# Not So Great Expectations: An Analysis of Expectation Determinants and the Predictability of Expectation Errors

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# An Analysis of Expectation Determinants and the Predictability of Expectation Errors

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**Abstract:** In this paper, I use novel survey data from the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE) to analyze expectations of national inflation, national stock market returns, personal credit access, and personal financial wellbeing to test the rational expectations hypothesis (REH). For each of these variables, I examine the determinants of expectations as well as the predictability of expectation errors. Overall, my results indicate that prior personal experience, prior variable performance, and demographic characteristics can predict errors in expectation of both national and individual variables. Such results are inconsistent with the REH because they imply that information available at time *t* can be used to predict expectation errors at time *t+1*. In other words, individuals are predictably biased when forming expectations about the future.

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## **Introduction:**

I use the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE) to examine the determinants of expectations as well as the predictability of expectation errors. More specifically, I examine expectations of inflation, stock market returns, personal credit access, and personal financial wellbeing. For each of these variables, I ask: how do individuals form expectations and are expectations predictably erroneous?

I have results for the determinants of expectations and for expectation errors. My determinants of expectations results indicate that expectations tend to be highly extrapolative from personal experience even for national-level variables such as inflation and stock market returns. Furthermore, the results indicate consistent differences in expectations across groups. For example, men tend to be more optimistic than women about the stock market. For national-level variables such as inflation and stock returns, such evidence of differences across demographics is inconsistent with the rational expectations hypothesis (REH), which implies that forecast differences should only occur based on differences in information. However, there is no reason to think that men have access to consistently better information than women about the stock market.[1]

Most importantly for testing rational expectations, I find that expectation errors at time $t+1$ demonstrate consistent predictability using information from time $t$. For example, it is not just that women have lower stock market expectations than men. Women also systematically demonstrate a predictable downward bias in their forecasts of stock market returns compared to men and to reality, holding other variables equal: their expectation of stock market returns predictably fall short of the realization. Overall, such predictability of forecast errors using information available

[1] However, differences across group expectations for individual-level variables of credit access and personal financial wellbeing are not inconsistent with the REH as these different groups might experience different outcomes. On the other hand, all groups experience the same outcome for national-level variables.

at time *t*, such as one's gender or personal experience, is inconsistent with the rational expectations hypothesis (REH), which implies that errors in expectation are random. In other words, REH implies that individuals do not repeatedly make the same forecasting mistakes, contrary to what my results indicate.

These findings are novel for three reasons. First, the results contribute to the literature that evaluates the REH. Second, they rely upon a novel dataset, the Federal Reserve Bank of New York's SCE, which is unique in both its frequency as well as its methodology in eliciting expectations. Third, I directly measure the predictability of errors in addition to examining the determinants of beliefs. In other words, I explicitly observe differences in expectations between groups as well as consistent over/underreaction to information available at time *t* when forming beliefs about time *t+1*.

I will now expand on each of these three contributions. First, my findings are inconsistent with the REH, a concept that has served as the cornerstone of many macro and microeconomic models that have been developed over the past half-century. Examples of models contingent on REH include the Efficient Markets Hypothesis as well as the Capital Asset Pricing Model.

Second, my results rely on a novel consumer survey dataset, the NY Fed SCE. My work is some of the first to use this dataset to examine the REH. This dataset is unique in that, unlike other commonly cited survey datasets such as the Michigan Survey of Consumers, it provides detailed demographic information of individual respondents including race, gender, age, income, personal perception of health, financial risk tolerance, employment status, and education. This rotational panel surveys a large sample of 1200 individuals across the country on the high-frequency basis of once a month. It then rotates these individuals every 12 months. Simply put, the SCE is differentiated in the granularity of individual information it provides along with its number and frequency of responses.

Additionally, the SCE's methodology for eliciting expectations is unique. Specifically, it relies on qualitative estimates, binary-outcome probability estimates, as well as probability density estimates within its questionnaire. For qualitative answers, respondents mark a number from 1-5 indicating their expectation (1 being negative outlook and 5 being positive outlook, depending on the variable). For binary-outcome probability estimates, individuals are asked to write down a specific probability regarding the likelihood of a future event occurring. For example, individuals are asked, "*what is the probability that the stock market will be higher 12 months from now*?" For density estimates, respondents are asked to assign probabilities to different future outcomes such that all the probabilities add to 1.

Methodologically, I first focus on the determinants of expectations prior to examining the predictability of expectation errors. In this way, I am able to examine which variables influence beliefs as well as how groups consistently err in forming their beliefs.

In the next section, I walk through the prior literature related to my research question. Then, I describe my dataset and variables in more detail. After this, I describe the logical underpinning for the empirical tests that I perform. I then outline the results of my regressions and discuss the qualitative implications thereof.

## **Review of Previous Literature**:

In this section, I discuss recent literature examining the REH as well as how my paper supplements this body of research. The first serious rebuttal to Muth's theory came in 1986 by Michael Lovell who used empirical evidence examining macroeconomic variables such as wages and prices to argue that such sweeping acceptance of REH was misguided and perhaps detrimental to the many economic models.

Since then, significant work has been done, much in the past 5-10 years, that uses novel empirical methods to test the validity of REH in a variety of contexts. For example, irrational expectations for macroeconomic variables such as inflation and unemployment has been found by multiple papers (Aggarwal, Mohanty, and Song 1995, Coibion and Gorodnichenko 2012, Coibion and Gorodnichenko 2015, Fuhrer 2017, Bordalo, Gennaioli, Ma, and Shleifer 2018, Kuchler and Zafar 2019). Furthermore, analyses of the rationality of expectations regarding other variables such as the stock market (La Porta 1996, Bacchetta, Mertens, Wincoop 2009, Amronin and Sharpe 2014, Greenwood and Shleifer 2014, Adam, Marcet, and Buetel 2017 Bordalo, Gennaioli, La Porta, Shleifer 2019), credit spreads (Bordalo, Gennaioli, Shleifer 2018 and Carvahlo, Gao, and Ma 2019), and corporate earnings (DeBondt and Thaler 1990, Ben-David et al. 2013, Gennaioli, Ma, and Shleifer 2016, Bouchand, Krueger, Landier, and Thesmar 2018) have indicated significant inconsistencies. Even various controlled experiments have found evidence in direct refutation of rational expectations (Hommes et al. 2004, Beshears et al. 2013, Frydman and Nave 2017, Landier, Ma, and Thesmar 2017).

These papers use a variety of empirical strategies to test the validity of the REH. They can be grouped broadly into two categories. The first category includes papers that examine revisions to expectations. In theory, these revisions represent the incorporation of new information, and thus, by using these revisions to predict expectation error, one effectively tests whether the information is accurately incorporated as per the REH. Papers that take this approach include Cocco, Gomes, and Lopes 2020, Fuhrer 2017, Coibion and Gorodnichenko 2012, Bordalo, Gennaioli, Ma, and Shleifer 2018, Bacchetta, Mertens, and Wincoop 2009, and Bordalo, Gennaioli, and Shleifer 2016.

The second category includes papers that examine the determinants of expectations. Specifically, they examine information available at time $t$ and determine how it influences forecasts made at time $t$ about the future value of a variable at time $t+1$. Using this methodology, one can see the ways in which theoretically uncorrelated information influences one's expectations (i.e. how personal experience influences expectation of national-level variables). Papers that utilize this methodology include Kuchler and Zafar 2019 and Greenwood and Shleifer 2014.

Furthermore, prior literature evaluating the REH relies heavily on only a few datasets. More specifically, many of these papers rely on highly granular financial data (e.g. forex rates for Bachetta, Mertens, and Wincoop 2009) or various professional forecaster surveys such as the Survey of Professional Forecasters (SPF), the ECB Survey of Professional Forecasters, and the Blue-Chip Survey. Other papers examine consumer survey collections such as the Michigan Survey of Consumers (Fuhrer 2017) and the British Household Panel Survey (Cocco, Gomes, and Lopes 2020), but only one of the papers that I referenced analyzes the New York Federal Reserve's Survey of Consumer Expectations (Kuchler and Zafar 2019). However, Kuchler and Zafar do not examine the predictability of errors. Instead, they look at the determinants of expectations for variables that are different than the ones I examine in this paper. Overall, my work adds to the literature in that it utilizes an identification strategy that directly tests the REH, and it applies this methodology to a novel dataset.

## **Data:**

In this section, I discuss my primary dataset, the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE). While I gather inflation data and stock market return data from the U.S. Bureau of Labor Statistics (BLS) and Robert Shiller's Online Data Library, respectively, I reserve discussion of these two datasets to **Appendix B1**. For the SCE, I explain the methodology behind the construction of each variable I use in my regressions. Finally, I provide summary statistics for all of my regression variables.

### NY Federal Reserve Survey of Consumer Expectations (SCE):[2]

This dataset provides observations from the period of June 2013 until March 2019 at a monthly frequency. Each month, approximately 1200 household heads across the U.S. are surveyed via an online questionnaire that takes 15-20 minutes to complete. The dataset is a rotational panel as each user is surveyed repeatedly for up to 12 months. New respondents for the survey are chosen on a monthly basis by sampling from The Conference Board's *Consumer Confidence Survey*. The respondents are chosen such that they meet demographic targets similar to those of the American Community Survey according to attributes of gender, income, geography, and age. This dataset yields over 92,000 expectation observations from over 13,300 individuals.

Furthermore, the SCE is unique in that its structure is largely grounded in careful research that was conducted under the Household Inflation Expectations Project (HIEP). This project represented a collaboration between RAND Corporation, Federal Reserve Banks, academic

[2] Available at: https://www.newyorkfed.org/microeconomics/sce; most of the information regarding the dataset is from Armantier et al. 2016

economists, psychologists, and survey design experts, and it took place between 2006 and 2012 (Armantier et al. 2016). During the project, the team refined their elicitation methodology by adding questions to RAND Corporation's American Life Panel (ALP) along with conducting "in-depth cognitive interviews" (Armantier et al. 2016). The overall target of the project was to experiment with different forms of expectation elicitation both through question wording and formatting (e.g. density forecasts, binary-outcome probability forecasts, etc.) with the goal of being able to elicit the most precise and representative expectation responses. Many of the findings of the HIEP (see van der Klaauw et al. 2008; Armantier et al. 2013) manifest within the SCE.

Below, I describe the elicitation methodology behind each of my four dependent variables: expectations for the stock market, inflation, personal financial wellbeing, and credit access.

First, with regard to stock market expectations, respondents are explicitly asked, "*What do you think is the percent chance that 12 months from now, on average, stock prices in the U.S. stock market will be higher than they are now?*" Prior to being asked, each respondent was primed with an introduction on the use of percentages that read, "*In some of the following questions, we will ask you to think about the percent chance of something happening in the future. Your answers can range from 0 to 100, where 0 means there is absolutely no chance, and 100 means that it is absolutely certain. For example, numbers like: 2 and 5 percent may indicate "almost no chance"; 18 percent or so may mean "not much chance"; 47 or 52 percent chance may be a "pretty even chance"; 83 percent or so may mean a "very good chance"; 95 or 98 percent chance may be "almost certain".*" The main rationale behind this primer is to ensure that the respondents conceptualize percentages in a uniform manner such that the percentages they write down closely mirror their internal beliefs. In other words, the primer is an attempt to mitigate elicitation biases. Individual respondents type their answer directly into a box or click on a sliding scale. The survey designers even go to the trouble to prevent response anchoring by not including a marker on the sliding scale until the individual clicks somewhere on the scale (Armantier et al. 2016).

