Claremont Colleges
Scholarship @ Claremont

CMC Senior Theses | CMC Student Scholarship

2012

Aggregated Versus Disaggregated Forward Looking Information: Effects on Risk Taking

Rishabh Parekh
Claremont McKenna College

Recommended Citation
Parekh, Rishabh, "Aggregated Versus Disaggregated Forward Looking Information: Effects on Risk Taking" (2012). *CMC Senior Theses*. Paper 398.
http://scholarship.claremont.edu/cmc_theses/398

This Open Access Senior Thesis is brought to you by Scholarship@Claremont. It has been accepted for inclusion in this collection by an authorized administrator. For more information, please contact scholarship@cuc.claremont.edu.

CLAREMONT McKENNA COLLEGE

AGGREGATED VERSUS DISAGGREGATED FORWARD LOOKING INFORMATION: EFFECTS ON RISK TAKING

SUBMITTED TO

PROFESSOR ANANDA GANGULY

AND

DEAN GREGORY HESS

BY

RISHABH PAREKH

FOR

SENIOR THESIS

SPRING 2012

4/23/12

Abstract

In previous research, aggregation of returns has been found as a way to counteract the risk averse behavior that is the result of investors' myopia. This paper expands the study of aggregation by analyzing its effect on forward looking probabilities. Namely, through the disaggregation of future information, subjects become myopic and trade with varying risk preferences. In an experimental market, subjects trading securities with disaggregated forward looking information are found to 'buy high and sell low', while subjects trading the same securities, but with aggregated information, trade with more consistent risk preferences.

Acknowledgements

I would like to first thank Professor Ananda Ganguly for his immeasurable contributions to this paper. Every time my research reached the brink of failure, his encouragement, guidance, experience, and dedication introduced new wind into my deflated sails. He put up with my fits of teenage attitude with resounding patience, and for all of the help that he has given me, I am truly grateful. I would also like to express my sincerest gratitude to the Man, the Myth, the Legend: Professor Manfred Keil, who for some reason beyond me, took me under his wing and provided invaluable counsel and advice.

To my parents, whom I have never properly thanked, I would like to say that I will never be able to repay you for all that you have given me. Your sacrifices and altruistic natures have given me all the opportunities in the world to succeed, and I hope that I can live my life with half the values and virtues that you have shown me over the past 21 years. I do not know where I would be without you guys, so thank you.

Table of Contents

I. Introduction 1
II. Literature Review 3
III. Research Question 11
IV. Methodology 14
V. Result 19
VI. Conclusion 31
Bibliography 34
Appendix 35

I. Introduction

According to the Efficient Market Hypothesis, the majority of market participants are *rational* actors who price all past public information into the price of a financial security. Efficient market proponents acknowledge that from time to time prices will change, not as a result of new information, but rather as a shift in investor's risk preferences. But what if these shifts were not completely due to rationality, but also due to behavioral biases?

Past research by Gneezy, Kapteyn, and Potters (2003) finds evidence that presenting individuals aggregated returns (as opposed to disaggregated returns) for a financial security actually leads to an increase in the price an individual would pay for the security. This higher price is not the result of additional information being priced in (as individuals who receive the aggregated returns actually receive less return information, i.e. none of the intermediate returns), but rather a change in investors' risk preferences as a result of how the returns are presented to them. This is an interesting phenomenon because individuals provided with disaggregated returns can very easily aggregate them by themselves. By choosing not to, individuals end up imposing extra risk aversion on themselves, which Benartzi and Thaler (1995) show can be suboptimal if the risk aversion prevents individuals from taking gambles that, though risky, have expected cumulative long term gains in far excess of their expected cumulative long term losses.

This paper expands on the previous literature of aggregation and risk taking by exploring the effects of aggregating forward looking data (which in this paper are probabilities of future outcomes) as opposed to backwards looking data (past returns).

When investors are making decisions related to financial securities, they usually consult forward looking information in addition to any backwards looking information. Therefore, understanding how the presentation of forward looking information affects risk preferences can give additional insights into behavioral biases that market participants face and help them correct for it. Whereas past research finds that disaggregation of returns leads to less risk taking, this paper finds that disaggregation of forward looking information leads to excess risk taking when future prospects of returns are optimistic and insufficient risk taking when future prospects of returns are bleak.

To arrive at this conclusion, an experimental market is set up in which subjects trade financial securities with one another. These securities pay out dividends based on probabilities for the present period of trading as well as future periods. There are two possible securities that subjects can trade. The first provides separate (disaggregated) probabilities for each period, while the other provides averaged (aggregated) probabilities for the future periods. Transaction prices are analyzed to see if subjects exhibit different risk preferences when they trade the two securities.

As it turns out, when trading the security with disaggregated probabilities, subjects tend to focus on each individual period as opposed to all of the periods they have probabilities for. The result is that when the probabilities look optimistic, subjects (rationally) become more risk seeking when they trade for the security, and actually pay a premium. When the probabilities look more bleak, subjects (rationally) become less risk seeking, and actually sell at a discount. However, subjects had these probabilities all along, and if they considered them all equally when making buy and sell decisions, as

they are forced to do with the security with aggregated probabilities, they would have had a better chance of avoiding 'buying high and selling low'.

This paper is organized as follows: the next section discusses previous research in greater detail and how the focus of this study builds off of it, while Section III summarizes the research question. Section IV explains the methodology used to create and run the experiments, and Section V analyzes the results that were obtained. Finally, Section VI concludes the paper and offers a few avenues of further research.

II. Literature Review

Myopic loss aversion is a term first introduced by Benartzi and Thaler (1995) in a study that examines the equity risk premium from a behavioral finance perspective.[1] This study is in response to a previous paper by Prescott and Mehra (1985) that explores why such a premium exists in the first place given historical returns. Analyzing stock and Treasury Bill returns from 1889-1978, Prescott and Mehra find that the real return on equities is about 7% per annum, while the real return on Treasuries is less than 1%, forming an equity risk premium of approximately 6%. With such a large discrepancy in returns, Prescott and Mehra have trouble understanding why any rational investor with a long time horizon would invest in Treasuries at all. They test to see if risk preferences are the driver behind some investors' choice of Treasuries over equities by determining the coefficient of relative risk aversion that would make investors willing to accept such a

[1] The equity risk premium is defined as the excess return on the overall stock market over the risk-free return. The excess risk is compensation for investors who are willing to take on the risk inherent in the stock market.

discrepancy in returns.[2] Prescott and Mehra find that a coefficient of approximately 30 would be necessary to explain such a large premium, which is far out of the range of values (1.0-5.0) that most academics believe the coefficient to be in. To fully understand just how risk averse an individual with a coefficient of 30 is, Mankiw and Zeldes (1991) provide the following question and illustration: If such a person is confronted with a gamble that has a 50% chance of paying $50,000 and a 50% chance of paying $100,000, what amount of *guaranteed* cash would he have to receive to willingly pass up the gamble? It turns out that for an individual with a risk coefficient of 30, the amount is only $51,209, which very likely is not the amount the average stock market investor would demand. Prescott and Mehra are not able to determine the reason(s) for such a premium, acknowledging the equity risk premium to be a true puzzle.

Benartzi and Thaler (1995) offer an explanation of their own via the concept of myopic loss aversion, which combines previously argued ideas of loss aversion and mental accounting. Loss aversion is a major component in Kahneman and Tversky's Prospect Theory (1979), which describes the differences in utility that come about as a result of gains and losses. According to Prospect theory, individuals receive utility from gains and disutility from losses; however, losses create more disutility than a gain of the same magnitude creates positive utility. For example, the utility gained by finding $100 will not be able to offset the disutility caused by losing $100. Mental accounting, on the other hand, refers to the way in which individuals and households use an accounting framework when analyzing economic decisions and results in their daily lives. An

[2] The coefficient of relative risk aversion is a measure of how willing someone is to take on a risky gamble instead of settling on a fixed outcome.

anecdote that Thaler (1985) uses to describe one example of mental accounting is as follows: A husband and wife, after a successful fishing trip, pack their fish and send it home on an airline. Unfortunately, the fish are lost, so the airline compensates the couple $300 for their loss. Upon receiving the money, the couple goes to a fine restaurant and spends $225, more than they had ever spent on a meal before. The couple received a $300 'windfall gain', and therefore spent it loosely on food. However, it is highly unlikely that they would have done so if the couple had generated the $300 through daily income, especially given that they had never spent so much on a single meal before. In either case, the value of $300 is the same, but in one instance the $300 is mentally accounted for as a 'windfall gain' while in the other instance it is accounted for as 'daily income'. The idea of mental accounting posits that this changes how the couple values the $300 and makes decisions.

The area of mental accounting most pertinent to this paper is how individuals choose (or do not choose) to use aggregation. Thaler discusses two main types of aggregation: cross-sectional and inter-temporal. Using a stock portfolio as an example, cross-sectional aggregation would involve analyzing portfolio returns as a whole as opposed to returns on individual stocks. Inter-temporal aggregation, on the other hand, involves analyzing a portfolio on a yearly basis as opposed to on a daily basis. Analyzing individual stocks and checking a portfolio on a daily basis are examples of being myopic. Going back to the example used above regarding gaining and losing $100, if an individual does not use aggregation and he is loss averse, then he will face a net negative change in utility. In this case, the individual is suffering from myopic loss aversion. By focusing on each instance of a loss or gain individually, the individual's loss aversion

magnifies the loss and creates net disutility. However, if the individual uses aggregation when engaging in mental accounting, then he will only notice the net financial change in position is $0, which does not trigger any loss aversion, and therefore no disutility.

