

Cramer's Rule: How Information Content Moves Markets

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Introduction

When Jim Cramer offers investment advice on his CNBC show *Mad Money*, he influences market prices (Engelberg et al., 2009). By analyzing text from transcripts of the show, we explore the relationship between what Cramer says and the magnitude and direction of his price effect. We demonstrate that Cramer’s influence is more complex than simply drawing investor attention to particular stocks and is in fact related to the content of his recommendations.

A cursory viewing of *Mad Money* reveals that Cramer generally provides no new information about stocks, but instead argues that they may be mispriced by investors with access to identical information. The puzzle of the Cramer effect is why, despite containing little new information about stock fundamentals, does Cramer’s advice influence investors to alter their valuations and thus the stock price?

An intuitive explanation is that markets are informationally incomplete, that investors are not aware of all the securities they could trade, and that when Cramer recommends a stock, he simply draws attention to it. Had investors known about the stock, they would have incorporated this knowledge into their decisions and the stock would have been priced appropriately. Merton (1987) formalized this explanation in his “investor recognition hypothesis.” In his model, stocks with low investor recognition earn higher returns to compensate holders for being imperfectly diversified. Indeed, stocks with no media coverage earn higher returns when controlling for common risk factors (Fang and Peress, 2008), and increased investor attention to a particular Cramer recommendation (as measured by Nielsen television ratings) significantly increases the market’s response to Cramer’s advice (Engelberg et al., 2009). The story behind this hypothesis is that Cramer simply draws attention to stocks which lacked investor awareness and were therefore earning higher returns.

Another potential explanation for the Cramer effect is that markets are affected by noise traders who, unlike rational investors who only consider fundamentals, irrationally act on noise coming from media coverage, pundits, and their own generally uninformed research (DeLong et al., 1990). These noise traders are swayed by media content that expresses optimistic or pessimistic sentiment about stocks without providing any new information on fundamentals. There is some empirical evidence that media content affects stock prices. For example, Tetlock (Forthcoming) conducted a simple binary text analysis of a daily *Wall Street Journal* column and found, consistent with the theoretical predictions of DeLong et al. (1990), that pessimistic media content induces downward pressure on stock prices and that the price impact of this pressure reverses itself over time. A similar trend is evident in the price impact of Cramer’s recommendations. When he mentions a stock on his show, it initially undergoes a significant price change which reverses over the next 30 days (Engelberg et al., 2009). As Cramer rarely discusses obscure stocks, it could be that the magnitude and direction of his influence on the market is not simply attentional, but rather related to the content of what he says—essentially, that the content of his recommendations creates changes in sentiment that move the market.

To explore the source of Cramer’s price effect and to extend work on sentiment analysis beyond simple binary characterizations of positive and negative coverage, we constructed a model of Cramer’s influence on investor sentiment based on content features derived from *Mad Money* transcripts. Applying recent developments in generative text analysis (Blei et al., 2003), we estimated posterior probabilities that Cramer discussed specific topics in his recommendations and assessed the relative impact of these different topics on the magnitude and direction of Cramer’s influence

on stock prices. Our analysis suggests that the topics of Cramer’s discourse explain a significant amount of the variance in the abnormal returns generated the day after he recommends a stock. The results imply that Cramer is more influential when he presents specific kinds of arguments or discusses particular rationales for investments, demonstrating the influence of topical information content on individual economic decisions and aggregate market outcomes.

Data: *Mad Money* Transcripts

CNBC’s *Mad Money* airs weekdays at 6pm. Fans of the show produce a website ¹ which records transcripts for each show. We watched a random sample of transcribed shows and found the accuracy of these transcripts to be quite high. The transcripts for each show are segmented into comments about a particular stock, either that Cramer has chosen to discuss or that a caller has asked about. We call these segments recommendations, which is our level of analysis. Each recommendation is for one stock and occurs on a specific date. We filtered and analyzed the text of Cramer’s comments associated with each recommendation as inserted by transcribers. We then collected historical and current price data for these stocks from the CRSP database in order to estimate models of the impact of Cramer’s substantive comments on the market price and abnormal returns of each stock. We omitted recommendations for tickers that were either not listed in CRSP, or for which there was not sufficient historical data to estimate an abnormal return model (477 obs). We restricted our analysis to snippets which contained fewer than 50 words to ensure that we only included segments where Cramer provided a reasonably detailed discussion of the stock. The resulting data set consists of 6059 recommendation events for 1687 distinct stocks occurring during 638 episodes of *Mad Money* from 11/3/2005 to 11/07/2008.

