Journal of Finance and Economics, 2021, Vol. 9, No. 3, 142-146
Available online at http://pubs.sciepub.com/jfe/9/3/4
Published by Science and Education Publishing
DOI:10.12691/jfe-9-3-4

TV Financial Analyst Predictive Power: The Case of *Jim Cramer* of Mad Money

Frederick Adjei[1], Mavis Adjei[2,*]

[1]Economics and Finance, Southeast Missouri State University, Cape Girardeau, USA
[2]Department of Marketing and Management, SIU Carbondale, Carbondale, USA
*Corresponding author: fadjei@semo.edu

Received May 13, 2021; Revised June 18, 2021; Accepted June 25, 2021

Abstract In this study, using a unique dataset collected by web-scraping (using *Python Programming Language*), we assess analyst predictive power and whether analyst experience is associated with predictive power by tracking *Jim Cramer*'s predictive power for future stock returns over a two-year period. We find that *Jim Cramer*'s accuracy may be limited to *positive* and *buy* recommendations. Additionally, we find that there is improvement in recommendation accuracy with increase in analyst experience. However, the improvements are concentrated in the *positive* and *buy* recommendations. Finally, the *featured stock* segment of *Jim Cramer*'s show seems to have the highest recommendation accuracy for both *positive* and *negative* recommendations.

Keywords: *financial analyst recommendations predictive power*

Cite This Article: Adjei Frederick, and Mavis Adjei, "TV Financial Analyst Predictive Power: The Case of *Jim Cramer* of Mad Money." *Journal of Finance and Economics*, vol. 9, no. 3 (2021): 142-146. doi: 10.12691/jfe-9-3-4.

1. Introduction

Financial analyst recommendations are integral in informing the trading decision making process of many investors. Analysts, via different media, simply offer their informed opinions about the future prospects of specific firms, economic sectors and/or the macroeconomy. Extant research such as Brennan and Subrahmanyam [1] and Irvine [2] indicate that there is a measurable reaction in the market following analyst recommendations.

Though these findings indicate the significance of financial analysts' recommendations, there remains the issue of the determinants of an analyst's predictive power for future stock returns. Several studies have attempted to answer this question with conflicting results. Harvey, Mohammed, and Rattray [3] find that more experienced financial analysts outperform less experienced analysts on *buy* recommendations, however, the study also find that junior analysts perform better than senior analysts on *sell* recommendations. Li, Sullivan, Xu, and Gao [4] examining analyst gender and performance, find that female sell-side analysts' predictions have lower idiosyncratic risks than those of their male counterparts.

In this study, using a unique dataset collected by web-scraping (using *Python Programming Language*), we assess whether a value indicator such as analyst experience is associated with higher predictive power by tracking an analyst's predictive power for future stock returns over a period. Usually, more experienced analysts work for highly reputable brokerage houses, making it difficult to isolate the effects of only *analyst experience* on predictive power. Our focus on just one analyst allows for a longitudinal study of analyst predictive power as his experience increases, mitigating the *brokerage house effects*.

We examine the evolution of Jim Cramer's predictive power over the last 15 years. Jim Cramer hosts the CNBC TV show: "Mad Money", beginning in 2005, with recommendations posted on the show's website: https://madmoney.thestreet.com/screener/index.cfm. Using a web-scraping technique (*Python*), we obtain data from the Jim Cramer Show's website, and examine the future returns of stocks recommended on the show. This unique dataset presents an opportunity for an in-depth examination of a financial analyst.

Upon completing our study, we find that Jim Cramer's accuracy may be limited to *positive* and *buy* recommendations. Additionally, we find that there is improvement in recommendation accuracy with increase in analyst experience. However, the improvements are concentrated in the *positive* and *buy* recommendations. Finally, the *featured stock* segment of the show seems to have the highest recommendation accuracy for both *positive* and *negative* recommendations.

2. Literature Review and Hypothesis Development

Naturally, given the variability of analyst attributes, one would expect that a set of optimal attributes would confer the best predictive powers on an analyst. Recent research suggests that analyst attributes such as gender, experience (number of years as analyst), and size of affiliated brokerage house affect the accuracy of analyst recommendations. Malloy [5] investigates the connection between the proximity of a financial analyst to a firm and the accuracy of forecasts for that firm and finds that local analysts' recommendations impact prices more than nonlocal analysts' recommendations, with the effects being strongest for companies positioned in remote areas or small cities.