Returning to the equity risk premium, Benartzi and Thaler explain the puzzle using myopic loss aversion. Due to a significant amount of volatility in the market, there are periods of excessive gains and of excessive losses, but in the long run, the gains have exceeded the losses to create an annualized 7% real return for equities. Imagine that instead the real return is much closer to 1%, which is what Treasuries offer, but with the same level of volatility. As explained above in the $100 example, an individual who is myopic will face much more disutility from the losses caused by the volatility that he will face utility from the gains. He will choose to stay out of the market for equities, and instead will likely settle for Treasuries. Even after the equity premium rises to 4%, the utility from gains is still not enough to offset the disutility from losses, even though, when aggregated, the financial returns of equities outpace Treasuries by 4% on average, per year. Benartzi and Thaler find that it is only when there is 6% annual premium that myopic individuals feel that the gains from equities create enough utility to offset the losses. The loss aversion and disaggregation lead to risk aversion, causing individuals to allocate less of their investments into equities. Given how strongly equities have outperformed bonds over the long run, such an under-allocation to equities will likely

lead to less capital appreciation, which is clearly the suboptimal decision/outcome for an investor with a long time horizon.[3]

Thaler, et al. (1997) and Gneezy and Potters (1997) extend Benartzi and Thaler's work on myopic loss aversion by examining ways in which levels of MLA can be alleviated. Both papers find that using aggregation likely forces individuals out of a mental accounting framework and decreases MLA. Thaler, et al. run an experiment in which subjects are given an initial monetary endowment and then have the chance to allocate it into stock or bond funds. All receive historical return data on the funds, but not necessarily at the same frequency. Investors get monthly, yearly, or 5-yearly returns, and based on these returns decide how much of their monetary endowment to allocate between stocks and bonds. Thaler, et al. find that subjects are willing to hold a greater allocation of stocks to bonds when they receive aggregated return data (yearly and every 5 years) as opposed to when they receive disaggregated (monthly) return data. Subjects in turn make more money in the long run (at the end of the experiment). These results are consistent with MLA because through the simple act of aggregating returns, subjects are forced into an aggregated framework that prevented their loss aversion from triggering risk aversion.

Gneezy and Potters (1997) also give subjects an initial endowment and the chance to allocate it to assets that pay out in aggregate or disaggregate form. Unlike Thaler, et al., subjects are first informed of the probability of a gain or a loss, and are then informed of their return. As expected, individuals show less signs of MLA (that is, they allocate

[3] For example, $1 invested in the S&P 500 back in 1926 would be worth over $1100 by 1996, whereas a similar investment in US 10 Year Treasuries would grow to $12.87 (Thaler, et al. 1997).

more of their endowment to the assets) when the asset returns are given in aggregate at the end of every third period as opposed to when they were presented in disaggregated pieces at the end of every period. The results also show that it is forward looking anticipation, and not the actual return data, that affects the degree of MLA. Allocations to assets remain relatively constant, even though, as the experiment progresses, subjects see more and more losses. It is the fact that subjects *anticipate* making money one-third of the time and losing money two-thirds of the time that affects asset allocation, not the *actual result* of making or losing money. Otherwise, as subjects progressively see more and more losses as a function of how long they do the experiment, their allocation to assets would have decreased.

Consider the following gamble that subjects in Gneezy and Potter's experiment face over a number of periods: there is a (1/3) chance of winning \$2.50 and a (2/3) chance of losing \$1.00. If analyzed myopically, or one period at a time, subjects will see that there is a two-thirds chance of a loss. In terms of utility,[4]

$$U(\Pi_1): 0 < \frac{1}{3}(\$2.50) + \frac{2}{3}\lambda(-\$1.00)$$

[4] The utility equations (and the ones that follow) are meant to determine when an individual is willing to buy a security. If the right hand side of the equation is greater than zero, then positive utility will result from buying the security (should buy). If less than zero, then negative utility will be generated (should not buy). And if equal to zero, then the individual will be indifferent

which is positive as long as an individual's loss aversion coefficient, λ, is less than 1.25.[5] If analyzed in aggregated fashion, or at the end of every third period, subjects will instead see the following payoff-probability scenario:

$$U(\Pi_2): 0 < \frac{1}{27}(\$7.50) + \frac{6}{27}(\$4) + \frac{12}{27}(\$0.50) + \frac{8}{27}\lambda(-\$3.00)$$

which creates positive utility as long as λ>1.56. Also, there is now less than a one-third chance of a loss. Though this is the same gamble, aggregation is all that is needed to make an individual less risk averse.

Taken together, Thaler, et al. (1997) and Gneezy and Potters (1997) infer that subjects use whatever data they can to create an expectation for the future and then determine how they will allocate their capital going forward. How this data is mentally accounted, be it aggregated or disaggregated, can affect expectations and in turn levels of MLA. Namely, aggregating returns decreases MLA while disaggregating returns increases MLA. In both studies, subjects who used mental accounting on aggregated data took on more risk and outperformed other subjects who used mental accounting on the disaggregated data.

Gneezy, Kapteyn, and Potters (2003) go a step further by putting subjects in a market environment to understand the effects of different levels of MLA in market interactions. In their experiment, some subjects trade assets that report returns in an aggregated manner while others trade assets that report returns in a disaggregated

[5] A coefficient of 1 means that a loss hurts as much as a gain. A coefficient of 1.25 means that a loss creates 25% more disutility than a similar gain.

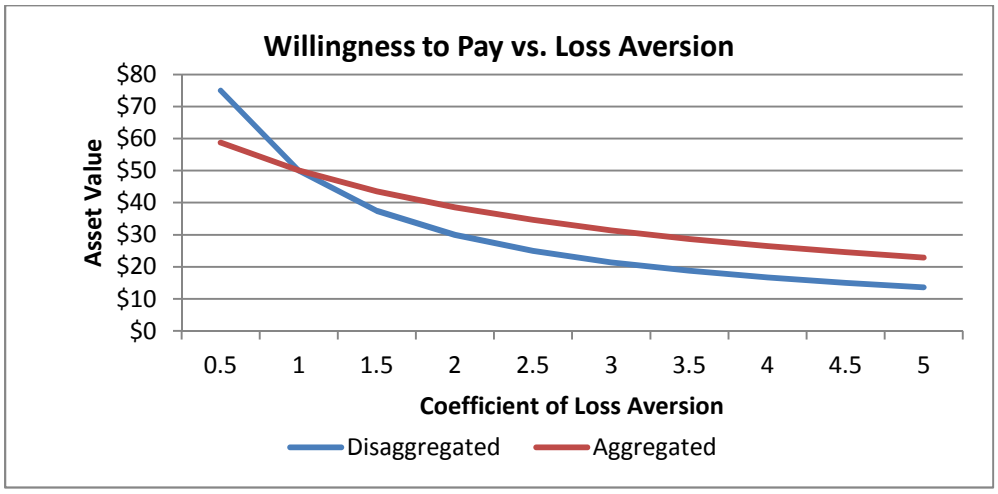
manner. As expected, there is less risk aversion (as conveyed by a greater willingness to pay for an asset) when subjects trade assets with aggregated returns.

Consider a gamble similar to the one above, but now with a payoff-probability profile of a (1/3) chance of winning \$150 and a (2/3) chance of winning \$0. Also, subjects are required to now pay a price, *p*, for this gamble. The utility functions are as follows for disaggregated returns and aggregated returns, respectively:

$$U(\Pi_3): 0 = 3 * \left[\frac{1}{3}(\$150 - p) + \frac{2}{3}\lambda(\$0 - p)\right]$$

$$U(\Pi_4): 0 = \frac{1}{27}(\$450 - 3p) + \frac{6}{27}(\$300 - 3p) + \frac{12}{27}(\$150 - 3p) + \frac{8}{27}\lambda(\$0 - 3p)$$

which yields the following relation between price, *p*, and loss aversion, λ:



As shown, subjects using an aggregated framework look at all returns at once, becoming less risk averse, as demonstrated by their greater willingness to pay, as long as their $\lambda > 1$.

III. Research Question

In the research summarized above, the main conclusion is that through aggregation of returns, i.e. not disclosing the intermediate returns, subjects become more willing to take on risk. In an investment environment, as portrayed in Benartzi and Thaler (1995), the implication is that aggregation of information will lead to increased risk preferences, which will in turn lead to a greater allocation into equities. Note, however, that all of this research is conducted with *past returns* as the aggregated or disaggregated stimulus to which the subjects are responding. In this paper, I argue that in reality, investors do not exclusively use past returns to predict future returns and decide on their investment allocations. Instead, they also obtain forward looking data to aid in predicting future returns. In the previous experiments, subjects either do not receive forward looking data (e.g. Thaler, et al. (1997)) or they receive forward looking data in the form of probabilities that do not change (Gneezy and Potters (1997) and Gneezy, Kapteyn, and Potters (2003)). Therefore, even in the latter, subjects' expectations of future returns remained constant. Relatedly, the aggregation that is employed does not truly aggregate probabilities, as the probabilities do not change over time. True aggregation would require subjects to know the probabilities of certain payouts over, for example, three periods, but not know the intermediate probabilities. This in turn would require varying probabilities, which are employed in this paper.

In reality, stock market participants obviously do not receive probabilities of what returns will be like for individual stocks or the market as a whole in the future. Instead, investors try to derive something similar by listening to the guidance given during earnings calls, reading the projections offered in the Management Discussion and

Analysis (MD&A) section of financial statements, and going through analyst reports that explicitly offer projections. Often times, this forward looking information will pertain to both the short term and long term, similar to company management offering guidance for an upcoming quarter as well as the entire fiscal year. Depending on how stable earnings and cash flows are, some companies will even offer five year estimates of earnings and free cash flows. With forward looking information so readily available, it does not make sense for investors to rely solely on past returns when trying to predict future stock prices (and therefore stock returns). Even if an investor does not have the time and resources to access this forward looking information, it would still make sense to use whatever he can, especially when there might be persistent foreseeable economic headwinds/tailwinds in the future that were not experienced in the past.

This paper looks to answer the question of whether or not subjects are myopic when given this forward looking information. In previous research, subjects who are given disaggregated data did not aggregate it on their own, thereby exhibiting myopia and trading with different risk levels than those who were given only aggregated data. It is therefore the expectation that subjects will exhibit myopia by focusing more on the immediate period than on future periods. This myopia, in conjunction with different future expectations, will in turn trigger varying levels of risk preferences.