The next dependent variable is inflation expectations. Unlike binary-outcome stock market expectations, inflation expectations are elicited via a forecast density. Below is a copy of the exact form which the question takes on the survey:

**Figure 1: Inflation Expectation Elicitation Format[3]**

**Q9**

Now we would like you to think about the different things that may happen to inflation **over the next 12 months**. We realize that this question may take a little more effort.

In your view, what would you say is the percent chance that, **over the next 12 months**...

*Instruction H4.*

| | |
|---|---|
| the rate of inflation will be 12% or higher (bin 1) | _____ percent chance |
| the rate of inflation will be between 8% and 12% (bin 2) | _____ percent chance |
| the rate of inflation will be between 4% and 8% (bin 3) | _____ percent chance |
| the rate of inflation will be between 2% and 4% (bin 4) | _____ percent chance |
| the rate of inflation will be between 0% and 2% (bin 5) | _____ percent chance |
| the rate of deflation (opposite of inflation) will be between 0% and 2% (bin 6) | _____ percent chance |
| the rate of deflation (opposite of inflation) will be between 2% and 4% (bin 7) | _____ percent chance |
| the rate of deflation (opposite of inflation) will be between 4% and 8% (bin 8) | _____ percent chance |
| the rate of deflation (opposite of inflation) will be between 8% and 12% (bin 9) | _____ percent chance |
| the rate of deflation (opposite of inflation) will be 12% or higher (bin 10) | _____ percent chance |
| **TOTAL** | **100** |

The elicitation of forecast densities represents one of the major innovations of the SCE when compared to other consumer surveys. The use of forecast densities enables the SCE to elicit "subjective probability distributions" for a "continuous outcome" such as inflation (Armantier et

[3] Available at: https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr800.pdf?la=en

al. 2016). Within the density forecast, one is able to gauge additional information such as the level of uncertainty in the response, the mean or median of the probability density, and the perception of tail risks (Armantier et al. 2016). For my regressions, I primarily rely on the probability density mean response for each observation, which is calculated from the forecast density according to the methodology espoused by Engelberg, Manski and Williams (2009). This subjective distribution mean, according to this aforementioned paper, allows for a more precise and unbiased elicitation of inflation expectations.

I also want to make note of the SCE's explicit use of the word "inflation," which differentiates it from many other surveys that refer to changes in "price" (e.g. Michigan Survey of Consumers). The primary reason that many surveys do not ask directly about inflation is that it is considered a complicated subject. However, Armantier et al. (2016) present significant evidence to suggest that this notion is misguided. Specifically, Armantier et al. (2016) reference papers published by Leiser and Drori (2005), Svenson and Nilsson (1986), van der Klaauw et al. (2008), and Bruine de Bruin et al. (2012), which indicate that "the vast majority of consumers have a good understanding of the concept of inflation." Furthermore, within the SCE itself, between May 2013 and September 2015, survey respondents were asked, "*On a scale of 1 to 7, how well would you say you understand what "inflation" means?*" Of the respondents, only 44 of the 5182 (less than 0.9 percent) said they had "no understanding," while over 82 percent of the respondents chose 5 or more (Armantier et al. 2016).

The last two dependent variables from the SCE dataset are expectations of credit access as well as expectations of personal financial wellbeing. In addition to using the expectations of each of these variables, I use the perceptions of past performance in order to measure the extent of extrapolation. Each of these variables is elicited using a more traditional methodology of asking respondents to choose, from five different options, the singular option with most aptly characterizes their current perception/expectation.

For the perception of credit access at time *t*, the survey asks respondents: "*Compared to 12 months ago, do you think it is generally harder or easier these days for people to obtain credit or loans (including credit and retail cards, auto loans, student loans, and mortgages)?*" Respondents are then able to choose one of the following 5 options: "*Much harder (1); Somewhat harder (2); Equally easy/hard (3); Somewhat easier (4); or Much easier (5).*" Similarly, the expectation for credit access asks respondents: "*And looking ahead, do you think that 12 months from now it will generally be harder or easier for people to obtain credit or loans (including credit and retail cards, auto loans, student loans, and mortgages) than it is these days?"* They are given the same five options listed in the prior question about current perception of credit access. Within the remainder of this paper, I operate under the assumption that this variable refers to *personal* credit access, which is reflected in my regression specifications. It can indeed be argued that this variable perhaps refers to regional or national credit access given the ambiguity of the word "people," but I believe, given that the survey also elicits the prior perception of credit access at an individual-level, respondents will record their personal expectation.

With regard to personal financial wellbeing perceptions and expectations, a similar elicitation method is used. For the perception, individuals are asked: "*Do you think you (and any family living with you) are financially better or worse off these days than you were 12 months ago?*" For the expectation, they are similarly asked: "*And looking ahead, do you think you (and any family living with you) will be financially better or worse off 12 months from now than you are these days?*" In each case, they are able to choose one of five options which are as follows:

"*Much worse off (1); Somewhat worse off (2); About the same (3); Somewhat better off (4); and Much better off (5).*"

Below I provide summary statistics for these aforementioned variables as well as other explanatory variables from the SCE dataset that I use within my regressions. The summary statistics are separated into two tables. The first table **(Table 1)** presents demographic variables, current perception variables, and variables for prior inflation and stock market returns. The second table **(Table 2)** presents the summary statistics of the expectation variables as well as the expectation errors, which are constructed by subtracting the expectation of a given variable from its ultimate realization.[4] This expectation error construction stems from the methodology in Bachetta, Mertens, and Wincoop (2009). These expectation error variables allow me to explicitly measure the predictability of errors at time *t+1* using information at time *t*.

[4] In order to construct the error term for the individual-level variables of credit access and personal financial wellbeing, I take advantage of the fact that each individual responds to the survey for 12 months. Within the error term, the "expectation" represents the month 1 response and the "realization" represents the month 12 perception of the prior 12 months. Technically, this only represents an 11-month lag between expectation and realization, but I believe that this temporal discrepancy is close enough to 12 months such that it will not bias my coefficients.

## Table 1: Explanatory Variable Descriptive Statistics

Summary statistics of explanatory variables: number of observations, means, standard deviation, and ranges are presented. Each observation from the BLS and the Robert Shiller Data Library represents 1 month while each observation from the SCE represents a unique individual. A distribution of the 12-month-forward inflation rate and the 12-month-forward return of the S&P 500 over the observational period are included in **Appendix A1 (Figures 2 and 3)**.

| VARIABLES | Source | Format | (1) N | (2) mean | (3) sd | (4) min | (5) max |
|---|---|---|---|---|---|---|---|
| inflation_12mo_pctchange | BLS | Percentage | 70 | 1.519 | 0.820 | -0.200 | 2.900 |
| inflation_12mo_pctchange_fwd[5] | BLS | Percentage | 66 | 1.550 | 0.839 | -0.200 | 2.900 |
| sp500_12monthchange_backward | Robert Shiller Data Library | Percentage | 70 | 11.75 | 8.556 | -8.538 | 27.90 |
| sp500_12monthchange_forward[6] | Robert Shiller Data Library | Percentage | 66 | 9.420 | 7.664 | -8.538 | 22.62 |
| $\delta stocks\_up_{t+1}$[7] | Robert Shiller Data Library | Dummy | 66 | 84.80 | 36.10 | 0 | 100 |
| financial wellbeing $t$[8] | SCE | 1-5 scale | 12,110 | 3.106 | 0.958 | 1 | 5 |
| credit access $t$[9] | SCE | 1-5 scale | 12,109 | 2.741 | 1.035 | 1 | 5 |
| working full-time | SCE | Dummy | 12,116 | 0.558 | 0.497 | 0 | 1 |
| male | SCE | Dummy | 12,106 | 0.506 | 0.500 | 0 | 1 |
| white | SCE | Dummy | 12,116 | 0.832 | 0.374 | 0 | 1 |
| age | SCE | Years | 12,077 | 49.84 | 15.16 | 2 | 92 |
| education[10] | SCE | 1-8 scale | 12,080 | 4.337 | 1.512 | 1 | 8 |
| income[11] | SCE | 1-11 scale | 11,977 | 6.417 | 2.776 | 1 | 11 |
| health[12] | SCE | 1-5 scale | 8,011 | 3.666 | 0.979 | 1 | 5 |
| financial risk-loving[13] | SCE | 1-7 scale | 8,012 | 3.427 | 1.566 | 1 | 7 |

[5] 4 observation discrepancy due to exclusion of data from Dec 2020, Jan 2020, Feb 2020, and March 2020

[6] 4 observation discrepancy due to exclusion of data from Dec 2020, Jan 2020, Feb 2020, and March 2020

[7] Where $\delta stocks\_up_{t+1}$ represents a dummy variable (either 0 percent or 100 percent) for whether the S&P 500 was up in the subsequent year after the expectation was made.

[8] Current financial wellbeing as compared to 12-months prior is measured on a scale of 1-5 such that each number corresponds to: *Much worse off (1); Somewhat worse off (2); About the same (3); Somewhat better off (4); and Much better off (5).*

[9] Credit access compared to 12-months prior is measured on a scale of 1-5 such that each number corresponds to the following "ease of credit access": *Much harder (1); Somewhat harder (2); Equally easy/hard (3); Somewhat easier (4); or Much easier (5).*

[10] Education measured by a categorical method, but unlike income, this variable is time-invariant. The survey specifically asks, "*What is the highest level of school you have completed, or the highest degree you have received?*" The respondent then chooses from 9 different options where option 9 is "*other*." Respondents that chose 9 are excluded from the regressions. Options 1-8 are listed as follows: *Less than high school (1); High school diploma (or equivalent) (2); Some college but no degree (including academic, vocational, or occupational programs) (3); Associate/Junior College degree (including academic, vocational, or occupational programs) (4); Bachelor's Degree (For example: BA, BS) (5); Master's Degree (For example: MA, MBA, MS, MSW) (6); Doctoral Degree (For example: PhD) (7); and Professional Degree (For example: MD, JD, DDS) (8)*.

[11] Respondents can fall into 1 of 11 income categories. The 1st of the 11 income categories represents individuals whose total combined pre-tax income of all household members is less than $10,000. From there, the categories increment by $10,000 such that the 6th category represents individuals with incomes ranging from $50,000 to $59,999. From there the increments increase such that the 7th category represents ranges from $60,000 to $74,999, the 8th category represents $75,000 to $99,999, the 9th category represents $100,000 to $149,999, the 10th category represents $150,000 to $199,999, and the 11th category represents incomes greater than $200,000.

[12] With regard to self-reported health, each respondent is asked to rank his or her health according to the following scale *Poor (1), Fair (2), Good (3), Very good (4),* or *Excellent (5)*. The number of observations is lower since this question was not asked until April 2015.

[13] Financial risk tolerance is coded on a scale of 1 to 7 such that 1 represents an individual who is "*not willing at all*" to take risks on financial matters whereas a 7 represents an individual who is "*very willing*" to take financial risks. The number of observations is lower because this question was not asked until April 2015.

A few trends are apparent from **Table 1**. First, the BLS data indicates that the average prior inflation over a 12-month period, during the 70 months for which data was collected, was just over 1.5 percent while the 12-month forward inflation averaged 1.5 percent. This mean along with the corresponding standard deviation of approximately 0.8 indicate that inflationary/deflationary pressure was relatively muted during the period of observation.

