Do Educational Background and Macro Shocks Impact the Performance of Sell-Side Research Analysts in the Energy Sector?

Fahim Rahmani

A Thesis
In
The Department of Finance

Presented in Partial Fulfillment of the Requirements
For the Degree of Master of Science (Finance) at
Concordia University
Montreal, Quebec, Canada

May 2020

CONCORDIA UNIVERSITY

School of Graduate Studies

This is to certify that the thesis prepared

By: Fahim Rahmani

Entitled: Do Educational Background and Macro Shocks Impact the Performance of Sell-Side Research Analysts in the Energy Sector?

and submitted in partial fulfillment of the requirements for the degree of

Master of Science (Finance)

complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the final Examining Committee:

______________________________ Chair

Chair's name

______________________________ Co-Supervisor

Lawrence J. Kryzanowski

______________________________ Co-Supervisor

David Newton

______________________________ Examiner

Gregory J. Lypny

Approved by ____

Dr. Nilanjan Basu, Graduate Program Director

May 4, 2020 ____

Dr. Anne-Marie Croteau, Dean of Faculty

Abstract

Do Educational Background and Macro Shocks Impact the Performance of Sell-Side Research Analysts in the Energy Sector?

Fahim Rahmani

This thesis explores the performance of sell-side equity research analysts in the energy sector, specifically how the educational background of these analysts affects the accuracy of their forecasts of earnings per share. I further examine how macro-economic shocks impact forecasting accuracy by conducting difference-in-differences regressions. Finally, I also briefly examine herding, documenting how educational background affects this behaviour. This thesis expands on the literature of sell-side analyst performance, while addressing a topic, education, which few academic papers cover. I also offer insights on analyst behaviour and performance during significant macroeconomic shocks to provide a more complete narrative of the work of sell-side equity research analysts. The thesis limits its scope on equity analysts to those covering the energy sector between 2009 and 2017.

Acknowledgements

I would like to express my deepest gratitude to Professors Lawrence Kryzanowski and David Newton, my thesis co-supervisors, particularly for their patience and guidance. Both Professors spent a lot of their time and effort to guide me in this process and tackle any challenges I faced along the way. Without their persistent help and supervision, I cannot imagine the fruition of this project. I would further like to thank Professor Gregory Lypny, the third thesis committee member for my defense, for his direction and support. Professor Lypny was able to join at a critical moment of the writing process and provide necessary feedback to improve and ultimately, finalize this project.

I would also like to thank my friends and family for their unwavering support and motivation throughout my years of study and throughout the process of researching and writing this thesis.

I would finally like to thank my boss and coworkers who allowed me to take the necessary time off in order to complete this project. Their understanding and support allowed me the much needed time to complete this thesis in a timelier manner. Thank you.

Table of Contents

List of Tables and Figures

1. <u>Introduction</u>

The performance of equity research analysts has been studied extensively over the past few decades. Researchers have tried to identify factors that allow analysts to offer more accurate earnings estimates. Studies range from gender to company resources to the work experience of analysts, and to a more limited extent to educational background and industry experience (discussed more fully in Section 2). Barber & Odean (2001) show that individuals from different career backgrounds perform differently in their personal portfolios based on characteristics that help them perform well in their own industries. A common question that arises for equity research desks is whether to hire an analyst with industry experience or with financial knowledge if a choice must be made between the two. This thesis seeks to examine the relation between the forecast performance of equity research analysts and analyst characteristics such as education. I ask whether the educational background of an analyst has any impact on the analyst's forecasting accuracy for U.S. energy stocks included in the S&P 500 from 2009 to 2017. I assess the impact of educational backgrounds on the relative forecasting errors of equity analysts and analyst herding behaviour as captured by relative forecasting optimism. I also analyze the impact of quasi-natural shocks at the macro level on the consensus forecasting accuracy of analysts for untreated and treated samples by industry or the educational background of analysts to assess another dimension of analyst performance.

This thesis is divided into several sections. I begin with a literature review in Section 2 that covers the educational impact on financial management, equity analyst performance, analyst education and experience, profiles based on profession and education, analyst compensation impacts and herding behavior. In Section 3, I formulate my testable hypotheses. This is followed by a description of the sample and data collection in Section 4 and the methodology in Section 5. Section 6 reports the results and discusses them. This is followed by concluding remarks.

2. <u>Literature Review</u>

2.1 *Education and Fund Managers*

Most of the literature pertaining to the impact of educational background on capital market performance considers the abilities of fund managers rather than equity analysts. Shukla

& Singh (1994) examine if the educational backgrounds of mutual fund managers is a factor that explains performance differentials by testing whether CFA (Chartered Financial Analysts) outperform their non-CFA peers. They find that while CFA-managed funds performed better based on risk-adjusted metrics (namely Sharpe, Treynor and Jensen's alpha), the difference is not statistically significant. However, the study did find significant differences in risk management. The CFA-managed portfolios were riskier but better diversified.

Andreu & Puetz (2017) consider whether having more degrees translates to better fund management performance. They question whether managers who spend time and money to earn an additional degree truly receive marginal benefits. Comparing managers with both a MBA and a CFA to those with only one of these, the authors find that managers with two degrees take fewer risks and follow less extreme investment styles, leading them to manage funds with less extreme performance outcomes based on risk management proxies like return volatility, market beta, unsystematic risk and tracking error. Managers with more than one degree do not earn higher returns for their funds as measured by the Jensen's alphas of their funds. These results seem consistent with the idea that personal risk attitudes dominate educational attainment for investment decisions.

While managers with superior education do not deliver higher returns, those with superior education do seem to show a better capacity to manage risk. This may be due to the added time spent learning technical concepts taught in these programs. However, there is no compelling evidence that more education helps managers earn higher fund returns. Collectively, this research provides some basis that education has an impact on financial decision making. In this thesis, I ask if this might be the case for those industry professionals primarily involved in financial forecasting.

2.2 *Equity Analyst Performance*

Bradley, Gokkaya, Liu & Wie (2017) study the effect of previous industry experience on forecasting ability based on the conjecture that pre-analyst experience is of critical importance in monitoring a particular stock. Their results show that possessing past industry experience allows analysts to be better equipped at identifying strategies that do not add value to shareholders (namely managerial concerns). Their study illustrates the importance of diverse professional backgrounds and work experience in the fields that the analysts follow.

Clement (1999) studies how ability (as measured by experience), resources (as measured by employer size) and portfolio complexity (as measured by the number of stocks covered) affect the forecast accuracy of analysts. His findings suggest that analysts with more experience, that work for larger employers and that cover fewer stocks have, on average, smaller forecast errors. Clement's study shows the importance that analyst characteristics have on determining forecasting ability in addition to providing a rationale for the inclusion of some control variables that may impact performance studies. Mikhail, Walther & Willis (1997) also report that forecasting ability consequently improves as analyst experience increases.

Kumar (2009) analyzes the differences in forecasting abilities based on gender. Kumar finds that in a male-dominated industry where approximately 16% of analysts are women, that women that are most likely to enter this job market show superior forecasting skills because of a self-selection bias. According to Eckel & Grossman (2008), Halek & Eisenhauer (2001) and Hartog, Ferrer-i-Carbonell & Jonker (2003) women are more risk averse and less competitive than men. Consequently, women are less likely to become financial analysts than men, but the ones that do are believed to be a better fit for the job and more likely to succeed. Evidence of this is that female analysts tend to issue bolder and more accurate forecasts than those issued by men. Thus, Kumar's paper demonstrates the effect of self-selection bias and how it can create asymmetric skill levels in equity analysis. This suggests that analysts that do not fit the stylized mold of an equity analyst may outperform those that do.

Yates, McDaniel & Brown (1991) compare the forecasting abilities of undergraduate students to graduate (MBA) students. They report that although both parties had poor forecasting abilities, undergraduate students outperformed graduate students, suggesting an "inverted" expertise effect. The authors attribute this result to graduate students being more likely to issue forecasts that differ from stock to stock, instead of issuing an almost general forecast, and responding to cues they thought were predictive when they were not. This was explained by the conjecture that semi-experts (i.e. graduate students) were more likely to have knowledge about more weak cues than undergraduate students, but lacking the necessary feedback mechanisms to correct for any issues with those cues. Thus, the forecasts of MBA students are more likely to be affected by noise, reducing their overall accuracy. Their study complemented the work of Von Holstein (1972) which found that, in terms of forecast accuracy, statisticians outperformed stock market experts, who outperformed university business students, who outperformed university business teachers who outperformed bankers.

Kim, Nekrasov, Shroff & Simon (2012) study if analysts are able to correctly undo the effects of accounting conservatism that may alter the accuracy of forecasted earnings. Adjusting for conservatism in estimates ensures that analysts focus more on core earnings rather than one-time events that may distort the predictability of sustainable earnings. The authors find that only sophisticated analysts deal with this aspect in their reports. The authors define sophisticated analysts by their knowledge and the ability to use more rigorous valuation models such as the DCF, residual income model and valuation multiples. Thus, analysts with deeper knowledge of model intricacies can rely less on valuation heuristics and use the appropriate model to account for exceptional earnings adjustments. For this study, the results may suggest that analysts with a formal financial education are potentially more capable of correcting for conservatism bias and thus might provide more accurate forecasts.

2.3 *Analyst Experience/Education*

Kaden, Madureira, Wang & Zach (2012) explore the industry experience of analysts and the impact of such experience on forecasts. Their study finds that analyst recommendations are enhanced when company-specific material and industry expertise are utilized because they both provide distinct but complementary information. They note an interesting finding that firm recommendations may not coincide with the general industry outlook of a firm. Bradshaw, Drake, Myers & Myers (2012) discuss and generally support the findings of Kaden, Madureira, Wang & Zach. Comparing the bottom-up approach to a top-down analysis, they conclude that research analysts suffer from a myopic view, where analysts may offer "buy" recommendations for a firm, but then suggest a "sell" position for the overall industry. Many analysts with limited industry knowledge focus on ranking firms within their respective sectors instead of developing a recommendation for the firm as a part of the overall stock market.

2.4 *Herding*

Herding is a behavioural heuristic that has sustained popularity in the financial literature. Herding revolves around the social pressure to conform. Bikhchandani, Hirshleifer, & Welch (2006) and Welch (1999) find that herding is strongly caused by informational effects, sanctions against deviants, payoff externalities and conformity. All investors deal with the issue of information asymmetry; we follow others when we think they know something we do not, and we are afraid of missing out. Given the belief that the first investor may know something that is unknown to the second investor, the second investor may decide to "herd", or follow the actions of the first investor based solely on that belief. The question I pose in the thesis is whether certain educational majors (Finance, Economics, Engineering, etc.) are more likely to herd in terms of their forecasts due to differences in their schooling.