According to Loewenstein's (2006) concept that more information is always preferable to less information when it is obtained costlessly, subjects should prefer to have disaggregated forward looking probabilities as opposed to aggregated probabilities because disaggregated probabilities simply give them more information. After all, with

disaggregated probabilities, subjects will know more information about each individual period than subjects with only aggregated information. Also, the disaggregated probabilities can be used to create aggregated probabilities, but the reverse is not true. For these reasons, subjects should be willing to pay a premium for disaggregated forward looking data over what they would pay for aggregated data. However, Gneezy et al. (2003) found the opposite to be true, as subjects paid more for aggregated return data. It is my contention that this is a result of not using true aggregation. Also, while it is likely that subjects will be more myopic with disaggregated forward looking data, it does not necessarily follow that this myopia will trigger risk aversion. Gneezy and Potters use a probability profile that made the probability of a loss twice as likely as the probability of a gain, and they kept the probabilities constant. Infrequent, favorable probability profiles when the *anticipation* of future returns (based on the probabilities of payouts) are constantly changing from period to period may actually trigger risk seeking behavior. Infrequent, unfavorable probability profiles, on the other hand, may trigger risk averse behavior. Therefore, the main hypothesis of this paper is that disaggregation of information will in fact trigger more myopia than aggregation of information, but that disaggregation will not necessarily exacerbate levels of myopic loss aversion. As mentioned above, if myopia causes subjects to focus on short term probabilities that are very optimistic, it is unlikely that loss aversion will be triggered. However, if myopia focuses subjects on short term probabilities that suggest a very pessimistic outcome, then there is a much greater chance that loss aversion will be triggered.[6] This hypothesis is in contrast with the previous studies' results that myopia, which leads to a mental

[6] Or perhaps, more accurately, *prospective* loss aversion, as we are discussing a prospective loss as opposed to an actual loss

accounting framework that uses disaggregation, accompanies higher levels of loss aversion. Rather, because probabilities are always changing, subjects' *anticipation* of future returns will also change, and with it their level of risk aversion. Sometimes they may be more risk seeking, and other times they may be more risk averse.

IV. Methodology

In different sessions of the experiment, subjects make buy and sell decisions for two different financial securities. The securities are designed such that any significant differences in the transaction prices for the two securities will help determine whether subjects are more risk seeking or more risk averse between aggregated versus disaggregated forward-looking information. More specifically, it is expected that securities with disaggregated forward looking information will trade with indications of myopia, though the myopia will not necessarily lead to risk aversion.

In each of the experimental sessions, subjects trade two different securities: "Gold" and "Blue". The securities have three-period life spans, and at the end of each period, pay out one of four possible dividend values in a fictional currency called Units. The probability of each dividend value being paid out is revealed to subjects at the beginning of a security's life span (every third period). Gold and Blue securities differ in that the probability of each possible dividend outcome is revealed for *each period* for Gold securities and *as an average for the three periods* for Blue securities. Other than that, Gold and Blue securities are similar. Since the name 'Gold' is used in the

experiment to stand for disaggregated securities and 'Blue' is used to stand for aggregated securities, for simplicity, this paper only uses the terms Disaggregated (hereafter, DAG) and Aggregated (hereafter AG) for Gold and Blue, respectively.

Unlike past experiments on MLA in which probabilities of future outcomes are held constant, this experiment's approach involves probabilities that change from period to period. The changing probabilities will ensure that subjects do not focus on just returns (backwards looking data), but also on forward looking probabilities. Subjects are given probabilities for the current period as well as the remaining periods of a security's lifespan. This is similar to real life conditions in which a company's management will give guidance for the upcoming quarter (short term) and the upcoming year (long term). Using these probabilities and the corresponding dividend values, subjects are able to determine an expected value for what a security will pay out in the current period as well as in the remaining periods that it exists for. Summing up the expected values, a subject can determine an estimate of the security's financial value.

As mentioned before, while the two securities are very similar, they differ in how their forward-looking information (probabilities) is presented. Each security can have one of four dividend payouts: a Boom or high dividend; a Good or medium-high dividend; a Bad or medium-low dividend; and a Bust or low dividend. For the DAG security, participants receive probabilities of each of these outcomes for the current period as well as the other two periods that the security exists for. Therefore a total of 12 probabilities are presented for DAG securities at all times, though after each period, some of the probabilities become old, and therefore irrelevant. For the AG security, the four

probabilities from each of the three periods are averaged, so subjects are shown a total of only 4 probabilities, representing averages for the security's three period lifespan. See **Table 1** for an example of how the probabilities are presented to subjects.

Table 1: Probability Presentation for the DAG (Disaggregated Information) and AG (Aggregated Information) Securities

Gold (DAG) Security

Period	Boom	Good	Bad	Bust
1	10%	20%	30%	40%
2	25%	25%	25%	25%
3	40%	30%	20%	10%

Blue (AG) Security

Period	Boom	Good	Bad	Bust
1	25%	25%	25%	25%
2				
3				

Note: This Table provides information for the probability of Boom, Good, Bad, and Bust outcomes for each security. A Boom outcome represents a dividend of 500 Units, Good represents 300 Units, Bad represents 0 Units, and Bust represents -150 Units.

Table 1 shows a sample DAG security on the left and a sample AG security on the right. Note that it is not the case that the probabilities are constant at 25% for periods 1-3 for the AG security; 25% is an average: in this case, it is the average of the probability values for the DAG security in periods 1-3.

Subjects are allowed to trade both securities concurrently. Therefore, any observed differences in transaction prices can be attributed to the aggregated versus disaggregated presentation of forward looking information, as other factors are held constant. The experimental setup is akin to investors making investment decisions based on disaggregated, (e.g., quarterly) guidance as opposed to aggregated, (e.g., annual) guidance. Or on a more extreme level, making investment decisions based on daily news (day trading) as opposed to quarterly/yearly guidance.

It is important to also note that in any one experimental session, the two securities did not have the same underlying probabilities. If they did, then there would be a clear

correlation in their returns, which subjects would likely notice. Once noticed, subjects would be able to infer the underlying probabilities for the AG security simply by looking at the DAG security, which would confound the DAG vs. AG treatment. Therefore, there are two sets of different probabilities that are used for all of the sessions. To simplify the following explanation, these probabilities will be referred to as Probability sets A and B. In one session, A is disaggregated, while B is aggregated. In another session, B is disaggregated, while A is aggregated. Because two different probability sets are used, there is no clear correlation between the two security's probabilities or returns *within* any experimental session.

Subjects are put through three periods of practice before 15 periods of trading for real money. Subjects are never actually told the number of periods in the experiment to prevent end-of-experiment behavior (i.e. extreme risk taking as a 'last ditch' effort to make profits). To understand the experimental set up, the 15 periods can also be thought of as 5 separate three-period trading sessions. In the first period of each session (i.e. periods 1, 4, 7, 10, and 13), subjects receive an endowment of two securities of each kind, as well as a cash loan with which they can buy more securities. The cash loan provided is set to be large enough for a subject to buy all the securities in the market at a rational price. This large repayable loan ensures that a subject is able to exploit an economic opportunity without having to worry about a cash restraint.

At the start of each unit of three periods, probabilities of dividend payouts for the upcoming three periods are revealed. As stated before, the DAG security had 3 sets of four probabilities revealed, while the AG security had 1 averaged set of 4 probabilities

revealed (revisit **Table 1** for an example). With these probabilities, and with dividend values that are given out in the instructions of the experiment, subjects can then estimate a security's value by determining the expected value of future dividend payouts (after all, a security should have fundamental value equal to the sum of the three dividends it will pay out).[7] To ensure that all subjects can in fact determine the expected value, an Excel spreadsheet is provided that has a template that calculates expected values for them. Subjects are given up to one minute to make these calculations, formulate a trading strategy, etc. before trading would begin.

Trading is conducted using a double oral auction format. Subjects give oral bid and ask orders, which are recorded into a computer program and presented for everyone to see. Any time a trade occurs, the two subjects involved record the transaction in their own personal trading log. In this log, subjects can see their past transaction history, their current cash and security balances, the past dividends earned, and total profits/losses. In addition to the personal transaction logs, the computer program also stores transaction history for each subject, enforcing no-cash-overdraft and no-short-selling rules. At any point in time during the experiment, a subject can access the computer program to see a snapshot of their transaction history to double check their work for errors. Any mistakes that subjects make in their own transaction log have no bearing on how the experiment runs. After three minutes (or a unanimous vote to end a trading session), trading is stopped and the dividend values for the two securities are revealed.

[7] Because there are no borrowing costs in this experiment, no discount of future dividends is required

All subjects were from the Claremont Colleges, with the majority being Claremont McKenna College students. The subjects were recruited by sending out emails to the entire student body advertising a trading simulation that offered cash compensation. To further establish the market environment, compensation is based on performance, so there is an incentive to be thoughtful, profit-maximizing (though not necessarily rational), market participants. An average of 9 subjects was used per session, ranging from 7 to 10 subjects. There were a total of 6 sessions run, and the average payout to each subject was $20, ranging $15.25 to $28.25.

V. Result

Recall that the primary hypothesis of this paper is that disaggregating forward looking information (or probabilities of outcomes in the case of this experiment) will make subjects myopic, though not necessarily risk averse. To test for myopia, two securities are used: one that forces subjects into an aggregated mental accounting framework, and the other that allows subjects to be myopic.

As mentioned in the Methodology section, there are two different sets of probabilities that are being used in each session, which will be referred to as Set A and Set B. The following chart describes how the probabilities are used and presented to subjects during each session:

Session	Disaggregated (DAG) Security	Aggregated (AG) Security
1	Set A	Set B
2	Set B	Set A
3	Set B	Set A
4	Set A	Set B

As shown above, Probability Set A is disaggregated in sessions 1 and 4 and aggregated in sessions 2 and 3. Conversely, Probability Set B is disaggregated in sessions 2 and 3 and aggregated in sessions 1 and 4.

If subjects trade the DAG and AG securities with different levels of risk aversion, the effects will be reflected in the transaction prices. As shown before, a greater willingness to pay results from more risk seeking behavior, while a lower willingness to pay results from more risk averse behavior. However, the two securities, even when they have the same *underlying* probabilities, will not necessarily have the same exact expected value because of the differing level of aggregation in the *available* probability information. Therefore, the securities are not supposed to trade at the same price by design. Specifically, it is possible to calculate the expected value for every single period for the DAG security because of the disaggregated nature of the probabilities. For the AG security, on the other hand, it is only possible to calculate the expected value for all three periods. Therefore, the best a subject can do to estimate expected value in periods two and three for the AG security is to reduce one-third a security's value after each period. Even with the same underlying probabilities, the AG and DAG security can trade at significantly different prices for completely rational reasons.

