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Confirmation Bias in Financial Markets: Impact on Trading Behavior

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CONFIRMATION BIAS IN FINANCIAL MARKETS: IMPACT ON TRADING BEHAVIOR

by

Eddie E. Khachikian

A thesis submitted in partial fulfillment of the requirements
for graduation with Honors in the Finance

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All requirements for graduation with Honors in the
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Confirmation Bias in Financial Markets: Impact on Trading Behavior

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Abstract

This thesis studies the existence of confirmation bias in financial markets using real trading data and survey results. With this unique data set, I am able to observe whether and how confirmation bias may affect trading behaviors of investors in financial markets. Survey respondents are asked to forecast which one out of six listed firms will achieve the highest return next month. Some respondents were also asked to provide justification when forecasting. The sample used for this experiment comprised of student traders enrolled in a semester-long course who were surveyed prior to company contract trading at the Iowa Electronic Markets (IEM). This thesis examines whether forecasting unconsciously altered their trading behavior, resulting in additional confidence towards their initial forecast, which would indicate signs of confirmation bias. I find that traders that forecasted Microsoft to earn the highest return also ended up with higher net aggregate positions in the Microsoft contract, traded at the IEM. This finding is consistent with confirmation bias affecting investment decisions of traders in my sample. The main limitations of this study are the small sample size and differences in the popularity across firms traded at IEM that could bias the main results.

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1. Introduction

1.1. Bias

People instinctually tend to be adamant towards their initial beliefs due to the innate displeasure of feeling wrong in one's understanding. One can conclude that this habitual confidence stems from a conscious or unconscious desire to be correct in one's opinions and ideals, which is called bias. The Merriam-Webster dictionary defines bias as "an inclination of temperament or outlook" which, in more simple terms, means to be inclined towards current habits or beliefs; also implying an unconscious leaning towards a certain supported belief or idea. Unconsciously being more attentive to information supporting predisposed beliefs and ideas is referred to as a more specific type of bias: confirmation bias.

1.2. Confirmation Bias

Confirmation bias is often used while reasoning and choosing any belief. When considering a simple argument, someone might point out an opinion that another initially disagrees with and immediately recalls information and facts that only supports the same corresponding opinion. In this action, the individual arguing their side may be exactly that, one-sided, and in turn avoid even thinking of information that would argue against their belief. Any encounter that does not consider both sides of an argument fairly equally is likely to include some confirmation bias. If an argument or explanation of reasoning contains any bias, it tends to be flawed because of the lack of objectiveness in the search for a correct answer or solution to a problem. This lack of objectiveness will lead to a distinct disregard towards information that refutes the current belief. However, individuals that may have considerably greater awareness and intelligence should be able to differentiate themselves by attempting to consistently consider all aspects of any dilemma, not only those that may support a desirable or preferable belief. This definitely is not as simple to put into action as it is into words because, most of the time, the exclusion of contrary information is done

unconsciously. However, somehow reminding oneself to be attentive to all possibilities is a strong defense against confirmation bias.

Though confirmation bias is not defined as an unconscious act, it is often true when observing financial situations because most individuals are not likely to purposely disregard information if it could lead to a loss of money. People generally put a large amount of importance on their money and will take necessary actions, such as further research and a more open perspective, to attain earnings and avoid losses. Although it may sometimes be beneficial to behave according to a certain bias, people are more likely to simply overlook information unknowingly rather than intentionally disregarding information that would disprove their beliefs. Britannica provides a credible definition of confirmation bias as "the tendency to process information by looking for, or interpreting, information that is consistent with one's existing beliefs". When referencing a financial activity, such as investing or trading, confirmation bias can be detrimental by leading to overlooked or missed opportunities or a loss of wealth due to overconfidence.

2. Literary Review: Confirmation Bias

2.1. History

The term confirmation bias originates from the field of psychology dating back to 1960 in an experiment by an English psychologist, Peter Wason, who tested individuals on guessing a sequence to a set of numbers. The set of numbers is 2, 4, and 6 and individuals can ask if any other set of numbers is acceptable and follows the same rule as the sequence (Nickerson, 1998). The first assumptions are usually that the rule is a set of even numbers, or increasing by 2, which if testing either of those hypotheses, one would seem to prove themselves correct, although they are not. In turn, participants would tend to seek information that confirms their beliefs while rarely considering testing sequences that do not follow their predisposed belief (Mynatt et al., 1977). The correct rule is a simple one: a set of increasing numbers. If one would simply test a sequence in which they

believe should not follow the rule, they are more likely to come to the correct solution because they may come across some sequence that follows the rule which they initially believed would not. This motion actually considers counterarguments to one's own current beliefs which in turn avoids confirmation bias and creates a more credible opinion.

The framework behind confirmation bias has existed many years prior to the actual terminology, and probably since the beginning of human reasoning, likely due to overconfidence in one's beliefs. People do not want to be proven incorrect in their ideals and will focus on information and reasoning that is in support of their beliefs. Francis Bacon, a famous English philosopher, born in the 16th century, expressed the idea that human's "draw all things to support and agree" with their predisposed opinions (Nickerson, 1998). This is clearly problematic because only entertaining information from one side of an argument, or that affirms one's sense of self, will likely lead to misjudgment. Historical analysis suggests that a requirement to avoid confirmation bias when forming a hypothesis should include testing alternative hypotheses, paired with finding evidence to confirm the current hypotheses (Mynatt et al., 1977). The consistent nature for people to search for evidence confirming the current hypothesis without testing alternative theories is the driver behind confirmation bias. Following this rule and testing all possible outcomes to a question will likely diminish confirmation bias and build a more reputable opinion. As one might concur, dismissing or ignoring relevant information that may disprove a predisposed belief will likely lead to many issues executively, politically, and financially.

2.2. Modern Confirmation Bias

A common issue leading to confirmation bias is the lack of considering one's alternative beliefs. In the article "Confirmation Bias in Complex Analyses", Lehner et al. (2008) recommend a procedure to avoid confirmation bias by exhibiting more analysis of competing hypotheses, or Analysis of Competing Hypotheses (ACH). This correlates to the earlier notion of focusing on

conflicting ideas to one's current belief because this analysis requires the individual to consider varying possibilities or hypotheses more deeply. Without considering and entertaining all possibilities regarding a certain instance, it is much easier to agree with a false belief.

