Personal Experiences and Expectations about Aggregate Outcomes*

Theresa Kuchler† Basit Zafar‡

Abstract

We use novel survey data to document that individuals extrapolate from recent personal experiences when forming expectations about aggregate economic outcomes. Recent locally experienced house price movements affect expectations about future US house price changes, and higher experienced house price volatility causes respondents to report a wider distribution over expected US house price movements. Similarly, we exploit within-individual variation in employment status to show that individuals who personally experience unemployment become more pessimistic about future nationwide unemployment. The extent of extrapolation is unrelated to how informative personal experiences are; it is also inconsistent with risk-adjustment, and more pronounced for less sophisticated individuals.

*This version: November 20, 2017. We are grateful to Markus Brunnermeier, Suzanne Chang, Eduardo Davila, Xavier Gabaix, Ed Glaeser, Camelia Kuhnen, Ulrike Malmendier, Stefan Nagel, Alexi Savov, Johannes Stroebel, Michael Weber, an anonymous referee and seminar participants at the AEA 2016 Annual Meetings, New York University, National University of Singapore, London School of Economics, Baruch, Christmas Meeting of German Economists Abroad, Reserve Bank of India, Bank of Spain, Society of Economic Dynamics, and the LMU Munich Workshop on Natural Experiments and Controlled Field Studies for helpful suggestions. We thank Luis Armona, John Conlon, Michael Kubiske and Max Livingston for excellent research assistance. Any errors that remain are ours. The views expressed in this paper do not necessarily reflect those of the Federal Reserve Bank of New York or the Federal Reserve System as a whole.

†New York University, Stern School of Business, theresa.kuchler@nyu.stern.edu

‡Arizona State University, basitak@gmail.com

Expectations play a key role in economic models of decision-making under uncertainty. Recent work has explored empirical measures of expectations to inform the modeling of the expectation formation process (see Barberis et al., 2015; Fuster et al., 2010) and has documented the substantial effect that personal experiences have on expectations of aggregate economic outcomes (see, for instance, Malmendier and Nagel, 2011, 2016; Malmendier et al., 2017). However, little is known about what exactly represents the relevant set of "personal experiences". For instance, local house price movements can differ substantially across the US.[1] Do differences in such locally experienced house prices lead individuals to have different expectations about aggregate price changes despite witnessing the same past aggregate price movements? Similarly, unemployment rates rose during the financial crisis throughout the entire US. But does personally experiencing unemployment rather than simply witnessing times of high unemployment affect individuals' expectations about the aggregate unemployment rate? And does the answer depend on characteristics of the individuals?

In this paper, we address these questions to better understand how individuals form expectations. We focus on expectations about house price changes and unemployment, since there tend to be substantial differences between local or personal experiences and aggregate measures in both domains. Housing and labor markets therefore offer a rich empirical setting to analyze which type of personal experiences affect expectations and whether their effect varies by individual characteristics. In addition, both markets are of interest in and of themselves. House price expectations play an important role in understanding housing booms and busts (e.g., Piazzesi and Schneider, 2009; Goetzmann et al., 2012; Glaeser et al., 2013; Burnside et al., 2016; Glaeser and Nathanson, 2017; Case et al., 2012; Bailey et al., forthcoming), while employment expectations matter for the speed of economic recovery after recessions, and can influence households' job search behavior (see Carroll and Dunn, 1997; Tortorice, 2011; Hendren, 2015). Our results therefore help to understand how expectations about these two key aggregate outcomes are formed while also providing insight into the expectation formation process more generally.

We analyze data from the Survey of Consumer Expectations (SCE), a relatively new monthly online survey of approximately 1,200 US household heads, fielded by the Federal Reserve Bank of New York since 2012. The survey elicits consumer expectations about various economic outcomes, including house price changes and labor market outcomes, and

[1] For instance, in Arizona prices increased dramatically during the boom with annual increases of up to 30% in 2005, followed by deep drops in the subsequent bust of over 25% in 2008. During the same time, house prices in Indiana were quite stable with average changes of less than 1% per year.

collects rich data on respondents' personal backgrounds and economic situations. Two features of the survey are important for our purposes. First, the survey is a panel tracking the same individuals monthly for up to twelve months. Second, the data contain ZIP code information for the respondent, which allows us to exploit variation in locally experienced house prices to estimate the effect of past experience on expectations.

We use the entire history of locally experienced house price changes to measure each individual's personal experience,[2] and find that past locally experienced house prices significantly affect expectations about future changes in US house prices. For instance, respondents in ZIP codes with a 1 percentage point higher change in house prices in the previous year expect the year-ahead increase in US house prices to be 0.1 percentage points higher. We find that this extrapolation from local experiences increases the cross-sectional dispersion in expectations by nearly 9 percent. Consistent with Malmendier and Nagel (2016) in the case of inflation expectations, we also find that more recently experienced house price changes have a substantially stronger effect than earlier ones.

The SCE also elicits respondents' subjective distribution of future house price changes. We can therefore also investigate the impact of experiences on the second moment of house price expectations. We find that respondents who experience more volatile house prices locally report a wider distribution over expected future national house price movements: the standard deviation of year-ahead expected house price changes is 0.045 (0.27) percentage points higher for respondents who experienced a 1 percentage point higher standard deviation in ZIP (MSA) house price changes in the past 5 years.

Next, we turn to the effect of personal unemployment experiences on US unemployment expectations. This analysis leverages the rich panel component of the survey, something that is absent from most other consumer surveys of expectations.[3] The panel structure allows us to focus on individuals who experience job transitions during the period they are in the survey (for example, individuals who were previously employed and lose their jobs, or who were unemployed and find a new job), and to exploit this *within-individual* variation in personal

[2]Our ability to exploit within-cohort variation in experiences allows us to conduct additional analysis, such as estimating the horizon over which individuals' experiences matter, which the prior literature, due to data limitations, has been unable to do.

[3]Previous studies have mostly overlooked the panel dimension of survey expectations (see Keane and Runkle, 1990; Madeira and Zafar, 2015, for exceptions), and instead have studied the aggregate evolution of beliefs in repeated cross-sections. However, this complicates the interpretation of previous work on learning in expectation updating. This, again, is largely a result of data limitations: The Michigan Survey of Consumers - the main survey on consumer expectations in the US - has a very limited panel component, resurveying just a third of the respondents only once, six months after the first survey.

experiences to estimate their effect on expectations about the aggregate unemployment rate. We find that experiencing unemployment leads respondents to be significantly more pessimistic about future US unemployment: when transitioning to unemployment, respondents believe the likelihood of US unemployment increasing over the next twelve months to be 1.44 percentage points higher than when employed (relative to the average stated likelihood of 38 percent).[4]

We next explore the potential mechanisms that are consistent with the observed extrapolation from personal experiences to aggregate outcomes, and the resulting implications for understanding how individuals form expectations. First, the effect of personal experiences on expectations about aggregate outcomes suggests that respondents either do not know all relevant and publicly available information or do not use it optimally. All respondents in our sample are forming expectations about the same aggregate outcome, in our case the change in US house prices or nationwide unemployment. Therefore the optimal weighting of each piece of information should be the same for each respondent. This is not what we find.

In a second step, we therefore analyze whether respondents optimally rely on personal experiences because of otherwise limited information. In this case, respondents should rely more heavily on their personal information when it is more informative about the aggregate outcome. However, we find that how predictive local house price changes were of aggregate price changes in the past is not associated with differences in the extent of extrapolation from locally experienced house prices. Optimal usage of limited information therefore is unlikely to explain our results.

Third, we study which respondents are more likely to extrapolate from their experiences when forming expectations. We find that less sophisticated respondents (those with low numeracy skills or without a college degree) extrapolate more from local house price changes and personally experienced unemployment than more sophisticated respondents. We do not find evidence for differential extrapolation from experiences by age. We also do not find any difference in the extent of extrapolation between homeowners and renters, indicating that risk-adjustment is unlikely to drive our results.[5]

[4] It is worth pointing out that the stated expectations in our survey data are predictive of actual outcomes. We find that respondents' beliefs about their own labor market prospects are associated with actual subsequent outcomes: respondents who believe they are more likely to lose their job are indeed more likely to subsequently do so. In addition, expectations about future house price changes are related to whether respondents consider housing a good investment.

[5] The idea is that while past price increases are good for homeowners, they are bad for renters. Risk-adjustment by homeowners therefore should amplify any extrapolation from past experiences whereas it should dampen the effect for renters.

Taken together, what do our findings imply about the expectation formation process? The fact that extrapolation from own local or personal experiences is substantial, unrelated to the informativeness of the experiences, and stronger for less sophisticated individuals suggests that it is unlikely to be due to optimal use of even potentially limited information. Rather, our results suggest that respondents naively extrapolate from their own experiences when forming expectations. Our results are therefore broadly consistent with models of adaptive and extrapolative updating (as in Fuster et al., 2010; Greenwood and Shleifer, 2014).

To further understand the role of experiences in the expectation formation process, we explore whether extrapolation is domain specific or whether personal experiences in one domain - the housing market or unemployment - affect expectations about other aggregate economic outcomes, such as stock prices, interest rates, or inflation. We find no significant effect of locally experienced house price changes on expectations about any other aggregate outcome. Similarly, own unemployment has no significant effect on most of these other expectations. This indicates that respondents rely on their own experiences in a given domain when forming expectations about that particular domain, but that experiences in one domain do not affect expectations about other outcomes. This is not to say that expectations about one aggregate outcome are uncorrelated with expectations about other aggregate outcomes. In fact, we find substantial co-movement between expectations about other aggregate outcomes and expected house price changes or expected unemployment. However, this co-movement is not driven by own experiences in one domain but rather by other factors affecting expectations about both aggregate outcomes.

To evaluate the magnitude and direction of co-movement between expectations about different aggregate outcomes, we turn to the relationship between expected inflation, expected unemployment and expected interest rates. According to the "Taylor-rule" expected inflation should be positively related to expected future interest rates (Taylor, 1993). Expected unemployment, a measure of the output gap, should be negatively related to expected interest rates. We find that expected inflation negatively affects expected interest rates in the cross-section, but has no effect when including individual fixed effects. Expected unemployment is strongly positively related to expected interest rates, both in the cross-section and within-individual - the opposite of what the Taylor rule would suggest. This reinforces the notion that individuals do not appear to form expectations about economic aggregates in line with predictions from economic theory.

We see our paper as making two contributions. First, our findings contribute to a large literature that tries to understand how individuals form expectations about various outcomes. Several papers have previously documented that past experiences affect consumers' expectations of inflation and future returns in financial markets. Malmendier and Nagel (2016) find that individuals' inflation expectations are influenced by the inflation experienced during their lifetime.[6] Vissing-Jorgensen (2004) shows that young investors with little experience expected the highest stock returns during the stock market boom of the late 1990s,[7] and Amromin (2008) and Greenwood and Shleifer (2014) find that stock return expectations are highly correlated with past returns and the level of the stock market. Compared to this previous body of work, our setting enables us to exploit the substantial cross-sectional and individual variation in house prices and employment experiences. This allows us to expand on previous findings and provide a more nuanced view of what type of own experiences matter - the aggregate experiences during a person's lifetime versus local or personal experiences - and which individuals most rely on their own experiences. We also show that the level of own past experiences affects the expected level of future price changes and that own past experienced volatility affects the variance of the distribution of expected future price changes. To our knowledge, this extrapolation of both the first and second moment has not been documented in the literature before.[8] Our empirical approach to exploit geographic variation in locally experienced house prices in the cross-section is closely related to Bailey et al. (forthcoming) who show that locally experienced house prices of an individual's friends influence her expectations about local house price changes. Their findings are complementary to ours suggesting that, in addition to own locally experienced house price changes, those same experiences by friends affect expectations. In fact, Armona et al. (2016) show that the impact of own local experiences on attitudes towards housing seem

[6] While not studying expectations directly, several papers have shown how experiences affect subsequent investment decisions, possibly through expectations. For instance, Malmendier and Nagel (2011) show that bond and stock returns experienced during an individual's lifetime affect risk taking and investment decisions, and Knüpfer et al. (2016) show that labor market experiences during the Finnish Great Depression affect portfolio choices. Kaustia and Knüpfer (2008) and Chiang et al. (2011) find that the returns investors experience in IPOs affect their decisions to invest in subsequent IPOs. Similarly, Koudijs and Voth (2014) find that previous exposure to potential losses leads lenders to lend more conservatively.

[7] Consistent with such expectations, Greenwood and Nagel (2009) show that younger mutual fund managers invested more heavily in technology stocks during this time.

[8] Appendino (2013), using the Survey of Consumer Finances (SCF), finds that experienced stock market volatility is a strong predictor of the share of liquid assets invested in stocks. He argues that this is due to experienced volatility influencing investors' beliefs. This inference is, however, based on suggestive evidence since the SCF does not contain data on subjective beliefs. Likewise, Armona et al. (2016) show that both home price expectations and the subjective downside risk in expected home price changes explain behavior in a stylized housing-related portfolio allocation decision.

to be of a similar magnitude as that of friends' imputed experiences on housing attitudes. Bailey et al. (forthcoming) and Bailey et al. (2017) also show that, by affecting expectations, friend experiences directly affect investment behavior in the housing market, reinforcing the importance of understanding the expectation formation process.

Our second contribution is to the literature that tries to understand aggregate dynamics in the housing and labor market.[9] Overly optimistic beliefs are often cited as major contributors to the run up in house prices prior to the recent financial crisis (see, for instance, Piazzesi and Schneider, 2009; Goetzmann et al., 2012; Burnside et al., 2016; Case et al., 2012; Glaeser and Nathanson, 2017). Our findings of extrapolation from recent personal experiences provide a plausible foundation for such overly optimistic beliefs. High house price growth in the early 2000s could have led consumers to extrapolate based on their recent experiences, which would have led them to become overly optimistic. Similarly, our finding that individuals extrapolate from local house prices to US-wide house prices suggests an explanation for why out-of-town buyers, especially those from areas with higher past price appreciation, may be overly optimistic about home prices in other locations, as is argued by Chinco and Mayer (2016). As such, extrapolation from local experiences suggests one possible explanation for heterogenous beliefs about nationwide home price changes and disagreement between market participants of different backgrounds providing support to models in which expectation heterogeneity motivates individuals to trade and influences asset valuations (e.g., Harrison and Kreps, 1978; Hong and Stein, 1999, 2007; Geanakoplos, 2009; Scheinkman and Xiong, 2003; Simsek, 2013; Brunnermeier et al., 2014).

For unemployment, we can observe how the same individual changes her expectations as her labor market experiences change while in the sample. This individual-level variation in experiences – which, to our knowledge, has not been exploited in prior applications – allows us to filter out confounding factors that are likely to be especially important when studying the effect of own employment experiences. Our results suggest that during an economic downturn individuals who receive a bad labor market shock may become overly pessimistic about labor market conditions (see Tortorice, 2011). This may lead them to invest less in job search or accept less suitable positions, thereby prolonging the effect of the initial shock. Importantly, extrapolation from own employment experiences to aggregate employment conditions can also make individuals unaware of the vastly different employment prospects across the US,

[9] Woodford (2013) provides an overview of the implications for macro models when deviating from the assumption of rational expectations, and notes that "behavior ... will depend (except in the most trivial cases) on expectations".

preventing them from re-locating to areas with better employment prospects or re-entering the labor market after a local shock has subsided. Our results therefore point at expectations as a possible channel to explain the persistent effects of differences in local unemployment shocks long after the Great Recession, as shown by Yagan (2016).

The paper proceeds as follows. Section 1 describes our data and Section 2 the empirical strategy. Section 3 presents results on experiences and house price expectations, and Section 4 on experiences and unemployment expectations. Section 5 shows results by respondent characteristics. Section 6 explores the relationship between experiences and expectations about other outcomes, and Section 7 investigates the link between expectations and actual outcomes. The final section concludes.

1 Data

Our data are from the Survey of Consumer Expectations (SCE), a monthly survey fielded by the Federal Reserve Bank of New York since late 2012.[10] The SCE is an internet-based survey of a rotating panel of approximately 1,200 household heads.[11] Respondents participate in the panel for up to twelve months, with a roughly equal number rotating in and out of the panel each month. Each survey typically takes about fifteen to twenty minutes to complete and elicits consumer expectations on house price changes, inflation, labor market outcomes and several other economic indicators. When entering the survey, respondents answer additional background questions.