To control for differences in expected value, the *difference* (hereafter, deviation) of a security's transaction prices from its expected value is used as the dependent variable. If subjects exhibit the *same* level of risk aversion when they trade the securities, then the deviations will not be significantly different for the two securities. If, on the other hand, subjects do exhibit *different* levels of risk aversion, then a standard two sample t-test will be able to detect when the difference is statistically greater than zero (relatively risk seeking) and when it is statistically less than zero (relatively risk averse). In addition to t-tests, regression analysis is also used to determine if there are myopia-induced differences in risk preferences.

Expected value is chosen as the benchmark by which price deviations were measured for two reasons. The first is that the expected value is the payout, in dividends, that a security will make over the course of its lifetime, and therefore is the value of the security in the long run. Absent any behavioral biases or risk preferences that are more apparent in the short run, expected value is the best proxy for security value because it is the same for all individuals, regardless of their personal biases. The second reason is that all subjects are actually given a spreadsheet that, when used properly, computes the expected value for subjects. Subjects are basically given the expected value, so if there is any value on which all subjects are anchored, it is this expected value. Finding any patterns in pricing deviations from expected value is therefore a significant result.

T-Tests for Preliminary Analyses

Note that in all of the following analyses, data gathered in the first four periods (-2 through 1) is thrown out on account of those periods being practice periods.

There are three ways in which t-tests can be applied to determine if investors are being myopic. The first way is to compare security deviations from the same session; in other words, to observe the deviations of the AG and the DAG securities in the same period. The results of all four sessions are presented in **Exhibits 1-4** in the Appendix.

Running a t-test on the differences of deviations between the DAG and AG security illustrates if each difference is statistically significant from zero; that is, there is a statistically significant difference in risk preference that is driving the way subjects price securities. If subjects are myopic, then they should analyze the DAG security independently in each period, concentrating more on the current period than the later periods. In periods where the probabilities look very favorable, subjects should be relatively risk seeking when compared with how they price the AG security, whose probabilities are more average. This will in turn lead to a higher, positive t-statistic. If, on the other hand, the probabilities look really weak, then subjects should be relatively risk averse compared with how they price the AG security. This will in turn lead to a lower, negative t-statistic.

Table 2: Summary of T-Tests of Same Sessions, Different Underlying Probabilities

	Boom	Bust
Number of Occurences	16	20
Positive Difference	12	9
Statistically Significant Positive Difference	7	5
Negative Difference	4	9
Statistically Significant Negative Difference	1	3

As can be seen in **Tables 2**, which summarizes **Exhibits 1-4**, the results are not very conclusive when DAG and AG securities from the same session are compared to one another. Out of the 56 periods of data, there are sixteen that have very positive looking probabilities. These periods are referred to as 'Boom' periods, not necessarily because the dividend that is paid out is high, but because subjects expect the dividend to be high. These periods had an expected value of over 250 Units, whereas a period with equal probabilities has an expected value of 163 Units. Another twenty periods have very negative looking probabilities. These periods are referred to as 'Bust' periods, again due to subjects expecting the dividend to be low. These periods had an expected value under 100 Units. Hereafter, any references to 'Boom' and 'Bust' periods will refer to the *expectations* for the period's dividend payout and not the *actual* dividend payout that occurred. These terms will also be synonymous with 'optimistic' and 'positive' outlooks/probabilities for 'Boom' periods, and 'pessimistic' and 'negative' outlooks/probabilities for the 'Bust' periods.

Of the sixteen 'Boom' periods, subjects displayed relative risk seeking behavior in twelve of them, as represented by the positive t-statistics, and displayed relative risk averse behavior in four of them. Of the twelve positive t-statistics, seven are statistically significant, while of the four negative t-statistics, only one is statistically significant. These results would imply that 'Boom' periods trigger risk seeking behavior.

The 'Bust' period results, on the other hand, are much more inconclusive, if not counterintuitive. Of the twenty 'Bust' periods, nine had positive t-statistics and another

nine had negative t-statistics.[8] Of the nine positive t-statistics, five were statistically significant, which means that subjects were risk seeking when they saw 'Bust' probabilities. This outcome is counterintuitive to the concept of loss aversion, which would predict that subjects become more loss averse when the probability of losing money increases. However, looking at the five instances more closely raises the possibility that the t-tests are being distorted by a 'cyclicality' effect in the AG security. See the Appendix for more details. Unfortunately, the cyclicality effect cannot be controlled for in a standard t-test, so the results from these t-tests are inconclusive.

Table 3: Summary of T-Tests of Same Underlying Probabilities, Different Sessions

	Boom	Bust
Number of Occurences	8	10
Positive Difference	6	5
Statistically Significant Positive Difference	6	1
Negative Difference	2	5
Statistically Significant Negative Difference	0	3

T-Tests are also used to compare the deviations for DAG and AG securities that have the same underlying probabilities. For example, the deviations for the AG security from sessions 1 and 4 can be compared with the deviations for the DAG security from sessions 2 and 3, as all four have Probability Set A as the underlying probabilities. The results from the t-tests can be seen in **Exhibit 5** and **Exhibit 6**, and, though the results are mixed again, they are better than those in **Exhibits 1-4**. **Table 3** provides a summary of **Exhibit 5** and **Exhibit 6**. Subjects show more significant signs of myopia when they trade during an expected Boom period as opposed to an expected Bust period. When expecting a Boom, subjects show statistically significant excess risk seeking behavior six

[8] Two were not able to be analyzed because there was only one transaction per period.

out of eight times. When expecting a Bust, subjects only showed statistically significant excess risk averse behavior in three out of the ten periods. In fact, in periods in which the outlook is negative, half the time subjects displayed risk seeking behavior greater than when they traded the AG security (though only once is it statistically significant). Again, it would appear that a 'cyclicality' effect is distorting the t-test results. See the Appendix for further commentary. Though the results from the second round of t-tests are more intuitive and supportive of the hypothesis, the results are once again far from conclusive.

The third application of t-tests analyzes the average deviations based on future expectations. For example, a subject's willingness to pay for a security during an expected Boom period is compared to his willingness to pay for a security during an expected Bust period. This difference in deviations is then tested for significance. The benefit of this last round of t-tests is that it removes the cyclicality effect of the AG security by only focusing on the DAG security. Results can be seen in **Table 4** and **Table 5**. The average deviation during a Boom period is almost 34 Units, whereas the average deviation during a Bust period is a little under -2 Units. The difference in deviations as a result of future outlooks is statistically significant in almost all cases, which indicates that subjects do exhibit risk seeking behavior in some periods and risk averse behavior in other periods, but all in regards to the same security. In other words, subjects are myopic on short term information. Had they traded with the future periods in mind, they would not have overpaid for a security in period one, just so that they could then sell it for a depressed price in period three.

Table 4: Summary of Deviations Based on Dividend Expectations

	X_{Boom}	X_{Good}	X_{Bad}	X_{Bust}	X_{AG}
Avg Devation	33.7	28.9	14.1	-2.4	-21.7

Table 5: Differences in Deviations Based on Dividend Expectations

	$X_{Boom} - X_{Good}$	$X_{Boom} - X_{Bad}$	$X_{Boom} - X_{Bust}$	$X_{Good} - X_{Bad}$	$X_{Good} - X_{Bust}$	$X_{Bad} - X_{Bust}$
Difference	4.8	19.6	36.1	14.8	31.3	16.5
T-Stat	0.5	1.8	4.3	1.3	3.7	1.6
P-Value	-	4.3%	0.0%	9.8%	0.0%	6.2%

Interestingly, the average deviation for the AG security is -21.7 Units, which means that subjects, on average, displayed risk averse behavior towards the security. This result would explain the inconclusiveness of the first two rounds of t-tests. Subjects, regardless of probabilities, are already likely to underprice the AG security compared to the DAG security. This 'discount' made it easier for a t-statistic to be positive and significant, potentially overstating the difference in deviations during Boom periods. And on the other hand, the 'discount' also made it more difficult for the t-statistic to be negative and significant, understating the difference in deviations during Bust periods. Therefore, to test for myopia and the varying levels of risk preferences that it induces, it will not be possible to compare the deviations of the DAG security to the AG security using simple t-tests.

Regressions

An alternative to running t-tests is to run a regression model that can control for a variety of factors, including the underpricing seen in the AG security. Seven regression models were run, and the results can be seen in **Exhibit 7** and **Exhibit 8**.[9] The first regression model is relatively basic and presented in Column 1 of **Exhibit 7**. Despite the

[9] For a full list of definitions for each variable, refer to the Appendix

simplicity, the results are quite powerful, explaining why the t-tests are inconclusive and also finding the effects the t-tests are meant to find.

The first major reason why the t-tests are inconclusive is the negative coefficient on the variable 'Expected Value'. The negative value means that as the expected value increases, subjects become more likely to underprice the security relative to its expected value. In other words, as the expected value increases, the deviation naturally increases as well, irrespective of probabilities. In the majority of the periods in which securities are being compared by t-tests, the expected values are different (the exceptions being the first of every three periods in which the AG and DAG securities have the same underlying probabilities), and hence the problems. The second reason why the t-tests are inconclusive is apparent by the negative coefficient on the 'AG Dummy' variable, which essentially controls for the type of security that is being analyzed in the regression. The negative coefficient means that subjects, on average, underprice the AG security by 19.1 Units, which is very close to the -21.7 value that was found earlier by simply averaging deviations for the AG security. This finding supports the conclusion mentioned above that there is underpricing for the AG security that distorts the t-test results.

When controlling for expected value and type of security (the factors that rendered the t-test inconclusive), signs of myopia become much more clear. The two variables that detect myopia are 'Boom Outlook DAG' and 'Bust Outlook DAG', which test for the deviations given an expected Boom period or an expected Bust period. There is a clear, statistically significant difference in deviations, and therefore risk preferences, when subjects are expecting a Boom versus a Bust for the DAG security. The coefficient

on the 'Boom Outlook DAG' variable means that subjects are willing to pay 52 Units in excess of expected value (all else constant) to acquire a security during a Boom period, whereas subjects are willing to sell a security for 37 Units below its expected value during a Bust period (which is the coefficient on the 'Bust Outlook DAG' variable). As most groups of three periods have both an expected Boom and Bust period within them, these findings mean that even though subjects know that the future periods have very pessimistic (optimistic) probabilities, subjects still overvalue (undervalue) the security in the first period and then undervalue (overvalue) it in the third period.

