Stock Analysts Efficiency in a Tournament Structure:
The Impact of Analysts Picking a Winner and a Loser

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Abstract:

A financial analyst who can give accurate return predictions is highly valued. This study uses a unique data set comparing CNBC's *Fast Money's* 'March Madness' stock picks as a proxy for analysts' stock return predictions. With this data, set up as a tournament, the analysts pick both a winner and a loser. With the tournament structure, I find that these analysts have no superior ability to pick the winning stock in terms of frequency. However, I do find that taking a long/short portfolio of their picks yields an abnormal return. Showing that although they do not pick the winning stock more often, they do pick the stocks that have the best returns over our sample.

JEL Classifications: G12, G14, G15
Keywords: Market Efficiency, Stock Analysts, CNBC's Fast Money, Anchoring

I. Introduction

Historically there has been a significant and consistent bias for stock analysts to recommend more buys than sells. Although analysts' ability has been tested, testing analysts' ability has been difficult because of this bias. In particular, when an analyst makes a buy recommendation, it is not clear what the benchmark is. This benchmark would be more clear if these analysts would simultaneously recommend a pair of stocks; one buy and the other sell. Different from previous studies, this study capitalizes on a unique data set that provides pairs of buy and sell recommendations.

In March of 2007 and 2008, CNBC's show *Fast Money* ran a 'March Madness' stock tournament. This tournament was established to be the stock market equivalent of the NCAA's March Madness Basketball tournament. The tournament matched stocks of four different industries (Tech/Telecom, Health/Homes, Financials, and Commodity/Industrial) against each other. The idea of CNBC's March Madness was to take the most 'loved' stocks on Wall Street, set up as a 64 stock tournament, and find what will be the best performing stock over the next year.[1] The stocks were first matched within industry and when a winner from each of the four industries was picked, it was matched against a winner from another industry to find the overall top pick for that year. As previously mentioned, since there is no clear benchmark for a single buy (or sell) recommendation, traditional measures of analyst ability compare the analysts' picks relative to the overall market or industry. However, these measures may not necessarily reflect the information the analysts intend to deliver. For example, there are various industry definitions which challenge the accuracy of industry benchmark. This study can

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[1] This is a quote for CNBC's host Dylan Ratigan from his March 26, 2008 show. Video located here: http://www.cnbc.com/id/15840232?play=1&video=697464925.

take this a step further. The tournament structure allows for the measure of the stocks they pick as their winning stocks outperform the stocks they pick to lose.

This data comes from very public (television) analysts. Most studies of similar nature have focused on one person's stock picks, primarily Jim Cramer. In addition to having both buy and sell recommendations, the data are based on a group of analysts picking one stock after deliberating on its ability to increase in value over the subsequent year. Using multiple analysts, rather than one person, could increase the knowledgebase being brought into each decision. In this sense, this study is more representative of the analyst profession than those studies focusing on an individual analyst.

CNBC's *Mad Money* host Jim Cramer has been the focus of many studies. Keasler and McNeil (2010) find a positive and significant announcement return, followed by a reversal that leads to no evidence of positive longer-term abnormal returns. Engelberg, Sasseville, and Williams (2009) and Neumann and Kenny (2007) also find short term abnormal returns, however Neumann and Kenny (2007) warn small traders about transaction costs eliminating any returns when following Jim Cramer's picks. Similar results have been found by Pari (1987) and Ferreira and Smith (2003) when looking at *Wall $treet Week*.[2]

Using this dataset, I test the analysts' ability to pick the best returning stocks over multiple time periods: a one-month, two-month, three-month, six-month, and twelve-month time horizon. The next section will discuss both analyst bias and the data in more

[2] In addition to these studies the Wall Street Journal's Dart Board column has been studied by Barber and Loeffler (1993), Metcalf and Malkiel (1994), Albert and Smaby (1996), Greene and Smart (1999), Liang (1999), and Pruitt, Van Ness, and Van Ness (2000), Business Week's Inside Wall Street Column has been looked at by Sant and Zanam (1996), and Business Weeks's Heard on the Street by Liu, Smith, and Syed (1990), Beneish (1991), Liu, Smith, and Syed (1992), Bauman, Datta, and Iskandar-Datta (1995), and Sarkar and Jordan (2000).

detail. Section three will provide an overview of the tests to measure analysts' ability. Section four lays out our main results. I find that analysts do not predict a winner more often than a random guess, which challenges their ability to predict future returns. I use the Fama and French (1993) three factor model, with Carhart's (1997) fourth factor, to measure if the analysts could have done better if they had used these models. I find no evidence that they would have done better with these models and no evidence they used the four factor model for their analysis. Because I have matching buy/sell recommendation pairs, I put together a long/short portfolio of these picks to find that following their recommendations would have made 7.72% in 2007 and 12.72% in 2008. These results show that although they do not have a superior ability to pick winning stocks, they do pick the stocks that have the largest returns over this period; keeping in mind that the 2007 and 2008 returns were a unique time period for the financial markets. The last section concludes.

