesting that Jim would back up the truck and load it up with stock]. In other words, the mentioned stock is so great that you should buy as much as possible.
Special Mention (SM)	Some stocks receive "*Special Mention*" designation indicating that the stock received special attention from Jim in terms of time spent discussing it and the strength of host's opinion. Special mention designation could be assigned to a stock regardless of the segment it appeared in.

TABLE 3: Mean CAR across Different Segments and Designations

Group	Days	N	Mean CAR	Positive: Negative	Portfolio t. s. (CDA) t	Jackknife Z
Opening Segment	(-30,-10)	704	0.75%	371:333>>	2.186*	1.911*
	(-10,-2)	704	1.06%	387:317>>>	4.751***	3.532***
	(-2,-1)	704	0.27%	356:348)	3.601***	2.621**
	(0,0)	704	0.28%	362:342>	3.688***	2.409**
	(+1,+1)	704	1.21%	465:239>>>	16.174***	11.875***
	(+2,+30)	704	-2.05%	296:408<<<	-5.109***	-5.826***
Main Segment	(-30,-10)	1663	0.95%	904:759>>>	3.645***	3.531***
	(-10,-2)	1663	0.85%	873:790>>>	4.981***	4.020***
	(-2,-1)	1663	0.29%	882:781>>>	5.150***	4.502***
	(0,0)	1663	0.57%	927:736>>>	10.052***	7.394***
	(+1,+1)	1663	1.06%	950:713>>>	18.707***	11.169***
	(+2,+30)	1662	-2.27%	717:945<<<	-7.420***	-7.929***
Closing Segment	(-30,-10)	689	0.83%	374:315>>>	2.209*	1.044
	(-10,-2)	689	0.81%	358:331>	3.315***	2.286*
	(-2,-1)	689	0.18%	347:342)	2.157*	1.869*
	(0,0)	689	0.07%	326:363	0.800	0.660
	(+1,+1)	689	0.57%	400:289>>>	6.917***	5.324***
	(+2,+30)	689	-1.11%	322:367	-2.510**	-4.270***
CEO Interview	(-30,-10)	132	0.91%	66:66	1.129	0.413
	(-10,-2)	132	1.36%	76:56>	2.588**	2.465**
	(-1,-1)	132	-0.13%	59:73	-0.76	-0.847
	(0,0)	132	0.74%	68:64	4.188***	1.879*
	(+1,+1)	132	1.00%	90:42>>>	5.720***	5.088***
	(+2,+30)	132	-2.77%	51:81<	-2.923**	-3.397***
Lightning Round	(-30,-10)	4807	1.07%	2618:2189>>>	6.842***	5.958***
	(-10,-2)	4807	0.55%	2460:2347>>>	5.374***	2.905**
	(-2,-1)	4807	0.06%	2331:2476	1.860*	0.970
	(0,0)	4807	0.12%	2363:2444>	3.459***	2.639**
	(+1,+1)	4807	0.21%	2450:2357>>>	6.003***	5.283***
	(+2,+30)	4807	-2.49%	2023:2784<<<	-13.494***	-15.304***
Sudden Death	(-30,-10)	261	0.74%	142:119>	1.305$	0.853
	(-10,-2)	261	-0.22%	123:138	-0.588	-0.975
	(-2,-1)	261	0.08%	119:142	0.659	0.120
	(0,0)	261	0.05%	124:137	0.377	0.516
	(+1,+1)	261	0.15%	116:145	1.229	0.234
	(+2,+30)	261	-1.80%	104:157<<	-2.700**	-3.451***
Special Mention	(-30,-10)	2547	0.93%	1374:1173>>>	4.212***	3.637***
	(-10,-2)	2547	1.05%	1379:1168>>>	7.266***	6.630***
	(-1,-1)	2547	0.26%	1320:1227>>>	5.384***	5.325***
	(0,0)	2547	0.21%	1285:1262>>	4.351***	3.720***
	(+1,+1)	2547	1.27%	1635:912>>>	26.214***	19.491***
	(+2,+30)	2547	-2.20%	1107:1440<<<	-8.452***	-10.032***
'Mon Back	(-30,-10)	215	-0.22%	103:112	-0.291	-0.091
	(-10,-2)	215	-1.65%	97:118	-3.380***	-3.026**
	(-1,-1)	215	-0.27%	91:124(	-1.681*	-2.081*
	(0,0)	215	-0.05%	97:118	-0.283	-0.888
	(+1,+1)	215	0.83%	139:76>>>	5.067***	4.921***
	(+2,+30)	215	-2.25%	99:116	-2.560**	-3.423***

In this and all the other tables presented in this paper. The symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively. The symbols (,< or),> etc. correspond to $,* and show the significance and direction of the generalized sign test.