In contrast to what is found in past research by Gneezy and Potters (1997), subjects' level of risk aversion is also found to be affected by past returns. Gneezy and Potters found that subjects' risk preferences were not affected by the actual return values, but rather by the level of aggregation of the returns. Based on the negative coefficient on the 'Last Return' variable, it would appear that subjects are in fact affected by actual return values. More specifically, the greater the previous period's dividend return, the greater subjects underprice a security, and vice versa. This may be an example of the disposition effect, in which subjects are much more willing to sell winners than losers. The 'Surprise' variable (last period's dividend payout minus last period's expected value) finds that when subjects get a dividend payout in excess of the expected value, subjects actually become more risk seeking, and vice versa. This result seems contradictory to the results found from the 'Last Return' variable.

To get more insight into the 'Surprise' variable, as well as the myopia subjects exhibit, a more complex regression model is also run and is presented in **Exhibit 8**. As

can be seen, the Boom and Bust outlook variables have been split up depending on which period they occur on. Also, a surprise is now differentiated between a positive surprise and a negative surprise, though the original 'Surprise' variable still remains to capture the effects of everything in between. Analyzing the deviations during expected Boom and Bust periods, now that they are controlled for by period, reveal that subjects exhibit the most severe myopia when they are expecting a Bust to occur in a third period. Subjects undervalue the security by more than 70 units, whereas they only undervalue it by 25 Units if they expect a Bust in the first period. The difference shows that subjects are not completely myopic, as they must be looking at (the more optimistic) future probabilities when they are pricing the security in period 1. The Boom outlook paints a slightly different story. Subjects are myopic in both cases, but prove to be more risk seeking in the first period, even though the probabilities usually get worse in periods two and three.

Interestingly, there is a large, negative coefficient on the negative surprise dummy variable, which shows that risk aversion in induced after negative dividend shocks in the DAG security, even though such shocks have no bearing on future returns. Incidentally, there is also a negative coefficient on the positive surprise dummy variable. Though it is not significant in this regression model, a glance at columns 2-4 shows that it becomes progressively more significant. This may be another instance of the disposition effect, where subjects are willing to cash in on a (unexpected) winner. Of course, the negative coefficient on the negative surprise dummy variable contradicts the disposition effect. However, as this paper's main focus is how presentation of probabilities affects risk preferences and not returns, it will have to suffice that the returns are controlled for, but left unexplained.

To see if the regression results are robust over different periods, the extensive regression model is run again over the second half of all the sessions (periods 7-15). The results in Column II of **Exhibit 8** are very similar to those in Column I, though subjects show insignificant levels of risk seeking behavior if they see Boom probabilities in period one. This is not to say that subjects become any less myopic, as the coefficients on the 'Bust Outlook' variables become even more negative (though standard deviation does decrease, which may partially be a result of a lower number of observations, n).

Regressions are also run for each security separately to better isolate the factors that affect risk preferences. The results of the regression that isolates the AG security can be seen in the Column II and III of **Exhibit 7**, while the results that isolate the DAG security are in Columns III and IV in **Exhibit 8**. The main takeaway from AG security's regression is that there are no clear signs of myopia when subjects trade the security. The only statistically significant variable is the expected value, which actually has a coefficient lower (more negative) than most of the other models. Return data and surprise dividend outcomes, which are really the only other information that subjects get about the securities, do not show any statistical significance (though they are almost significant at the 10% level). These results appear to be robust over the second half of sessions (periods 7-15) as well, as the regression in Column III has very similar results. From Columns III in **Exhibit 8** we see that no variables drop out of significance completely, while some variables do become more significant. The positive surprise dummy, for instance, becomes far more significant, while the negative surprise dummy variable actually becomes less significant. When the results are tested to see if they are robust over different time periods (periods 7-15), the results are similar to those in

Column II. The 'Boom Outlook in Per 1' variable once again drops out of significance, while most other coefficients increase in magnitude. The most important takeaway is simply that there is evidence that subjects are myopic when trading the DAG security, and no evidence to suggest that they are myopic when trading the AG security.

VI. Conclusion

The purpose of this experiment was to determine the effect aggregation of forward looking data has on individuals. The results suggest that disaggregated information induces myopia. More specifically, individuals are more likely to focus on the information pertaining to the near future than they are on the information pertaining to the more long term. As a result of this myopia, individuals will exhibit risk preferences that they would not otherwise exhibit if they analyzed all forward looking data in aggregate. For example, if the short term outlook for a security is very optimistic (pessimistic), individuals are likely to be relatively risk seeking (risk averse) and overvalue (undervalue) the security, even though the long term outlook might be pessimistic (optimistic).

These results were obtained by running experiments in which subjects could trade two different types of securities for which they were given forward looking information. For one of the securities, aggregated forward looking data was provided, making it impossible to be myopic, while for the other security, the data was left disaggregated. As expected, subjects with aggregated information traded with no signs of myopia, while subjects with disaggregated information did trade with signs of myopia.

The economic and financial implications of myopia are not clear based on the results of the previous studies that have been discussed in this paper. As Benarzi and Thaler (1995) show, myopia reduces risk taking, causing what appears to be the suboptimal allocation to equities for individuals who are long term investors, therefore leading to suboptimal returns. As Gneezy, Kapteyn, and Potters (2003) show, subjects who were forced into a mental accounting framework that uses aggregation actually became risk seeking, paying higher than the expected value for an asset. This is in contrast to the subjects who, due to using mental accounting on disaggregated data, had a higher level of MLA and therefore paid less for an asset. As these assets paid out dividends, it therefore follows that the subjects who are more myopic have a greater chance of making a profit. In this case, being myopic and having a mental accounting framework that allowed for disaggregation actually led to optimal returns. While this study will not definitively determine if myopia has positive or negative implications, it adds upon previous literature by making the case that myopia leads to suboptimal decision making. This is because individuals become too risk seeking (greedy) when future outlooks (probabilities of returns) are positive, and too risk averse (pessimistic) when future outlooks are negative. This leads to overpaying for securities during positive outlooks and selling securities at a discount during negative outlooks. Both practices should combine to yield suboptimal returns over the long run.

The effects of aggregation of forward looking data on risk preferences has not been as thoroughly researched as the effects of aggregating backwards looking return data. This opens the door for further research similar to what has already been done for the topic of aggregating return data. Such areas include cross sectional aggregation (as

opposed to the intertemporal aggregation used in this experiment) and ways to decrease the level of myopia that individuals experience. Tracking the earnings made by individuals who are myopic as opposed to those who are not in the experimental set-up used here will further illuminate what the implications of myopia are for investors. Finally, integrating the two forms of aggregation (both of returns and probabilities) and observing the impacts can provide a more holistic understanding of the effects of aggregation and investor risk taking.

Bibliography

Benartzi, Shlomo, and Richard H Thaler. "Myopic Loss Aversion and the Equity Premium Puzzle." *Quarterly Journal of Economics*, 1995: 73-91.

Gneezy, Uri, and Jan Potters. "An Experiment on Risk Taking and Evaluation Periods." *The Quarterly Journal of Economics*, 1997: 631-641.

Gneezy, Uri, Kapteyn Arie, and Jan Potters. "Evaluation Periods and Asset Prices in a Market Experiment." *The Journal of Finance*, 2003: 821-833.

Kahneman, Daniel, and Amos Tversky. "Prospect Theory: An Analysis of Decision Under Risk." *Econometrica*, 1979: 263-292.

Loewenstein, George. "The Pleasures and Pains of Information." *Science*, 2006: 704-706.

Mankiw, N Gregory, and Stephen P Zeldes. "The Consumption of Stockholders and Nonstockholders." *Journal of Financial Economics*, 1991: 97-112.

Mehra, Rajnish, and Edward C Prescott. "The Equity Premium: A Puzzle." *Journal of Monetary Economics*, 1985: 145-161.

Thaler, Richard H, Amos Tversky, Daniel Kahneman, and Alan Schwartz. "The Effect of Myopia and Loss Avesrion on Risk Taking: An Experimental Test." *The Quarterly Journal of Economics*, 1997: 647-660.

Thaler, Richard. "Mental Accounting and Consumer Choice." *Marketing Science*, 1985: 199-214.

Appendix

Exhibit 1: T-Test Results for DAG (Session 1) vs AG (Session 1)

Period	X_{DAG}	X_{AG}	$X_{DAG} - X_{AG}$	t-stat	p-value	Expectation
2	-59.7	-95.0	35.3	0.98	-	Average
3	82.0	-52.8	134.8	6.02	0.00%	Boom
4	-86.0	-71.7	-14.3	-1.34	-	Bust
5	59.5	-26.3	85.8	13.72	0.04%	Good
6	-4.7	26.0	-30.7	-0.58	-	Bust
7	119.2	-107.5	226.7	13.81	0.00%	Boom
8	7.4	-48.0	55.4	2.10	2.12%	Bust
9	36.0	-19.0	55.0	n/a	-	Bust
10	-207.8	-103.0	-104.8	-3.27	2.74%	Average
11	-24.5	14.3	-38.8	-3.11	3.99%	Good
12	47.5	62.3	-14.8	-1.15	-	Boom
13	-81.5	-62.3	-19.3	-0.68	-	Boom
14	36.2	-1.0	37.2	n/a	-	Good
15	17.3	0.0	17.3	0.35	-	Bust

Exhibit 2: T-Test Results for DAG (Session 2) vs AG (Session 2)

Period	X_{DAG}	X_{AG}	$X_{DAG} - X_{AG}$	t-stat	p-value	Expectation
2	-21.5	-77.0	55.5	0.44	-	Bust
3	43.5	5.0	38.5	3.73	1.02%	Boom
4	-2.0	-152.0	150.0	4.67	0.10%	Boom
5	34.0	6.0	28.0	1.12	-	Bad
6	49.3	8.0	41.3	n/a	-	Bust
7	-50.8	-80.0	29.2	1.00	-	Bust
8	-19.0	2.0	-21.0	-1.48	-	Bad
9	56.0	-4.0	60.0	6.00	5.26%	Good
10	-15.3	-60.3	44.9	0.96	-	Boom
11	40.7	-102.5	143.2	5.09	0.48%	Bad
12	51.1	11.7	39.4	2.31	6.79%	Bust
13	-31.0	-66.5	35.5	2.24	4.41%	Bust
14	-16.5	-39.3	22.8	4.41	0.48%	Bad
15	73.3	49.0	24.3	0.67	-	Boom