Bikhchandani et al. (2006) also argue that employers inadvertently create an environment that dissuades investors from straying away from the herd. Much like animals that stay in herds to avoid detection from predators, investors and analysts may herd to avoid detection or replication as well. For example, if a fund manager takes a contrarian position from the general consensus on an asset and then earns a gain, the manager would be praised for the manager's success. In contrast, if the fund suffers a loss, its manager would be criticized for taking an opposing view from the public. Furthermore, if a manager takes a position in conformity with the market consensus, then he/she would receive praise in the eventuality of a success, but, in the event of a loss, the manager would be able to hide in the herd of other losing fund managers and not be singled out for criticism. If a manager's job or level of compensation depends on fund performance, then it is understandable as to why a fund manager would prefer to keep with the herd than to try to stand out. Similarly, Sharfstein & Stein (1990) argue that herding may be a rational behaviour for managers that are concerned with their reputations. Those managers would prefer to "share the blame" rather than bear the risk of being singled out. Bikchandani et al. (2006) also find that labor markets have a deep impact on herding behaviour. Herding is incited in labor markets with fewer opportunities and markets with bigger negative consequences in the event of a loss. Olsen (1996) supports these findings and adds that herding among analysts is due to an innate human desire for consensus (i.e. comfort in numbers).

Groysberg, Healy & Maber (2011) associate the compensation of research analysts to a Mirrlees-type contract. In other words, under a normal set of circumstances, analyst compensation is unrelated to performance, but in adverse forecasting situations, such as if an analyst were to stray away from the herd and publish a significantly different result, the probability of employment termination increases. Yet, more accurate analysts may have more opportunities to transition to a larger and higher status firm. Therefore, for an average research analyst, increased forecasting accuracy will not offer higher compensation, except in the case where it helps the said analyst to get formally lauded in a widely-recognized ranking, or in the case of job transitioning, but having larger relative forecast errors than your peers will increase the probability of dismissal.

Jegadesh & Kim (2007) examine the herding behaviour of security analysts. They find that more established analysts, with more experience and that work for large brokerage firms, are more likely to herd than newcomers. A possible interpretation of these results may be the presence of a jaded mentality. It may also be that analysts from larger firms have more at stake, given higher expectations of performance relative to those analysts at small, unknown firms, and are thus more prone to herd. Clement & Tse (2005) find that analyst boldness increases with prior accuracy, brokerage size and experience but decreases with the number of industries the analyst follows. Clement & Tse also find that analysts least likely to herd are more accurate because their recommendations contain more private information. This presents an interesting dichotomy for the employer that seeks the highest level of quality from the work of his employees. On the one hand the employer desires analysts who resist herding temptations as they appear most accurate in these conditions, but at the same time these employers create herding incentives due to the fact that analysts are not willing to stand out and risk being punished for negative performance.

3. Hypotheses

Building on the previous literature and available information, I address the following questions in the remainder of the thesis.

1. Does educational background impact the relative earnings forecast accuracy of sell-side equity research analysts?

Specifically, I ask whether analysts that have relevant industry education, such as engineering graduates, are more accurate than analysts with finance or other business majors in analyzing energy stocks. I use the initial and final published estimates of quarterly earnings by my sampled analysts to assess how accuracy changes as the period to the release of actual earnings gets closer.

Shukla & Singh (1994), Andreu & Puetz (2017), Dincer, Gregory-Allen & Shawky (2010) test how fund managers with different education levels perform while Yates, McDaniel & Brown (1991) test the performance of students with different levels of education and Von Holstein (1972) tests the forecasting performance of different professions. In a similar vein, I am interested in whether the added effort of getting a CFA title, graduate or doctoral degree provides benefits to equity researchers in terms of accuracy. Thus, my second hypothesis is:

2. Does having a higher degree of education, i.e. having a graduate or doctoral degree or CFA membership, improve the quarterly earnings forecast accuracy of sell-side equity research analysts?

The third hypothesis seeks to determine how quasi-natural macro shocks impact the accuracy of equity research analysts to consider how forecasting performance varies in different macroeconomic scenarios. Using the difference-in-differences regression method, I ask the following question:

3. Is the relative earnings forecast accuracy of equity research analysts, conditional or unconditional on their educational background, affected by quasi-natural macro shocks?

Finally, I consider the literature on analyst compensation and herding as previously reviewed to develop the final hypothesis:

4. Is forecasting accuracy of equity research analysts positively related to the consensus estimates?

4. Sample and Data Collection

My sample of stocks is confined to energy firms, denoted by the GICS code 1010, that were part of the S&P 500 between 2009 and 2017. All the firms had a December 31 fiscal year end.

Given the technical nature of the energy industry and the need for a strong understanding of the mechanics and science behind the operations of the firms in this industry, heterogeneity in the education of the analysts following these firms can plausibly lead to heterogeneous comprehensions of firm operations and their effects on earnings. Since no current dataset provides personal analyst information, the analyst names from IBES were used to search and find equity analyst bios, which were then hand-collected from a combination of Bloomberg LP, Thomson Reuters and LinkedIn profiles until a sample of 203 analysts was collected. These sources provided information on the analyst's gender, undergraduate degrees, graduate degrees, doctoral degrees and CFA memberships which were organized into dummy variables to be used for the analysis conducted in the thesis. Analysts with engineering, physics and chemistry majors were placed in the Engineering group, analysts with economics degrees were placed in the Economics group, analysts with finance degrees were placed in the Finance group, other business majors, such as marketing and management, were put in the Business Group and the rest were put in the Other group. Some of these majors include non-technical and non-business disciplines such as history, anthropology, psychology, and political science. I collected firm EPS values and the published estimates for these analysts from the Institutional Brokers' Estimate System (IBES). I collect both the initial and final estimates to track how forecasts change over time for different educational backgrounds.

Other variables were manually calculated, such as work experience, stock specific work experience, number of analysts covering the selected stocks, number of days the forecast was published before the end of the quarter and number of stocks covered by a given analyst. Experience was calculated by measuring the difference between the earliest and latest published quarterly earnings estimates of each analyst. The number of analysts covering a given stock was found by counting the number of analysts publishing an estimate on a stock during a specific quarter. The number of days the forecast was published was measured by finding the difference between the date of the quarter end and the date the forecast was published. Coverage was measured by counting the number of estimates for separate stocks published for each quarter. Stock market capitalization, used to account for the effect that firm size could have on forecasting accuracy, measured in billions of USD (U.S. Dollars), was provided by Compustat.

Macroeconomic data were also employed in my analysis. The West Texas Intermediate (WTI) futures return, considered to be one of the staple benchmarks for oil price return in the NYMEX, was taken from the St. Louis Fed database. The CBOE Volatility Index (VIX) return was gathered from the Chicago Board of Exchange. The VIX is a key measure of investor sentiment of near-term volatility conveyed by the S&P 500 stock index option prices.

5. Methodology

To compare analyst performance based on education, I create a variable that measures performance on a relative scale. Using the same methodology as Clement (1999), Dreman & Berry (1995), Higgins (1998), Jacob, Rock & Weber (2008) and Kumar (2009), a proportional mean absolute relative forecast error ($PMAFE_{ijt}$) is calculated for the forecast of each analyst for a stock for each fiscal quarter. Using a relative accuracy measure as opposed to an absolute measure allows us to standardize the accuracy of analysts. Each $PMAFE_{ijt}$ was calculated as follows:

$$PMAFE_{ijt} = (AFE_{ijt} - \overline{\text{AFE}}_{\text{it}}) / \overline{\text{AFE}}_{\text{it}} \quad (1)$$

Where AFE_{ijt} is the absolute forecast error for analyst *i* for stock *j* for quarter *t* whose calculation is given by:

$$AFE_{ijt} = \frac{1}{n} \sum Forecast\ Error_{ijt} \quad (2)$$

Where $\overline{\text{AFE}}_{\text{it}}$ is the mean absolute forecast error for analyst *i* for stock *j* for quarter *t* and is found by taking the mean of AFE_{ijt} for all analysts that made forecasts for stock *j* for quarter *t*.

Clement (1998) finds that the difference between $\overline{\text{AFE}}_{\text{it}}$ and AFE_{ijt} is more volatile for large EPS firms than for small EPS firms. Accordingly, dividing the difference by $\overline{\text{AFE}}_{\text{it}}$ reduces heteroscedasticity. The $PMAFE_{ijt}$ then becomes the dependent variable in some of my segmented regressions that are used to analyze educational impact on forecast accuracy.

I use a Generalized Least Squares Estimation using element-wise or segmented, regressions to test hypotheses 1, 2 and 4. This method fits a linear model for the data. Using an element-wise regression rather than a simple multiple linear regression accounts for residual dependence in the model and is therefore more robust to heteroscedasticity. The reason is that the procedure assumes that regression coefficients are similar across clusters, or primary sampling units (PSUs), but may exhibit differences between PSUs. The first PSU adjusts for systematic concerns coming from different stocks, the second PSU by analyst, and the final PSU accounts for time between a forecast of earnings and the disclosure of actual earnings. The first regression specification tested is:

$$PMAFE_{ijt} \\ = f\ [\ ENG_{it}, ECON_{it}, FIN_{it}, BUS_{it}, GRAD_{it},\ \ CFA_{it}, PHD_{it}, COV_{ijt}, EXP_{it}, EXPCO_{ijt}, \\ DAYS_{ijt}, VIX_t\ , Mkt\_Cap_{ijt}, WTI_t, NoAnalysts_{jt}, FY_{10\ldots17} + \varepsilon_{ijt}] \quad (3)$$

I modify the regressions using first the PSU by grouping educational backgrounds together to search for other potential relationships. Namely, my groupings are all non-finance business majors; Economics or Business majors; Engineers with CFA memberships; and Non-Finance Business majors with CFA titles. I consider that these groups highlight diverse educational backgrounds and offer potentially interesting results. I run the following regression with these groupings:

$$PMAFE_{ijt} = f\ [\ ENG_{it}, ECONorBUS_{it}, ENG\&CFA_{it}, ECONorBUS\&CFA_{it}, GRAD_{it}, \\ CFA_{it}, PHD_{it}, COV_{ijt}, EXP_{it}, EXPCO_{ijt}, \\ DAYS_{ijt}, VIX_t\ , Mkt\_Cap_{ijt}, WTI_t, NoAnalysts_{jt}, FY_{10\ldots17} + \varepsilon_{ijt}] \quad (4)$$

I further analyze how Economics or Finance degrees and Economics or Finance degrees with CFA memberships perform in terms of forecast accuracy relative to their counterparts using the following regression:

$$PMAFE_{ijt} \\ = f\ [\ \ ECONorFIN_{it},\ ECONorFIN\&CFA_{it}, CFA_{it}, COV_{ijt}, EXP_{it}, EXPCO_{ijt}, DAYS_{ijt}, \\ VIX_t\ , Mkt\_Cap_{ijt}, WTI_t, Days,\ NoAnalysts_{jt}, FY_{10\ldots17} + \varepsilon_{ijt}] \quad (5)$$

I define the variables used in equations (1) through (5) in Table 1.