Conversely, the Robert Shiller S&P 500 data tells a different story about financial markets. Mean prior 12-month performance of the S&P 500 is 11.75 percent, and the mean 12-mont-forward performance is 9.4 percent. Furthermore, the constructed dummy variable shows that, of the 66 12-month-forward observations, 85 percent of these signify a 12-month period over which the S&P rose. In other words, the period of observation (2013-2019) coincides with one of the most spectacular stock market bull runs ever witnessed in American history. The potential biases in my results as a function of this bull run are discussed more thoroughly when contextualized with the expectation data and the expectation errors.

The variables in **Table 1** from the SCE indicate that individuals, on average, feel that they are slightly better off than a year prior as is made clear from the mean of 3.106 on "financial wellbeing *t*" (where 3 on the scale implies that an individual is in *about the same* financial position as 1 year prior). On the other hand, with regard to credit access at time *t*, individuals report a mean of 2.741 (on a scale of 1-5), indicating that, on average, they find it harder to get loans now compared to a year prior.

With regard to demographic characteristics, the means indicate that the average respondent is white, middle-aged, full-time employed, college-educated, and receives an income of just over $50,000. Furthermore, the average respondent is slightly risk-averse, reports good health, and is equally likely to be male or female.

## Table 2: Expectation Variable Descriptive Statistics

Summary statistics of forecast variables: number of observations, means, standard deviation, and range are presented. Each observation represents a unique individual. The inflation expectations with "outliers removed" imply that the dataset was constrained such that responses with expectations greater than 10 percent or less than -10 percent were excluded. Respondent expectation and expectation error distributions are presented in **Appendix A2 (figures 4-11).**

| | | | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|---|---|
| VARIABLES | Formula | Format | N | mean | sd | min | max |
| inflation rate t+1 expectation[14] | $E_{i,t}(inflation_{t+1})$ | Percentage | 10,052 | 2.789 | 2.971 | -9.923 | 9.988 |
| p(stock_higher) at t+1 expectation[15] | $E_{i,t}(p(stocks\_higher_{t+1})$ | Percentage | 11,996 | 48.15 | 21.83 | 0 | 100 |
| credit access t+1 expectation[16] | $E_{i,t}(credit\_access_{i,t+1})$ | 1-5 scale | 12,109 | 2.757 | 0.952 | 1 | 5 |
| financial wellbeing t+1 expectation[17] | $E_{i,t}(financial\_wellbeing_{i,t+1})$ | 1-5 scale | 12,110 | 3.336 | 0.899 | 1 | 5 |
| inflation error | $inflation_{t+1} - E_{i,t}(inflation_{t+1})$ | Difference of percentages | 9,477 | -1.220 | 3.121 | -10.05 | 12.23 |
| stock error | $\delta stocks\_up_{t+1} - E_{i,t}(p(stocks\_higher_{t+1})$ | Difference of dummy and probability | 11,288 | 37.69 | 41.24 | -100 | 100 |
| credit access error[18] | $credit\_access_{i,t+1} - E_{i,t}(credit\_access_{i,t+1})$ | Difference of two 1-5 scale variables | 3,379 | 0.161 | 0.937 | -3 | 4 |
| financial wellbeing error | $financial\_wellbeing_{i,t+1} - E_{i,t}(financial\_wellbeing_{i,t+1})$ | Difference of two 1-5 scale variables | 3,377 | -0.110 | 0.918 | -4 | 4 |

**Table 2** describes the survey expectations themselves as well as the constructed expectation error terms. Several trends are apparent within these summary statistics. First, on average, respondents expect inflation to be 1.2 percent higher than the realization, which is reflected by the negative mean for "inflation error." In other words, individuals appear to be overly pessimistic (assuming pessimism implies an expectation of higher inflation) in their inflation forecasts.

[14] Inflation expectation represents forecast density mean (in percent)

[15] This expectation represents the probability (between 0 and 100) that the individual respondent assigns to the proposition that the stock market will be higher in 12 months

[16] 12-month-forward credit access expectations are measured on a scale of 1-5 such that each number corresponds to the following "ease of credit access": *Much harder (1); Somewhat harder (2); Equally easy/hard (3); Somewhat easier (4); or Much easier (5).*

[17] Personal financial wellbeing 12-month forward expectations are measured on a scale of 1-5 such that each number corresponds to: *Much worse off (1); Somewhat worse off (2); About the same (3); Somewhat better off (4); and Much better off (5).*

[18] Decrease in observation numbers is due to fact that error term construction required individual realization observation. Hence, I could only have observations for respondents who lasted for the entire 12 months of the survey.

One potential reason is that the average age of the respondents is approximately 50 years old. Therefore, these individuals have lived much of their lives through periods of higher U.S. inflation (which had an average of over 4 percent between 1970 and 2007). Perhaps, when individuals are forecasting future inflation, they are overweighting these prior inflation experiences.

Conversely, a second potential explanation is that individuals simply do not grasp the concept of inflation. While the SCE presents evidence (see Armantier et al. 2016) that respondents comprehend inflation,[19] evidence within the survey data contradicts this conclusion. For example, many inflation expectation outliers had to be removed from the dataset. Specifically, over 1000 unique individuals responded with inflation expectations that did not fall within a band of -10 percent to 10 percent. Within this set of excluded responses, over a quarter of these individuals (over 250 people) expected 12-month-forward inflation of over 25 percent. It is improbable that these 1000 excluded individuals (a significant percentage of total respondents) can be characterized as fully grasping the concept of inflation given their recorded expectations.

Similar to the consistent errors in inflation expectations, the positive mean on stock market expectation error (37.69) implies expectations that are, on average, 37 percent lower than the actual realization. In other words, individuals consistently assign too low a probability to positive stock market returns when compared to the observed probability of positive returns. Specifically, while individuals assign a probability of approximately 48 percent, the observed probability during the time period of the survey is over 80 percent.

[19] Within the SCE itself, between May 2013 and September 2015, survey respondents were asked, "*On a scale of 1 to 7, how well would you say you understand what "inflation" means?*" Of the respondents, only 44 of the 5182 (less than 0.9 percent) said they had "*no understanding*," while over 82 percent of the respondents chose 5 or more.

One potential explanation for this discrepancy is as follows: individuals are usually taught, as per the Efficient Markets Hypothesis, that stock market returns are random. That is to say: the stock market has a 50 percent chance of increasing and a 50 percent chance of decreasing. Given this context, an average expectation of nearly 50 percent probability that the stock market increases over the next 12 months appears more reasonable.

Finally, with regard to expectations of the individual-level variables of credit access and financial wellbeing, respondents demonstrate irrational optimism about financial wellbeing and irrational pessimism about credit. Nonetheless, their errors in expectation are much closer to zero than those for inflation and stock market returns. In other words, individuals are measurably more rational when forecasting their own lives than when forecasting national outcomes such as inflation or the stock market.

**Regression Specifications:**

In my regressions, I seek to answer two overarching questions: First, what are the determinants of individual expectations? Second, are individual expectations predictably irrational?

Determinants of Expectation:

With the determinants of expectations regressions, I test the extent to which individuals extrapolate from both prior personal experience and prior national-level variable performance. In addition, I examine the extent to which different groups hold persistently different expectations. For national-level variables such as inflation and stock market returns, I test both national-level and individual-level priors (e.g. prior S&P 500 returns and prior personal financial wellbeing). Significant extrapolation from personal experience or prior variable performance when forming expectations about such national-level variables could indicate irrationality. Furthermore, REH postulates that expectations for national-level variables (e.g. inflation and stock market performance) should not vary across demographics, as this would imply different informational access according to variables such as race, gender, or employment status, which is highly unlikely.[20]

For the determinants of expectation regression specifications, the dependent variable represents the expectation in question and the explanatory variables represent information available at time $t$ which might influence the formation of the expectation for time $t+1$. For example, I include potential variables from which individuals might extrapolate as well as the

[20] For personal level variables (e.g. credit access and personal financial wellbeing), expectation differences between demographics are not necessarily inconsistent with the REH because, for individual-level expectation variables, different groups can experience different realizations.

demographic variables found in **Table 3**, which allow me to identify group expectation differences. In addition, I experimented with controls of national GDP, national unemployment, national personal consumption, and commuting-zone level average wage change, but none of these controls had any significant effect on my results. Thus, they are not included in my regression results. The four different models are as follows:

Note: Within these regressions, I rely on only one observation per individual in order to avoid significant econometric complications. More specifically, I use the initial observation of each respondent. In addition, for each of my dependent variables I include year fixed effects. The term $\boldsymbol{indiv\_chars_i}$ refers to a vector of individual attributes including age, gender, education, income, employment status, ethnicity, health, and risk appetite.

1. Inflation Expectations

$$E_{i,t}(inflation_{t+1}) = \alpha + \beta_1 financial\_wellbeing_{i,t} + \beta_2 prior12mo\_inflation_t + \beta_3 \boldsymbol{indiv\_chars_i} + \gamma_y + \epsilon_{i,t} \tag{1}$$

2. Stock Market Expectations

$$E_{i,t}(p(stocks\_higher_{t+1}) = \alpha + \beta_1 financial\_wellbeing_{i,t} + \beta_2 prior12mo\_\Delta SP500t + \beta_3 \boldsymbol{indiv\_chars_i} + \gamma_y + \epsilon_{i,t} \tag{2}$$

3. Credit Access Expectations

$$E_{i,t}\left(credit\_access_{i,t+1}\right) = \alpha + \beta_1 financial\_wellbeing_{i,t} + \beta_2 credit\_access_{i,t} + \beta_3 \boldsymbol{indiv\_chars_i} + \gamma_y + \epsilon_{i,t} \tag{3}$$

4. Personal Financial Wellbeing Expectations

$$E_{i,t}\left(financial\_wellbeing_{i,t+1}\right) = \alpha + \beta_1 financial\_wellbeing_{i,t} + \beta_2 \boldsymbol{indiv\_chars_i} + \gamma_y + \epsilon_{i,t} \tag{4}$$

Predictability of Errors:

In order to examine the predictability of expectation errors, I adopt regression specifications similar to those used by Bachetta, Mertens, and Wincoop (2009) such that I subtract the expectation of a variable from its ultimate realization in order to construct a dependent variable error term. Via this specification, I can empirically examine whether individuals err in their forecasts in predictable ways. Are such forecasts predictably biased as a function of extrapolation or personal characteristics? Evidence of predictability of error at time *t+1* using information at time *t* is inconsistent with the REH, which implies that the error term (realization minus expectation) should be random.

The constructions for these regressions are detailed below:

Note: Again, I include year fixed effects and rely only on the initial observation of each respondent in order to avoid econometric complications. The term $\boldsymbol{indiv\_chars_i}$ refers to a vector of individual attributes including age, gender, education, income, employment status, ethnicity, health, and risk appetite.

