Title
Individual Investor Decision-Making

Author
Thornton, Joshua

Publication Date
2022

UNIVERSITY OF CALIFORNIA,
IRVINE

Individual Investor Decision-Making

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Management

by

Joshua Thornton

Dissertation Committee:
Professor David Hirshleifer, Chair
Professor Lu Zheng
Associate Professor Christopher Schwarz
Associate Professor Zheng Sun

2022

DEDICATION

I dedicate this dissertation to my wife, Melissa, for her patience, encouragement and willingness to bluntly tell me what I need to hear; to my daughter, Lennon, for reminding me not to take myself too seriously; to my mom for sharing her love of math; and to my dad for demonstrating the joy and fulfillment that a career in academia can offer.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

I would like to thank David Hirshleifer for his mentorship and advice throughout this process. I would not be the scholar I am today without his influence. Both chapters of this dissertation have benefited greatly from his comments. I would also like to thank Lu Zheng, Christopher Schwarz, and Zheng Sun for sitting on my committee and providing valuable feedback. Finally, I would like to thank the numerous friends and colleagues whose comments have improved this research: Kenneth Ahern, Damon Clark, Rawley Heimer, Zoran Ivković, Theresa Kuchler, Yue Li, Chad Marxen, Gerard Rothfus, Jinfei Sheng, Yushui Shi, and Johannes Stroebel.

VITA

Joshua Thornton

EDUCATION

Doctor of Philosophy in Finance **2022**
University of California, Irvine *Irvine, California*

Bachelor of Science in Mathematics **2014**
Pepperdine University *Malibu, California*

WORKING PAPERS

Peer Effects in Financial Expectations **November 2021**
Southern Finance Association

Does Sunshine Cloud Investor Judgment? **March 2022**
Southwestern Finance Association

Disposition Effect: Growth Versus Value **January 2021**
University of California, Irvine

RESEARCH EXPERIENCE

Graduate Research Assistant **2017–2022**
University of California, Irvine *Irvine, California*

TEACHING EXPERIENCE

Teaching Assistant **2017–2022**
University of California, Irvine *Irvine, California*

ABSTRACT OF THE DISSERTATION

Individual Investor Decision-Making

By

Joshua Thornton

Doctor of Philosophy in Management

University of California, Irvine, 2022

Professor David Hirshleifer, Chair

Chapter 1: I provide causal evidence that neighborhood financial expectations affect individual financial expectations. I instrument for neighborhood financial expectations with average financial expectations of neighbors' nonlocal family members. Consistent with social interaction driving this effect, I show that social individuals are more influenced by neighborhood financial expectations. Additionally, I provide evidence that individuals who expect their financial situation to improve are less likely to save. This suggests that surveyed expectations reflect actual expectations and that individuals act in accordance with their expectations. Finally, I show that individuals who take neighborhood expectations into account form more accurate expectations.

Chapter 2: Evidence from psychology literature confirms the long-held intuition that mood affects judgment. Specifically, individuals who are in a negative mood are more likely to think critically and avoid heuristic processing. This paper uses two proxies for mood, weather and media pessimism, to show that investors make better selling decisions when they are feeling sad. A one-unit increase in cloudiness leads to 1.54% 3-factor alpha improvement at a 4-month horizon. The disposition effect, which decreases in magnitude when investors are in a negative mood, provides an explanation for these results.

Chapter 1

Peer Effects in Financial Expectations

1.1 Introduction

Investor beliefs influence trading activity, which in turn influences asset prices (Giglio et al. (2020)). Furthermore, investor beliefs are a key building block in economic models. It is crucial to understand underlying beliefs because these beliefs affect a variety of outcomes. For example, during the U.S. Civil War, the value of the greenback rose and fell based on public beliefs (McCandless (1996)). Similarly, diminished expectations of nuclear war cause individuals to save more (Russett and Slemrod (1993)), and CFO's expectations of earnings growth explain corporate investment plans and actual investment (Gennaioli, Ma, and Shleifer (2016)). Furthermore, large political shifts such as Prohibition (Brittanica (2019)) or the legalization of same-sex marriage (Ball (2015)) occurred on the heels of shifts in public opinion. In this paper, I study one potential determinant of individual beliefs: peers.

Peers have been shown to influence a variety of economic outcomes.[1] However, there is less

[1] Previous work has documented peer effects in stock market participation (Hong, Kubik, and Stein

evidence on whether peers affect underlying beliefs. To my knowledge, this paper is the first to provide causal evidence of peer effects in one specific type of belief: financial expectations. In this study, financial expectations refer to surveyed individual-specific beliefs about one's future financial situation. These beliefs are important because they are a key building block in economic models and are related to individual behavior, e.g. savings decisions.

A number of theoretical papers study social transmission of beliefs.[2] However, an important next step in social finance is to empirically test whether and how beliefs are socially transmitted. This paper provides evidence of a simple mechanism that individuals use to form beliefs: people update their beliefs based on the beliefs of their peers. Additionally, I provide evidence that this mechanism is rational in the sense that individuals who are influenced by neighborhood financial expectations form more accurate financial expectations.

There are many reasons that an individual might take the beliefs of her neighbors into account when forming her own financial expectations. For example, the beliefs of one's neighbors might provide information about the local labor market, local housing market, or the overall economy. While this information may be available from other sources, it is often easier to obtain information from word-of-mouth communication. As Ellison and Fudenberg (1995) point out, economic agents "often choose not to perform studies or experiments, but instead rely on whatever information they have obtained via casual word-of-mouth communication." Individuals often rely on this sort of information when making a variety of decisions ranging from choosing a mechanic to purchasing a vacation rental. Consistent with my rationality results, Ellison and Fudenberg (1995) show that word-of-mouth communication may lead players to adopt superior strategies, particularly when each individual receives little information.

(2004); Brown et al. (2008); Kaustia and Knüpfer (2012)), asset purchases (Ivković and Weisbenner (2007) and Bursztyn et al. (2014)), hours worked (Weinberg, Reagan, and Yankow (2004)), housing decisions (Bailey et al. (2018)), and financial literacy (Haliassos, Jansson, and Karabulut (2020)).

[2]See Burnside, Eichenbaum, and Rebelo (2016), Han, Hirshleifer, and Walden (2020), and Hirshleifer (2020)

One of the main challenges in identifying peer effects is the reflection problem. In seminal work on peer effects, Manski (1993) describes a problem that arises when a researcher tries to infer whether the average behavior of a group influences the behavior of individuals in that group. This challenge is aptly named the reflection problem because it is akin to trying to interpret the almost simultaneous movements of a person and her reflection in the mirror.

The reflection problem is particularly relevant in this paper because individuals are not randomly assigned to neighborhoods. Therefore, observed correlation between an individual's financial expectations and the financial expectations of her neighbors could reflect the fact that neighbors have similar environments. Additionally, even if one can rule out environmental effects, it is difficult to determine whether an individual's financial expectations are driven by a response to her peers' financial expectations or by shared exogenous characteristics, such as wealth, marital status, or race.

In order to identify social influence, I use an instrumental variables strategy similar to that of Brown et al. (2008), who find evidence of peer effects in stock market participation. I instrument for the average financial expectations of an individual's neighbors with the average financial expectations of neighbors' nonlocal family members. Whereas the average financial expectations of these nonlocal family members are likely to be correlated with the financial expectations of an individual's neighbors,[3] there is much less reason to think that the individual's financial expectations will be directly influenced by the expectations of her neighbors' nonlocal family members. The instrumental variable should only affect an individual's financial expectations indirectly; through social interaction with her neighbors.

Even with the instrumental variables approach, it is possible that individuals stochastically self-select into neighborhoods based on traits that are correlated with financial expectations and are similar among family members. For example, individuals, their neighbors, and their

[3]Family members are a particularly influential set of individuals. For example, Case and Katz (1991) show that family adult behaviors are strongly associated with similar youth behaviors.

neighbors' nonlocal family members are likely to have similar wealth. Therefore, if wealth is correlated with financial expectations, it might be driving my results. To address these alternate explanations, I include individual fixed effects, year fixed effects, and time-varying controls. The individual fixed effects control for observable and unobservable individual characteristics that are fixed over time, such as race, gender, and risk tolerance; the year fixed effects control for sample-wide time trends; and the time-varying controls rule out specific observables, such as wealth and education, that could be driving my results.

Using this approach, I find evidence of substantial peer effects in financial expectations. A one standard deviation increase in neighborhood financial expectations leads to a 2.36% increase in individual financial expectations. To put this in perspective, a one standard deviation increase in the financial expectations of an individual's family is associated with an 8.64% increase in the individual's financial expectations. Therefore, the magnitude of the neighborhood effect is nearly 27% as large as the magnitude of the family effect.

Survey responses from the British Household Panel Survey (BHPS) allow me to study direct proxies for beliefs as opposed to trying to infer beliefs from economic outcomes. Recent work has shown that survey measures of investor expectations are reflections of widely shared beliefs. These beliefs have important asset pricing implications and are negatively correlated with model-based expected returns (Greenwood and Shleifer (2014)).

The BHPS also has data that can be used to infer an individual's level of social connectedness. In a similar vein to Ivković and Weisbenner (2007), I use three sociability proxies to evaluate alternative explanations for my results. If, for example, my results were driven by regional shocks, then one would expect sociability to have no influence on the magnitude of peer effects. Similarly, if my results were driven by common characteristics, such as education or income, one would not expect peer effects to vary with changes in sociability. However, I find that peer effects are stronger for individuals who are more socially connected. This evidence supports the hypothesis that individuals are influenced by their neighbors' financial expectations and is difficult to reconcile with competing explanations.

Next, I use savings data from the BHPS to test the joint hypothesis that survey responses reflect actual beliefs and that individuals act in accordance with these beliefs. I find that individuals who expect their financial situation to improve are less likely to save than individuals who expect their financial situation to worsen. This evidence is consistent with the joint hypothesis stated above.

Lastly, I test whether these observed peer effects are rational. I construct a measure of financial expectation error by calculating the absolute difference between an individual's financial expectations and her realized change in financial situation. I find that individuals with small financial expectation errors display a statistically significant peer effect, while individuals with large expectation errors do not. Therefore, individuals seem to be making good use of information when they take their neighbors' financial expectations into account.

This paper contributes to four streams of literature. First, it extends the literature on peer effects by providing evidence of causal peer effects in financial expectations. This evidence is complementary to the work of Ahern, Duchin, and Shumway (2014), who find positive peer effects in risk aversion.

Second, this paper contributes to the literature on belief formation. I provide evidence that individuals use the financial expectations of their peers as an input when forming their own financial expectations. Therefore, theoretical models of belief formation should consider social interactions because they are an important microfoundation for individual beliefs.

Third, this paper contributes to the household finance literature by studying the rationality of peer effects in financial expectations. I provide evidence that individuals who display peer effects form more accurate financial expectations. Therefore, individuals can benefit by updating their beliefs based on the beliefs of their peers.

Fourth, this paper extends the social finance literature by providing evidence of social transmission of financial expectations. Thus, my results support the premise of theoretical papers that model the process by which ideas are transmitted (Burnside, Eichenbaum, and Rebelo (2016) and Han, Hirshleifer, and Walden (2020)).

1.2 Data Description

My data come from a panel survey of U.K. residents called the British Household Panel Survey (UK Data Service (2018)). This survey was carried out by the ESRC UK Longitudinal Studies Centre with the Institute for Social and Economic Research at the University of Sussex. The BHPS is an annual survey of each adult (age 16+) member of a nationally representative sample of more than 5,000 households. Descriptive statistics for BHPS variables of interest can be found in Table 1.1.

The BHPS was administered in annual waves from 1991 to 2008. In each of the 18 waves, the same individuals were re-interviewed. Additional subsamples were added to the BHPS in 1997 and 1999. After 2008, the BHPS became part of a new survey called Understanding Society. However, this new survey does not contain many of the variables that are crucial for my analysis. Therefore, I focus on data from the first 18 waves.

The survey waves were administered at least six months apart, so repeated measurement issues are unlikely to bias my results. The stated aim of the BHPS is to maximize the advantages of panel data to permit research into a wide range of social science topics.[4]

Many questions in the BHPS were asked in every wave. These are referred to as "core" questions. The first core variable I use is FISITX. This variable allows me to measure an individual's financial expectations. Respondents were asked the following question: "Looking

[4]For additional information on specifics of this survey, see Taylor et al. (2018).

ahead, how do you think you yourself will be financially a year from now, will you be...(1) Better off than you are now, (2) Worse off than you are now, Or (3) About the same?" Additionally, respondents were allowed to answer "Don't know" on any of the survey questions. I code individual financial expectations as 1 if an individual believes she will be better off, 0 if an individual believes she will be about the same, and -1 if an individual believes she will be worse off.

I use a second core variable (FISITC) to evaluate the rationality of peer effects in financial expectations. This variable measures the change in each individual's financial situation over the last year. I calculate an individual's financial expectation error as the absolute value of the difference between FISITX and next year's FISITC. This measure captures the absolute difference between an individual's financial expectations and her realized change in financial situation.

Next, I use three variables as proxies for sociability. The first, FRNA, is a variable that measures the frequency with which an individual talks to her neighbors. The second, LKNBR, equals one if an individual likes her neighborhood and zero otherwise. The third, ORGM, equals one if an individual is a member of a local organization and zero otherwise.

The BHPS also has data on individual savings behavior. Respondents were asked the following question: "Do you save any amount of your income for example by putting something away now and then in a bank, building society, or Post Office account other than to meet regular bills?" I construct a dummy variable (SAVE) that equals one if individuals save and zero otherwise.