Exhibit 3: T-Test Results for DAG (Session 3) vs AG (Session 3)

Period	X_{DAG}	X_{AG}	$X_{DAG} - X_{AG}$	t-stat	p-value	Expectation
2	-0.3	15.0	-15.3	-2.81	1.31%	Bust
3	54.9	52.0	2.9	0.20	-	Boom
4	8.0	-26.0	34.0	2.94	1.98%	Boom
5	78.0	41.8	36.2	1.26	-	Bad
6	66.4	93.0	-26.6	-1.47	-	Bust
7	-48.3	-32.5	-15.8	-0.42	-	Bust
8	-23.3	72.0	-95.3	-5.71	0.83%	Bad
9	50.7	96.0	-45.3	-1.07	-	Good
10	13.6	-231.2	244.8	13.54	0.07%	Boom
11	7.7	-60.0	67.7	6.10	0.09%	Bad
12	-12.6	63.0	-75.6	-5.91	0.03%	Bust
13	-52.2	-43.2	-9.0	-0.48	-	Bust
14	0.6	34.0	-33.4	-3.65	1.12%	Bad
15	57.9	79.0	-21.1	-2.13	3.15%	Boom

Exhibit 4: T-Test Results for DAG (Session 4) vs AG (Session 4)

Period	X_{DAG}	X_{AG}	$X_{DAG} - X_{AG}$	t-stat	p-value	Expectation
2	-26.1	30.0	-56.1	-1.55	-	Average
3	45.3	28.0	17.3	1.60	-	Boom
4	2.8	-56.7	59.4	4.34	0.40%	Bust
5	7.8	2.0	5.8	0.51	-	Good
6	12.0	26.7	-14.7	-0.84	-	Bust
7	11.3	-46.9	58.1	7.58	0.01%	Boom
8	-7.5	-11.3	3.8	0.31	-	Bust
9	6.0	21.8	-15.8	-1.51	9.29%	Bust
10	-108.8	-60.9	-48.0	-2.33	2.67%	Average
11	-0.8	1.0	-1.8	n/a	-	Good
12	-1.7	-1.3	-0.4	-0.05	-	Boom
13	-38.8	-39.6	0.7	0.09	-	Boom
14	25.3	8.8	16.5	0.63	-	Good
15	14.1	-5.0	19.1	3.49	2.68%	Bust

The first column of data represents the average deviation of transaction prices from expected value (transaction price – expected value) for the DAG security. The second column of data represents the average deviation of transaction price from expected value for the AG security. The third column is the difference between column one and two. The fourth fifth columns show the resulting t-statistic and p-value,

respectively, to determine whether or not the difference in pricing (risk preference) is statistically significant.

In every group of three periods, subjects tend to trade the AG security at a clear discount to its expected value, and as time goes on, transaction prices approach expected value or even exceed it. As this is a clear trend that occurs regardless of probabilities and returns, this initial underpricing can possibly be subjects' unwillingness to overprice a security for three full periods. If this is the case, then it is possible that the DAG security suffers from the same effect, though it may not be as clear because of the volatility of the probabilities and expected values. Fortunately, the t-test is applied to the difference of the first two columns, which means the effect should be subtracted out if it is present for both securities.

Of the five instances in which there was a positive t-statistic for a Bust period, four have deviations that are less than 15 Units, and of these four, three occur in the first or second period of a security's lifecycle, when the underpricing of the AG security is typically the strongest. This underpricing increases the chance of a positive t-statistic, which is what produces the counter-intuitive results. Of the three statistically significant negative t-statistics, not one occurred in the first of a three period life-cycle when the underpricing of the AG security is at its highest. It would therefore appear that the results of the t-tests summarized in **Exhibits 1-4** are all potentially distorted by the AG security's 'cyclicality'.

Exhibit 5: T-Test Results for DAG (Sessions 1, 4) vs AG (Sessions 2, 3)

Period	X_{DAG}	X_{AG}	$X_{DAG} - X_{AG}$	t-stat	p-value	Expectation
2	-35.3	-26.8	-8.5	-0.40	-	Average
3	65.1	22.6	42.5	2.81	0.61%	Boom
4	-41.6	-89.0	47.4	1.55	7.08%	Bust
5	37.4	29.9	7.5	0.48	-	Good
6	3.7	64.7	-61.0	-1.91	7.42%	Bust
7	76.0	-59.6	135.6	4.88	0.00%	Boom
8	7.4	37.0	-29.6	-1.52	8.17%	Bust
9	19.3	56.0	-36.7	-1.07	-	Bust
10	-133.6	-133.5	-0.1	-0.00	-	Average
11	-6.1	-88.3	82.3	4.15	0.35%	Good
12	26.4	43.8	-17.3	-1.02	-	Boom
13	-55.9	-52.5	-3.4	-0.30	-	Boom
14	31.8	-14.8	46.6	2.03	3.16%	Good
15	17.2	69.0	-51.8	-5.26	0.12%	Bust

Exhibit 6: T-Test Results for DAG (Sessions 2, 3) vs AG (Sessions 1, 4)

Period	X_{DAG}	X_{AG}	$X_{DAG} - X_{AG}$	t-stat	p-value	Expectation
2	-11.5	-59.3	47.8	0.82	-	Bust
3	58.5	-25.9	84.4	4.85	0.05%	Boom
4	1.4	-61.7	63.1	4.27	0.14%	Boom
5	75.0	-10.6	85.6	4.27	0.39%	Bad
6	65.4	26.3	39.1	1.35	-	Bust
7	-54.2	-70.2	16.0	1.00	-	Bust
8	-29.0	-48.0	19.0	0.75	-	Bad
9	57.3	16.0	41.3	3.76	0.33%	Good
10	5.3	-76.2	81.5	5.02	0.01%	Boom
11	19.6	11.6	8.0	0.65	-	Bad
12	20.1	36.9	-16.8	-0.99	-	Bust
13	-47.7	-47.8	0.2	0.01	-	Bust
14	-11.1	6.8	-17.9	-3.57	0.30%	Bad
15	69.2	-2.5	71.7	2.96	1.39%	Boom

Focusing on just column one, it becomes apparent that the five instances of risk seeking behavior during a Bust period are more on a relative level that an absolute level. In three out of the five instances, the average deviation is actually negative (suggesting risk aversion), which means that the reason for the positive value in column three is the fact that the AG security is traded with extra risk aversion (i.e. it is the first or second period in a security's three period life-cycle).

The results of the second group of t-tests raise the potential that the 'cyclicality' effect in the AG security is not completely shared by the DAG security. Instead, the cyclicality appears to increase the difference in the deviations (column 3), which pushes more Boom periods into significance, and more Bust periods out of significance. The cyclicality effect could be the discount subjects apply to the AG security for not having as much information as the DAG security. In period 1, the DAG security has 3 periods of extra information that the AG security does not have; in period 2, the DAG has 2 periods of extra information; and in period 3, the DAG only has one period of extra information.

Exhibit 7: Basic & Aggregated (AG) Regression Models

VARIABLES	Basic (Periods 2-15)	AG Only (Periods 2-15)	AG Only (Periods 7-15)
Expected Value	-0.291**	-0.341**	-0.344**
	(0.03)	(0.03)	(0.03)
Boom Outlook DAG	52.33**		
	(8.88)		
Bust Outlook DAG	-36.96**		
	(9.31)		
Last Return	-0.0673	0.0236	-0.1347
	(0.03)	(0.12)	(0.16)
Surprise	0.0723*	-0.0272	-0.1527
	(0.03)	(0.11)	(0.16)
AG Dummy	-19.12**		
	(6.89)		
Period 1	-17.94*		
	(7.92)		
Period 3	-12.24		
	(7.44)		
Run 1	-8.53	-28.30**	-16.97
	(5.99)	(9.27)	(11.75)
Run 2	-5.690	-32.48**	-9.619
	(6.28)	(9.47)	(12.07)
Run 3	18.62**	21.00*	21.550
	(6.07)	(9.35)	(12.23)
Constant	108.4**	90.30**	68.25**
	(14.65)	(19.57)	(25.98)
Observations	462	210	126
R-squared	0.512	0.514	0.550

Standard errors in parentheses

** p<0.01, * p<0.05

Exhibit 8: Extended & Disaggregated (DAG) Regression Models

VARIABLES	Extended (Periods 2-15)	Extended (Periods 7-15)	DAG Only (Periods 2-15)	DAG Only (Periods 7-15)
Expected Value	-0.320**	-0.298**	-0.353**	-0.330**
	(0.03)	(0.03)	(0.03)	(0.04)
Boom Outlook DAG Per 1	62.73**	52.72**	63.61**	56.83**
	(11.44)	(12.15)	(10.79)	(11.26)
Boom Outlook DAG Per 3	32.03**	15.88	26.17**	11.57
	(10.07)	(14.57)	(9.37)	(13.78)
Bust Outlook DAG Per 1	-24.76*	-34.84*	-23.99*	-27.03*
	(10.52)	(13.55)	(9.67)	(13.00)
Bust Outlook DAG Per 3	-70.41**	-88.40**	-80.87**	-90.88**
	(11.66)	(14.97)	(11.75)	(15.48)
Last Return	-0.079*	-0.129*	-0.140**	-0.174**
	(0.04)	(0.05)	(0.04)	(0.05)
Surprise	0.086*	0.112*	0.191**	0.206**
	(0.04)	(0.05)	(0.05)	(0.06)
Positive Surprise Dummy	-16.08	-31.03*	-32.08**	-42.04**
	(11.68)	(13.32)	(11.75)	(12.59)
Negative Surprise Dummy	-39.65**	-54.40**	-22.46	-36.61*
	(12.70)	(14.44)	(13.04)	(14.51)
AG Dummy	-22.22**	-29.32**		
	(8.30)	(10.67)		
Period 1 AG	-17.06*	-15.54		
	(8.67)	(11.30)		
Period 3 AG	-5.14	0.10		
	(9.45)	(12.78)		
Run 1	-9.90	-2.37	5.70	11.00
	(5.95)	(7.23)	(7.22)	(8.51)
Run 2	-8.71	5.26	12.50	13.97
	(6.30)	(7.75)	(7.88)	(9.94)
Run 3	13.20*	8.49	6.38	-2.91
	(6.16)	(7.53)	(7.64)	(9.40)
Last Period Effect	2.82	14.65	2.85	18.04
	(9.05)	(10.67)	(9.93)	(11.95)
Constant	122.1**	124.5**	138.1**	138.0**
	(13.78)	(16.25)	(16.09)	(18.13)
Observations	462	296	252	169
R-squared	0.531	0.583	0.576	0.652