Confirmation bias is arguably more prevalent in modern-day interactions due to the creation of technology and the internet. Social media, targeted advertisements, and biased news reporting has created major polarization and a deeper confidence in possibly incorrect beliefs due to extensive flooding of agreeable information. The polarized communities formed through social networks of likeminded people are referred to as echo chambers (Del Vicario et al., 2017). Echo chambers embrace and strengthen confirmation bias in individuals because the majority, if not all, the information they are receiving or exposed to is already in support of their pre-disposed beliefs. This leads to common misconceptions as if a false idea is passed down enough times, it is likely to be believed as cross-referencing an idea is one of the best ways to prove it.

2.3. Behavioral Finance

In the field of finance, there is the study of behavioral finance which investigates psychology's influence on financial markets and investors. Cookson et al. (2021) expands on behavioral finance beginning with a phenomenon known as disagreement, where people inherently have a "selective exposure to confirmatory information". With this, he also expands on selective exposure theory which is defined as "the study of biased information acquisition" (Knobloch-Westerwick, 2014). Cookson combined these concepts to explain that echo chambers "emerge when individuals tilt their *information acquisition* toward sources that *confirm* their prior views" (Cookson et al., 2021). It is common for financial investors or traders to be following social networks that endorse their existing beliefs regarding financial markets, which leads to confirmation bias in trading behavior.

Echo chambers can be unintentional as they often arise through social media algorithms that solely recommend information based on commonly researched topics or the social networks one

follows. Through reviewing the social media page StockTwits, a large social network for investors and traders, Cookson finds behavior exemplifying confirmation bias through its follower's social media activity. When observing the differences in the newsfeed of potential investors, he finds that "a bull[ish investor] will see 62 more bullish messages and 24 fewer bearish messages than a bear[ish] investor over the same period" (2021) of time. It would be beneficial for investors to entertain information that may disprove their current beliefs or financial stance on a stock based on the fact that they prioritize their wealth over anything else when trading. However, this does not seem to be the case as investors tend to exemplify confirmation bias, even before they are exhibiting true trading behavior, through the information they expose themselves to.

In her article, Nelson (2014) analyzes the possibility that economists are affected in their analyses by stereotypes and confirmation bias. She introduced an idea by Kahneman (2003) on the cognitive sciences of human behavior in that humans tend to systematically deviate from norms of context-free impartiality and logic. In other words, people do not always treat all aspects of a situation equally and can often stray from logic. This supports the theory that economists may be facing bias and stereotype in their behaviors as humans would cognitively tend to. It seems difficult to completely be free of confirmation bias as an economist or financial analyst because the monetary desire of a financially positive scenario would lead most humans to confirm that scenario through the discovery of new information.

Camerer (1987) ran an experiment to test whether judgment bias and choice violations have an effect in financial markets. He uses experimental markets to test traders that are paid dividends in specific circumstances to see if they judge the probability of the event based on prior information or on the "representativeness" of the sample. He suggests, with reference to Kenneth Arrow (1982), that evidence of judgment bias is reported in traders in the use of the representativeness heuristic with over-reaction to current information. This over-reaction can also be characterized as overconfidence in current beliefs held by traders which is considered a form of confirmation bias.

2.4. Confirmation Bias in Finance

Political occasions can also be tied to changes in the economy as there may be uncertainty in expectations which leads to an instability of the market. This uncertainty leads financial analysts and traders to exhibit confirmation bias through assessing their financial positions and beliefs. The 1993 Canadian election included a contract market stemming from the belief from economists that "markets are efficient aggregators of information" (Forsythe et al., 1998). These shares of contracts were identified with political parties in reference to the number of seats to be won by the corresponding party. This framework created a market where the cost of the contract reflected the percentage of seats that were expected to win by the corresponding party. This is one of few ways to measure confirmation bias through numbered data as the change in cost reflects the change in popular opinions.

Forsythe et al., (1998) conducted an experiment on judgment bias and traders' behaviors and expectations regarding the election market in 1993. This directly relates to our own research and experiment without the aspect of political parties. They gauge traders' expectations regarding the results of the election through the value of the corresponding contracts in order to measure effects of certain events. However, the data collected in this paper through surveying future investors are expectations prior to trading. This observes how deeply traders follow through with their forecasts, rather than being able to judge their expectations during the trading period as the election contracts allows by viewing prices at specific periods in time. Confirmation bias is investigated within our investors and market to see if forecasting has any impact on trading behavior and if forecasting with further reason reinforces confirmation bias in the individual.

The fact that traders do not want to lose money enhances confirmation bias in an economic market because the trader sets a goal of making a profit and chooses a hypothesis that might support this. The trader further tends to support this hypothesis through research and affirmation from

sources in support of the theory rather than trying to disprove ideas that contradict the hypothesis. It is common to search for positive reasons why the trade may be successful, and the following information may persuade the trader to follow an unprofitable path that could have been avoided if more information was indulged. Forsythe et al. expresses the importance of "distinguish[ing] the average trader from the marginal trader" (1998). Although, the marginal trader may still be somewhat biased, their increased attentiveness to the changes in the market will lead to a lower likelihood of persistence towards their initial biases if there is evidence found through their attentiveness that guides them in a different direction. The same level of biased traders that are inattentive to the changes in the companies are likely to exhibit more confirmation bias.

