The Journal of Behavioral Finance & Economics Volume 2, Issue 1, Spring 2012 **50-81**

ISSN: 1551-9570

Fear in Asset Allocation During and After Stock Market Crashes An Experiment in Behavioral Finance

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Abstract

We test for the presence of fear in an experiment in which subjects make portfolio allocation decisions with market returns from the Great Crash of 1929. Half the subjects make allocation decisions prior to the market crash while the other half make allocation decisions at the start of the crash. The results show that subjects who start the experiment with declining stock returns allocate 8% less to stocks than subjects who start the experiment with increasing stock returns. Risk aversion, hedging and reactive loss aversion are all present in subjects' behavior, but cannot explain a significant fraction of the variance in stock allocations during and after crashes. It is also found that fear during and after crashes is associated with the behavior of male participants.

Fear in Asset Allocation During and After Stock Market Crashes
An Experiment in Behavioral Finance

"Now a practical theory of the future based on these three principles[1] has certain marked characteristics. In particular, being based on so flimsy a foundation, it is subject to sudden and violent changes. The practice of calmness and immobility, of certainty and security, suddenly breaks down. New fears and hopes will, without warning, take charge of human conduct. The forces of disillusion may suddenly impose a new conventional basis of valuation. All these pretty, polite techniques, made for a well-panelled Board Room and a nicely regulated market, are liable to collapse. At all times the vague panic fears and equally vague and unreasoned hopes are not really lulled, and lie but a little way below the surface."

-John Maynard Keynes

[1] The three principles include: "*(1) We assume that the present is a much more serviceable guide to the future than a candid examination of past experience would show it to have been hitherto. In other words we largely ignore the prospect of future changes about the actual character of which we know nothing.*
(2) We assume that the existing state of opinion as expressed in prices and the character of existing output is based on a correct summing up of future prospects, so that we can accept it as such unless and until something new and relevant comes into the picture.
(3) Knowing that our own individual judgment is worthless, we endeavor to fall back on the judgment of the rest of the world which is perhaps better informed. That is, we endeavor to conform with the behavior of the majority or the average. The psychology of a society of individuals each of whom is endeavoring to copy the others leads to what we may strictly term a conventional judgment.

1. Introduction

In this paper we consider the impacts of asset crashes on the rationality of the individual investor. A recent Money magazine column opened with the question "What would it take to diminish the terrifying memories of the worst financial crisis since the Depression? Well, a massive bull market could do the trick" (Bigda & Wang, 2011). Our experimental evidence suggests that while a massive bull market cannot hurt, it is not likely to completely erase the memory of the crash.

As Keynes noted in 1937, the gap between rationality and fear may be as slim as water on a flat rock. If investors fall prey to fear during stock market crashes, the question addressed in this paper is what effect this has on subsequent investment behavior.

This paper examines the asset allocation behavior of investors under extreme conditions. In an asset allocation experiment, subjects were exposed to the equity return stream of one of the most volatile periods in stock market history, the period surrounding the stock market collapse of 1929, often refereed to as *Black Tuesday*. The results from this experiment show that risk-taking behavior is influenced by age and gender, the history of the prior returns, and the magnitude of asset declines. But the primary finding from the experiment is that even after controlling for several rational factors that impact subject asset allocation decisions there is a leftover amount of stock selling, which we attribute to fear, which causes diminished risk taking behavior. This result is consistent with the findings of Malmendier and Nagel (2001), who suggest that the market returns investors experience early in their life have a long term impact on future allocations to risky assets.

The asset allocation experiment and results are summarized next. Subjects made asset allocation decisions for 20 years and had a choice of one risky asset and one riskless asset. The experimental design is a 2x2 between subject design. One factor varied the return stream on the equity investment; one group of subjects (the UP group) began investing in a strong bull market where the returns on the risky asset were significantly positive in Years 1-4. The other group (the DOWN group) began investing in a steep bear market where the returns on the risky asset were significantly negative in Years 1-4. The initial equity returns for the UP group came from the time period from 1925-1928 and the returns for the DOWN group began with the equity returns from 1929-1932. Both groups then received the same equity returns from 1933-1944. The second experimental factor varied whether subjects received a happy or sad face (the FACE group) to highlight the prior year's return or simple received quantitative feedback data (the NO FACE group).

Summarizing some important regression results from the experiment's data, we find that a variable derived from the Consumption Capital Asset Pricing (C-CAPM) model is among the most influential factors in predicting the allocation to the risky investment. After controlling for this rational explanation of investment behavior, the results show that subjects in the DOWN group allocate about 7.5% less to the risky asset, and each year of age adds about 0.2% to holdings of the risky asset. Additionally, after controlling for age, gender and the C-CAPM variable, subjects were also sensitive to losses incurred in prior periods, reducing their stock holdings by 2 to 3 percentage points after three periods of cumulative losses and by as much as 7-8 percentage points following a single period of losses. Finally, our analysis highlights the importance of the year 1931. The return on the Dow Jones Industrial Average was -53% in 1931, making it the worst performing year of the Dow in history. Following this year (1933) in the experiment, and after controlling for all of the prior factors just identified, male subjects allocate about 17% less to the risky asset in the next year (1934) of the experiment. We interpret this statistically significant and quantitatively large finding as evidence of the existence fear in these subjects' allocation decisions.

The remainder of this paper is organized as follows: Section 2 reviews the literature which motivated this study. Section 3 presents the data and methodology. Section 4 discusses our results. Section 5 summarizes the major findings and concludes the paper.

2. Relevant literature and motivation for the study

Modern Portfolio Theory (MPT) is an optimal model of how investors should make investment decisions. If investors are only concerned with the mean and variance of their portfolio returns over a single period, MPT[2] shows how investors can maximize expected utility by splitting their asset allocation between the riskless asset and the risky market portfolio. One of the underlying assumptions in the model is that investors can and should behave perfectly rational in making investment decisions (see Markowitz (1952, 1959), Sharpe (1964), Lintner (1965), Mossin (1966)). The rationality assumption, pervasive in economics, allows for the development of the foundational models in financial economics such as the Capital Asset Pricing Model (CAPM) and the Consumption Capital Asset Pricing Model (C-CAPM) (Breeden, 1979; Lucas, 1978). These foundational models have provided key insights into how investors should behave and how financial assets should be priced in markets, and have led to the practical development of many widely used pricing models such as the Black Scholes option pricing model (Black & Scholes, 1973).

The long history of market booms and busts calls into question the perfect rationality of investors and markets. Keynes (1936) supposedly lost vast sums of money in the stock market and suggested that "animal spirits," existed in markets and that market behavior could be better explained by a Keynesian beauty contest.[3] Asset price bubbles and crashes have appeared throughout history (i.e. Shiller (2006), Mackay (1841)). Within the realm of the stock market, Black Tuesday in 1929 stands out as one of the most dramatic and volatile stock market periods, closely followed the technology bubble crash of 2000-2002 and the real estate and debt market crash of 2007-2009.

The concern in this paper is the extent to which market crashes affect the behavior and rationality of investors. Malmendier and Nagel (2010) examine the impact of the Great Depression on the investment behavior of individuals who lived through it and find that they are less willing to take financial risk than those who did not experience that period. Choi et al. (2009) and Vissing-Jorgensen (2003) support Malmendier and Nagel's conclusion that memory has a significant impact on willingness to take financial risk. Thaler and Johnson (1990) also support Malmendier and Nagel and discuss being "snakebit" in which a person once burned tends to be less willing to take on risk in the future. Even highly quantitative examinations such as Mandelbrot (1963) have found long-term memory in market participants. Other studies have found that investors tend to overreact to past market performance by taking on more risk after

[2] Modern Portfolio Theory implies that investors behave as if they had quadratic utility functions over the relevant range and that returns are normally distributed.

[3] The naïve strategy would be to choose the contestant who was the most beautiful. Keynes argues that a more sophisticated approach would be to make the decision based upon an estimate of what the majority thought beauty was. Keynes believed this same approach could be used in the stock market, not to make the decision based upon fundamental value but rather on perceived value.

markets have gone up and investing more conservatively after markets have gone down (see i.e. DeBondt & Thaler (1985), Barberis, Shleifer & Vishny (1998), Odean (1998)).