Finally, I utilize demographic information on each individual. The BHPS includes demographic information such as annual income (FIYR), job industry (JBSIC), education level (QFEDHI), marital status (MASTAT), race (RACE), and interview area (IVIA). The first five variables are included as controls. The last, interview area, is used to determine which individuals are neighbors. Because each interviewer covers a specific geographic area, individuals in the same interview area live near each other. When an individual moves out of an interview area, she is assigned a new interviewer and a new interview area.

1.2.1 Neighborhood Financial Expectations

In order to construct neighborhood financial expectations, I use two variables: interview area (IVIA) and financial expectations (FISITX). Interview area allows me to determine which individuals are neighbors because each interviewer covers a specific geographic area. Therefore, individuals in the same interviewer area live in relatively close proximity to one another and are more likely to have social interactions with one another than individuals in two different interview areas.[5]

Overall, there are 250 interview areas which cover the roughly 10,000 participants in the initial BHPS sample. This means that the average interview area consists of 41 people who live near each other. Near is a relative term because the geographic size of interview areas varies with population density. For example, within the region of inner London there are 13 different interview areas. However, in the entire region of Wales there are only 12 different interview areas. This makes sense because the populations of inner London and Wales were comparable in 1991. Furthermore, this layout of interview areas is actually beneficial for studying social interactions. Compared to individuals who live in densely populated cities, individuals who live in rural areas are more likely to interact with people who live further away.

For each individual, I calculate neighborhood financial expectations as the average financial expectation of one's neighbors in a given year. Because financial expectations are either positive (1), negative (-1) or neutral (0), the average financial expectations of one's neighbors

[5]Interview areas are comparable in size to Metropolitan Statistical Areas (MSA). This definition of neighborhood is widely used in empirical studies in economics and finance, e.g. Brown et al. (2008).

can be thought of as the proportion of neighbors who are optimistic about next year's financial prospects minus the proportion of neighbors who are pessimistic. Therefore, this variable provides a good measure of the average financial expectations in an individual's neighborhood.

1.2.2 Sociability Proxies

I construct three sociability proxies using responses from the BHPS. The first proxy is most closely related to neighborhood sociability because it measures the frequency with which an individual talks to her neighbors. This variable equals one if an individual talks to her neighbors most days of the week; two if she talks to them once or twice a week; three if she talks to them once or twice a month; four if she talks to them less than once a month; and five if she never talks to her neighbors. This proxy directly measures how socially connected an individual is to her neighbors. Unfortunately, this is not a core question on the BHPS. Therefore, data availability for this proxy is limited to a subset of survey waves.

The second proxy measures whether or not an individual likes her neighborhood. This proxy is based on a core question in which respondents were asked the following: "Overall, do you like living in this neighbourhood?...(1) Yes, (2) No." The intuition behind this proxy is that an individual who likes her neighborhood is more likely to have social interactions with her neighbors. Alternatively, an individual who dislikes her neighborhood is probably not very socially connected to her neighbors. Clearly, this is an imperfect measure of sociability, but it is at least likely to be correlated with sociability. Additionally, this variable is the only sociability proxy that is a core question, meaning that this question was asked in each of the 18 survey waves.

The third proxy for sociability is based on an individual's involvement in local organizations. The BHPS asks respondents to identify whether or not they belong to local organizations such as: trade unions, environmental groups, parents assocations, tenants groups, religious groups, voluntary service groups, and sports clubs. This proxy is a dummy variable that equals one if a respondent is a member of any organization and zero otherwise. It has clear sociability implications. If a person is a member of a local organization, she is more likely to be socially connected. Unfortunately, these organization questions are not core questions. Therefore, data availability for this proxy is limited.

1.2.3 Identification Strategy

My hypothesis is that an individual's financial expectations are influenced by the financial expectations of her neighbors. The difficulty in testing this hypothesis is described in detail in Brown et al. (2008), but it comes down to an inability to control for unobserved time-varying factors. The panel dataset allows me to control for individual and year fixed effects. Therefore, my method rules out time invariant factors and sample-wide trends. Furthermore, I control for observed time-varying variables, such as wealth, that could explain the correlation between individual financial expectations and average neighborhood financial expectations. However, it is still possible that unobserved time-varying factors, such as changes in a community's information set, could explain my results. Thus, in order to identify causal peer effects in financial expectations, I need to find a source of exogenous variation in the financial expectations of an individual's neighbors. I use the financial expectations of neighbors' nonlocal family members as a source of exogenous variation.

Because survey respondents are not randomly assigned to neighborhoods, I use an instrumental variables strategy to find exogenous variation in neighborhood financial expectations. I instrument for neighborhood financial expectations with the average financial expectations of neighbors' nonlocal family members. This instrument is likely to be correlated with the financial expectations of an individual's neighbors[6], but it is not likely to be correlated with

[6] Case and Katz (1991) show that family behaviors are strongly correlated.

the financial expectations of the individual, except through the individual's social interactions with her neighbors.

Homophily is a key concern in studies of peer effects. Individuals, their neighbors, and their neighbors' nonlocal family members likely exhibit similarity along various unobservable dimensions, e.g. political beliefs, religion, and race. If these unobservables are the true drivers of my results, then the instrument might fail the exclusion restriction. While I cannot fully address homophily due to the nonrandom assignment of individuals to neighborhoods, the included controls address many alternative explanations. The individual fixed effects control for time-invariant individual characteristics such as religion and race; the year fixed effects control for sample-wide trends such as nationwide economic optimism; and the time-varying controls (wealth and education) rule out specific alternative explanations. In addition to the above controls, the reverse causality results in Figure 1.1 provide evidence against homophily.

I utilize the unique nature of my dataset to develop an instrument that relies on the financial expectations of neighbors' nonlocal family members. The BHPS is conducted at the individual and household level. This allows me to determine which individuals in my sample have ever been a part of the same household.

For the purpose of this study, a family member is someone who lived in the same household as a given individual at some point previously in the sample. Therefore, a nonlocal family member is likely to be a divorced spouse, an adult child, a sibling, or anyone else who at one point lived in the same household as the individual but has since moved to a different interview area.

In order to construct the instrument, I begin by identifying each family member who is no longer living in the same interview area. Next, for a given year, I calculate the average financial expectations of each person's nonlocal family members. Finally, I calculate the average financial expectations of the nonlocal family members of each individual's neighbors.

1.3 Results

1.3.1 Panel Regressions

In order to determine whether there is a relationship between individual financial expectations and neighborhood financial expectations, I run two panel regressions. The first regression, reported in Column (1) of Table 1.2, is a simple regression of individual financial expectations on neighborhood financial expectations with no additional controls. The second regression, reported in Column (2), includes wealth, individual fixed effects, and year fixed effects as controls. Throughout the analysis, standard errors are clustered at the neighborhood level.

Both specifications show a highly significant, positive relationship between individual financial expectations and neighborhood financial expectations. Including the additional controls decreases the magnitude of the coefficient by over 50%. However, this is expected because individual and year fixed effects remove a substantial amount of variation. What is more striking is that there is a strong relationship between individual and neighborhood financial expectations, even after controlling for individual and year fixed effects. One standard deviation in the residualized treatment variable is 0.097. Therefore, a one standard deviation increase in neighborhood financial expectations is associated with a 2.45% $(0.097 * 0.253)$ increase in individual financial expectations.

In order to determine if these magnitudes are economically meaningful, I consider the effects of a particularly influential set of individuals: family members.[7] Next, I compare the peer effects in financial expectations to the family effects in financial expectations. Table 1.3 presents results from a regression of individual financial expectations on the average financial expectations of the individual's family members. I include controls for wealth, individual

[7] This test is similar to the test of parental influence on stock market participation in Brown et al. (2008).

fixed effects and year fixed effects.

The results from this regression show a positive, statistically significant relationship between individual financial expectations and average family financial expectations. To compare the magnitude of the family effect to the magnitude of the peer effect, I calculate the standard deviation in the residualized treatment variable as 0.379. A one standard deviation increase in the financial expectations of one's family is associated with an increase of 8.64% ($0.379 * 0.228$) in one's own financial expectations. Therefore, the neighborhood effect from Table 1.2 is roughly 28% as large as the family effect.

These results provide evidence that the financial expectations of individuals are correlated with the financial expectations of their neighbors. Furthermore, this correlation is not entirely driven by time-invariant individual characteristics or by sample-wide trends. Even after including individual and year fixed effects, the relationship is statistically and economically significant. Therefore, if unobserved factors are driving these results, they must be time-varying or neighborhood specific.

1.3.2 Reverse Causality

Based on these panel regressions alone, it is not necessarily true that individuals take their neighbors' financial expectations into account when forming their own financial expectations. It is also possible that individuals move to neighborhoods where people have similar financial expectations. In this case, reverse causality could be driving the results.

While financial expectations might not be the primary factor that influences neighborhood choice, it is possible that people unintentionally choose to live near people with similar financial expectations. For example, individuals might move to an area based on the prospects of the local housing market. Other individuals in that area are likely to have similar positive beliefs about the local housing market. If neighbors have similar beliefs about the local housing market, they might also have similar beliefs about future financial prospects.

I test for reverse causality by running four subsample regressions. Individuals are split into subsamples based on how long they have lived in the same neighborhood. If an individual moves or is newly added to the survey, she would be placed into the subsample that is associated with zero years in the neighborhood. In each of these regressions, I use the same specification as in Column (2) of Table 1.2.

If individuals are indeed taking neighborhood financial expectations into account when forming their own financial expectations, then one would expect the coefficients to get larger the longer an individual lives in the same neighborhood. This is because when an individual first moves to a neighborhood, she might not know her neighbors very well. However, as years go by, she will likely get to know her neighbors better and be more influenced by their financial expectations.

On the other hand, if reverse causality is driving the observed relationship, we would expect the coefficients to either stay flat or get progressively smaller the longer an individual lives in a neighborhood. To see this, consider an individual who moves to a neighborhood because residents of that neighborhood have similar financial expectations to her own. This similarity should be strongest immediately after the move. As time passes, if there is no social transmission of beliefs and ideas, people's financial expectations will either maintain the same level of correlation or start to diverge. This would manifest itself as either flat or decreasing coefficients on neighborhood financial expectations.

Figure 1.1 provides evidence against reverse causality. As discussed previously, if reverse causality were driving the results, one would expect the coefficients for year 0 and year 1 to be the highest, with either flat coefficients or a steady decline in the years that follow. Instead, the results suggest that an individual is increasingly influenced by her neighbors' financial expectations the longer she lives in the neighborhood. The coefficient on neighborhood financial expectations is largest for individuals who have lived in the same neighborhood for three or more years. This is consistent with the social transmission of financial expectations among neighbors.

In peer-effect studies, homophily is a key concern. Because individuals tend to be attracted to people who are similar to themselves, it is likely that individuals in the same neighborhood are similar along various unobservable dimensions, such as political beliefs, religion, or race. If these common unobservables were driving my results, then one would expect to see coefficients of similar magnitudes regardless of how long an individual has lived in a neighborhood. While homophily cannot be fully ruled out in a setting without random assignment into peer groups, the results from Figure 1.1 provide evidence against homophily and in support of the social transmission of beliefs.

1.3.3 First-Stage Regression

In order to provide causal evidence that individuals are influenced by their neighbors' financial expectations, I utilize an instrumental variables strategy. Table 1.4 provides results from the first-stage regression of average financial expectations of one's neighbors on average financial expectations of neighbors' nonlocal family members. Because the instrument is highly correlated with neighborhood financial expectations, it meets the first criterion for an instrument in two-stage least squares.

In Column (1) of Table 1.4, I report the coefficient from a baseline specification with no other controls. In Column (2), I control for wealth, individual fixed effects, and year fixed effects. This second specification will ultimately be included in the two-stage least squares. In both specifications, there is a highly significant relationship between neighborhood financial expectations and the financial expectations of neighbors' nonlocal family members. The t-

statistic for the second specification is 3.66. The corresponding F statistic is 13.40, and the Kleibergen-Paap rk Wald F statistic is 15.11. These statistics indicate that the instrument is sufficiently powerful.[8]

1.3.4 Reduced Form Regression

Angrist and Krueger (2001) argue that it is important to report reduced-form estimates because these estimates are unbiased. Therefore, reduced-form estimates can mitigate concerns about weak instruments. Table 1.5 reports estimates from a reduced-form regression of individual financial expectations on the financial expectations of neighbors' nonlocal family members. Column (1) of Table 1.4 reports results from a baseline specification with no other controls. Column (2) reports results from a specification in which I control for wealth, individual fixed effects, and year fixed effects.

Results from the reduced-form regression provide evidence for the causal relationship of interest. In both specifications, the sign of the coefficient is positive and statistically different from zero, albeit only marginally significant in the second specification. Thus, the financial expectations of neighbors' nonlocal family members should be a valid instrument for neighborhood financial expectations.

1.3.5 Instrumental Variable Regression

Table 1.6 reports the main set of results using my instrumental variables strategy. The dependent variable of interest is the average financial expectations of an individual's neighbors. Standard errors are clustered at the neighborhood level to allow for correlation within neigh-

[8]The BHPS data likely fails the i.i.d assumption necessary for the Stock and Yogo (2005) critical values. Therefore, Baum, Schaffer, and Stillman (2007) recommend using the older "rule of thumb" which says that the F statistic should be at least 10 to avoid weak-identification issues.

borhoods. To strengthen my identification, this specification controls for wealth, individual fixed effects and year fixed effects.

I include individual fixed effects because there are likely observable and unobservable individual characteristics that could be correlated with neighborhood financial expectations and individual financial expectations. Some examples include: race, marital status, and education. Additionally, I control for year fixed effects because there could be sample-wide trends in financial expectations. For example, during the 1990's, the dot-com bubble might have caused the entire sample to be more optimistic about the future. The inclusion of year fixed effects means that I am no longer using year variation in any variable to identify my key effect of interest. Thus, sample-wide time trends in economic variables are not driving my results. Finally, I control for wealth because this is a time-varying variable that could be correlated with both individual financial expectations and neighborhood financial expectations.