1.1 Expectations about Aggregate House Price Changes and Unemployment Rates

Each month, respondents answer a set of questions about expected US house price changes. First, respondents are asked whether they believe US home prices will increase or decrease over the next 12 months and by what amount. The numerical response to this question is the respondent's point estimate of the year-ahead change in home prices. Second, the survey elicits a distribution of expected house price changes over the same 12-month horizon.

[10] See Armantier et al. (Forthcoming) for additional information.

[11] The monthly survey is conducted over the internet by the Demand Institute, a non-profit organization jointly operated by The Conference Board and Nielsen. The sampling frame for the SCE is based on that used for The Conference Board's Consumer Confidence Survey (CCS). Respondents to the CCS, which itself is based on a representative national sample drawn from mailing addresses, are invited to join the SCE internet panel. The response rate for first-time invitees is around 55%.

Specifically, respondents are asked to assign a probability to a range of possible house price changes such that the total of all probabilities adds up to 100 percent. The range of possible house price changes starts with a decrease of more than 12 percent, then proceeds in steps of two to four percentage points: -12 to -8 percent, -8 to -4 percent, -4 to -2 percent and -2 to 0 percent, up until an increase of more than 12 percent. Appendix A.1 shows the exact phrasing of the question. Using the midpoint of these bins and the individual-specific probability assigned to each bin, we compute the standard deviation of the individuals' expected distribution. Finally, respondents are asked about their expectation for the one year change in house prices between two and three years ahead.

In addition, the SCE asks respondents how likely they think it is that national unemployment will be higher a year later. The wording of the questions is: "*What do you think is the percent chance that 12 months from now the unemployment rate in the U.S. will be higher than it is now?*" The response to this question is the focus of our analysis of unemployment expectations. Respondents are also asked about their current employment situation, based on which we classify respondents into five categories: employed (either full or part-time), searching for work (the unemployed), retired, student or out of the labor force (e.g., homemaker, permanently disabled). Depending on their current employment status, respondents answer additional questions about their personal employment prospects. Appendix A.2 shows the exact phrasing of these questions.

1.2 Past House Price Changes

We rely on the CoreLogic Home Price Index (HPI) to construct individual-level house price experiences. The CoreLogic HPI is a repeat sales index that tracks changes in sales prices for the same homes over time, which provides a more accurate constant-quality view of pricing trends than basing analysis on all home sales. Crucially, for our purposes, the index is geographically comprehensive, with separate series at the ZIP code, metropolitan statistical area (MSA), and state level. The data set goes back to 1976 allowing us to construct individual-level house price experiences at various local levels and over long horizons. Since the index relies on repeat sales, less-populated ZIP codes are less likely to be covered, but data is available for ZIP codes covering 59% of the US population. Our analysis will use the index at all three levels, ZIP code, MSA, and state, with universal coverage at the state level. Throughout the paper, we use year-over-year changes in each month.

1.3 Sample Description and Summary Statistics

Our sample contains all respondents who answer the questions about expected house price changes and expected unemployment changes, for whom we have basic demographic information and who are at least 25 years old. Our sample period spans from December 2012 till April 2017. The final sample contains 8,104 respondents. For all cross-sectional analyses, we focus on the most recent observation for each respondent, but all results are robust to choosing different observations. Table 1 shows summary statistics of our sample. Respondents in our sample are on average 51 years old, 85% are white and 9% black. 68% of respondents are married and 54% are men. 55% went to college and the average yearly household income is $81,000. Our sample has respondents with higher income and higher educational attainment than the US household population overall. While our main analysis does not use weights, the weighted results for the overall sample are qualitatively similar. In addition to basic demographic information, respondents were asked a series of five or six questions based on Lipkus et al. (2001) and Lusardi (2009), that provides an individual-specific measure of numeracy. Respondents, on average, answer 80% of the questions correctly and at least a quarter answer all of them correctly. Three-quarters of the respondents own their home. On average, respondents have lived in their current ZIP code for 12 years and in their current state for 35 years. However, there is substantial heterogeneity in our sample, with a quarter of respondents having moved to their current ZIP code within the past three years.

On average, respondents expect house prices to rise by 5.5% in the coming year. Figure 1 shows the distribution of all expected house price changes. Respondents give a wide variety of answers around the mean point estimate, though 5% is the most common answer. Calculating the standard deviation of expected house price changes from the probabilities assigned to each possible range of house price changes, yields an average expected standard deviation of 2.75 percent.

Table 1 also shows that past house prices in the respondents' ZIP codes, MSAs and states vary substantially. Prices have increased by 6% on average in the past year, though by only 2.5% for respondents in the 25$^{\text{th}}$ percentile and almost 9% for respondents in the 75$^{\text{th}}$ percentile.[12] Data on past house price changes is available for 6,032 of the 8,104 respondents at the zip code level, but for everyone at the state level.

Table 2 shows each respondent's current and previous employment status in each monthly module. Respondents answer on average 7 survey modules for a total number of 56,413

[12] Appendix Table A1 shows additional summary statistics of the history and variability of past house price changes over different time horizons, confirming the substantial heterogeneity.

respondent-month observations. 68.3% of respondents are employed when answering the survey, 4.2% are currently looking for work. The remaining respondents are either students, retired, or out of the labor force for other reasons. While in the panel, a substantial number of respondents experience changes in their employment status. Of special interest to us are the 271 instances in which respondents lose their previous employment and the 323 instances where respondents find a new job out of unemployment, since we can exploit these within-individual changes in employment experiences to estimate their effect on expectations.

2 Understanding the Effect of Experiences on Expectations

2.1 Estimating the Effect of Experiences on Expectations

To analyze the effect of personal experiences on an individual's expectation about aggregate outcomes, we estimate the following regression equation:

$$expectation_{it}^{d} = \alpha + \beta experience_{it}^{d} + \delta X_{it} + \gamma I_t + \epsilon_{it}, \tag{1}$$

where $expectation_{it}^{d}$ is respondent i's expectation about aggregate outcome d reported at time t and $experience_{it}^{d}$ is an individual's experience related to outcome d. X_{it} are individual-specific control variables, such as demographics, and I_t are time fixed effects which absorb the effect of any variable that does not vary by individual, such as the values of other aggregate outcomes. β is the parameter of interest.

To estimate the effect of experience on expectations about house prices, we estimate Equation 1 where $expectation_{it}^{d}$ is either the expected year-ahead or the expected two-year-ahead change in US house prices, as stated by respondent i at time t. We proxy for experienced house prices, $experience_{it}^{d}$, with the past local house price changes where the respondent currently lives. We discuss the different functional form assumptions we make to capture past experiences below. Throughout, we use year-on-year changes in home prices to filter out seasonal effects.

To estimate the effect of own unemployment experience on unemployment expectations, we estimate Equation 1 where $expectation_{it}^{d}$ is the percentage chance that US unemployment will be higher a year later, as stated by respondent i in month t and $experience_{it}^{d}$ is the individual's own employment status in month t.

2.2 Interpreting the Effect of Experiences on Expectations

What does the estimated coefficient β on past experiences tell us about expectation formation? To outline what we can learn from our results, here we lay out basic assumptions about the data generating process and individuals' expectation formation and describe the implications.

2.2.1 Data generating process

Aggregate outcome A_t is a weighted average of individual or local outcomes, L_t, with the weights of each location or individual, constant over time, i.e.,

$$A_t = \sum_l w_l L_{t,l}.$$

For instance, aggregate house price changes are a weighted average of local house price changes and aggregate unemployment rates are a weighted average of individual employment status indicators.

We assume that next period's value of aggregate outcome A, depends on its own past values in the last S periods, other currently known information G_t and a random error term, η_{t+1}, and that each term enters additively. Hence, A_{t+1} can be expressed as follows

$$\begin{aligned} A_{t+1} &= \sum_{s=0}^{S} b_s A_{t-s} + \gamma G_t + \eta_{t+1} \\ &= \sum_{s=0}^{S} b_s \sum_l w_l L_{t-s,l} + \gamma G_t + \eta_{t+1} \end{aligned}$$

2.2.2 Full Information

First, we assess whether respondents weigh own experiences correctly by assuming that they know past realizations of aggregate outcome A, as captured by the following null hypothesis:

Hypothesis 2.1. *Individuals know all relevant public information and weigh all information correctly, including their own.*

Assume individual i's expectation about next period's aggregate outcome A_{t+1} at time t

is:

$$E[A_{t+1}|t,i] = \sum_{s=0}^{S} \hat{b}_s \sum_{l} \hat{w}_l L_{t-s,l} + \hat{\gamma} G_t + f(\mathbf{X_i}).$$

That is, individuals believe the weights on each past observation, b_s, to be $\hat{b}_s$ and the weight on each location, w_l to be $\hat{w}_l$. $f(\mathbf{X_i})$ captures the effect of individual characteristics. Under the null hypothesis that individuals know all relevant public information and weigh it correctly, that is $\hat{b}_s = b_s$ and $\hat{w}_l = w_l$ for all l. The individual's expectation can than be written as:

$$\begin{aligned} E[A_{t+1}|t,i] &= \sum_{l} \sum_{s=0}^{S} b_s w_l L_{t-s,l} + (\hat{w}_i - w_i) \sum_{s=0}^{S} b_s L_{t-s,i} + \gamma G_t + f(\mathbf{X_i}) \\ &= \sum_{l} \sum_{s=0}^{S} b_s w_l L_{t-s,l} + w_{miss} \sum_{s=0}^{S} b_s L_{t-s,i} + \gamma G_t + f(\mathbf{X_i}), \end{aligned}$$

where $L_{t-s,i}$ is the outcome in i's status or location in year $t-s$. Under the null hypothesis, $\sum_l \sum_{s=0}^{S} b_s w_l L_{t-s,l} + \gamma G_t$ does not vary in the cross-section and is absorbed by the time fixed effect in equation (1). The coefficient on individual i's experience, $w_{miss} = \hat{w}_i - w_i$, should be zero. This is true irrespective of the weights b_s on past experiences. Hence, we can test the null hypothesis without making any assumptions on the true data generating process (beyond additivity). No matter how we weigh past experiences, a non-zero coefficient indicates that individuals either do not know all relevant public information or do not weigh it correctly.

2.2.3 Limited Information

Rather than assuming full information, we also want to know whether individuals' limited information about other variables leads them to rely on their personal experiences. That is, whether the use of own experiences appears to be optimal given limited information about other outcomes.

Let the following be the actual best predictor of aggregate outcome A_{t+1} using only own or local experiences, L_i:

$$E^*[A_{t+1}|t,i] = v_{own,i} \sum_{s=0}^{S} d_s L_{t-s,i} + \delta G_t.$$

Note that the optimal weight, $v_{own,i}$ on own experiences, as well as the weight on each past observation, d_s, likely differs from the corresponding optimal weight when other information is also available. Respondents believe the best predictor to be:

$$E[A_{t+1}|t,i] = \hat{v}_{own,i} \sum_{s=0}^{S} \hat{d}_s L_{t-s,i} + \delta G_t.$$

We want to know whether respondents use their own experiences optimally, given their knowledge. That is whether $\hat{v}_{own,i} = v_{own,i}$, as outlined by the following null hypothesis:

Hypothesis 2.2. *Given limited information about other variables, individuals weigh their own experiences optimally.*

To assess this hypothesis we need to estimate the weights individuals put on their own experiences, $\hat{v}_{own,i}$, and compare them to their true informativeness in the data, $v_{own,i}$. To do this, however, we need to make assumptions about what respondents believe about the data generating process and, hence, the weighting of past data, $\hat{d}_s$. We can then construct $\sum_{s=0}^{S} \hat{d}_s L_{t-s,i}$ and estimate $\hat{v}_{own,i}$.

We choose two approaches: First, we assume that only the most recent experiences matter, i.e., $\hat{d}_s = d_s = 1$ for $s = 0$ and $\hat{d}_s = 0$ for all $s > 0$. We can apply this approach to both our settings, house prices and unemployment. We measure own employment experiences by an individual's employment status, which we only observe for the months that individuals are in our sample. Since there is almost no variation in the history of an individual's employment status, we cannot estimate differential weighting parameters on past experiences. This is not the case for past local house prices, so we use a second approach for past house price experiences. Specifically, following Malmendier and Nagel (2011), we assume exponential weighting of past experiences and estimate the weighting parameter and the time horizon over which past experiences matter from the data. Section 3.3 describes our approach in detail and illustrates the application to the housing market. This approach is quite flexible and allows for a variety of assumptions that individuals may have about the underlying data generating process. As shown by Malmendier and Nagel (2016) it is approximately equivalent to a constant gain learning process. Such a constant gain learning process results, for instance, when agents estimate the model parameters of an AR(1) process recursively from past data. A constant gain learning process can also capture that individuals may optimally put more weight on recent observations because they do not know the entire past history (limited memory), believe in structural changes or consider recent experiences more informative for other reasons.

Given our two approaches for how individuals may weigh past data, we estimate the effect of past experiences, $\sum_{s=0}^{S} \hat{d}_s L_{t-s,i}$, on expectations about aggregate outcomes,$E[A_{t+1}|t,i]$. That is, we estimate $\hat{v}_{own,i}$.

We then estimate the equivalent in the data. That is we regress previous realized outcomes, $A_{t+1}[t,i]$, on past local experiences, $\sum_{s=0}^{S} \hat{d}_s L_{t-s,i}$, to get an estimate of $v_{own,i}$. Under the null hypothesis that individuals optimally use their own experiences because of limited information, the weight assigned to such a signal – own experiences in this case – depends on its informativeness. That implies that extrapolation from local experiences, captured by $\hat{v}_{own,i}$, should be greater in areas where these experiences are more informative about national aggregates, as captured by larger estimates of $v_{own,i}$. Whether this is the case in our results then allows us to evaluate whether optimal use of limited information can explain our findings or whether other explanations are needed.

3 Experiences and US House Price Expectations

We start with the relationship between house price expectations and locally experienced house price changes over the past year. We then construct a measure of experiences that captures the total effect of house price dynamics over many years.

3.1 Prior Year Local Experiences and US House Price Expectations

Figure 2 provides a first look at the relationship between locally experienced house price changes and expectations about aggregate house price changes. Panel A sorts respondents into deciles based on the change in local house prices in the prior year. On average, respondents in ZIP codes with higher price changes over the past year expect year-ahead US house prices to increase more. Similarly, panel B shows that respondents in states with higher increases in house prices in the prior year on average expect US house prices to be higher in the coming year. These graphs suggest that respondents are influenced by local house price experiences when reporting expectations about nationwide home prices.

In Table 3 we formalize this analysis. We estimate the effect of the previous year's house price change in the respondent's ZIP code (column 1), MSA (column 2), and state (column 3) on her expected year-ahead house price changes, as well as the expected year-ahead house price change in two years, i.e., the change in home prices between two and three years after the respondent takes the survey.[13] The estimates confirm that past local experience significantly affect expectations about US house prices both in the coming year, as well as further in the future. The effect is of similar magnitude irrespective of whether ZIP code, MSA, or state level house prices are used: a one percentage point increase in past local house prices increases expected house price changes by between 0.1 and 0.2 percentage points.[14] Weighting our estimates so that the sample is representative of the US population yields similar conclusions and if anything larger estimates. This is due to the fact that less sophisticated respondents are underrepresented in our sample but rely more strongly on own experiences, as we show below.[15]

While house prices vary substantially in the cross-section they vary much less from month to month. In addition, they are measured more noisily, attenuating any estimates. Nevertheless, in unreported regressions, we estimate the equivalent of equation (1) in the full panel with individual fixed effects. The effect of past experiences is therefore captured by how individuals adjust their expectations from month to month as local house prices change. We do not find significant effects on the year-ahead house price changes. For the two-year-ahead house price changes we find a statistically significant effect of month-to-month changes when using ZIP code level house prices.

As outlined in section 2.2.2, the fact that we find a significant effect of local experiences

[13] In January 2014, the survey question was *"Now we would like you to think about home prices further into the future. Over the 12-month period between January 2016 and January 2017, what do you expect will happen to the average home price nationwide?"*

[14] The fit of our model, as measured by the R^2 is in line with other papers trying to understand the determinants of individual level expectations, such as Das et al. (2017), Malmendier et al. (2017) or Armona et al. (2016).