Theory

Abnormal Return Model—We use a Fama-French three-factor model (Fama and French, 1992) to measure the abnormal return for each stock. The model explains the return of a security at time t as linear function of the return of three constructed stock portfolios:

$$R_t - rf_t = \alpha + b_1(MKT_t - rf_t) + b_2SMB_t + b_3HML_t + \epsilon_t$$

where rf_t is the risk-free rate of return at time t , and MKT , SMB , and HML are Fama-French factor portfolio returns downloaded from Ken French’s website. ²

For each recommendation event, we estimate a three-factor model for the stock over the period from $[t - 155, t - 5)$. The abnormal return for a stock at time t is the stock’s actual return minus the return predicted by the pricing model estimated for that event.

Generative Topic Model—We represent the *Mad Money* transcript segments as vectors of term frequencies and use latent Dirichlet allocation (LDA) (Blei et al., 2003) to extract topics from the text by assuming that each document is created as a series of random draws from topic-proportion and term distributions. LDA is a generative model, meaning it maps parameter values for the

¹<http://www.madmoneymoneyrecap.com/>

²http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

random process to a posterior distribution for the words in the text segments. See Blei and Lafferty (2009) for a readable introduction to the LDA generative model.

We estimate the parameters of an LDA topic model for the *Mad Money* transcript segments using a variational expectation maximization (EM) procedure. The key parameters resulting from the estimation are α and the term distributions for each topic k , β_k . In an LDA model, the estimated value of α can be interpreted as the degree to which topics are likely to co-occur within documents. For topic k , its term distribution β_k represents the probability of observing a word conditional on it belonging to that topic. We apply Bayes' theorem to estimate the probability that a segment of text discusses a given topic. Let β_{kw} be the probability that term w was generated for topic k and p_w be the unconditional probability of drawing term w in the corpus.

$$P_{dk} = P(\text{topic}(d) = k) = \sum_{w \in d} \frac{\beta_{kw}}{p_w}$$

We perform this calculation for each document and topic, resulting in K independent variables P_{dk} .

Topic Influence Model—Our topic influence model explains the abnormal return for the day after Cramer's recommendation as a linear function of features constructed from the text and control variables C_i for various aspects of the recommendation event. The variables of interest in the model are the γ_k coefficients, which represent the effect of an increase in the likelihood that Cramer is speaking about a particular topic on the abnormal returns of the stock.

$$AR_{st} = \alpha_0 + \sum_{i=1}^J \alpha_i C_i + \sum_{k=1}^K \gamma_k P_k + \mu_{st}$$

Results

Topic Characterization—Using the method described in Blei and Lafferty (2009), we produced sets of sample phrases which allow us to understand and interpret the underlying topic word distributions estimated by LDA. The technique involves recursively searching for n -grams and applying a likelihood-ratio test to determine which are most likely to be generated for a given topic. Table 1 lists the top phrases for some topics in our model.

Clear categories emerge from the words representing topics, delineated not only by the presence of certain descriptive keywords, but also by their co-occurrence in the text of Cramer's advice. Topics range from advice based on trading strategies, for instance based on company management (Topic 1) or a momentum strategy for under priced and cheap equities (Topic 2), to recommendations based on industry plays (e.g. Alternative Energy—Topic 6; Oil and Gas—Topic 7; Retail—Topic 9), or regional strategies (e.g. China—Topic 13).

Topic Influence Regression—Using our LDA model, we estimate posterior probabilities for the top 20 topics given the text in each recommendation snippet. The probabilities become independent variables in our topic influence regression. We additionally include control variables for number of words, days since the beginning of the sample, day of the week, and the market and individual stock return and standard deviation for the week before the recommendation event. Initial results are shown in Table 2.

Table 1. Examples of Topics and Sample Keywords

	Topic	Sample Keywords
1	<i>Strength of Management</i>	run, ceo, management, dividend, guy
2	<i>Medical Technology</i>	medical, tech, device, diagnostics, hologic, instruments, technology, healthcare
4	<i>Cheap Momentum Strategy</i>	cheap, book, lot of trading, risk, game, momentum, hot, bet, trade
5	<i>Aerospace</i>	million, British Airways, real, sales, billion, aerospace, world, Boeing
6	<i>Alternative Energy</i>	solar, business, FSLR, EMC, power, cheap, ice, NYX
7	<i>Oil and Gas</i>	oil, natural gas, energy, gas, HAL, rig, drilling, XOM, oil service
9	<i>Retail</i>	low, retail, buying, stores, WMT, JCP, retailer, TGT, sears
13	<i>China Play</i>	pull the trigger, China, GME, CAT, ERTS, Chinese
14	<i>Biotech / Pharma</i>	drug, CELG, RAD, biotech, CVS, WAG, DNA, drugs, AMGN,
15	<i>Financial</i>	pharma, bank, gold, GS, fed, banks, wrong
16	<i>High Tech / Internet</i>	GOOG, MSFT, tech, technology, speculative, CSCO, internet, wireless, YHOO, IPO

The results demonstrate 1) that the length of Cramers discourse is correlated with the magnitude of the Cramer effect, 2) that the substance of Cramers comments evaluated as a whole explain a significant amount of variance in the abnormal returns to stocks following a recommendation, and 3) that certain topics are more highly correlated with both the magnitude and direction of the movement in stock prices than others, implying that some topics are more persuasive (either negatively or positively) than others.