The coefficient of 0.512 on neighborhood financial expectations in Table 1.6 is the main result of this paper. This coefficient is statistically significant and suggests that a 10% increase in neighborhood financial expectations leads to a 5.12% increase in an individual's financial expectations. When interpreting results from a model with fixed effects, one must be careful to identify plausible counterfactual shifts in the independent variable because adding fixed effects removes a substantial amount of potential variation. In this case, given that one standard deviation in the residualized treatment variable is 0.046, a 10% increase is certainly plausible. Stated differently, a one standard deviation increase in the financial expectations of one's neighbors leads to a 2.36% ($0.046 * 0.512$) increase in one's own financial expectations.

To determine if these magnitudes are economically meaningful, I again consider the family effects in financial expectations. As previously shown, a one standard deviation increase in the financial expectations of one's family is associated with an increase of 8.64% in one's own financial expectations. Therefore, the causal peer effects in financial expectations are roughly

27% as large as the family effects in financial expectations. This is striking, considering that family members are very influential in individual decision-making.

1.3.6 Sociability Results

I provide additional evidence for the social transmission of beliefs using three proxies for sociability. Recall that the first proxy measures the frequency with which an individual interacts with her neighbors. The second proxy is a dummy variable that equals one if an individual likes her neighborhood and zero otherwise. The third proxy is a dummy variable that equals one if an individual is a member of a social organization and zero otherwise.

Figures 1.2 through 1.4 present point estimates and 95% confidence intervals from regressions using these three proxies for sociability. In each regression, I use the main instrumental variables specification from Table 1.6, but I split my sample based on each sociability proxy. For example, I present results from five subsample regressions to evaluate the first sociability proxy. Individuals are placed into each of the subsamples based on the frequency with which they interact with their neighbors. I use a similar methodology to split individuals into subsamples for the second and third sociability proxies.

Results for the first sociability proxy are reported in Figure 1.2. The coefficients on neighbors' financial expectations are largest for individuals who talk with their neighbors on a daily basis and smallest for individuals who never or rarely talk to their neighbors. In fact, the peer effect is only statistically significant for individuals who talk to their neighbors on a daily basis. These results provide evidence in support of the social transmission of financial expectations. Individuals who interact with their neighbors on a daily basis are the most likely to be socially connected to their neighbors.

Results from the second sociability proxy are reported in Figure 1.3. Based on these subsample regressions, it is clear that there is only a statistically significant peer effect for individuals who like their neighborhood. This evidence also supports the social transmission hypothesis because individuals who like their neighborhood are more likely to be socially connected with their neighbors than individuals who dislike their neighborhood.

Finally, Figure 1.4 provides results for the third sociability proxy. There is only a statistically significant peer effect for individuals who are members of local organizations. The peer effect for nonmembers is indistinguishable from zero. Again, this evidence supports the social transmission hypothesis because individuals who belong to local organizations are more likely to be socially connected to their neighbors than individuals who don't belong to any local organizations.

Overall, the sociability proxies provide evidence that supports the social transmission hypothesis and is difficult to reconcile with competing explanations. Individuals who are more socially connected are more influenced by the financial expectations of their neighbors. On the other hand, individuals who are not very socially connected display coefficients that are statistically indistinguishable from zero. This evidence provides an important insight into the mechanism driving peer effects in financial expectations.

One plausible alternative explanation for my results from Section 1.3.5 is that individuals, their neighbors, and their neighbors' nonlocal family members all share common information sources. For example, maybe individuals are more likely to read the same newspapers and watch the same news channels as their neighbors and their neighbors' nonlocal family members. My instrumental variables strategy is not able to differentiate between this common information hypothesis and the social transmission hypothesis. However, the common information hypothesis does not explain the sociability results from Figures 1.2 through 1.4.

While one could still argue that these sociability proxies are instead proxies for shared information, information sharing is most likely to arise as the result of social interaction. For example, it is possible that individuals who talk to their neighbors more frequently are more likely to read the same newspaper as their neighbors. However, this increased propensity to read the same newspaper is likely due to increased social interaction. Therefore, social interaction would still be driving these results.

It is also possible that common characteristics are driving my results from Section 1.3.5. For example, individuals might be similar to neighbors' nonlocal family members based on race, wealth, or education level. Again, the sociability results from Figures 1.2 through 1.4 provide evidence that supports the social transmission hypothesis and is difficult to reconcile with this alternative explanation.

1.3.7 Expectations and Actions

One common criticism of survey expectations is that we cannot be sure if they are related to actual behavior. It is possible that framing affects survey responses or that individuals do not actually mean what they say. In this section, I test the relationship between financial expectations and savings behavior using a methodology that is very similar to Cocco, Gomes, and Lopes (2020). The results provide evidence that individuals behave in a manner that is broadly consistent with their financial expectations.

I study the relationship between financial expectations and savings behavior by regressing the savings dummy variable (SAVE) on individual financial expectations. The savings dummy variable equals one if an individual saved money over the past year and zero otherwise. As before, I control for wealth, individual fixed effects, and year fixed effects. Standard errors are clustered at the neighborhood level.

Results from Table 1.7 show a statistically significant, negative relationship between individual financial expectations and the savings dummy. This means that individuals who expect their financial situation to improve are less likely to save. Therefore, individual savings behavior is consistent with surveyed financial expectations. This finding provides evidence in support of the joint hypothesis that surveyed beliefs reflect actual beliefs and that individuals act in accordance with their beliefs.

1.3.8 Peer Effects and Rationality

Lastly, I analyze the rationality of these observed peer effects. It is possible that learning from the financial expectations of one's neighbors is a good idea. These expectations might provide information about the local labor market or the local housing market. Furthermore, neighborhood financial expectations might provide information about the general direction of the economy.

On the other hand, it is also possible that individuals who update based on the beliefs of their peers are making a mistake. For example, neighborhood financial expectations might not provide any additional information about local market conditions. Furthermore, even if neighborhood financial expectations provide information, individuals might not correctly use this information. For instance, they might put too much weight on the financial expectations of their peers. This could lead to irrational herding behavior, especially if neighborhood financial expectations crowd out individual information.

To assess the rationality of these observed peer effects, I compare each individual's financial expectations (FISITX) with the realized change in that individual's financial situation the following year (FISITC). Financial expectation error is calculated as the absolute value of the difference between FISITX and FISITC. Next, I split individuals into two groups based on their financial expectation error for each year. Individuals in the "small" subsample have errors that are smaller than the median error, and individuals in the "large" subsample have errors that are larger than the median error. Lastly, I run subsample regressions using the main instrumental variables specification from Table 1.6.

Figure 1.6 presents point estimates and 95% confidence intervals from these subsample regressions. As can be seen from the figure, individuals with small financial expectation errors display a statistically significant peer effect in financial expectations. Individuals with large errors do not. Therefore, individuals are displaying at least a degree of rationality and seem to be making good use of information when they take their neighbors' financial expectations into account.

1.4 Conclusion

Historically, shifts in beliefs have caused substantial changes in outcomes as varied as individual savings, corporate investment plans, currency value, marriage norms, and Prohibition. Furthermore, investor beliefs are fundamental in economic models and have been shown to influence asset prices. I provide evidence of causal peer effects in one particular type of belief: financial expectations.

In order to address the reflection problem (Manski (1993)), I combine an instrumental variables strategy with individual and year fixed effects. I instrument for neighborhood financial expectations with the average financial expectations of neighbors' nonlocal family members. I show that a one standard deviation increase in neighborhood financial expectations leads to a 2.36% increase in individual financial expectations. This result is economically meaningful because it amounts to approximately 27% of the family effect in financial expectations.

Using three proxies for sociability, I provide additional evidence that social transmission is the mechanism driving this result. I find that socially connected individuals are more influenced by their neighbors' financial expectations. These results are consistent with the social transmission hypothesis and are difficult to reconcile with competing explanations.

Next, I test the joint hypothesis that surveyed financial expectations reflect actual beliefs and that individuals act in accordance with these beliefs. Consistent with this joint hypothesis, I show that individuals who expect their financial situation to improve are less likely to save than individuals who expect their financial situation to worsen.

Lastly, I provide evidence that individuals form more accurate expectations when they take their peers' financial expectations into account. This evidence suggests that individuals are behaving rationally when they form expectations based on the expectations of their peers.

These findings help to explain how beliefs spread through a population. If individuals form beliefs based on the beliefs of their peers, it is plausible that a relatively small shock to the financial expectations of a few particularly connected individuals could lead to a multiplier effect that shifts the beliefs of an entire population.[9] This in turn could explain the existence of booms and busts that seem unrelated to observable fundamentals. The recent surge in the stock prices of Gamestop and AMC provide salient examples of the potential price impact of a small number of socially well-connected investors.

[9] Hirshleifer (2020) provides an example of a model in which bias iterates socially and induces a multiplier.

Table 1.1: **Descriptive Statistics.**

The table below provides descriptive statistics for the individuals interviewed in the first wave of the British Household Panel Survey. The only exception is the "Talks to neighbors" variable, which is from the 1997 wave of the BHPS.

	mean	sd	min	max
Age	45.73	50.62	16	102
Male	0.47	0.50	0	1
Married	0.59	0.49	0	1
Financial expectations	0.12	0.62	-1	1
Talks to neighbors (1997)	2.01	1.04	1	5
Likes neighborhood?	0.87	0.34	0	1
Org. member	0.54	0.50	0	1

Table 1.2: **Panel Regression.**

The table below provides results for the panel regression of individual financial expectations on neighborhood financial expectations. Column (1) reports baseline results with no additional controls. Column (2) reports results from a specification that controls for wealth, individual fixed effects, and year fixed effects. There are fewer observations in Column (2) because the individual fixed effects force me to drop roughly 6,000 singleton observations. Standard errors are clustered at the neighborhood level. Additionally, the standard errors allow for heteroskedasticity.

	(1) No Controls	(2) Additional Controls
Neighborhood financial expectations	0.518^{***}	0.253^{***}
	(31.73)	(17.12)
Observations	236,763	230,962
Adj. R-squared	0.015	0.262
Individual FE	NO	YES
Year FE	NO	YES
Time-varying controls	NO	YES

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.3: **Family Effects Regression.**

The table below provides results for the regression of individual financial expectations on average financial expectations of the individual's family members. This specification controls for wealth, individual fixed effects, and year fixed effects. Standard errors are clustered at the neighborhood level. Additionally, the standard errors allow for heteroskedasticity.

	(1) Financial expectations
Financial expectations of family members	0.228***
	(37.62)
Observations	194,030
Adj. R-squared	0.2775
Individual FE	YES
Year FE	YES
Time-varying controls	YES

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.4: **First-Stage Regression.**

The table below provides results for the first-stage regression of average neighborhood financial expectations on average financial expectations of neighbors' nonlocal family members. Column (1) reports baseline results with no other controls. Column (2) reports results from a specification that controls for wealth, individual fixed effects, and year fixed effects. There are fewer observations in Column (2) because the individual fixed effects force me to drop roughly 6,000 singleton observations. Standard errors are clustered at the neighborhood level. Additionally, the standard errors allow for heteroskedasticity.

	(1) No Controls	(2) Additional Controls
Financial expectations of nonlocal family members	0.341***	0.099***
	(7.04)	(3.66)
Observations	236,666	230,864
Adj. R-squared	0.020	0.385
Individual FE	NO	YES
Year FE	NO	YES
Time-varying controls	NO	YES

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1.1: **Reverse Causality Test.**

The figure below shows point estimates and 95% confidence intervals for the coefficients from four regressions of individual financial expectations on neighborhood financial expectations. The regressions are subsample regressions, where subsamples are split based on the number of years an individual has lived in her neighborhood. All regressions control for wealth, individual fixed effects, and year fixed effects. Standard errors are clustered at the neighborhood level. Additionally, the standard errors allow for heteroskedasticity.