1. Inflation Errors

$$inflation_{t+1} - E_{i,t}(inflation_{t+1}) = \alpha + \beta_1 financial\_wellbeing_{i,t} + \beta_2 prior12mo\_inflation_t + \beta_3 \boldsymbol{indiv\_chars_i} + \gamma_y + \epsilon_{i,t} \tag{5}$$

2. Stock Market Errors[21]

$$\delta stocks\_up_{t+1} - E_{i,t}(p(stocks\_higher_{t+1}) = \alpha + \beta_1 financial\_wellbeing_{i,t} + \beta_2 prior12mo\_\Delta SP500t + \beta_3 \boldsymbol{indiv\_chars_i} + \gamma_y + \epsilon_{i,t} \tag{6}$$

3. Credit Access Errors

$$credit\_access_{i,t+1} - E_{i,t}\left(credit\_access_{i,t+1}\right) = \alpha + \beta_1 financial\_wellbeing_{i,t} + \beta_2 credit\_access_{i,t} + \beta_3 \boldsymbol{indiv\_chars_i} + \gamma_y + \epsilon_{i,t} \tag{7}$$

[21] Where $\delta stocks\_up_{t+1}$ represents a dummy variable (either 0 percent or 100 percent) for whether the S&P 500 was up in the subsequent year after the expectation was made.

4. Personal Financial Wellbeing Errors

$$financial\_wellbeing_{i,t+1} - E_{i,t}(financial\_wellbeing_{i,t+1}) = \alpha + \beta_1 financial\_wellbeing_{i,t} + \beta_2 \boldsymbol{indiv\_chars_i} + \gamma_y + \epsilon_{i,t} \quad (8)$$

**<u>Regression Results:</u>**

For each of my four dependent variables, I present the regressions for the determinants of the expectation as well as the regressions examining the predictability of the expectation error term. My explanatory variables within each regression are labeled and correspond to the equation specifications. Furthermore, I have added notes to each of the tables that detail relevant units and other idiosyncrasies associated with the regressions.

Inflation Expectations:

**Table 3: Determinants of Inflation Expectations**

| VARIABLES | (1)<br>inflation_exp | (2)<br>inflation_exp | (3)<br>inflation_exp | (4)<br>inflation_exp |
|---|---|---|---|---|
| financial wellbeing *t* | -0.242*** | -0.296*** | -0.218*** | -0.213*** |
| | (0.0350) | (0.0382) | (0.0434) | (0.0438) |
| inflation_12mo_prior | 0.183* | 0.195* | 0.00545 | -0.00454 |
| | (0.101) | (0.100) | (0.102) | (0.102) |
| age | | 0.00536** | 0.00494* | 0.00437* |
| | | (0.00234) | (0.00260) | (0.00256) |
| male | | -0.0330 | -0.104 | -0.0653 |
| | | (0.0619) | (0.0694) | (0.0705) |
| income | | 0.0645*** | 0.0707*** | 0.0765*** |
| | | (0.0144) | (0.0168) | (0.0171) |
| working full-time | | 0.135* | 0.144* | 0.150* |
| | | (0.0716) | (0.0817) | (0.0813) |
| white | | 0.291*** | 0.181* | 0.163* |
| | | (0.103) | (0.0964) | (0.0960) |
| education | | 0.0528** | 0.0740** | 0.0778*** |
| | | (0.0206) | (0.0277) | (0.0273) |
| health | | | -0.164*** | -0.152*** |
| | | | (0.0382) | (0.0387) |
| financial risk-loving | | | | -0.0723*** |
| | | | | (0.0258) |
| Constant | 3.275*** | 2.194*** | 2.758*** | 2.933*** |
| | (0.179) | (0.246) | (0.309) | (0.308) |
| Observations | 10,046 | 9,913 | 6,638 | 6,634 |
| R-squared | 0.011 | 0.019 | 0.014 | 0.016 |
| Year FE | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: In these cross-sectional OLS regressions, my dependent variable is the expectation of inflation at time *t+1*. An expected inflation rate of 1% is coded as 1. My independent variables represent information available at time *t*. The number of observations in columns 4 and 5 is due to the fact that neither health nor financial risk appetite were measured until April 2015. Finally, my standard errors across each of these regressions are clustered at a month-year level.

**Table 4: Inflation Error Predictability**

| VARIABLES | (1)<br>inflation error | (2)<br>inflation error |
|---|---|---|
| financial wellbeing *t* | 0.293*** | 0.198*** |
| | (0.0409) | (0.0479) |
| inflation_12mo_prior | -0.252 | -0.00848 |
| | (0.170) | (0.166) |
| age | -0.00496** | -0.00420 |
| | (0.00246) | (0.00270) |
| male | 0.0448 | 0.0872 |
| | (0.0646) | (0.0753) |
| income | -0.0638*** | -0.0751*** |
| | (0.0148) | (0.0178) |
| working full-time | -0.146* | -0.170* |
| | (0.0750) | (0.0877) |
| white | -0.279** | -0.136 |
| | (0.108) | (0.101) |
| education | -0.0548** | -0.0793** |
| | (0.0216) | (0.0294) |
| health | | 0.142*** |
| | | (0.0405) |
| financial risk-loving | | 0.0687** |
| | | (0.0276) |
| Constant | -0.553 | -0.875** |
| | (0.348) | (0.433) |
| Observations | 9,349 | 6,071 |
| R-squared | 0.093 | 0.041 |
| Year FE | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: In these cross-sectional OLS regressions, my dependent variable is the error in inflation expectation measured as $inflation_{t+1} - E_{i,t}(inflation_{t+1})$. My independent variables represent information available at time $t$. The decreased number of observations in columns 2 is due to the fact that neither health nor financial risk appetite were measured until April 2015. Finally, my standard errors across each of these regressions are clustered at a month-year level as the inflation realization is equivalent for every observation within a given month-year.

Stock Market Expectations:

**Table 5: Determinants of Stock Market Expectations**

| VARIABLES | (1)<br>p(stock_higher) | (2)<br>p(stock_higher) | (3)<br>p(stock_higher) | (4)<br>p(stock_higher) |
|---|---|---|---|---|
| financial wellbeing *t* | 3.782*** | 3.349*** | 3.459*** | 3.355*** |
| | (0.269) | (0.262) | (0.368) | (0.365) |
| sp500_12month_return | 0.108** | 0.123*** | 0.116** | 0.123** |
| | (0.0415) | (0.0392) | (0.0521) | (0.0517) |
| age | | -0.0540*** | -0.0425** | -0.0310 |
| | | (0.0144) | (0.0184) | (0.0185) |
| male | | 5.094*** | 4.647*** | 3.966*** |
| | | (0.428) | (0.545) | (0.565) |
| income | | 0.129 | 0.0847 | -0.0149 |
| | | (0.0817) | (0.0997) | (0.102) |
| working full-time | | -1.775*** | -1.203** | -1.359** |
| | | (0.508) | (0.597) | (0.598) |
| white | | 0.332 | 0.439 | 0.850 |
| | | (0.563) | (0.701) | (0.705) |
| education | | 0.888*** | 0.300 | 0.226 |
| | | (0.194) | (0.209) | (0.208) |
| health | | | 0.445 | 0.274 |
| | | | (0.316) | (0.309) |
| financial risk-loving | | | | 1.282*** |
| | | | | (0.194) |
| Constant | 35.09*** | 32.42*** | 32.83*** | 29.81*** |
| | (1.042) | (1.648) | (2.222) | (2.218) |
| Observations | 11,990 | 11,804 | 7,892 | 7,888 |
| R-squared | 0.030 | 0.049 | 0.044 | 0.051 |
| Year FE | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: In these cross-sectional OLS regressions, my dependent variable is the expected probability that the U.S. stock market will be higher 12 months in the future. A probability of 50% is coded as 50. The decreased number of observations in columns 4 and 5 is due to the fact that neither health nor financial risk appetite were measured until April 2015. Finally, my standard errors across each of these regressions are clustered at a month-year level.

## Table 6: Stock Market Error Predictability

| VARIABLES | (1)<br>stock error | (2)<br>stock error |
|---|---|---|
| financial wellbeing *t* | -3.101*** | -2.732*** |
| | (0.409) | (0.502) |
| sp500_12month_return | -2.853*** | -3.115*** |
| | (0.894) | (1.113) |
| age | 0.0396* | 0.0272 |
| | (0.0220) | (0.0277) |
| male | -5.352*** | -4.564*** |
| | (0.556) | (0.676) |
| income | -0.0810 | -0.0309 |
| | (0.148) | (0.185) |
| working full-time | 1.256* | 1.768** |
| | (0.698) | (0.690) |
| white | -0.485 | -0.923 |
| | (0.769) | (1.060) |
| education | -0.942*** | -0.233 |
| | (0.276) | (0.290) |
| health | | -0.481 |
| | | (0.530) |
| financial risk-loving | | -1.406*** |
| | | (0.333) |
| Constant | 89.11*** | 88.87*** |
| | (11.48) | (9.637) |
| Observations | 11,112 | 7,197 |
| R-squared | 0.259 | 0.223 |
| Year FE | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: In these cross-sectional OLS regressions, my dependent variable is expectation error measured as $\delta stocks\_up_{t+1} - E_{i,t}(p(stocks\_higher_{t+1})$. The decreased number of observations in column 2 is due to the fact that neither health nor financial risk appetite were measured until April 2015. Finally, my standard errors across each of these regressions are clustered at a month-year level given that the realization is constant across individuals in any given month of any year.

Credit Access Expectations:

**Table 7: Determinants of Credit Access Expectations**

| VARIABLES | (1) credit access *t+1* | (2) credit access *t+1* | (3) credit access *t+1* | (4) credit access *t+1* |
|---|---|---|---|---|
| financial wellbeing *t* | 0.0917*** | 0.0881*** | 0.0731*** | 0.0721*** |
| | (0.00741) | (0.00677) | (0.00832) | (0.00837) |
| credit access *t* | 0.634*** | 0.624*** | 0.625*** | 0.625*** |
| | (0.00783) | (0.00818) | (0.0114) | (0.0114) |
| age | | -0.000138 | 8.02e-05 | 0.000164 |
| | | (0.000480) | (0.000627) | (0.000636) |
| male | | 0.0151 | 0.0125 | 0.00749 |
| | | (0.0122) | (0.0175) | (0.0179) |
| income | | 0.0109*** | 0.0103*** | 0.00952*** |
| | | (0.00249) | (0.00338) | (0.00339) |
| working full-time | | -0.0467*** | -0.0578*** | -0.0590*** |
| | | (0.0143) | (0.0167) | (0.0165) |
| white | | 0.0886*** | 0.0943*** | 0.0979*** |
| | | (0.0157) | (0.0199) | (0.0197) |
| education | | 0.0139*** | 0.000703 | 0.000126 |
| | | (0.00474) | (0.00590) | (0.00585) |
| health | | | 0.00746 | 0.00605 |
| | | | (0.00845) | (0.00841) |
| financial risk-loving | | | | 0.0101* |
| | | | | (0.00585) |
| Constant | 0.735*** | 0.594*** | 0.642*** | 0.620*** |
| | (0.0281) | (0.0399) | (0.0495) | (0.0521) |
| Observations | 12,101 | 11,911 | 7,902 | 7,898 |
| R-squared | 0.502 | 0.505 | 0.493 | 0.493 |
| Year FE | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: In these cross-sectional OLS regressions, my dependent variable is expectation of credit access. The decreased number of observations in columns 3 and 4 is due to the fact that neither health nor financial risk appetite were measured until April 2015. Finally, my standard errors across each of these regressions are clustered at a month-year level.