5.1 ***Difference-in-differences***

In this section of the thesis, I use the Difference-in-Differences, or DiD, method to test the hypothesis that quasi-natural macro-level shocks to the energy industry affect $PMAFE_{ijt}$. My methodology is similar to that of Butler & Cornaggia (2008), Wu & Zang (2009), Hong & Kacperczyk (2010), Merkley, Michaely & Pacielli (2013), Chen, Harford & Lin (2015) and Dyck et al. (2019). DiD allows us to better isolate the impact of quasi-natural (exogenous) shocks that occur to the industry on the $PMAFE_{ijt}$ over time. For these tests, I use Verleger's (2019) article that identifies oil disruptions between 1973 and 2018.

To be considered a global oil market disruption, an event must create a material impact on supply and/or price of oil, measured by the price of Brent Crude futures. Given that only three events occur in my sampled period, namely the Collapse of Libyan production (January 2011), the Second Libyan collapse (July 2014) and the 2017 OPEC production cut (January 2017), I use these three events to test the impact of these shocks on the consensus forecasting accuracy of my sample of energy analysts. Using a two-period model to test the impact of the quasi-natural shocks, I emulate Dyck et al. (2019) by creating an average of the $PMAFE_{ijt}$ before and after the shocks, called $PMAVG_{ijt}$, which addresses any autocorrelation in the $PMAFE_{ijt}$. The DiD model without an indicator variable is given by:

$$y_{it} = \beta_0 + \beta_1 Post\ Event + \epsilon_{it\varepsilon} \tag{6}$$

Energy companies in the S&P500 operate in different parts of the supply chain of the industry. Arguments can be made that significant variations in oil prices have a systematic effect on the EPS for all firms, or that certain firms are more at risk to such shocks given the nature of their operations. Dyck et al. (2019) use the Sector Industry Classification as their indicator variable to separate their sample into treated and control firms. Similarly, I use the Global Industry Classification Standard (GICS) for such a separation. The energy industry group can be sub-divided into two industries: Energy, Equipment & Services; and Oil, Gas & Consumable Fuels. This provides my first separating factor for the indicator variable. These two industries can be further split into seven sub-industries: Oil & Gas Drilling; Oil & Gas Equipment & Services; Integrated Oil & Gas; Oil & Gas Exploration & Production; Oil & Gas Refining & Marketing; Oil & Gas Transportation; and Coal & Consumable Fuels. From among these seven sub-industries, I consider Integrated Oil & Gas, Oil & Gas Exploration & Production, and Oil & Gas Refining & Marketing to be potentially the more volatile sub-industries for a given quasi-natural shock. Consequently, I use firms in these groups, initially separate, and then unified as my treated group for further DiD tests. My generic model for these DiD tests is as follows:

$$y_{it} = \beta_0 + \beta_1 Post\ Event + \beta_2 SEP_{it} + \beta_3 SEP_{it} * Post\ Event + \epsilon_{it\varepsilon} \tag{7}$$

I define the variables used in equations (6) and (7) in Table 1.

5.2 *Persistence of Differences between Analyst and Consensus Forecasts*

To analyze the persistence of differences between analyst and consensus forecast accuracies I use a new dependent variable, as in Chung & Kryzanowski (1999), Jacob et al. (1999), Clement (1999), Hong & Kubik (2003), Cowen, Groysberg & Healy (2006) and Hilary & Hsu (2013). The variable is the Relative Forecast OPTimism ($RFOPT_{ijt}$) for analyst *i* for stock *j* for quarter *t*. Unlike other measures of forecast accuracy, $RFOPT_{ijt}$ provides an unambiguous directional measure of relative accuracy where larger values indicate less standardized accuracy. $RFOPT_{ijt}$ is computed using:

$$RFOPT_{ijt} = (AFE_{ijt} - \overline{\mathrm{AFE}}_{\mathrm{it}}) / \sigma(AFE_{jt}) \quad (8)$$

Comparisons based on analyst, stock and quarter allows me to control for any company-specific or time-specific factors that can affect standardized analyst optimism or pessimism. The numerator ($AFE_{ijt} - \overline{\mathrm{AFE}}_{\mathrm{it}}$) of equation (8) gives the consensus-adjusted forecast accuracy for each analyst *i* for stock *j* during quarter *t*. The denominator of equation (8), $\sigma(AFE_{jt})$, standardizes the consensus-adjusted forecast accuracy across time by deflating the numerator by the standard deviation of the forecast accuracies of all analysts for stock *j* for quarter *t*.

I measure how RFOPT is related to an analyst's previous relative forecast accuracy by using a 4-quarter moving average of $PMAFE_{ijt}$. For this test, I use:

$$RFOPT_{ijt} = f\ [GENDER_{ijt}, ENG_{ijt}, ECON_{ijt}, FIN_{ijt}, BUS_{ijt}, GRAD_{ijt}, CFA_{ijt}, PHD_{ijt}, COV_{ijt}, EXP_{ijt}, EXPCO_{ijt}, DAYS_{ijt}, VIX_t, Mkt\_Cap_{it}, WTI_t, Days, MA_{jt}, FY_{10\ldots17} + \varepsilon_{ijt}] \quad (9)$$

Where all the variables are as defined in Table 1.

Moreover, I use the same three PSUs used in earlier regressions to test for the persistence of differences between analyst and consensus forecast accuracies, namely:

$$RFOPT_{ijt} = f\ [ENG_{it},\ ECONorBUS_{it},\ ENG\&CFA_{it},\ ECONorBUS\&CFA_{it}, CFA_{it}, COV_{ijt}, EXP_{it}, EXPCO_{ijt}, DAYS_{ijt}, VIX_t, Mkt\_Cap_{ijt}, WTI_t, Days,\ MA_{jt}, NoAnalysts_{jt}, FY_{11\ldots17} + \varepsilon_{ijt}] \quad (10)$$

and

$$RFOPT_{ijt} = f\ [\ ECONorFIN_{ijt},\ ECONorFIN\&CFA_{ijt}, CFA_{it}, COV_{ijt}, EXP_{ijt}, EXPCO_{ijt}, DAYS_{ijt}, VIX_t\ , Mkt\_Cap_{ijt}, WTI_t, Days,\ MA_{ijt}, NoAnalysts_{jt}, FY_{10\ldots17} + \varepsilon_{ijt}] \qquad (11)$$

I define the variables in equations (8), (9), (10) and (11) in Table 1.

5.3 Methodology for Tests of the Herding Hypothesis

I explore the methodology used to determine the presence of herding in this section. I define herding as the behavior of analysts to publish estimates close to the consensus estimates. I assume that analysts who issue estimates not dissimilar to the consensus are following the "herd", while those that issue bolder forecasts rely more on their own intuition.

Referencing Salamouris & Muradoglu (2010), I create a herding variable that calculates the absolute value of the difference between an estimate published by an analyst for a certain stock at a specific end of quarter period and the consensus estimate of all other analysts covering the same stock at that point in time, which is given by:

$$HM_{ijt} = |F_{ijt} - \bar{F}_{\text{jt}}| \qquad (12)$$

HM_{ijt} is included as an independent variable in equation (13) to track how herding impacts the performance of analysts. In addition, I also include new variables that consist of the product of dummy education variables and HM_{ijt}. These new variables will help determine herding behaviour across different educational backgrounds. I define the new variables in Table 1.

$$|RFOPT_{ijt}| = f\ [\ ENG \times HM_{ijt},\ ECONorFIN\&CFA \times HM_{it},\ GRAD \times HM_{ijt}, PhD \times HM_{ijt}\ ,\ HM_{ijt} +\ \ \varepsilon_{ijt}\ ] \qquad (13)$$

6. <u>Empirical Results</u>

I report the frequency of occurrence of each educational variable in my selected sample in Table 3. In some cases, analysts' education fits several categories, such as in the event of an analyst having completed a double major. I therefore count the analyst in both categories, as the analyst benefits from the knowledge and experience of both majors. Unsurprisingly, economics and finance majors are most common for equity research analysts. I also find that a majority of my sample analysts attended graduate school (58%), but only 2% completed a doctorate degree. Analyzing the untabulated descriptive statistics for work-related variables, I find that the average analyst simultaneously covers 19 stocks, has 9.90 years of experience as an analyst and has 6.38 years of experience covering the sampled stocks. I also find that analysts, on average, publish their initial estimates 280 days before the end date for a quarterly forecast, or three quarters beforehand as most analysts forecast quarterly earnings three quarters in advance, and their final estimate for a quarterly forecast, on average, 50 days before the end of the quarter, or less than one quarter beforehand.

6.1 *General Regression*

I present the results from conducting a series of regressions using each of the three PSUs in Tables 4 and 5. These regressions use the initial (Table 4) and final (Table 5) estimates of $PMAFE_{ijt}$ as the dependent variable and include dummy variables representing all the educational degrees.

I find very few significant variables in Table 4. When segmenting by stock and forecast date, engineers have a higher proportional forecast error at 5%, meaning that they perform worse than their peers. Analysts with higher coverage also have higher forecast errors. I deduce that an analyst covering more stocks is more time constrained, which may affect his or her accuracy. Interestingly, analysts with more experience covering a stock perform worse than their counterparts. This result does not support the previous literature that analysts with more experience perform better on a relative scale. However, this may be due to the industry and time period that I examine in this thesis. I also find, as expected, that the earlier the estimate is published, as estimated by the "Days" variable, the larger the forecast error.

Based on Table 5, I find few significant results again when I examine the final estimates of the quarterly earnings made by analysts. For example, only the variable Economics is significant for choice of a major, indicating that economists perform worse than their peers, but in only the regression specification with variables clustered at the stock level. I do, however, find that analysts with graduate degrees provide less accurate forecasts when segmenting the independent variables on stock as well as forecast dates. This result partially corroborates the findings of Yates, McDaniel & Brown (1991) that find that graduate students are inferior forecasters. Again, analysts with higher stock-specific experience perform worse, although overall experience does not seem to have any significant impact. Days to forecast to the end quarter, again shows a positive relationship with $PMAFE_{ijt}$. This implies that the further away the forecast date is from the end period (i.e. when the actual earnings for the quarter are released), the larger is the forecast error. Both the market cap and VIX variables show some inverse significance to $PMAFE_{ijt}$, meaning that smaller firms and less expected market volatility are associated with lower forecast errors.