Clement [6] suggests that analyst characteristics such as size of affiliated brokerage house, general experience, brokerage-specific experience, and number of companies followed, are determinants of analyst accuracy. Hong and Kubik [7] find that analyst forecast accuracy is correlated with the degree of analysts' determination to join a highly reputable brokerage house. Brown and Mohammad [8] find that past analyst forecast accuracy is a determinant of future forecast accuracy. Similarly, Li [9] shows that high-ranked analysts with high prior performance (risk-adjusted) outperform other analysts. Hong, Kubik, and Solomon [10] find that new analysts have a higher risk of unemployment as a result of inaccurate forecasts and hence likely to be trepidatious, reducing the number of predictions they make.

Another kind of analyst whose popularity is increasing is a Robo-Analyst. As the name indicates, it is financial analysis technology; machine-learning algorithms working on large volumes of financial data, mass-producing recommendations with little human involvement. Driskill et al., [11] and Hirshleifer et al., [12] suggest that Robo-Analysts are better outfitted to collect and deconstruct huge volumes of financial reports and promptly incorporate the details into their financial models than human analysts, who are limited by physical and cognitive constraints. Additionally, because Robo-Analysts are typically encoded to follow an exact algorithm with minimal human interference, their recommendations may be more reliable and less prone to human behavioral biases such as optimism bias and conflict of interest [13]. Robo-Analysts tend to focus on recommendations and not earnings forecasts.

The aforementioned studies indicate that financial analysts add to an investor's trading decision-making process. However, according to Fama [14], an investment strategy founded on analyst recommendations violates the Efficient Market Hypothesis [EMH]. EMH asserts that asset prices are unpredictable; follow a random walk. This theory implies that a trading strategy based on analyst recommendations should not result in positive abnormal returns; analyst recommendations do not add value if analysts use publicly available information only. Consistent with the EMH, Barber, Lehavy, McNichols, and Trueman [15] find that the abnormal returns attainable by following financial analyst recommendations are negligible after accounting for transaction costs.

Intuitively, one would expect that higher analyst experience would be positively correlated with the accuracy of both *buy* and *sell* recommendations. However, the extant research suggests that the association is more complicated and sometimes inconsistent.

For example, the study by Harvey, Mohammed, and Rattray [3] which finds that *more experienced* financial analysts outperform less experienced analysts on *buy* recommendations, and *less experienced* financial analysts outperform more experienced analysts on *sell* recommendations, shows the connection between analyst experience and predictive power is not well established. Our study, using a unique dataset collected by web-scraping (using *Python*), examines the association between analyst experience and predictive power for both positive and negative recommendations by tracking *Jim Cramer*'s predictive power for future stock returns on the following segments of the show, namely: guest *interview*, *mailbag, featured stock, lightning round, and discussed stock.*

Hypothesis I: *Jim Cramer makes accurate recommendations.*

Hypothesis II: *Jim Cramer's experience is positively correlated with accuracy of his recommendations.*

Hypothesis III: *Jim Cramer's accuracy of recommendations is the same on all segments of the show.*

3. Data

Using *Python*, we web-scrape data on *Jim Cramer*'s recommendations from the show's website: https://madmoney.thestreet.com/screener/index.cfm. Our dataset is composed of recommendations from the beginning of the show: January 2005 to March 2021, resulting in 2032 stock recommendations. Additionally, we web-scrape daily and monthly stock price data from *yahoo.com/finance* database on the recommended stocks for the study period. From the price data, we compute daily and monthly stock returns.

4. The Forecasting Model

We examine the relationship between *Jim Cramer*'s recommendations and future stock market returns by employing the forecasting model of Fama and French [16]. In univariate regressions using *Jim Cramer*'s recommendation as a predictor [17]; we estimate the forecasting model of Fama and French [16];

$$\sum_{n=1}^{N} \frac{r_{t+N}}{N} = a + b\text{x}JCR + u_{t+N,t} \qquad (1)$$

where r_{t+N} is the continuously compounded monthly excess stock return computed as the continuously compounded monthly stock return minus the monthly continuously compounded one-month Treasury bill rate, N is the forecasting horizon in months, $\boldsymbol{b}$ is a matrix of slope coefficients, *JCR* is *Jim Cramer*'s recommendation converted to a Likert scale: sell (-2), negative (-1), positive (1), and buy (2). $u_{t+N,t}$ is the regression residual. We run the univariate regressions for different horizons: N = 2, 6, 12, 18, and 24 months.