Cipriano and Gruca (2015) ran an experiment investigating an idea particularly similar to the hypothesis tested in this thesis. They searched for confirmation bias's effects on market prices in financial markets through traders that forecasted and explained their forecast in real-money box office movie markets. The null hypothesis tested in this thesis is that the net positions of traders forecasting a company to win a contract race, with or without justification, are not significantly different from traders who do not forecast and do not show signs of confirmation bias in traders; leaving the alternative hypothesis to state that forecasting does affect net positions and shows evidence of confirmation bias in traders. They mention a market model by Kent Daniel, et al. (1998) that states "trader overconfidence is the source of the biased assimilation form of confirmation bias". Biased assimilation is the tendency to be more positive towards information one already agrees with and negative towards information inconsistent with one's beliefs. Cipriano believes when estimating an asset's value, traders tend to overweigh the accuracy of initial private information and underweight value-relevant, public information unless it confirms the initial private information. Confirmation bias is present in traders when ignoring relevant information that is not in-line with the pre-existing beliefs of the financial markets.

Cipriano, Gruca, and Goins (2015) ran another experiment using a nearly identical experimental variable to the previous experiment: four real-money prediction markets with security values tied to a movie's box office performance. Traders again submitted forecasts prior to the opening of the trading markets. Through examining the trading volume, timing, prices, and trader returns they found that in three of the four markets, there were indications of over-confidence associated with traders that forecasted the winning contract. Over-confidence may be a key driver to confirmation bias as being over-confident can lead to *confirming* one's initial beliefs.

3. Data

In this thesis, I study how confirmation bias may affect traders and investors in financial markets. My data sample is based on contract trading activity by student traders and the survey they were given prior to the beginning of the trading period. The survey asks to forecast winning contracts with and without reasoning and was conducted in a local market to view if forecasting increases confirmation bias in trading behaviors of investors by viewing net aggregate positions of traders at different time periods.

3.1. Iowa Electronics Market: Basics

The market used for data collection to evaluate the hypothesis of the thesis was the Iowa Electronic Markets. The traders for this market consisted of students in the Investment Management course at the University of Iowa. The data collected and used for the purposes of this thesis took place in the Fall 2020 semester.

The Iowa Electronics Market consists of two main markets: the Inter-Industry Returns Market and the Index Returns Market. The trading periods for these two markets both take place in monthly periods and open and close at the same time (the Monday after the third Friday of every month). The data collected began September 21st, 2020 as that was the opening day of the first period of Iowa

Electronic Markets. The closing date of the first period of trading was October 19th, 2020 but the final trade of this period took place on October 17th.

3.2. Contracts and Bundles

For the purposes of this thesis, the primary focus was the Inter-Industry Returns Market, which contained a contract for each of the individually listed company's common stock; Walt Disney Company (DIS), Simon Property Group (SPG), Walgreens Boots Alliance (WBA), General Motors Company (GM), Microsoft Corporation (MSFT), and Exxon Mobil Corporation (XOM). The contracts are traded freely by the participating student traders which their trading behavior formulates the contract market prices. Contracts are traded between $0 and $1 because these are the liquidation amounts for losing and winning contracts respectively. Every trading period is open for 4 weeks before the payoff at the end when the winning contract is liquidated for $1 and all other contracts liquidated for $0. The trading period observed in this thesis of 2 weeks consists of half of a full 4-week trading period. The winning contract is determined by being the company with the highest rate of return based on their stock price in the 4-week trading period. Student traders decide a price they are willing to buy or sell each contract for, between $0 and $1, and the IEM algorithm uses the supply and demand between traders to create current contract prices. Traders may commit to market order, in which they can execute a buy or sale of a contract immediately, based on current market prices. They may also commit to a limit order to execute a buy or sale of a contract, set for any period of time, for the price point of their choosing.

Traders can also purchase two types of bundles in either market, market price bundles or fixed price bundles, both of which contain one of every contract in its corresponding market. A market price bundle's cost is equal to the sum of all contract's current trading market prices in the Iowa Electronics Market. A fixed price bundle's cost is always equal to $1 and is usually more popular because it is uncommon for the market price bundle to cost under a dollar. However, purchasing a

market price bundle for under $1 would lead to instant profit because at least one of the contracts will be liquidated for $1, therefore should be executed at any given time. Each of these two bundles grant the same contents to the buyer's portfolio: one of each contract in its respective market.

3.3. Compared to Stock Exchange and Trading Strategy

Iowa Electronic Market contracts are bought and sold at any price between $0 and $1 and can be traded for at any time, as long as it falls within the (4-week) monthly trading period. For this reason, the IEM differentiates itself from the usual stock exchange because in most stock exchanges, traders may only buy or sell stocks between 9:00 A.M. and 5:00 P.M., eastern standard time, Monday through Friday. In the IEM, at the end of each trading period, the contract with the highest percentage rate of return during that period, also considered the winning contract, is liquidated for $1 while all other contracts are liquidated for $0. The goal of trading these contracts in the Inter-Industry Returns Market would be to observe all the companies' news and returns to predict which of the six companies will achieve the greatest level of return. The level of return is determined by percentage change in common stock price from the beginning to the end of the trading period.

Similar to trading stocks on a standard stock exchange, traders may use all publicly available information to research recent company-specific news and current financial data, paired with some intuition, to trade contracts as they see fit. This will lead to the market contracts, in essence, creating their own prices based on the amount the buyers are willing to pay and the amount the sellers are willing to receive for the specified contract. Traders that are assessing the six companies in the market the most consistently and accurately tend to obtain greater profits because they take advantage of buying contracts predicted to be undervalued and sell contracts predicted to be overvalued. Active traders also further their advantage through purchasing market price bundles that are valued under $1 because they are more likely to come across them than traders that are paying less attention or are less active in the Iowa Electronic Markets.

3.4. IEM Survey Data appendix survey questions

Prior to trading, a survey was presented to the student traders with randomly allocated questions to create three testing groups: forecasting with reason, forecasting without reason, and the control (no forecast). These groups were randomly created through the Qualtrics Online Survey Software by randomization of who received which questions. The forecasting with reasoning question asked the student which company they believe will win and why they believe this to be the case while the forecasting without reason question excluded the explanation (Ref. Appx. 1). For a company to win a contract race, they must receive they greatest rate of return (percentage increase) on their company's stock price compared to the other five companies, in every 4-week trading period. A winning company contract, at the every 4-week trading, has a payoff value of $1 while all other company contracts have payoff values of $0. The survey was given to student traders on September 22, 2020, the same date as the beginning of the trading period and it is assumed the student trader's forecasts are targeted for this upcoming trading period after the survey takes place. The control group was not presented either question on forecasting but was presented a filler, irrelevant question to be able to label it as the control group. This survey will serve as part of the data necessary to find if confirmation bias exists in investors' trading behaviors.