TABLE 4: Initial vs. Repeat "Buy" Recommendations

Days	N	Mean CAR	Positive: Negative	Portfolio Time Series (CDA) t	Jackknife Z
INITIAL RECOMMENDATONS					
(-30,-10)	1069	1.68%	620:449>>>	5.103***	6.334***
(-10,-2)	1069	1.45%	622:447>>>	6.698***	5.108***
(-1,-1)	1069	0.33%	565:504>>>	4.648***	3.102***
(0,0)	1069	0.43%	570:499>>>	5.924***	4.059***
(+1,+1)	1069	1.43%	674:395>>>	19.914***	13.336***
(+2,+30)	1069	-1.50%	499:570	-3.882***	-3.970***
REPEAT RECOMMENDATIONS					
(-30,-10)	7091	0.90%	3773:3318>>>	7.480***	5.709***
(-10,-2)	7091	0.53%	3630:3461>>>	6.773***	4.492***
(-1,-1)	7091	0.12%	3502:3589>>	4.485***	3.777***
(0,0)	7091	0.20%	3536:3555>>>	7.667***	6.206***
(+1,+1)	7091	0.36%	3716:3375>>>	13.955***	11.057***
(+2,+30)	7090	-2.20%	3012:4078<<<	-15.665***	-16.591***

TABLE 5: Regression Results for Initial "Buy" Recommendations

	Model with Segments Only							**Model with Segments and "Special Mention" Designation**						
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF	B	Std. Error	Beta			Tolerance	VIF
(Constant)	**4.133**	**1.210**		**3.417**	**0.001**			**3.345**	**1.211**		**2.762**	**0.006**		
TIME	**-0.000**	**0.000**	**-0.125**	**-3.350**	**0.001**	0.533	1.876	**-0.000**	**0.000**	**-0.102**	**-2.718**	**0.007**	0.523	1.913
VIEWERS	0.021	0.036	0.018	0.583	0.560	0.797	1.255	0.010	0.035	0.008	0.270	0.787	0.793	1.261
NYSE	**-0.004**	**0.002**	**-0.058**	**-1.834**	**0.067**	0.748	1.337	**-0.004**	**0.002**	**-0.056**	**-1.802**	**0.072**	0.748	1.337
AMEX	0.007	0.008	0.024	0.859	0.390	0.948	1.055	0.007	0.008	0.025	0.887	0.375	0.948	1.055
PRE-EVENT PRICE	**-0.000**	**0.000**	**-0.113**	**-3.623**	**0.000**	0.764	1.309	**-0.000**	**0.000**	**-0.113**	**-3.646**	**0.000**	0.764	1.309
PRE-EVENT TURNOVER	**0.089**	**0.034**	**0.072**	**2.615**	**0.009**	0.989	1.011	**0.088**	**0.034**	**0.071**	**2.619**	**0.009**	0.989	1.011
CEO SEGMENT	-0.011	0.010	-0.031	-1.126	0.260	0.955	1.048	-0.014	0.010	-0.039	-1.413	0.158	0.951	1.052
LIGHTNING ROUND	**-0.016**	**0.003**	**-0.208**	**-6.298**	**0.000**	0.683	1.464	0.002	0.005	0.032	0.518	0.605	0.187	5.341
SUDDEN DEATH	**-0.023**	**0.009**	**-0.076**	**-2.630**	**0.009**	0.899	1.112	-0.006	0.009	-0.020	-0.636	0.525	0.756	1.322
CLOSING SEGMENT	0.000	0.007	-0.002	-0.057	0.955	0.818	1.223	-0.005	0.007	-0.022	-0.740	0.459	0.799	1.252
OPENING SEGMENT	**0.009**	**0.005**	**0.056**	**1.660**	**0.097**	0.649	1.541	0.004	0.005	0.025	0.720	0.472	0.622	1.608
MON BACK	0.000	0.009	0.001	0.020	0.984	0.911	1.098	-0.001	0.009	-0.003	-0.105	0.916	0.910	1.099
CRAMER OWNS	0.007	0.008	0.023	0.812	0.417	0.954	1.048	0.008	0.008	0.028	1.003	0.316	0.952	1.050
PRIMACY	**0.014**	**0.003**	**0.126**	**4.307**	**0.000**	0.876	1.141	**0.014**	**0.003**	**0.123**	**4.246**	**0.000**	0.876	1.141
RECENCY	0.003	0.004	0.027	0.885	0.376	0.828	1.207	0.003	0.004	0.024	0.814	0.416	0.828	1.208
MEMORY DECAY	0.000	0.001	-0.002	-0.068	0.946	0.932	1.073	-0.001	0.001	-0.015	-0.534	0.594	0.922	1.084
SIC CLUTTER	**0.001**	**0.000**	**0.065**	**2.281**	**0.023**	0.932	1.073	**0.001**	**0.000**	**0.066**	**2.363**	**0.018**	0.932	1.074
OVERALL CLUTTER	0.000	0.000	-0.038	-1.278	0.201	0.857	1.166	0.000	0.000	-0.022	-0.748	0.455	0.845	1.183
LOG (MARKET CAP)	**-0.005**	**0.001**	**-0.185**	**-5.203**	**0.000**	0.591	1.693	**-0.004**	**0.001**	**-0.159**	**-4.461**	**0.000**	0.576	1.737
SM								**0.023**	**0.005**	**0.290**	**4.514**	**0.000**	0.177	5.640
MODEL FIT:														
R^2	0.218							0.233						
Adjusted R^2	0.204							0.219						
F-value	15.420							15.938						
Sig. (F)	.000							.000						