The idea that greed and fear are periodic components of financial markets is in the background of Minsky's financial instability hypothesis (Minsky, 1992). The financial instability hypothesis is a theory of endogenous changes in risk preferences over the financial cycle, as they reflect on corporate debt structure and its impact on economic activity. Minsky suggests that like many actors in a capitalist economy bankers behave entrepreneurially and seek out market innovations. Bankers and other financial market participants are profit-driven and subject to forces of greed and fear. A long period of prosperity eventually erases memories of panics and crashes, attenuating fear and leading to increasingly risky decisions. Minsky proposes that this fear attenuation progressively tilts the debt-income relations of economic units from hedge to speculative finance at first, and then from speculative to Ponzi finance, the most fragile debt-income structure. When Ponzi finance prevails, the economy becomes unstable and asset values eventually collapse. The crash acts by attenuating greed, and for as long as the memories about the crash remain fresh, debt structures are of the hedge type, the most prudent, since behavior is dominated by fear. What this paper tests for is the presence of fear during and after a crash in asset prices.

To examine how subjects react to market crashes in an experimental setting we begin by specifying how they should behave assuming they invest rationally. To do this, we use the C-CAPM as the model of how subject should behave. The C-CAPM encompasses the standard CAPM, and describes how risk-averse agents make rational asset allocations (see Cochrane 2005). A fully worked-out version of the C-CAPM model is available upon request from the authors.

Breeden (1979) and Lucas (1978) are given credit for developing the Consumption Capital Asset Pricing Model (C-CAPM). The C-CAPM examines aggregate consumption and how the risky asset interacts with consumption. In this model, what the investor spends is uncertain because their wealth is uncertain. Several authors have empirically examined the C-CAPM (see i.e., Breeden et al. (1989) Mankiw and Shapiro (1986)) with moderate levels of success. In this experiment the C-CAPM model provides a basic variable intended to capture the risk aversion and hedging motives of the participating subjects. The basic intuition embedded in the reduced-form formula of the C-CAPM is that for a risky asset to act as a hedge asset it has to provide high payoffs in the bad times, when a rational individual has a high valuation for consumption (technically, when the marginal utility of consumption is high). This timing of payoffs issue is captured by the covariance between the risky asset's returns and the marginal utility of consumption. If the covariance is positive the risky asset displays high payoffs when the marginal utility of consumption is high (which itself happens when the level of consumption is low, given the assumption that the utility function of consumption is increasingly concave). If the asset is a hedge, then a rational individual is willing to accept a negative excess return up to a point because the risky asset protects her with high payoffs in the bad times. The higher the positive value of the covariance, the stronger the desire to hold this asset as a hedge and the higher the willingness to tolerate a negative expected excess return.

3. Experimental Design and Procedures

An experiment was designed in which the subjects experienced the returns from the period surrounding the Crash of 1929. Subjects made repeated asset allocation decisions choosing between a risk free asset and a risky asset. The risk free asset had constant return of 4% while the risky asset returns were those of the Dow Jones Industrial Average (DJIA). The subjects were divided into two groups. One group experienced returns from 1925-1944 the other from 1929-1948. Returns over that period are shown in the figure below.

[Insert Figure I Here]

One of the behaviors examined in the paper is how the initial asset returns affect subsequent subject behavior. One group experiences mostly positive returns for the first four periods while the second group experiences four periods of large negative returns. As seen in Figure I, in the Up condition the initial returns on Stocks for Years 1-4 are 30%, 0.3%, 29%, and 48%; in the Down condition the initial returns on Stocks for Years 1-4 are -17%, -34%, -53%, and -23%. The annual returns on the stock investment from Years 5-20 in the Up condition are identical to the returns in the Down condition from Years 1-16. Table I summarizes the information on the stream returns each group faced.

[Insert Table I Here]

The basic task for subjects in the experiment was to allocate an endowment of money across a riskless (Cash) and risky (Stock) investment options. Subjects made these allocation decisions using a spreadsheet interface which is shown in Table II. Each subject was given a $5.00 endowment to begin the experiment. Each "Year," the subject chose how to invest their endowment. The subjects had two investment choices: United States Stocks (S), Cash (C). To make an asset allocation decision a subject would enter a number in the appropriate cell for a chosen investment. For example, if a subject chose to invest 50% of his funds in United States Stocks for that year, he would enter 50 in the Asset Allocation Column for US Stocks. A spreadsheet was built with checks and controls to insure accuracy in decision entry. Once a subject was satisfied with his or her asset allocation decisions for a particular year, he or she would then click a "Final Decision" button on the spreadsheet and the investment returns for that year would be displayed. After a subject had finished reviewing the results, he or she would then click a button to begin making decisions for the next year.

[Insert Table II Here]

Subjects were recruited through an advertisement in the campus mail sent to all University of Nevada, Reno staff employees, approximately 1,400 employees. The flyer stated that a subject could earn between $5.00 and $50.00 depending upon performance for participation in a one hour experiment on investment decision making. Fifty nine subjects signed up to participate in the experiment.

The experiment was conducted in a computer lab in the College of Business at the University of Nevada, Reno. Upon sitting down, each subject received a copy of the human subject consent form and condition instructions. The experiment began with the reading aloud of the consent form and instructions. After consent was obtained, each subject received a $5.00 show-up fee. Since the recruitment flyer stated that subjects would receive a minimum compensation of $5.00, the show-up fee was given to fulfill this promise. Subjects were then told that any further compensation in the experiment was contingent on their performance in an asset allocation task.

After all the instructions were read and questions answered, the subjects then made two practice decisions for which they were not paid. After their practice decisions, the subjects had a final opportunity to ask any remaining questions. Each subject then proceeded at his or her own pace in making their asset allocation decisions for each of the 20 years. Most subjects took 25 to 45 minutes to make all of their decisions. After all the decisions were completed, each subject filled out a short questionnaire and a receipt documenting their earnings. Each subject then walked to the back of the room where they were paid individually and anonymously in cash for their performance, thanked, and dismissed from the laboratory.

The subject pool was 41% male and 59% female. The average age of participants was 40, with 19% in the 18-25 age bracket, 37% in the 25-39 age bracket, 31% in the 40-59 age bracket and 14% were 60 or older. Each subject was asked to self report on how much experience he or she had with investment decisions similar to those in the experiment. On a 1-7 scale (1= none at all, 7 =a great deal) the average response to this investment experience question was 3.2, with 36% answering 1 or 2, 58% answering 3, 4 or 5, and 7% answering 6 or 7.

4. Discussion of Results

4.1 Condition Effects

The design of the experiment is a 2x2 (Up/Down x Face/No Face) between subjects design. To test for condition effects, a repeated measures ANOVA is conducted using the Proc Mixed procedure in SAS. Two dependent measures are used: 1) the percentage asset allocation to the stock investment (PS); and 2) the change in the percentage asset allocation to the stock investment from the prior period (ChS). The independent variables include the condition variables UP (Up/Down) and FACE (Face/No Face), the repeated measure variable YEAR, and the interaction effects (UP*FACE, UP*YEAR, FACE*YEAR, UP*FACE*YEAR). For both dependent variables there are significant effects for YEAR ($p<0.01$) and the UP*YEAR ($p<0.01$) interaction effect; the FACE variable shows no significance in either model and will be dropped from future analyses.

Table III and Figures II and III show how asset allocation to Stocks varies across the Up/Down conditions and Year. In the Up condition the average allocation to Stocks (S) across subjects is 60%. In the Down condition the average allocation to S across subjects is only slightly less at 59.5%. The highest (lowest) allocation to S in the Up condition is in Year 5 (14) at 67.3% (46.8%). To test if the condition mean allocation to S in a particular year (UP*YEAR) is statistically significant, the overall condition mean is subtracted from each subject's yearly allocation to S and then a difference in means test estimates whether the yearly condition mean is significantly different from zero. In the Up condition the only average yearly allocation to S that is statistically significant is the lowest allocation to S in year 14 ($p<0.05$) of 48.5%. Difference in means tests show that in the Down condition the two lowest allocations to S in years 3 (47.6%) and 5 (45.1%) are statistically significant ($p<0.05$ and $p<0.01$ respectively). In addition, the highest allocation to S in the Down condition in Year 15 (70.7%) is statistically significant ($p<0.05$).