3.5. Time Periods and Trader Activity

The traders are observed only through the first two weeks (September 22nd-October 2nd) of trading to see if they are more prone to holding their forecasted company's contract. Our observation method includes calculating and viewing net aggregate positions of traders' contracts for only the first two weeks of trading. The first two weeks of trading are likely to be more directly related to the forecasts from the survey compared to later periods of trading because the traders are more likely to remember and act on their corresponding survey forecasts.

How actively a certain trader is trading, given they invest a relatively greater amount of money in their forecasted company contract than other traders, can also be assessed to argue towards confirmation bias. One may argue that a less active, and hence, less knowledgeable, trader seems more likely to follow initial instincts and beliefs than a trader that is aware of current market activity and may change their financial stance, according to their initial forecast, based on that fact. Traders' total holdings are determined by calculating the total sum of all trades, contract and bundle purchases and sales, for each specific buyer at a specified time period.

I use the IEM market price data of every single trade to determine and assess net aggregate positions of traders. For each trader and each company-specific contract, I compute the net aggregate position by adding all contract purchases and subtracting all contract sales for each specific contract in a given time for each individual trader, including bundle purchases and sales. This allows me to view if traders that believed in certain companies prior to trading are more confident in their initial forecast and, in turn, trade heavier on that specific stock than those with no forecast. I also assess if traders without an explanation to their forecast were less likely to follow-through and trust that company through trading behavior than those with explanation. These assessments are used to observe the level or existence of confirmation bias in traders based on forecasting and if forecasting with reason changes said behavior.

3.6. Data Retrieval and Variables

The majority of the data used for the purposes of this thesis is created through the Iowa Electronic Markets (IEM) student trading data (Ref. Section 3.1.). Professor Thomas Gruca assisted greatly in analyzing and providing this data for the purposes of this research thesis. The data includes the date of each trade, if the trade was a bundle, the asset ID of the contract traded, the quantity traded, the price of the trade, the seller's ID if applicable, and the buyer's ID if applicable. When referencing the date, we used the first two weeks of trades, from September 21st, 2020 to October

2nd, 2020, for our initial data analysis and results. Bundles include one of each of the six contracts at a fixed price of $1 if a trader wants to buy or sell one; a less common market-price bundle also exists which is valued at the sum of all the contract's market prices. The main asset IDs are 3203, 3204, 3205, 3206, 3207, and 3208 and are representative of a contract in Walt Disney, General Motors, Microsoft, Simon Property Group, Walgreens, and Exxon Mobil respectively (matched alphabetically by stock ticker; DIS, GM, MSFT, SPG, WBA, XOM). The quantity represents how many contracts were traded in that trade for that specified contract and the price represents the price at which each contract traded for. The seller's and buyer's ID references the trader ID associated to each participating trader. The list of trader ID's to student name was provided by Professor Sinagl in order to be used to assess trading activity compared to their results from the survey.

4. Methodology

4.1. Qualtrics Survey Questions

The survey given to the student traders, composed by Professor Petra Sinagl and myself, was conducted through the University of Iowa's student website with Qualtrics Online Survey Software. The importance of this survey stems from one question forming two posed to the students: Which company between the six do you believe will be the winning contract? The second, potential follow-up question included justifying reasoning of the first question's answer. (Ref. Sect. 3.3. and Appx. 1) With only slightly fewer than a hundred participants in the survey, dividing the test groups created by this question (Ref. Section 3.4.) into three groups makes for generally small test sample sizes at about 33 per group. The test groups lack of size is more prevalent when considering the fact that

	DIS Chose	DIS Justified	GM Chose	GM Justified	MSFT Chose	MSFT Justified	SPG Chose	SPG Justified	WBA Chose	WBA Justified	XOM Chose	XOM Justified
	7	6	2	1	19	19	2	0	3	2	3	2
Totals:	13		3		38		2		5		5	

Table 1: Amounts of each contract forecasted/justified to win by each trader

there are six contracts to choose between, estimating an average of about 11 total forecasts, with and without justification, per contract. The actual survey yielded exactly 31 responses for the control group, 30 for the forecast with justification group, and 36 for those forecasting without any justification. However, the survey's results (Ref. Table 1) included more outliers as Microsoft received over half of the total forecasts with 38 out of the total 66 forecasts while Walt Disney received the second most forecasts at 13. The company with the lowest number of forecasts was Simon Property Group with only two forecasts and both of them without justification (leaving SPG Justified the only variable with zero forecasts and unable to make any inferences or regressions). Simon Property Group, General Motors, Walgreens, and Exxon Mobil all have five or less forecasts, making it difficult to make a viable or confident judgment on the resulting data. As Microsoft has a decent number of forecasts and both variables are equal at 19 each, it is the most viable contract to observe for data analysis and inferences. Walt Disney may have enough of a sample size to observe but is still generally too small.

For use as the independent variable in regression analysis, a table was created using the results from the Qualtrics survey data. Each company contract is designated two rows (one for choosing a forecast and one for justifying the forecast) in addition to the control group at the end for a total of 13 rows of data (Ref. Table 2). The number "1" is given for the trader's answer or position in reference to the survey and the number "0" for all 12 other entries. If the trader was not asked any forecasting question, they are assigned "1" for control and "0" for all other entries.

DIS CHOSEN	DIS JUSTIFIED	GM CHOSEN	GM JUSTIFIED	MSFT CHOSEN	MSFT JUSTIFIED	SPG CHOSEN	SPG JUSTIFIED	WBA CHOSEN	WBA JUSTIFIED	XOM CHOSEN	XOM JUSTIFIED	Control
1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	1	0	0	0	0	0	0	0

Table 2: *Example of survey results coding method; 1: trader is in corresponding category, 0: trader is not in corresponding category*

4.2. IEM Methodology

After receiving the data from the Iowa Electronics Market, the first two weeks of all trades (09/22/20 – 10/02/20) were separated which accounts for the first half of the first trading period because each trading period before liquidation is a 4-week period. It is also the most recent trading activity since the student traders have taken the survey and will lead to more current reactions stemming from the survey opinions.