[15] Table A2 in the appendix shows estimates of the effect of zip, MSA and state level home prices on expectation for the sample of respondents for which all three are available. The estimates are very similar in magnitude to the ones for the respective full samples in Table 3. The table also includes all three measures of local house prices simultaneously. State level house prices have the biggest and only significant effect for year-ahead house price changes. For two-year-ahead house price change expectations, ZIP code and state level house price changes both have significant effects.

at all indicates that we can reject the null hypothesis that respondents know all relevant information and use it correctly. In addition, the effect of past local house prices is of very similar magnitude irrespective of whether respondents are asked about US house prices in the coming year or two years ahead. The actual predictiveness of past house prices, however, varies substantially by horizon: Because of momentum and a certain degree of co-movement across US localities, past local house prices are somewhat predictive of year-ahead US house prices. However, house prices display medium-term reversal and past year's local house prices are virtually unrelated to US house price movements between two and three years in the future.[16] Respondents, however, appear to extrapolate from local to aggregate prices in similar ways in both the short and medium term horizons irrespective of their actual informativeness. This indicates that local experiences are likely not being used in a way that is consistent with their true informativeness.

Relying on locally experienced house prices when forming expectations about the aggregate increases the dispersion in expectations across individuals. To quantify this effect, we compare the variation in expectations predicted by our model to the variation predicted by a model in which local house prices do not affect aggregate expectations but aggregate information and individual characteristics still do. Using our zip code level estimates, we find that relying on locally experienced house prices increases the dispersion in expectations by 8.8%.[17]

3.2 Informativeness of Local Experiences

In this section, we assess whether reliance on locally experienced house price changes depends on their true informativeness in the data. As pointed out in section 2.2.3, whether this is the case allows us to see whether respondents optimally rely on local information because of otherwise limited knowledge. We capture the informativeness of local house price changes by the equivalent of regression equation (1) in the actual data: we regress national house price changes on prior year local house price changes. The regression coefficient captures the best point estimate of the relationship between past local and US house price changes,

[16] For the localities of our survey respondents, a regression of national house price changes on prior year house price changes yields a coefficient estimate for prior year house price changes that ranges from .35 (for ZIP code level house prices) to .46 (for state level house prices). The coefficient on house price changes 3 years prior is essentially zero.

[17] Based on the results in column 1 of Table 3, we construct predicted values of the model and compute the standard deviation of expected aggregate house price changes. We then set the coefficient on local experiences to zero and again construct predicted values and the standard deviation. Estimates are slightly larger using our MSA or state level results.

or how much they move with each other. The R^2 of the regression captures the goodness of fit or what fraction of US house prices can be explained by variation in local house prices.[18] We then divide locations into terciles based on the magnitude of the regression coefficients.

Table 4 shows that there is no differential effect of past local prices on year-ahead expectations by the magnitude of the true effect of past local prices on national house prices.[19] This is despite the fact that the average coefficient on past price changes for actual national price changes in the data is 0.56 in ZIP codes in the highest tercile, more than twice that in the lowest tercile (with the difference being highly statistically significant). If anything, the point estimate of the effect of past local price changes on expectations is largest in areas with medium predictiveness in the data when using ZIP or state level prices and in the least predictive states when using MSA level house prices.

Next, we split our sample along two dimensions: as in Table 4, by the magnitude of the coefficient on local house prices but also by the fit of the regression, captured by the correlation between local and national house prices (or the R^2 of the regression). Figure 3 shows the estimated effect of past local house prices on national house price expectation. Again, we find no systematic differences by either dimension.[20]

As outlined in section 2.2.3, when individuals optimally rely on their local experiences because of otherwise limited information, the extent of extrapolation from these local experiences should be greater when they are more informative. Our finding that the extent of extrapolation does not depend on measures of informativeness is therefore inconsistent with the optimal use of limited information.

[18]Note that in the basic regression of national house price changes on prior year local house price changes, the R^2 of the regression equals the correlation between the two variables.

[19]All results are very similar when using the expected one-year house price change in two years, instead of the expected house price change in the coming year.

[20]We also estimate the coefficient between local and national home price changes over the past 10, 15 and 20 years instead of over the whole sample period since 1976 as in the baseline. The magnitude of the effect of past local prices and their informativeness in the data are similar irrespective of the horizon used. Appendix Figure A1 shows that the exact estimates for the specification reported in Table 4 vary when using different time horizons, but that the qualitative results remain very much the same. A t-test confirms no statistically different effect between areas with low and high predictiveness in the real data, even for MSA estimates for which the point estimates show the largest difference between the two groups.

3.3 History of Local House Prices and US House Price Expectations

So far, we have measured respondents' experience of past house prices by the house price change in the previous year only. However, respondents' experience of local house prices may also be shaped by house price dynamics in earlier years. In this section we construct each respondent's experience as a weighted average of past house price changes. This allows us to estimate which earlier experiences matter and how earlier experiences factor into the expectation formation process.

Weighted Average of Past House Price changes as an Experience Measure As noted in section 2.2.3, we follow the approach of Malmendier and Nagel (2011) to capture the history of past prices flexibly in one experience variable. Each person's house price experience is calculated as the weighted average of past local house price changes. The weights are determined by the parameter λ which allows the weights to increase, decrease or be constant over time. Specifically, respondent i's house price experience in year t is measured by H_{it}, calculated as follows:

$$H_{it} = \sum_{s=0}^{S_i - 1} d_{i,s}(\lambda) L_{t-s,i}, \tag{2}$$

where

$$d_{i,s}(\lambda) = \frac{(S_i - s)^{\lambda}}{\sum_{s=0}^{S_i-1} (S_i - s)^{\lambda}}. \tag{3}$$

As before, $L_{t-s,i}$ is the change in local house prices in year $t-s$ in respondent i's location. The weights depend on the experience horizon of the individual (S_i), how long ago the home price change was realized (s), and the weighting parameter λ. Note that in the case where $\lambda = 0$, H_{it} is a simple average of past changes in home prices over the experience horizon. If $\lambda > 0$ ($\lambda < 0$), the weighting function gives more (less) weight to recently experienced house price changes. We estimate λ later in the paper. Finally, we need to determine when respondents start to experience local house prices, captured by the experience horizon, S_i. Our ZIP code level house price data are available only since 1976, so this is the earliest year we can start measuring respondents' house price experiences. We consider two types of experience horizons. First, we consider a fixed number of past years, such as the past 3 or 5 years, and assume that respondents experience and recall past house prices over this time horizon. Second, we consider different *individual-specific* horizons (after 1976) for when a respondent starts experiencing local house prices: the year or year before she moves to her current ZIP code, the year she moves to her current state of residence, the year she turns 13, or her year of birth. Each of these horizons makes different assumptions about when and how respondents perceive local house prices. We show results for all of these possible horizons and let the estimates inform us about which one yields the best fit in our data.

Figure 4 illustrates how the geographic variation in house prices translates into the weighted experience variable depending on the weighting parameter λ. Panel A shows yearly changes in house prices in three states with different house price dynamics: Arizona experienced high increases in house prices in the early 2000s and a large decline after the onset of the financial crisis in 2008. New York experienced large increases in house prices in the 1980s. Prices also increased in the early 2000s and declined afterwards, though both the increase and subsequent decline of house prices were substantially smaller than in Arizona. House prices in Indiana have been relatively stable over the last decade.

As a result, the weighted house price experience in Indiana, reported in Panel D, is very similar for respondents of all experience horizons (irrespective of whether recent or earlier experiences are weighted more). In Arizona and New York, however, weighted experience varies substantially with experience horizon and the weighting parameter λ. Respondents with a 5 or 10 year experience horizon who heavily overweight recent experiences (that is, $\lambda > 1$) tend to have large positive weighted home price experiences, since home price increases in the recovery after the crisis receive more weight. Weighted home price experiences also increase as early experiences are overweighted (that is, $\lambda < 0$) since for respondents with 10-year horizon experiences, these overweight the run-up in prices in the early 2000s. In New York, unlike in Arizona, respondents with a 30 year horizon also have high weighted house price experiences when early experiences receive higher weights since these capture the 1980s when New York experienced large increases in house prices.

History of Past House Prices and Expectations We consider values of the weighting parameter λ ranging from -2 to 20 in intervals of .1. For each λ on this grid, we calculate the weighted average of past house price changes and use it as our measure of past experiences to estimate Equation 1. We then compare the R^2 of these regressions to determine which values of λ and experience horizon S_i yield the best fit for our data.

Figure 5 plots the fit of the regression, measured by the R^2, along the range of weighting parameters λ for each considered experience horizon. Local experience is captured by ZIP code level house prices. The top panel shows the results for horizons of a fixed number of years for each individual ranging from the last two years to the start of our data series in 1976. For comparison, the straight horizontal, solid line also shows the fit of the regression when using only the previous year's house price change. Panel B shows results for horizons which depend on each individual's personal situation: the time the respondent has lived in her current ZIP code, her current state, the time since the respondent was 13 years old, and the time since her birth.

The overall best fit is achieved when experience is measured by a weighted average of house price changes over the past four years. Including earlier house price changes in addition to only the most recent year's house price change therefore improves the fit of the regression. Relatively short horizons of a few years yield a better fit compared to longer horizons, and using individual-specific horizons does not improve fit. Even for respondents who have lived longer in their current ZIP code or state, the most recent years appear to matter most for forming expectations.

For each fixed year horizon considered, Table 5 lists the highest R^2 and the associated weighting parameter λ, the coefficient on the weighted average of past experiences, its standard error and the effect of a one standard deviation increase in the experience variable. While the overall best fit is achieved by a four year fixed horizon, weighted past experiences have a significant effect on expectations for all horizons and the estimated effect is similar in magnitude: a one standard deviation increase in the experience variable increases expectations by .63 to .67 percentage points for fixed year horizons.

For each specification, Figure 6 illustrates the weights on each year's house price return implied by best-fit values of λ as shown in Table 5. The best-fit weighting parameter λ is higher the longer the horizon over which experiences are calculated, as shown in Table 5. However, the weight assigned to each year's house price by the optimal weighting parameter λ is very similar. Only house price changes in the previous three years receive substantial weight, whereas changes in earlier years receive very low weights. As the horizon increases and earlier years are included, the optimal weighting parameter λ increases such that the effective weights assigned to each year's house price are very similar. Therefore, no matter the length of the horizon, at the optimal weighting parameter only house price changes in the most recent years affect expectations. For longer horizons, the estimates of λ are much higher than in Malmendier and Nagel (2011), suggesting that in the case of housing, individuals put substantially more weight on very recent realizations. Appendix B replicates the analysis of this section using state and MSA level house price changes instead of ZIP code level changes. The results are very similar. Specifically, the optimal weighting parameters and estimated effects obtained for each horizon are qualitatively similar to the ones presented in Table 5.

Table 6 shows the equivalent to the analysis in Table 4 but with the history of past house prices rather than just the previous year's house price change as a measure of experiences. For each horizon we use the optimal value of the weighting parameter λ as shown in Table 5 and split respondents by how much this measure moves with US house price changes in the data. Again, we find that the effect of local house price experiences on expected US house price changes does not vary with how aligned these experiences are with US house price changes in the actual data. This confirms that the extrapolation from local experiences we observe is inconsistent with optimal use of limited information.

3.4 Volatility of Prior Year Local Experiences

So far, we have focused on the effect of the *level* of experienced house price changes on the *level* of expected future house prices changes. We next analyze whether the effect of past experiences on expectations extends to the second moment: we estimate whether respondents who have experienced more volatile house price changes locally, report a distribution of expected year-ahead US house price changes with a higher standard deviation relative to respondents who live in areas with more stable house price changes in the past. Table 7 presents the results. We measure experienced volatility by the standard deviation of house price changes in the respondent's ZIP code (column 1), MSA (column 2) and state (column 3). The standard deviation of past house price changes is calculated over different horizons: the past 5, 10 and 20 years, as well as since the beginning of our CoreLogic data on local house prices in 1976.[21] For each horizon and house price measure, the various cells in Table 7 present the estimated coefficient and corresponding standard error on locally experienced volatility. In all specifications we include deciles of the previous year's change in house prices to control for different levels of house prices changes, as well as respondent demographics and survey date fixed effects.[22]

Table 7 shows that respondents in areas which experienced more volatile house price changes report a wider distribution of expected year-ahead house prices. A one percentage

[21] When analyzing the effect of past price changes, we computed weighted averages of all past house price changes. We choose not to follow this approach here, because we can only calculate the standard deviation over at most a handful of non-overlapping horizons in our data and the analysis would be very sensitive to the number and length of non-overlapping horizons chosen.

[22] The standard deviation of past house price changes is positively correlated with the level of expected house price changes but the effect becomes statistically insignificant once we include richer controls for the history of past price changes.

point increase in the experienced standard deviation in the respondent's ZIP code increases the expected standard deviation by 0.03 to 0.045 percentage points. Taking into account the extent of variation in past experiences, a one standard deviation increase in the standard deviation of experienced house price changes in the last 10 years (3.82 according to Appendix Table A1) increases the standard deviation of expected house price changes by 0.11 percentage points (3.82*.0291 = .11). The estimated effects are much larger in magnitude when using MSA level measures: a corresponding change results in a 0.49 percentage point increase in the standard deviation of expected home price changes. Using state-level house price measures yields smaller estimates which are often not statistically significant.

Our results indicate that respondents not only rely on the levels of past house price changes, but also their volatility when forming expectations about US house price changes.

3.5 Robustness - Distinguishing Local and National House Prices and Recall of Past House Prices

Our analysis on home price expectations is based on two implicit assumptions: (1) respondents understand that they are being asked for their national home price expectations and not local price changes, and (2) respondents are aware of changes in the local housing market. In Appendix C, we analyze data from a subset of respondents who answered additional questions on local house price expectations and past house price changes in an extra module of the SCE in February of each year. First, Appendix Table A4 shows that most respondents who are asked about both national and local house price changes give different answers - the average absolute difference is 5.5 percentage points and only 20% of respondents give the same answer - indicating they understand they are being asked about different outcomes. Second, Appendix Table A5 shows that respondents have decent if not perfect recall of past local house price changes. A one percentage point increase in actual past house price changes increases perceived house price changes by about 0.3 percentage points. In addition, replacing actual house price changes with recalled house price changes in the analysis in Table 3 yields highly significant and larger estimates, indicating that extrapolation from recalled house price changes is stronger than from actual house price changes.

4 Own Experiences and US Unemployment Expectation

4.1 Employment Status Changes

In this section we turn to unemployment expectations. We measure individual's experiences by their own employment status and focus on individuals who experience job transitions during the time in our panel. This *within-individual* variation allows us to estimate the effect of an individual's changes in actual personal experiences (over time) on expectations. Unlike the relatively small changes from month to month in local house price changes, employment status changes are discrete and notable, which provide us with enough variation to identify the effect of an individual's changing experiences on her expectations.

4.2 Employment Status Changes and Expectations

Figure 7 shows average national unemployment expectations for employed and unemployed respondents over our sample period. All respondents adapt their expectations over time to changes in economic conditions. At every point in time, however, respondents looking for work consider an increase in unemployment to be on average 7 percentage points more likely than their employed counterparts.

Table 8 formally estimates this difference in nationwide unemployment expectations between employed and unemployed respondents. The estimation includes time fixed effects to absorb changes in economic conditions over time and isolate the effect of employment status. The first two columns confirm the findings of Figure 7: In the cross-section, those searching for work are 6.7 percentage points more pessimistic about nationwide year-ahead unemployment compared to their employed counterparts. Retired respondents are more optimistic than others, and those out of the labor force are slightly more pessimistic. Controlling for demographics and local unemployment rates in the second column, reduces the difference between employed and unemployed respondents to 5.5 percentage points, indicating that differences in characteristics partially explain differences in expectations. To address this concern, columns III and IV of Table 8 include individual fixed effects which absorb any potential differences in characteristics between individuals. The resulting estimates capture how much a given respondent's expectation changes as her own employment status changes. The estimates suggest that individuals, on average, become 1.44 percentage points more pessimistic (optimistic) after becoming unemployed (finding a new job out of unemployment).[23] Therefore, as respondents' experiences change over time, their expectations change accordingly. However, the within-individual results yield substantially lower effects of own unemployment compared to the cross-sectional results, indicating that individuals who are consistently employed are more optimistic about unemployment (and consistently unemployed individuals are more pessimistic) compared to the respondents who are in and out of jobs during our sample period.