The average change in the allocation to S (defined as the allocation to S in time period t minus the allocation to S in time period t-1) across the twenty years is almost identical in the Up and Down conditions at 0.2% and -0.2% respectively. But the overall average change in the allocation to S does not show the significant change on a year by year basis. In the Up condition, the least squares means test show that there is significant difference in the allocation to S in years 10 (11.3%, p<0.01), 14 (-16.4%, p<0.01), 15 (16.9%, p<0.01), and year 16 (8.2%, p<0.05). In the Down condition, there is significant difference in the allocation to S in years 3 (-11.5%, p<0.01), 6 (13.9%, p<0.01), 10 (-10.3%, p<0.05), 11 (14.3%, p<0.01) and year 20 (9.0%, p<0.05).

The pattern in the change in the allocation to S is quite consistent and it appears as if subjects are predominantly responding in manner consistent with beliefs of positive autocorrelation in market returns. As shown in Table III, in the Up condition in 15 out of 19 years when the return on Stock investment is positive (negative) in the prior year there is an increase (decrease) in the average allocation to S in the current year. In the Down condition this positive autocorrelation belief pattern is found in 13 of 19 years. On average subjects tend to increase allocation to S following years of positive returns and decrease allocation to S following years of negative returns on S.

This positive autocorrelation pattern is consistent across the Up and Down conditions as seen in Figure IV.

[Insert figure IV here]

Figure IV overlaps the level of S and the change in S allocations in the Up and Down conditions and matches up the years in which the S returns were the same. After matching the years in which subjects in the Up and Down conditions received the same returns on S, a differences in least squares means test reveal no statistical significant difference in any year on either the level of S or the change in S. Figure IV clearly shows that in both the Up and Down increases (decreases) in allocation to S followed years in which the return on S is positive (negative).

4.2 The Identification of Fear in Stock Allocations

Our strategy to identify the presence of fear in stock allocations relies on three key elements, which involve exploiting the experimental design, separating rational and emotional responses (i.e., separating risk aversion and loss aversion from fear), and separating fear from anxiety, a confounding emotion.

The experimental design was such that, by construction, the only difference between the Up & Down groups is one of timing in the return streams to which they were exposed. Recall that the subjects in the Down group started the experiment with precipitous falls in stock prices that mimic the falls that actually took place during the Great Depression whereas the subjects in the Up group only saw those falls in later years and started the experiment observing solid gains in stock returns. Therefore, since the stream of returns only differed in their timing, there should be no difference in the allocations of both groups if both groups display full rationality. But, if the Up group holds more stocks after controlling for rational factors affecting the subjects' behavior, then there is evidence that some response beyond purely rational risk-aversion may be at play for the subjects who started the investment experiment under "depression-like conditions" and had no chance to experience the "good times" first.

Next, we propose that if fear is present, it should show up during large declines in the stock market. Hence, we first create dummy variables to separate CHANGES in the stock market from DECLINES in the stock market with the idea that for fear to matter the DECLINE variables need to be significant, not just changes. We create dummy variables for CHANGES (positive or negative values) in stocks' returns higher than or equal to 15%, 25% and 40% respectively and DECLINE dummy variables for stock market DECLINES (negative values only) higher than or equal to 15%, 25%, and 40% respectively. Since fear is more likely to be present during large declines than during mild declines, in which anxiety is more likely to be the dominant emotion, we expect to find that only DECLINES larger than or equal to 40% are the significant ones, both statistically and quantitatively, when trying to explain portfolio allocations to stocks.

To avoid confounding fear with risk aversion, we constructed a variable modeled after C-CAPM which was designed to capture the rational response that risk-averse rational agents would display in the face of rapidly falling stock prices.[4] The C-CAPM variable displays only cross-subjects variation, since there is only one value of the covariance per subject for the whole 20 periods of the experiment. In the C-CAPM, the covariance between the marginal utility of the account balance (which proxies for consumption in our case) and the returns of the risky asset (stocks, in our case) is a core conceptual ingredient. Proceeding in this way we achieve two things. First, we isolate the rational component of the subjects' behavior, and second we avoid confounding fear with risk aversion.

Another potential confounding factor when trying to identify fear is loss aversion. In order to control for loss aversion, a set of loss aversion variables was created and used as explanatory variables in the asset allocation regressions. Among those variables, we used the monetary value of losses lagged one period, a dummy variable to identify periods that display losses, and losses as a percent of $5, the initial account balance; this last variable uses the initial amount of money in subjects' accounts as a reference value.

4.3 Regression Results

The presence of fear should be negatively and monotonically related to the changes in stock market returns. However, fear requires significant declines in the market, (as opposed to moderate or small declines) and should operate independently of risk aversion and loss aversion. The following general model is used to explore subject behavior:

$$STOCKS_{it} = \alpha_0+\alpha_1 CCAPM_i+\alpha_2 DECLINE(j)_t+\alpha_3 DOWN_i+\alpha_4 GENDER_i+\alpha_5 AGE_i+\alpha_6 LOSS\ AVERSION_{it}+\alpha_7 NOCHANGE50_i+\alpha_8 GENDER_i*DECLINE(j)_t+\varepsilon_{it} \quad (1)$$

The following information was given to subjects regarding the investments and potential return on the assets in the experiment. To explain the Stock investment, subjects were told:

U.S. Stocks – This is a portfolio of stocks made up of the largest companies in the United States. This is also called a Large Cap Index. The stocks in this index include a representative sample of the leading companies in leading industries in the U.S. economy. U.S. Stocks – The annualized return on Stocks has averaged 7.7% from 1921-2009. One year during this time period the return on Stocks was as high as 66.7% and another year as low as (negative) -52.7%. The majority of the annual returns on Stocks fell within one standard deviation of the average, or between -12.3% and 27.7%.

Subjects were told that Cash was a riskless investment and would always generate an annual return of 4%.

[4] The C-CAPM variable is for each subject the covariance between the marginal utility of his/her account balance and the return stream the subject was confronted with. The marginal utility of the account balance was calculated as the inverse of the dollar amount in the subjects' account in each period, since the utility function was assumed to be logarithmic, a function that is both consistent with the risk-aversion assumption of the C-CAPM and standard in empirical applications. For a more detailed explanation of C-CAPM please see Cochrane (2005).