I computed traders' positions in individual contracts by summing up each individual contract purchase and sale by each respective trader. Two following pivot tables were created: (Ref. Tables 3.1, 3.2) the first for contract purchases and the second for contract sales. The variable "IsBundle" is shown because we needed to filter out one of the bundle sub-variables which duplicates bundle purchases and sales. There was one entry for each asset ID as well as an additional entry that gave a bundle its own asset ID. We filtered the data so that the bundles will only be counted once for each individual contract.

Bundle		Sum of Quantity	Contract ID's			
SALES/ SELLERS	3203	3204	3205	3206	3207	3208
26300	2	4	2	3	4	3
26988	3	14	6	2	1	2
27245	0	0	2	0	0	0

Table 3.1: *Example of actual 2-week purchase trading data for each contract per trader*

Bundle		Sum of Quantity	Contract ID's			
BUYS/ BUYERS	3203	3204	3205	3206	3207	3208
26988	4	18	6	2	2	3
27245	2	2	2	2	2	2
27249	1	1	1	1	1	1

Table 3.2: *Example of actual 2-week purchase trading data for each contract per trader*

I then combined these two tables into one by subtracting the sales from the purchases for each individual trader and contract to create the net asset positions (Ref. Table 4) and further matched the trader ID to the name of the trader using data provided by Professor Sinagl and Excel formula function "VLOOKUP".

Trader ID	3203	3204	3205	3206	3207	3208	Names
26988	1	4	0	0	1	1	ExampleName
27245	2	2	0	2	2	2	ExampleName
27249	1	1	1	1	1	1	ExampleName
27250	0	0	0	0	0	1	ExampleName

Table 4: *Example of trading purchases and sales combined results; VLOOKUP Excel formula used in the last column to find trader names that match trader IDs*

On the same sheet, as more variables are added horizontally (Ref. Table 5), they are kept in line to match the information to reference the trader in the same column. In order to find net holdings of individual contracts, relative to other contracts, I first computed the minimum position of the six contracts for each trader and subtracted that minimum from each of the six contract positions to create an unbalanced net portfolio which rids bundles held for each trader. Next, I multiplied the holding positions by the price of the contracts to get the total value of each holding, valued at current market prices from the end of October 2nd, 2020 to provide the unbalanced priced holdings on this date for each contract and trader.

Unbalanced Net Portfolio						Unbalanced Priced Holdings @ 10/2						
3203	3204	3205	3206	3207	3208	3203	3204	3205	3206	3207	3208	SUM
1	1	0	1	1	3	$ 0.165	$ 0.200	$ -	$ 0.200	$ 0.179	$ 0.393	$ 1.137
1	4	0	1	1	1	$ 0.165	$ 0.800	$ -	$ 0.200	$ 0.179	$ 0.131	$ 1.475
2	2	0	2	2	2	$ 0.330	$ 0.400	$ -	$ 0.400	$ 0.358	$ 0.262	$ 1.750

Table 5: *Example of each trader's net aggregate portfolio results; net portfolio excludes all bundles currently held; holdings are dated and priced at 10/2/20*

The unbalanced priced holdings are all the dollar values, based on contract prices on October 2nd, 2020, of unique contracts held by each trader, which exclude bundles held, giving a more accurate weight on individual traders' contract preference. They are each then divided by the sum

of all the unbalanced priced holdings for each trader to create balanced priced holdings (Ref. Table 6) for each contract and trader. This is also used as the dependent variable for running regression analysis to try to find correlation with the amount held by a trader and their survey forecast.

Balanced Priced Holdings (Dependent Variable)						
SUM	3203	3204	3205	3206	3207	3208
$ 1.137	$ 0.145	$ 0.176	$ -	$ 0.176	$ 0.157	$ 0.346
$ 1.475	$ 0.112	$ 0.542	$ -	$ 0.136	$ 0.121	$ 0.089
$ 1.750	$ 0.189	$ 0.229	$ -	$ 0.229	$ 0.205	$ 0.150

Table 6: *Example of dollar value of each contract held by every trader priced on 10/2/20 (balanced to total $1 for each trader)*

4.3. Regression Methodology

Regression analysis via Excel is used to compare the balanced priced holdings for each contract as the dependent variable (Ref. Table 6) against the respective contract's "chose" and "justified" columns from the survey responses (Ref. Table 2) as the independent variable, resulting in 6 initial regressions, separated for each individual company contract. With these regressions, I aim to find out whether traders with initial beliefs that a certain contract will win invested relatively more money in this contract than the average trader.

The null hypothesis tested by these regressions is that the net positions of traders forecasting a company to win a contract race, with or without justification, are not significantly different from traders who do not forecast and do not increase confirmation bias in traders; leaving the alternative hypothesis to state that forecasting affects net positions and confirmation bias in traders.

Our regression model equation is:

Net Position of Trader X in Contract Y

*= Intercept + B1 * "chosen" dummy variable + B2 * "justified" dummy variable + residual*

I regress the net position of a trader X in contract Y on two dummy variables that are created based on survey results. The "'chosen' dummy variable" equals 1 when traders X answered the forecasting only question (Ref. Appx. 1) in reference to contract Y. The "'justified'" dummy variable"

equals 1 when traders X answered the forecasting with justification question (Ref. Appx. 1) in reference to contract Y. Variables "B1" and "B2" are the regression coefficients attached to these two variables, respectively. Dummy variables for both, chosen and justified, categories are specific to an individual contract and individual trader. If the trader forecasted for either the "chosen" or "justified" category, based on the survey observations (Ref. Appx. 1 and Section 4.1), the dummy variable for that corresponding category will be 1 and the other will be 0. The "control" column from the survey responses (Ref. Table 2) are accounted for when running the initial forecast regressions for all of the individual companies because if a trader was in the control group, the first 12 columns corresponding to company forecasts would be "0".