**Table 8: Credit Access Error Predictability**

| VARIABLES | (1)<br>credit access error | (2)<br>credit access error |
|---|---|---|
| financial wellbeing *t* | 0.0346* | 0.0257 |
| | (0.0185) | (0.0253) |
| credit access *t* | -0.352*** | -0.353*** |
| | (0.0158) | (0.0209) |
| age | 0.00105 | -0.000483 |
| | (0.00153) | (0.00214) |
| male | 0.0258 | -0.00319 |
| | (0.0295) | (0.0400) |
| income | -0.00673 | -0.00911 |
| | (0.00615) | (0.00860) |
| working full-time | 0.0577 | 0.0123 |
| | (0.0404) | (0.0486) |
| white | -0.0330 | -0.0809 |
| | (0.0445) | (0.0572) |
| education | 0.00449 | 0.00303 |
| | (0.0121) | (0.0159) |
| health | | -0.000318 |
| | | (0.0164) |
| financial risk-loving | | 0.0234 |
| | | (0.0155) |
| Constant | 0.990*** | 1.126*** |
| | (0.126) | (0.168) |
| Observations | 3,331 | 2,118 |
| R-squared | 0.148 | 0.145 |
| Year FE | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: In these cross-sectional OLS regressions, my dependent variable is error in credit expectations measured as $easier\_credit_{i,t+1} - E_{i,t}(easier\_credit_{i,t+1})$. Overall observation numbers are lower since I require that the respondent remained in the survey for 12-months in order to have a realization variable. The decreased number of observations in columns 2 is due to the fact that neither health nor financial risk appetite were measured until April 2015. Finally, my standard errors across each of these regressions are clustered at a month-year level. SE clustering at the individual level produced generally lower SEs.

Personal Financial Wellbeing Expectations:

**Table 9: Determinants of Personal Financial Wellbeing Expectations**

| VARIABLES | (1)<br>financial<br>wellbeing *t+1* | (2)<br>financial<br>wellbeing *t+1* | (3)<br>financial<br>wellbeing *t+1* | (4)<br>financial<br>wellbeing *t+1* |
|---|---|---|---|---|
| financial wellbeing *t* | 0.398*** | 0.377*** | 0.370*** | 0.366*** |
| | (0.0110) | (0.0119) | (0.0159) | (0.0158) |
| age | | -0.0117*** | -0.0112*** | -0.0107*** |
| | | (0.000624) | (0.000817) | (0.000813) |
| male | | -0.0133 | -0.0115 | -0.0375 |
| | | (0.0190) | (0.0250) | (0.0249) |
| income | | -0.00508 | -0.0119*** | -0.0159*** |
| | | (0.00316) | (0.00399) | (0.00398) |
| working full-time | | -0.0371* | -0.0336 | -0.0394 |
| | | (0.0197) | (0.0243) | (0.0242) |
| white | | -0.177*** | -0.129*** | -0.112*** |
| | | (0.0244) | (0.0252) | (0.0247) |
| education | | -0.00572 | -0.0246*** | -0.0273*** |
| | | (0.00677) | (0.00820) | (0.00824) |
| health | | | 0.0752*** | 0.0684*** |
| | | | (0.00870) | (0.00865) |
| financial risk-loving | | | | 0.0503*** |
| | | | | (0.00549) |
| Constant | 2.100*** | 2.982*** | 2.800*** | 2.685*** |
| | (0.0357) | (0.0589) | (0.0805) | (0.0822) |
| Observations | 12,104 | 11,912 | 7,903 | 7,899 |
| R-squared | 0.186 | 0.230 | 0.223 | 0.231 |
| Year FE | YES | YES | YES | YES |

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: In these cross-sectional OLS regressions, my dependent variable is expectation of personal financial wellbeing. The decreased number of observations in columns 3 and 4 is due to the fact that neither health nor financial risk appetite were measured until April 2015. Finally, my standard errors across each of these regressions are clustered at a month-year level

## Table 10: Personal Financial Wellbeing Error Predictability

| VARIABLES | (1)<br>better off error | (2)<br>better off error |
|---|---|---|
| financial wellbeing *t* | -0.105*** | -0.112*** |
| | (0.0208) | (0.0298) |
| age | 0.00658*** | 0.00532*** |
| | (0.00124) | (0.00161) |
| male | 0.0861** | 0.109** |
| | (0.0363) | (0.0456) |
| income | 0.0169*** | 0.0152* |
| | (0.00608) | (0.00753) |
| working full-time | 0.00499 | -0.0527 |
| | (0.0418) | (0.0518) |
| white | 0.134*** | 0.100* |
| | (0.0392) | (0.0523) |
| education | 0.0167 | 0.0371** |
| | (0.0121) | (0.0141) |
| health | | 0.0132 |
| | | (0.0235) |
| financial risk-loving | | -0.0292*** |
| | | (0.0102) |
| Constant | -0.482*** | -0.372*** |
| | (0.102) | (0.135) |
| Observations | 3,329 | 2,116 |
| R-squared | 0.035 | 0.041 |
| Year FE | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: In these cross-sectional OLS regressions, my dependent variable is personal financial wellbeing expectation error measured as $better\_off_{i,t+1} - E_{i,t}(better\_off_{i,t+1})$. Overall observation numbers are lower since I require that the respondent remained in the survey for 12-months in order to have a realization variable. The decreased number of observations in columns 2 is due to the fact that neither health nor financial risk appetite were measured until April 2015. Finally, my standard errors across each of these regressions are clustered at a month-year level. SE clustering at the individual level produced generally lower SEs.

## Discussion of Results:

### Inflation Expectations:[22]

From the regressions in **Table 3**, I find two results. First, evidence is presented that inflation expectations are extrapolative from prior personal experience but not from prior inflation performance. Second, I find evidence of differences in expectations across demographics. With regard to extrapolation from prior personal experience, the results imply that, for example, if personal financial wellbeing over the previous year increases by 1 point (scale of 1-5), inflation expectations decrease by 0.2 percentage points. While extrapolation from personal experience for inflation expectations is not, in and of itself, inconsistent with the REH, such a magnitude of extrapolation from prior personal financial wellbeing when compared with the lack of extrapolation from prior inflation performance, appears problematic for the REH. This is because national inflation is not determined by personal financial wellbeing. In other words, just because an individual is better off than a year prior, they should not, holding other variables constant, be significantly more optimistic about inflation.

The second finding from **Table 3** indicates significant differences in expectation across demographics. For example, an individual that is 1-point healthier (on a scale of 1-5) reports expectations that are 0.15 percentage points lower (i.e. they are more optimistic). This finding is inconsistent with the REH because it implies that there must be informational differences between the healthy and the unhealthy regarding inflation, which is highly unlikely. Similarly, individuals who are more educated have more pessimistic expectations of future inflation than their counterparts, despite likely having equal informational access.

[22] Optimism implies negative inflation expectations while pessimism implies positive expectation.

**Table 4** demonstrates results about the predictability of inflation expectation errors. First off, the strong positive coefficient on prior personal financial wellbeing indicates over-extrapolation. More specifically, individuals who report positive prior financial wellbeing (greater than 3 on a scale of 1-5) tend to be overly optimistic about inflation whereas individuals who report negative prior financial wellbeing (less than 3) tend to be overly pessimistic in their forecasts.

In addition to predictable errors based on extrapolation, the results from **Table 4** indicate predictability of errors based on group characteristics. For example, **Table 3** implies that unhealthy respondents are consistently more pessimistic than healthy respondents about inflation. **Table 4** then goes on to make the stronger point that, in addition to being more pessimistic, unhealthy individuals are also more irrational in their expectations.[23] Similarly, **Table 4** suggests that full-time employed, wealthy, and more educated individuals tend to be overly pessimistic when compared to their respective omitted groups. One potential rationale for this discrepancy is that these individuals perceive higher rates of inflation from which they extrapolate. This perception is largely driven by increases in housing prices. For example, someone that is poor and unemployed is less likely to be as exposed to rent and home price increases as a wealthier counterpart.

To summarize, the evidence from **Tables 3** and **4** implies that individuals over-extrapolate from prior personal experience and that different demographics repeatedly err in their expectations. Each of these results is inconsistent with the REH because, in both cases, information available at time $t$ can predict the magnitude and sign of forecasting errors.

[23] To be fair, the healthy also appear to be more pessimistic than reality in their expectation, but the extent of the error in their expectations is less than that of the unhealthy.

Stock Market Expectations:

First, I want to clarify the meaning of stock market expectations within the context of the SCE. Unlike inflation expectations, which represent the percent by which respondents expect CPI to increase in a year, stock market expectations convey the probability that U.S. stock prices will be higher in a year. This difference is subtle but important for the interpretation of regressions.

The results for the determinants of stock market expectations are outlined in **Table 5**. A few trends are apparent. First, individuals appear to extrapolate both from their personal financial experiences as well as prior performance of the S&P 500 index. However, extrapolation from prior personal experience is stronger in magnitude. Specifically, a 1-point increase in reported personal financial wellbeing (measured on a scale of 1-5) translates to a nearly 3.4 percentage point increase in the probability with which an individual expects the stock market to be higher in a year. On the other hand, a 1 percent increase in the S&P 500 over the prior year translates to only an approximately 0.11 percentage point increase in this same probability.

Second, within **Table 5**, there is significant evidence of consistent expectation differences between demographics. For example, those working full-time have stock market expectations that are 1.3 percentage points lower than those who are not working full-time. On the other hand, men, on average, assign a probability of stock market increase that is 4 percentage points higher than women. In addition, individuals who describe themselves as financially risk-loving expect, for a 1-point increase in risk tolerance (scale of 1-7), stocks to be higher with nearly 1.3 percent greater probability.

Furthermore, the results in **Table 6** confirm that these aforementioned forecast differences translate to predictable forecast errors. For example, for a 1-point decrease in financial wellbeing, forecast error jumps by nearly 3 points. Similarly, a 1-percentage-point decrease in the S&P 500, increases forecast error by 3.1 points. In other words, if the stock market has been down or if an individual has had a bad prior year financially, their stock market expectations are significantly more irrational, in the context of my results.

These results for stock market expectations are problematic for rational expectations for two reasons. First, different groups of individuals, assuming equal informational access, should not differ in their expectation according to REH. Second, and more importantly, given that prior stock market returns and prior personal experience have little to no bearing in influencing future stock market returns, it is therefore irrational that individuals rely upon these variables so heavily when forecasting the future.

Credit Access Expectations:

Credit access represents the first dependent variable for which the realization and the expectation are both measured at an individual level. Each individual, even for the same time period, can have a different realization. This is unlike expectations for the stock market or inflation where the realization is the same for all individuals in a given time period. Thus, differences between group expectations are not necessarily inconsistent with the REH in the context of credit access expectations or personal financial wellbeing as different groups often experience different outcomes.

Within **Table 7**, the regressions present evidence of extrapolation from both personal financial experience as well as credit access experience. Extrapolation from personal financial experience is much weaker than extrapolation from prior perception of credit access. To quantify this discrepancy: if an individual's financial wellbeing increases by 1 point (on a scale of 1-5), his or her expectation of credit access (on a scale of 1-5) increases by only about 0.07 points. On the other hand, if an individual's perception of prior credit access increases by 1 point (on a scale of 1-5), his or her expectation increases by over 0.6 points. In other words, extrapolation from prior credit access is approximately an order of magnitude stronger.

The predictability of errors results in **Table 8** indicate that this magnitude of extrapolation from prior credit access is irrational: respondents tend to over-extrapolate. For example, individuals who have reported prior difficult access to credit (a 1 or 2 on a scale of 1-5) are consistently overly pessimistic. Conversely, individuals who reported prior easy credit access (a 4 or 5 on the scale) tend to be overly optimistic.