II. Analysts Bias and Tournament Data

Much of the prior research supports the idea that analysts' stock ratings are informed (e.g., Stickel 1995, Womack 1996, Barber et al. 2001, 2003, 2006, Jegadeesh et al. 2004, Moshirian, Ng, and Wu 2009). However, it has also been shown that analysts tend to issue optimistic stock recommendations (Francis and Philbrick 1993, Hodgkinson 2001, Boni and Womack 2002, Conrad et al. 2006, Dugar and Nathan 1995, Lin and McNichols 1998, Irvine 2004, O'Brien et al. 2005, Jackson 2005, Barber et al. 2006, Cowen et al. 2006, and Niehaus and Zhang 2010). Mikhail, Walther, and Willis (2004) show that, after controlling for transaction costs, following analysts' recommendations

does not produce better performance than average returns. Cornell (2001) finds that analysts are disinclined to change recommendations when negative changes occur. Eames, Glover, and Kennedy (2002) find that analysts tend to process information in a biased manner while Friesena and Wellerb (2006) find that analysts are overconfident regarding their own information.

McNichols and O'Brien (1997) find that the stocks added to analysts' lists are weighted toward "strong buy" recommendations relative to their existing list. In addition, the stocks that analysts drop tend to have lower ratings than the continuously covered ones. They argue that there is a self-selection bias in analyst forecasts and recommendations. O'Brien, McNichols, and Lin (2005) show that affiliated analysts, who have investment banking ties, are slower to downgrade from Buy and Hold recommendations, but faster to upgrade from Hold recommendations. Based on this finding, they suggest that banking ties increase analysts' reluctance to reveal negative news.

To eliminate any forms of bias, the data must be detailed. Information is increased when there is a set of stocks the analysts must decide between. CNBC's television show *Fast Money* ran a March Madness tournament during the month of March in 2007 and 2008. These tournaments followed the structure of the NCAA's March Madness in basketball where CNBC had the 64 'most loved' stocks on Wall Street in the tournament.[3] Because this is a television show, these stocks were determined by the host Dylan Ratigan and the producer of the show. Sixteen stocks were picked for each of the

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[3] The data are of the "most loved" stocks of Wall Street. These stocks are chosen by the producer and host and there is no clear reason on why these stocks are picked. Because these stocks can make the tournament through affinity, it is a TV show where the producer is worried about ratings, or randomness we take the stocks in the tournament as given.

four industries: Tech/Telecom, Health/Homes, Financials, and Commodity/Industrial. These stocks were each ranked, so the number one seed of each industry would play the sixteenth seed, the second seed would play the fifteenth seed, and so on.[4] This bracket was released before the tournament began and the analysts had time to prepare their bracket (i.e. who they would pick). Brackets for both years can be found in the appendix.

The stocks chosen to be in the tournament were not decided by the analysts. For this reason, there might be a concern that these stocks were chosen purely to boost ratings. However, given that the decision to place the stocks in the tournament are independent of the analysts themselves, and that the analysts are forced to pick a winner (and implicitly a loser), the choice of stocks put in the tournament do not bias the results. However, the decision of what stocks make it to the second, and subsequent, rounds of the tournament are not independent of the analysts themselves. Stocks making it to the second round of the tournament necessarily made it past the first round vote. Because this decision is based on the analyst's vote, there is a potential for selection bias in later rounds. For this reason, I use the first round of the tournament for this analysis.

Matchups were announced on air, where the *Fast Money* analysts would reveal their thoughts on the two stock matchup and vote for a winner. The host, Dylan Ratigan (he has since left the show), was joined by four analysts that rotated between Guy Adami (formally executive director at CIBC World Markets), Pete Najarian (co-founder of optionMONSTER.com), Karen Finerman (President and co-founder of Metropolitan Capital Advisors, Inc.), Jeff Macke (founder and president of Macke Asset Management), Tim Seymour (runs a hedge fund specializing in global and emerging markets and founder of EmergingMoney.com), and Joe Terranova (Chief Alternatives Strategist for

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[4] There is no evidence that the rankings affect the outcomes of any tests.