Next, I group some educational backgrounds together to see how this affects the regression results. Here, I group economics students with business students, economics or business students with the CFA title, and engineers with the CFA title. Table 6 reports the results for the forecast errors using the initial forecasts for the Engineers with CFA titles, and the Non-Finance Business majors with and without CFA titles. I find no significant results for Engineers with or without CFA memberships, but I do find one result for Non-Finance Business majors without a CFA who perform worse when clustered by Forecast Date, and three significant results for Non-Finance Business majors with CFA titles. Interestingly, Non-Finance Business majors with CFAs perform worse than their counterparts, despite their diverse educational backgrounds. I find results for the Coverage, Experience Company and Days variables that are consistent with my previous findings.

While Engineers and Non-Finance Business majors without CFA titles show no significant variation in performance in Table 7, Engineers and Non-Finance Business majors with CFA titles significantly do worse and analysts with CFA titles that do not have these two types of majors do significantly better (lower $PMAFE_{ijt}$). The results are somewhat unexpected because analysts with, for example, an engineering degree and a CFA title have a more diverse education and therefore a larger pool of information from which to draw on to provide meaningful forecasts. Firms with smaller market caps seem easier to forecast but only significantly in one of the three regressions. Similarly, I observe more accurate forecasts during periods where the market expects near-term volatility but significance is obtained in only two of the three regressions. I find no additional significant values using the initial (final) estimates of earnings when I group Finance majors with Economics majors with and without CFA titles in Table 8 (Table 8).

Tables 4 through 9 were implemented to test my first two hypotheses, which are:

1. Does educational background impact the relative accuracy of sell-side equity research analysts?
2. Does having a higher degree of education, i.e. having a graduate or doctoral degree or CFA title, improve the accuracy of sell-side equity research analysts for the energy sector?

Overall, I find little supporting evidence that educational background has any significant impact on the quarterly earnings forecast performance of equity research analysts in the energy sector. The few exceptions include Engineers with or without CFA titles and Non-Finance Business majors with CFA titles that sometimes perform worse depending on the choice of data clustering. Similarly, additional education past an undergraduate degree rarely shows any significant value in terms of better forecast accuracy of quarterly earnings; except for analysts with CFA titles that outperformed their counterparts (see Table 7). In fact, analysts with graduate degrees underperformed (see Table 5), supporting the findings of Yates, McDaniel & Brown (1991).

6.2 Difference-In-Differences Analysis

We now address the third previously asked question: Are the earnings forecasts of equity analysts affected by quasi-natural shocks at the macro level? I test this hypothesis by using the Difference-in-Differences method, which I conduct initially with no separator variable, then using educational degrees as my separator and finally industry sectors as my separators.

Before proceeding I acknowledge that an important assumption for the validity of a DiD analysis is the parallel trend assumption which implies that the time series of outcomes in the treated and control group should differ by a fixed amount in every period and should exhibit a common set of period-specific changes in the periods prior to the shock. Unfortunately, there is no definitive test to examine the validity of this assumption for a two-group, two-period DiD. One common approach is to examine a plot of the values of the dependent variable in periods around the macro shock. Unfortunately, the inferential sturdiness of visual evidence is low for noisy data or short time series as this makes it difficult to separate genuine deviations from the common trends and statistical noise. This needs to be kept in mind when examining the plots presented in this thesis.

6.2.1 Absence of a Treatment Assignment Rule

Table 10 provides summary statistics for the forecast accuracy based on the initial and final earnings forecasts for each of the three oil price disruptions. I find low adj. R-Squares for my DiD models using initial forecasts of earnings that do not include a separator dummy variable. However, I do find a significant post-event dummy variable for two of the three events examined herein. My models show that forecast accuracy improved significantly after the second Libyan collapse, and worsened after the OPEC production cut. The results for the first Libyan collapse are significant but mixed, they indicate better and worse forecast accuracy using the initial and final forecasts of the analysts. As expected, earnings forecast accuracy deteriorates after the two Libyan collapses which increased uncertainty and improved after the OPEC production cut which increased market certainty. Thus, I find that forecast accuracy changes significantly after oil price disruptions but that the direction of the change depends upon the event being examined and to a lesser extent on whether the initial or final forecasts of the analysts are used.

6.2.2 Presence of a Treatment Assignment Rule Based on Analyst Education

In this section, I use a treatment assignment rule that separates the forecasts into treated and control groupings based on the education of the analysts to test the forecasting accuracy differences of equity analysts with different educational backgrounds. The variable of interest in all these regressions is the interacted term consisting of the separator dummy variable and the post-event dummy variable.

I first use business degrees as my separator to determine how earnings forecast accuracy is affected by the three quasi-natural shocks when the analysts are separated by their educational achievements. I find no significant changes in accuracy for the initial and final forecasts of analysts separated by their educational achievements (see GROUPED BUSINESS*POST EVENT in Table 11). I conclude that the change in the earnings forecast accuracy of analysts with business degrees is not significantly different than that of their peers after the three macro shocks to the energy industry.

My next set of models separates my sample of analysts based on whether their undergraduate degrees are in a Non-Finance Business major or not. Table 12 shows the results for the initial and final estimates of the forecast accuracy of the analysts for firm earnings. I find only one statistically significant interaction variable; namely for the initial forecasts of firm earnings for the OPEC Production Cut where the Non-Finance Business majors exhibit relatively poorer forecast accuracy after this macro shock. However, visual examination of Figure 1 shows that the DiD model appears to violate the parallel-trend assumption which may suggest that the causal effect may not be robust.

Next, I assess the performance of analysts with Economics or Finance majors and CFA titles (treated) compared to the remaining analysts (control) around the three quasi-natural shocks to oil prices. Table 13 shows that only analysts with Economics and Finance majors and CFAs have a significantly different performance for their initial estimates; better around the Second Libyan Collapse and worse for the OPEC production cut. However, I find no significant difference in the forecasting performance of analysts with Economics or Finance majors and CFA titles relative to their peers (ECON OR FINANCE&CFA*POST EVENT) in all six cases examined in Table 13.

6.2.3 Presence of a Treatment Assignment Rule Based on Industry Sectors and Sub-sectors

In this section, I replace educational backgrounds as the variable for separating the analysts' forecasts into treated and control groups using stocks grouped by industry and sub-sectors. I first split the stocks by GICS industry into Energy Equipment & Services (treated) or Oil, Gas & Consumable Fuels (control). Based on Table 14, I find that the forecasts for the Energy Equipment & Services companies were significantly less (more) accurate for initial (final) forecasts around the First Libyan Collapse. I find mixed significant differences in relative forecast accuracy between the treated and control groups in three of the six cases examined in Table 14. The final forecasts are significantly and relatively less accurate for the treated sample after both Libyan Collapses and the initial forecasts are significantly and relatively more accurate for the treated sample after the OPEC production cut. Figures 2 through 4 illustrate the average PMAFE for the control (0) and treatment (1) groups over three pre-shock and three post-shock periods for the final estimates during the Libyan Collapse 1, the final estimates during the Second Libyan Collapse, and the initial estimates during the OPEC Production Cut, respectively. Visual examination of Figures 2 and 3 appears to provide support for the parallel trend assumption and by extension for the DiD results for the final estimates during both Libyan Collapses. In contrast, a visual examination of Figure 4 does not appear to provide support for the parallel trend assumption around the OPEC Production Cut, which questions the robustness of the DiD results for this shock.

I now use three sub-industry identifiers as the separator variable. My first treated sample consists of stocks that fall into the Integrated Oil & Gas sub-industry. The results are reported in Table 15. I find the interaction variable to be statistically significant (and negative) for all three shocks using the final estimates of the analysts. This suggests that the earnings for Integrated Oil & Gas stocks (treated) are more accurately forecasted by the analysts compared to the control stocks after the occurrence of the three quasi-natural shocks at the macro level. I further analyze the robustness of these significant findings by testing the parallel trend assumption for all three shocks using final estimates. Figures 5 through 7 display the graphical representation of the dependent variables around these three shocks. I find that the assumption only appears to hold for one case, the Libyan Collapse 1.

I now use the Oil & Gas Exploration & Production stocks as the treatment group. I find significant interaction variables for four of the six cases reported in Table 16. The forecast accuracy for the treated group is relatively lower post-event for the final forecasts for the First Libyan Collapse and the OPEC Production Cut, relatively lower post-event for the initial forecasts for the OPEC Production Cut, and significantly better after the Second Libyan Collapse. Finally, I select the members of the Oil & Gas Refining & Marketing sub-group as the treatment group. I again find significant interaction variables for four of the six cases reported in Table 17. The forecast accuracy for the treated group is relatively lower post-event for the final forecasts for the First Libyan Collapse and the Second Libyan Collapse, and relatively better for the initial and final forecasts for the OPEC Production Cut.

In summary, there is some evidence that educational background and industry sub-group membership affects the forecasting accuracy of equity analysts in the event of a shock at the more macro level. However, I cannot identify any systematic direction in the changes in forecast accuracy around industry-specific shocks at the macro level.

6.3 ***Persistence of Differences between Analyst and Consensus Forecasts***

In this section, I present and discuss the results of my tests for the persistence of differences between analyst and consensus forecasts. As noted earlier, I use a moving average variable (MA) that tracks the moving average of $PMAFE_{ijt}$ over the preceding four periods in order to examine the persistence of the forecasts of analysts.

Table 18 reports the results for regression (9). I first observe that the MA variable is significant and positive in all three cases, suggesting that analyst forecasting performance is somewhat persistent over time. For the various educational classifications, I find that only analysts with PhD degrees have significantly different (negative) coefficient estimates, indicating more accurate forecasts. I also find a significant positive relation between RFOPT and the number of years an analyst has covered a specific stock, and the number of days between the date of an estimate and the release of actual earnings. I also notice a significant negative relation between RFOPT and a stock's market cap, the number of analysts covering a stock, the WTI returns, and the VIX (but not for the Forecast Date PSU).

Table 19 reports the results for regression (10) which examines persistence of forecast accuracy when the educational classifications of analysts are regrouped into analysts with Non-Finance Business majors with or without CFA titles and Engineering majors with or without CFA titles. I observe that the MA variable is significant and positive in all three cases, suggesting once again that analyst forecasting performance is somewhat persistent over time. For the various educational classifications, I find that analysts that are CFAs and do not have Engineering or Non-Finance Business degrees have significantly better standardized consensus-adjusted forecast accuracy. It also appears that analysts with Engineering or Non-Finance Business degrees that have CFAs have significantly worse standardized consensus-adjusted forecast accuracy. These results are consistent with my earlier results based on Tables 6 and 7 that show that analysts with CFA titles are more accurate and those with Engineering degrees and CFA titles or those with Non-Finance Business degrees and CFA titles fare worse. I also find a significant positive relation between RFOPT and the number of years an analyst has covered a specific stock, and the number of days between the date of an estimate and the release of actual earnings. I also observe a significant negative relation between RFOPT and a stock's market cap, the number of analysts covering a stock, and the VIX (not for the Forecast Date PSU). The coefficient for WTI is still negative but is now no longer significant.