In contrast to the regressions in **Tables 4** and **6**, there is little evidence to suggest consistent expectation errors between different groups of individuals. While the results in **Table 7** indicate that some groups differ in their credit access expectations, **Table 8** indicates that these differences in expectation are explained by differences in realization. In other words, these forecast differences do not result in predictable errors. Therefore, forecast error is predictable from individual prior credit access but not individual demographic characteristics.

Personal Financial Wellbeing Expectations:

Similar to credit access, personal financial wellbeing also has individual-specific realizations. The results within **Table 9** and **10** imply several trends. First, **Table 9** indicates that individuals extrapolate from prior financial wellbeing when forming their expectations about the future. For example, a 1-point increase in current personal financial wellbeing (scale of 1-5) translates to an approximately 0.36-point increase in expectation (scale of 1-5). **Table 10** goes on to indicate that individuals tend to overreact when extrapolating from these prior experiences. Specifically, individuals reporting increased current financial wellbeing are irrationally optimistic in their expectations.[24] In other words, all individuals, on average, expect to do better than they actually will, but individuals who have done well in the past are predictably more irrational in their optimism about the future.

Second, **Tables 9** and **10** indicate that expectations differ across demographics *and* that expectation error is predictable based on demographic attributes. For example, certain groups including financial risk-lovers, non-whites, women, and the young tend to be more optimistic than their omitted counterparts **(Table 9)**, *and* they are also less rational in these forecasts than these omitted counterparts **(Table 10)**. Such evidence of error predictability based on group attributes as well as prior financial wellbeing is inconsistent with the REH, because, in both cases, one is able to predict the error in expectation at time *t+1* using information available at time *t*, implying a non-random error term.

[24] A 1-point increase in prior financial wellbeing translates to a 0.1-point decrease in the error (i.e. the expectation becomes further divorced from the realization and the error becomes more negative)

**Conclusion:**

In this section, I will bring together the recurring findings across each of my sets of regressions and then attempt to contextualize them with regard to their impact on broader societal dynamics. I also want to highlight potential areas for further research on the topic of REH as it relates to economic expectations.

Broadly speaking, my regression results for the determinants of expectations indicate that, across expectations of national inflation and stock market return as well as individual credit access and financial wellbeing, there is significant extrapolation from prior personal experience. Furthermore, there exist significant differences between the expectations of different groups. With regard to national-level variables such as inflation and stock market performance, evidence of differences in group expectation is inconsistent with the REH. This is because the REH implies that expectation differences are due to informational discrepancies. As I discussed in my results section, it is improbable that, for example, men have access to different information about the stock market than women, holding other variables constant. Nonetheless, men are consistently more optimistic about the stock market than women.[25]

Most importantly for testing the REH, my regression tables for expectation errors demonstrate that information available at time $t$ can be used to predict error in expectation at time $t+1$. Specifically, these results indicate that prior personal experience, prior dependent variable performance, and demographic attributes are correlated with consistent biases in individual

[25] While group expectation differences are still present for the individual-level variables of credit access and financial wellbeing, these differences are not necessarily inconsistent with REH as these different groups experience different outcomes (i.e. personal financial wellbeing is not the same for every respondent while stock market return is).

expectations. In other words, these three types of variables can predict forecasting errors that individuals repeatedly make.

Such consistent evidence of predictable irrationality on behalf of individuals is important. It undermines the REH and thus undermines some of the major macroeconomic and microeconomic models that have been developed over the past half-century. Many of these models contain, as a central tenant, the assumption that individuals make rational forecasts about the future. Even more importantly, individuals are shown to act upon their forecasts, regardless of their rationality. Over time, these tangible decisions and actions manifest in the real economy and coalesce into real effects on the lives of individuals. Thus, it is crucially important how these opinions are developed. Do people make the same mistakes? Are the opinions upon which they act biased in predictable ways? If the case is yes, then many of these models operate on assumptions that are not true in real world. In other words, if the foundation of a model is inaccurate, what does this imply about the projections of this model?

My work adds to a growing body of economic literature that documents the manifest irrationality of individual forecasts and provides evidence that is inconsistent with the REH. More work needs to be done to quantify the extent of this irrationality across different forecasts. Perhaps these same tendencies of individuals can be explored across different variables relating to expectations of other unrelated fields. Furthermore, adding more complicated controls relating to personal characteristics or prior personal experience could improve the robustness of testing the REH (e.g. controlling for individual political characteristics, personality traits coded by social media profiles, or closely controlling for local economic activity across all variables). Overall, the evidence presented documents the consistent deviations from rationality on behalf of individual forecasts, thereby calling into question both the decisions that these individuals make as well as the economic models that assume rational expectations.

**<u>Appendix A1</u>: Histogram of Inflation and Stock Market Forward Returns**

**Figure 2**

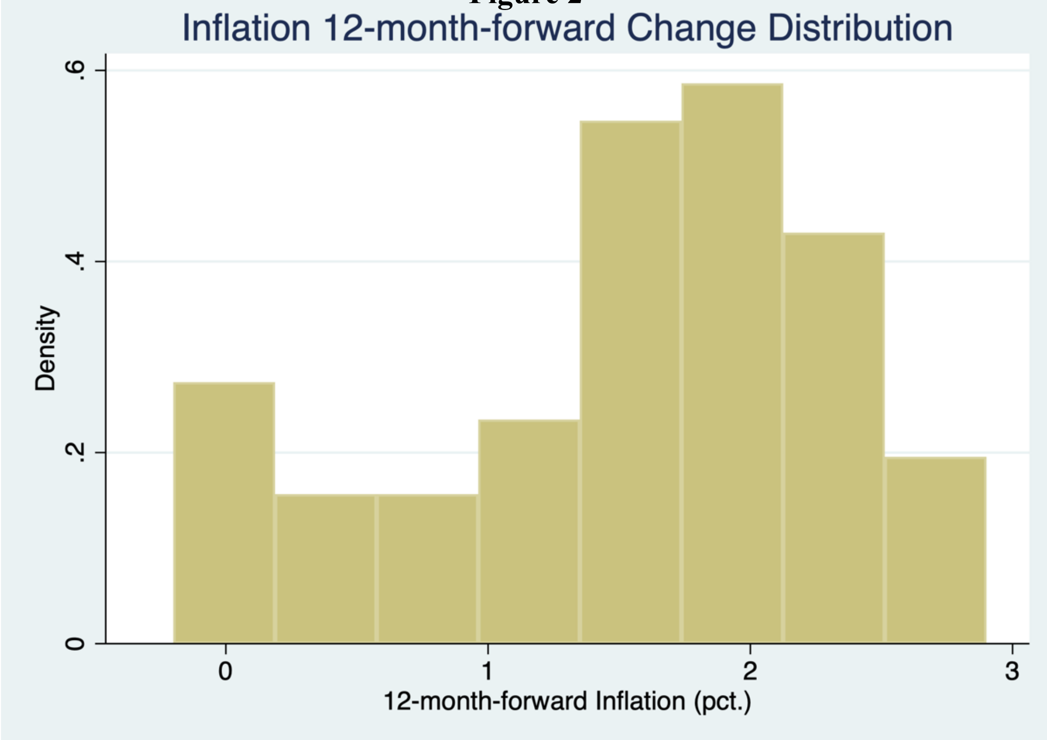
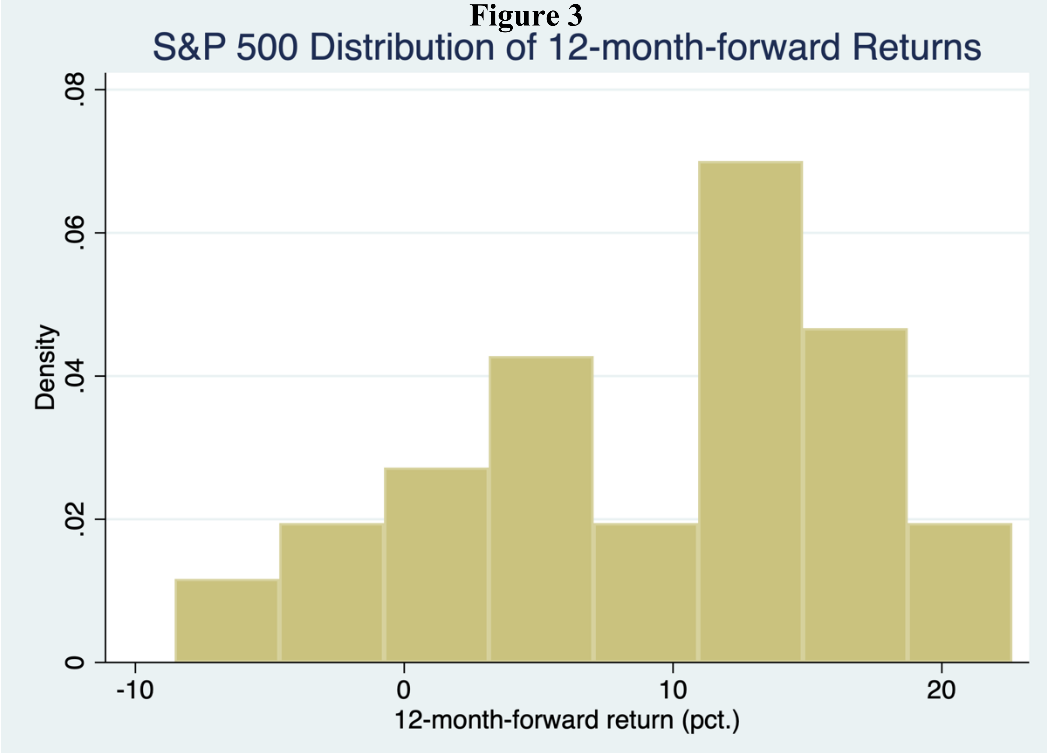