Birtus Investment Partners). And of course this is an investment TV show; as such the show has a disclaimer stating that all opinions are that of the shows participants and not CNBCs.[5]

With four *Fast Money* analysts on each show, if the vote ended with a tie Dylan Ratigan would cast the final vote based on the arguments made. The winning stock would move on to the next round until one stock was deemed champion. This stock was said to be the stock they believed would have the best returns over the next year. The final four for each year are presented in Figure 1. In 2007 Berkshire Hathaway won the tournaments and in 2008 Goldman Sachs was declared the winner.

Figure 1: the final four stocks chosen for 2007 and 2008

Fast Money Madness 2007

Tech/Telecom: APPL				Financials: BRK
	APPL		BRK	
Health/Home: MO		BRK		Commodity/Industrial: BHP

Fast Money Madness 2008

Tech/Telecom: MSFT				Financials: GS
	MSFT		GS	
Health/Home: MO		GS		Commodity/Industrial: FCX

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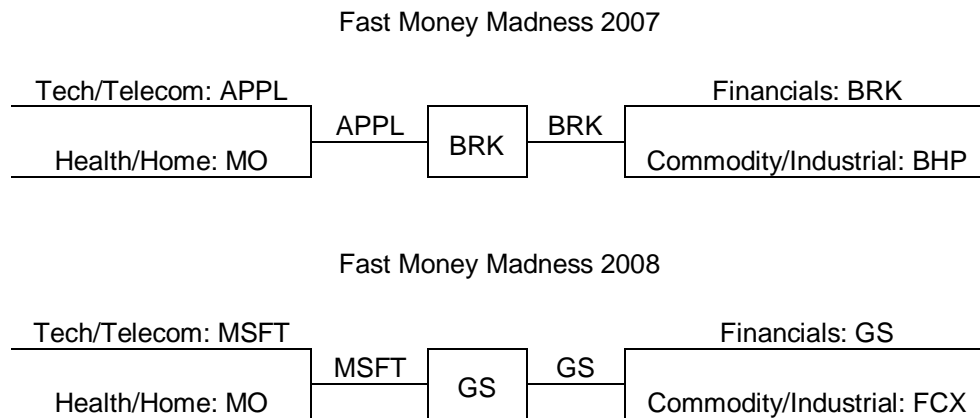
[5] This is an expert from the show's disclaimer:

"…All opinions expressed by the Fast Money Participants are solely their opinions and do not reflect the opinions of CNBC, NBC UNIVERSAL, their parent company or affiliates, and may have been previously disseminated by them on television, radio, internet or another medium.

You should not treat any opinion expressed on this website as a specific inducement to make a particular investment or follow a particular strategy, but only as an expression of an opinion. Such opinions are based upon information the Fast Money Participants consider reliable, but neither CNBC nor its affiliates and/or subsidiaries warrant its completeness or accuracy, and it should not be relied upon as such…"

III. Tests for Measuring Analysts' Ability

To measure the analysts' ability, four different tests are used: Testing the ability of the analysts, comparing this to the four-factor model, testing if the analysts used the four factor model, and finding a long/short portfolio outcome.

Testing Analyst Ability to Predict More Often

In 2007 and 2008 CNBC's *Fast Money* held March madness tournaments to determine the best stock picks for the upcoming year. The tournament brackets (available in the Appendix) reveal the rankings and chosen winners for each stock, for each year, by the *Fast Money* analysts.[6] These data are matched with data from CRSP (Center for Research in Security Prices) on each stock represented in the sample. With this data I find the percentage return for each stock, over a one, three, six, and twelve-month period, to determine which stock was truly a winner, measured by the stock with the higher percentage return over that time period.

I look at each matchup of stocks in the tournament to compare the *Fast Money* predicted winner to the actual percentage return winner. If the market is fully efficient then all the public information is already incorporated into the current stock price. If each stock has the same systematic and idiosyncratic risk, the analysts, who use only the public information, have no advantage in predicting future return.[7] If this occurs, the predicted outcome, x, has no correlation to the actual outcomes, y. Using a probit model, if the outcomes follow market efficiency, β_1 in equation (1), will not be statistically significantly different from 0. In addition, because there is one winner and one loser of

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[6] The rankings are not relevant to our analysis because the choice of rankings may have been done only for television rankings.
[7] I assume that analysts do not have/use material nonpublic information throughout this paper.

every matchup, thus β_0 will be equal to 0.5 or a random probability of predicting the correct outcome.

$$y = \beta_0 + \beta_1(x) + \varepsilon \qquad (1)$$

However, if the β_1 is statistically greater than 0, this provides evidence that the group of analysts has a superior ability to accurately predict winners.