Table 20 reports the results for regression (11) which examines the persistence of forecast accuracy when the educational areas of analysts are regrouped into analysts with Economics or

Finance majors with or without CFA titles. I observe once again that the MA variable is significant and positive in all three cases, suggesting that analyst forecasting performance is somewhat persistent over time. I find that analysts with either an Economics or Finance degree without a CFA designation have significantly better standardized consensus-adjusted forecast accuracy while those with a CFA designation have significantly worse standardized consensus-adjusted forecast accuracy. I find that the relations between the other independent variables and standardized consensus-adjusted forecast accuracy to be similar to what was found previously.

6.4 ***Herding Results***

In this final section, I discuss the results from running regression (13) that are shown in Table 21. I observe that the herding variable HM is statistically significant at 99% in all three PSU models. This result suggests that herding has a positive association with EPS forecasting accuracy, which supports the argument in favor of herding for research analysts with no formal education in finance, economics or engineering (i.e. analysts with general business or other unrelated educational backgrounds).

When I examine herding behaviour based on the educational background of analysts, I find that only two interaction variables show any statistical significance at conventional levels in my three models: Economics or Finance majors with CFA titles (Analyst PSU significant at 95%) and analysts with doctorate degrees (Stock and Analyst PSUs significant at 95%). Thus, the absolute forecast accuracy of analysts with either Economics or Finance degrees with a CFA designation are significantly and positively related with the absolute difference of the forecasts of the analyst from those of all other analysts for one of the three models, while the absolute forecast accuracy of analysts with a PhD degree are significantly and negative related with the absolute difference of the forecasts of the analyst from those of all other analysts for two of the three models.

7. Conclusion

This thesis examines the effects that educational background and shocks at the more macro industry level have on the forecasting accuracy of equity research analysts that covered US energy stocks after the 2008 sub-prime mortgage crisis. I find that educational background has a minimal impact on the relative earnings forecast accuracy of equity research analysts. I find little evidence that the education of analysts is associated with earnings forecast accuracy after three quasi-natural shocks but some evidence for the industry sub-sector for which forecasts are being made that in some cases is not likely to be robust because the parallel trend assumption appears to not be satisfied. My last set of tests find support that the forecast accuracy of analysts exhibits time-series persistence.

The reader should be careful in generalizing from the results reported in this thesis. Thesis limitations include the examination of forecast accuracy for only one industry and for a specific time period, and the possibility that omitted variables such as work experience outside of capital markets or within the industry itself may have materially affected the reported findings.

Bibliography

Ackerman, P.L. & Beier, M.E. (2003). Intelligence, personality, and interests in the career choice process. *Journal of Career Assessment, 11,* 205-218.

Andreu, L., & Puetz, A. (2017) Choosing two business degrees versus choosing one: What does it tell about mutual fund managers' investment behaviour? *Journal of Business Research, 75*, 138-146.

Barber. B.M., & Odean, T. (2001) Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics, Feb. 2001.* 261-292.

Bikhchandani, S., Hirshleifer, D. & Welch, I. (2006). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy, 100,* 992-1026.

Bradley, D., Gokkaya, S., Liu, X., & Wie, F. (2017). Are all analysts created equal? Industry expertise and monitoring effectiveness of financial analysts. *Journal of Accounting and Economics, 63,* 179-206.

Bradshaw, M.T., Drake, M.S., Myers, J.N. & Myers, L.A. (2012). A re-examination of analysts' superiority over time-series forecasts of annual earnings. *Review Of Accounting Studies, 17,* 944-968.

Butler, A. & Cornaggia, J. (2008). Does access to external finance improve productivity? Evidence from a natural experiment. *Journal of Financial Economics, 99,* 184-203.

Chen, T. Harford, J. & Lin, C. (2015). Do analysts matter for governance? Evidence from natural experiments. *Journal of Financial Economics, 115,* 383-410.

Chevalier, J., & Ellison, G. (1999). Are some mutual managers better than others? Cross-sectional patterns in behaviour and performance. *Journal of Finance, 54,* 874-899.

Chung, R., & Kryzanowski, L. (1999). Accuracy of consensus expectations for top-down earnings per share forecasts for two S&P indexes. *Applied Financial Economics, 9,* 233-238.

Clement, M.B., & Tse, S.Y. (2005). Financial analyst characteristics and herding behaviour in forecasting. *Journal of Finance, 60,* 307-341.

Clement, M.B. (1999) Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics, 27,* 285-303.

Cohen, D., Lefranc, A. & Saint-Paul, G. (1997). French unemployment: a transatlantic perspective. *Oxford Univ. Press, ISSN 0266-4658,* 267-285.

Cooper, R.A., Day, T.D. & Lewis, C.M. (2001). Following the leader: a study of individual analysts' earnings forecasts. *Journal of Financial Economics, 61,* 383-416.

Cowen, A., Groyberg, B. & Healy, P. (2006). Which types of analyst firms are more optimistic? *Journal of Accounting and Economics, 41,* 119-146.

Cremers, K. M., & Petajisto, A. (2009). How active is your fund manager? A new measure that predicts performance. *The review of financial studies*, *22*(9), 3329-3365.)

Dincer, O.C., Gregory-Allen, R. B., & Shawky H.A., (2010). Are you smarter than a CFA'er? Manager qualifications and portfolio performance. *SSRN 1458219*

Dreman, D.N. & Berry, M.A. (1995). Analyst forecasting errors and their implications for security analysis. *Financial Analysts Journal, May-June 1995, 30*-41.

Dyck, A. et al., (2019) Do institutional investors drive corporate social responsibility? International evidence. *Journal of Financial Economics, 131*, 693-714.

Eckel, C.C. & Grossman, P.J. (2008). Men, women and risk aversion: Experimental evidence. *Handbook of Experimental Economics Results, 1,* 1061-1073.

Groysberg, B., Healy, P.M., & Maber, D.A. (2011). What drives sell-side analyst compensation at high-status investment banks? *Journal of Accounting Research, 49,* 969-1000.

Halek, M. & Eisenhauer, J.G. (2001). Demography of risk aversion. *The Journal of Risk and Insurance, 68,* 1-24.

Hartog, J., Ferrer-i-Carbonell, A., & Jonker, N. (2003). Linking measured risk aversion to individual characteristics. *Kyklos, 55.*

Higgins, H.N. (1998) Analyst forecasting performance in seven countries. *Financial Analysts Journal,* 58-62.

Hilary, G. & Hsu, C. (2013). Analyst forecast consistency. *Journal of Finance, 68,* 271-296.

Hivde, H.K., (2003). Education and the allocation of talent. *Journal of Labor Economics, 21,* 945-977.

Hong, H. & Kacperczyk, M. (2010). Competition and bias. *Quarterly Journal of Economics, 14,* 366-382.

Hong, H. & Kubik, J.D. (2003). Analyzing career concerns and biased earnings forecasts. *Journal of Finance, 58,* 313-351.

Irvine, P.J. (2003). The incremental impact of analyst initiation of coverage. *Journal of Corporate Finance, 9,* 431-451.

Jackson, A. (2005). Trade generation, reputation and sell-side analysts. *Journal of Finance, 60,* 673-717.

Jacob, J. et al. (1999). Experience in forecasting performance of security analysts. *Journal of Finance, 58,* 313-351.

Jacob, J., Rock, S., & Weber, D.P. (2008). Do non-investment bank analysts make better earnings forecasts? *Journal of Accounting, Auditing & Finance,* 24-60.

Jegadesh, N. & Kim, W. (2007) Do analysts herd? An analysis of recommendations and market reactions, *Oxford University Press for Society for Financial Studies, 23,* 901-937.

Kaden, O., Madureira, L., Wang, R. & Zach, T. (2012). Analysts' industry expertise. *Journal of Accounting and Economics, 54,* 95-120.

Kim, J.B., Nekrasov, A., Shroff, P.K. & Simon, A. (2012) Do analysts understand the valuation implications of accounting conservatism when forecasting target prices? *American Accounting Association Annual Meeting.*

Kumar, A. (2009). Self-selection and the forecasting abilities of female equity analysts. *Journal of Accounting, 48,* 393-435.

Merkley, K., Michaely, R. & Pacielli, J. (2013). Does the scope of the sell-side analysts industry matter? An examination of bias, accuracy and information content of analyst reports. *Journal of Finance, 72,* 2-62.

Mikhail, M.B., Walther, B.R. & Willis, R.H. (1997). Does forecast accuracy matter to security analysts? *The Accounting Review, 74,* 185-200.

Mincer, J. (1991). Education and unemployment. *NBER Working Paper No. 3838.*

Mufti, A.A., Bakht, B., Tadros, G., Horosko, A.T., & Sparks, G. (2005). Are civil structural engineers "risk averse"? Can civionics help? *Sensing Issues in Civil Structural Health Monitoring.*

Olsen, RA. (1996). Implications of herding behavior for earnings estimation, risk assessment and stock returns. *Financial Analysts Journal, 52,* 37-41.

Salamouis, I. S., & Muradoglu, Y. G. (2010). Estimating analyst's forecast accuracy using behavioural measures (Herding) in the United Kingdom. *Managerial Finance, 36-3,* 234-256.

Saks R.E., & Shore, S.H. (2005). Risk and career choice. *The B.E. Journal of Economic Analysis & Policy, 5.*

Sharfstein, D.S., & Stein J.C., (1990). Herd behaviour and investment. *American Economic Review, 80,* 465-479.

Shukla, R., & Singh, S. (1994). Are CFA charterholders better equity fund managers. *Financial Analyst Journal, 50,* 68-74.

Skatova, A, & Ferguson E. (2014). Why do different people choose different university degrees? Motivation and the choice of degree. *Frontiers of Psychology, 5,* 1-15.

Spector, P.E., Jex, S.M. & Chen, P.Y. (1995). Relations of incumbent affect-related personality traits with incumbent and objective measures of characteristics of jobs. *Journal of Organizational Behaviour, 16.*

Verleger, Dr. P. K. (2019). 19 Historical Oil Disruptions, And How No. 20 Will Shock Markets. Retrieved from https://oilprice.com/Energy/Oil-Prices/19-Historical-Oil-Disruptions-And-How-No20-Will-Shock-Markets.html.

Von Holstein, S. (1972). Probabilistic forecasting: An experiment related to the stock market. *Organizational Behavior & Human Performance, 8,* 139-158.

Welch, I. (1999). Herding among security analysts. *Journal of Financial Economics, 58,* 369-396.

Wu, J., & Zang A. (2009). What determines financial analysts' career outcomes during mergers? *Journal of Accounting and Economics, 47,* 59-86.

Yates, F.J., McDaniel, L.S. & Brown, E.S. (1991). Probabilistic forecasts of stock prices and earnings: The hazards of nascent expertise, *Organizational Behavior and Human Decision Processes, 49,* 60-79.