Standard errors in parentheses

** p<0.01, * p<0.05

Definition of Regression Variables

- **Expected Value** – The Expected Value of a security in a particular period
- **Boom Outlook Per #** – Dummy variable that equals 1 when the expected value for the period alone exceeds 250
- **Bust Outlook Per #** – Dummy variable that equals 1 when the expected value for the period alone is below 100
- **Last Return** – Dividend value paid at the end of the most preceding period
- **Surprise** – Dividend minus the Expected Value, both of the most preceding period
- **Positive Surprise Dummy** – Dummy variable that equals 1 when an expected Bust period yields a Boom or Good dividend
- **Negative Surprise Dummy** – Dummy variable that equals 1 when an expected Boom period yields a Bad or Bust dividend
- **AG Dummy** – Dummy variable that controls for type of security (AG = 1)
- **Period 1** – Variable that controls for transaction in the first period
- **Period 3** – Variable that controls for transaction in the third period
- **Period 1 AG** – Interaction variable that controls for the AG security in Period 1
- **Period 3 AG** – Interaction variable that controls for the AG security in Period 3
- **Run 1** – Controls for the first experimental session
- **Run 2** – Controls for the second experimental session
- **Run 3** – Controls for the third experimental session

Experiment Instructions

Thank you for agreeing to participate in our study of decision making. You will be able to earn real U.S. dollar profits in this study by making intelligent decisions. You will receive $5 for participating and following these instructions. In addition, separate payments will be based on your performance during the experiment. Keep in mind that there are no right or wrong answers. We are trying to find out how intelligent economic agents make decisions in specified circumstances.

You are an Investor

You are an investor, and you will be trading in a financial market (this room) that contains two different assets. You will be trading with the other investors (participants) in this room for a number of periods. Each period is broken down into two parts. The first part, which lasts up to 1 minute, is time for investors to make calculations (more on this later) and to prepare for trading, and the second part, which lasts up to 3 minutes, is the time when trades can be made in the market (you may still make calculations). In total, each period lasts up to 4 minutes.

All transactions in this experiment will be conducted in an experimental currency we'll call Units. We'll convert your Unit earnings to U.S. $ at the end of the experiment at the rate of U.S. $ 1= 470 Units

You Can Trade Assets

As mentioned above, you will trade in two different assets in each market. The two different assets have the following attributes:

- The two assets have underlying companies that are in different closed economies. **There is therefore no correlation in the returns of the two assets**
- The assets pay out income (dividends) at the end of every period
- Each asset lasts for three periods (One asset will pay out 3 dividends during the course of its lifetime. Then it ceases to exist, so its value becomes 0. Therefore an asset should be worth the value of all the dividends it will pay out. For example, in period 1 it should be worth the future three dividend payouts. In period 2 it should be worth the future 2 dividend payouts, and in period 3 it should be worth the final dividend payout)
- The dividend (in Units) that is paid out is not constant from period to period. Instead, there are four possible dividends that correspond with one of four

economic conditions: Boom, Good, Bad, Bust. They will not change at any point during the experiment:

	Boom	Good	Bad	Bust
Dividend Value	500	300	0	-150

- Probabilities predicting which state the economy will be in (Boom, Good, Bad, or Bust) in the upcoming periods are revealed to investors at the beginning of the asset's life (every third period: periods 1, 4, 7, 10, 13)
- Economic conditions will not necessarily be the same for the two assets. (e.g., just because one asset is in a Boom period does not mean that the other one will also be in a Boom.) As mentioned in the first point, there is no correlation between the two assets; not in terms of probabilities, current returns, or even future returns.

The two assets are similar with one exception: the detail with which the probabilities of economic conditions are presented. Both assets have known probabilities for the upcoming three periods of economic conditions. The Gold Asset has three sets of individual probabilities for all four economic states across the three periods, while the Blue Asset has one set of probabilities (averaged across the three periods) for all four economic states. Here is a sample of what the probabilities provided at the beginning of an asset's life may look like:

Gold Asset

Period	Boom	Good	Bad	Bust
1	25%	25%	25%	25%
2	20%	20%	25%	35%
3	30%	30%	20%	20%

Blue Asset

Period	Boom	Good	Bad	Bust
1	27%	23%	25%	25%
2				
3				

These probabilities correspond to four possible dividend values shown on page 1. Using a combination of the dividend values and the probabilities, it is possible to compute an expected value for an asset, which may be a good proxy for the asset's actual value. For those of you who haven't taken statistics in a while, here is a quick refresher:

Using Expected Value

Let's say we are playing a game where I roll a die and you get paid one dollar for the number of dots that face up. So, you receive $1 if I roll a one, $2 if I roll a two, […], and $6 if I roll a 6. How much money would you pay me to play this game? Clearly you

shouldn't pay $6 per roll, because your expected earnings on average are almost certainly going to be less than that amount. And I too shouldn't accept $1 per roll, because my expected payments on average are almost certainly going to be more than that amount. We can calculate the total amount that will be paid out on average, if the die were to be rolled a very large number of times. Here is the calculation:

Expected Value = Prob(rolling a 1) x $1 + Prob(rolling a 2) x $2 + … + Prob(rolling a 6) x $6

Expected Value = (1/6) x $1 + (1/6) x $2 + … + (1/6) x $6

Expected Value = $3.50

If we were to play the game one time, you will receive anywhere from $1-6. However, after repeated rolls, the average amount of money that you will receive each time is $3.50. If I therefore charge you $3.50 per roll, for a large number of rolls, we both have a good chance of breaking even.

Your Financial Portfolio

At the beginning of every third period, you are given two Gold Assets and two Blue Assets. These assets are yours to trade with and will exist for the next three periods, after which new assets will be given to you. Additionally, you will also receive 10,000 Units with which you can trade for additional Gold Assets, as well as another 10,000 Units with which you can trade for additional Blue Assets (if you use up all of your cash for the Gold Asset, you cannot use cash from the Blue Asset to buy more Gold Assets). Both grants of 10,000 Units are actually loans to you, and they must be repaid at the end of three periods (don't worry, there is no interest charged and therefore no interest payment/expense). At the end of a period, you will receive dividends based on the number of assets you own.

How Each Trading Period Works

At the beginning of every third period, investors will receive two of each asset (four new assets in total), as well as two 10,000 Unit loans (20,000 Units in total). Next, probabilities for the next three periods will be revealed to all the investors. After the probabilities are revealed, investors have up to one minute to make calculations/formulate a trading strategy. The Excel spreadsheet has a template that can help during this one minute. If you do not want to use the template, simply switch to another Excel sheet or use a pen, paper, and calculator.

After the one minute is over, trading will begin. Trading will take place for up to three minutes, and investors will use the excel spreadsheet on the computer in front of them to record their actions in the market. Trading is very much like an auction. You will raise your hand and say a buy/sell price and it will be recorded into the market. There are some basic rules to trading:

- You can only buy/sell one of each asset at a time. For example, you can buy/sell one share of both the Gold and Blue Asset at the same time. However, you cannot buy two shares of the Gold Asset at the same time. Instead, you will have to put in one order after the other
- A trade occurs when the Buy (offer to buy) price equals the Sell (offer to sell) price
- You should only offer a Buy price that is less than the Sell price, and an Sell price that is greater than the Buy price
- You can't sell assets that you do not have (cannot have a negative asset balance)
- You cannot buy assets if they make your cash balance go negative
- You can only offer a buy or sell price that is not already in the market
- You cannot trade with yourself

Using the Trading Platform

There are four parts to the trading platform, which we will discuss together as a group:

1. Investor's personal transaction log named "Trader #"

This excel spreadsheet is for you to make updates/entries. Whenever you buy or sell an asset, make a note of the transaction here. This sheet contains your current cash and asset balance, transaction history, dividend payments, and profits/(losses). (see Figure 1)

2. Investor's personal transaction log named "Trader #" (KEY)

This sheet is meant as a way for you to double check that your personal transaction log is mistake-free. This sheet contains an investor's asset and cash balance, transaction history, dividend payments, and profits/(losses) that *we* have on record for you. You do not need to make any updates/entries onto this sheet. **This sheet updates every 20-30 seconds, so it will not show the trades immediately. Please be patient!**

3. Expected Value Calculator

You can use this 'calculator' as an aid to estimating asset prices (see Figure 2)

4. The Market

This part aggregates all buy and sell orders from the investors and displays data from the financial market. Past prices are listed and graphically displayed. (see Figure 3)

5. Past returns and future probabilities

Past dividends and future probabilities are revealed here (see Figure 4).

Making (Real) Money

You can make profit in 3 ways:

1. You buy an asset for a price lower than the dividends it pays out
2. You buy an asset for a low price and then sell it for a high price
3. You sell an asset to get guaranteed cash in hand

You will receive extra compensation in real US dollars at the end of the experiment based on the *Grand* Total Profit you accrue. Notice that 'Mkt Value of Assets' is not included in the Grand Total Profit calculation. This is a separate column that reflects the current market value of your portfolio of assets. The assets will only generate profits once you either sell them or receive dividends from them.

But Don't Get Too Greedy..

Unfortunately, there is no benevolent US Government or TARP Fund that will bail you out in the event that you run excessively large losses. Therefore, we may ask you to leave the experiment if you lose too much money (consider this the equivalent of you going bankrupt). But do not worry! This experiment is designed to make you money. This section is merely a plea to encourage you to make decisions intelligently.