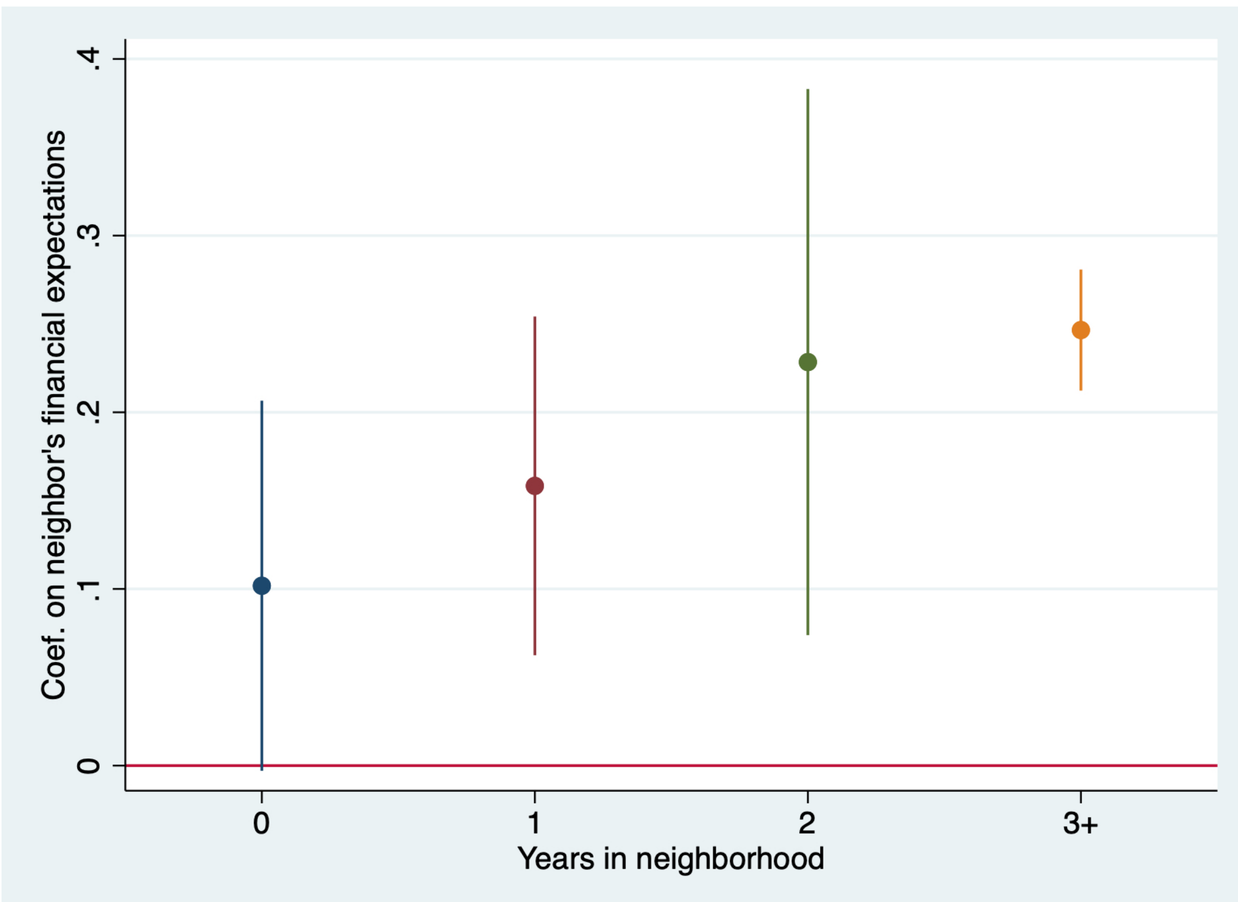


Table 1.5: **Reduced-Form Regression.**

The table below provides results for the reduced-form regression of individual financial expectations on average financial expectations of neighbors' nonlocal family members. Column (1) reports baseline results with no other controls. Column (2) reports results from a specification that controls for wealth, individual fixed effects, and year fixed effects. There are fewer observations in Column (2) because the individual fixed effects force me to drop roughly 6,000 singleton observations. Standard errors are clustered at the neighborhood level. Additionally, the standard errors allow for heteroskedasticity.

	(1) No Controls	(2) Controls
Financial expectations of	0.274^{***}	0.0508^{*}
nonlocal family members	(5.55)	(1.91)
Observations	236,666	230,864
Adj. R-squared	0.001	0.260
Individual FE	NO	YES
Year FE	NO	YES
Time-varying controls	NO	YES

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, $^{**>*}$ $p < 0.01$

Table 1.6: **Instrumental Variables Regression.**

The table below provides results for the instrumental variables regression of individual financial expectations on average neighborhood financial expectations. I instrument for neighborhood financial expectations with the average financial expectations of neighbors' nonlocal family members. This specification controls for wealth, individual fixed effects, and year fixed effects. Standard errors are clustered at the neighborhood level. Additionally, the standard errors allow for heteroskedasticity.

	Financial expectations
Neighborhood financial	0.512^{***}
expectations	(3.04)
Observations	230,868
Individual FE	YES
Year FE	YES
Time-varying controls	YES

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1.2: **Interaction Frequency.**

The figure below shows point estimates and 95% confidence intervals for the coefficients from instrumental variables regressions of individual financial expectations on neighborhood financial expectations. The regressions are subsample regressions, which are split based on how often an individual talks to his or her neighbors. All regressions control for wealth, individual fixed effects, and year fixed effects. Standard errors are clustered at the neighborhood level. Additionally, the standard errors allow for heteroskedasticity.

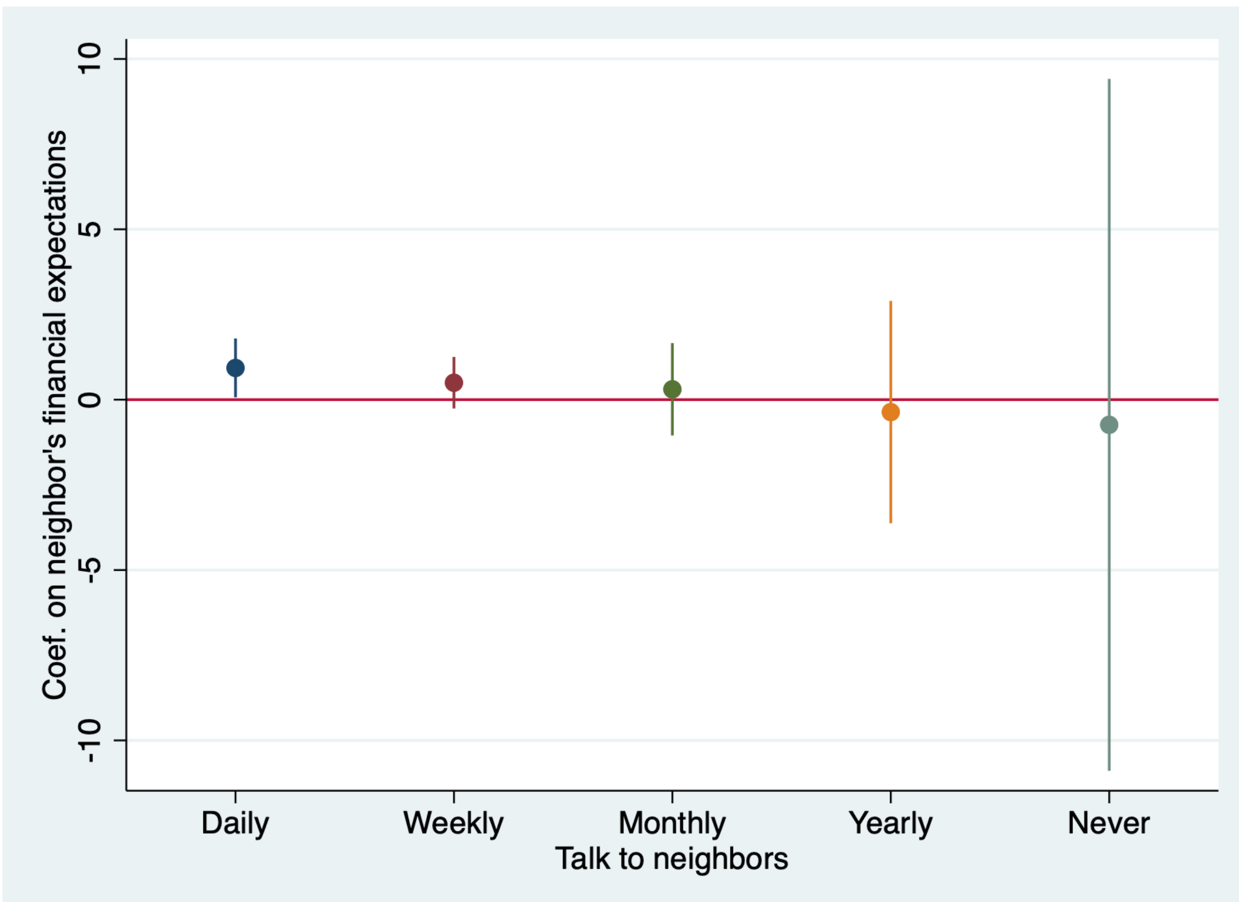


Figure 1.3: **Opinion of Neighborhood.**

The figure below shows point estimates and 95% confidence intervals for the coefficients from instrumental variables regressions of individual financial expectations on neighborhood financial expectations. The regressions are subsample regressions, which are split based on whether or not an individuals like his or her neighborhood. All regressions control for wealth, individual fixed effects, and year fixed effects. Standard errors are clustered at the neighborhood level. Additionally, the standard errors allow for heteroskedasticity.

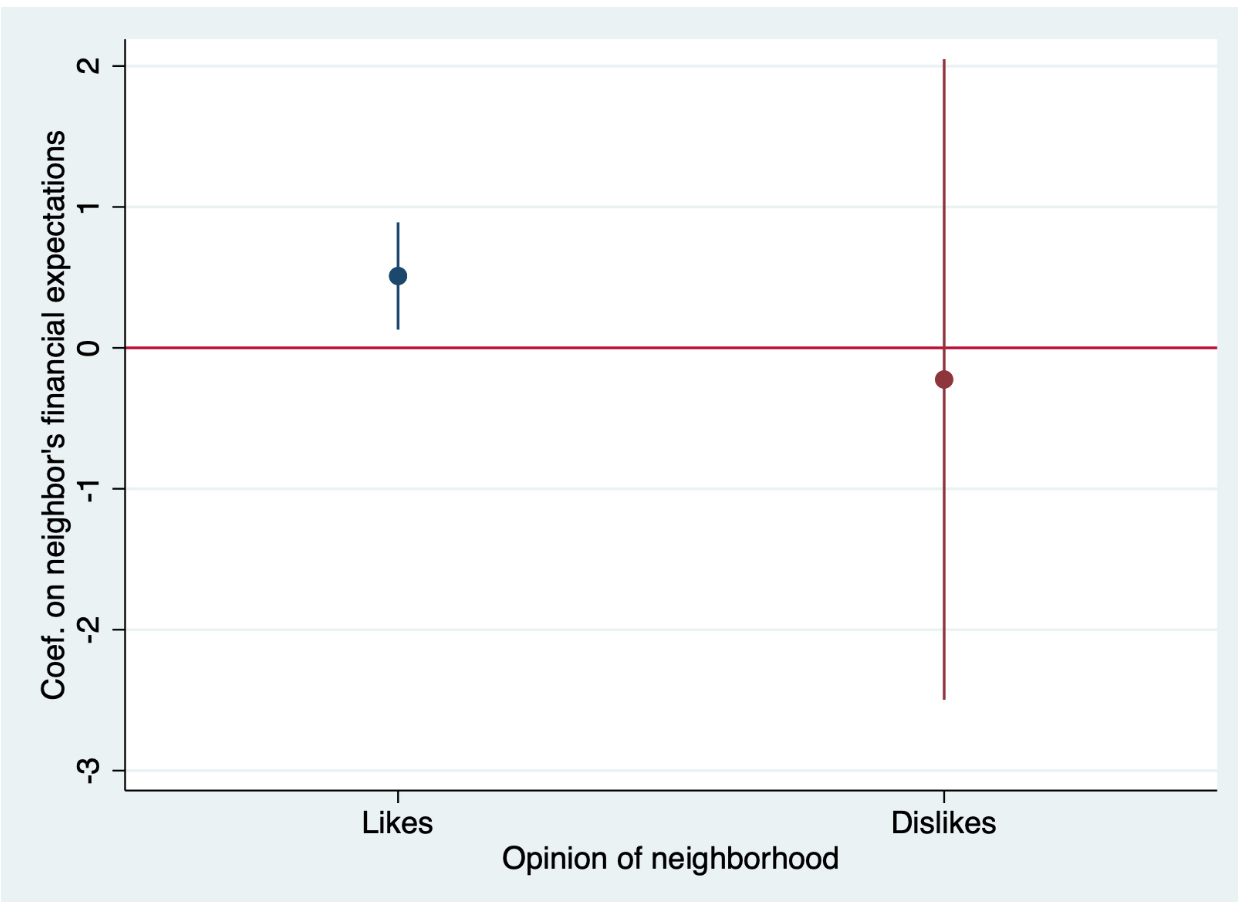


Figure 1.4: **Organization Membership.**

The figure below shows point estimates and 95% confidence intervals for the coefficients from instrumental variables regressions of individual financial expectations on neighborhood financial expectations. The regressions are subsample regressions, which are split based on whether or not an individual is a member of a local organization. All regressions control for wealth, individual fixed effects, and year fixed effects. Standard errors are clustered at the neighborhood level. Additionally, the standard errors allow for heteroskedasticity.

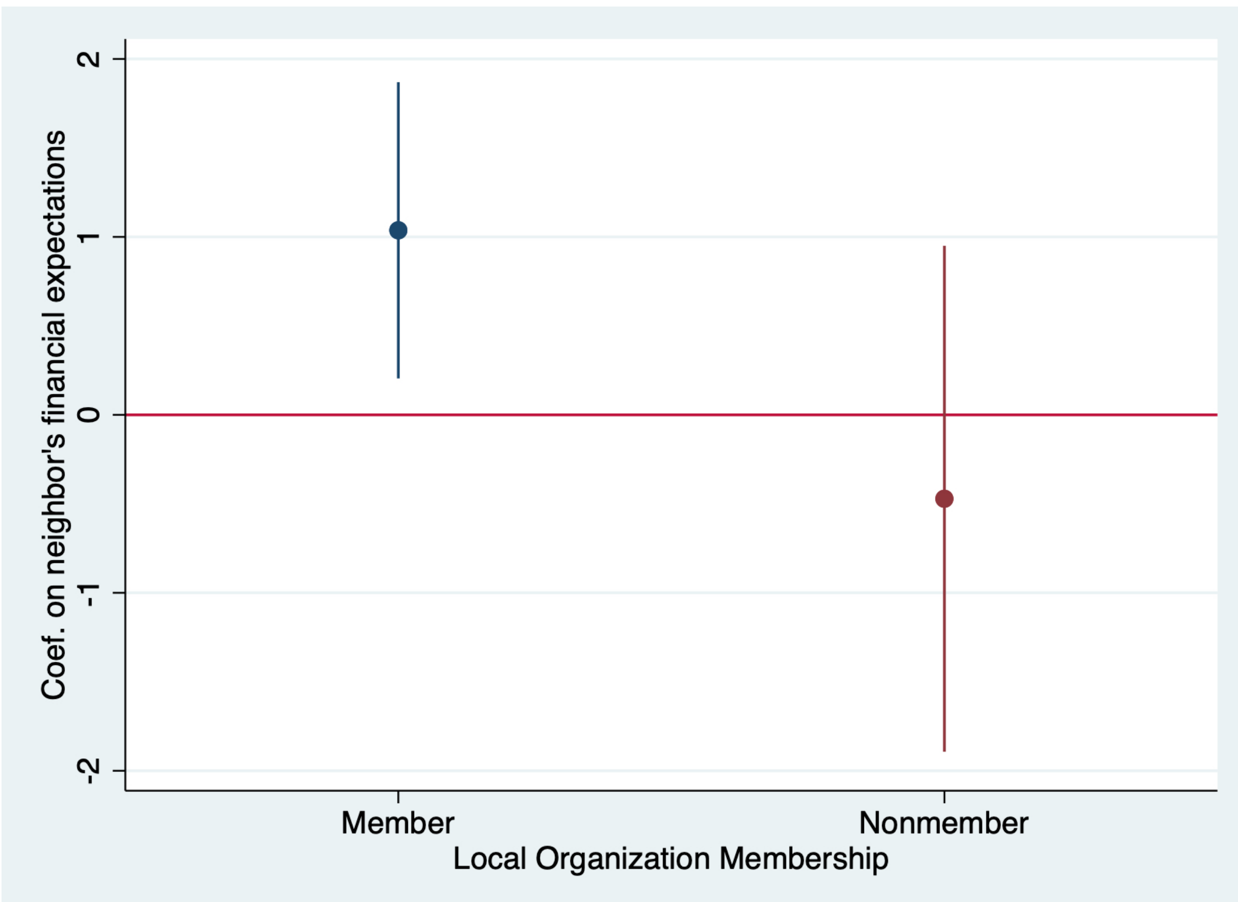


Figure 1.5: **Desire to Move.**

The figure below shows point estimates and 95% confidence intervals for the coefficients from instrumental variables regressions of individual financial expectations on neighborhood financial expectations. The regressions are subsample regressions, which are split based on whether or not an individual wants to move. All regressions control for wealth, individual fixed effects, and year fixed effects. Standard errors are clustered at the neighborhood level. Additionally, the standard errors allow for heteroskedasticity.