Appendix I

Table 1: Definition and Description of Variables Used in Regressions	
Description of Independent and Dependent variables used in all regressions and figures are presented.	
VARIABLE	**DESCRIPTION**
FY10-FY17	Dummy variables representing year of the forecast
ENG	Dummy variable identifying analysts with Engineering degrees
ECON	Dummy variable identifying analysts with Economics degrees
FIN	Dummy variable identifying analysts with Finance degrees
BUS	Dummy variable identifying analysts with Business degrees other than Finance and/or Economics
GRAD	Dummy variable identifying analysts with Graduate degrees
CFA	Dummy variable identifying analysts with CFA title
PhD	Dummy variable identifying analysts with Doctoral degrees
COV	Number of stocks covered by analyst(*i*) at time(*t*)
EXP	Years of experience as an analyst covering any stocks.
EXPCO	Years of experience as analyst(*i*) covering a specific stock (*j*) at time(*t*)
DAYS	Number of days between the issuance of the estimate and the end of the forecast quarter
VIX	CBOE Volatility Index monthly return.
MKT_CAP	Market Capitalization of stock(*j*) measured in (USD$) Billions.
WTI (Oil)	West Texas Intermediate monthly futures return.
LOCATION	Dummy variable for the location of the analyst's office. 1 for offices in financial cities (ex. New York) and 0 for offices in industry cities (ex. Houston)
NoANALYSTS	Number of analysts covering stock(*j*) at time(*t*).
ECONorBUS	Dummy variable identifying analysts with Economics or Business degrees other than Finance
ECONorBUS&CFA	Dummy variable identifying analysts with Economics or Business degrees other than Finance AND a CFA designation
ENG&CFA	Dummy variable identifying analysts with Engineering degrees AND a CFA designation
ECONorFIN	Dummy variable identifying analysts with Economics or Finance degrees
ECONorFIN&CFA	Dummy variable identifying analysts with Economics or Finance degrees AND a CFA designation
POST EVENT	Dummy variable identifying estimates after a quasi-natural event
GICS	Dummy variable identifying stocks that fall into the Oil, Gas & Consumable Fuels industry (GICS code 101020)
Grouped Business	Dummy variable identifying analysts with any type of business school degrees
Integrated Oil & Gas	Dummy variable identifying stocks that fall into the Integrated

	Oil & Gas sub-industry (GICS code 10102010)
Marketing & Refining	Dummy variable identifying stocks that fall into the Oil & Gas Refining & Marketing sub-industry (GICS code 10102030)
Exploration & Production	Dummy variable identifying stocks that fall into the Oil & Gas Exploration & Production sub-industry (GICS code 10102020)
MA	Moving average of their PMAFE, using 4 previous periods
HM	Herding variables that measures the absolute value difference between an analyst's forecast and the consensus forecast (excluding analyst i)
ENG&HM	Product of dummy variable identifying analysts with Engineering degrees and HM variable. Tracks herding behaviour of analysts with Engineering degrees.
ECONorFIN&CFA&HM	Product of dummy variable identifying analysts with Economics or Finance degrees with a CFA designation and HM variable. Tracks herding behaviour of analysts with Engineering degrees.
GRAD&HM	Product of dummy variable identifying analysts with Graduate degrees and HM variable. Tracks herding behaviour of analysts with Graduate degrees.
PhD&HM	Product of dummy variable identifying analysts with Doctoral degrees and HM variable. Tracks herding behaviour of analysts with Doctoral degrees.
PMAFE	**Proportional Mean Forecast Absolute Error for Analyst(i)'s EPS estimate on stock(j) at time(t).**
RFOPT	**Relative Forecast Optimism for Analyst(i)'s EPS estimate on Stock(j) at quarter(t).**

Table 2: Quasi-Natural Oil Shocks

List of all quasi-natural macro-economic shocks affecting energy sector (1973-2018)

Event	Start Date	Duration (Weeks)	Price Change (%)	Supply Loss (%)
Arab Embargo	Oct-73	4	231.6	-3.3
Iranian oil strikes	Oct-79	2	15.1	0.2
Saudi Arabia's refusal to increase output	Jan-79	2	64.5	-2.5
Saudi Arabia's cut in supply to major companies	May-79	1	30.7	-0.2
Hostage-taking at US embassy in Iran	Nov-79	14	17.8	-0.3
Outbreak of Iran/Iraq War	Sep-80	2	28.4	-1.5
Iraq invasion of Kuwait	Aug-90	6	58.4	-0.5
OPEC unilateral production cut	Jan-99	12	43.5	0.1
Venezuela oil strike	Nov-02	2	117.5	-5.1
Hurricanes Katrina/Rita	Aug-08	4	11.2	-1.2
Unexpected cut in Nigerian production	Early-07	4	18.8	-1.1
Surge in Chinese distillate demand	Late-07	6	31.1	0.7
EU enforcement of 10-ppm sulfur diesel	Spring-08	6	45.2	-1.3
Collapse of Libyan production	Jan-11	3	27.7	-0.7
Second Libyan collapse	Jul-14	3	15.8	1.3
OPEC 2017 production cut	Jan-17	Ongoing	7.8	-1.7
Hurricane Harvey	Sep-17	3	12.7	-0.6
First Venezuelan production collapse	Nov-17	Ongoing	12.7	0.5
Conoco attachment of Venezuelan assets	May-18	Ongoing		-0.9

***Table retrieved from https://oilprice.com/Energy/Oil-Prices/19-Historical-Oil-Disruptions-And-How-No20-Will-Shock-Markets.html

Table 3: Descriptive Statistics

Breakdown of sampled analysts based on qualitative variables are presented.

[redacted]

***Proportion is calculated by dividing the frequency by the total number of analysts. Analysts that have multiple degrees are counted once for each relevant category.

Table 4: Initial Estimates of General Regression

Regression results showing the relationship between PMAFE and education variables and control variables on initial EPS estimates are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 5: Final Estimates of General Regression

Regression results showing the relationship between PMAFE and education variables and control variables on final EPS estimates are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 6: Initial Estimates of Non-Finance Business Regression

Regression results showing the relationship between PMAFE and education variables, focusing on Engineers with or without the CFA designation and non-finance business degrees (Economics or Business) and control variables on initial EPS estimates are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 7: Final Estimates of Non-Finance Business Regression

Regression results showing the relationship between PMAFE and education variables, focusing on Engineers with or without the CFA designation and non-finance business degrees (Economics or Business) and control variables on final EPS estimates are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 8: Initial Estimates of Economics or Finance Regression

Regression results showing the relationship between PMAFE and education variables, focusing Finance or Economics degrees with or without the CFA designation and control variables on initial EPS estimates are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 9: Final Estimates of Economics or Finance Regression

Regression results showing the relationship between PMAFE and education variables, focusing Finance or Economics degrees with or without the CFA designation and control variables on final EPS estimates are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 10: Difference-in-Differences Test With No Separator

Difference-in-differences with no Separator variable using initial and final EPS estimates for the three sampled quasi-natural macro shocks are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 11: Difference-in-Differences Test With Business Separator

Difference-in-differences with all Business degrees being the control sample using initial and final EPS estimates for the three sampled quasi-natural macro shocks are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 12: Difference-in-Differences Test With Non-Finance Separator

Difference-in-differences with Non-Finance degrees with CFA designation being the control sample using initial and final EPS estimates for the three sampled quasi-natural macro shocks are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 13: Difference-in-Differences Test With Econ. or Finance Separator

Difference-in-differences with Economics or Finance degrees with CFA designation being the control sample using initial and final EPS estimates for the three sampled quasi-natural macro shocks are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 14: Difference-in-Differences Test With GICS Separator

Difference-in-differences with stocks with the GICS code of 101020 being the control sample using initial and final EPS estimates for the three sampled quasi-natural macro shocks are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 15: Difference-in-Differences Test With Integrated Separator

Difference-in-differences with stocks with the GICS code of 10102010 being the control sample using initial and final EPS estimates for the three sampled quasi-natural macro shocks are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 16: Difference-in-Differences Test With Exploration Separator

Difference-in-differences with stocks with the GICS code of 10102020 being the control sample using initial and final EPS estimates for the three sampled quasi-natural macro shocks are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 17: Difference-in-Differences Test With Marketing Separator

Difference-in-differences with stocks with the GICS code of 10102030 being the control sample using initial and final EPS estimates for the three sampled quasi-natural macro shocks are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 18: General Regression for Persistence of Differences

Regression results showing the relationship between RFOPT and education variables and control variables on EPS estimates are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 19: Non-Finance Business Regression for Persistence of Differences

Regression results showing the relationship between RFOPT and education variables, focusing on Engineers with or without the CFA designation and non-finance business degrees (Economics or Business) and control variables on EPS estimates are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 20: Economics or Finance Regression for Persistence of Differences

Regression results showing the relationship between RFOPT and education variables, focusing Finance or Economics degrees with or without the CFA designation and control variables on EPS estimates are reported.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Table 21: Regression for Herding Behaviour

Regression results showing the relationship between the absolute value of RFOPT and herding as well as education variables using final EPS estimates and consensus estimates.

[redacted]

* represents statistical significance at 90%; ** represents statistical significance at 95%; *** represents statistical significance at 99%.

Figure 1: Initial Estimates of OPEC Production Cut for Non-Finance Degrees

Visual test of parallel trend assumption for DiD test during the OPEC Production Cut period. I compare the average PMAFE of the initial EPS estimates for Non-Finance degrees with CFA titles (1), the control sample, to the remainder of the sample (0).