TABLE 6: Regression Results for Repeat "Buy" Recommendations

	Model with Segments Only							Model with Segments and "Special Mention" Designation						
	Unstandardized Coefficients		Standardized Coefficients	t-value	Sig.	Collinearity Statistics		Unstandardized Coefficients		Standardized Coefficients	t-value	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF	B	Std. Error	Beta			Tolerance	VIF
(Constant)	**0.962**	**0.297**		**3.235**	**0.001**			0.053	0.316		0.169	0.865		
TIME	**-0.000**	**0.000**	**-0.045**	**-3.124**	**0.002**	0.650	1.538	-0.000	0.000	-0.001	-0.092	0.927	0.573	1.746
VIEWERS	0.014	0.010	0.019	1.393	0.164	0.738	1.356	**0.017**	**0.010**	**0.024**	**1.765**	**0.078**	0.736	1.359
NYSE	**-0.001**	**0.001**	**-0.024**	**-1.870**	**0.062**	0.805	1.242	**-0.001**	**0.001**	**-0.025**	**-1.912**	**0.056**	0.805	1.242
AMEX	0.002	0.002	0.010	0.863	0.388	0.936	1.068	0.002	0.002	0.011	0.923	0.356	0.936	1.068
PRE-EVENT PRICE	-0.000	0.000	-0.018	-1.429	0.153	0.861	1.162	-0.000	0.000	-0.019	-1.526	0.127	0.861	1.162
PRE-EVENT TURNOVER	**0.027**	**0.011**	**0.029**	**2.491**	**0.013**	0.966	1.035	**0.028**	**0.011**	**0.030**	**2.553**	**0.011**	0.966	1.035
CEO SEGMENT	0.001	0.002	0.006	0.492	0.623	0.883	1.133	0.000	0.002	0.000	0.023	0.982	0.880	1.136
LIGHTNING ROUND	**-0.003**	**0.001**	**-0.060**	**-3.837**	**0.000**	0.549	1.821	**0.004**	**0.001**	**0.085**	**3.627**	**0.000**	0.242	4.130
SUDDEN DEATH	-0.002	0.002	-0.017	-1.359	0.174	0.849	1.178	**0.004**	**0.002**	**0.029**	**2.142**	**0.032**	0.707	1.415
CLOSING SEGMENT	0.001	0.001	0.010	0.696	0.487	0.641	1.559	**-0.004**	**0.001**	**-0.053**	**-3.245**	**0.001**	0.501	1.994
OPENING SEGMENT	**0.007**	**0.001**	**0.083**	**5.921**	**0.000**	0.683	1.463	0.002	0.001	0.019	1.188	0.235	0.523	1.914
MON BACK	**0.004**	**0.002**	**0.026**	**2.261**	**0.024**	0.985	1.015	**0.003**	**0.002**	**0.022**	**1.856**	**0.064**	0.983	1.017
CRAMER OWNS	0.001	0.001	0.012	0.977	0.329	0.933	1.071	0.001	0.001	0.009	0.739	0.460	0.933	1.072
PRIMACY	**0.004**	**0.001**	**0.045**	**3.771**	**0.000**	0.928	1.077	**0.004**	**0.001**	**0.045**	**3.799**	**0.000**	0.928	1.077
RECENCY	**0.002**	**0.001**	**0.030**	**2.421**	**0.016**	0.878	1.139	**0.002**	**0.001**	**0.027**	**2.232**	**0.026**	0.877	1.140
MEMORY DECAY	0.000	0.000	0.017	1.384	0.166	0.927	1.079	0.000	0.000	0.014	1.170	0.242	0.926	1.079
SIC CLUTTER	0.000	0.000	0.017	1.378	0.168	0.881	1.135	0.000	0.000	0.019	1.526	0.127	0.881	1.136
OVERALL CLUTTER	**-0.000**	**0.000**	**-0.022**	**-1.826**	**0.068**	0.919	1.088	**-0.000**	**0.000**	**-0.020**	**-1.701**	**0.089**	0.919	1.089
LOG (MARKET CAP)	**-0.002**	**0.000**	**-0.132**	**-9.725**	**0.000**	0.726	1.378	**-0.002**	**0.000**	**-0.123**	**-9.055**	**0.000**	0.721	1.387
COVERAGE INTENSITY	-0.002	0.004	-0.007	-0.584	0.559	0.968	1.033	-0.002	0.004	-0.007	-0.575	0.565	0.968	1.033
RETURN SINCE LAST RECOMMENDATION	**0.073**	**0.025**	**0.037**	**2.909**	**0.004**	0.812	1.232	**0.079**	**0.025**	**0.040**	**3.133**	**0.002**	0.811	1.233
FLIP	**0.003**	**0.001**	**0.043**	**3.674**	**0.000**	0.955	1.048	**0.003**	**0.001**	**0.044**	**3.706**	**0.000**	0.955	1.048
RETURN SINCE LAST x RECOMMENDATION FLIP	**0.289**	**0.067**	**0.054**	**4.299**	**0.000**	0.844	1.185	**0.282**	**0.067**	**0.053**	**4.209**	**0.000**	0.843	1.186
SPECIAL MENTION	N/A	NA	NA	NA	NA	NA	NA	**0.012**	**0.001**	**0.220**	**8.274**	**0.000**	0.188	5.321
MODEL FIT:														
R^2	0.054							0.064						
Adjusted R^2	0.051							0.060						
F-value	17.70							19.98						
Sig. (F)	**.0000**							**.0000**						