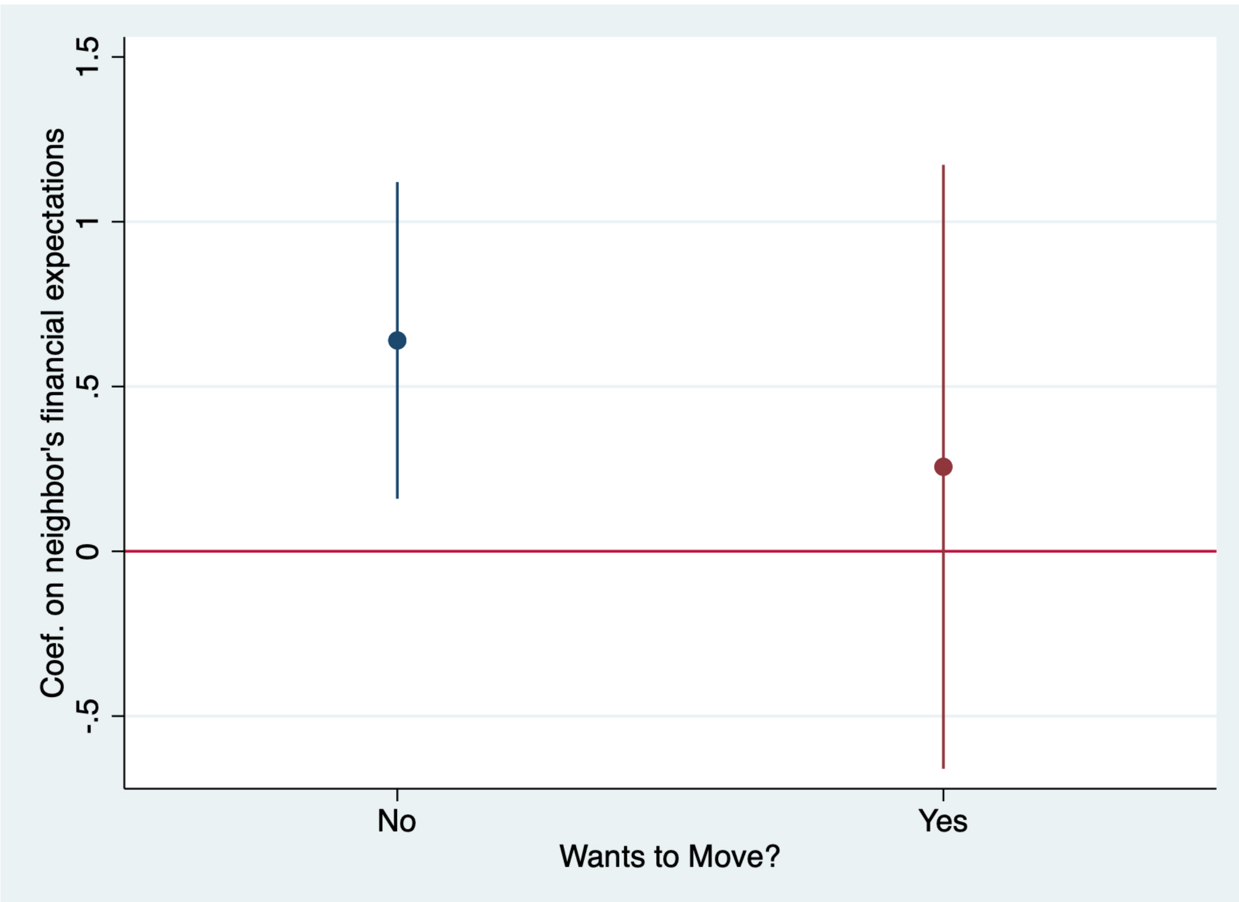


Table 1.7: **Savings Regression.**

The table below provides results for a panel regression of a savings dummy variable on individual financial expectations. This specification controls for wealth, individual fixed effects, and year fixed effects. Standard errors are clustered at the neighborhood level. Additionally, the standard errors allow for heteroskedasticity.

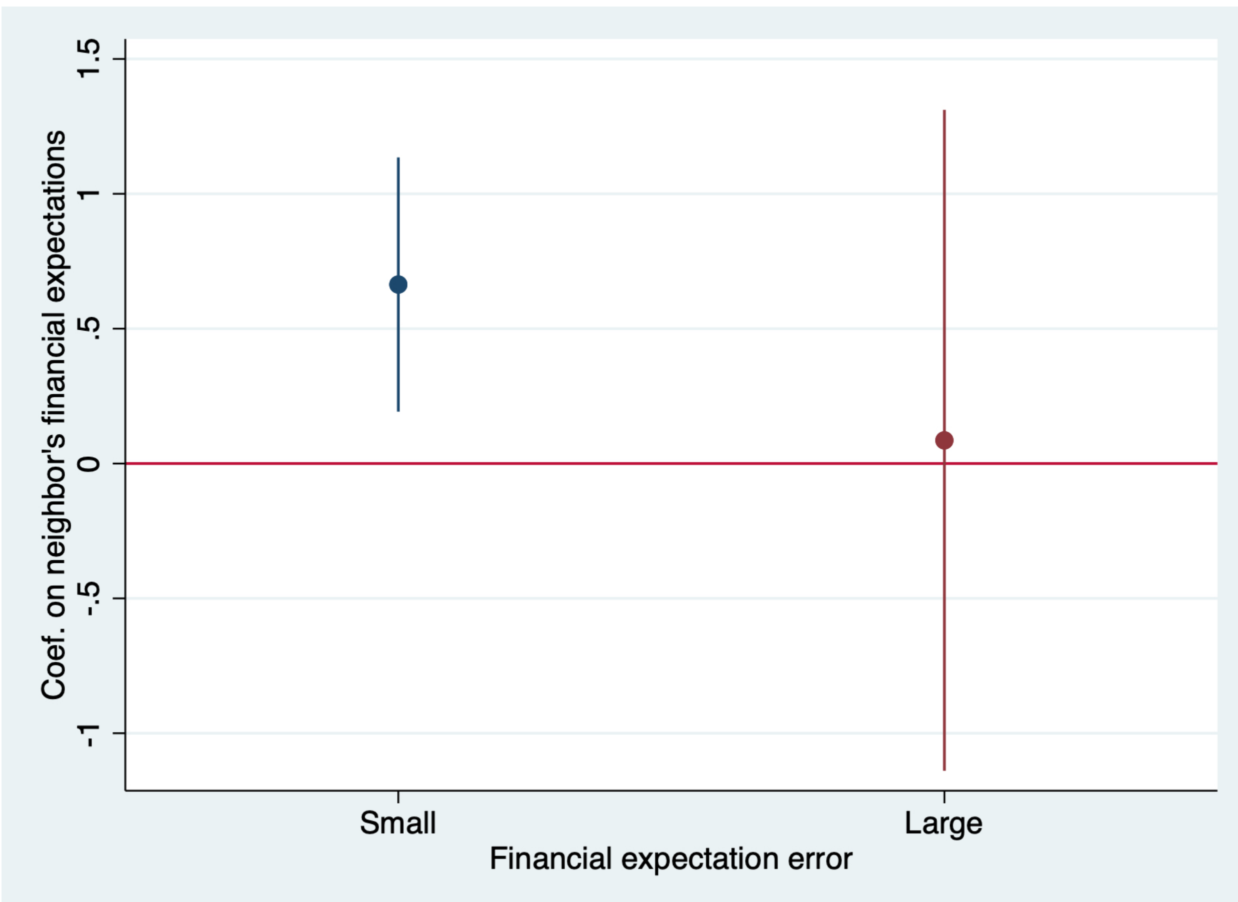
	(1) Savings dummy
Financial expectations	-0.0111***
	(-5.29)
Observations	230,962
Adj. R-squared	0.361
Individual FE	YES
Year FE	YES
Time-varying controls	YES

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, **>* $p < 0.001$

Figure 1.6: **Rationality of Peer Effects.**

The figure below shows point estimates and 95% confidence intervals for the coefficients from instrumental variables regressions of individual financial expectations on neighborhood financial expectations. The regressions are subsample regressions, which are split based on financial expectation error for each individual in each year. All regressions control for wealth, individual fixed effects, and year fixed effects. Standard errors are clustered at the neighborhood level. Additionally, the standard errors allow for heteroskedasticity.



Chapter 2

Does Sunshine Cloud Investor Judgment?

2.1 Introduction

A considerable amount of research in behavioral finance has focused on documenting and explaining various behavioral biases that contribute to systematic and persistent investor errors. Recently, a growing literature has examined the cognitive processes and mechanisms that lead to these biases (for a review, see Frydman and Camerer (2016)).

I examine the relationship between mood and investor decision-making using two proxies for mood: weather and media pessimism. In order to evaluate investor decision-making, I calculate ex-post 3-factor alphas at 1-month, 4-month, and 12-month horizons. I find no discernible relationship between mood and buying decisions. However, selling decisions improve substantially when investors are in a negative mood. For example, a one-unit increase in cloudiness, which is equivalent to a move from one of the sunniest days of the year to one of the cloudiest days of the year, improves the 4-month 3-factor alpha by 1.54%.

This is striking, considering the difference in average alphas between an investor in the top performance decile and the bottom performance decile is 1.56%. Therefore, the mood-induced alpha improvement is economically meaningful.

Next, I consider the disposition effect as an underlying mechanism that could be driving this alpha improvement. The disposition effect refers to the tendency of investors to sell winners more readily than losers Shefrin and Statman (1985). Winners are defined as stocks that are trading above their purchase price, and losers are stocks that are trading below their purchase price.

I consider the disposition effect for three reasons. First, it is one of the most robust and well-documented investment mistakes. Second, the disposition effect is a selling phenomenon, so it can offer a potential explanation for my results on selling decisions. Third, it is unclear what drives the disposition effect. Using local cloudiness and media pessimism as proxies for investor mood, I find that a decrease in the valence of investor mood leads to a decrease in the magnitude of the disposition effect.

Lastly, I provide evidence that the improved selling decisions discussed above are likely to come from stocks that are trading at a gain. Investors who are in a negative mood are more likely to hold on to winners. Furthermore, the alpha improvement is even larger when the sample is restricted to winners. For example, a one-unit increase in cloudiness leads to a 2.59% alpha improvement at the 4-month horizon for winners. This alpha improvement is substantially larger than the difference in average alphas between investors in the top performance decile and those in the bottom performance decile.

Extensive research in psychology and marketing confirms the link between mood and judgment. Early papers in psychology observed that almost any target is likely to be judged more favorably when the evaluator is in a positive rather than a negative mood Clore, Schwarz, and Conway (1994). Schwarz and Clore also find that subjects report more happiness and life satisfaction when in a good mood compared to a bad mood Schwarz and Clore (1983).

Furthermore, these positive evaluations translate into overt behavior. For example, Hirshleifer and Shumway find that sunshine is strongly significantly correlated with stock returns across 26 different countries Hirshleifer and Shumway (2003). The authors argue that weather is unlikely to affect the rational price of a nation's stock market index because agriculture only plays a modest role in modern economies. Thus, mood-driven sentiment has an effect on investment decisions at the aggregate market level.

Not only does mood influence the valence of judgements, it also affects an individual's cognitive processing strategy. To differentiate between processing strategies, I rely on the dual-processing framework Kahneman (2015). Under this framework, individuals either use an intuitive, heuristic approach to processing (System 1) or an analytic, detail-oriented approach (System 2). Most studies in this area find that people in negative emotional states are more likely to engage in systematic processing, whereas people in positive emotional states are more prone to heuristic processing. For example, positive mood leads to more heuristic processing when evaluating print ads Batra and Stayman (1990). Similarly, participants are more likely to rely on general knowledge structures under happy as opposed to sad moods Bless et al. (1996). These findings lead to my prediction that sad investors will make better decisions and display smaller magnitudes of the disposition effect.