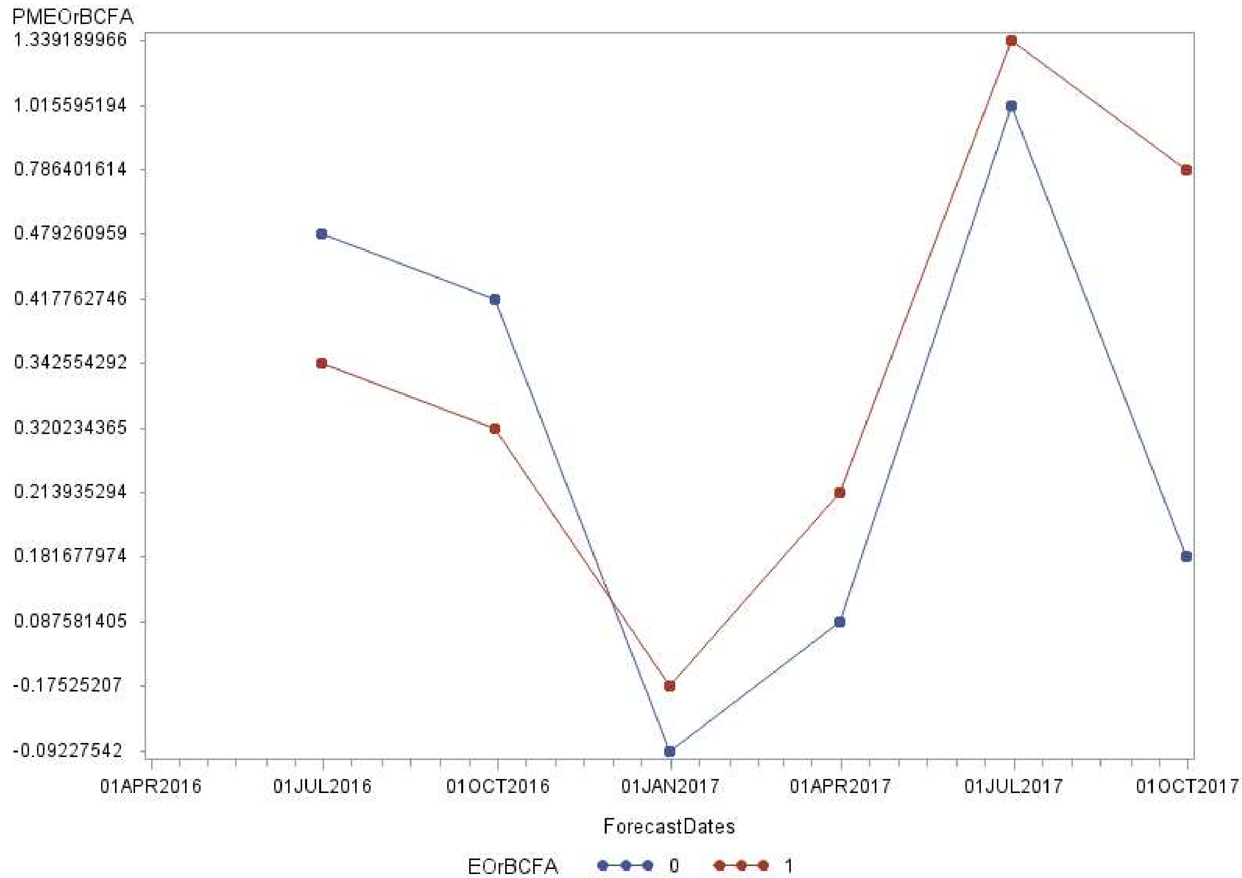

Figure 2: Final Estimates of Libyan Collapse 1 with GICS Separator

Visual test of parallel trend assumption for DiD test in the time surrounding the First Libyan Collapse. I compare the average PMAFE of the final EPS estimates for stocks with the GICS code or 101020 (1), the control sample, to the remainder of the sample (0).

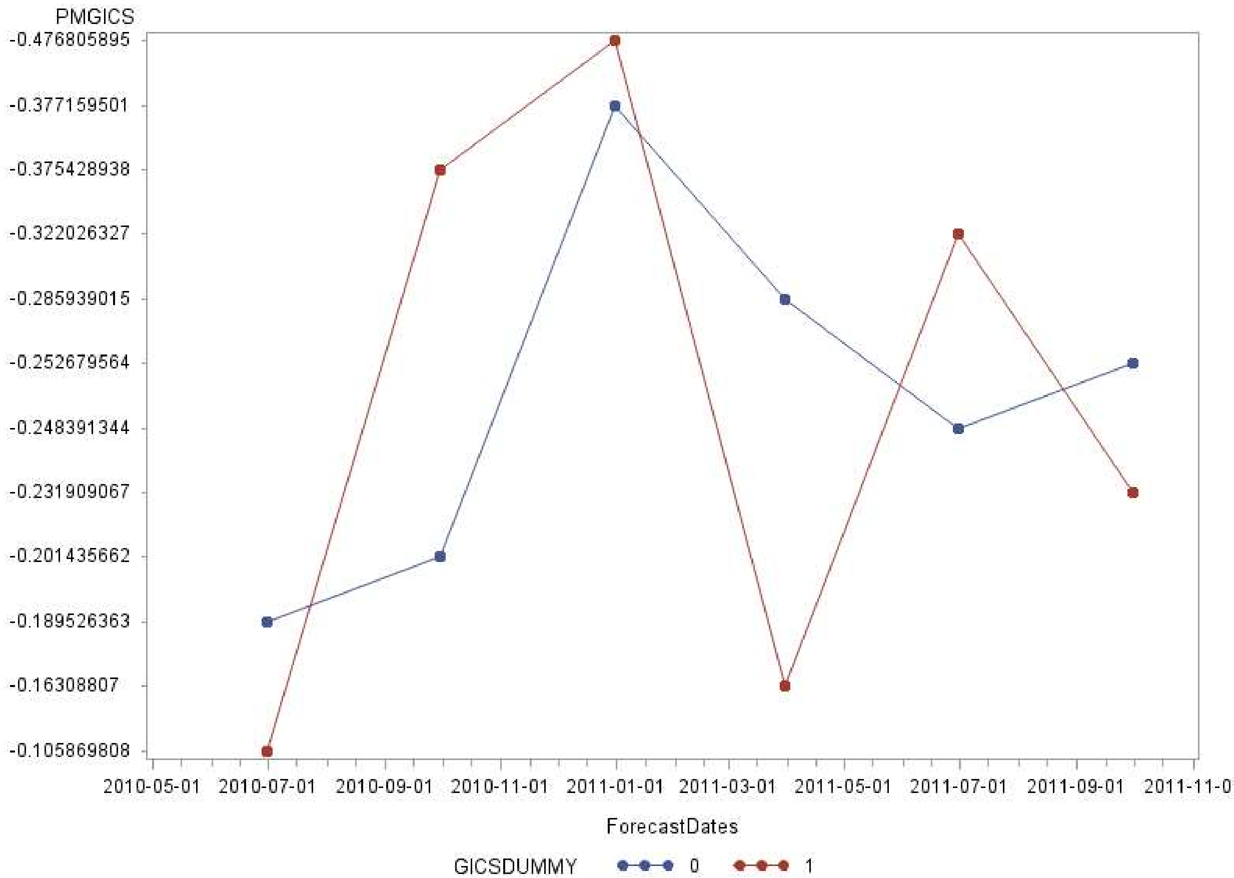

Figure 3: Final Estimates of Second Libyan Collapse with GICS Separator

Visual test of parallel trend assumption for DiD test around the time of the Second Libyan Crisis. I compare the average PMAFE of the final EPS estimates for stocks with the GICS code or 101020 (1), the control sample, to the remainder of the sample (0).

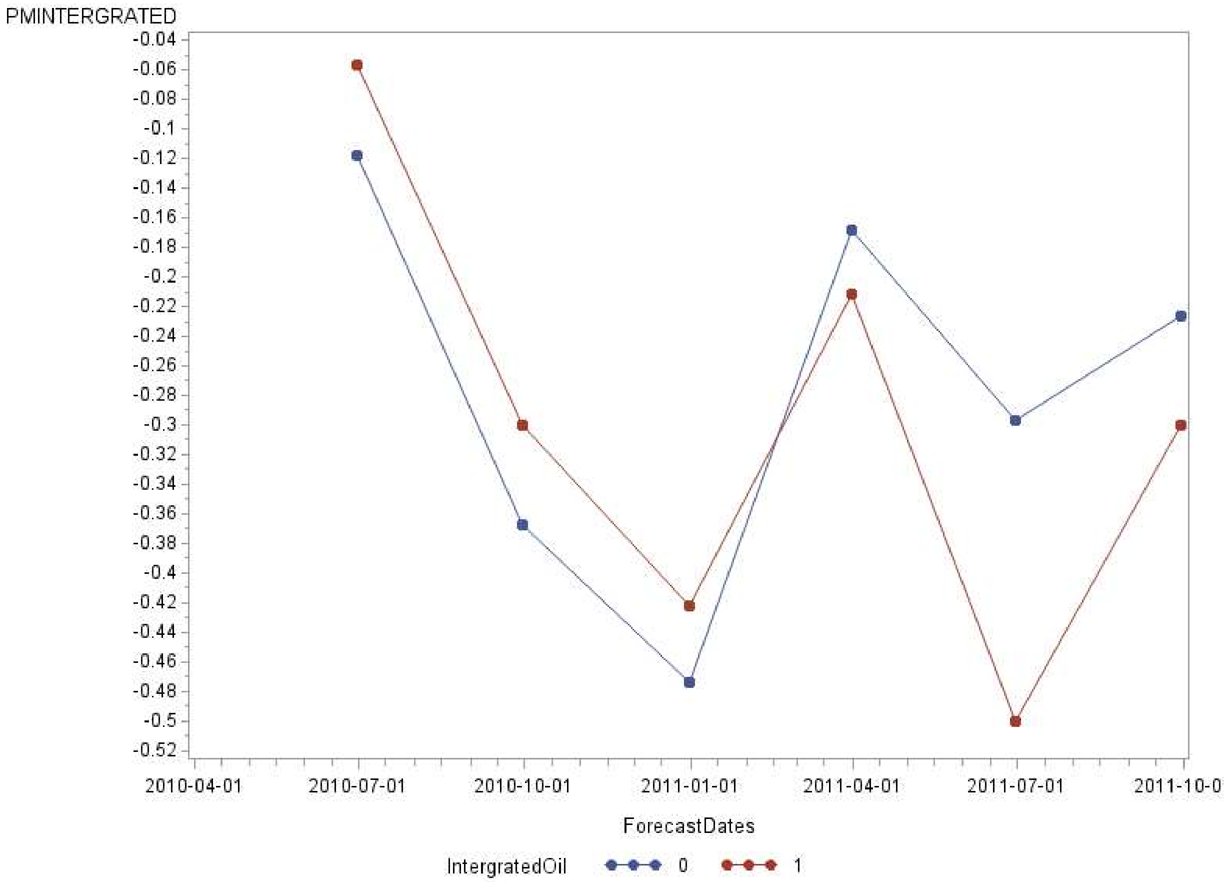

Figure 4: Initial Estimates of OPEC Production Cut with GICS Separator

Visual test of parallel trend assumption for DiD test around the time of the OPEC Production Cut. I compare the average PMAFE of the initial EPS estimates for stocks with the GICS code or 101020 (1), the control sample, to the remainder of the sample (0).