Using the Four Factor Model Outcomes

According to the CAPM theory (Sharpe 1964), in a two-stock match, the stock with a higher systematic risk should have a higher expected return. With the same idiosyncratic risk, this stock should have a higher chance to be the winner in the match. Under this scenario, if the market is efficient, according to CAPM, it is predicted that the stock with a higher beta is more likely to win each matchup. Empirically, since the four-factor model (Fama and French (1993) three factor model with Carhart's (1997) fourth factor) has a higher power than CAPM in explaining the historical stock returns, the four-factor model is used.

To estimate the beta loadings, I use CRSP monthly returns (with dividend reinvestment) in the five years before the *Fast Money* show to find the expected beta at the point the analysts make their decision. Table 1 shows the summary statistics for the beta loadings of sample firms. As shown in the table, the betas on the market risk premium have an average of 1.14. This shows that the stocks in the sample, on average, are slightly more risky than the market portfolio. The betas in our sample range between - 0.1 and 3.4. This wide range shows that the *Fast Money* analysts have a choice over the

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firms with very low systematic risk and the firms with very high systematic risk. The

betas on the other three factors all have a wide range.

Table 1: Summary statistics for the beta loadings in the four-factor model
This table shows the summary statistics for the beta loadings in the four-factor model. The beta loadings for a stock are estimated by regressing the excess return of the stock monthly return on the market excess return (R_m-R_f), the small-minus-big factor, the high-minus-low factor, and the momentum factor over the 60 months prior to each *Fast Money* show, with a constant term. The factors are downloaded from Kenneth R. French's website.

	Mean	Std. Dev.	Min	Max
A	0.011	0.020	-0.045	0.13
β (Rm-Rf)	1.140	0.589	-0.094	3.394
β (SMB)	-0.038	0.829	-5.575	3.29
β (HML)	-0.198	1.302	-8.53	2.435
β (UMD)	0.127	0.728	-2.642	4.50

With the Fama and French (1993) three factor model, with Carhart's (1997) fourth factor,

I can measure if using this model would predict the actual winning stock at a higher rate

than the analysts did. With the simulated outcomes of this tournament, using the four

factor model, I predict the outcomes and measure how the four factor model does

compared to the actual outcomes.

To proxy for the expected value of the factors, I use the historical averages of

these factors during the 10-year period prior to the *Fast Money* show. Using the four

factor prediction for each matchup, including the predicted alpha, I can determine which

stock is predicted to win based on the four factor model, *FFwin*, at the time the decision

on the winner is made. With each predicted four factor winner, I regress the predicted

winner on the actual winner using a Probit model.

$$y = \beta_0 + \beta_1 FFwin + \varepsilon \qquad (2)$$

If the four-factor model can predict a stock's future return, then I expect to have a

positive β_1. Otherwise, I am expecting the predicted outcome, *FFwin*, to have no

correlation to the actual outcomes, *y*. Again, because there is one winner and one loser of every matchup, β_0 will be equal to 0.5 or a random probability of predicting the correct outcome.

The Analysts Anchoring on the Four Factor Model

Following Campbell and Sharpe (2009) I look at the possibility that the *Fast Money* analysts used anchoring in their decisions for the best stock. Given that Fama and French's (1993) three factor model, with Carhart's (1997) fourth factor, is thought to have superior ability to predict outcomes, I test if the *Fast Money* analysts used this four factor model when determining their picks.

I first do a probit regression to analyze if the four factor model picks are significantly related to the *Fast Money* analysts' picks. I follow Equation (2), above, testing if the four factor picks are the same as the *Fast Money* analysts' picks.

With the estimated alpha and betas of the four factor model, next I take the difference in the betas between the two stocks in each matchup, stock a and stock b, to find the difference in each estimate, *Δ α*. The estimated beta coefficient on each of the four factors, the market return minus the risk free rate (R_m-R_f), the market capitalization (SMB), book to price ratio (HML), and Carhart's four factor on momentum (UMD), are used to predict if the *Fast Money* analysts' use these factors to pick a winning stock.