Table 7: Findings with Regard to Original Hypotheses

HYPOTHESIS	Support
H1: Consumer reaction to an initial stock recommendation is stronger than it is to subsequent recommendations.	**Supported.**
H2: Positive price abnormalities occur on the trading day that follows the *Mad Money* broadcast. Stocks prices start gravitating to their original levels on the second trading day.	**Supported.**
H3: Recency effect of stock pick order is associated with stronger consumer response.	**Supported** for repeat recommendations.
H4: Primacy effect of stock pick order is associated with stronger consumer response.	**Supported.**
H5: An increase in the number of total recommendations in the same show decreases the response to a recommendation.	**Marginally Supported** for repeat recommendations.
H6: Increase in the number of similar "buy" recommendations in the same show decreases the response to a recommendation.	**Not Supported**.
H7: Consumer response to more (less) elaborate recommendations is stronger (weaker).	**Supported.** In regressions without *SM* designation, less elaborate segments are associated with a reduction in the size of abnormal return. Introducing *SM* variable into regressions produces significant positive coefficient and the segment related variables lose their significance or even reverse their sign.
H8: The magnitude of stock price fluctuations induced by the show declines over time.	**Supported** for initial recommendations.
H9: When the host reverses his recommendation on a stock, the resulting stock price change is greater than the one that would have taken place on a repeated recommendation.	**Supported**, recommendation reversals increase the size of abnormal return.
H10: Accuracy of host's previous pick for a given stock influences the strength of consumer response.	**Supported.**
H11: Accuracy of previous prediction moderates consumer response to recommendation reversals.	**Supported.**