A potential problem associated with the Fama and French multi-period model is serial correlation in the residuals leading to a *Type II Error*. Additionally, the regression residuals may be conditionally heteroskedastic. To resolve both potential problems: the induced autocorrelation and the conditional heteroskedasticity, we employ a generalized method of moments (GMM) estimator [18].

The GMM estimator θ = (a, $\boldsymbol{b}$) has an asymptotic distribution $\sqrt{T}(\hat{\theta} - \theta) \sim N\ (0,\ \Omega)$, where $\Omega = Z_0^{-1} S_0 Z_0^{-1}$, $Z_0 = E(x_t x_t')$, $x_t = (1\ X_t')'$, and S_0 is the spectral density. The spectral density within a specific spectrum of frequencies can be expressed as the variance attributable to those frequencies. With the null hypothesis that expected stock returns cannot be predicted,

$$S_0 = \sum_{j=-N+1}^{N-1} E\left(w_{t+N} w'_{t+N-j}\right), \tag{2}$$

where S_0 is estimated at a frequency of zero and $w_{t+N} = u_{t+N,t}\, x_t$ and with a Newey-West correction (N-1 moving average lags). The GMM estimation results in the asymptotic Z statistic.

Another potential problem with regressions which use the same data for multiple time periods is that the regression coefficients might be correlated, undermining the validity of the results from any particular time-horizon's regression. To reduce the effect of this potential correlation problem, we employ the Joint Slopes Test proposed by Richardson and Stock [19]. The test averages the regression coefficients from regressions of multiple time horizons and determines the significance of the mean regression coefficient. To apply the Joint Slopes Test, we estimate the GMM estimator with a set of regressions in which the coefficients are constrained to be the same across all horizon-regressions in the set [19], converting the multiple-equation GMM estimator to a special case of a single-equation GMM estimator. We proceed as follows;

$$\sum_{n=1}^{N=1} \frac{r_{t+1}}{2} = a + b_2 \mathrm{x} JCR + u_{t+1,t} \tag{3}$$

$$\sum_{n=1}^{N=6} \frac{r_{t+1}}{6} = a + b_6 \mathrm{x} JCR + u_{t+1,t} \tag{4}$$

$$\sum_{n=1}^{N=12} \frac{r_{t+12}}{12} = a + b_{12} \mathrm{x} JCR + u_{t+12,t} \tag{5}$$

$$\sum_{n=1}^{N=18} \frac{r_{t+18}}{18} = a + b_{18} \mathrm{x} JCR + u_{t+18,t} \tag{6}$$

$$\sum_{n=1}^{N=24} \frac{r_{t+24}}{24} = a + b_{24} \mathrm{x} JCR + u_{t+N,t}, \tag{7}$$

where r_{t+N} is the continuously compounded excess monthly stock return computed as the continuously compounded monthly stock return minus the monthly continuously compounded one-month Treasury bill rate, N is the forecasting horizon in months, ***JCR*** is *Jim Cramer*'s recommendation converted to a Likert scale: sell (-2), negative (-1), positive (1), and buy (2). $u_{t+N,t}$ is the regression residual. $u_{t+N,t}$ is the regression residual and b is a slope coefficient. Note that $b = b_2 = b_6 = b_{12} = b_{18} = b_{24}$ and hence S_0 cannot be calculated with a Newey-West correction owing to the concurrent use of several time horizons.

5. Empirical Results

This section depicts the results of the forecasting regressions. Table 1 presents the results of the univariate forecasting regressions. For the full sample, the results show significant (1% level) beta coefficients for the *JCR* variable for all horizons, indicating that Jim Cramer makes accurate recommendations. The finding signifies that for the two-month horizon all the way up to the 24-month horizon, Jim Cramer's show calls accurate predictions on future stock performance and suggests that analyst recommendations have value. Azevedo and Muller [20] also find that analyst recommendations are correlated with abnormal returns in international markets.

Furthermore, we follow Harvey, Mohammed, and Rattray [3] and separate our sample into *buy* and *sell* recommendations, as we notice from previous research, such as Coleman, Merkley, and Pacelli [21] that the recommendation accuracy may be different in the subsamples. However, when we bifurcate the sample into a positive recommendations (composed of *positive* and *buy* recommendations) subsample and a negative recommendations (composed of *negative* and *sell* recommendations) subsample, and rerun our regressions, we find that the significant beta coefficients only persist in the positive subsample. This finding indicates that Jim Cramer's accuracy may be limited to *positive* and *buy* recommendations. This one-sided accuracy is consistent with the findings of extant research such as Li, Sullivan, Xu, and Gao [4] who find that female sell-side analysts' predictions have lower idiosyncratic risks than those of their male counterparts, and with Dong and Hu [22] who assert a long-recognized optimistic bias in analyst recommendations.