Table 2: The difference in the alpha and betas of the four factor model

α_a -α_b	→	Δ α
β (Rm-Rf)$_a$ - β (Rm-Rf)$_b$	→	Δ β (Rm-Rf)
β (SMB)$_a$ - β (SMB)$_b$	→	Δ β (SMB)
β (HML)$_a$ - β (HML)$_b$	→	Δ β (HML)
β (UMD)$_a$ - β (UMD)$_b$	→	Δ β (UMD)

The differences are used to predict the *Fast Money* picks, *y*. This probit model, equation 3, will reveal if the *Fast Money* analysts' chosen winner is related to the relative difference in the four factor model. Finding significant coefficients reveals the factor, or factors, that were used by the analysts at *Fast Money* to make their decisions on expected winning stocks.

$$y = \beta_0 + \alpha_1(\Delta\alpha) + \beta_1(\Delta\beta(Rm - Rf)) + \beta_2(\Delta\beta(SMB)) + \beta_3(\Delta\beta(HML))$$

$$+ \beta_4(\Delta\beta(UMD)) + \varepsilon \qquad (3)$$

For Equation (3), the predicted winner is stock a (beating stock b). So the relative difference in a and b is consistent.

Portfolio

Even though there is no statistical evidence the analysts have a superior ability to predict the winners, it is possible that the stocks they chose as winners significantly outperform their losing counterpart from a portfolio's point of view; especially given that these events occurred during the financial crisis in 2007 and 2008. Therefore, I examine the performance of hedged portfolio for each year. To construct the hedged portfolio, an equal-weighted long position in all stocks the analysts chose to win and an equal-weighted short position in all the stocks chose to lose. Since a wining stock in the first round can continue to be a winner/loser stock in the second round and so on, I continue to use only the first round to avoid a stock to be in both the winner stock portfolio and in the loser stock portfolio.

IV. Results

The results of each of the four sections listed above are now discussed.

Testing Analyst Ability to Predict More Often

By rule, having one winner and one loser in each contest, the β_0 is equal to 0.5,

showing the constant is an equal probability of getting it correct and wrong. Table 3

shows the results from a set of Probit regressions showing the accuracy of analyst

predictions on the first round of the tournament.

Table 3: Probit regression results testing the accuracy of *Fast Money trader* predictions in
the first round of the tournament
The dependent variables in this table are actual outcomes based on cumulative stock returns over the 1, 2,
3, 6, and 12-month periods after the *Fast Money* show. More specifically, the 1 month actual outcome will
have a value of 1 if the stock has a higher return than its match stock from the end of March to the end of
April in the year of *Fast Money* show. The predicted outcome is the 0/1 indicator for loser/winner in a two-
stock match from the *Fast Money* show. The marginal effect from Probit regression models are reported.
The number of observations are 64 for all models (32 matches $\times$ 2 years).

	1 Month: Actual Outcome	2 Month: Actual Outcome	3 Month: Actual Outcome	6 Month: Actual Outcome	12 Month: Actual Outcome
Fast Money Predicted Outcome	0.222 (1.59)	0.088 (0.62)	-0.034 (0.25)	-0.033 (0.25)	0.039 (0.28)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.03	0.01	0.07	0.00	0.01
Correct Picks	41/63	38/63	41/63	43/63	40/63
Absolute value of z statistics in parentheses					
* significant at 5%; ** significant at 1%					

Table 3 shows that the ability to predict a winner in the first round is not significantly

different from a random guess, the predicted probability at X-bar. This shows that

although these picks are highly publicized, the analysts have no predictive abilities when

it comes to choosing the stocks that are actually going to outperform another stock over a

time period. However the analysts average just over 40 picks, out of 63, correct.

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Using the Four Factor Model Outcomes

As found above, the *Fast Money* analysts have no predictive power. The classic test to see if they could have done better is to compare them to another stock prediction mechanism. To do this, I test if using the four factor model would have been able to predict winners over the same time periods.

Recall that the test this only in the first round to control for any bias in the selection to the later rounds. Table 4 analyzes how the tournament predictions would have looked if the four factor model was used to determine the outcomes of each stock matchup in the first round.

Table 4: Probit regression results testing the power for the four-factor predicted winners to explain the actual outcomes based on the first round of the tournament
The dependent variables in this table are actual outcomes based on cumulative stock returns over the 1, 2, 3, 6, and 12-month periods after the *Fast Money* show. More specifically, the 1 month actual outcome will have a value of 1 if the stock has a higher return than its match stock from the end of March to the end of April in the year of *Fast Money* show. The *FFwin* is an indicator variable, which takes 0/1 for the losers/winners of each match based on the Fama-Franch three factors augmented by Carhart factor model. The marginal effect from Probit regression models are reported.