Both the number of words and its quadratic term are significant, indicating that Cramer is more influential when he speaks longer, but the marginal effect diminishes as he spends more time on a recommendation. One explanation for this result is that Cramer is more persuasive the longer he talks. However, an equally plausible alternative explanation is that the longer he talks the more people see his discourse about that particular stock creating more aggregate attention for his recommendation.

The topics themselves also have significant explanatory power. Eight of the twenty topic probabilities are significant at the 10% level. The F statistic for the restriction that all 20 topic coefficients are equal to zero is 2.57, which is significant at the 1% level, indicating that topics generally have a significant effect of the magnitude of the Cramer effect. The regression also shows that the specific subject of Cramers discourse affects his level of influence. Some topics are associated with downward price pressure on stocks following a recommendation. For example, a one standard deviation increase in the likelihood that a recommendation discusses railway stocks or transportation (Topic 20) is associated with a 6.7% decrease in the stock price relative to expected returns. Other topics are associated with an upward lift in prices. For example, a one standard deviation increase in the likelihood that a recommendation discusses the most significant topic, renewable energy (Topic 6), is associated with an 11% increase stock prices. Other topics have no effect, demonstrating the ability of our text analysis to distinguish important topics from those that are non-influential. These results demonstrate the influence of topical information content on individual economic decisions and aggregate market outcomes.

Model:	without topics	with topics
Number of words	0.517 (0.047)***	0.325 (0.110)***
Number of words squared	-0.244 (0.047)***	-0.196 (0.050)***
Previous Stock Price	-0.065 (0.019)***	-0.068 (0.020)***
Topic 1: Strength of Management		-0.047 (0.027)*
Topic 2: Medical Technology		-0.030 (0.026)
Topic 4: Cheap Momentum Strategy		0.110 (0.036)***
Topic 5: Aerospace		0.063 (0.035)*
Topic 6: Alternative Energy		0.110 (0.031)***
Topic 7: Oil and Gas		-0.018 (0.022)
Topic 9: Retail		-0.022 (0.026)
Topic 10: Uncategorized		-0.078 (0.033)**
Topic 13: China Play		0.027 (0.029)
Topic 14: Biotech/Pharma		0.007 (0.027)
Topic 15: Financial		0.008 (0.025)
Topic 16: High Tech/Internet		0.010 (0.030)
Topic 19: Agriculture		0.050 (0.023)**
Topic 20: Railway/Transportation		-0.066 (0.027)**
Control Variables	time, time squared, market return previous week, market return st. dev., stock return previous week, stock return st. dev., day of week dummies, lightning round dummy	
F-value (d.f.)	24.08*** (14)	11.52*** (34)
R^2	0.053	0.061
Observations	6059	6059
Note: *, **, and *** denote significance at the 10%, 5% and 1% levels respectively		

Future Work

Identification—If we accept DeLong’s interpretation of investor sentiment, we may naturally ask the question of whether Cramer is affecting investor sentiment or astutely observing mispricing resulting from noise traders who already own the stock. We also omit potentially important variables which could be correlated with topic probabilities and abnormal returns, such as attributes of the stocks. As a result, our present topic influence model does not have a causal interpretation. We propose to address these identification problems by constructing a matched sample of stocks which are equally likely to have been discussed by Cramer, but which were not. Using such a sample will allow us to measure the causal treatment effect of Cramer’s discussion. Our propensity score estimates will employ search engine volume as a measure of investor attention, features of news about the stock, as well as industry and performance variables. We will also explore the use of stock fixed effects to control for time invariant stock related omitted variables.

Additional Content Features—Topics represent only one set of dimensions for the information Cramer delivers during his show. For instance, topic probabilities do not account for whether his recommendations contain non-redundant information. It is natural to expect that when Cramer’s

recommendation is based on a novel argument, one that he has not delivered in his prior shows, viewers may pay closer attention or feel his advice has given them a better reason to act. The inverse also seems plausible: a recommendation that rehashes the same points made in a previous segment or episode may fail to have the same impact it did when they were first invoked. Yang et al. (2002) describe one possible procedure for novelty detection and their technique conditions the detection on the topic of the document. We expect including novelty will show that when Cramer delivers non-redundant information, he exhibits greater influence.

Does Cramer’s advice follow a single logical track, or meander across several? We conceptualize this quality with the terms focus and diversity. Aral and Van Alstyne (2009) create five measures of diversity which characterize whether a text document is about a focused set of topics. The value for these measures can be thought of as the “variance” of a document’s content and could be related to how viewers perceive and understand Cramer’s advice. By including measures for novelty and diversity in our future analysis, we may draw new conclusions regarding the interaction between information and influence.

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