Next, we test the hypothesis that the accuracy of Jim Cramer's recommendation is correlated with his experience. To this end, we split our study period into three 5-year periods and run the prediction regressions for these periods. Our findings, presented in Table 2, show that consistent with our earlier findings, there is an improvement in recommendation accuracy after the first five years and the improvements are concentrated in the *positive* and *buy* recommendations. Our findings are also consistent with Harvey, Mohammed, and Rattray [3] who find that *more experienced* financial analysts outperform less experienced analysts on *buy* recommendations, and *less experienced* financial analysts outperform more experienced analysts on *sell* recommendations. Additionally, our findings lend support to those of Park and Park [23] and Chemmanur, Karagodsky, and Toscano [24] who find that equity analysts recommendations have high predictive power.

Finally, we examine Jim Cramer's recommendation accuracy on different segments of his show. The results, presented in Table 3, show that the *featured stock* segment has recommendation accuracy for both *positive* and *negative* recommendations. The other segments show mixed results. These mixed results are consistent with the findings of the other studies mentioned above and in the literature review section of the paper.

Table 1. Univariate Forecasting Regressions

	Full Sample		***Positive Sample***		***Negative Sample***	
N	*JCR*	adj. R^2	*JCR*	adj. R^2	*JCR*	adj. R^2
2	0.0011***	0.0002	-0.0003	0.0000	0.0016	0.0000
6	0.0009***	0.0006	-0.0003	0.0000	0.0009	0.0000
12	0.0008***	0.0009	-0.0005	0.0000	0.0006	0.0000
18	0.0005***	0.0008	-0.0009***	0.0000	0.0005	0.0000
24	0.0005***	0.0006	-0.0011***	0.0004	0.0003	0.0000
Z(*JCR*)Avg.	0.0005***		-0.0011***		0.0003	

This table presents the univariate forecasting regression results in equation (1).

$$\sum_{n=1}^{N} \frac{r_{t+N}}{N} = a + \boldsymbol{b} \,\mathrm{x}\, JCR + u_{t+N,t} \tag{1}$$

where r_{t+N} is the continuously compounded monthly excess stock return computed as the continuously compounded monthly stock return minus the monthly continuously compounded one-month Treasury bill rate, N is the forecasting horizon in months, $\boldsymbol{b}$ is a matrix of slope coefficients, *JCR* is *Jim Cramer*'s recommendation is converted to a Likert scale: sell (-2), negative (-1), positive (1), and buy (2). $u_{t+N,t}$ is the regression residual. We run the univariate regressions for different horizons: N = 2, 6, 12, 18, and 24 months.

The GMM estimator θ = (a, $\boldsymbol{b}$) has an asymptotic distribution $\sqrt{T}(\hat{\theta} - \theta) \sim N(0, \Omega)$, where $\Omega = Z_0^{-1} S_0 Z_0^{-1}$, $Z_0 = E(x_t x_t')$, $x_t = (1\ X_t')'$, and S_0 is the spectral density. The spectral density within a specific spectrum of frequencies can be expressed as the amount of the variance attributable to those frequencies. With the null hypothesis that expected stock returns cannot be predicted,

$$S_0 = \sum_{j=-N+1}^{N-1} E\left(w_{t+N} w'_{t+N-j}\right) \tag{2}$$

where S_0 is estimated at a frequency of zero and $w_{t+N} = u_{t+N,t}\, x_t$ and with a Newey-West correction (*N*-1 moving average lags).

Table 2. Learning

	First 5 years	***Second 5 years***	***Third 5 years***
Sample	Z(*JCR*)Avg	Z(*JCR*)Avg	Z(*JCR*)Avg
Full	-0.0001	0.0008***	0.0003***
Positive	-0.0003	-0.0085***	-0.0024***
Negative	0.0003	0.0016	-0.0006

This table presents the univariate forecasting regression results in equation (1).

$$\sum_{n=1}^{N} \frac{r_{t+N}}{N} = a + \boldsymbol{b} \,\mathrm{x}\, JCR + u_{t+N,t} \tag{1}$$

where r_{t+N} is the continuously compounded monthly excess stock return computed as the continuously compounded monthly stock return minus the monthly continuously compounded one-month Treasury bill rate, N is the forecasting horizon in months, $\boldsymbol{b}$ is a matrix of slope coefficients, *JCR* is *Jim Cramer*'s recommendation is converted to a Likert scale: sell (-2), negative (-1), positive (1), and buy (2). $u_{t+N,t}$ is the regression residual. We run the univariate regressions for different horizons: N = 2, 6, 12, 18, and 24 months.