where, $STOCKS_{i,t}$ is the percentage of stocks that subject *i* held in period *t*; DECLINE(j) is a dummy variable that captures the decline of the DJIA (j =15%-24%, 25%-39%, 40% or larger); CCAPM is the covariance between the stream of returns faced by subject i and the marginal utility of consumption (proxied by the inverse of the account balance, under the assumption of logarithmic utility), the key component of C-CAPM model which captures the risk aversion and hedging motives in subjects' behavior (this variable only displays cross-subjects variation, but no time variation, since it is calculated for each subject as the covariance of the inverse of the subject's account balance and stocks' returns over the 20 year period of the experiment); DOWN is the group of subjects which experienced negative stock market returns during the first four periods of their experiment; GENDER is a dummy variable which takes the value of 1 if the subject was male, 0 otherwise; AGE is a continuous variable which captures the age of the subject; NOCHANGE50 is a dummy variable which captures the group of subjects who did not change their allocations during at least 50% of the observations; GENDER*DECLINE(j) is an interactive variable which is the product of GENDER and DECLINE. LOSS AVERSION is a set of proxy variables for loss aversion. As explained above, different proxies were tried, including the first lag of losses expressed in dollar terms, as a percent of the initial account balance, or as a dummy variable. All regression tables present three estimation procedures, namely Ordinary Least Squares (OLS), Random Effects (RE), and subjects' Fixed Effects (FE). The OLS regressions are always the first column in our regression tables and present the basic correlations present in the data. It exploits both cross-sectional and over-time variation in the data, but the downside is that any unobserved characteristic (either time-specific or individual-specific) is not explicitly accounted for by the deterministic part of the econometric model, and so it ends up in the residual term, which may give rise to biased estimates. The Fixed Effect estimation, located in the last column of our regression tables, contains regressions that rely exclusively on the "over-time" variation of the data, since all unobserved subject-specific, cross-sectional information is absorbed by the inclusion of subject-specific dummy variables (for that reason, explanatory variables that display only cross-sectional variation are dropped from the estimations under this procedure). The inclusion of subject-specific dummy variables is intended to absorb all individual-specific characteristics in the deterministic part of the econometric model, preventing them from biasing the estimates. Hence, our reason to include the FE estimates in our tables is to check that the OLS coefficients are more or less stable when unobserved characteristics of the subjects participating in the experiment are controlled for, and not because we think that the FE estimates are necessarily the appropriate estimation method in this case. We are fully aware that valuable cross-sectional information is being lost when this method is used. Finally, the RE estimation which is located in the second column of our regression tables, after the OLS estimates and before the FE estimates, is a weighted average of the purely cross-sectional estimator (the one that relies exclusively on cross-sections or 'across-subjects' information averaged over the twenty time periods of the experiment) and the fixed effect estimator described before. In this case, the unobserved individual-specific characteristics are assumed to have a random nature, instead of the deterministic, time-invariant, persistent pattern assumed by the FE estimates. The pragmatic approach we follow in terms of method of estimation selection allows us to show how the estimates of the key parameters vary depending upon the source of variation in the data that each method exploits (across, within, or both). Remarkably, some of the key parameter estimates of interest for our study remain quite stable across methods, as we show below.

Results of the first regression are shown below.[5]

[Insert Table IV Here]

As shown in Table IV, price declines of 15%-24% are not statistically significant independently of CCAPM, the covariance variable that represents C-CAPM, and gender and age effects. The C-CAPM variable shows that the subjects' behavior displays a rational component in that the subjects recognize that stocks act as hedges against risk, paying high returns when the accounts balances are low (i.e., when the marginal utility of those balances is high). Hence, subjects with more positive covariances (subjects that are hedged more by stocks) demand more stock. The effect is strong both statistically and quantitatively. Note also how males hold some extra 6-7 percentage points of their portfolios in stocks and how every additional year of age has a small positive impact in the share of stocks held in the portfolio. The result concerning male behavior introduces a new and interesting dimension to the results; males hold more stocks than females beyond what is rational (as the CCAPM variable is capturing hedging considerations and rationality). Further, this result raises an important question: is it possible that the large reduction in the percentage of stock held when the market experiences large declines (40% or more) is primarily or entirely driven by male behavior. This question is later addressed in Table VIII below.

In the models estimated in Table IV the intercepts can be interpreted as the percentage of the deterministic allocation that is not explained by the model(s) and is attributable to numerous other deterministic factors for which we do not control. Note how the parameter estimates remain quite stable across specifications.

When the DECLINE variable is increased to capture declines in the 25-39%% range, the results are re-examined and shown in Table V below.

[Insert Table V Here]

As shown in Table V, Declines of 25% or more are also not statistically significant though in both Tables IV and V the coefficient is negative and increases in value as would be expected. In the third iteration of this model, declines in the risky asset of 40% or greater are examined. The results are shown in Table VI below.

[Insert Table VI Here]

Declines in stocks of 40% or more are statistically and quantitatively important above and beyond the influence of the C-CAPM variable. The coefficient increases monotonically as the magnitude of the declines increases, with Declines of 40% or more leading subject to reduce their exposure to stocks by approximately 8%.[6] This is a first indication that fear may be present (above and beyond the influence of risk aversion and hedging) during large stock market declines.

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[5] In Tables IV and V, the declines modeled are 15% and 25% with a dummy capturing either 15%-24% or 25% to 39% respectively. Neither of these results is significant. In the tables after that, the DECLINE dummy variable takes the value of 1 only if the decline in the DJIA is 40% or larger, 0 otherwise.

[6] In this experiment, subjects were given expected returns at the beginning of the experiment. A more rational allocation strategy after a big decline in prices would be an increase in allocation to stocks.

Next a new dummy variable identifying the DOWN group is introduced. This variable captures whether the group experienced four periods of negative stock market returns in their first four tries in the experiment (the alternative group received four positive returns in their first four tries) to test if they do hold less stock after controlling for the C-CAPM variable. The results are shown below in Table VII.

[Insert Table VII Here]

In this regression, DECLINE40, CCAPM, and DOWN are all significant. The coefficients for DECLINE40 and DOWN are both negative indicating that if the DECLINE is greater than or equal than 40% on average the subject allocated 8% less to stocks and that if the group experienced a series of negative stock market returns at the beginning of the experiment, the subject held 7.5% less stock than if they had not.

Both these coefficients suggest that fear may have been present in the subjects' stock allocations. Large losses lead to reductions in the percentage of stocks held and that is independent of the risk aversion of the subject (which is captured by C-CAPM). The statistically significant coefficient for the DOWN variable is consistent with the findings of Malmendier and Nagel (2010).

In the next regression the subjects' GENDER is interacted with the variable DECLINE40 to investigate if the gender of subjects plays any role in explaining "excess-stock selling" during stock market crashes.

[Insert Table VIII Here]

The results shown in Table VIII indicate that the coefficient of the interaction variable GENDER*DECLINE40 that identifies males and the dummy variable that identifies 40% or greater declines in the stock market is negative and highly significant and, interestingly, makes the DECLINE40 coefficient insignificant, indicating that panics are driven only by male behavior or, more simply, fear is present in the male subjects but not the female subjects. Additionally, the coefficient is large, indicating that males who experience the large declines in the stock market allocate almost 17% less to stocks than females who experienced the same decline.

Next, we introduce a variable that helps improve the fit of the OLS regressions without modifying any previous result in any significant way. Since a non-trivial fraction of the subjects did not modify their allocations during long periods of time, we include a dummy variable to identify subjects who did not modify their allocations significantly during the 20 periods of the experiment. This new variable will of course have no impact on the FE estimates, but will make a small positive contribution to improving the OLS results. Since the subjects have only the information about the distribution of returns that was given to them at the beginning of the experiment, and it is unlikely that the subject recognizes the returns as being those of the Great Depression, there is no new "real" information upon which to change their allocations other than the return information. So, a rational response from the subject might be to not change their allocation over the entire experiment. Subjects that did not change their allocations at least 50% of the time were identified with a dummy variable (NOCHANGE50). This was done to control for and isolate the other subjects, the ones who were more prone to change their allocations. The results are shown in Table IX below.

[Insert Table IX Here]

As Table IX indicates, NOCHANGE50 is positive and significant but does not change the previous results in any meaningful way and improves the fit of the OLS regression.

The interpretation of the intercept, which is the percentage of stocks held which are explained by things other than the variables we used in the particular regression model. In the series of regressions run, the coefficient of the intercept declines as more variables are added.

Hence, in the final regression model, the coefficients for CCAPM, GENDER, AGE, DOWN, GENDER*DECLINE40, NOCHANGE50 are all statistically significant at conventional levels with the signs of the coefficients being meaningful and intuitively sensible.

4.4 Discussion and robustness: The Role of Loss Aversion

Another potentially confounding effect (other than risk aversion and hedging) may stem from subjects' reactions to gains and, in particular, losses. Strong negative reactions to losses, if present, may proxy for the residual effects --captured by DECLINE40 & DOWN—which we interpreted as fear in our previous regressions. To control for the potential confounding effects of subjects' reacting to losses more strongly than to gains, we constructed proxy variables intended to isolate this effect. We first need to know if subjects do react more strongly to losses than to gains. In the present case, the regression coefficient associated with gains/losses is intended to capture how subjects react to gains/losses, as opposed to how they choose when offered a mixed gamble containing a potential gain and a potential loss of equal monetary value, the standard setup to test for loss aversion. Hence, if losses dominate gains in our regression framework, we would obtain what we like to call a form of 'reactive loss aversion'. To test that hypothesis, we constructed a variable containing the monetary gains and losses experienced by each individual subject lagged one period, and included that variable to our baseline specification. Results are displayed in Table X.