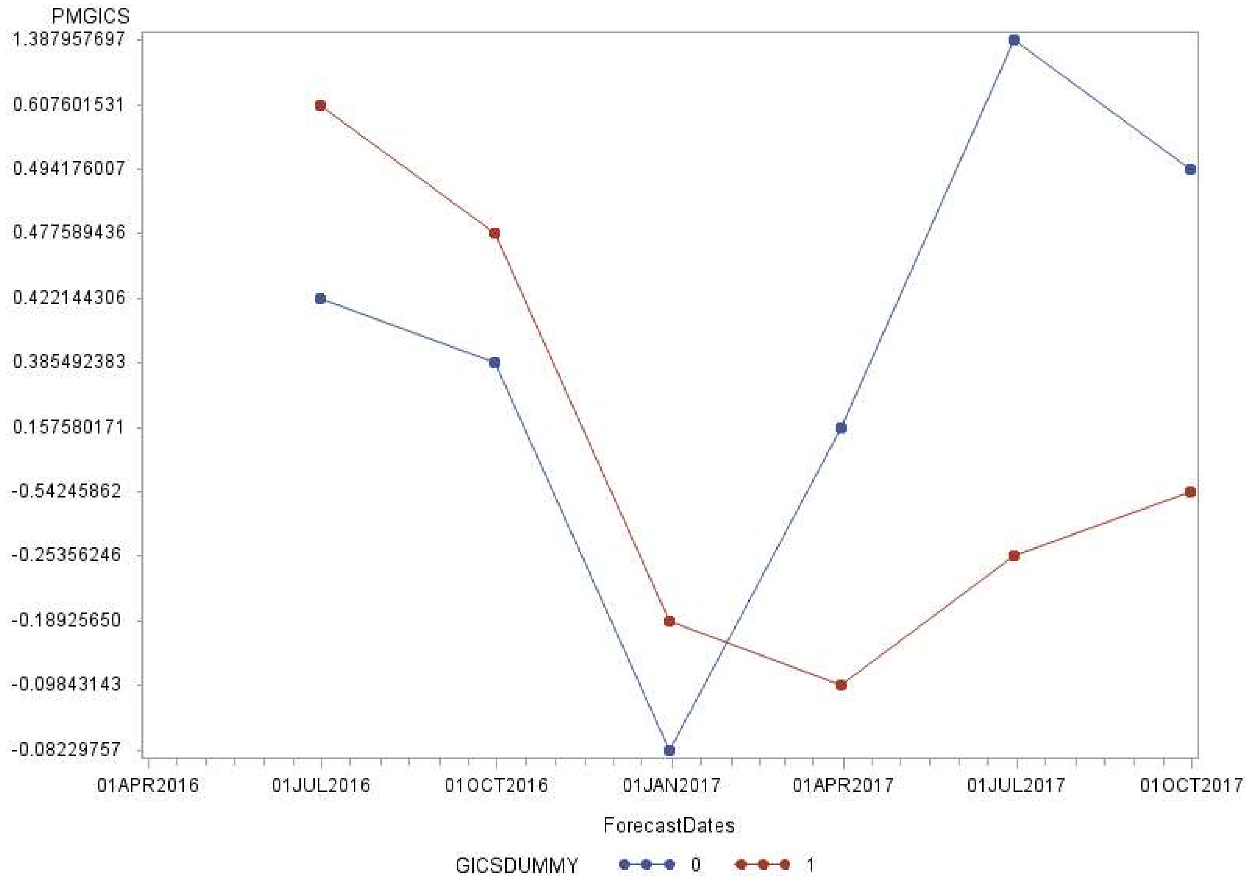

Figure 5: Final Estimates of Libyan Collapse 1 with Integrated Separator

Visual test of parallel trend assumption for DiD test around the time of the First Libyan Collapse. I compare the average PMAFE of the final EPS estimates for stocks with the GICS code or 10102010 (1), the control sample, to the remainder of the sample (0).

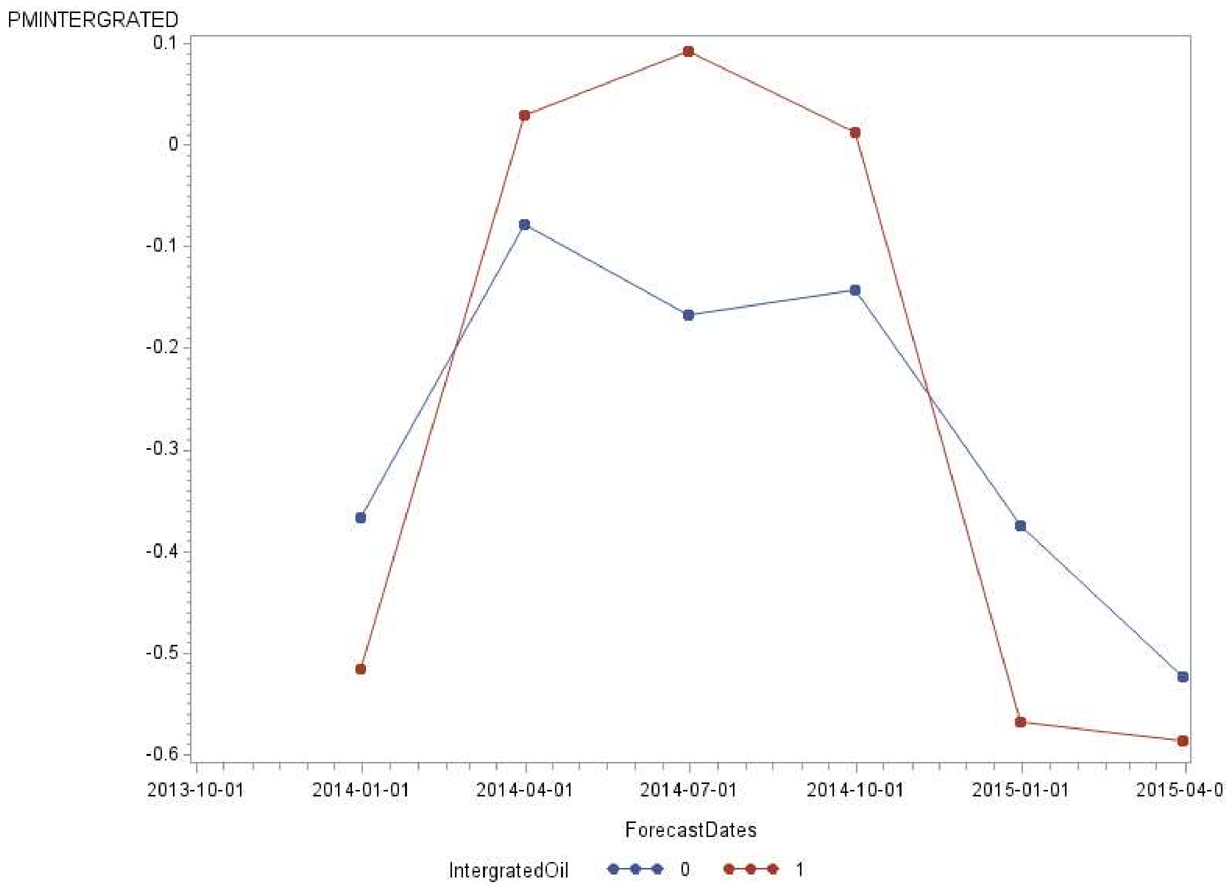

Figure 6: Final Estimates of Second Libyan Collapse with Integrated Separator

Visual test of parallel trend assumption for DiD test around the time of the Second Libyan Collapse. I compare the average PMAFE of the final EPS estimates for stocks with the GICS code or 10102010 (1), the control sample, to the remainder of the sample (0).

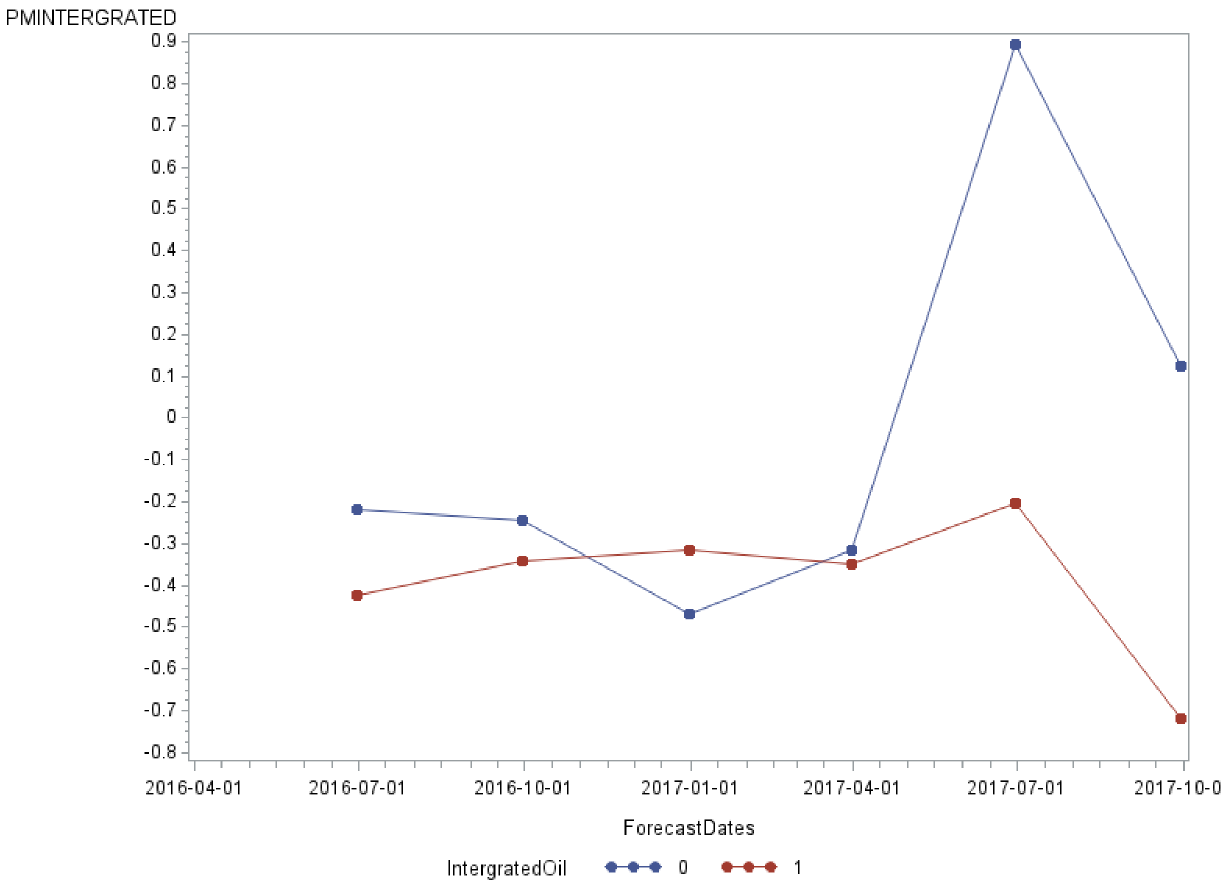

Figure 7: Final Estimates of OPEC Production Cut with Integrated Separator

Visual test of parallel trend assumption for DiD test around the time of the OPEC Production Cut. I compare the average PMAFE of the final EPS estimates for stocks with the GICS code or 10102010 (1), the control sample, to the remainder of the sample (0).