The GMM estimator θ = (a, $\boldsymbol{b}$) has an asymptotic distribution $\sqrt{T}(\hat{\theta} - \theta) \sim N(0, \Omega)$, where $\Omega = Z_0^{-1} S_0 Z_0^{-1}$, $Z_0 = E(x_t x_t')$, $x_t = (1\ X_t')'$, and S_0 is the spectral density. The spectral density within a specific spectrum of frequencies can be expressed as the amount of the variance attributable to those frequencies. With the null hypothesis that expected stock returns cannot be predicted,

$$S_0 = \sum_{j=-N+1}^{N-1} E\left(w_{t+N} w'_{t+N-j}\right) \tag{2}$$

where S_0 is estimated at a frequency of zero and $w_{t+N} = u_{t+N,t}\, x_t$ and with a Newey-West correction (*N*-1 moving average lags).

Table 3. Segments

Segments	*Interview*	Lightening	*Discussed*	Mail	*Featured*
Full	0.0017***	0.0005***	0.0003	-0.0017***	0.0004***
Positive	0.0150***	-0.0004	0.0051***	0.0013	-0.0034***
Negative	0.0018	-0.0019	-0.0161	0.0039	-0.0017***

This table presents the univariate forecasting regression results in equation (1).

$$\sum_{n=1}^{N} \frac{r_{t+N}}{N} = a + \boldsymbol{b} \,\mathrm{x}\, JCR + u_{t+N,t} \tag{1}$$

where r_{t+N} is the continuously compounded monthly excess stock return computed as the continuously compounded monthly stock return minus the monthly continuously compounded one-month Treasury bill rate, N is the forecasting horizon in months, $\boldsymbol{b}$ is a matrix of slope coefficients, *JCR* is *Jim Cramer*'s recommendation is converted to a Likert scale: sell (-2), negative (-1), positive (1), and buy (2). $u_{t+N,t}$ is the regression residual. We run the univariate regressions for different horizons: N = 2, 6, 12, 18, and 24 months.

The GMM estimator θ = (a, $\boldsymbol{b}$) has an asymptotic distribution $\sqrt{T}(\hat{\theta} - \theta) \sim N(0, \Omega)$, where $\Omega = Z_0^{-1} S_0 Z_0^{-1}$, $Z_0 = E(x_t x_t')$, $x_t = (1\ X_t')'$, and S_0 is the spectral density. The spectral density within a specific spectrum of frequencies can be expressed as the amount of the variance attributable to those frequencies. With the null hypothesis that expected stock returns cannot be predicted,

$$S_0 = \sum_{j=-N+1}^{N-1} E\left(w_{t+N} w'_{t+N-j}\right) \tag{2}$$

where S_0 is estimated at a frequency of zero and $w_{t+N} = u_{t+N,t}\, x_t$ and with a Newey-West correction (*N*-1 moving average lags). **This table only presents results of the Joint Slopes tests.**

6. Conclusions

In this study, using a unique dataset collected by web-scraping (using *Python*), we assess analyst predictive power and whether a value indicator such as analyst experience is associated with higher predictive power by tracking an analyst's predictive power for future stock returns over a period. We find that Jim Cramer's accuracy may be limited to *positive* and *buy* recommendations.

Additionally, we find that there is improvement in recommendation accuracy with increase in analyst experience. However, the improvements are concentrated in the *positive* and *buy* recommendations. Finally, we find that the *featured stock* segment seems to have the highest recommendation accuracy for both *positive* and *negative* recommendations.

Overall, the study shows mixed results on Jim Cramer's recommendation accuracy. Our findings indicate that investors should not rely on analyst recommendations, especially negative recommendations, but rather focus more on holding well diversified portfolios.

As with every study, there are some limitations of this study. Due to the short life of the *Jim Cramer* show, just 15 years, our results in the subperiods did not have statistical power owing to the limited sample sizes. Additionally, the show does not discuss many stocks, and this limits the number of recommendations to be analyzed. A third limitation relates to our forecasting model. As discussed earlier, a potential issue with the Fama and French multi-period model is the problem of serial correlation and possibly conditional heteroskedasticity in the residuals. We take steps to ameliorate these problems, however, they may persist affecting the validity of our results.