[Insert Table X here]

As Table X shows, the coefficient of the gains/losses variable (called LOSSES_L1) displays a negative coefficient, suggesting that losses do in effect have a stronger impact than gains on subjects' reactions, and it is statistically significant at the 10% level in the OLS specification, but not in the Random Effects or Fixed Effects specifications (if the variable NOCHANGE50 is dropped, then LOSSES_L1 becomes significant at 10% in all specifications, which shows the lack of statistical robustness of LOSSES_L1).

Interestingly, the introduction of the LOSSES_L1 variable did not fundamentally change the significance of the main variables that capture the fear effect, as DECLINE40 and DOWN retained their quantitative and statistical significance.

In the next table, Table XI, the interaction variable DECLINE40*GENDER is added to the specification displayed in the previous table to re-test for the role of male subjects in the production of the fear effect.

[Insert Table XI Here]

As Table XI shows, the interaction variable DECLINE40*GENDER remains the most important quantitative explanatory factor of the share of stocks even after controlling for ‘reactive loss aversion’ and C-CAPM, a result consistent with recent findings in the neuroscience literature that “automatic emotional responses such as fear (e.g., responses mediated by the amygdala) often trump more controlled or higher level responses (e.g., responses mediated by the pre-frontal cortex”) Lo et al.(2005, p. 357).

To control for the robustness of the previous results we tried other proxies of ‘reactive loss aversion’, such as the monetary losses expressed as a percent of $5 lagged one period. This measure uses $5, the initial account balance, as the reference value and is more prospect theory-oriented than the previous one. Results were very similar to the ones obtained with the variable monetary gains & losses lagged one period: losses matter, but do not eliminate the fear factor, captured by DOWN and DECLINE40 or, alternatively, by DOWN & DECLINE40*GENDER, a variable that remains quantitatively the strongest.

5. Conclusion

In this experiment, we attempted to isolate an emotional response that can be plausibly called fear. We could also trace back that fear to the behavior of male participants. Our strategy involved separating fear from different confounding effects. Some of the confounding effects, such as risk aversion, hedging and ‘reactive loss aversion’ were measured by constructing proxy variables which were used as explanatory variables in regressions that explained the subjects’ allocations to stocks. Other confounding factors, such as anxiety, were identified by introducing discrete threshold effects in the data. Risk aversion and the hedging motive were captured by the C-CAPM variable, itself inspired in the C-CAPM model that is standard in mathematical economics and finance. Reactive loss aversion was captured with two different variables. We also made an effort to separate fear from other emotions, in particular anxiety. We think it is plausible to assume that subjects felt anxious in the presence of stock market returns falling 15%, or even 25%, but more likely experienced fear in the presence of stock market returns falling beyond 40%, since in that case falls of that magnitude essentially wipe out their account balances in a few periods. Our results do not deny that agents behave rationally. Indeed the C-CAPM variable displays the expected positive sign (in the presence of a hedging motive induced by the profile of the given stock returns) and stays quantitatively important in all regressions. But our results show that in specific circumstances, such as in the presence of dramatic market declines, rationality is neither the only force, nor the major one driving stock allocations. The risk aversion and hedging motives stressed in the traditional literature on rational behavior stay significant in all circumstances, but during significant market downturns agents react by reducing their stock allocations above and beyond what a rational response would suggest. Our results also indicate that the panic is exclusively due to the behavior of males in our sample, another interesting result, which opens new lines for further research in related areas, such as neuroeconomics & finance.

Definition of variables used in Regression Analyses

DECLINE15: dummy variable used to capture falls in stock returns higher than or equal to 15%

DECLINE 25: dummy variable used to capture falls in stock returns higher than or equal to 25%

DECLINE40: dummy variable used to capture falls in stock returns higher than or equal to 40%

C-CAPM: covariance between stock market returns faced by individual j during his 20 years of investing and the inverse of the account balances held by individual j during her 20 years of investing. Assumptions: (1) utility from consumption for all subjects is logarithmic, so that the marginal utility of consumption is the inverse of consumption; (2) consumption is proxied by the account balance of every subject.

DOWN: dummy variable used to identify subjects who start the experiment facing (sharp) declines in stocks' returns.

GENDER: Dummy variable used to identify the gender of subjects in the experiment. GENDER = 1 if subject is male, 0 if subject is female.

AGE: Indicator variable that captures the age, expressed in years, of every subject in the experiment

GENDER*DECLINE40: Interaction variable between DECLINE40 and GENDER

NOCHANGE50: dummy variable which captures the group of subjects who did not change their allocations during at least 50% of the observations

LOSSES_L1: Monetary value of gains & losses incurred by each subject during the previous period

Table I - Returns Experienced by Different Groups

		Annual Return on Stock Investment	
Year	Cash	Up Condition	Down Condition
1	4%	30%	-17%
2	4%	0%	-34%
3	4%	29%	-53%
4	4%	48%	-23%
5	4%	-17%	67%
6	4%	-34%	4%
7	4%	-53%	39%
8	4%	-23%	25%
9	4%	67%	-33%
10	4%	4%	28%
11	4%	39%	-3%
12	4%	25%	-13%
13	4%	-33%	-15%
14	4%	28%	8%
15	4%	-3%	14%
16	4%	-13%	12%
17	4%	-15%	27%
18	4%	8%	-8%
19	4%	14%	2%
20	4%	12%	-2%

Table II - Subject User Interface

FINAL DECISION
Click here after you have made your asset allocation decisions.

Year	Beginning Account Balance ($)	Cash	U.S. Stock Index Fund	Allocation (Must Sum to 100%)	Portfolio Expected Return %	Portfolio Standard Deviation %
Practice 1	5.00	25	75	100%	6.8%	15.0%
Practice 2	5.80	10	90	100%	7.3%	18.0%
1	5.00	0	100	100%	7.7%	20.0%
2	6.50	0	100	100%	7.7%	20.0%
3	6.52	0	100	100%	7.7%	20.0%
4	8.40	0	100	100%	7.7%	20.0%
5	12.45	0	100	100%	7.7%	20.0%
6	10.31	0	100	100%	7.7%	20.0%
7	6.83	0	100	100%	7.7%	20.0%
8	3.23	0	100	100%	7.7%	20.0%
9	2.49	0	100	100%	7.7%	20.0%
10	4.14	0	100	100%	7.7%	20.0%
11	4.32	0	100	100%	7.7%	20.0%
12	5.98	0	100	100%	7.7%	20.0%
13	7.46	0	100	100%	7.7%	20.0%
14	5.01	0	100	100%	7.7%	20.0%
15	6.42	0	100	100%	7.7%	20.0%
16	6.23	0	100	100%	7.7%	20.0%
17	5.44	0	100	100%	7.7%	20.0%
18	4.60	0	100	100%	7.7%	20.0%
19	4.95	0	100	100%	7.7%	20.0%
20	5.64	0	100	100%	7.7%	20.0%

Table III - Asset Allocation to Stocks by Year

Year	Up Condition Returns	% Allocation to S in Up Condition	Average Change in % Allocation to S (t - (t-1))		Down Condition Returns	% Allocation to S in Up Condition	Average Change in % Allocation to S (t - (t-1))
1	*30%*	63.8			*-17%*	66.2	
2	*0%*	61.2	-2.6		*-34%*	59.1	-7.1
3	*29%*	64.9	3.7		*-53%*	**47.6***	**-11.5****
4	*48%*	65.8	0.9		*-23%*	50.4	2.8
5	*-17%*	67.3	1.5		*67%*	**45.1****	-5.3
6	*-34%*	59.7	-7.6		*4%*	59.0	**13.9****
7	*-53%*	56.5	-3.2		*39%*	61.5	2.5
8	*-23%*	50.8	-5.7		*25%*	58.8	-2.7
9	*67%*	50.3	-0.4		*-33%*	61.8	3.0
10	*4%*	61.7	**11.3****		*28%*	51.5	**-10.3***
11	*39%*	57.4	-4.3		*-3%*	65.9	**14.3****
12	*25%*	60.2	2.8		*-13%*	60.9	-5.0
13	*-33%*	63.2	3.0		*-15%*	60.0	-0.9
14	*28%*	**46.8***	**-16.4****		*8%*	63.8	3.8
15	*-3%*	63.8	**16.9****		*14%*	**70.7***	6.9
16	*-13%*	55.6	**-8.2***		*12%*	68.5	-2.2
17	*-15%*	59.0	3.4		*27%*	63.1	-5.4
18	*8%*	61.2	2.2		*-8%*	59.2	-3.8
19	*14%*	63.4	2.2		*2%*	54.2	-5.0
20	*12%*	67.2	3.8		*-2%*	63.2	**9.0***
Average	***6%***	**60.0**	**0.2**		***1%***	**59.5**	**-0.2**
STD		**27.6**	**20.1**			**30.9**	**26.6**
***p<0.05, **p<0.01**							