The regression is carried out through the standard pre-programmed Excel regression tool which is based on the ordinary least squares method for estimating linear regression model parameters. This method minimizes least squares of residual errors and provides sum of square differences between the observed and predicted values. This will provide data with statistics such as P-value, T-statistic, significance-F, and independent variable coefficients to determine whether or not there is any significance between the priced holdings per trader and that same trader's initial forecast and how impactful or significant the data may be. Resulting regressions are shown under the regression results section. (Ref. Section 5.2.)

Significance-F statistic includes a balanced combination of the 2, "chosen" and "justified", independent dummy variables and refers to the probability that the null hypothesis is true; a low probability would mean the null hypothesis should be rejected. In other words, the significance-F represents the percentage of forecasts for that given company that did not have any effect on net positions of traders. P-value is identical to significance-F but is only representative for each independent dummy variable (only forecasted or forecasted and justified). T-statistic refers to the variation in the sample data and directly affects the P-value and so is not required to be detailed in

each analysis (greater T-statistic = lower P-value). Coefficients are the level of balanced holding percentage per forecast-type; a positive and greater coefficient represents greater holdings when forecasted (and justified) for the company implying greater levels of confirmation bias may exist in that instance.

5. Results with Discussion and Contribution

5.1. Assessing Confirmation Bias

Firstly, net positions of traders and their trading activity are matched against their specified company forecast as to which company they believe will win the contract race, which took place prior to trading in the survey. If the net aggregate positions, or balanced priced holdings, of traders that forecasted success of their companies are greater than the average net aggregate position of that specific contract per trader, then confirmation bias may exist for those specified traders. The average balanced priced holdings for all traders are shown below (Ref. Table 7).

Average Trader's Balanced Priced Holdings per Contract					
DIS	GM	MSFT	SPG	WBA	XOM
$ 0.159	$ 0.081	$ 0.207	$ 0.074	$ 0.089	$ 0.094

Table 7: *Average total balanced priced holdings: dollar value of each contract held by every trader priced on 10/2/20 (balanced to $1 for each trader)*

Any pattern found in this observation that includes a trader's higher than average net position for the contracts forecasted to win can be explained by an unconscious confirmation bias in investors and trading behavior. Evidence of this is seen in many traders that have a greater than average balanced priced holding in either Disney or Microsoft while also being the company they forecasted to win. However, there does not seem to be a large difference between forecasting with or without reasoning as many forecasters without justification were still likely to hold their forecasted company's contract at a greater value than the average trader but not much greater than those with justification. The student traders may unintentionally fixate on trading the contract of the company they projected to win and not only potentially ignore information about the other five companies, but also ignore

negative information that may somewhat disprove the initial forecast. In this event, confirmation bias is a reasonable explanation as to why the traders are not as open to outside and differing information as they normally may have been if they did not forecast prior to trading; or did not provide reason.

5.2. Regression Results and Contribution

When observing the regression results, balanced priced holdings for each individual company contract (Ref. Table 6) are used as the dependent variable against the survey results coding (Ref. Table 2) as the independent variable. To evaluate the null hypothesis, that the net positions of traders forecasting a company to win a contract race, with or without justification, are not significantly different from traders who do not forecast and do not increase confirmation bias in traders, I use a 10% level for significance (P-value).

If P-values are less than 10% and the estimated coefficient attached to one of the dummy variables is positive, I reject the null hypothesis and accept the alternative consistent with a presence of confirmation bias among the sample of student traders. I also report the value of estimated coefficients for the dummy variables to indicate the change in balanced holding percentage per forecast.

5.2.1. Microsoft Corporation (MSFT) Regression Analysis (Ref. Table 8.1)

Microsoft received by far the greatest number of forecasts with 38 (Ref. Section 4. Table 1), split perfectly for forecasts with and without justification, and is thus observed with the most confidence. Given a significance-F < 0.06 means, for Microsoft, there is less than a 6% chance the forecasts combined do not affect net position levels of traders or raise evidence of confirmation bias. With a P-value < 0.02 and a positive estimated coefficient (of about 0.21) attached to the justified dummy variable, I conclude that an average trader that forecasted Microsoft to win and justified why, had about a $0.21 higher net aggregate position in Microsoft. These results are consistent with the existence of confirmation bias among student traders.

Since the P-value falls within our significance level of < 10%, we reject the null hypothesis and claim the alternative: that forecasting, especially with justification, leads to different net positions and shows signs of confirmation bias. This means that confirmation bias seems to be playing a role in this scenario as traders that justified their reasoning towards their beliefs that Microsoft will be the winning contract also had the tendency to hold a greater percentage of Microsoft contracts in their portfolio.

If we only focus on the chosen dummy variable, we cannot come to the same conclusion confirming the existence of confirmation bias because the chosen dummy variable P-value of 0.58 > 0.1. This means there is a 58% chance that the forecasts without justification for Microsoft, do not significantly affect confirmation bias in traders. The null hypothesis should then be accepted and disregard forecasts without justification. Traders who only forecasted Microsoft to win without providing justification did not have significantly different net positions from the average trader.

5.2.2. Walt Disney Company (DIS) Regression Analysis (Ref. Table 8.2)

Disney regression data results are the second best option because it received the second greatest number of forecasts; but with a total of only 13, it is still not too sufficient to make a strong claim for or against the null hypothesis based on the resulting statistics. The significance-F of 0.24 > 0.1 for Disney, there is about a 24% chance the forecasts combined do not affect net position levels of traders or raise evidence of confirmation bias. This exceeds our significance level of 10% and thus, the results are weakened in confidence. With a P-value of 0.095, almost equal to the significance level, and a positive estimated coefficient (of again about 0.21), attached to the chosen dummy variable, I conclude that an average trader that forecasted Disney to win without justifying why, had about a $0.21 higher net aggregate position in Disney. These results are consistent with the existence of confirmation bias among student traders but weakened due to the fact that the P-value is near 10% and only 7 students forecasted without justification for Disney.