	1 Month: Actual Outcome	2 Month: Actual Outcome	3 Month: Actual Outcome	6 Month: Actual Outcome	12 Month: Actual Outcome
FFwin	0.2	0.15	0.155	-0.007	-0.0114
	(1.55)	(1.15)	(1.21)	(0.05)	(0.09)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.03	0.02	0.02	0.00	0.00
Correct Picks	35/62	35/62	25/62	27/62	32/59
Absolute value of z statistics in parentheses					
* significant at 5%; ** significant at 1%					

Finding no significant results shows that the four factor model has no superior ability to predict the actual winner. These results are similar to the results found earlier by the *Fast Money* analysts, except that now the average number that are correct picks is now 31.

Table 5 uses the four factors individually to see if the individual use of each factor would have been a good predictor of the outcomes. Although there are no consistent prediction, having a relatively higher historical alpha and beta on the excess market return (i.e. the return to the market minus the risk free rate), relative to the other stock in the matchup, predicts a higher probability of the actual winner in three months and six months respectively. Also having a lower beta on SMB or a smaller beta on UMD increases the ability to find the actual winner over one and six months respectively.

Table 5: Probit regression results testing the power for the four-factor loadings to explain the actual outcomes in the first round of the tournament

The dependent variables in this table are actual outcomes based on cumulative stock returns over the 1, 2, 3, 6, and 12-month periods after the *Fast Money* show. More specifically, the 1 month actual outcome will have a value of 1 if the stock has a higher return than its match stock from the end of March to the end of April in the year of *Fast Money* show. The marginal effect from Probit regression models are reported.

	1 Month: Actual Outcome	2 Month: Actual Outcome	3 Month: Actual Outcome	6 Month: Actual Outcome	12 Month: Actual Outcome
Δ α	9.322	4.516	11.447	5.442	2.985
	(1.93)	(1.02)	(2.24)*	(1.25)	(0.69)
Δ β (Rm-Rf)	0.083	0.068	0.223	0.183	0.081
	(0.84)	(0.73)	(2.19)*	(2.07)*	(0.92)
Δ β (SMB)	-0.184	0.017	-0.051	-0.056	0.025
	(2.28)*	(0.24)	(0.67)	(0.81)	(0.35)
Δ β (HML)	0.007	-0.027	0.056	0.025	0.002
	(0.10)	(0.44)	(0.79)	(0.40)	(0.03)
Δ β (UMD)	-0.134	0.014	-0.212	-0.221	-0.116
	(1.18)	(0.13)	(1.83)	(1.97)*	(1.07)
Observations	62	62	62	62	59
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.13	0.06	0.19	0.08	0.05
Absolute value of z statistics in parentheses					
* significant at 5%; ** significant at 1%					

The Analysts Anchoring on the Four Factor Model

This section analyzes the possibility that the *Fast Money* analysts anchored their decisions on the four factor model. Although the results of the analysts ability to predict

outcomes and four factor model's ability to predict outcomes are the same, finding no

significant evidence that they have a superior ability to correctly predict the outcomes,

this could be caused by the analysts using the four factor model to make their picks.

To measure any anchoring in the process, for each stock, I first estimate the betas

on the fourth factors using past 5 years of data. Then the betas and the four factors over

the past 10 years to predict a winner out of a two-stock pair. Historical estimates are used

to determine the expected choice at the time of the tournament. The winner has a value of

1 for the FFwin variable and the loser has a value of 0. Using a Probit regression, I test if

using the four factor model's predicted winner is significantly related to the predicted

winner by the *Fast Money* analysts, Table 6.

Table 6: Probit regression results testing the power for the four-factor predicted winners
to explain the analyst predictions of the tournament
The dependent variables in this table are predicted winners from the *Fast Money* show, which takes 0/1 for
the losers/winners of each match in the show. The *FFwin* is an indicator variable, which takes 0/1 for the
losers/winners of each match based on the Fama-French three factors augmented by Carhart factor model.
The marginal effects from Probit regression models are reported.

	Fast Money Predicted Winner
FFwin	0.114
	(0.93)
Year Fixed Effect	Yes
Pseudo R2	0.03
Absolute value of z statistics in parentheses	
* significant at 5%; ** significant at 1%	

Using this measure, there is no evidence that the *Fast Money* analysts used the four factor

model in their predictions.

I also estimate the difference in the alpha and the betas for each of the four

factors, presented in Table 7. Although when combined I find no evidence that the *Fast*

Money analysts use the four factor model, this will reveal whether the analysts were using an individual factor in their predictions.