Finally, the last two columns of Table 8 explore whether the effect of unemployment differs when respondents lose their job relative to when respondents find a job out of unemployment. In the cross section, reported in column V, we see that expectations of respondents who have recently found a new job do not differ significantly from those of respondents who have been employed throughout the sample period. Respondents who lost their job or entered the sample looking for a job are substantially more pessimistic. When including individual fixed effects in column VI of Table 8, however, we find the opposite: there is no significant difference between recent job losers and employed respondents, but respondents who find a new job out of unemployment become significantly more optimistic once they have found a job.

4.3 Informativeness of Own Employment Status

We next assess whether respondents' updating of their expectations when they experience unemployment is consistent with its informational content. To do so, we calculate what our estimates imply about how informative individual job loss is about aggregate unemployment. Based on the phrasing of the survey question, there are two possible outcomes: unemployment increasing, or not increasing. Assuming that all respondents are Bayesion updaters we can back out how informative own unemployment would need to be about aggregate unemployment to justify the observed difference in expectations between employed and unemployed respondents of 1.44 percentage points that we observe in the data.

Appendix E shows the calculation. We assume that all respondents agree that the unconditional probability of national unemployment increasing is 38% (the average expectation of all respondents in our sample), and that the probability of job loss is 5.6% if unemployment was not going to increase (the average local unemployment rate in our sample). Further, we assume that the probability of job loss is higher by factor x if unemployment was going to increase relative to if unemployment was not going to increase. Based on these assumptions,

[23] In unreported results we investigate whether the effect of job loss or finding a job out of unemployment varies by the length of unemployment and find no evidence for a systematic effect of unemployment length.

we find that respondents would need to be about 6 percent more likely to lose their job if unemployment were truly going up than they would be if unemployment were not going to increase to justify the estimated difference in posterior beliefs of 1.44 percentage points.

5 Effects by Respondent Characteristics

Next, we explore which respondent characteristics affect the influence of past experiences on expectations about nationwide outcomes. Specifically, we investigate whether results differ by proxies for sophistication (such as a college degree or the respondent's numeracy score), by age and by home ownership (which allows to assess whether reporting of risk-adjusted probabilities could explain our results). We report results for the expected year-ahead house price change, but results are qualitatively similar when using the expected one-year house price change in two years.

A college degree and higher numeracy can be viewed as proxies for the respondent's sophistication. If respondents extrapolated from own experiences to aggregate outcomes because of cognitive biases, we would expect sophisticated individuals to be less prone to rely on their own experience (either locally experienced house prices or own employment status) when reporting expectations for nationwide outcomes.[24]

This is investigated in Table 9. The top panel shows that the effect of past house prices for respondents with low numeracy is 0.14, whereas the estimate for respondents with high numeracy is 0.06. At 0.08 the difference between low and high numeracy respondents is the lowest for ZIP code level house prices, but larger and statistically significantly different from zero for MSA and state level house prices. Similarly, the lower panel of Table 9 shows that past local house prices affect expectations about US house price changes substantially more for respondents who did not go to college relative to those who did. Note, however, that while the effect is smaller, past experiences still significantly affect expectations for college graduates and high-numeracy respondents.

Models of age-dependent updating predict that the effect of recent past experiences on expectations should decrease with age. If individuals form expectations based on the entire history of local house prices they have themselves witnessed, one would expect younger respondents with a shorter prior experience history to react more strongly to the most

[24] Less sophisticated individuals may have less accurate non-local information (Madeira and Zafar (2015)) making them optimally rely more heavily on their own experiences. However, optimal reliance on local information would suggest that the effect of local information should vary with its informativeness which we did not find to be the case in section 3.2.

recent house price changes than older respondents. Our results in section 3.3 indicated that it is the more recent years of experienced house price changes that matter the most for expected house price changes. Considering age-specific experience horizons did not improve the fit in the data. The results in Table 10 are consistent with these earlier findings: Recent local house price changes affect expectations strongly for all respondents and, notably, the magnitude of the estimates is very similar for all ages. The results also control for the zip code tenure and are very similar when restricting the sample to respondents who have moved to the ZIP code in the last ten years (unreported results), indicating that this effect is not driven by older respondents living in their current ZIP code for very long times. In addition, when we estimate the effect of respondents' entire history of prior house price changes, we also do not find substantial differences by respondent age (unreported results).

A potential concern about our results is that instead of actual probabilities, respondents report risk-adjusted probabilities in the survey and that past experiences systematically affect the extent of risk adjustment. Specifically, past increases in house prices make homeowners better off and, hence, potentially less risk averse. Therefore, higher increases in past house prices would increase risk-adjusted expectations of future house price changes by decreasing the risk adjustment even if there was no effect on expectations of the actual likelihood of price changes. However, the effect of past experiences on the extent of risk adjustment should be the opposite for renters. Unlike for homeowners, higher increases in past house prices are detrimental for renters (see Stroebel and Vavra, 2014), making them more risk averse and increasing the risk adjustment contained in risk-adjusted expectations. Thus, while risk adjustment should amplify any extrapolation from past experiences for homeowners, it should dampen extrapolation from past prices for renters. However, Table 11 shows that there is no evidence of a stronger effect of past house prices for homeowners compared to renters. If anything, the point estimates suggest a slightly lower effect for homeowners, though the estimate is not significantly different from that of renters. Risk adjustment, therefore, does not appear to be an important driver of our results.

Finally, in unreported regressions, we also estimate whether the effect of locally experienced house prices differs by region and by local characteristics, such as the peak to trough price changes during the crisis or the volatility of local house prices, and do not find significant effects. Whether respondents report a high or low likelihood of moving in the near future also does not affect the extent of extrapolation from local house prices in the data.

Table 12 shows similar effects of respondent characteristics on the extent of extrapolation from own unemployment to national unemployment. Personal unemployment has the largest effect, an increase of 5 percentage points, on US unemployment expectations for respondents with numeracy in the lowest tercile. Respondents with higher numeracy are significantly less influenced by changes in their own employment status when forming expectations about national unemployment. We also find a smaller, though not statistically significantly different effect of own employment for college graduates relative to respondents who did not go to college. Finally, the last column of Table 12 shows that there is also no evidence of greater extrapolation from personal labor market experiences to national unemployment for younger respondents.

Overall, our results show strong evidence of extrapolation from own experiences to nationwide expectations, which is substantially stronger for less sophisticated individuals. Our earlier results in section 3.2 showed that the extent of extrapolation is unrelated to the informativeness of local information in the data. Jointly, our findings therefore suggest that behavioral biases rather than the optimal use of limited information lead individuals to rely on their own or personal experiences when forming expectations about the aggregate.

6 Expectations of Other Outcomes

Do experiences in one domain, such as the labor or housing market, affect expectations about other aggregate outcomes, as well? Table 13 shows the effect of own employment status (Panel A) and past local house price experiences (Panel B) on expectations about other aggregate economic outcomes. The first two columns of Table 13 show that unemployed respondents feel they are worse off than they were a year ago and also expect to be worse off a year later.[25] This confirms that personal unemployment has strong negative effects on individuals' perceptions of their own well being. There is no such effect of past local house price changes confirming that, unlike personal unemployment, local house prices are not major determinants of individual well-being. The remaining columns, columns III to IX, estimate the effect of experiencing unemployment (Panel A) and of past house prices (Panel B) on expectations about interest rates, US stock prices, inflation, government debt and house price changes. Local house price changes are not systematically related to expectations about any of these other aggregate outcomes in a statistically significant way. This also suggests that there are is no other unobserved factor that is correlated with past house price

[25] It is interesting to note that the estimate on "out of labor force" is qualitatively similar to that of the unemployed respondents. This would suggest that the transition to out of the labor force is partly driven in our sample by the same factors that lead respondents to become unemployed.

growth driving our result.

Experiencing unemployment also has no effects on expectations about interest rates, stock prices, inflation and government debt. However, we find a negative effect on expected house price growth. This could indicate that losing one's job leads individuals to be more pessimistic about the economy in general. However, any such general pessimism does not seem to be pervasive since other outcomes are not significantly affected. Overall, the results indicate that extrapolation from past local experiences appears to be mostly domain specific: Experiences in the housing market affect expectations about housing and those in the labor market affect labor market expectations, whereas those about other macroeconomic outcomes are mostly unaffected.

Next, we turn to how expectations about different macroeconomic outcomes move with each other. Table 14 adds respondents' expectations about unemployment and house prices as explanatory variables and shows how they affect expectations about the other macroeconomic outcomes considered. Respondents who expect higher unemployment going forward also expect to be worse off. Higher expected unemployment is also associated with higher expected interest rates, stock prices and inflation. Similarly, respondents who are more optimistic about house price changes are also more optimistic about their own situation going forward. Higher expected house price changes are also associated with higher interest rates, stock prices, inflation and government debt. Note that earlier we did not find an effect of own home price experiences on these outcomes, indicating that the co-movement of expectations about aggregate outcomes is driven by factors other than own experiences that influence expectations about all of these outcomes.

It is difficult to judge and interpret the co-movement of expectations about specific aggregate outcomes since they can move with each other for different reasons. For instance, respondents may expect good economic conditions and hence, low unemployment and high stock prices. However, they may also expect that liberalizations of trade policy or labor regulation will lead to higher unemployment but benefit firms, increasing stock prices.

We therefore turn to the relationship between inflation and unemployment expectations and expected interest rates. Since Taylor (1993), it has become standard to think of the Federal Reserve as setting interest rates according to a "Taylor rule". It suggests that interest rates should increase with higher expected inflation and decrease with higher expected unemployment, a measure of the output gap. We test whether individuals' expectations are consistent with such a Taylor rule. Table 15 presents the results estimated in the cross-section in Panel A and in the full panel with individual fixed effects in Panel B. Panel A, column 1, shows that in the cross-section, higher expected inflation is associated with lower expected interest rates, and that higher expected unemployment is associated with higher interest rates. This is the opposite of what the Taylor rule predicts. The remaining columns show that these patterns are very consistent across different sample splits along demographics. Panel B shows the same relationship but includes individual fixed effects. That is, we identify the effect of expected inflation and unemployment only off of changes in these expectations by the same individual. Persistent differences between individuals are filtered out by the fixed effect. The effect of expected inflation - strongly negative in the cross-section - is very small and not statistically significant from zero in the fixed effect regression. The strong positive effect of expected unemployment remains. Hence, the negative relationship between expected inflation and expected interest rates in the cross-section seems to be driven primarily by fixed individual characteristics, rather than by respondents adjusting their interest rate expectations as their inflation expectations change. Similar to the cross-sectional results, the strong positive relationship between expected unemployment and interest rates is pervasive across different demographics.

Overall, our results show that individuals do not seem to form expectations according to a Taylor rule. Carvalho and Nechio (2014) conduct a similar exercise with the Michigan Survey of Consumers. Over their sample period spanning 1978-2007, they find evidence of some respondents forming expectations in a way consistent with a Taylor rule. One possibility for why we find contrasting results could be that inflation, interest rates, and unemployment were all very low during our sample period, which may have caused respondents to be inattentive. Similarly, the zero lower bound in the aftermath of the Great Recession prevented monetary policy from tightly adhering to a Taylor rule. Therefore, consistent with our other results, respondents may be extrapolating from their recent experiences and not perceive the Taylor rule to be a good description of monetary policy.

7 Expectations and Outcomes

The results so far show that recent personal and local experiences significantly affect individuals' expectations of future economic outcomes. Our interest in these expectations stems from the belief that they influence individuals' current and planned economic activity and economic outcomes. In this section, we assess the extent to which expectations elicited in our survey data are associated with actual future outcomes and intended actions.

7.1 Labor Market Expectations and Realized Outcomes

In addition to respondents' expectations about nationwide unemployment, respondents in the SCE also assess their own employment prospects. Specifically, employed respondents state how likely they think they are to lose their job. Table 16 analyzes the extent to which these self-assessed employment prospects are indicative of actual future employment outcomes both in the cross-section, as well as within-respondent over time. The dependent variable in the table is a dummy for whether the respondent actually loses her job over the specified horizon. Respondents who think they are more likely to lose their job when they first enter the panel are in fact more likely to do so in the following months: Panel A of the table, which exploits cross-sectional variation, shows that an increase of 1 percentage point in the reported likelihood of losing a job over the next 12 months is associated with a 0.14 percentage point increase in the actual likelihood of losing a job over the next six months. Moreover, the lower panel of Table 16 shows that as respondents become more pessimistic about losing their job they are indeed at an increased risk of being laid off, particularly over a one-month horizon. Respondents' expectations about future job loss are therefore strongly related to actual job loss, indicating that respondents' expectations are predictive of actual, real life outcomes.[26]

7.2 House Price Expectations and Attitudes towards Housing

A substantial number of respondents experience a job loss during their time in the survey, which allows us to relate prior job loss expectations to actual outcomes. However, this is not the case for housing market outcomes, such as buying a new home. We therefore turn to a subset of respondents who answered additional questions about local house prices expectations. Specifically, these respondents were asked whether they considered buying a home in their zip code today a good investment.[27] This allows us to evaluate whether respondents who are more optimistic about future house prices are more likely to consider buying a home a good investment.[28] Table 17 shows that respondents who expect house

[26] Stephens Jr (2004) and Dickerson and Green (2012) also find that expectations of unemployment are predictive of future employment outcomes and Buchheim and Link (2016) find that firms' expectations are informative of their future business condition.

[27] In addition, respondents were asked about local house price expectations and past local price changes, as outlined in Appendix Section C.

[28] Prior evidence indeed suggests that expectations are related to actual, as well as intended future investment decisions. See Gennaioli et al. (2015) for the effect of expectations on actual investment and D'Acunto et al. (2015) for intended purchases.

prices to increase more, either nationally or in their current ZIP code, indeed rate investing in real estate in their current ZIP code as more attractive.

8 Conclusion

This paper documents that recent personal experiences affect expectations about aggregate house price changes and unemployment. Recent local house price dynamics significantly affect expectations of US house prices. Likewise, experiencing unemployment leads respondents to be significantly more pessimistic about nationwide unemployment. We also document evidence of extrapolation beyond the first moment: individuals who have experienced more volatile housing price changes also perceive future year-ahead house price changes to be more uncertain. Importantly, the effect of these personal experiences is not related to their true informativeness in the data. It is notable that both of our approaches – exploiting local variation in house prices in the cross-section, and within-person changes in labor market status – yield similar conclusions regarding the tendency of households to extrapolate from local experiences.

Our paper builds on the burgeoning literature on experiences and expectations in at least three ways. First, we add to this literature by showing that the type of personal experiences that affect expectations are often local or truly personal and can differ from the aggregate outcomes individuals have seen in their lifetime. Second, the rich data on sample respondents' demographics and circumstances allows us to investigate heterogeneity in expectation formation, which further helps to inform us about the underlying updating mechanisms. For example, we find that less sophisticated individuals extrapolate more from their own experiences, which casts doubt on the updating patterns being optimal. Third, we relate expectations about the labor and housing markets to expectations about other aggregate outcomes, such as interest rates, stock prices, government debt or inflation. While we find that labor and housing market *experiences* do not affect expectations about these other economic outcomes, labor and housing market *expectations* do. This suggests that co-movement of expectations is driven by other factors affecting expectations in multiple domains. Fourth, we investigate whether respondents form expectations according to a Taylor rule, and do not find evidence of that. This finding warrants further research, but could be a result of households being inattentive or extrapolating from recent aggregate trends.

Collectively, our results therefore suggest that respondents naively extrapolate from their own recent experience in the given domain when forming expectations about aggregates, and that it is not necessarily consistent with macro economic models. Our findings offer further support for theories exploring the implications of extrapolative expectations in areas other than unemployment or housing markets (Barberis et al., 2015; Fuster et al., 2010). Beyond implications for the modeling of expectations, our results also have important implications for understanding aggregate fluctuations in labor and housing markets.

In terms of future research, whether housing experts, like individual consumers as in this paper, also exhibit a tendency to extrapolate from own experiences (as suggested by recent work[29]) would be an interesting question to further explore. Similarly, our data coincides with a period where home prices have either remained steady or risen across localities, the labor market has continuously improved, and inflation and interest rates have remained low. As macroeconomic conditions change over time and a longer time series of the survey data used in our paper becomes available, it will be interesting to investigate what role, if any, the macroeconomic environment plays in how individuals form expectations about aggregate outcomes.