Since the P-value falls within our significance level of < 10%, we reject the null hypothesis and claim the alternative: that forecasting, especially with justification, leads to different net positions and shows signs of confirmation bias. This means that it is plausible confirmation bias may be playing a role in this scenario as traders that forecasted without reasoning that Disney will be the winning contract, also had the tendency to hold a greater percentage of Disney contracts in their portfolio.

If we only focus on the justified dummy variable, we cannot come to the same conclusion confirming the existence of confirmation bias because the justified dummy variable P-value of 0.73 > 0.1. This means there is a 73% chance that the forecasts with justification for Disney, do not significantly affect confirmation bias in traders. The null hypothesis should then be accepted and disregard forecasts with justification. Traders who only forecasted Microsoft to win and provided justification did not have significantly different net positions from the average trader.

5.2.3. Exxon Mobil Corporation (XOM) Regression Analysis (Ref. Table 8.3)

Only 5 total forecasts for Exxon Mobil to win makes claims based on the statistics weaker due to lower predictive power on a small sample size. However, received the best significance-F of 0.006 < 0.1, meaning there is about a 1% chance the forecasts combined do not affect net position levels of traders or raise evidence of confirmation bias. With also the best P-value of 0.001 < 0.1 and the greatest positive estimated coefficient (of about 0.52), attached to the justified dummy variable, I conclude that an average trader that forecasted Exxon Mobil to win while justifying why, had about a $0.52 higher net aggregate position in Exxon contracts. These results are consistent with the existence of confirmation bias among student traders but weakened due to the fact that only 2 students forecasted with justification for Exxon Mobil to win.

If these results were given in a larger sample, we would reject the null hypothesis and claim that confirmation bias seems to be playing a role in this scenario as traders that justified their reasoning

towards their beliefs that Exxon will be the winning contract also had the tendency to hold a greater percentage of Exxon Mobil contracts in their portfolio.

If we only focus on the chosen dummy variable, we cannot come to the same conclusion confirming the existence of confirmation bias because the chosen dummy variable P-value of 0.77 > 0.1 is too high and is paired with a negative coefficient. This means there is a 77% chance that the forecasts without justification for Exxon, do not significantly affect confirmation bias in traders. The null hypothesis should then be accepted and disregard forecasts without justification. Traders who only forecasted Exxon to win without providing justification did not have significantly different net positions from the average trader.

5.2.4. General Motors Company (GM) Regression Analysis (Ref. Table 8.4)

The combination of the small number of total forecasts of 5, the significance-F and P-values being well over 10%, and a negative coefficient for the chosen dummy variable leads to a high chance that the null hypothesis is true. The null hypothesis should then be accepted and both forecasts with and without justification should be disregarded. Traders forecasted General Motors to win did not have significantly different net positions from the average trader or show any signs of confirmation bias.

5.2.5. Walgreens Boots Alliance (WBA) Regression Analysis (Ref. Table 8.5)

Similar to the situation with General Motors, Walgreens total forecasts were also only 5, face even more severe statistics with the significance-F and P-values close to 1, and again a negative coefficient for the chosen dummy variable. This means there is almost a 100% chance that the null hypothesis is true for traders forecasting for Walgreens. The null hypothesis is accepted, and we conclude that traders forecasted Walgreens to win did not have significantly different net positions from the average trader or show any signs of confirmation bias.

5.2.6. Simon Property Group (SPG) Regression Analysis (Ref. Table 8.6)

With the smallest sample size with total forecasts of only 2 while the forecast with justification received 0 votes, meaning no analysis can be made because there is no data for the justification dummy variable. With a P-value of $0.007 < 0.1$ and coefficient of 0.31 for the chosen dummy variable, I conclude that an average trader that forecasted Simon Property Group to win without justifying why, had about a $0.31 higher net aggregate position in SPG. These results are consistent with the existence of confirmation bias among student traders. However, with the very small sample size of only 2 forecasts, we cannot make a strong claim that there is in fact evidence of confirmation bias behind forecasting without justification in this instance.

5.3. Discussion of Results

A common problem with the regression results, which aim to find if there is a greater holding in some company contracts when forecasted for them to win, is that there are not enough total forecasts, or too small of a sample size. Out of the six contracts forecasted for, each of the bottom four contracts only received between 2 to 5 forecasts. These are too small of sample sizes to make a strong prediction on the effects of confirmation bias because it is not reasonable to make a prediction or claim on a hypothesis based on the actions of only a few people. When a sample size is too small in any statistical analysis, predictive power is not accurately depicted because we cannot confidently anticipate specific trading behaviors. The fact that some companies are much more well-known and popular than others, such as Microsoft and Disney, also leads to issues with regression results because these mentioned companies, being the most popular, clearly received the most forecast votes as well. This may be due to popularity bias which in one aspect can be complimented by confirmation bias if the trader has the tendency to confirm their beliefs by primarily considering positive information about the company. This bias in popular companies also led to the other four companies having much lower total forecasts which made it difficult to make a strong claim based

on those corresponding regression results. Some student traders may have also not given their full attention or shown much care towards this trading exercise which would further lead to inaccurate results. In this event, confirmation bias would not be able to be predicted because this sort of behavior is not representative of an active trader that cares about their money.

6. Conclusion

6.1. Further Research

The basis of this experiment is to test if confirmation bias exists in investors and traders that forecast their beliefs towards an investment and further leads to a higher likelihood of purchasing or holding that investment. To better test this hypothesis, the experiment should be replicated with a much larger sample size since the total amount of forecasts for our entire experiment was only 66 split amongst six companies; averaging only 11 forecasts per company which would be too small of sample sizes to make a credible claim on resulting analysis. Another problem, as mentioned in the previous section, is the inclusion of only a couple popular companies matched in contract trading against much less popular companies. One way to solve this problem could be to use the largest market capitalization and most popular companies to represent the six competing company contracts; an example of six large and popular companies, as of today, are Microsoft, Tesla, Amazon, Google, Facebook, and Apple. This may reduce the possibility of traders having a higher holding percentage for a company simply because the trader held their popular choice.