Table 7: Probit regression results testing whether the *Fast Money* analysts used the four-factor loadings to make their predictions

The dependent variable in this table is the predicted outcome, which is the 0/1 indicator for loser/winner in a two-stock match from the *Fast Money* show. The marginal effect from Probit regression models are reported.

	Fast Money predicted Winner
Δ α	2.57
	(0.76)
Δ β (Rm-Rf)	0.046
	(0.56)
Δ β (SMB)	-0.084
	(1.19)
Δ β (HML)	0.011
	(0.21)
Δ β (UMD)	0.035
	(0.72)
Pred. Prob at X-bar	0.5
Pseudo R2	0.03
Absolute value of z statistics in parentheses	
* significant at 5%; ** significant at 1%	

There are no factors with a significant impact on the picks. The overall evidence shows that the *Fast Money* analysts did not use the Fama-French and Carhart's four factors in their decisions.[8]

Portfolio

I also examine the performance of hedged, long/short, portfolio for the *Fast Money* analysts. The hedged portfolio consists of an equal-weighted long position in all

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[8] The F-test for the regression on the whole also rejects that the *Fast Money* analysts used the four factor model.

the stocks chosen to win and an equal-weighted short position in all the stocks chosen to lose in the first round.

I examine the hedging portfolio return of the first round based on the analyst prediction. For year 2007, the equal-weighted portfolio based on the winner stocks earn an annual return of 4.35%, based on 31 winning stocks, from April 2007 to March 2008.[9] During the same period, the loser portfolio earns a return of -3.37% with 31 losing stocks.[10] Consequently, the hedging portfolio earns a return of 7.72%. The S&P 500 returned -10.77% during this time period. These results show that the wining portfolio in the first round actually performs much better than loser portfolio economically. For year 2008, the winner portfolio earns an annual return of -33.21% from April 2008 to March 2009, which is exactly the time of the financial crisis. At the same time, the losing portfolio earns a return of -45.93%. Therefore, the hedging portfolio experiences an annual return of 12.72%. The S&P 500 returned -42.42% during this period. These findings again show that analyst predictions are economically significant, even during the financial crisis.

I also examine the hedging portfolio return of the first round based on the four factor model predictions. For year 2007, the equal-weighted portfolio based on the wining stocks earns an annual return of 2.37% from April 2007 to March 2008. During the same period, the loser portfolio earns a return of -0.27%.[11] Consequently, the hedging portfolio earns a return of 2.64%. Compare to our previous analysis prediction results, these results show that analysts actually perform better than the four factor model

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[9] There are 31 winning stocks in 2007 because AMGN, Amgen, Inc, does not have the required return information from CRSP. I have tested the results using yahoo.finance and get similar results.
[10] There are 31 losing stocks in 2007 because FIG, Fortress Investment Group LLC, does not have historical return information before 2007.
[11] The four factor estimates use 30 distinct matches because we are missing data on AMGN and FIG.

predictions. For year 2008, the wining portfolio earns an annual return of -35.17% from April 2008 to March 2009. At the same time, the losing portfolio earns a return of -43.97%. Therefore, the hedging portfolio experiences an annual return of 8.8%. These findings again show that analyst predictions are better than four factor model's predictions, even during the financial crisis.

V. Conclusions and Discussion

In 2007 and 2008 CNBC's television show *Fast Money* ran a March Madness stock tournament to determine which stocks would perform the best over the next year. I measure if the analysts on this show have a superior ability to predict the winning stocks, over the losing stocks, with a probability above random chance. I find no evidence that these analysts have the ability to pick the better performing stocks over either of these years. I also analyze if these analysts were using the Fama and French (1993) three factor model, with Carhart's (1997) fourth factor, to make their picks. There is no evidence they used the four factor model in their analysis.

However, when looking at hedged long/short portfolio I find that the analysts would have returned a yearly return of 7.72% from their 2007 picks and 12.72% from their 2008 picks, when the S&P 500 returned -10.77% and -42.42% during this same period. Following the tournament structure, if an investor would have used the four factor model to pick the winning and losing stocks for the long/short hedged portfolio they would have returned a yearly return of 2.64% from the 2007 picks and 8.8% from the 2008 picks. This reveals that although the analysts were not able to predict the winning stocks consistently, the stocks they chose to win were the stocks that had the highest

relative return over this period, relative to both a four-factor portfolio and to the market on the whole.