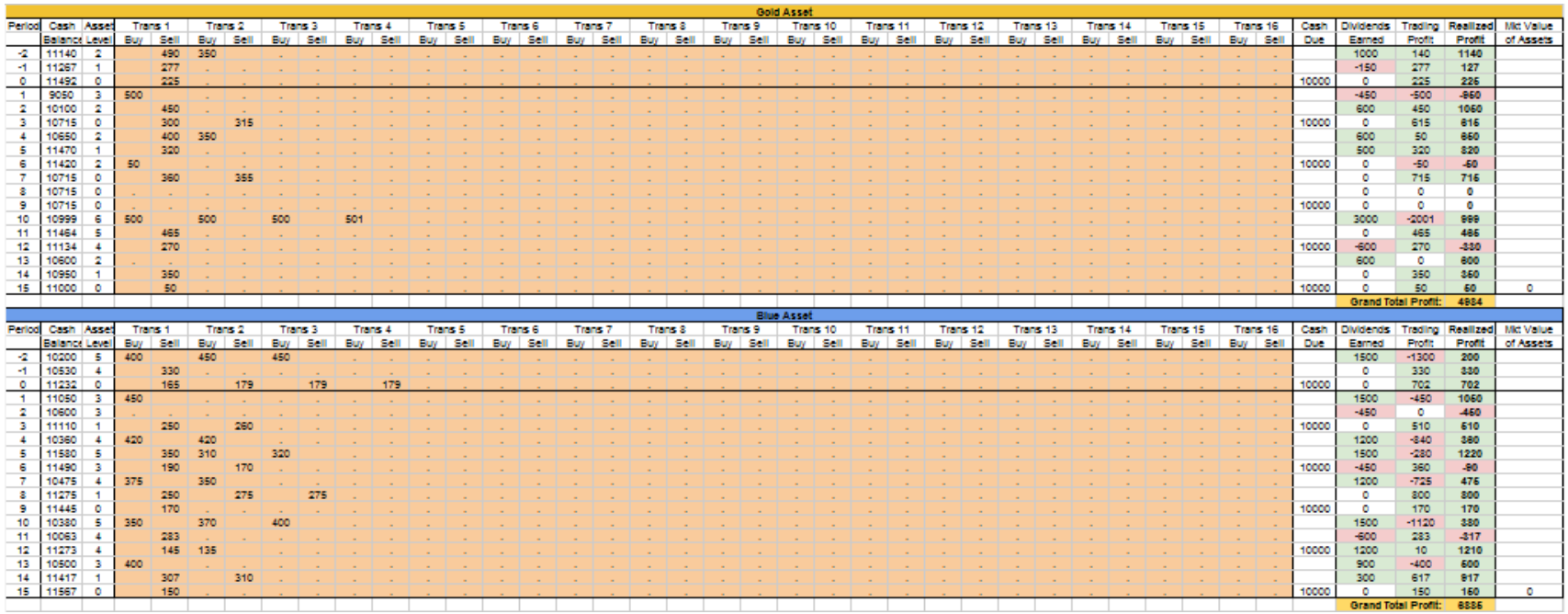
And Please Don't be an Outsider Trader

My hope for the next 1.5-2 hours is that you have fun and maybe even (more like most likely) make some money, and in return I get some pretty interesting data. To help me continue to get good data, please do not leave here today and tell others the specifics of this experiment. It is fine, in fact encouraged, to tell your friends that you traded assets, made money, and had fun. But please do not tell people other details of the experiment (any number values at all). Thesis requires a lot of time and effort, and I've had to reach into more than one piggy bank to fund these experiments; it would be really unfortunate if future data was corrupted by some investors knowing more than they should. So please, enjoy the trading environment while you're inside the market, but as soon as you leave, resist the temptation to give away inside information to your friends!

Ready, Set.. Go!

We will now begin a practice session. After that, we will commence trading. When we are finished, you will receive your performance based compensation.

Figure 1: Investor's Personal Transaction Log



Gold Asset

Period	Cash Balance	Asset Level	Trans 1 Buy	Trans 1 Sell	Trans 2 Buy	Trans 2 Sell	Trans 3 Buy	Trans 3 Sell	Trans 4 Buy	Trans 4 Sell	Trans 5 Buy	Trans 5 Sell	Trans 6 Buy	Trans 6 Sell	Trans 7 Buy	Trans 7 Sell	Trans 8 Buy	Trans 8 Sell	Trans 9 Buy	Trans 9 Sell	Trans 10 Buy	Trans 10 Sell	Trans 11 Buy	Trans 11 Sell	Trans 12 Buy	Trans 12 Sell	Trans 13 Buy	Trans 13 Sell	Trans 14 Buy	Trans 14 Sell	Trans 15 Buy	Trans 15 Sell	Trans 16 Buy	Trans 16 Sell	Cash Due	Dividends Earned	Trading Profit	Realized Profit	Mkt Value of Assets
-2	11140	2		490	350																													1000	140	1140	
-1	11267	1		277																														-150	277	127	
0	11492	0		225																													10000	0	225	225	
1	9050	3	500																															-450	-500	-950	
2	10100	2		450																														600	450	1050	
3	10715	0		300		315																											10000	0	615	615	
4	10650	2		400	350																													600	50	650	
5	11470	1		320																														500	320	820	
6	11420	2	50																														10000	0	-50	-50	
7	10715	0		360		355																												0	715	715	
8	10715	0																																0	0	0	
9	10715	0																															10000	0	0	0	
10	10999	6	500		500		500		501																									3000	-2001	999	
11	11464	5		465																														0	465	465	
12	11134	4		270																													10000	-600	270	-330	
13	10600	2																																600	0	600	
14	10950	1		350																														0	350	350	
15	11000	0		50																													10000	0	50	50	0
																																		Grand Total Profit:			4884	

Blue Asset

Period	Cash Balance	Asset Level	Trans 1 Buy	Trans 1 Sell	Trans 2 Buy	Trans 2 Sell	Trans 3 Buy	Trans 3 Sell	Trans 4 Buy	Trans 4 Sell	Trans 5 Buy	Trans 5 Sell	Trans 6 Buy	Trans 6 Sell	Trans 7 Buy	Trans 7 Sell	Trans 8 Buy	Trans 8 Sell	Trans 9 Buy	Trans 9 Sell	Trans 10 Buy	Trans 10 Sell	Trans 11 Buy	Trans 11 Sell	Trans 12 Buy	Trans 12 Sell	Trans 13 Buy	Trans 13 Sell	Trans 14 Buy	Trans 14 Sell	Trans 15 Buy	Trans 15 Sell	Trans 16 Buy	Trans 16 Sell	Cash Due	Dividends Earned	Trading Profit	Realized Profit	Mkt Value of Assets
-2	10200	5	400		450		450																											1500	-1300	200	
-1	10530	4		330																														0	330	330	
0	11232	0		165		179		179		179																							10000	0	702	702	
1	11050	3	450																															1500	-450	1050	
2	10600	3																																-450	0	-450	
3	11110	1		250		260																											10000	0	510	510	
4	10360	4	420		420																													1200	-840	360	
5	11580	5		350	310		320																											1500	-280	1220	
6	11490	3		190		170																											10000	-450	360	-90	
7	10475	4	375		350																													1200	-725	475	
8	11275	1		250		275		275																										0	800	800	
9	11445	0		170																													10000	0	170	170	
10	10380	5	350		370		400																											1500	-1120	380	
11	10063	4		283																														-600	283	-317	
12	11273	4		145	135																												10000	1200	10	1210	
13	10500	3	400																															900	-400	500	
14	11417	1		307		310																												300	617	917	
15	11567	0		150																													10000	0	150	150	0
																																		Grand Total Profit:			8886	

Figure 2: Expected Value Calculator

Per	Boom	Good	Bad	Bust
1	30%	30%	20%	20%
2	20%	30%	30%	20%
3	20%	20%	30%	30%

Boom	Good	Bad	Bust
20%	30%	30%	20%

Dividend Values

Boom	Good	Bad	Bust
300	200	100	0

Dividend Values

Boom	Good	Bad	Bust
300	200	100	0

EV = Expected Value

	Gold Asset					Blue Asset				
Per	Boom	Good	Bad	Bust	EV	Boom	Good	Bad	Bust	EV
1	90	60	20	0	170	60	60	30	0	150
2	60	60	30	0	150	60	60	30	0	150
3	60	40	30	0	130	60	60	30	0	150
EV	210	160	80	0	450	180	180	90	0	450

SAMPLE PRACTICE PROBLEM

Probabilities

1	2	3	4	5	6	Total
17%	17%	17%	17%	17%	17%	100%

Payouts Based on Value Rolled

1	2	3	4	5	6
$1	$2	$3	$4	$5	$6

Expected Value Calculation

1	2	3	4	5	6	EV
0.17	0.33	0.50	0.67	0.83	1.00	3.50

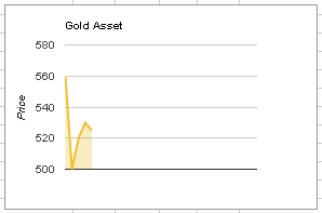
Figure 3: The Market

Gold Asset					
Trader		Buy	Sell		Trader
1					1
2					2
3	518	518			3
4			525	525	4
5					5
6	521	521			6
7			539	539	7
8					8
9					9
10					10
11					11
12					12

Blue Asset					
Trader		Buy	Sell		Trader
1					1
2	490	490			2
3			500	500	3
4	470	470			4
5					5
6			500	500	6
7					7
8			495	495	8
9					9
10			490	490	10
11					11
12					12

Period	Gold Asset	
0	Buy	Sell
GO	521	525

Last Trade: 525

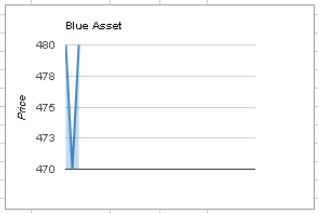


Recent Prices
560
500
520
530
525
*

Blue Asset	
Buy	Sell
490	490

Trading...

Last Trade: 490



Recent Prices
480
470
480
490
*

Figure 4: Past returns and future probabilities

	Possible Gold Dividend Values				Possible Blue Dividend Values			
	Boom	Good	Bad	Bust	Boom	Good	Bad	Bust
	500	300	0	-150	500	300	0	-150

	Gold Asset				Blue Asset			
Period	Boom	Good	Bad	Bust	Boom	Good	Bad	Bust
-2	30%	30%	20%	20%				
-1	20%	30%	30%	20%	20%	30%	30%	20%
0	20%	20%	30%	30%				
1								
2								
3								
4								
5								
6								
7								
8								
9								
10								
11								
12								
13								
14								
15								

Dividends Paid Out			
Period	Gold Asset	Blue Asset	
-2	500	300	earned
-1			
0			
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			
11			
12			
13			
14			
15			