References

Gene Amromin. *Expectations of risk and return among household investors: Are their Sharpe ratios countercyclical?* Divisions of Research & Statistics and Monetary Affairs, Federal Reserve Board, 2008.

Maximiliano Appendino. Lifetime experience of volatility: A new determinant of household demand for stocks. Working Paper, 2013.

Olivier Armantier, Giorgio Topa, Wilbert van der Klaauw, and Basit Zafar. An overview of the survey of consumer expectations. *Economic Policy Review*, Forthcoming.

Luis C. Armona, Andreas Fuster, and Basit Zafar. Home price expectations and behavior: evidence from a randomized information experiment. Working Paper, 2016.

Michael Bailey, Eduardo Davila, Theresa Kuchler, and Johannes Stroebel. House price beliefs and mortgage leverage choice. Working Paper, 2017.

[29] Malmendier et al. (2017), for example, show that personal inflation experiences influence the leanings of central bankers.

Michael Bailey, Rachel Cao, Theresa Kuchler, and Johannes Stroebel. The economic effects of social networks: Evidence from the housing market. *Journal of Political Economy*, forthcoming.

Nicholas Barberis, Robin Greenwood, Lawrence Jin, and Andrei Shleifer. X-capm: An extrapolative capital asset pricing model. *Journal of Financial Economics*, 115(1):1–24, 2015.

Markus K. Brunnermeier, Alp Simsek, and Wei Xiong. A welfare criterion for models with distorted beliefs. *Quarterly Journal of Economics*, 129(4):1753–1797, 2014.

Lukas Buchheim and Sebastian Link. Do firms expect firm-specific shocks? Working Paper, 2016.

Craig Burnside, Martin Eichenbaum, and Sergio Rebelo. Understanding booms and busts in housing markets. *Journal of Political Economy*, 124(4):1088–1147, 2016.

Chris Carroll and Wendy Dunn. Unemployment expectations, jumping (s, s) triggers, and household balance sheets. In *NBER Macroeconomics Annual 1997, Volume 12*, pages 165–230. MIT Press, 1997.

Carlos Carvalho and Fernanda Nechio. Do people understand monetary policy? *Journal of Monetary Economics*, 66(Supplement C):108 – 123, 2014. ISSN 0304-3932. doi: https://doi.org/10.1016/j.jmoneco.2014.04.013. URL http://www.sciencedirect.com/science/article/pii/S0304393214000713.

Karl Case, Robert Shiller, and Anne Thompson. What have they been thinking? homebuyer behavior in hot and cold markets. *Brookings Papers on Economic Activity*, pages 265–298, 2012.

Alberto Cavallo, Guillermo Cruces, and Ricardo Perez-Truglia. Inflation expectations, learning and supermarket prices: Evidence from field experiments. Technical report, National Bureau of Economic Research, 2014.

Yao-Min Chiang, David Hirshleifer, Yiming Qian, and Ann E. Sherman. Do investors learn from experience? evidence from frequent ipo investors. *Review of Financial Studies*, 24 (5):1560–1589, 2011.

Alex Chinco and Christopher Mayer. Misinformed speculators and mispricing in the housing market. *Review of Financial Studies*, 29(2):486–522, 2016.

Francesco D'Acunto, Daniel Hoang, and Michael Weber. Inflation expectations and consumption expenditure. Working Paper, 2015.

Sreyoshi Das, Camelia M Kuhnen, and Stefan Nagel. Socioeconomic status and macroeconomic expectations. Working Paper, 2017.

Andy Dickerson and Francis Green. Fears and realisations of employment insecurity. *Labour Economics*, 19(2):198–210, 2012.

Andreas Fuster, David Laibson, and Brock Mendel. Natural expectations and macroeconomic fluctuations. *Journal of Economic Perspectives*, 24(4):67–84, 2010.

John Geanakoplos. The leverage cycle. In D. Acemoglu, K. Rogoff, and M. Woodford, editors, *NBER Macroeconomics Annual 2009, Volume 24*, pages 1–66. University of Chicago Press, 2009.

Nicola Gennaioli, Yueran Ma, and Andrei Shleifer. Expectations and investment. In *NBER Macroeconomics Annual 2015, Volume 30*. University of Chicago Press, 2015.

Edward L. Glaeser and Charles G. Nathanson. An extrapolative model of house price dynamics. *Journal of Financial Economics*, Forthcoming, 2017.

E.L. Glaeser, J. Gottlieb, and J. Gyourko. Can cheap credit explain the housing boom? In E. L. Glaeser and T. Sinai, editors, *Housing and the Financial Crisis*, pages 301–359. University of Chicago Press, 2013.

William N. Goetzmann, Liang Peng, and Jacqueline Yen. The subprime crisis and house price appreciation. *The Journal of Real Estate Finance and Economics*, 44(1-2):36–66, 2012.

Robin Greenwood and Stefan Nagel. Inexperienced investors and bubbles. *Journal of Financial Economics*, 93(2):239–258, 2009.

Robin Greenwood and Andrei Shleifer. Expectations of returns and expected returns. *Review of Financial Studies*, 27(3):714–746, 2014.

J. Michael Harrison and David M. Kreps. Speculative investor behavior in a stock market with heterogeneous expectations. *Quarterly Journal of Economics*, 92(2):323–336, 1978.

Nathaniel Hendren. Knowledge of future job loss and implications for unemployment insurance. Working Paper, 2015.

Harrison Hong and Jeremy C. Stein. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance*, 54(6):2143–2184, 1999.

Harrison Hong and Jeremy C. Stein. Disagreement and the stock market. *Journal of Economic Perspectives*, 21(2):109–128, 2007.

Markku Kaustia and Samuli Knüpfer. Do investors overweight personal experience? evidence from ipo subscriptions. *The Journal of Finance*, 63(6):2679–2702, 2008.

Michael P. Keane and David E. Runkle. Testing the rationality of price forecasts: New evidence from panel data. *The American Economic Review*, pages 714–735, 1990.

Samuli Knüpfer, Elias Henrikki Rantapuska, and Matti Sarvimäki. Formative experiences and portfolio choice: Evidence from the finnish great depression. Working Paper, 2016.

Peter Koudijs and Hans-Joachim Voth. Leverage and beliefs: Personal experience and risk taking in margin lending. Working Paper 19957, National Bureau of Economic Research, March 2014.

Isaac M Lipkus, Greg Samsa, and Barbara K. Rimer. General performance on a numeracy scale among highly educated samples. *Medical Decision Making*, 21(1):37–44, 2001.

A Lusardi. Household saving behavior: The role of literacy, information and financial education programs. In C. Foote, L. Goette, and S. Meier, editors, *Policymaking Insights from Behavioral Economics*, pages 109–149. Federal Reserve Bank of Boston, 2009.

Carlos Madeira and Basit Zafar. Heterogeneous inflation expectations, learning, and market outcomes. *Journal of Money, Credit, and Banking*, 47(5):867–896, 2015.

Ulrike Malmendier and Stefan Nagel. Depression babies: Do macroeconomic experiences affect risk taking? *The Quarterly Journal of Economics*, 126(1):373–416, 2011.

Ulrike Malmendier and Stefan Nagel. Learning from inflation experiences. *The Quarterly Journal of Economics*, 131(1):53–87, 2016.

Ulrike Malmendier, Stefan Nagel, and Zhen Yan. The making of hawks and doves: Inflation experiences on the fomc. Technical report, National Bureau of Economic Research, 2017.

Monika Piazzesi and Martin Schneider. Momentum traders in the housing market: Survey evidence and a search model. *The American Economic Review*, 99(2):pp. 406–411, 2009.

Jose A. Scheinkman and Wei Xiong. Overconfidence and speculative bubbles. *Journal of Political Economy*, 111(6):1183–1220, 2003.

Alp Simsek. Speculation and risk sharing with new financial assets. *Quarterly Journal of Economics*, 128(3):1365–1396, 2013.

Melvin Stephens Jr. Job loss expectations, realizations, and household consumption behavior. *Review of Economics and Statistics*, 86(1):253–269, 2004.

Johannes Stroebel and Joseph Vavra. House prices, local demand, and retail prices. Technical report, National Bureau of Economic Research, 2014.

John B. Taylor. Discretion versus policy rules in practice. In *Carnegie-Rochester conference series on public policy*, volume 39, pages 195–214, 1993.

Daniel L. Tortorice. Unemployment expectations and the business cycle. *The BE Journal of Macroeconomics*, 12(1), 2011.

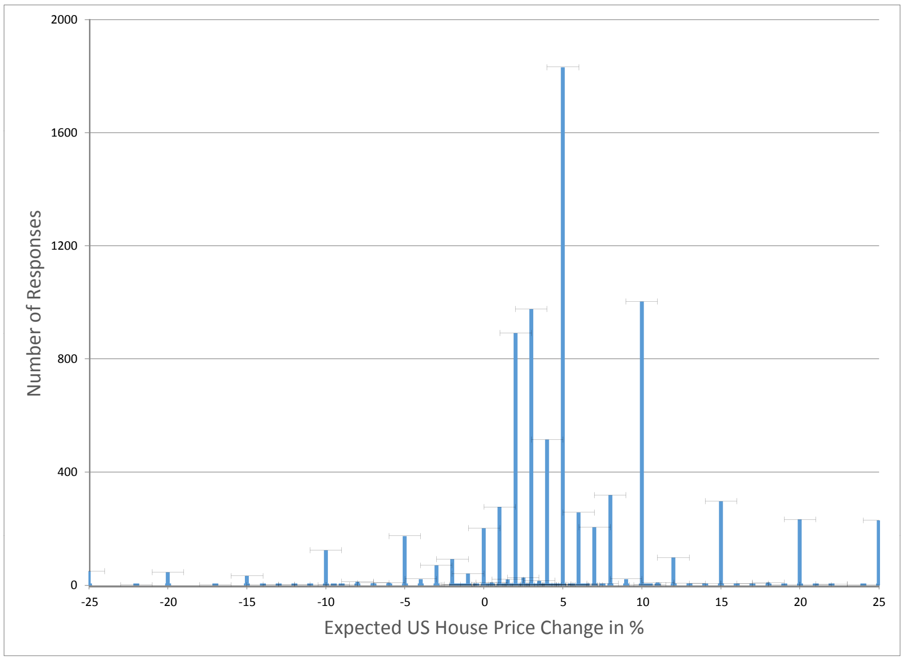
Annette Vissing-Jorgensen. Perspectives on behavioral finance: Does" irrationality" disappear with wealth? evidence from expectations and actions. In *NBER Macroeconomics Annual 2003, Volume 18*, pages 139–208. The MIT Press, 2004.

Neil D. Weinstein. Unrealistic optimism about future life events. *Journal of personality and social psychology*, 39(5):806, 1980.

Michael Woodford. Macroeconomic analysis without the rational expectations hypothesis. *Annu. Rev. Econ.*, 5(1):303–346, 2013.

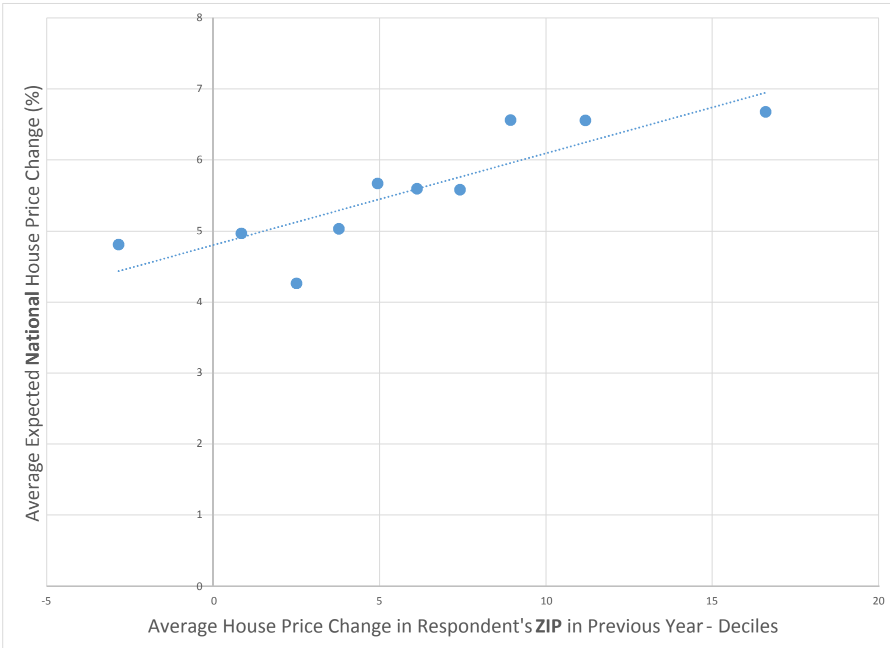
Danny Yagan. The enduring employment impact of your great recession location. Working Paper, 2016.

Figure 1: Distribution of Expected National House Price Changes

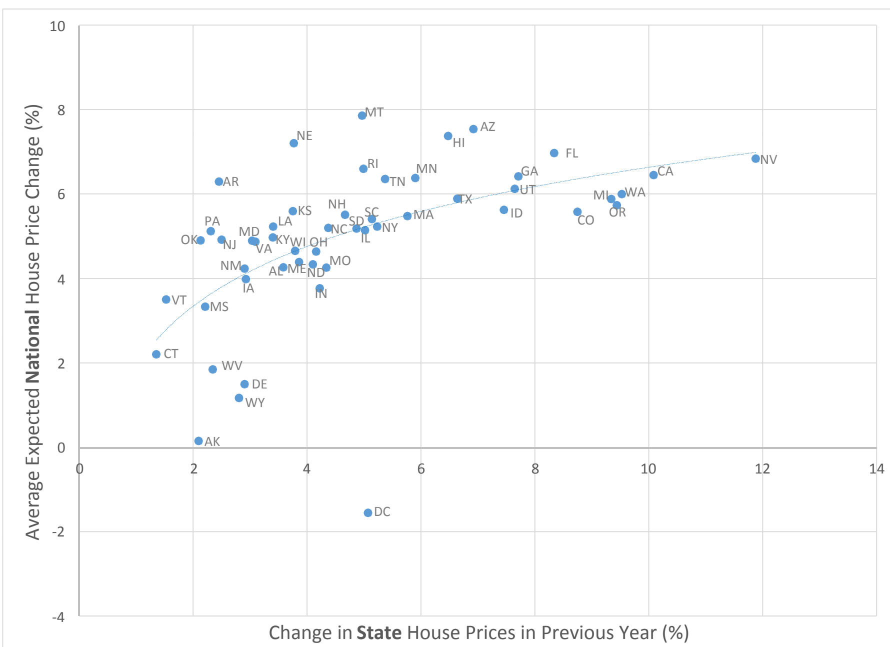


The figure shows the distribution of expected house price changes for the coming year in percentage points as stated by the respondents in our sample.

Figure 2: Local House Price Experience and National House Price Expectation



(a) ZIP Level House Price Change



(b) State Level House Price Change

The figure shows the relationship between local house price changes in the prior year and expected national house price changes in the next year. For each decile of past price changes in the respondent's ZIP code, Panel A shows the average past house price changes and the average expected national house price changes. Panel B shows the average past house price changes and the average expected national house price changes for each state.