APPENDIX A: Summary of Market Reaction to "Buy" Recommendations

Day	N	MAR	CAR	Positive: Negative	Portfolio Time Series (CDA) t	Jackknife z	MARV
-30	8160	0.06%	0.06%	4016:4144>>	2.113*	2.773**	0.0475***
-29	8160	0.04%	0.10%	3873:4287	1.523$	0.905	0.075***
-28	8160	0.06%	0.16%	4012:4148>	2.160*	2.596**	0.0565***
-27	8160	0.05%	0.21%	3964:4196	1.904*	1.380$	0.0358***
-26	8159	0.05%	0.26%	3973:4186)	1.963*	1.793*	0.0587***
-25	8159	0.03%	0.29%	3965:4194	0.99	1.058	0.0529***
-24	8160	0.04%	0.33%	3934:4226	1.528$	2.071*	0.0694***
-23	8160	0.09%	0.42%	4063:4097>>>	3.412***	3.903***	0.0727***
-22	8160	0.07%	0.49%	3938:4222	2.728**	2.079*	0.1183***
-21	8160	0.06%	0.55%	3970:4190)	2.069*	1.683*	0.1127***
-20	8160	0.05%	0.60%	3988:4172>	1.809*	2.179*	0.0802***
-19	8160	0.04%	0.64%	3950:4210	1.342$	1.710*	0.0806***
-18	8160	0.03%	0.67%	3924:4236	1.121	0.426	0.0766***
-17	8160	0.05%	0.72%	3983:4177)	1.922*	1.789*	0.0811***
-16	8160	0.06%	0.78%	3919:4241	2.161*	2.177*	0.0866***
-15	8160	0.03%	0.81%	3961:4199	1.199	1.634$	0.1008***
-14	8160	0.04%	0.85%	3953:4207	1.283$	1.227	0.134***
-13	8160	0.06%	0.91%	3980:4180)	2.263*	1.451$	0.1255***
-12	8160	0.02%	0.93%	3983:4177)	0.682	1.086	0.1226***
-11	8160	0.04%	0.97%	3910:4250	1.342$	0.348	0.1272***
-10	8160	0.04%	1.01%	3976:4184)	1.299$	0.585	0.1511***
-9	8160	0.03%	1.04%	3911:4249	1.121	0.987	0.1407***
-8	8160	0.11%	1.15%	3950:4210	4.020***	1.897*	0.1733***
-7	8160	0.06%	1.21%	3838:4322(	2.092*	0.351	0.1691***
-6	8160	0.10%	1.31%	3979:4181)	3.714***	2.373**	0.2049***
-5	8160	0.08%	1.39%	4017:4143>>	2.836**	3.324***	0.2158***
-4	8160	0.05%	1.44%	3895:4265	1.790*	0.82	0.1825***
-3	8160	0.09%	1.53%	4005:4155>	3.327***	4.142***	0.2429***
-2	8160	0.10%	1.63%	4049:4111>>	3.786***	2.923**	0.2741***
-1	8160	0.14%	1.77%	4058:4102>>>	5.128***	4.305***	0.2989***
0	8160	0.23%	2.00%	4123:4037>>>	8.241***	6.923***	0.4584***
1	8160	0.50%	2.50%	4403:3757>>>	18.243***	15.120***	0.7334***
2	8159	-0.05%	2.45%	3857:4302	-1.654*	-2.796**	0.3608***
3	8158	-0.09%	2.36%	3705:4453<<<	-3.376***	-4.485***	0.2891***
4	8158	-0.08%	2.28%	3818:4340<	-2.983**	-4.447***	0.2682***
5	8159	-0.08%	2.20%	3838:4321(	-3.003**	-3.612***	0.244***
6	8159	-0.08%	2.12%	3721:4438<<<	-2.926**	-4.169***	0.2228***
7	8159	-0.16%	1.96%	3701:4458<<<	-5.701***	-6.046***	0.2141***
8	8158	-0.06%	1.90%	3856:4302	-2.294*	-2.703**	0.1822***
9	8158	-0.07%	1.83%	3756:4402<<<	-2.422**	-3.096***	0.2154***
10	8158	-0.03%	1.80%	3849:4309(	-1.029	-1.757*	0.1973***
11	8157	-0.10%	1.70%	3775:4382<<	-3.542***	-4.305***	0.1796***
12	8157	-0.06%	1.64%	3862:4295	-2.144*	-2.789**	0.1794***
13	8158	-0.06%	1.58%	3805:4353<	-2.349**	-3.266***	0.1924***
14	8158	-0.06%	1.52%	3769:4389<<<	-2.331**	-2.573**	0.2138***
15	8157	-0.06%	1.46%	3849:4308(	-2.066*	-2.471**	0.1814***
16	8157	-0.06%	1.40%	3808:4349<	-2.020*	-3.120***	0.1526***
17	8157	-0.11%	1.29%	3666:4491<<<	-3.902***	-5.258***	0.1746***
18	8157	-0.09%	1.20%	3832:4325<	-3.195***	-3.211***	0.1651***
19	8156	-0.13%	1.07%	3710:4446<<<	-4.592***	-6.179***	0.1943***
20	8155	-0.03%	1.04%	3887:4268	-1.027	-1.589$	0.1784***
21	8154	-0.08%	0.96%	3745:4409<<<	-3.054**	-4.516***	0.1993***
22	8154	-0.08%	0.88%	3729:4425<<<	-2.994**	-3.949***	0.1851***
23	8154	-0.08%	0.80%	3751:4403<<<	-3.001**	-3.387***	0.1678***
24	8153	-0.11%	0.69%	3727:4426<<<	-3.925***	-4.723***	0.1214***
25	8153	-0.06%	0.63%	3854:4299	-2.347**	-2.795**	0.151***
26	8153	-0.07%	0.56%	3825:4328<	-2.428**	-2.703**	0.1489***
27	8151	-0.07%	0.49%	3834:4317(	-2.564**	-2.782**	0.1344***
28	8151	-0.12%	0.37%	3710:4441<<<	-4.512***	-5.726***	0.1245***
29	8151	-0.06%	0.31%	3814:4337<	-2.173*	-3.281***	0.1331***
30	8151	-0.09%	0.22%	3765:4386<<<	-3.325***	-4.574***	0.1689***