**Figure 3**



**<u>Appendix A2:</u> Histograms of Expectation and Expectation Error Terms**

**Figure 4**

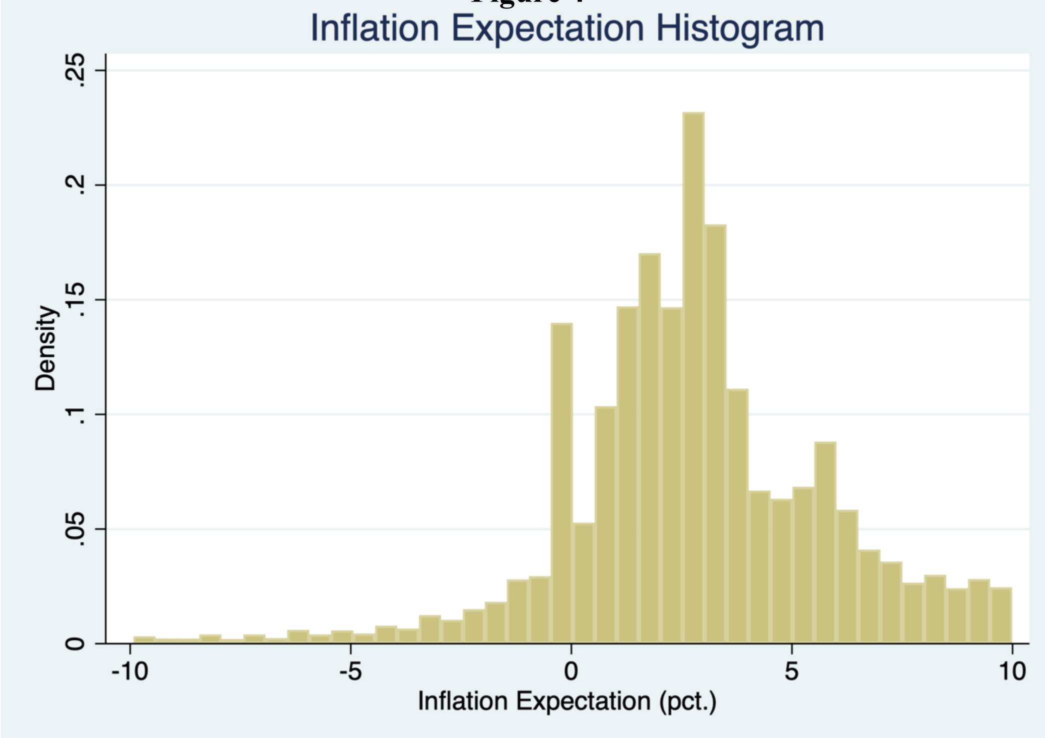



**Figure 5**

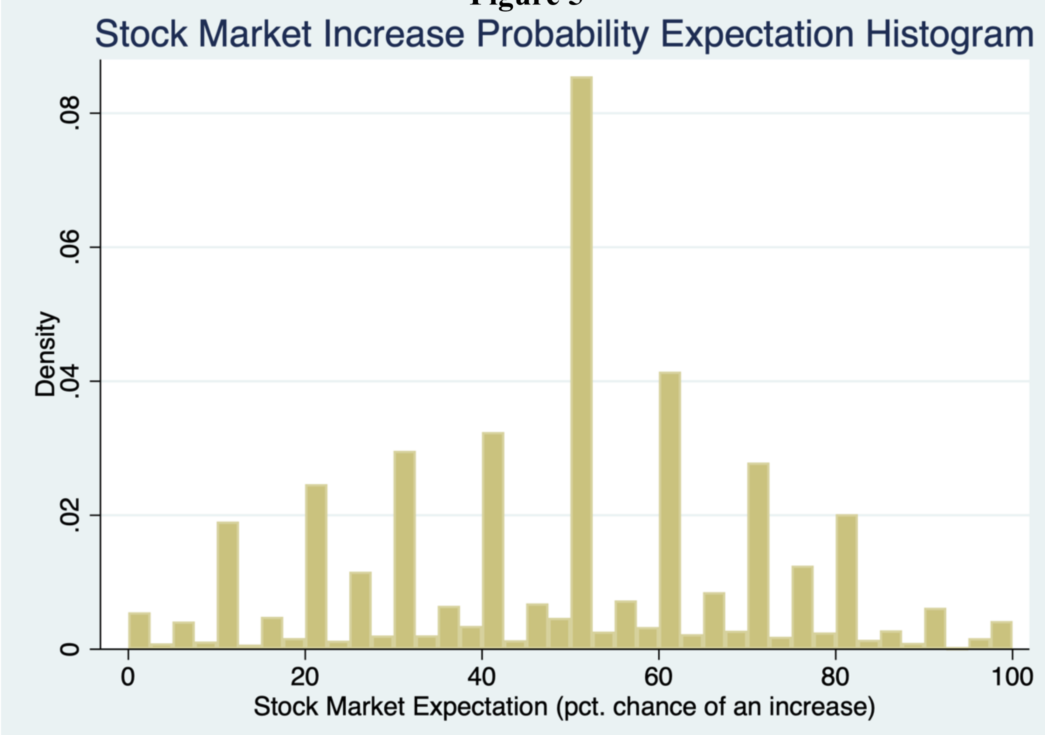


**Figure 6**

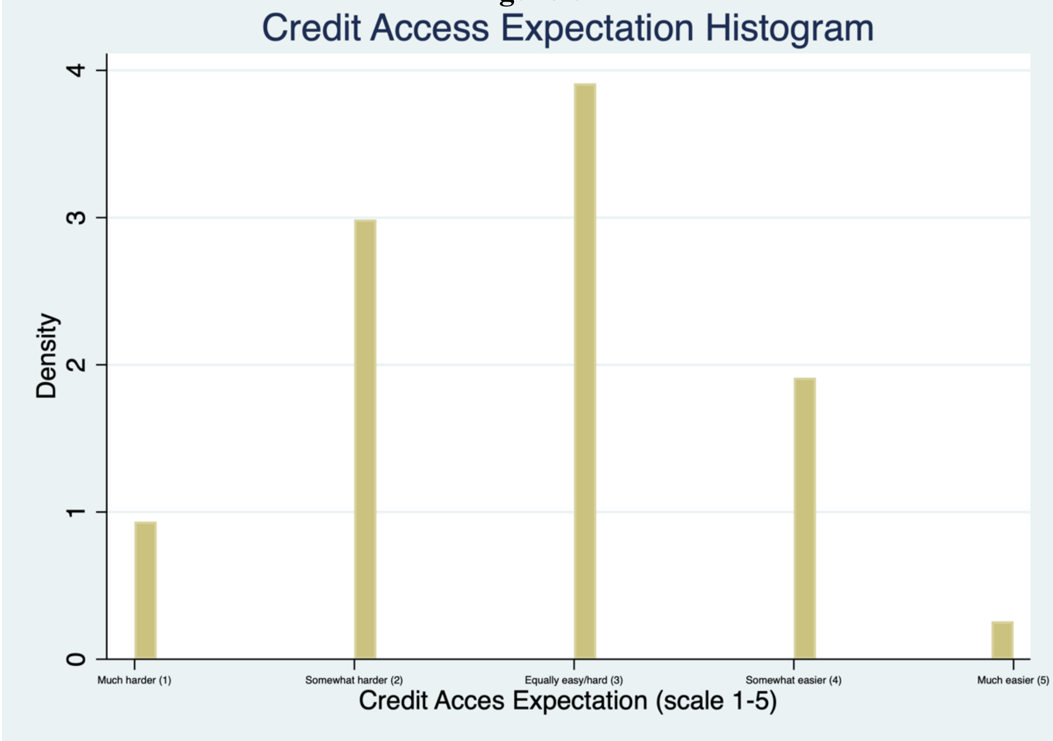



**Figure 7**

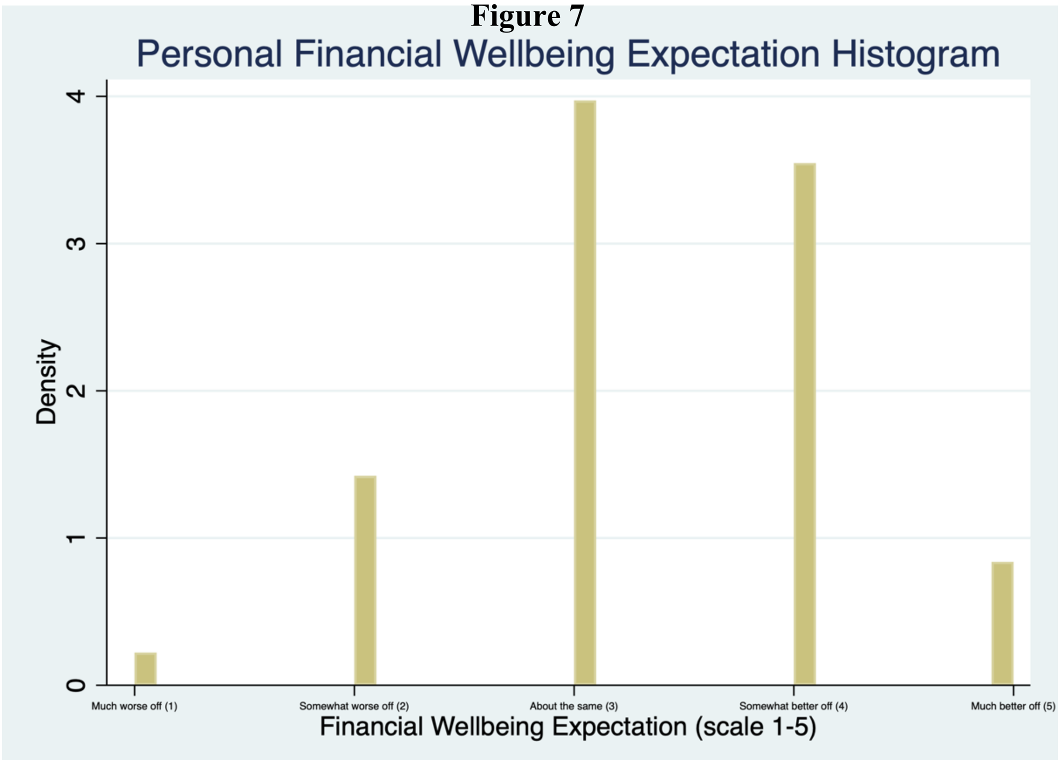


**Figure 8**

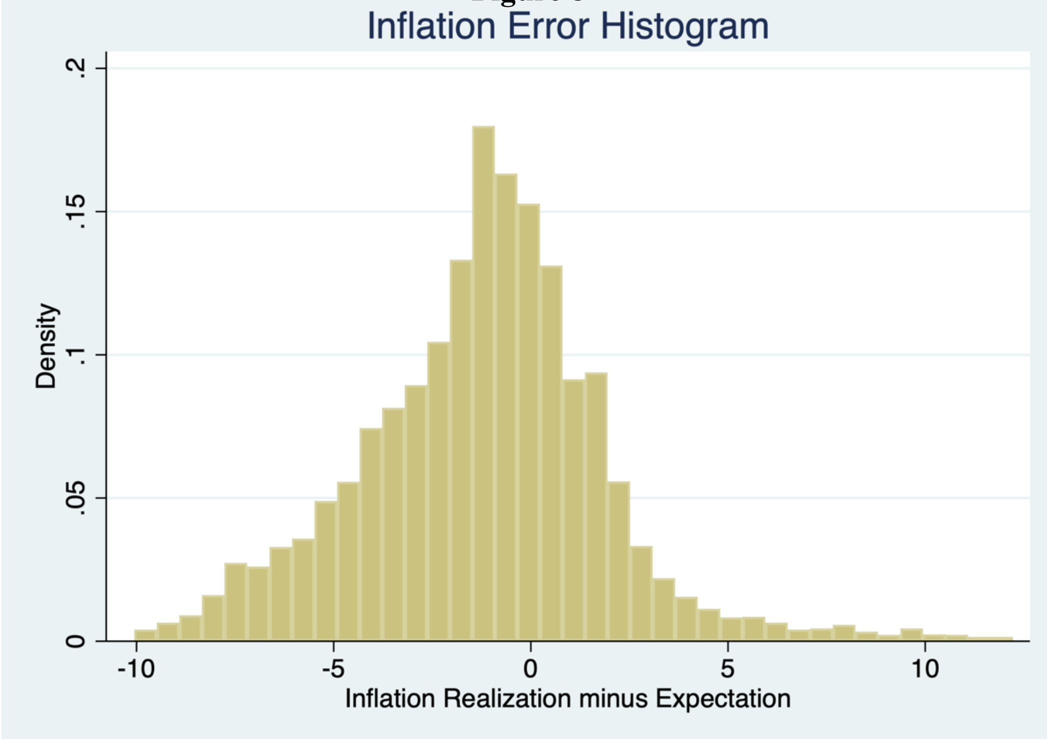



**Figure 9**

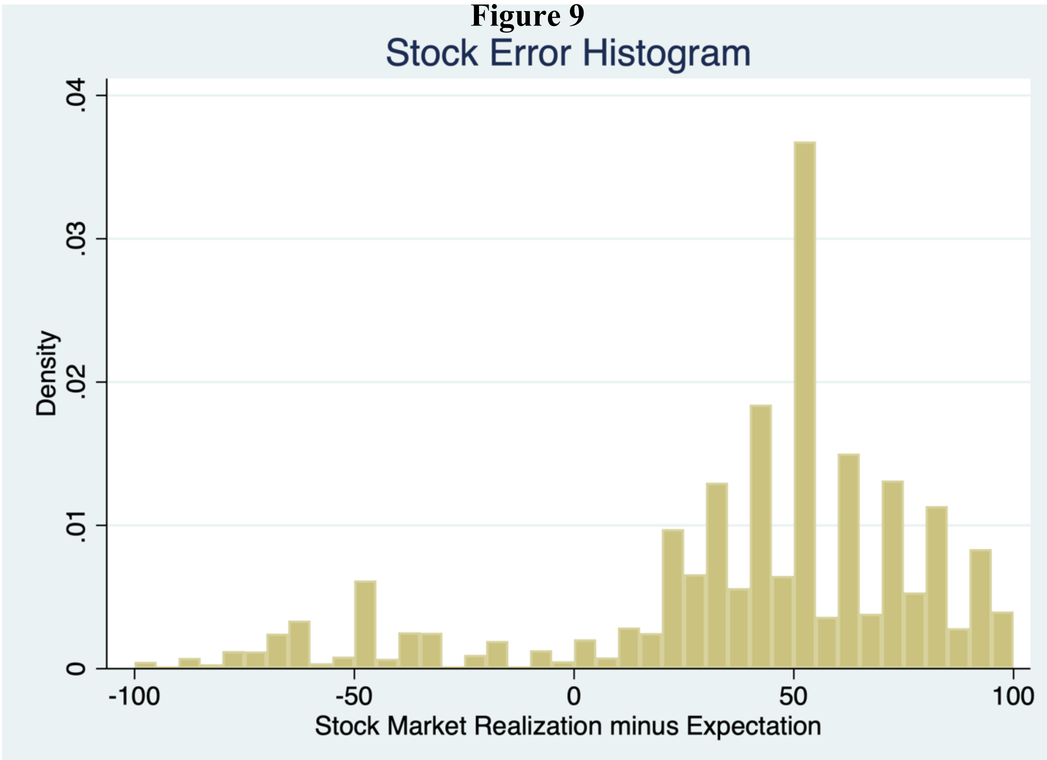


**Figure 10**

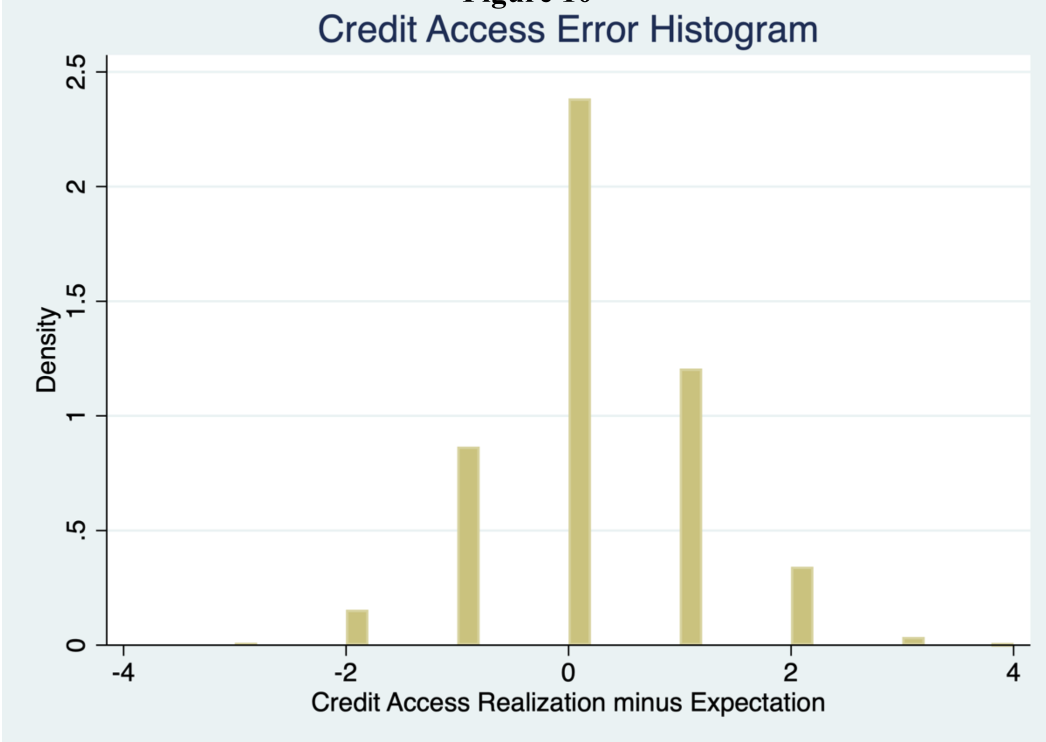
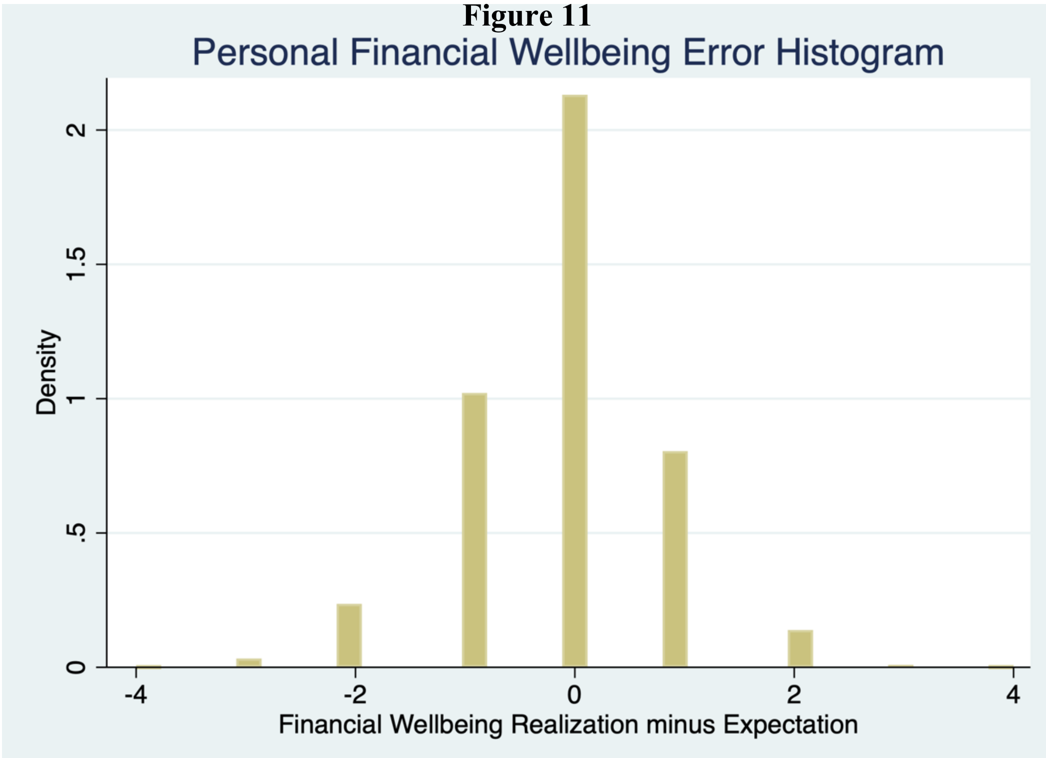



**Figure 11**



## <u>Appendix B1</u>: Further Descriptions of BLS and Robert Shiller Data

<u>Bureau of Labor Statistics Inflation Data:</u>[26]

The national-level inflation data that I use in my regressions was obtained from the U.S. Bureau of Labor Statistics. Specifically, each observation in the raw dataset represents the monthly level of the CPI for all urban consumers, which is the most-widely quoted CPI. This data is not seasonally adjusted, and it accounts for the time period from June 2013 until March 2019. From this raw data, I calculate the 12-month-forward and backward percent changes in CPI for each date when possible given lack of future data. The rationale behind these variable constructions is to ensure the existence of both a prior from which consumers can extrapolate as well as a realization to measure against the consumer's expectation.

Using national-level inflation data, in particular the widely cited urban consumer CPI[27], makes sense in the context of my regressions because the SCE itself specifically asks respondents about national inflation rather than say, "prices." Furthermore, as is noted above, the urban consumer CPI is the measure of inflation with which the highest number of American consumers are acquainted. As such, it potentially serves as a base for their future forecasts and represents a clear way to measure the accuracy of these forecasts.

[26] Available at: https://data.bls.gov/cgi-bin/surveymost
[27] https://www.bls.gov/cpi/questions-and-answers.htm#Question_15

Robert Shiller Online Data Library: [28]

From the Robert Shiller Online Data Library, I gather the historical performance of the S&P 500 Index. I extract observations of the closing index value of the S&P 500 for the first day of each month between the months of June 2013 and March 2019. I use the S&P 500 as a proxy variable to represent the "overall stock market" as it is posed in the SCE questionnaire. I then calculate the 12-month-forward and 12-month-prior performance for each date in my extracted dataset.[29] The 12-month-prior performance variable is used so that I can measure the extent of extrapolation for future stock market forecasts within the SCE. On the other hand, the 12-month-forward performance variable is used to represent the ultimate realization of stock prices so that I can estimate the error between realization and expectation.