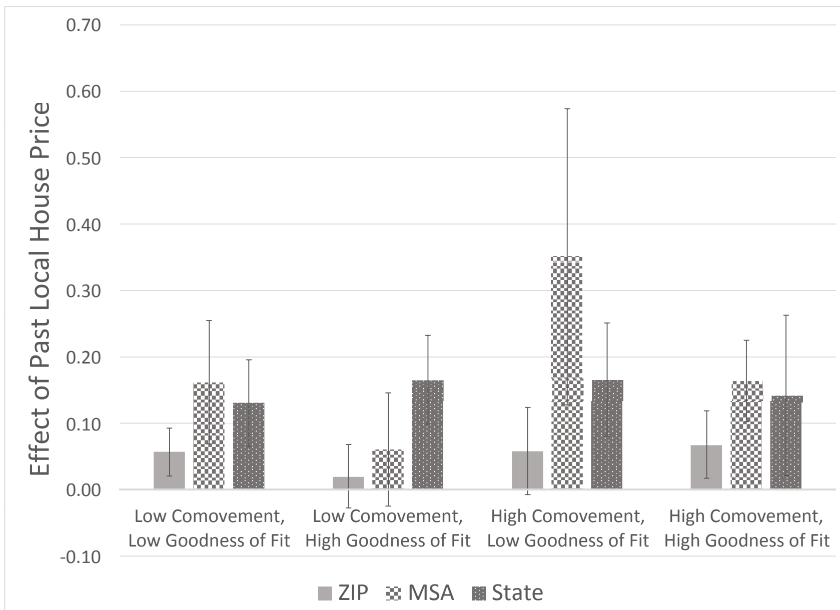
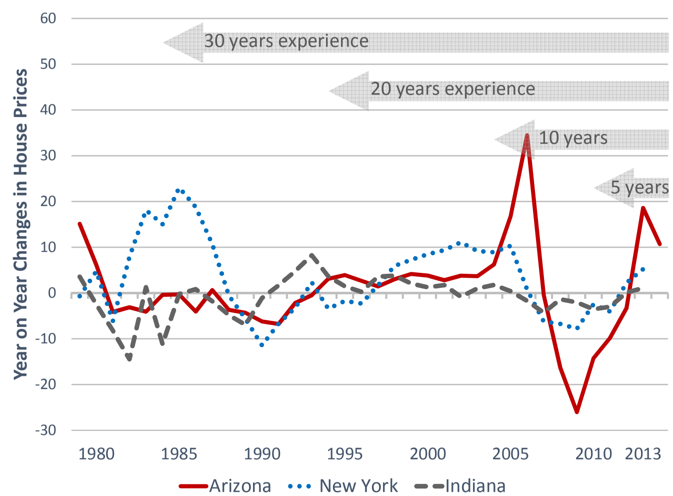


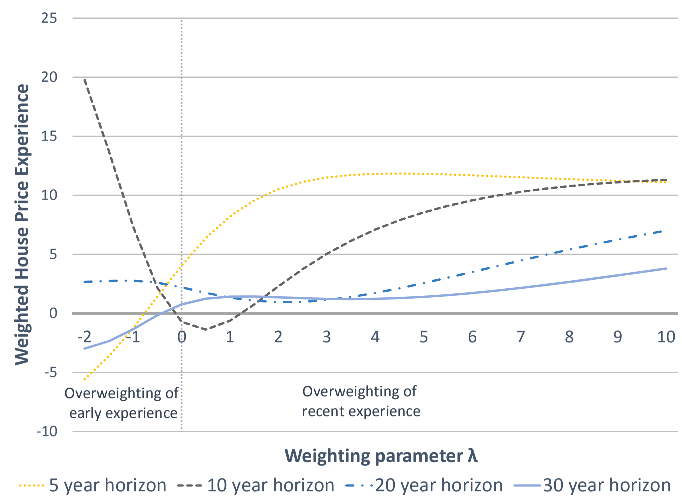
Figure 3: House Price Changes and Expectations by Magnitude and Informativeness of Effect in Data

The figure shows the effect of prior year local house price changes on expectations about national house price changes in regression estimates of Equation 1. Standard errors are clustered at the state level. The dependent variable is the expected change in year-ahead house prices in percentage points as stated by the respondent. Past house price change is the change in the previous calendar year in the ZIP code, MSA or state where the respondent lives, as labeled. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey, respondents' age and age squared and indicators for whether respondents own their home, are male, married, went to college and are white or black. Respondents are grouped into four groups based on the coefficient on prior local house price changes in a regression of national house price changes on prior year local price changes in the years since availability of our house price data, as well as the correlation between these two variables over the same horizon.

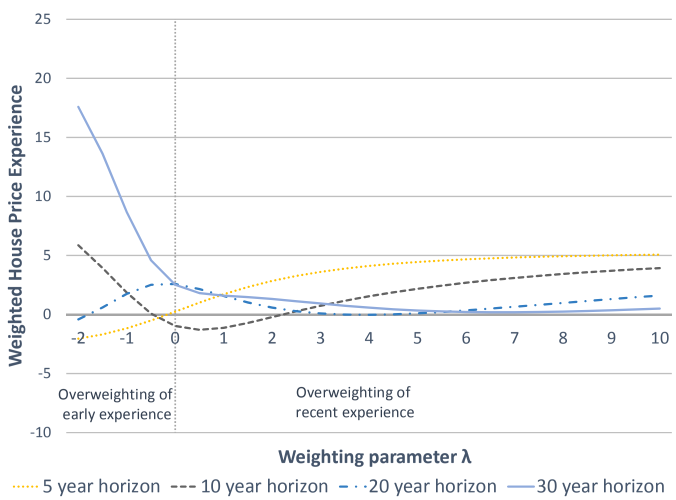
Figure 4: House Prices and Weighted Experience



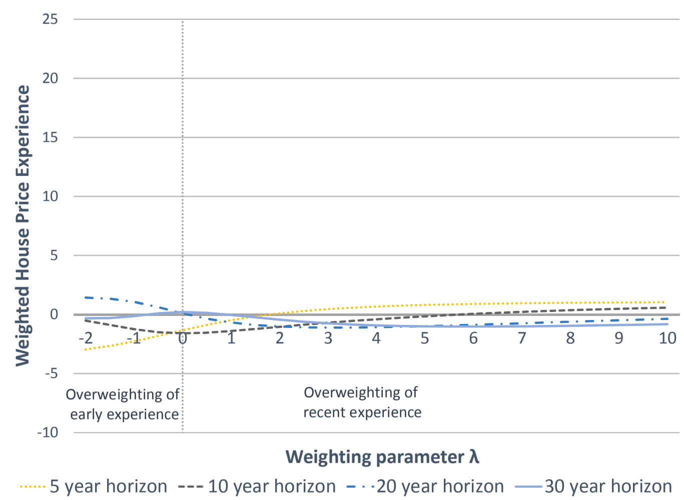
(a) House Price Changes Over Time



(b) Arizona - Weighted Experience



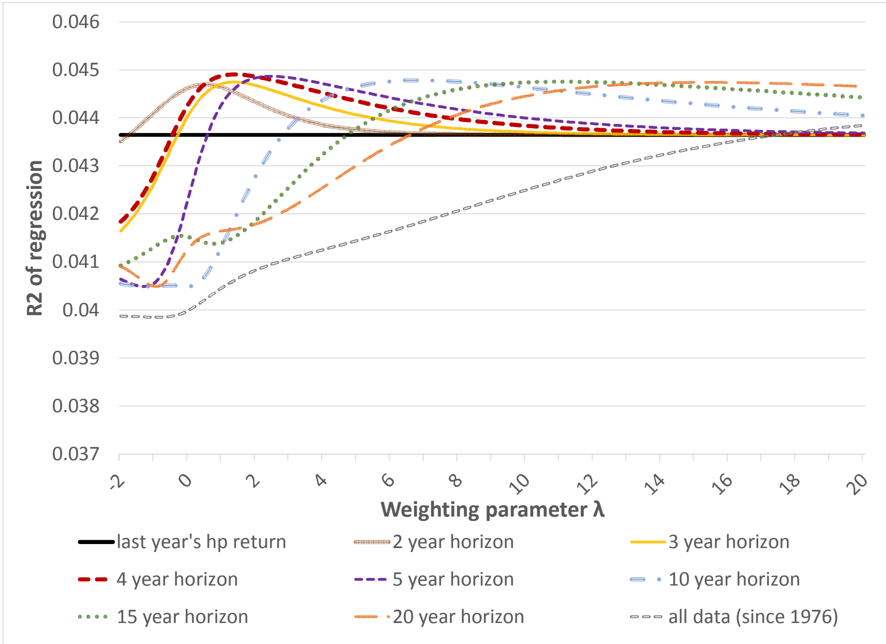
(c) New York - Weighted Experience



(d) Indiana - Weighted Experience

Panel A shows yearly changes in house prices in Arizona, Indiana and New York. The remaining panels show how the weighted house price experience of respondents with experience horizons of 5, 10, 20 and 30 years in Arizona (Panel B), New York (Panel C) and Indiana (Panel D) changes as the weighting parameter λ changes. The weighting parameter λ determines the weighting of past changes when past experience is measured by a weighted average of past house price changes according to Equation 2.

Figure 5: Weighted Average of ZIP Code House Prices and Expectation



(a) Fixed Year Horizons (All Respondents)

(b) Individual Specific Horizons (Respondents with Years Lived in ZIP Available)

For each horizon, the figure shows how the R^2 of the regression estimates of Equation 1 changes as the weighting parameter λ changes. The weighting parameter λ determines the weighting of past changes when past experience is measured by a weighted average of past house price changes according to Equation 2.

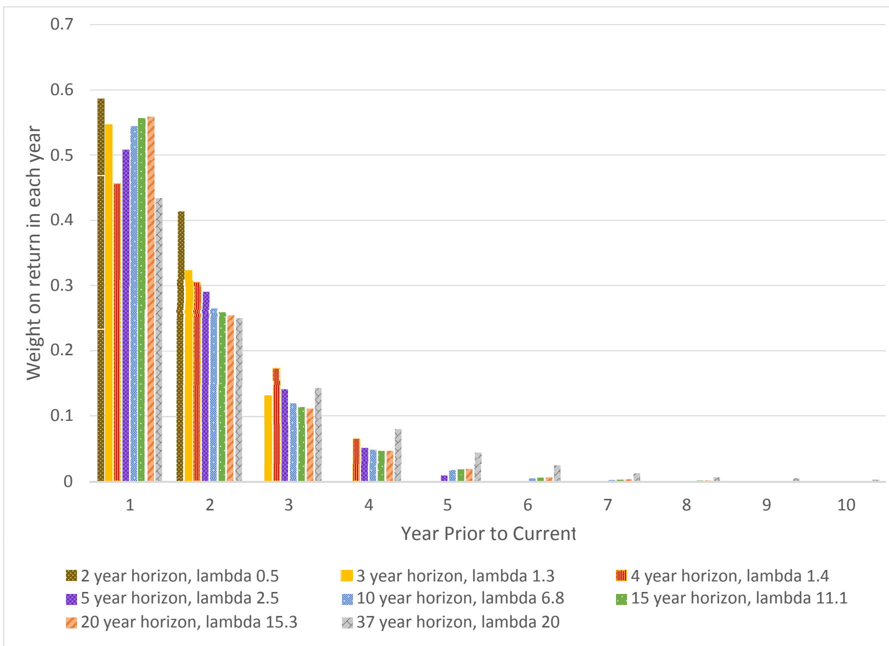


Figure 6: Weights Implied by Optimal Weighting Parameter - ZIP Code House Prices

The figure shows the weights on the house price changes in the past 10 years implied by the optimal weighting parameters corresponding to the specifications with the highest R^2 as shown in Table 5.

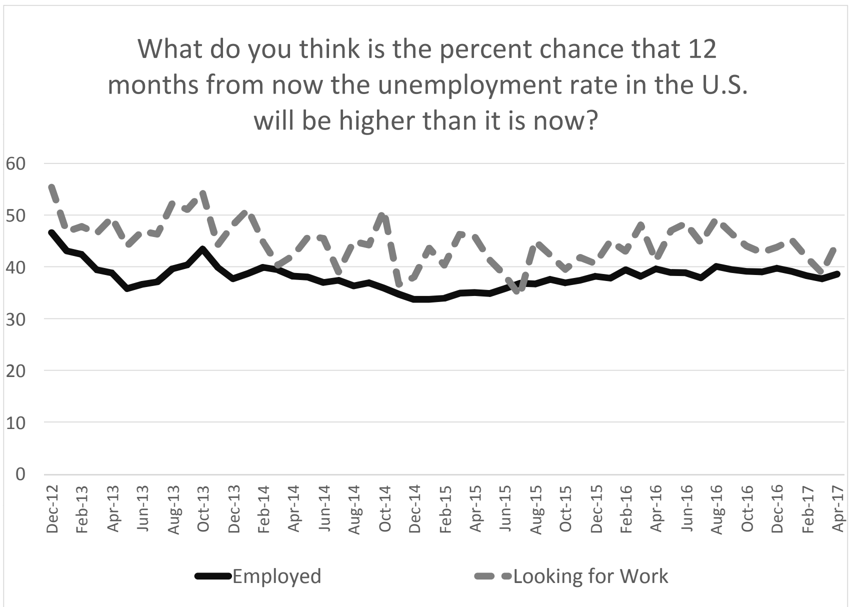


Figure 7: Employment Status and Unemployment Expectations Over Time

The figure shows the average percentage chance of US unemployment being higher a year later as reported by respondents of the Survey of Consumer Expectations (SCE) in each month, split by whether respondents are currently employed or searching for work.

	N	Mean	Std. Dev.	25th pctile	50th pctile	75th pctile
Respondent Characteristics						
Age	8,104	51.00	14.38	39	52	62
White	8,104	0.85	0.35	1	1	1
Black	8,104	0.09	0.28	0	0	0
Male	8,104	0.54	0.50	0	1	1
Married	8,104	0.68	0.47	0	1	1
College (at beginning of sample)	8,104	0.55	0.50	0	1	1
Income	8,104	80,694	52,784	45,000	67,500	125,000
Numeracy score (% correctly answered)	7,695	0.80	0.22	0.60	0.80	1.00
Homeowner	8,104	0.76	0.43	1	1	1
Years lived in current ZIP	8,099	11.88	11.27	3	8	17
Years lived in current state	8,100	34.69	19.98	18	34	50
Expected House Price Changes						
Expected house price change (point estimate)	8,104	5.46	8.65	2.00	5.00	8.00
Expected house price change (distribution)	7,835	4.45	5.56	1.63	3.46	6.09
Expected std of house price change	7,835	2.75	2.62	1.13	1.78	3.42
Expected change of house price change > 12%	7,866	8.52	20.50	0.00	0.00	5.00
Expected house price change in 2 years	7,907	5.39	7.30	2.00	5.00	8.00
Past House Price Experience - Last year's hp change						
Most recent yearly return in ZIP code	6,032	5.95	5.44	2.50	5.57	8.89
Most recent yearly return in MSA	6,925	5.56	4.00	2.96	5.03	7.44
Most recent yearly return in State	8,104	5.77	3.40	3.46	5.44	7.14
Unemployement Expectations						
Expected likelihood of higher unemployment						
all	8,104	36.54	23.05	20.00	35.00	50.00
only employed	5,686	36.94	22.79	20.00	36.00	50.00
only unemployed	329	43.50	25.39	20.00	47.00	60.00
Local Unemployment rate	8,104	5.59	1.97	4.20	5.20	6.60
Own employment expectations of employed						
Likelihood of job loss if employed	4,896	14.75	20.36	1.00	6.00	20.00
Would find new job within 3 months if lost job	4,973	51.94	32.48	20.00	50.00	80.00
diff. btw likelihood of own and US unemployment	4,896	22.08	27.34	5.00	20.00	40.00

Table 1: House Price Sample Summary Statistics

The table shows mean, standard deviation and the 25^{th}, 50^{th} and 75^{th} percentile for the characteristics, house price expectations and past house price experience of respondents of the Survey of Consumer Expectations (SCE) used throughout the paper. A respondent's numeracy score is the percentage of numeracy and financial literacy questions answered correctly.

			Current Employment Status					
			Employed	Looking for Work	Retired	Student	Out of Labor Force	Total
Previous Employment Status	New Entrant	N	5,636	418	1,490	68	492	8,104
		% row	69.5	5.2	18.4	0.8	6.1	100.0
	Employed	N	32,197	271	200	50	95	32,813
		% row	98.1	0.8	0.6	0.2	0.3	100.0
	Looking for Work	N	323	1,436	136	30	88	2,013
		% row	16.0	71.3	6.8	1.5	4.4	100.0
	Retired	N	199	116	9,842	4	121	10,282
		% row	1.9	1.1	95.7	0.0	1.2	100.0
	Student	N	48	26	3	302	8	387
		% row	12.4	6.7	0.8	78.0	2.1	100.0
	Out of Labor Force	N	104	84	137	7	2,482	2,814
		% row	3.7	3.0	4.9	0.2	88.2	100.0
	Total	N	38,507	2,351	11,808	461	3,286	56,413
		% row	68.3	4.2	20.9	0.8	5.8	100.0

Table 2: Employment Status Transitions from Month to Month

The table shows the number of observations for each combination of current and previous employment status reported by respondents in the Survey of Consumer Expectations (SCE). A respondent's previous employment status is unknown when she first enters the survey. In later modules, a respondent's previous employment status is the respondent's employment status in the previous survey module she participated in.