This paper extends the literature on behavioral finance by providing insights into the role of mood in investor decision-making. In congruence with the predictions of cognitive processing theory, I find that selling decisions improve and the disposition effect decreases for investors in negative moods. Since weather is exogenous and should not influence investment except through mood, it is likely that these relationships are causal. Thus, any explanation for the cause of the disposition effect should take mood into account.

This paper also contributes to the affect and cognition literature. I offer evidence that investors use mood as an input for decision-making, even when relatively large sums of money are at stake. Typically, laboratory experiments are only able to offer small amounts of money to incentivize participants. This leads to the common concern that investors might behave differently in the lab than in the real world. This natural experiment provides compelling evidence in support of the feelings as information theory of Schwarz 2012.

Additionally, I contribute to the literature on the disposition effect. Previous work examines the weather effect for individual investors in five major U.S. cities over a six-year period Goetzmann and Zhu (2005). The authors find virtually no difference in individuals' propensity to buy or sell stocks on cloudy days as opposed to sunny days. I extend this stream of research by considering the propensity to sell a stock conditional on whether that stock is trading at a gain. I find that investors are significantly more likely to hold on to winners when they are in a negative mood.

Finally, this paper extends the household finance literature by providing causal evidence of a relationship between mood and investor performance. When investors are in negative moods, they make better selling decisions, particularly for stocks trading at a gain. Additionally, investors in negative moods display reduced magnitudes of the disposition effect. Therefore, investors can benefit by considering their mood before making investment decisions.

2.2 Mood and Decision-Making

A robust finding in affect and cognition literature is that individuals who are in good moods evaluate a variety of targets more positively than individuals who are in bad moods Bagozzi, Gopinath, and Nyer (1999). These optimistic evaluations are due to the mood congruency effect, in which people who are in good moods find positive material more salient and people in bad moods find negative material more salient Forgas and Bower (1987).

Additional studies consider the effect of mood on cognition. In general, for unstructured, social reasoning tasks, individuals in negative moods are more inclined to use systematic processing and invest effort to conduct careful analysis. In contrast, individuals in positive moods are more likely to use heuristic processing and pay less attention to detail Bodenhausen, Kramer, and Süsser (1994). These differences in information processing strategies are coherent with the feelings as information theory of Norbert Schwarz. Under this theory, feelings serve as signals about situational processing requirements. For example, an individual in a bad mood might take her feelings as a signal of a problematic situation. She would then be more willing to invest effort and use a detail-oriented processing strategy to make a decision. On the other hand, if an individual in a good mood views his mood as a signal of a benign situation, he would see little need to expend his cognitive resources and might rely on simple heuristics to make a decision.

Additionally, studies have shown that mood effects on processing strategy are eliminated when the informational value of feelings are called into question Sinclair, Mark, and Clore (1994). This finding is consistent with the feelings as information explanation and is difficult to reconcile with many competing explanations. Therefore, individuals use mood, often subconsciously, as information to make judgments. When they realize that mood may have little informational value for the current decision, the effect of mood on processing style is eliminated.

Decision-making models, such as the affect infusion model Forgas (1995), predict that processing influences the degree to which emotion and mood affect judgement. Furthermore, the model predicts that mood is most likely to influence judgement in complex situations that require significant cognitive processing. Due to the complex and unpredictable nature of the stock market, investment decisions are an ideal setting to test the effects of mood on individual decision-making

2.3 The Disposition Effect

The disposition effect is one of the most robust and well-documented investment patterns. U.S. retail investors sell winners more readily than losers, and this behavior is not justified by subsequent performance Odean (1998). The disposition effect is present not only for individual investors, but also for institutional investors such as mutual funds and corporations Barber et al. (2007). Furthermore, the disposition effect is not unique to U.S. investors. Chinese investors also sell winners more readily than losers Feng and Seasholes (2005).

Even though the disposition effect is well-documented, its cause is still unclear. Early explanations propose a mixture of prospect theory, mental accounting, and regret aversion Shefrin and Statman (1985). However, Barberis and Xiong use a model of investor trading behavior with prospect theory preferences to show that these preferences do not guarantee a tendency to sell winners more readily than losers. In many cases, prospect theory preferences actually predict a reverse disposition effect. The authors instead propose "realization utility" as a driver of the disposition effect Barberis and Xiong (2009). With realization utility, investors get a burst of utility from realizing gains.

However, because there is little evidence of an upward jump in selling at zero profits, the disposition effect is *not* driven by a simple direct preference for selling a winner over a loser Ben-David and Hirshleifer (2012). Ingersoll and Jin 2013 expand upon the idea of realization utility by building a model that generates voluntary realized gains and losses. This model can be calibrated to realized levels of the disposition effect.

Even though the exact mechanism driving the disposition effect is still debated, it is clear that the disposition effect is affected by mood. Previous research has shown that emotions play an important role in driving this investment mistake. Summers and Duxbury (2007) employ experimental testing to examine the minimum conditions necessary to produce the disposition effect. By changing whether participants have a choice over which stock they hold, the authors manipulate whether participants feel responsibility for paper gains and losses. They hypothesize that manipulating responsibility will also affect whether or not participants feel emotions like regret and rejoicing. The disposition effect only occurs when individuals feel responsibility for gains or losses. Therefore, the authors conclude that emotions play an important role in economic decision-making and serve as a key driver for the disposition effect. Furthermore, Richards et al. 2018 find that individual investors' intuitive, emotional reactions explain susceptibility to the disposition effect, but regulation of emotions can help to overcome it.

2.4 Data

The main dataset used in the empirical analysis is the set of all trades of individual investors at a large U.S. discount brokerage house from January 1991 to November 1996. This dataset contains stock transactions from 111,284 unique accounts and provides a representative sample of U.S. retail investors. Additionally, I incorporate daily stock data from the Center for Research on Security Prices (CRSP). I obtain prices, returns, volume and market capitalization data at a daily frequency. I use this CRSP data to calculate various market-level controls as well as to determine which stocks are winners and losers.

Next, I use Diego García's measure of media pessimism as the media proxy for mood. This measure uses textual analysis to calculate daily media pessimism García (2013). As a proxy for sentiment, García uses the fraction of positive and negative words in two financial news columns from the *New York Times*. For further discussion about the creation of this media proxy, please see Diego García's paper.

In order to get cloudiness at the local level, I use weather data from the Iowa State airport weather database. This database contains hourly weather observations from airports around the world. I collect hourly weather variables for all U.S. airports from January 1991 to December 1996. I focus on cloudiness instead of other weather variables because Hirshleifer and Shumway find that this is the best proxy for mood Hirshleifer and Shumway (2003). In order to determine an investor's local weather, I use weather data from the airport that is nearest to that investor's home. My analysis will focus on the subset of investors for which I have a home address.

Finally, I use data from Kenneth French's website to calculate 3-factor alphas. I import daily data for *MKTRF*, *SMB*, and *HML*. *SMB* (Small Minus Big) is the average return on the three small portfolios minus the average return on the three big portfolios. *HML* (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios. *MKTRF* is the excess return on the market using value-weights. For additional information on this data, see Kenneth French's data library.

2.5 Mood Proxies

I use two proxies for mood: local weather and media pessimism. The better proxy is weather because it is exogenous. It is well-established in psychology literature that there is a correlation between sunshine and behavior. Lack of sunshine has been linked to depression Eagles (1994) and suicide Tietjen and Kripke (1994). Most evidence suggests that, holding all else constant, people feel better on sunny days. Sunshine, as opposed to news about sunshine, is positively associated with mood and therefore should influence investor processing strategies. This is an important distinction because it separates weather from news-related measures that are less exogenous.

The weather proxy for investor mood avoids many of the issues presented by other proxies for mood. Even though weather can affect economic fundamentals, its effects on long-term value are typically small. For example, cloudiness might affect economic output in a particular region, but it has low cross-location correlation. The amount of cloudiness in one zipcode is not generally representative of the cloudiness across the entire U.S. Moreover, weather is transient. Today's cloudiness is not highly correlated with next week's cloudiness. Thus, if weather influences the prevalence of investor biases, there is a clear psychological explanation but no plausible rational explanation. Weather is also unambiguously observable. Therefore, it provides an ideal setting to test whether or not mood affects investor decision-making.

In order to construct the weather proxy, I follow a methodology similar to previous work on weather-induced mood Goetzmann et al. (2015). First, I determine the airport nearest each investor using location coordinates and the haversine distance formula. Each investor is then matched with the nearest airport to provide local weather data. Next, I calculate average daily sky cloud cover using hourly values from 6 a.m. to 12 p.m. I focus on these hours to follow suit with previous research and because this is the time period during which investors are most likely to observe outdoor weather conditions.

As mentioned in previous literature, mood may have a short-term effect on individual decision-making Goetzmann et al. (2015). Therefore, I generate rolling averages of cloudiness for each weather station based on the weather from x days before the trade date. For robustness, I check various average weather time periods (3, 7, and 14 days). The results are similar for the 7-day and 14-day averages, so I report results for 7-day average cloudiness throughout the analysis.

Because the average amount of sunlight is a decreasing, convex function of sky cloud cover, I use a cloud cover measure (SKC) which is defined as the natural logarithm of one plus the moving average of airport-level cloud cover Goetzmann et al. (2015). Furthermore, because weather is the more exogenous proxy for mood, I require that each investor has at least one matched weather station to be included in the analysis.

As discussed in previous papers, it is important to deseasonalize the sky cloud cover measure Hirshleifer and Shumway (2003). In order to construct a deseasonalized *SKC*, I first calculate *Seasonal SKC* as the average daily cloud cover for a given airport and month over the entire sample period. Next, I define deseasonalized *SKC*, or *DKSC*, as the difference between *SKC* and *Seasonal SKC*. I will focus on *DSKC* for the majority of the analysis.

In addition to the weather proxy, I use media pessimism as a proxy for investor mood. Even though this proxy is subject to endogeneity concerns, it offers additional robustness to my results. Shiller, among others, argues that the news media plays an important role in causing market moves Shiller (2016). He contends that investors follow print media even though much of it is pure noise. Media pessimism is likely to be negatively correlated with investor mood because many investors seek information and advice from news outlets when making investment decisions. When the media is pessimistic about the stock market, investors are more likely to believe that the stock market will do poorly. This belief can lead to negative investor mood.

The media proxy is taken from Diego García's website García (2013). García constructs his media content measure using data from the *New York Times* Article Archive. In order to have a consistent set of articles, García focuses on two columns that were published daily during his time period: the "Financial Markets" column, and the "Topics in Wall Street" column. These columns provide a good measure of general market sentiment because they are essentially summaries of events on Wall Street from the previous trading day.

To quantify the content of these *New York Times* articles, García uses a "dictionary approach" in which he counts the number of positive versus negative words. To construct a proxy for media pessimism from García's data, I calculate the fraction of negative words in the *New York Times* columns. Next, I winsorize the data at the 1% and 99% levels in order to ensure that results are not sensitive to extreme values of the media proxy.

2.6 Mood and Investor Performance

2.6.1 Effect of Mood on Selling Decisions

In order to determine the effect of mood on selling decsions, I employ OLS panel regressions. I create Fama-French three-factor alphas at 1-month, 4-month, and 12-month time horizons ($ALPHA^k_{ijt}$). These alphas are constructed using daily data from Kenneth French's website. I regress each stock's excess return on *MKTRF*, *SMB*, and *HML*. I use 21 trading days, 84 trading days, and 250 trading days to estimate 1-month, 4-month, and 12-month alphas. These alphas are the dependent variables in my performance regressions.

Additionally, the two mood proxies discussed above are independent variables in my regressions. *DSKC*, or deseasonalized sky cloud cover, measures weather-induced mood, and *PESS* measures media pessimism captured by Diego García's measure.

Because there may be unobserved heterogeneity across traders and calendar time, I include trader and calendar time fixed effects. This strategy tightens the identification of mood's influence on the ex-post performance. Also, because weather is measured at the airport level, I cluster standard errors at the airport level.

$$ALPHA^k_{ijt} = \gamma_j + \gamma_t + \beta_1 \cdot DSKC_{jt} + \lambda_t + \epsilon_{ijt}. \tag{2.1}$$

$$ALPHA^k_{ijt} = \gamma_j + \gamma_t + \beta_1 \cdot PESS_t + \lambda_t + \epsilon_{ijt}. \tag{2.2}$$

Equation (2.1) captures the effect of weather-induced negative mood (cloudiness) on alphas at various horizons. Similarly, Equation (2.2) captures the effect of media-induced negative mood on alphas. In both equations, trader and calendar time fixed effects are γ_j and γ_t, respectively. The superscript, k, represents the time horizon of the return, which is either 1 month, 4 months, or 12 months. Also, λ_t controls for market return, market volume, and market volatility. The coefficient on β_1 measures the extent to which negative mood influences alpha.

Estimates of Equation (2.1) support the connection between mood and risk-adjusted returns, as seen in Panel A of Table 2.2. The signs of β_1 are negative at all time-horizons, but the results are only statistically significant at the 4-month and 12-month horizons. For selling decisions, a negative coefficient on β_1 corresponds to improved performance. All else equal, it is better to sell a stock that will perform poorly (have a smaller alpha) in the future. The magnitudes of these effects are striking. A one-unit increase in cloudiness, which is equivalent to a move from one of the sunniest days of the year to one of the cloudiest days of the year, causes investors to make better selling decisions that lead to a 1.54% 4-month alpha improvement. These same decisions lead to a 0.84% alpha improvement at the 12-month horizon.