APPENDIX B: Utilized Variables

VARIABLE	DESCRIPTION	SPECIAL DETAILS
AR_{i1}	next trading day abnormal return for stock *i*	
SPECIAL_MENTION $_{i0}$	Dummy variable indicating if stock *i* received a *SM* designation on the show at *t*=0	
MON_BACK $_{i0}$	Dummy variable indicating if stock *i* received this designation on the show at *t*=0	
SEGMENT $_{ij0}$	Dummy variable array with values taking on a value of 1 if recommendation for stock *i* aired during segment j on *t*=0, "*Discussion*" (also referred to as "*Main*") segment stocks and stocks with no segment designation serve as a reference category	Array columns are CEO_INTERVIEW, LIGHTNING_ROUND, OPENING_SEGMENT, CLOSING SEGMENT, and SUDDEN_DEATH
TURNOVER$_{i(t-1)}$	turnover ratio of stock *i* before the recommendation	Number of shares traded over number of shares outstanding.
MARKET CAP $_{i(t-1)}$	market cap of company *i* before the recommendation	
$VIEWERS_0$	correspond to *Nielsen* estimates for the audience size for the event date, *t*=0	
$NYSE_{i1}$, $AMEX_{i1}$, $NADAQ_{i1}$	market on which a given security *i* is traded	NASDAQ serves as a reference category
MEMORY DECAY$_{i1}$[12]	Number of days since recommendation for stock *i* until market opens on *t*=1	
COVERAGE INTENSITY$_{i0}$	intensity of coverage for stock *i* prior to the given event at *t*=0	$\frac{TOTAL\_NUMBER\_PREVIOUSPICKS_{it}}{TIME\_SINCE\_FIRST\_PICK_{it}}$
RETURN SINCE LAST $_{i(t-1)}$	pre-event daily return if one followed the last recommendation, "sell" stocks are considered sold short	$\frac{RETURN\_SINCE\_LAST\_PICK_{it}}{TIME\_SINCE\_LAST\_PICK_{it}}$
RECENCY$_{ij0}$	Dummy variable taking on a value of "1" if stock *i* was the last stock recommended in its segment *j*	
PRIMACY$_{ij0}$	Dummy variable taking on a value of "1" if stock *i* was the first stock recommended in its segment *j*	
RECOMMENDATION FLIP$_{i0}$	Dummy variable taking on a value of "1" if Cramer changed his recommendation for stock *i* at t=0	
EVENT DATE$_{i0}$	date on which recommendation took place, attempts to capture the investor learning	
OVERALL CLUTTER$_0$	the number of all positive and negative recommendations made on the same event show	
SIC CLUTTER$_{id0}$	the number of competing recommendations for stock *i* with the same SIC code *d* made on the same event show	SIC grouping is based on 2 digit SIC code header.
SHARE PRICE$_{i(t-1)}$	per share price for company *i* before the event	
CRAMER OWNS$_{i0}$	Dummy variable that takes on a value of "1" if Cramer's charitable trust owns a particular stock *i* at the time of recommendation	

[12] We also tried capturing day of the week and holiday break effects. Friday variable in the WEEKDAY array and MEMORY_DECAY variables are highly correlated, therefore we explored using just the decay variable vs. using day of week variables and the variable called HOLIDAY that signifies that the next work day after recommendation falls on one of the official exchange holidays. Neither of the methods produced any significant results when it comes to influencing the next day abnormal return. For simplicity of exposition, the final model uses MEMORY_DECAY variable only.

APPENDIX C: Correlation Table for Initial "Buy" Recommendations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1 RETURN	1.00																				
2 TIME	-0.04	1.00																			
3 VIEWERS	0.05	**-0.39**	1.00																		
4 NYSE	**-0.22**	-0.02	-0.03	1.00																	
5 AMEX	**0.06**	**0.10**	0.00	**-0.18**	1.00																
6 $PRICE_{(t-1)}$	**-0.25**	-0.04	-0.02	**0.27**	**-0.08**	1.00															
7 $TURNOVER_{(t-1)}$	**0.07**	0.03	-0.03	-0.04	0.00	-0.03	1.00														
8 CEO SEGMENT	-0.01	0.03	0.00	0.00	-0.02	-0.04	0.00	1.00													
9 LIGHTNING ROUND	**-0.30**	**-0.10**	0.04	**0.08**	-0.02	**0.10**	0.03	**-0.10**	1.00												
10 SUDDEN DEATH	**-0.06**	**0.18**	**-0.09**	0.03	-0.02	0.03	0.00	-0.01	**-0.14**	1.00											
11 CLOSING SEGMENT	0.02	**0.27**	**-0.07**	-0.01	**0.06**	-0.01	-0.01	0.04	**-0.18**	-0.02	1.00										
12 OPENING SEGMENT	**0.10**	**0.42**	**-0.24**	-0.03	0.02	**-0.07**	-0.01	-0.03	**-0.27**	-0.03	-0.04	1.00									
13 MON BACK	0.04	**0.13**	**-0.11**	0.01	-0.02	**-0.07**	0.00	-0.01	**-0.10**	-0.02	-0.02	**0.27**	1.00								
14 CRAMER OWNS	-0.02	**-0.09**	0.00	0.00	0.03	**0.08**	0.00	-0.01	0.02	-0.02	-0.02	0.00	-0.02	1.00							
15 PRIMACY	**0.20**	**0.11**	-0.04	**-0.09**	0.01	-0.05	-0.01	-0.04	**-0.27**	**0.09**	**0.11**	**0.09**	0.03	-0.05	1.00						
16 RECENCY	**0.10**	**0.11**	-0.03	0.01	-0.03	-0.05	-0.01	**0.14**	**-0.31**	0.03	-0.04	**0.22**	0.04	0.00	**-0.06**	1.00					
17 MEMORY DECAY	-0.01	-0.04	**-0.13**	0.01	-0.03	**0.06**	-0.02	0.02	0.04	**-0.07**	0.05	0.02	**-0.06**	-0.02	0.00	0.05	1.00				
18 SIC CLUTTER	**0.09**	**-0.14**	**0.07**	**-0.12**	-0.01	-0.03	0.02	0.02	-0.04	0.02	**-0.08**	**-0.07**	-0.03	0.01	-0.05	-0.04	**-0.09**	1.00			
19 OVERALL CLUTTER	-0.03	**-0.30**	-0.01	0.04	-0.02	**0.05**	**0.05**	**-0.09**	0.01	0.00	**-0.08**	**-0.08**	-0.05	**0.07**	-0.04	**-0.07**	0.03	**0.14**	1.00		
20 LOG (MARKET CAP)	**-0.32**	**-0.18**	0.03	**0.45**	**-0.12**	**0.47**	-0.05	-0.01	**0.23**	-0.02	-0.04	**-0.09**	**-0.07**	**0.16**	**-0.12**	**-0.10**	-0.02	-0.01	**0.11**	1.00	
21 SM	**0.36**	**0.06**	0.01	**-0.12**	0.02	**-0.14**	-0.02	**0.11**	**-0.86**	**-0.10**	**0.21**	**0.32**	**0.12**	-0.05	**0.24**	**0.29**	0.03	0.01	**-0.07**	**-0.29**	1.00