Table IV

Summary of Multiple Regression Analysis for Percentage of Stocks Held (N=1179)						
	OLS		RE		FE	
	coeff.	p-value	coeff.	p-value	coeff.	p-value
DECLINE15	-1.831	0.293	-1.838	0.179	-1.839	0.179
C-CAPM	14.45	0.000	14.451	0.000	dropped	.
AGE	0.175	0.002	0.175	0.289	dropped	.
GENDER	6.714	0.000	6.724	0.170	dropped	.
Constant	41.52	0.000	41.53	0.000	60.314	0.000
F-Stat	41.97		.		1.810	
prob > F	0.000		.		0.1791	
Wald chi2(4)	.		20.43		.	
prob > chi2	.		0.0004		.	
Adj-R-Squared	0.12					
within	.		0.0016		0.0016	
between	.		0.2559		0.0015	
overall	.		0.1251		0.0008	

Note: OLS = Ordinary Least Squares; RE = Random Effects; FE = Fixed Effects

Table V

Summary of Multiple Regression Analysis for Percentage of Stocks Held (N=1179)						
	OLS		RE		FE	
	coeff.	p-value	coeff.	p-value	coeff.	p-value
DECLINE25	-2.047	0.360	-2.052	0.242	-2.052	0.243
C-CAPM	14.45	0.000	14.45	0.000	dropped	.
AGE	0.175	0.002	0.175	0.289	dropped	.
GENDER	6.714	0.000	6.724	0.170	dropped	.
Constant	41.28	0.000	41.29	0.000	60.07	0.000
F-Stat	41.89		.		1.37	
prob > F	0.0000		.		0.2426	
Wald chi2(4)	.		19.99		.	
prob > chi2	.		0.0005		.	
Adj-R-Squared	0.12					
within	.		0.0012		0.0012	
between	.		0.2559		0.0015	
overall	.		0.1249		0.0006	

Note: OLS = Ordinary Least Squares; RE = Random Effects; FE = Fixed Effects

Table VI

Summary of Multiple Regression Analysis for Percentage of Stocks Held (N=1179)						
	OLS		RE		FE	
	coeff.	p-value	coeff.	p-value	coeff.	p-value
DECLINE40	-8.028	0.028	-8.032	0.005	-8.033	0.005
C-CAPM	14.45	0.000	14.45	0.000	dropped	.
AGE	0.1752	0.001	0.1749	0.289	dropped	.
GENDER	6.714	0.000	6.724	0.170	dropped	.
Constant	41.37	0.000	41.38	0.000	60.164	0.000
F-Stat	43.03		.		7.85	
prob > F	0.0000		.		0.0052	
Wald chi2(4)	.		26.47		.	
prob > chi2	.		0.0000		.	
Adj-R-Squared	0.12					
within	.		0.0070		0.0070	
between	.		0.2559		0.0015	
overall	.		0.1279		0.0036	

Note: OLS = Ordinary Least Squares; RE = Random Effects; FE = Fixed Effects

Table VII

Summary of Multiple Regression Analysis for Percentage of Stocks Held (N=1179)						
	OLS		RE		FE	
	coeff.	p-value	coeff.	p-value	coeff.	p-value
DECLINE40	-8.031	0.027	-8.033	0.005	-8.033	0.005
C-CAPM	15.79	0.000	15.79	0.000	dropped	.
AGE	0.212	0.000	0.212	0.199	dropped	.
GENDER	8.154	0.000	8.157	0.099	dropped	.
DOWN	-7.522	0.000	-7.525	0.133	dropped	.
Constant	42.18	0.000	42.18	0.000	60.163	0.000
F-Stat	39.02		.		7.85	
prob > F	0.0000		.		0.0052	
Wald chi2(4)	.		29.14		.	
prob > chi2	.		0.0000		.	
Adj-R-Squared	0.14					
within	.		0.007		0.0070	
between	.		0.2863		0.0015	
overall	.		0.1426		0.0036	

Note: OLS = Ordinary Least Squares; RE = Random Effects; FE = Fixed Effects

Table VIII

Summary of Multiple Regression Analysis for Percentage of Stocks Held (N=1179)						
	OLS		RE		FE	
	coeff.	p-value	coeff.	p-value	coeff.	p-value
DECLINE40	-1.137	0.809	-1.137	0.759	-1.137	0.759
C-CAPM	15.780	0.000	15.780	0.000	dropped	.
AGE	0.212	0.000	0.212	0.199	dropped	.
GENDER	9.000	0.000	9.000	0.069	dropped	.
DOWN	-7.522	0.000	-7.526	0.132	dropped	.
GENDER*DECLINE40	-16.950	0.022	-16.950	0.004	-16.95	0.004
Constant	41.830	0.000	41.840	0.000	60.16	0.000
F-Stat	33.52		.		8.2	
prob > F	0.0000		.		0.0003	
Wald chi2(4)	.		37.7		.	
prob > chi2	.		0.0000		.	
Adj-R-Squared	0.15					
within	.		0.0145		0.0145	
between	.		0.2863		0.0111	
overall	.		0.1465		0.0053	

Note: OLS = Ordinary Least Squares; RE = Random Effects; FE = Fixed Effects

Table IX

Summary of Multiple Regression Analysis for Percentage of Stocks Held (N=1179)						
	OLS		RE		FE	
	coeff.	p-value	coeff.	p-value	coeff.	p-value
DECLINE40	-1.137	0.809	-1.137	0.759	-1.137	0.759
C-CAPM	15.6	0.000	15.6	0.000	dropped	.
AGE	0.199	0.000	0.199	0.229	dropped	.
GENDER	8.292	0.000	8.299	0.099	dropped	.
DOWN	-7.506	0.000	-7.511	0.134	dropped	.
NOCHANGE50	4.877	0.008	4.873	0.379	dropped	.
GENDER*DECLINE40	-16.95	0.021	-16.95	0.004	-16.95	0.004
Constant	41.48	0.000	41.49	0.000	60.163	0.000
F-Stat	29.88		.		8.2	
prob > F	0.0000		.		0.0003	
Wald chi2(4)	.		38.39		.	
prob > chi2	.		0.0000		.	
Adj-R-Squared	0.15					
within	.		0.0145		0.0145	
between	.		0.2968		0.0111	
overall	.		0.1516		0.0053	

Note: OLS = Ordinary Least Squares; RE = Random Effects; FE = Fixed Effects

Table X

Summary of Multiple Regression Analysis for Percentage of Stocks Held (N=1064)						
	OLS		RE		FE	
	coeff.	p-value	coeff.	p-value	coeff.	p-value
DECLINE40	-8.92	0.019	-7.95	0.008	-7.81	0.008
C-CAPM	14.62	0.000	14.76	0.000	dropped	.
AGE	0.205	0.000	0.207	0.119	dropped	.
GENDER	7.56	0.000	7.58	1.890	dropped	.
DOWN	-7.28	0.000	-7.39	0.065	dropped	.
NOCHANGE50	4.23	0.034	4.34	0.327	dropped	.
LOSSES_L1	-0.86	0.091	-0.17	0.668	-0.073	0.853
Constant	41.75	0.000	41.75	0.000	59.80	0.000
F-Stat	23.45		.		3.64	
prob > F	0.0000		.		0.0267	
Wald chi2(4)	.		38.69		.	
prob > chi2	.		0.0000		.	
Adj-R-Squared	0.1345					
within	.		0.0071		0.0072	
between	.		0.2547		0.5413	
overall	.		0.1330		0.0042	