Future research could compare the predictive power of human financial analysts and Robo-analysts for future stock returns. Additionally, future research could explain the seemingly one-sided nature of the predictive power of financial analysts. For example, extant research indicates that experienced analysts perform better on *buy* recommendations while inexperienced analysts perform better on *sell* recommendations.

References

[1] Brennan, M.J., and A. Subrahmanyam (1995). Investment analysis and price formation in securities markets, Journal of Financial Economics, 38, 361 - 381.

[2] Irvine, Paul (2003). The incremental impact of analyst initiation of coverage. Journal of Corporate Finance, 9 (4), 431-451.

[3] Harvey, Campbell, Khalil Mohammed, and Sandy Rattray (2011). Do Analyst Experience, Location and Gender Affect the Performance of Broker Recommendations in Europe? Working paper.

[4] Li, Xi, Rodney Sullivan, Danielle Xu and Guodong Gao. (2013). Sell-Side Analysts and Gender: A Comparison of Performance, Behavior, and Career Outcomes, Financial Analyst Journal 69 (2), 83-94.

[5] Malloy, Christopher (2005). The geography of equity analysts, Journal of Finance 60, 719-755.

[6] Clement, M. (1999). Analyst Forecast Accuracy: Do Ability, Resources and Portfolio Complexity Matter? Journal of Accounting and Economics, 27 (3), 285-303.

[7] Hong, H., and J. D. Kubik (2003). Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts. Journal of Finance, 58, 313-351.

[8] Brown, L. and E. Mohammad (2001). Profiting from Predicting Individual Analyst Earnings Forecast Accuracy, working paper, Georgia State University.

[9] Li, X. (2005). The Persistence of Relative Performance in Stock Recommendations of Sell-Side Financial Analysts." Journal of Accounting and Economics, 40, 129-152.

[10] Hong, H.; J. D. Kubik; and A. Solomon (2000). Security Analysts' Career Concerns and Herding of Earnings Forecasts. RAND Journal of Economics, 3, 121 - 144.

[11] Driskill, M., M. Kirk, and J. W. Tucker (2018). Concurrent Earnings Announcements and Analysts' Information Production. The Accounting Review, forthcoming.

[12] Hirshleifer, D., Y. Levi, B. Lourie, and S. H. Teoh (2018). Decision fatigue and heuristic analyst forecasts. Working paper.

[13] Corwin, S. A., S. A. Larocque, and M. A. Stegemoller (2017). Investment banking relationships and analyst affiliation bias: The impact of the global settlement on sanctioned and non-sanctioned banks. Journal of Financial Economics, 124 (3), 614-631.

[14] Fama, Eugene (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. Journal of Finance, 25 (2), 383-417.

[15] Barber, Brad, Reuven Lehavy, Maureen McNichols, and Brett Trueman (2001). Can investors profit from the prophets? Security analyst recommendations and stock returns, Journal of Finance, 56 (2), 531-563.

[16] Fama E. F. and K. R. French (1989). Business conditions and expected returns on stocks and bonds, Journal of Financial Economics 25, 23-49.

[17] Li, Y., D. Ng, and B. Swaminathan (2013). Predicting market returns using aggregate implied cost of capital, Journal of Financial Economics, 110 (2), 419-436.

[18] Hansen, Lars Peter (1982). Large Sample Properties of Generalized Method of Moments Estimators, Econometrica, 50(4), 1029-1054.

[19] Richardson, M. and J.H. Stock (1989). Drawing inferences from statistics based on multiyear asset returns, Journal of Financial Economics 25, 323-348.

[20] Azevedo, Vitor and Sebastian Müller (2020). Analyst Recommendations and Anomalies Across the Globe, working paper.

[21] Coleman, Braiden , Kenneth J. Merkley, and Joseph Pacelli (2021). Human versus Machine: A Comparison of Robo-Analyst and Traditional Research Analyst Investment Recommendations, working paper.

[22] Dong, Yi and Nan Hu (2016). The Impact of NASD Rule 2711 and NYSE Rule 472 on Analyst Behavior: The Strategic Timing of Recommendations Issued on Weekends, Journal of Business Finance & Accounting, 43 (7-8), 950-975.

[23] Park, Sung Jun and Ki Young Park (2018). Can Investors Profit from Security Analyst Recommendations? working paper.

[24] Chemmanur Thomas J., Igor Karagodsky and Francesca Toscano (2020). Incentives, Clienteles, and Information Production: New Evidence from Investor-paid and Issuer-Paid Agency Credit Ratings and Equity Analyst Recommendations, working paper.