Through this unique setup I am able to test analysts' ability. These tournaments occurred during an interesting time in our history, during the financial crisis. These results show that there is some value added by these analysts, not in the analyst's ability to predict the winner, but their ability to find a relative winner when they are forced to choose both a winner and a loser. I encourage continued research on this analyst impact and if it is driven by talent, driven by the unique time in our history (the financial crisis), or a combination of increased value of an analysts during extreme events in the financial markets.

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Appendix: 2007 and 2008 tournament brackets

FAST MONEY MADNESS 2007

FAST MONEY MADNESS 2008

| Round 1 | Round 2 | SWEET SIXTEEN | ELITE EIGHT | FINAL FOUR | FINAL | FINAL FOUR | ELITE EIGHT | SWEET SIXTEEN | Round 2 | Round 1 |

Left side:

- 1 HEWLETT-PACKARD
- 16 WESTERN DIGITAL
  - HEWLETT-PACKARD
- 8 CORNING
- 9 INTEL
  - INTEL
    - HEWLETT-PACKARD
- 5 MICROSOFT
- 12 IBM
  - MICROSOFT
- 4 ORACLE
- 13 COMCAST
  - ORACLE
    - MICROSOFT
      - MICROSOFT
- 6 EMC
- 11 VERIZON
  - EMC
- 3 APPLE
- 14 RESEARCH MOTION
  - APPLE
    - APPLE
- 7 CISCO
- 10 DELL
  - CISCO
- 2 GOOGLE
- 15 AT&T
  - GOOGLE
    - GOOGLE
      - APPLE
        - MICROSOFT

- 1 PEPSI
- 16 HORMEL
  - PEPSI
- 8 MCDONALD'S
- 9 DISNEY
  - DISNEY
    - DISNEY
- 5 ALTRIA
- 12 PFIZER
  - ALTRIA
- 4 WAL-MART
- 13 TARGET
  - WAL-MART
    - ALTRIA
      - ALTRIA
- 6 COCA-COLA
- 11 MACY'S
  - COCA-COLA
- 3 PROCTER&GAMBLE
- 14 ANHEUSER-BUSCH
  - PROCTER&GAMBLE
    - PROCTER&GAMBLE
- 7 MERCK
- 10 UNITEDHEALTH
  - MERCK
- 2 JOHNSON&JOHNSON
- 15 HOME DEPOT
  - JOHNSON&JOHNSON
    - JOHNSON&JOHNSON
      - JOHNSON&JOHNSON
        - ALTRIA

Center:
- MICROSOFT
- **GOLDMAN SACHS**
- GOLDMAN SACHS

Right side:

- BERKSHIREHATHAWAY 1
- AMBAC 16
  - BERKSHIREHATHAWAY
- US BANCORP 8
- BANKOFAMERICA 9
  - BANKOFAMERICA
    - BERKSHIREHATHAWAY
- MASTERCARD 5
- AMERICANEXPRESS 12
  - MASTERCARD
- CHINA LIFE 4
- WELLS FARGO 13
  - WELLS FARGO
    - MASTERCARD
      - BERKSHIREHATHAWAY
        - GOLDMAN SACHS
- SIMON GROUP 6
- LEHMAN BROTHERS 11
  - LEHMAN BROTHERS
- GOLDMAN SACHS 3
- WASHINGTON MUT 14
  - GOLDMAN SACHS
    - GOLDMAN SACHS
- NYSE 7
- AIG 10
  - NYSE
- JPMORGAN CHASE 2
- CITIGROUP 15
  - JPMORGAN CHASE
    - JPMORGAN CHASE
      - GOLDMAN SACHS

- UTD TECHNOLOGIES 1
- SUNPOWER 16
  - UTD TECHNOLOGIES
- VALERO 8
- EXXON MOBIL 9
  - VALERO
    - VALERO
- POTASH 5
- BOEING 12
  - POTASH
- FREEPORTMCMORAN 4
- ARCHER DANIELS 13
  - FREEPORTMCMORAN
    - FREEPORTMCMORAN
      - FREEPORTMCMORAN
        - GOLDMAN SACHS
- ALCOA 6
- PG & E 11
  - ALCOA
- TOYOTA 3
- GENERAL MOTORS 14
  - GENERAL MOTORS
    - ALCOA
- 3M 7
- CATERPILLAR 10
  - CATERPILLAR
- BHP BILITON 2
- DUPONT 15
  - BHP BILITON
    - CATERPILLAR
      - CATERPILLAR
        - FREEPORTMCMORAN