APPENDIX D: Correlation Table for Repeat "Buy" Recommendations

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1	RETURN	1.00																								
2	TIME	**-0.03**	1.00																							
3	VIEWERS	**0.03**	**-0.47**	1.00																						
4	NYSE	**-0.07**	**0.08**	**-0.06**	1.00																					
5	AMEX	**0.03**	**-0.04**	**0.03**	**-0.22**	1.00																				
6	$PRICE_{(t-1)}$	**-0.06**	**0.08**	**-0.02**	**0.04**	**-0.10**	1.00																			
7	$TURNOVER_{(t-1)}$	**0.05**	0.00	**0.03**	-0.01	0.00	-0.01	1.00																		
8	CEO SEGMENT	**0.03**	**0.05**	-0.02	-0.01	0.00	**-0.04**	0.00	1.00																	
9	LIGHTNING ROUND	**-0.09**	**-0.25**	**0.14**	**-0.05**	**0.04**	**-0.05**	-0.01	**-0.16**	1.00																
10	SUDDEN DEATH	-0.01	**0.10**	**-0.05**	0.01	0.00	0.00	-0.01	**-0.02**	**-0.23**	1.00															
11	CLOSING SEGMENT	0.02	**0.26**	**-0.12**	0.01	-0.02	**0.03**	-0.01	**0.25**	**-0.39**	**-0.06**	1.00														
12	OPENING SEGMENT	**0.08**	**0.26**	**-0.12**	**0.03**	**-0.04**	**0.06**	0.01	-0.02	**-0.37**	**-0.06**	**-0.10**	1.00													
13	MON BACK	**0.02**	**0.07**	**-0.03**	-0.02	0.00	0.00	0.00	0.01	0.00	0.01	0.00	**0.03**	1.00												
14	CRAMER OWNS	**-0.03**	**-0.02**	0.01	**0.06**	**-0.02**	**0.10**	-0.01	**-0.03**	0.00	-0.02	0.01	0.01	**0.02**	1.00											
15	PRIMACY	**0.06**	**0.09**	**-0.03**	0.01	-0.01	0.00	0.01	0.01	**-0.21**	**0.07**	**0.08**	**0.09**	**0.04**	0.00	1.00										
16	RECENCY	**0.05**	**0.10**	**-0.04**	-0.01	0.00	0.01	0.01	**0.23**	**-0.25**	**0.09**	**0.10**	**0.05**	0.00	-0.01	**-0.03**	1.00									
17	MEMORY DECAY	0.01	**0.06**	**-0.17**	0.02	**-0.02**	0.01	-0.01	-0.02	**-0.05**	**-0.09**	**0.16**	**0.04**	-0.02	0.00	**-0.03**	**-0.03**	1.00								
18	SIC CLUTTER	0.01	**-0.10**	**0.07**	**-0.24**	0.00	0.00	0.01	**-0.04**	**0.04**	-0.01	**-0.06**	0.01	**-0.04**	-0.01	-0.02	**-0.04**	**-0.07**	1.00							
19	OVERALL CLUTTER	**-0.02**	**0.04**	**-0.16**	-0.02	-0.01	0.02	0.00	**-0.05**	**-0.04**	**0.03**	**0.03**	**0.08**	**-0.04**	0.00	**-0.09**	**-0.07**	**0.09**	**0.14**	1.00						
20	LOG (MARKET CAP)	**-0.15**	**0.11**	**-0.05**	**0.29**	**-0.15**	**0.35**	**-0.05**	**-0.08**	**-0.04**	0.01	0.00	**0.09**	0.02	**0.23**	0.00	**-0.05**	-0.01	**0.07**	**0.03**	1.00					
21	COVERAGE INTENSITY	0.01	**-0.08**	0.00	-0.01	0.02	**-0.02**	0.00	0.02	-0.02	-0.02	-0.01	**-0.02**	-0.01	-0.01	-0.02	**0.02**	0.00	**0.03**	**0.04**	**-0.05**	1.00				
22	RETURN SINCE LAST	**0.08**	**-0.02**	**0.02**	**-0.06**	0.01	**-0.02**	**0.16**	**0.02**	-0.02	**-0.02**	0.00	0.01	**-0.04**	**-0.04**	-0.01	-0.01	0.01	**0.07**	**0.07**	**-0.08**	**0.13**	1.00			
23	RECOMMENDATION FLIP	**0.07**	0.00	0.00	**-0.02**	0.00	**-0.07**	0.01	0.01	**-0.03**	0.00	**-0.02**	0.01	**-0.04**	**-0.11**	0.01	0.00	0.00	0.01	0.01	**-0.09**	-0.02	0.01	1.00		
24	RETURN SINCE LAST x RECOMMENDATION FLIP	**0.08**	0.00	0.01	**-0.03**	-0.02	-0.01	0.01	0.00	0.00	0.00	0.01	0.00	-0.01	-0.01	-0.02	-0.01	0.00	**0.03**	0.02	**-0.02**	0.00	**0.36**	**0.14**	1.00	
25	SPECIAL MENTION	**0.14**	**0.10**	**-0.08**	**0.02**	**-0.03**	**0.04**	0.01	**0.20**	**-0.79**	**-0.11**	**0.49**	**0.47**	0.02	**0.02**	**0.16**	**0.19**	**0.11**	**-0.03**	**0.04**	-0.01	**0.02**	0.01	0.02	0.00	1.00