Note: OLS = Ordinary Least Squares; RE = Random Effects; FE = Fixed Effects

Table XI

Summary of Multiple Regression Analysis for Percentage of Stocks Held (N=1064)						
	OLS		RE		FE	
	coeff.	p-value	coeff.	p-value	coeff.	p-value
DECLINE40	-1.93	0.691	-0.93	0.807	-0.79	0.833
C-CAPM	14.62	0.000	14.76	0.000	dropped	.
AGE	0.205	0.001	0.207	0.123	dropped	.
GENDER	8.51	0.000	8.53	0.036	dropped	.
DOWN	-7.28	0.000	-7.389	0.068	dropped	.
NOCHANGE50	4.23	0.033	4.34	0.331	dropped	.
GENDER*DECLINE40	-17.16	0.023	-17.22	0.004	-17.23	0.003
LOSSES_L1	-0.857	0.093	-0.163	0.684	-0.067	0.866
Constant	41.36	0.000	41.36	0.000	59.80	0.000
F-Stat	21.24		.		5.37	
prob > F	0.0000		.		0.0011	
Wald chi2(4)	.		46.63		.	
prob > chi2	.		0.000		.	
Adj-R-Squared	0.14					
within	.		0.0158		0.0158	
between	.		0.2546		0.0065	
overall	.		0.1372		0.0059	
OLS = Ordinary Least Squares						
RE = Random Effects						
FE = Fixed Effects						

Note: OLS = Ordinary Least Squares; RE = Random Effects; FE = Fixed Effects

Figure I

The graph below show the returns to which subjects were exposed. Subjects in the UP group were exposed to years 1925-1928, all of which were positive. Subjects in the DOWN group experienced the returns of 1929-1932 as their first four returns.