In order to assess the economic magnitude of these results, I adopt a methodology similar to Coval, Hirshleifer, and Shumway (2021). During the first half of my sample (1991-1993), I sort investors into performance deciles based on the average alpha of stocks they sold. During the second half of my sample (1994-1996), I compare the average alphas of selling decisions between investors in the top performance decile and investors in the bottom performance decile. For expositional clarity, I refer to investors in the top performance decile as skilled and those in the bottom performance decile as unskilled. At the 1-month and 4-month horizons, skilled investors outperform unskilled investors by 2.53% and 1.56%, respectively. At the 12-month horizon, skilled investors actually underperform the unskilled by 2.07%. Therefore, at the 4-month horizon, a one-unit increase in cloudiness causes an alpha improvement that is comparable in size to the difference in alphas between investors at the top performance decile and those at the bottom performance decile. Overall the difference in average alphas between skilled and unskilled investors suggests that a 1% or 2% change in alpha is economically meaningful.

An interesting difference can be seen in the estimates of Equation (2.2). Panel B of Table 2.2 shows that investors do not make significantly better selling decisions when media is more pessimistic. This might be surprising at first, but it makes sense because the media proxy is an aggregate measure of mood that is likely correlated with stock prices. Perhaps an increase in pessimism leads to poor short-term performance for sales because the market is low during a time of increased pessimism. On average, then, it would be better for an investor to hold stocks during times of low investor sentiment because prices are low and future returns will be high.

2.6.2 Does the Alpha Improvement Come from Winners or Losers?

The improvement in selling decisions found in the previous section could come from three channels. First, negative mood might make investors pickier about which stocks they sell. This would appear in the data as an unconditional reduction in the propensity to sell when mood decreases. Second, negative mood might cause investors to hold winners. This would result in a decrease in the propensity to sell stocks that are trading at a gain. Third, negative mood might make investors more willing to let go of losers. This would result in an increase in the propensity to sell stocks that are trading at a loss.

In order to determine which channel is leading to the alpha improvement, I run the following OLS panel regressions on three different samples. First, I run the regressions on the entire sample to see if mood influences unconditional propensity to sell. Next, I run the regressions on all stocks that are trading at a gain to determine if mood makes investors less likely to sell winners. Finally, I run the regressions on all stocks that are trading at a loss to determine if investors are more likely to sell losers when they are in a negative mood. In both regressions, the dependent variable $SALE_{ijt}$ equals one if investor j sells stock i on a given day t.

$$SALE_{ijt} = \gamma_j + \gamma_t + \beta_1 \cdot DSKC_{jt} + \lambda_t + \epsilon_{ijt}. \tag{2.3}$$

$$SALE_{ijt} = \gamma_j + \gamma_t + \beta_1 \cdot PESS_t + \lambda_t + \epsilon_{ijt}. \tag{2.4}$$

Equation (2.3) captures the effect of cloudiness on propensity to sell. Similarly, equation (2.4) captures the effect of media pessimism on propensity to sell. In both equations, trader and calendar time fixed effects are γ_j and γ_t, respectively. Furthermore, λ_t controls for market return, market volume, market volatility, and exposure to size and value. The coefficient on β_1 measures the extent to which negative mood influences selling propensity. This coefficient will help to determine which channel is driving the alpha improvement.

Estimates of equations (2.3) and (2.4) provide evidence in support of the second channel. The coefficients on the mood proxy are significant and negative in columns (2) and (5) of Table 2.3. This makes it clear that a decrease in mood causes investors to hold on to winners for longer. The results are mixed for the other two channels, depending on the mood proxy. In the sample that includes all stocks, cloudiness has no effect on propensity to sell, while media pessimism is associated with a decreased propensity to sell. Similarly, among stocks that are trading at a loss, cloudiness has no effect on propensity to sell, while media pessimism is associated with an increased propensity to sell. Because results are mixed for the first and third channels, I focus additional analysis on the second channel.

2.6.3 Effect of Mood on Selling Winners

Based on the results from Table 2.3, it is clear that negative mood causes investors to hold on to winners. To determine the investment performance implications of this decreased propensity to sell, I conduct analysis similar to that in Table 2.2. I run regressions identical to those in Section 6.1, except I restrict my sample to winners.

Results from Table 2.4, show that weather-induced negative mood leads to drastically improved performance on the sales of winners. The coefficients on *DSKC* are negative and significant at all time-horizons. The magnitude of these effects is nearly double that of the entire sample (presented in Table 2.2). A one-unit increase in cloudiness causes investors to make better selling decisions that lead to a 3.07% 1-month alpha improvement, a 2.59% 4-month alpha improvement, and a 1.4% 12-month alpha improvement.

To assess economic magnitude, I again compare these results to the difference in average alphas between investors in the top performance decile and those in the bottom performance decile. Recall that at the 1-month and 4-month horizons, skilled investors outperform unskilled investors by 2.53% and 1.56%, respectively. At the 12-month horizon, skilled investors actually underperform the unskilled by 2.07%. Therefore, when the sample is restricted to winners, a one-unit increase in cloudiness causes an alpha improvement much larger than the difference in average alphas between skilled and unskilled investors at all time horizons.

Interestingly, in this subsample, the results using the media proxy for mood are more in line with the weather proxy results. An increase in media pessimism leads to better selling decisions for winners. Even though these results are less statistically and economically significant than the results using the weather proxy, it remains clear that negative mood causes investors to make better decisions about selling stocks that are trading at a gain.

2.7 Mood and the Disposition Effect

Lastly, I consider the disposition effect as an underlying mechanism that could be driving these results. In order to analyze the effect of mood on the magnitude of the disposition effect, I use OLS panel regressions similar to the analysis from Section 2.6.2. The dependent variable $SALE_{ijt}$ equals one if investor j sells stock i on a given day t. The independent variable, *TGI*, is a "Trading Gain Indicator." *TGI* takes a value of one if the stock is trading at a paper gain or if the stock is sold for a gain. Otherwise, *TGI* takes a value of zero. In order to determine if a stock is trading at a gain, I compare the stock's daily low to its share-weighted, average purchase price. If the stock's daily low is above the average purchase price, then the stock is trading at a gain.

Again, I will use the two mood proxies as independent variables in my regressions. I focus on the interactions between each of these mood proxies and *TGI*. If negative mood makes investors more likely to engage in System 2 processing, then the disposition effect should decrease, and there should be a negative coefficient on these interaction terms.

Because there may be unobserved heterogeneity across traders and calendar time, I include trader and calendar time fixed effects. This will strengthen the identification of mood's influence on the disposition effect. Also, I cluster standard errors at the airport level because weather is measured at the airport level.

$$SALE_{ijt} = \gamma_j + \gamma_t + \beta_1 \cdot TGI_{ijt} + \beta_2 \cdot DSKC_{ijt} + \beta_3 \cdot TGI_{ijt} \times DSKC_{ijt} + \lambda_t + \epsilon_{ijt}. \tag{2.5}$$

$$SALE_{ijt} = \gamma_j + \gamma_t + \beta_1 \cdot TGI_{ijt} + \beta_2 \cdot PESS_{ijt} + \beta_3 \cdot TGI_{ijt} \times PESS_{ijt} + \lambda_t + \epsilon_{ijt}. \tag{2.6}$$

Equation (2.5) is the main regression to test the effect of weather-induced mood on the magnitude of the disposition effect. Equation (2.6) provides additional robustness by using an alternative proxy for mood, namely Diego García's measure of media pessimism García (2013). In both equations, trader and calendar time fixed effects are γ_j and γ_t, respectively.

Also, λ_t controls for market return, market volume, and market volatility. The coefficient on β_3 measures the extent to which the disposition effect changes as a result of a decrease in mood. Therefore, if negative mood causes investors to rely more on System 2 processing, this coefficient should be negative in both regressions.

Estimates of Equations (2.5) and (2.6) support the hypothesis that positive mood is associated with greater disposition effect. This can be seen in Table 2.5. Models (1) and (2) use the weather proxy for investor mood, and Models (3) and (4) use the media pessimism proxy for investor mood. The first specification for each proxy (Columns (1) and (3)) uses date fixed effects in addition to trader fixed effects. The second specification includes day, month, and year fixed effects instead of date fixed effects. This allows me to include market-level controls in this specification. Because there is no date-level variation in media pessimism, all variation is captured by the date fixed effects, and the coefficient on *PESS* drops out in Column (3).

Across all four models, the interaction term between *TGI* and the mood proxy is negative. This means that an increase in cloudiness or media pessimism leads to a decrease in the propensity to sell a stock trading at a gain. In other words, a decrease in mood leads to a decrease in the magnitude of the disposition effect. Because the magnitudes and signs of these effects are similar across different specifications and proxies, this effect is robust to various controls and proxies for mood.

This reduction in the disposition effect provides a plausible explanation for the previous results from sections 2.6.1, 2.6.2, and 2.6.3. Taken together, these results tell a coherent story. Negative mood causes individual investors to make better selling decisions, particularly for stocks that are trading at a gain. These better selling decisions occur because investors are more likely to hold winners, which leads to a reduction in the disposition effect. In effect, investors in negative moods perform better because they do not trade against the upside of the momentum anomaly.

2.8 Conclusion

Feelings as information theory predicts that negative mood causes investors to exert more effort and use a detail-oriented processing strategy. This detail-oriented processing strategy should lead to better selling decisions and reduced behavioral biases.

Using a representative dataset of individual investor trading activity, I provide causal evidence that negative mood improves selling decisions. In fact, at the 4-month and 12-month horizons, a one-unit increase in cloudiness leads to an alpha improvement of 1.54% and 0.84%, respectively. These alpha improvements are economically meaningful because they are similar in magnitude to difference in average alphas of investors in the top performance decile and those in the bottom performance decile.

Mood also has an effect on propensity to sell. Investors in negative moods are much more likely to hold winners. This leads to an even larger alpha improvement for stocks that are trading at a gain. For these stocks, a one-unit increase in cloudiness leads to an alpha improvement of 2.59% and 1.4% at the 4-month and 12-month horizons. These mood-induced alpha improvements for winners are larger than the difference in average alphas between skilled and unskilled investors.

Because my results pertain to selling decisions, I consider one of the most robust and well-documented patterns in selling behavior: the disposition effect. Using two proxies for mood, I show that the magnitude of the disposition effect decreases when investors are in a negative mood. Taking all of the evidence into account, a clear story emerges. Negative mood causes investors to make better selling decisions because it makes them more likely to hold on to winners, thereby reducing the disposition effect. In other words, investors in negative moods perform better because they are less likely to trade against the upside of the momentum anomaly.

Table 2.1: **Descriptive Statistics.**

Panel A provides trade-level descriptive statistics for purchases. Panel B provides trade-level descriptive statistics for sales. Panel C provides account-level descriptive statistics.

Panel A Purchases	N	mean	sd
Number of Shares	207,237	564.9	1,216
Principle	207,237	11,103	24,713
1-month alpha	207,224	-0.0322	0.919
4-month alpha	206,904	-0.0254	0.361
12-month alpha	202,666	-0.00740	0.220

Panel B Sales	N	mean	sd
Number of Shares	125,168	-673.6	1,384
Principle	125,168	-14,405	32,580
1-month alpha	125,159	-0.0264	0.829
4-month alpha	124,863	-0.0224	0.342
12-month alpha	121,959	-0.0104	0.181

Panel C Account-level statistics	N	mean	sd
Household income	26,860	60,737	24,070
Number of trades	26,860	12.34	27.56
Portfolio value	26,860	18,536	84,102

Table 2.2: **Effect of Mood on Selling Decisions.**

The table below shows results from OLS panel regressions of Equations (2.1) and (2.2). Panel A displays results using the weather proxy for investor mood, and Panel B displays results using the media pessimism proxy for investor mood. The dependent variable in models (1) and (4) is 1-month 3-factor alpha. Similarly, the dependent variable for models (2) and (5) is 4-month 3-factor alpha. Finally, the dependent variable for models (3) and (6) is 12-month 3-factor alpha. Additionally, I include investor and year-month-day fixed effects, and all standard errors are clustered at the airport level.

Panel A - Weather Proxy Daily alpha	(1) After 1 month	(2) After 4 months	(3) After 12 months
DSKC	-0.0125	-0.0154***	-0.00842***
	(-0.977)	(-2.916)	(-2.916)
Constant	0.166**	0.246***	-0.0464**
	(2.319)	(6.472)	(-2.341)
Observations	119,424	119,127	116,220
R-squared	0.133	0.169	0.187
Market-level controls	YES	YES	YES
Investor FE	YES	YES	YES
Year-month-day FE	YES	YES	YES
Date FE	NO	NO	NO

Panel B - Media Proxy Daily alpha	(4) After 1 month	(5) After 4 months	(6) After 12 months
PESS	0.000743	-0.00193	0.000548
	(0.244)	(-1.584)	(0.867)
Constant	0.162**	0.246***	-0.0492**
	(2.264)	(6.435)	(-2.468)
Observations	119,439	119,142	116,235
R-squared	0.133	0.169	0.187
Market-level controls	YES	YES	YES
Investor FE	YES	YES	YES
Year-month-day FE	YES	YES	YES
Date FE	NO	NO	NO

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.3: **Influence of Mood on Propensity to Sell.**

The table below shows results from OLS panel regressions of Equations (2.3) and (2.4). Panel A displays results using the weather proxy for investor mood, and Panel B displays results using the media pessimism proxy for investor mood. The dependent variable in all models is an indicator that equals one if a stock is sold and zero otherwise. Models (1) and (4) include all selling decisions. Models (2) and (5) restrict the sample to only include stocks that are trading at a gain. Finally, Models (3) and (6) only include stocks that are trading at a loss. Additionally, I include investor and year-month-day fixed effects, and all standard errors are clustered at the airport level.