When mainly considering Microsoft's contract trading in reference to the forecasts prior to trading, it is seen through the regression statistics that there is definitely some correlation for traders that forecasted with justification as they held generally $0.21 more in their balanced priced holdings for every forecast with justification. This company's regression data is the sole indicator used towards answering our hypothesis because it has the greatest number of forecasts. Microsoft received nearly three times the forecasts of Disney, which received the second most forecasts, and 19-times the

forecasts of Simon Property Group, which received the least. Although it can be inferred that some confirmation bias may exist through the resulting regression statistics, it may also be due to other factors mentioned previously such as giving little desire or attention to the IEM contract trading itself, or only siding with a familiar or popular choice.

REGRESSION STATISTICS

MSFT Regression Statistics	
Multiple R	0.24079586
R Square	0.05798265
Adjusted R Square	0.0381507
Standard Error	0.32663729
Observations	98

Table 8.1

ANOVA	*df*	*SS*	*MS*	*F*	*Significance F*
Regression	2	0.623870223	0.31193511	2.923699484	0.058586551
Residual	95	10.13573241	0.10669192		
Total	97	10.75960263			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.15775432	0.042168693	3.74102944	0.00031351	0.074038882	0.2414698
MSFT-CHOSEN	0.04738767	0.08598583	0.55111024	0.582851942	-0.123315783	0.2180911
MSFT-JUSTIFIED	0.20790827	0.08598583	2.41793649	0.017515785	0.03720482	0.3786117

DIS Regression Statistics	
Multiple R	0.172152061
R Square	0.029636332
Adjusted R Square	0.009207623
Standard Error	0.312115041
Observations	98

Table 8.2

ANOVA	*df*	*SS*	*MS*	*F*	*Significance F*
Regression	2	0.282646055	0.141323027	1.450719791	0.239546622
Residual	95	9.254500897	0.097415799		
Total	97	9.537146952			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.141038446	0.033853629	4.166124845	6.82567E-05	0.073830495	0.208246398
DIS-CHOSEN	0.207258091	0.122729829	1.688734454	0.094550274	-0.036391425	0.450907607
DIS-JUSTIFIED	0.045062849	0.131840945	0.341797074	0.733258543	-0.216674519	0.306800217

XOM Regression Statistics	
Multiple R	0.32146047
R Square	0.10333683
Adjusted R Square	0.08445971
Standard Error	0.21955463
Observations	98

Table 8.3

ANOVA	*df*	*SS*	*MS*	*F*	*Significance F*
Regression	2	0.527757716	0.2638789	5.4741843	0.005622031
Residual	95	4.579402172	0.0482042		
Total	97	5.107159889			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.08505999	0.022766754	3.7361493	0.0003189	0.039862271	0.1302577
XOM-CHOSEN	-0.03835767	0.128788209	-0.297835	0.7664792	-0.294034597	0.2173192
XOM-JUSTIFIED	0.51570924	0.156909024	3.2866767	0.0014214	0.204205441	0.827213

REGRESSION STATISTICS

GM Regression Statistics						
Multiple R	0.147022327					
R Square	0.021615565	Table 8.4				
Adjusted R Square	0.001017998					
Standard Error	0.177243385					
Observations	98					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	2	0.065935717	0.032967858	1.0494232	0.354162777	
Residual	95	2.98444568	0.031415218			
Total	97	3.050381397				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.079788499	0.018184788	4.387650824	2.9663E-05	0.043687131	0.1158899
GM-CHOSEN	-0.0797885	0.126642392	-0.63002994	0.53018748	-0.33120543	0.1716284
GM-JUSTIFIED	0.230770508	0.178173803	1.295198864	0.19839032	-0.12294921	0.5844902

WBA Regression Statistics						
Multiple R	0.02170136	Table 8.5				
R Square	0.00047095					
Adjusted R Square	-0.0205718					
Standard Error	0.18800637					
Observations	98					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	2	0.001582149	0.000791	0.022381	0.977873118	
Residual	95	3.357907604	0.035346			
Total	97	3.359489753				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.08981464	0.019495353	4.606977	1.27E-05	0.051111475	0.1285178
WBA-CHOSEN	-0.0216242	0.110282368	-0.19608	0.844966	-0.240562349	0.197314
WBA-JUSTIFIED	0.00999716	0.134362445	0.074404	0.940845	-0.256746015	0.2767403

SPG Regression Statistics						
Multiple R	0.28294926	Table 8.6				
R Square	0.08006028					
Adjusted R Square	0.06069313					
Standard Error	0.15675721					
Observations	98					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	2	0.203159164	0.1015796	4.133818167	0.01899197	
Residual	95	2.334418179	0.0245728			
Total	97	2.537577343				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.06761019	0.015998966	4.22591	5.46467E-05	0.035848227	0.0993722
SPG-CHOSEN	0.31052777	0.11199276	2.7727486	0.006690198	0.088194028	0.5328615
SPG-JUSTIFIED	0	0	65535	#NUM!	0	0

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Appendix 1: Survey Questions

Forecast Only

Q12

7. Which of the following will be the winning contract in the October 2020 IEM Inter-industry Returns Market (IntInd) (that is, will pay $1 at liquidation)?

- DISj20 (Disney)
- GMj20 (General Motors)
- MSFTj20 (Microsoft)
- SPGj20 (Simon Property)
- WBAj20 (Walgreens)
- XOMj20 (Exxon Mobil)

Forecast + Justification

Q26

7. Which of the following will be the winning contract in the October 2020 IEM Inter-industry Returns Market (IntInd) (that is, will pay $1 at liquidation)?

- DISj20 (Disney)
- GMj20 (General Motors)
- MSFTj20 (Microsoft)
- WBAj20 (Walgreens)
- XOMj20 (Exxon Mobil)

Q14

8. Provide a 140 character "tweet" as to why you think this contract will will be the winning contract.

Control

Q16

Are you excited for Hawkeye football?

- Yes
- Kind of
- Not really
- No