APPENDIX E: Descriptive Statistics

VARIABLE	Initial Recommendations			Repeat Recommendations		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
RETURN	1.42	.038	1069	0.36	0.025	7091
TIME	04/27/2006	182 00:42:18	1069	10/06/2006	184 07:25:02	7091
VIEWERS	.13	.033	1069	0.125	0.034	7091
NYSE	.61	.489	1069	0.620	0.486	7091
AMEX	.02	.139	1069	0.028	0.166	7091
SHARE PRICE $_{(t-1)}$	39.26	28.733	1069	53.799	56.406	7091
TURNOVER $_{(t-1)}$	.00	.031	1069	0.001	0.027	7091
CEO SEGMENT	.01	.105	1069	0.017	0.129	7091
LIGHTNING ROUND	.54	.499	1069	0.597	0.491	7091
SUDDEN DEATH	.02	.125	1069	0.034	0.182	7091
CLOSING SEGMENT	.03	.163	1069	0.093	0.291	7091
OPENING SEGMENT	.06	.239	1069	0.090	0.286	7091
MON BACK	.01	.118	1069	0.028	0.166	7091
CRAMER OWNS	.02	.129	1069	0.110	0.313	7091
PRIMACY	.12	.329	1069	0.096	0.295	7091
RECENCY	.10	.303	1069	0.109	0.312	7091
MEMORY DECAY	1.44	.859	1069	1.442	0.855	7091
SIC CLUTTER	5.00	4.087	1069	5.300	4.254	7091
OVERALL CLUTTER	35.66	8.355	1069	34.382	8.675	7091
LOG (MARKET CAP)	14.70	1.550	1069	16.142	1.713	7091
COVERAGE INTENSITY	NA			0.007	0.082	7091
RETURN SINCE LAST				0.002	0.013	7091
RECOMMENDATION FLIP				0.135	0.342	7091
RETURN SINCE LAST x RECOMMENDATION FLIP				0.000	0.005	7091
SPECIAL MENTION	.39	.488	1069	0.300	0.458	7091

APPENDIX F: Model Fit Change Statistics for Going from Segments only Model to Model that Includes “SM” Designation

Model	Initial Recommendations Model Statistics				Model Change Statistics		
	R	**R^2**	**Adjusted R^2**	**Std. Error of the Estimate**	**R^2 Change**	**F Change**	**Sig. F Change**
Segments Only	0.47	0.21832	0.20416	0.033832			
Segments and “SM” Designation	0.48	0.23323	0.21859	0.033524	0.015	20.38	**.000**
Model	**Repeat Recommendations Model Statistics**				**Model Change Statistics**		
	R	**R^2**	**Adjusted R^2**	**Std. Error of the Estimate**	**R^2 Change**	**F Change**	**Sig. F Change**
Segments Only	0.23	0.05446	0.05138	0.023998			
Segments and “SM” Designation	0.25	0.06353	0.06035	0.023884	0.009	68.46	**.000**