	I ZIP	II MSA	III State
	Expected 1 Year Change in US House Prices		
Past Local House Price Change	0.095***	0.172***	0.217***
	(0.0181)	(0.0332)	(0.0412)
Time Fixed Effects	Y	Y	Y
Demographics	Y	Y	Y
Effect of 1 std	0.516	0.686	0.738
Effect of 1 std when weighted	0.635	0.838	0.809
Number of observations	6,032	6,925	8,104
R squared	0.0436	0.0388	0.0367
	Expected 1 Year Change in US House Prices in 2 Years		
Past Local House Price Change	0.0886***	0.116***	0.144***
	(0.0178)	(0.0276)	(0.0390)
Time Fixed Effects	Y	Y	Y
Demographics	Y	Y	Y
Effect of 1 std	0.483	0.465	0.493
Effect of 1 std when weighted	0.657	0.578	0.570
Number of observations	5,881	6,758	7,907
R squared	0.0602	0.0496	0.0494

Table 3: Previous Year's House Price Change and House Price Expectations

The table shows regression estimates of Equation 1. The dependent variable is the expected change in house prices in percentage points as stated by the respondent. Past house price return is the change in the previous calendar year in the ZIP code (column 1), MSA (column 2) or state (column 3) where the respondent lives. Standard errors are clustered at the state level. Time fixed effects are included for each survey month. Demographics include indicators for each of the 11 possible categories eliciting household income in the survey, respondents' age and age squared and indicators for whether respondents own their home, are male, married, went to college and are white or black.

	Expected 1 Year Change in US House Prices		
	I	II	III
	ZIP	MSA	State
Local House Price Change	0.0760*	0.182***	0.163**
* Low Co-movement with US House Prices	(0.0391)	(0.0425)	(0.0626)
Local House Price Change	0.135***	0.156***	0.195***
* Medium Co-movement with US House Prices	(0.0456)	(0.0386)	(0.0532)
Local House Price Change	0.0173	0.108	0.161*
* High Co-movement with US House Prices	(0.0310)	(0.0787)	(0.0839)
Medium Co-movement with US House Prices	-0.466	0.567	-0.00409
	(0.468)	(0.457)	(0.665)
High Co-movement with US House Prices	0.147	0.963*	0.00332
	(0.443)	(0.544)	(0.620)
Constant	1.504	3.487	5.953
	(3.838)	(3.776)	(4.336)
Time Fixed Effects	Y	Y	Y
Demographics	Y	Y	Y
Low vs. High Co-movement	-0.0587	-0.0747	-0.00150
	(0.0482)	(0.0887)	(0.0877)
Number of observations	5,163	5,911	6,945
R squared	0.0447	0.0413	0.0374

Table 4: House Price Changes and Expectations by Magnitude of Effect in the Data

The table shows regression estimates of Equation 1. Standard errors are clustered at the state level. The dependent variable is the expected change in year-ahead house prices in percentage points as stated by the respondent. Past house price change is the change in the previous calendar year in the ZIP code (column 1), MSA (column 2) or state (column 3) where the respondent lives. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey, respondents' age and age squared and indicators for whether respondents own their home, are male, married, went to college and are white or black. Respondents are grouped into terciles based on the coefficient on prior local house price changes in a regression of national house price changes on prior year local price changes in the years since availability of our house price data.

	Best Fit Parameters for Weighted Past Experiences				
Horizon	R2	λ	coefficient	standard error of coefficient	effect of 1 standard deviatior
2 years	4.470%	0.5	0.136	0.018	0.626
3 years	4.475%	1.3	0.149	0.022	0.638
4 years	4.490%	1.4	0.165	0.022	0.668
5 years	4.487%	2.5	0.160	0.025	0.654
10 years	4.478%	6.8	0.158	0.023	0.641
15 years	4.475%	11.1	0.157	0.023	0.636
20 years	4.474%	15.3	0.156	0.023	0.634
all data	4.385%	20.0	0.178	0.028	0.642
Number of Individuals	6,032				

Table 5: Best Fit Parameters for Weighted ZIP Code Average as Measure of Experience

For each horizon, the table shows the parameters of the specifications with the highest R^2 in Equation 1 where past house price experiences are measured by a weighted average of past house price changes according to Equation 2. The estimated parameters shown are the R^2 of the regression, the corresponding estimate of λ, the coefficient on the experience variable, its standard error and the effect of 1 standard deviation of the experience variable on the expected house price change.

	Expected 1 Year Change in US House Prices				
	I	II	III	IV	V
	Weighted past house price changes over				
	2 years	3 years	5 years	10 years	15 years
Past House Price Changes	0.157***	0.147***	0.171***	0.170***	0.173***
* Low Comovement with US House Prices	(0.0325)	(0.0349)	(0.0352)	(0.0331)	(0.0322)
Past House Price Changes	0.114***	0.140***	0.130***	0.136***	0.132***
* Medium Comovement with US House Prices	(0.0349)	(0.0408)	(0.0459)	(0.0471)	(0.0427)
Past House Price Changes	0.137***	0.159***	0.158***	0.146***	0.158***
* High Comovement with US House Prices	(0.0376)	(0.0379)	(0.0545)	(0.0416)	(0.0500)
Medium Comovement with US House Prices	0.187	0.00795	0.379	0.140	0.171
	(0.438)	(0.434)	(0.446)	(0.450)	(0.430)
High Comovement with US House Prices	0.477	0.206	0.572	0.701*	0.490
	(0.469)	(0.377)	(0.403)	(0.381)	(0.411)
Constant	1.902	2.280	1.914	1.695	1.992
	(4.942)	(4.706)	(4.673)	(4.724)	(4.769)
Time Fixed Effects	Y	Y	Y	Y	Y
Demographics	Y	Y	Y	Y	Y
Low vs. High Coefficien	-0.0200	0.0113	-0.0134	-0.0241	-0.0147
	(0.0540)	(0.0522)	(0.0661)	(0.0590)	(0.0594)
Number of observations	6032	6032	6032	6032	6032
R squared	0.0452	0.0450	0.0455	0.0458	0.0454

Table 6: House Price Experiences and Expectations by Magnitude of Effect in the Data

The table shows regression estimates of Equation 1. Standard errors are clustered at the state level. The dependent variable is the expected change in year-ahead house prices in percentage points as stated by the respondent. Past house price experiences are measured by a weighted average of past house price changes according to Equation 2. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey, respondents' age and age squared and indicators for whether respondents own their home, are male, married, went to college and are white or black. Respondents are grouped into terciles based on the coefficient on prior local house price changes in a regression of national house price changes on prior year local price changes in the years since availability of our house price data. For each horizon, past house prices are weighted using the λ corresponding to the specifications with the highest R^2 as shown in Table 5.

	Std of expected house price change		
	I	II	III
	ZIP	MSA	State
Std of house price changes since			
5 years ago	0.0448***	0.272***	0.182**
	(0.0167)	(0.0856)	(0.0779)
10 years ago	0.0291**	0.137***	0.0813
	(0.0113)	(0.0454)	(0.0510)
20 years ago	0.0354***	0.156**	0.0695
	(0.00903)	(0.0587)	(0.0638)
1976 (all available data)	0.0366**	0.174**	0.0727
	(0.0146)	(0.0783)	(0.0677)
Last year's house price change (deciles)	Y	Y	Y
Demographics	Y	Y	Y
Number of observations	5,830	6,693	7,835

Table 7: Past Variation in House Price and Expected Variation

The table shows regression estimates of Equation 1. The dependent variable is the standard deviation of expected change in year-ahead house prices in percentage points as stated by the respondent. For each horizon, the table shows the estimated coefficient on the standard deviation of experienced changes. The standard deviation of past house price changes is based on house price in the ZIP code (column 1), MSA (column 2) and state (column 3) where the respondent lives. Standard errors are clustered at the state level. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey, respondents' age and age squared and indicators for whether respondents own their home, are male, married, went to college and are white or black.

	Percent Chance US Unemployment Higher in a Year					
	I	II	III	IV	V	VI
Employment Status						
Employed			omitted			
Looking for Work	6.734***	5.514***	1.442**	1.447**	5.724***	0.897
	(0.942)	(0.948)	(0.655)	(0.655)	(1.205)	(1.102)
Become Employed					1.122	-2.153*
					(1.115)	(1.116)
Became Unemployed					5.217***	-0.172
					(1.430)	(0.986)
Retired	-3.144***	-2.901***	-0.539	-0.528	-2.892***	-0.876
	(0.495)	(0.641)	(0.750)	(0.749)	(0.642)	(0.769)
Student	2.714	1.782	0.123	0.117	1.822	-0.439
	(2.030)	(2.069)	(1.685)	(1.686)	(2.072)	(1.731)
Out of the Labor Force	1.953**	0.690	-0.663	-0.663	0.720	-1.082
	(0.889)	(0.914)	(0.990)	(0.988)	(0.915)	(1.003)
Local Unemployment Rate			-0.137			
			(0.201)			
Local Unemployment (Decile Indicators)		Y		Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y	Y
Demographics		Y	Y	Y	Y	Y
Individual Fixed Effects			Y	Y		Y
Mean of dependent variable	37.87	37.87	37.87	37.87	37.87	37.87
Number of observations	60,700	60,700	60,700	60,700	60,700	60,700
Number of individuals	8,104	8,104	8,104	8,104	8,104	8,104

Table 8: Effect of Employment Status on Unemployment Expectations

The table shows regression estimates of Equation 1. Standard errors are clustered at the respondent level. The dependent variable is the percentage chance of US unemployment being higher a year later as stated by the respondent. Employment status is each respondent's self reported current employment status in columns 1 to 4. In column 5 and 6, respondents who are employed and were not previously unemployed during the sample are classified as *Employed*. Respondents who are looking for work and were not previously employed are classified as *Looking for Work*. Respondents who are currently employed but were unemployed in any previous survey module are classified as *Become Employed*. Respondents who are currently looking for work but were employed in any previous survey module are classified as *Become Unemployed*. Local unemployment is the unemployment rate in the ZIP code where the respondent lives. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey. When no individual fixed effects are included, demographics also include respondents' age and age squared, indicators for whether respondents are male, married, went to college and are white or black.

	Expected 1 Year Change in US House Prices		
	I	II	III
	ZIP	MSA	State
		By Numeracy	
Past Local House Price Change * Low Numeracy	0.141**	0.273***	0.317***
	(0.0652)	(0.0726)	(0.0777)
Past Local House Price Change * Medium Numeray	0.0951***	0.163***	0.210***
	(0.0276)	(0.0523)	(0.0568)
Past Local House Price Change * High Numeracy	0.0563**	0.0990***	0.157***
	(0.0217)	(0.0297)	(0.0417)
Medium Numeracy	-1.016*	-0.337	-0.429
	(0.507)	(0.550)	(0.510)
High Numeracy	-1.006**	-0.224	-0.364
	(0.471)	(0.509)	(0.489)
Time Fixed Effects	Y	Y	Y
Demographics	Y	Y	Y
Low vs. High Numeracy	-0.0844	-0.174***	-0.160**
	(0.0622)	(0.0638)	(0.0652)
Number of observations	5752	6593	7695
R squared	0.0479	0.0399	0.0377
		By college	
Past Local House Price Change * College	0.0784***	0.144***	0.181***
	(0.0207)	(0.0305)	(0.0495)
Past Local House Price Change * No College	0.115***	0.202***	0.261***
	(0.0334)	(0.0560)	(0.0465)
College	-0.221	-0.0733	0.122
	(0.344)	(0.345)	(0.332)
Time Fixed Effects	Y	Y	Y
Demographics	Y	Y	Y
No College vs College	-0.0367	-0.0578	-0.0796
	(0.0408)	(0.0592)	(0.0497)
Number of observations	6032	6925	8104
R squared	0.0438	0.0390	0.0369

Table 9: House Price Change and Expectations by Numeracy and College

The table shows estimates of Equation 1. Standard errors are clustered at the state level. The dependent variable is the expected change in year-ahead house prices in percentage points as stated by the respondent. Past house price change is the change in the previous calendar year in the ZIP code (column 1), MSA (column 2) or state (column 3) where the respondent lives. Time fixed effects are included for each survey month. Demographics include indicators for each of the 11 categories eliciting household income in the survey, respondents' age and age squared and indicators for whether respondents own their home, are male, married and are white or black.

	Expected 1 Year Change in US House Prices		
	I	II	III
	ZIP	MSA	State
Past Local House Price Change * Age 25-39	0.0497	0.175***	0.157***
	(0.0507)	(0.0534)	(0.0535)
Past Local House Price Change * Age 40-49	0.155***	0.207***	0.294***
	(0.0498)	(0.0693)	(0.0844)
Past Local House Price Change * Age 50-59	0.0632*	0.183***	0.215***
	(0.0322)	(0.0505)	(0.0683)
Past Local House Price Change * Age 60 plus	0.115***	0.145***	0.218***
	(0.0270)	(0.0387)	(0.0428)
Age 40-49	-0.357	0.280	-0.514
	(0.575)	(0.678)	(0.665)
Age 50-59	0.872	1.318**	0.606
	(0.609)	(0.615)	(0.617)
Age 60 plus	0.872	1.553***	0.735
	(0.578)	(0.507)	(0.541)
Time Fixed Effects	Y	Y	Y
Demographics	Y	Y	Y
Difference Age 60 plus vs. 25-39	0.0653	-0.0300	0.0614
	(0.0540)	(0.0413)	(0.0595)
Number of observations	6,028	6,921	8,099
R squared	0.0449	0.0392	0.0377

Table 10: House Price Change and Expectations by Age

The table shows regression estimates of Equation 1. Standard errors are clustered at the state level. The dependent variable is the expected change in year-ahead house prices in percentage points as stated by the respondent. Past house price change is the change in the previous calendar year in the ZIP code (column 1), MSA (column 2) or state (column 3) where the respondent lives. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey, indicators for whether respondents own their home, are male, married, went to college and are white or black. We also include indicators for each decile of years lived in the current ZIP code.

	Expected 1 Year Change in US House Prices		
	I	II	III
	ZIP	MSA	State
		By ownership	
Past Local House Price Change * Homeowner	0.0842***	0.161***	0.198***
	(0.0206)	(0.0338)	(0.0365)
Past Local House Price Change * Non-Homeowner	0.124**	0.203***	0.281***
	(0.0475)	(0.0609)	(0.0819)
Homeowner	-0.245	-0.435	-0.0990
	(0.480)	(0.518)	(0.537)
Time Fixed Effects	Y	Y	Y
Demographics	Y	Y	Y
Difference Non-Homeowner vs Homeowner	-0.0395	-0.0420	-0.0831
	(0.0547)	(0.0605)	(0.0715)
Number of observations	6,032	6,925	8,104
R squared	0.0438	0.0389	0.0369

Table 11: House Price Change and Expectations by Homeownership

The table shows regression estimates of Equation 1. Standard errors are clustered at the state level. The dependent variable is the expected change in year-ahead house prices in percentage points as stated by the respondent. Past house price change is the change in the previous calendar year in the ZIP code (column 1), MSA (column 2) or state (column 3) where the respondent lives. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey, respondents' age and age squared and indicators for whether respondents own their home, are male, married, went to college and are white or black.

	Percent Chance US Unemployment Higher in a Year		
	I	II	III
Employed		(omitted)	
Looking for work * Low Numeracy	5.092**		
	(2.368)		
Looking for work * Medium Numeracy	0.222		
	(1.118)		
Looking for work * High Numeracy	-0.494		
	(1.217)		
Looking for work * No College		2.412**	
		(1.151)	
Looking for work * College		0.400	
		(0.971)	
Looking for work * Age under 35			1.626
			(1.820)
Looking for work * Age 35 to 50			2.106
			(1.339)
Looking for work * Age 50 to 65			0.900
			(1.060)
Retired	0.772	1.542	1.315
	(2.177)	(2.097)	(2.135)
Student	-5.367	-4.891	-4.980
	(3.727)	(3.897)	(3.858)
Out of the Labor Force	1.170	3.434	3.188
	(2.584)	(3.146)	(3.141)
Time Fixed Effects	Y	Y	Y
Demographics	Y	Y	Y
Individual Fixed Effects	Y	Y	Y
Low vs. High Numeracy	-5.586**		
	(2.613)		
No College vs.College		-2.011	
		(1.451)	
Age under 35 vs. Age 50 to 65			-0.726
			(2.077)
Number of observations	3525	3775	3775
Number of individuals	424	432	432

Table 12: Effect of Unemployment on Expectations by Respondent Characteristics

The table shows regression estimates of Equation 1 with the indicator for searching for work interacted with numeracy, college and age. Standard errors are clustered at the respondent level. The dependent variable is the percentage chance of US unemployment being higher a year later as stated by the respondent. Employment status is self-reported current employment status. Local unemployment is the unemployment rate in the ZIP code the respondent lives in. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey.