Panel A	(1)	(2)	(3)
Weather Proxy	All stocks	Trading at a gain	Trading at a loss
DSKC	0.00163	-0.0160**	0.0122
	(0.368)	(-2.404)	(1.465)
Constant	0.276***	0.518***	0.436***
	(10.70)	(11.95)	(8.576)
Observations	328,353	92,234	90,375
R-squared	0.096	0.284	0.278
Market-level controls	YES	YES	YES
Investor FE	YES	YES	YES
Year-month-day FE	YES	YES	YES
Date FE	NO	NO	NO

Panel B	(4)	(5)	(6)
Media Proxy	All stocks	Trading at a gain	Trading at a loss
PESS	-0.00523***	-0.00488***	0.00386*
	(-4.577)	(-2.785)	(1.924)
Constant	0.285***	0.520***	0.429***
	(11.00)	(11.99)	(8.420)
Observations	328,606	92,264	90,450
R-squared	0.096	0.285	0.278
Market-level controls	YES	YES	YES
Investor FE	YES	YES	YES
Year-month-day FE	YES	YES	YES
Date FE	NO	NO	NO

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.4: **Alpha Effect of Holding Winners.**

The table below shows results from OLS panel regressions of Equations (2.1) and (2.2). The sample is restricted to stocks that are trading at a gain. Panel A displays results using the weather proxy for investor mood, and Panel B displays results using the media pessimism proxy for investor mood. The dependent variable in models (1) and (4) is 1-month 3-factor alpha. Similarly, the dependent variable for models (2) and (5) is 4-month 3-factor alpha. Finally, the dependent variable for models (3) and (6) is 12-month 3-factor alpha. Additionally, I include investor and year-month-day fixed effects, and all standard errors are clustered at the airport level.

Panel A - Weather Proxy Daily alpha	(1) After 1 month	(2) After 4 months	(3) After 12 months
DSKC	-0.0307*	-0.0259***	-0.0140***
	(-1.892)	(-3.700)	(-3.633)
Constant	0.0592	0.154***	-0.0783***
	(0.647)	(3.393)	(-3.322)
Observations	67,857	67,672	66,157
R-squared	0.180	0.205	0.240
Market-level controls	YES	YES	YES
Investor FE	YES	YES	YES
Year-month-day FE	YES	YES	YES
Date FE	NO	NO	NO

Panel B - Media Proxy Daily alpha	(1) After 1 month	(2) After 4 months	(3) After 12 months
PESS	0.00590	-0.00342**	-0.00150*
	(1.495)	(-2.071)	(-1.826)
Constant	0.0393	0.154***	-0.0793***
	(0.430)	(3.356)	(-3.344)
Observations	67,866	67,681	66,166
R-squared	0.180	0.205	0.239
Market-level controls	YES	YES	YES
Investor FE	YES	YES	YES
Year-month-day FE	YES	YES	YES
Date FE	NO	NO	NO

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.5: **Effect of Mood on the Disposition Effect.**

The table below shows results from OLS panel regressions of Equations (2.5) and (2.6). The dependent variable across all three models is *SALE*, an indicator variable that equals one when a stock is sold and zero otherwise. Models (1) and (2) use the weather proxy for investor mood, and Models (3) and (4) use the media pessimism proxy for investor mood. The first specification for each proxy (Columns (1) and (3)0 uses date fixed effects in addition to investor fixed effects. The second specification replaces date fixed effects with day, month, and year fixed effects in order to include market-level controls. In general, the first specification provides better identification because it absorbs date-level variation for all variables. The coefficient on the media proxy only appears in the final specification because there is no date-level variation in this variable. Additionally, all standard errors are clustered at the airport level.

VARIABLES	(1) Weather Proxy	(2) Weather Proxy	(3) Media Proxy	(4) Media Proxy
TGI	0.544***	0.546***	0.544***	0.546***
	(154.4)	(152.6)	(153.7)	(152.0)
DSKC	0.00296	0.00546		
	(0.634)	(1.209)		
TGI x DSKC	-0.0154*	-0.0147*		
	(-1.880)	(-1.795)		
PESS				0.00419***
				(3.839)
TGI x PESS			-0.0109***	-0.0116***
			(-5.930)	(-6.361)
Constant	0.219***	0.302***	0.219***	0.299***
	(207.4)	(13.17)	(208.04)	(13.00)
Observations	328,353	328,353	328,606	328,606
R-squared	0.341	0.333	0.341	0.334
Market-level controls	NO	YES	NO	YES
Investor FE	YES	YES	YES	YES
Date FE	YES	NO	YES	NO
Year-month-day FE	NO	YES	NO	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Bibliography

Ahern, Kenneth R., Ran Duchin, and Tyler Shumway, 2014, Peer effects in risk aversion and trust, *Review of Financial Studies* 27, 3213–3240.

Angrist, Joshua D., and Alan B. Krueger, 2001, Instrumental variables and the search for identification: From supply and demand to natural experiments, *Journal of Economic Perspectives* 15, 69–85.

Bagozzi, Richard, Mahesh Gopinath, and Prashanth Nyer, 1999, The role of emotions in marketing, *Journal of the Academy of Marketing Science* 27, 184–206.

Bailey, Michael, Ruiqing Cao, Theresa Kuchler, and Johannes Stroebel, 2018, The economic effects of social networks: Evidence from the housing market, *Journal of Political Economy* 126, 2224–2276.

Ball, Molly, 2015, America is ready for gay marriage, *The Atlantic* .

Barber, Brad M., Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, 2007, Is the aggregate investor reluctant to realize losses? Evidence from Taiwan, *European Financial Management* 13, 423–447.

Barberis, Nicholas, and Wei Xiong, 2009, What drives the disposition effect? an analysis of a long-standing preference-based explanation, *The Journal of Finance* 64, 751–784.

Batra, Rajeev, and Douglas M. Stayman, 1990, The role of mood in advertising effectiveness, *Journal of Consumer Research* 17, 203–214.

Baum, Christopher F., Mark E. Schaffer, and Steven Stillman, 2007, Enhanced routines for instrumental variables/generalized method of moments estimation and testing, *Stata Journal* 7, 465–506.

Ben-David, Itzhak, and David Hirshleifer, 2012, Are investors really reluctant to realize their losses? Trading responses to past returns and the disposition effect, *Review of Financial Studies* 25, 2485–2532.

Bless, Herbert, Norbert Schwarz, Gerald Clore, Verena Golisano, Christina Rabe, and Marcus Wölk, 1996, Mood and the use of scripts: Does a happy mood really lead to mindlessness?, *Journal of personality and social psychology* 71, 665–79.

Bodenhausen, Galen V., Geoffrey P. Kramer, and Karin Süsser, 1994, Happiness and stereotypic thinking in social judgment., *Journal of Personality and Social Psychology* 66, 621–632.

Brittanica, The Editors Encyclopedia, 2019, Prohibition.

Brown, Jeffrey R., Zoran Ivković, Paul A. Smith, and Scott Weisbenner, 2008, Neighbors matter: Causal community effects and stock market participation, *Journal of Finance* 63, 1509–1531.

Burnside, Craig, Martin Eichenbaum, and Sergio T. Rebelo, 2016, Understanding booms and busts in housing markets, *Journal of Political Economy* 124, 1088–1147.

Bursztyn, Leonardo, Florian Ederer, Bruno Ferman, and Noam Yuchtman, 2014, Understanding mechanisms underlying peer effects: Evidence from a field experiment on financial decisions, *Econometrica* 82, 1273–1301.

Case, Anne C., and Lawrence F. Katz, 1991, The company you keep: The effects of family and neighborhood on disadvantaged youths, NBER Working Paper No. 3705.

Clore, Gerald, Norbert Schwarz, and Micheal Conway, 1994, *Affective causes and consequences of social information processing*, 323–417 (Pyschology Press).

Cocco, João F., Francisco Gomes, and Paula Lopes, 2020, Evidence on expectations of household finances, Working paper, London Business School.

Coval, Joshua D, David Hirshleifer, and Tyler Shumway, 2021, Can Individual Investors Beat the Market?, *The Review of Asset Pricing Studies* raab017.

Eagles, John M., 1994, The relationship between mood and daily hours of sunlight in rapid cycling bipolar illness, *Biological Psychiatry* 36, 422–424.

Ellison, Glenn, and Drew Fudenberg, 1995, Word-of-mouth communication and social learning, *Quarterly Journal of Economics* 110, 93–125.

Feng, Lei, and Mark S. Seasholes, 2005, Do investor sophistication and trading experience eliminate behavioral biases in financial markets?, *Review of Finance* 9, 305–351.

Forgas, J. P., 1995, Mood and judgment: The affect infusion model (aim), *Psychological Bulletin* 117, 39–66.

Forgas, Joseph, and Gordon Bower, 1987, Mood effects on person-perception judgments, *Journal of personality and social psychology* 53, 53–60.

Frydman, Cary, and Colin F. Camerer, 2016, The psychology and neuroscience of financial decision making, *Trends in Cognitive Sciences* 20, 661–675.

García, Diego, 2013, Sentiment during recessions, *The Journal of Finance* 68, 1267–1300.

Gennaioli, Nicola, Yueran Ma, and Andrei Shleifer, 2016, Expectations and Investment, *NBER Macroeconomics Annual* 30, 379–431.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus, 2020, Five facts about beliefs and portfolios, Working paper, Yale School of Management.

Goetzmann, William N., Dasol Kim, Alok Kumar, and Qin Wang, 2015, Weather-induced mood, institutional investors, and stock returns, *Review of Financial Studies* 28, 73–111.

Goetzmann, William N., and Ning Zhu, 2005, Rain or shine: Where is the weather effect?, *European Financial Management* 11, 559–578.

Greenwood, Robin, and Andrei Shleifer, 2014, Expectations of returns and expected returns, *Review of Financial Studies* 27, 714–746.

Haliassos, Michael, Thomas Jansson, and Yigitcan Karabulut, 2020, Financial literacy externalities, *Review of Financial Studies* 33, 950–989.

Han, Bing, David Hirshleifer, and Johan Walden, 2020, Social Transmission Bias and Investor Behavior, *Journal of Financial and Quantitative Analysis* Forthcoming.

Hirshleifer, David, 2020, Presidential address: Social transmission bias in economics and finance, *Journal of Finance* 75, 1779–1831.

Hirshleifer, David, and Tyler Shumway, 2003, Good day sunshine: Stock returns and the weather, *The Journal of Finance* 58, 1009–1032.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein, 2004, Social interaction and stock-market participation, *Journal of Finance* 59, 137–163.

Ivković, Zoran, and Scott Weisbenner, 2007, Information Diffusion Effects in Individual Investors' Common Stock Purchases: Covet Thy Neighbors' Investment Choices, *The Review of Financial Studies* 20, 1327–1357.

Jr., Jonathan E. Ingersoll, and Lawrence Jin, 2013, Realization utility with reference-dependent preferences, *Review of Financial Studies* 26, 723–67.

Kahneman, Daniel, 2015, *Thinking, fast and slow* (Farrar, Straus and Giroux).

Kaustia, Markku, and Samuli Knüpfer, 2012, Peer performance and stock market entry, *Journal of Financial Economics* 104, 321–338.

Manski, Charles F., 1993, Identification of endogeous social effects: The reflection problem, *Review of Economic Studies* 60, 531–542.

McCandless, George T., 1996, Money, expectations, and the u.s. civil war, *The American Economic Review* 86, 661–671.

Odean, Terrance, 1998, Are investors reluctant to realize their losses?, *Journal of Finance* 53, 1775–1798.

Richards, Daniel W., Mark Fenton-O'Creevy, Janette Rutterford, and Devendra G. Kodwani, 2018, Is the disposition effect related to investors' reliance on system 1 and system 2 processes or their strategy of emotion regulation?, *Journal of Economic Psychology* 66, 79–92.

Russett, Bruce, and Joel Slemrod, 1993, Diminished expectations of nuclear war and increased personal savings: Evidence from individual survey data, *The American Economic Review* 83, 1022–1033.

Schwarz, Norbert, 2012, Feelings-as-information theory, in P. A. M. Van Lange, A. W. Kruglanski, and E. T. Higgins, eds., *Handbook of Theories of Social Psychology*, chapter 14, 289–308 (Sage Publicaitons Ltd., London, UK).

Schwarz, Norbert, and Gerald L. Clore, 1983, Mood, misattribution, and judgments of well-being: Informative and directive functions of affective states., *Journal of Personality and Social Psychology* 45, 513–523.

Shefrin, Hersh, and Meir Statman, 1985, The disposition to sell winners too early and ride losers too long: Theory and evidence, *The Journal of Finance* 40, 777.

Shiller, Robert J., 2016, *Irrational exuberance* (Princeton University Press, Princeton, NJ).

Sinclair, Robert C., Melivin M. Mark, and Gerald Clore, 1994, Mood-related persuasion depends on (mis)attributions, *Social Cognition* 12, 309–326.

Stock, James H., and Motohiro Yogo, 2005, Testing for weak instruments in linear iv regression., in D.W.K. Andrews, and J.H. Stock, eds., *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, 80–108 (Cambridge University Press, Cambridge).

Summers, Barbara, and Darren Duxbury, 2007, Unraveling the disposition effect: The role of prospect theory and emotions, Working paper, Leeds University Business School.

Taylor, Marcia Freed, John Brice, Nick Buck, and Elaine Prentice-Lane, 2018, *British Household Panel Survey User Manual Volume A: Introduction, Technical Report and Appendices* (University of Essex).

Tietjen, Glen H., and Daniel F. Kripke, 1994, Suicides in california (1968–1977): Absence of seasonality in los angeles and sacramento counties, *Psychiatry Research* 53, 161–172.

UK Data Service, 2018, British household panel survey: Waves 1-18, 1991-2009, http://doi.org/10.5255/UKDA-SN-5151-2.

Weinberg, Bruce A., Patricia B. Reagan, and Jeffrey J. Yankow, 2004, Do neighborhoods affect hours worked? Evidence from longitudinal data, *Journal of Labor Economics* 22, 891–924.