[28] Available at: http://www.econ.yale.edu/~shiller/data.htm

[29] However, I do not have values of future return for observations that would require prediction of the future, nor do I have values of past return for observations prior to June 2013.

## Appendix C1: Robustness Discussion

The primary issues that expectations datasets often fall victim to include measurement error and small sample bias. However, in order to circumvent these two issues, I included dependent variables that were elicited utilizing different methodologies (e.g. forecast densities for inflation, binary-outcome probability estimates for stock market expectations, and qualitative estimates for personal financial wellbeing and credit access). The strength of my results across these various elicitation methodologies serves to mitigate the probability of a certain type of measurement error biasing all of my results.

With regard to small sample bias, the SCE is unique in the number of individuals surveyed. As per **Tables 1** and **2**, the SCE records thousands of unique and independent observations which are used in my regressions. Furthermore, the demographics outlined in **Table 1** illustrate that the sample is reasonably representative of the broader population.

A third potential source of bias stems from heterogeneity in forecasting revisions across individuals. That is to say, the way in which individuals record expectations could evolve as their tenure within the SCE increases. To avoid the complications associated with potential heterogeneity in forecasting evolution as a function of tenure, I only include the initial observation of each individual within my regressions.

Finally, in order to better isolate the extent of extrapolation and demographic expectation differences, my regression tables indicate the effects of different sets of controls. Furthermore, I want to note that various alternate controls including national GDP, national unemployment, national personal consumption expenditure, as well as commuting zone level employment and commuting zone level wage change were tested as regressors, yet none had notable explanatory power nor did any have significant impacts upon the other variables included in the final results.

In addition, various different fixed-effect models were tried including regional, monthly, and local fixed effects, yet none of these specifications had significant impacts upon the coefficients and were thus excluded from my main results.

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