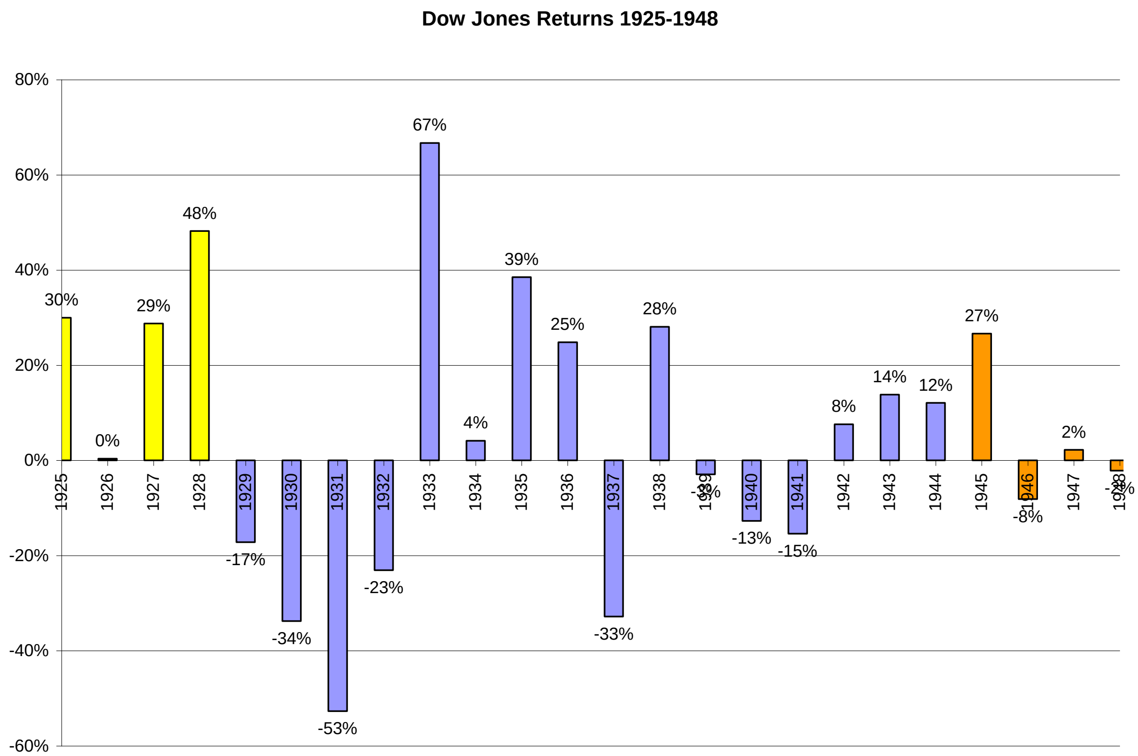


Figure II: Annual Change in Stock Allocation in Up Condition

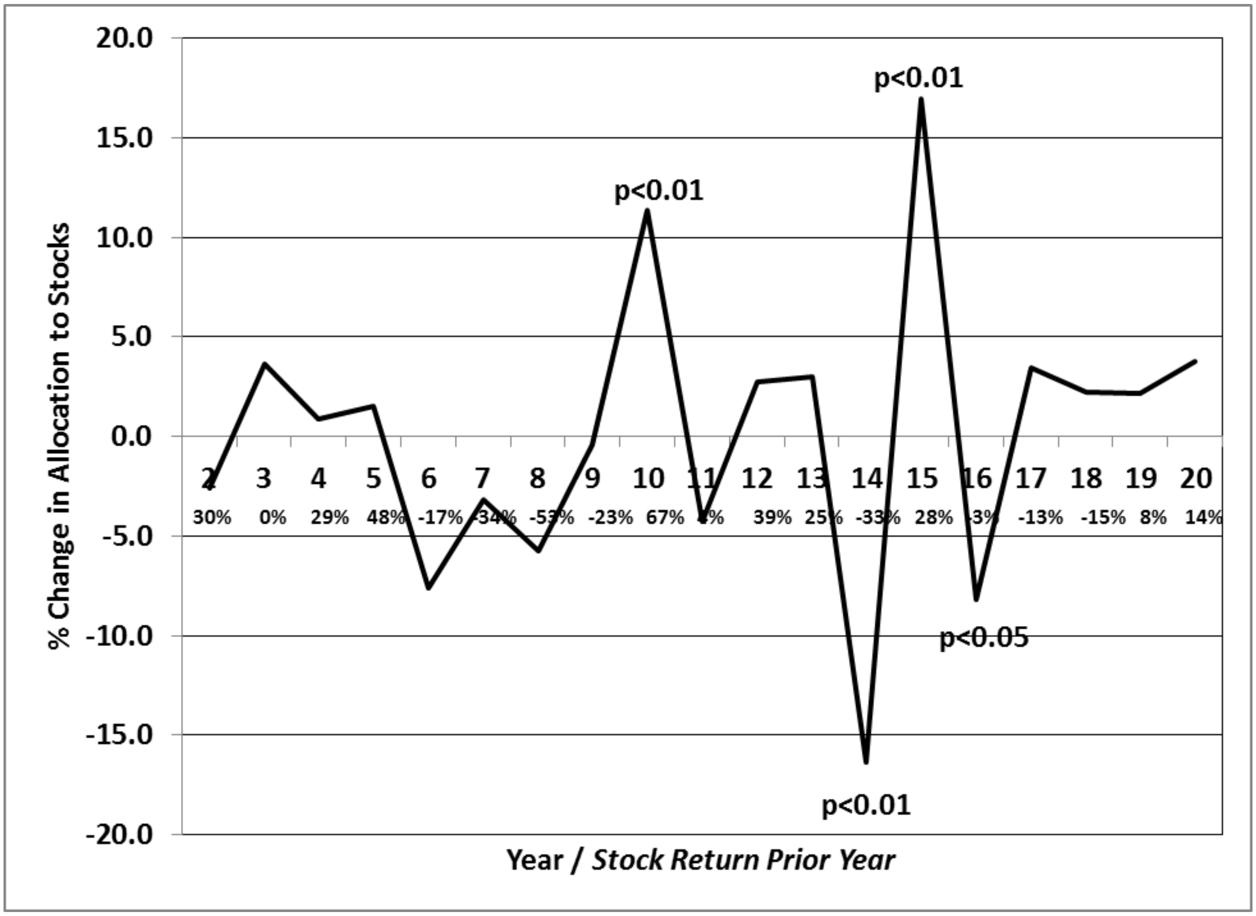


Figure III – Annual Change in Stock Allocation in Down Condition

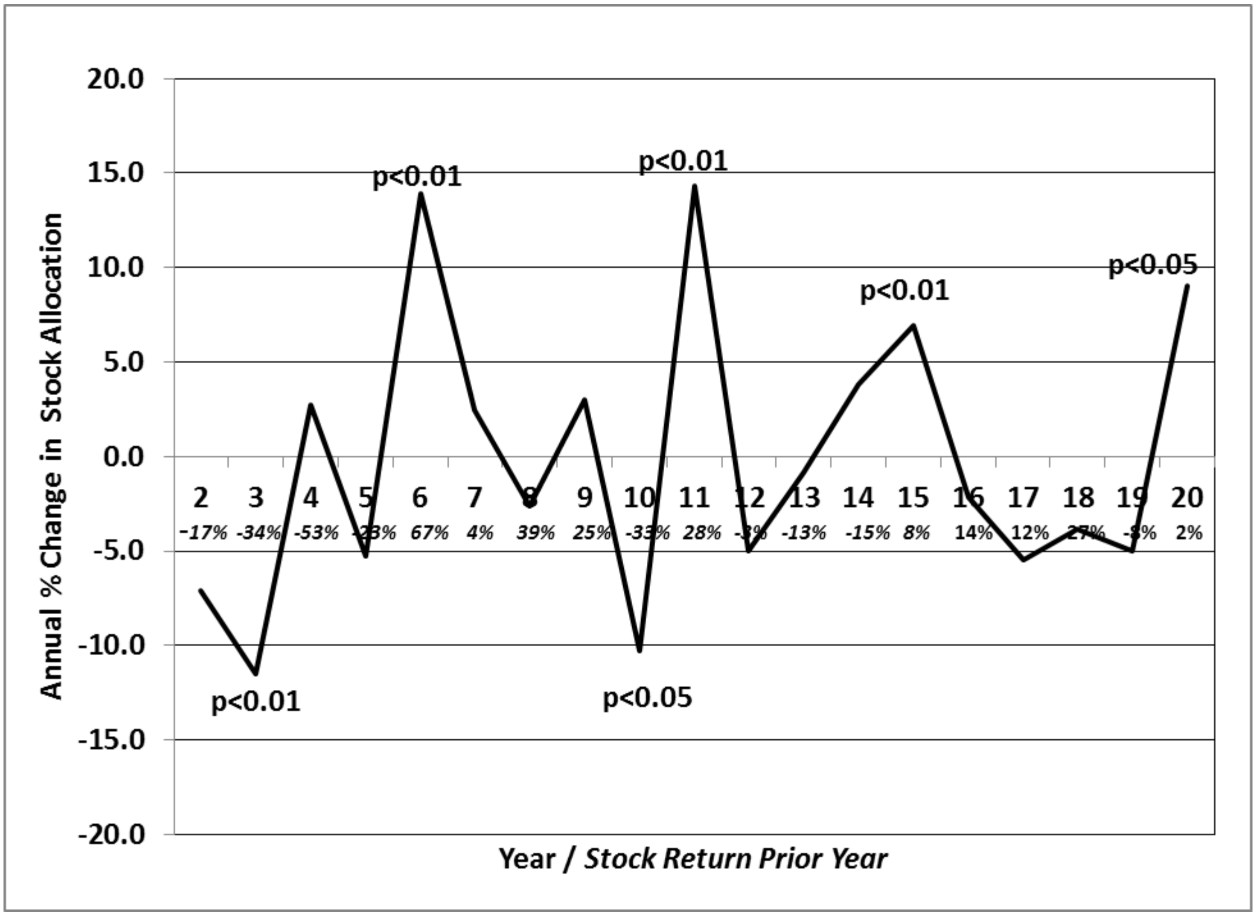
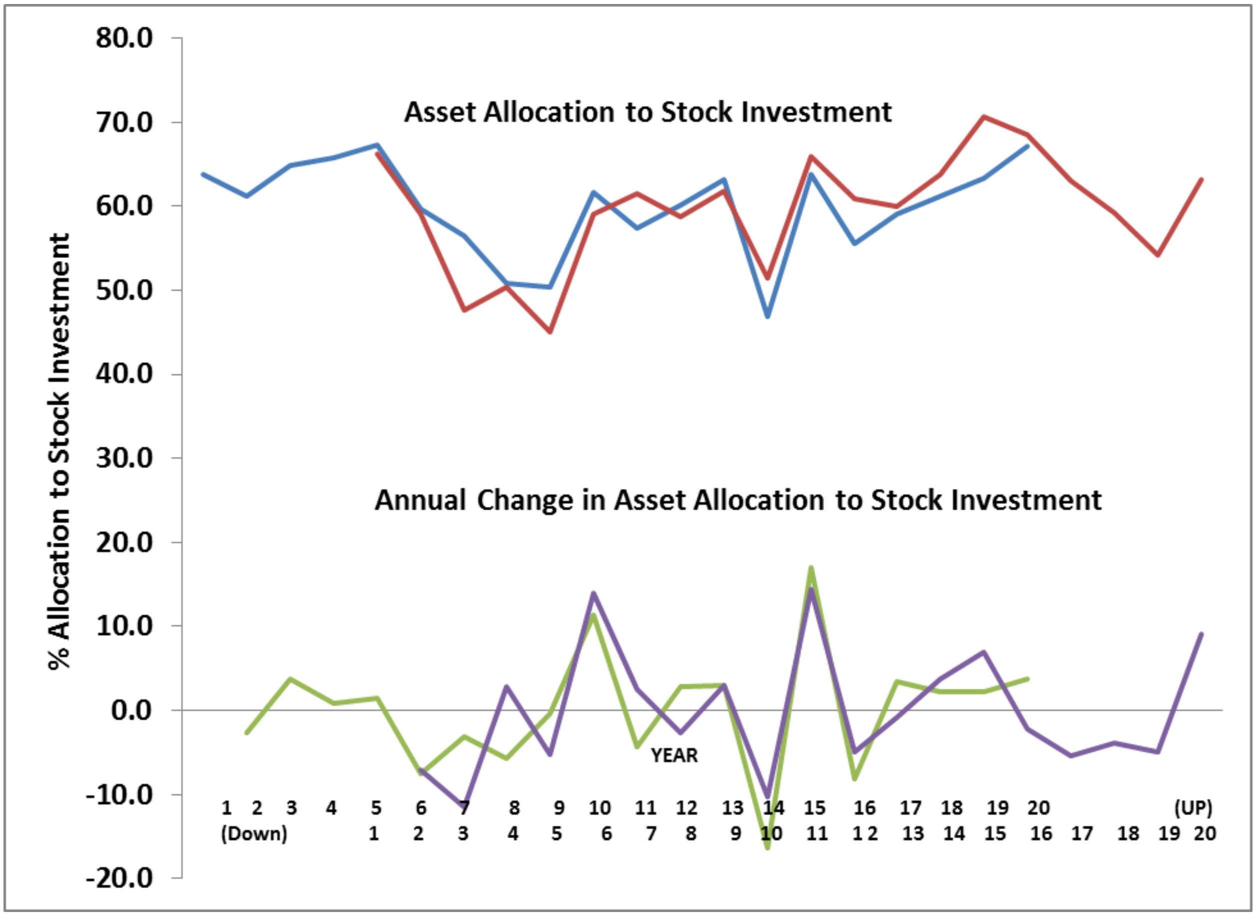


Figure IV – Allocation and Change in Allocation to Stock (S) in Up and Down Conditions



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