			Percentage chance that the following will be higher in a year						
	I	II	III	IV	V	VI	VII	VIII	IX
	Will be better off in a year	*Are* better off than year ago	interest rates on savings	US stock prices	Inflation 1 year	Inflation 3 years	government debt	home prices	unemployment
Panel A									
Employment Status									
Employed	(omitted)					(omitted)			
Looking for Work	-0.0573**	-0.476***	-0.253	-0.876	0.113	0.0802	45.60	-1.107**	
	(0.0265)	(0.0380)	(0.677)	(0.640)	(0.111)	(0.115)	(48.74)	(0.514)	
Retired	-0.0618**	-0.222***	0.332	-0.627	-0.000399	-0.175	-236.4	-0.589	
	(0.0273)	(0.0307)	(0.833)	(0.751)	(0.111)	(0.124)	(236.2)	(0.381)	
Student	-0.0800	-0.362***	-3.410*	-3.353**	0.0316	-0.112	64.44	1.019	
	(0.0719)	(0.0760)	(1.909)	(1.455)	(0.263)	(0.274)	(68.24)	(0.911)	
Out of Labor Force	-0.126***	-0.277***	-1.166	-1.895**	-0.0814	-0.143	537.4	-0.0235	
	(0.0329)	(0.0397)	(1.057)	(0.877)	(0.162)	(0.191)	(533.8)	(0.626)	
Local Unemployment Indicators	Y	Y	Y	Y	Y	Y	Y	Y	
Demographics	Y	Y	Y	Y	Y	Y	Y	Y	
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	
Individual Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	
Number of observations	60672	60663	60668	60147	52888	52881	52744	45281	
Number of individuals	8104	8103	8104	8104	7770	7752	7921	6038	
Panel B									
Prior Local House Price Change	0.00159	0.000350	-0.00896	0.00205	0.00828	-0.00296	-0.0523		-0.0625
(ZIP code level)	(0.00194)	(0.00224)	(0.0679)	(0.0744)	(0.0337)	(0.0379)	(0.0385)		(0.0610)
Local Unemployment Indicators	Y	Y	Y	Y	Y	Y	Y		Y
Demographics	Y	Y	Y	Y	Y	Y	Y		Y
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y		Y
Number of observations/ individuals	6030	6025	6029	5985	6003	6003	5881		6032

Table 13: Own Experiences and Expectations about Other Economic Outcomes

The table shows estimates of Equation 1 with the following dependent variables: whether the respondent believes they will be better off a year later (column 1) and are better off than a year ago (column 2), both on a 5 point scale; the percentage chance that interest rates on saving accounts (column 3) and US stock prices (column 4) will be higher a year later; expected inflation in the next year (column 5) and between two and three years from now (column 6); the expected change in government debt (column 7) and US home prices (column 8) and likelihood of higher unemployment (column 9). Fixed effects are included for each month. Local unemployment is the unemployment rate in the ZIP code the respondent lives in. Demographics include indicators for each income category. Without individual fixed effects, demographics include age and age squared, indicators for male, married, college and race being white or black. Controls also include past house price changes in Panel A, column 8. Standard errors are clustered at the individual level (Panel A) and state level (Panel B).

	Percentage chance that the following will be higher in a year								
	I	II	III	IV	V	VI	VII	VIII	IX
	Will be better off in a year	*Are* better off than year ago	interest rates on savings	US stock prices	Inflation 1 year	Inflation 3 years	government debt	home prices	unemployment
Panel A									
Expected US Unemployment	-0.00324***	-0.00186***	0.232***	0.197***	0.00969***	0.00977***	-0.465	0.00103	
	(0.000189)	(0.000172)	(0.00656)	(0.00640)	(0.000794)	(0.000859)	(0.531)	(0.00391)	
Employment Status									
Employed	(omitted)					(omitted)			
Looking for Work	-0.0526**	-0.473***	-0.589	-1.169*	0.104	0.0705	46.01	-1.109**	
	(0.0263)	(0.0381)	(0.656)	(0.615)	(0.110)	(0.115)	(49.17)	(0.515)	
Retired	-0.0636**	-0.223***	0.456	-0.547	0.0127	-0.163	-236.6	-0.589	
	(0.0273)	(0.0307)	(0.808)	(0.733)	(0.111)	(0.124)	(236.5)	(0.381)	
Student	-0.0796	-0.361***	-3.422*	-3.373**	0.0120	-0.117	65.35	1.020	
	(0.0709)	(0.0754)	(1.897)	(1.528)	(0.264)	(0.277)	(69.20)	(0.912)	
Out of Labor Force	-0.128***	-0.278***	-1.010	-1.743**	-0.0771	-0.129	537.0	-0.0234	
	(0.0331)	(0.0397)	(1.021)	(0.852)	(0.161)	(0.191)	(533.4)	(0.626)	
Local Unemployment Indicators	Y	Y	Y	Y	Y	Y	Y	Y	
Demographics	Y	Y	Y	Y	Y	Y	Y	Y	
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	
Individual Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	
Number of observations	60672	60663	60668	60147	52888	52881	52744	45281	
Number of individuals	8104	8103	8104	8104	7770	7752	7921	6038	
Panel B									
Expected US House Price Change	0.00490***	0.00356*	0.0885*	0.226***	0.246***	0.198***	0.305***		-0.0667
	(0.00138)	(0.00184)	(0.0446)	(0.0404)	(0.0527)	(0.0630)	(0.0881)		(0.0476)
Prior Local House Price Change	0.00113	0.0000144	-0.0175	-0.0198	-0.0150	-0.0218	-0.0804**		-0.0561
(ZIP code level)	(0.00196)	(0.00233)	(0.0688)	(0.0752)	(0.0337)	(0.0373)	(0.0398)		(0.0623)
Local Unemployment Indicators	Y	Y	Y	Y	Y	Y	Y		Y
Demographics	Y	Y	Y	Y	Y	Y	Y		Y
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y		Y
Number of observations/ individuals	6030	6025	6029	5985	6003	6003	5881		6032

Table 14: Own Experiences, Corresponding Expectations and Expectations about Other Economic Outcomes

The table shows estimates the same specifications as in Table 13 but adds in expected US unemployment changes in Panel A and expected US house price changes in Panel B as additional regressors.

	Expected Chance of Higher Interest Rates											
	I	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII
	All	Low Numeracy	Medium Numeracy	High Numeracy	College	No College	Owns Home	Renter	Age 25-39	Age 40-49	Age 50-59	Age 60+
Panel A: Cross-Section												
Expected Inflation 1 year	-0.0921***	-0.0580*	-0.144***	-0.186**	-0.229***	-0.0552*	-0.126***	-0.0288	-0.0365	-0.0537	-0.116**	-0.127***
	(0.0256)	(0.0329)	(0.0461)	(0.0764)	(0.0494)	(0.0289)	(0.0326)	(0.0411)	(0.0535)	(0.0547)	(0.0531)	(0.0478)
Expected Chance of	0.237***	0.353***	0.222***	0.177***	0.221***	0.259***	0.228***	0.276***	0.277***	0.250***	0.198***	0.230***
Higher Unemployment	(0.0120)	(0.0211)	(0.0218)	(0.0212)	(0.0174)	(0.0164)	(0.0141)	(0.0232)	(0.0236)	(0.0261)	(0.0256)	(0.0226)
Demographics	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual Fixed Effects	N	N	N	N	N	N	N	N	N	N	N	N
Number of observations	8070	2075	2380	3207	4404	3666	6103	1967	2077	1622	1827	2544
Panel B: Within Individual												
Expected Inflation 1 year	0.000895	0.0202	0.000225	0.0244	0.0113	0.000705	0.000554	0.0225	0.000707	0.00207	0.00352	0.00382
	(0.000844)	(0.0131)	(0.000280)	(0.0250)	(0.0178)	(0.000696)	(0.000512)	(0.0149)	(0.000660)	(0.0218)	(0.0217)	(0.0178)
Expected Chance of	0.233***	0.298***	0.220***	0.197***	0.217***	0.247***	0.221***	0.269***	0.257***	0.241***	0.235***	0.212***
Higher Unemployment	(0.00659)	(0.0134)	(0.0122)	(0.0109)	(0.00951)	(0.00917)	(0.00752)	(0.0135)	(0.0148)	(0.0152)	(0.0133)	(0.0107)
Demographics	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Number of observations	60498	14892	17057	23272	33460	27038	46200	14298	14706	11661	13838	20293
Number of individuals	8101	2087	2386	3216	4421	3682	6125	1976	2090	1625	1829	2559

Table 15: Expectations about Inflation, Unemployment and Interest Rates

The table shows regression estimates of the effect of expected inflation and expected unemployment on expected interest rates. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey. When no individual fixed effects are included, demographics also include respondents' age and age squared, indicators for whether respondents are male, married, went to college and are white or black. Standard errors are clustered at the individual level when including individual fixed effects in Panel A and at the state level in Panel B.

(A) Employment Prospects When Entering Sample

	Lose job within			
	1 month	3 months	6 months	9 months
Pr(job loss within 12 months)	0.0359***	0.0893***	0.140***	0.163***
	(0.0114)	(0.0174)	(0.0219)	(0.0239)
Local Unemployment (Indicators for Decile)	Y	Y	Y	Y
Demographics	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y
Number of observations	4865	4696	4463	4225

(B) Within Individual Changes in Employment Prospects

	Lose job within			
	1 month	3 months	6 months	9 months
Pr(job loss within 12 months)	0.0193***	0.0178*	0.0158	0.0134
	(0.00563)	(0.00922)	(0.0100)	(0.00963)
Local Unemployment (deciles)	Y	Y	Y	Y
Demographics	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y
Individual Fixed Effects	Y	Y	Y	Y
Number of observations	34261	32901	30870	28895
Number of individuals	4988	4809	4568	4324

Table 16: Predictiveness of Own Employment Prospects

The table shows regression estimates for whether respondents' self reported probability of losing their job is indicative of future job loss. The dependent variable is whether respondents report having lost their job within the next 1, 3, 6 or 9 months of the survey module. *Pr(job loss within 12 months)* is the percentage chance that the respondent will loose her job within the next 12 months as stated by the respondent (on a 0-1 scale). Panel A includes only the first survey module for each respondent. Panel B includes all survey modules and respondent fixed effects. Local unemployment is the unemployment rate in the ZIP code the respondent lives in. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey. When no individual fixed effects are included, demographics also include respondents' age and age squared, indicators for whether respondents are male, married, went to college and are white or black. Standard errors are clustered at the respondent level when applicable.

	Housing in ZIP is a good investment		
	I 1 year national expectations	II 1 year ZIP expectations	III 5 year ZIP expectations
Expectations - 1st tercile		(omitted)	
Expectations - 2nd tercile	0.290***	0.625***	0.400***
	(0.0709)	(0.0728)	(0.0752)
Expectations - 3rd tercile	0.230***	0.754***	0.593***
	(0.0773)	(0.0804)	(0.0767)
Time Fixed Effects	Y	Y	Y
Demographics	Y	Y	Y
Number of observations	3744	3670	3662

Table 17: House Price Expectations and Housing Investment

The table shows ordered logit regression estimates of the effect of expected house price changes on how attractive respondents consider investing in a home in their current ZIP code. Respondents can choose whether they consider such an investment to be a bad or very bad investment, neither a bad nor good investment, a good investment, or a very good investment. Demographics include indicators for each of the 11 possible categories eliciting household income in the survey, respondents' age and age squared and indicators for whether respondents own their home, are male, married, went to college and are white or black.

A Survey Questions

A.1 Monthly Survey Questions on House Prices

- *Next we would like you to think about home prices nationwide. Over the next 12 months, what do you expect will happen to the average home price nationwide?*
  Over the next 12 months, I expect the average home price to...

  - *increase by 0% or more*
  - *decrease by 0% or more*

  By about what percent do you expect the average home price to (increase/decrease as in previous question)? Please give your best guess.
  Over the next 12 months, I expect the average home price to (increase/decrease as in previous question) by ____ % .

- *And in your view, what would you say is the percent chance that, over the next 12 months, the average home price nationwide will...*

increase by 12% or more	____	*percent chance*
increase by 8% to 12%	____	*percent chance*
increase by 4% to 8%	____	*percent chance*
increase by 2% to 4%	____	*percent chance*
increase by 0% to 2%	____	*percent chance*
decrease by 0% to 2%	____	*percent chance*
decrease by 2% to 4%	____	*percent chance*
decrease by 4% to 8%	____	*percent chance*
decrease by 8% to 12%	____	*percent chance*
decrease by 12% or more	____	*percent chance*

- The wording of the next question depends on the month of the survey. In January 2014, the question would have asked the following:
  Now we would like you to think about home prices further into the future. Over the 12-month period between January 2016 and January 2017, what do you expect will happen to the average home price nationwide?
  Over the 12-month period between January 2016 and January 2017, I expect the average home price to...

- *increase by 0% or more*
- *decrease by 0% or more*

By about what percent do you expect the average home price to (increase/decrease as in previous question) over that period?
Over the 12-month period between January 2016 and January 2017, I expect the average home price to (increase/decrease as in previous question) by ____ % .

A.2 Monthly Survey Questions on Employment

- *What do you think is the percent chance that 12 months from now the unemployment rate in the U.S. will be higher than it is now?*
- *What is your current employment situation?*
  - *Working full-time (for someone or self-employed)*
  - *Working part-time (for someone or self-employed)*
  - *Not working, but would like to work*
  - *Temporarily laid off*
  - *On sick or other leave*
  - *Permanently disabled or unable to work*
  - *Retiree or early retiree*
  - *Student, at school or in training*
  - *Homemaker*
  - *Other (please specify)*
- Question on own employment prospects for employed respondents
  - *What do you think is the percent chance that you will lose your main job during the next 12 months?*
  - *Suppose you were to lose your main job this month. What do you think is the percent chance that within the following 3 months, you will find a job that you will accept, considering the pay and type of work?*

B History of Local House Prices and US House Price Expectations

Table A3 replicates the analysis in section 3.3 using state and MSA level house prices instead of ZIP code level house prices. The results are very similar.

C Robustness - Local House Prices

C.1 Distinguishing between Local and National House Prices

A potential concern about our results is that respondents do not fully understand that, despite the explicit wording, the survey asks about expectations of national rather than local house prices. A subset of the respondents was asked about zip code level house price expectations in addition to national house price expectations. If respondents incorrectly believed the question about national house prices to be about local house prices, we would expect similar answers to both questions. Table A4 shows that, on average, expectations about US house price growth are slightly higher than about ZIP code level house price growth. On the individual level, the differences are substantial, as indicated by the standard deviation of the difference being 9.6 percentage points and the average absolute difference being 5.5 percentage points. In addition, for respondents for whom the answer options matched exactly in both scenarios (respondents were randomized into different options of eliciting the ZIP code level house price expectations), only 20% of respondents state the exact same number for ZIP code and national-level house price change. Amongst all respondents, 24% and 40% of the respondents state numbers that are within one and two percentage point of each other, respectively. For all other respondents answers differ substantially. In unreported regressions, we find that more sophisticated respondents - those with a high numeracy score or with a college degree - are more likely to give similar answers to both questions. If respondents did not understand what they were being asked about, we would expect the opposite.

In addition, Table 1 indicates that when being asked about unemployment, respondents understand the difference between nationwide outcomes and personal outcomes. Employed respondents, on average, assign a probability of 15 percent to losing their job, but believe unemployment will be higher with probability of 37 percent - a substantial difference. This large average difference between the two is consistent with prior evidence that respondents overestimate their own ability,[30] and therefore their own employment prospects.

C.2 Recall of Past House Prices

To extrapolate from past local house prices, respondents need to know them. The first four columns of Table A5 show the relationship between recalled and actual house price changes, without controls and controlling for respondent demographics and time fixed effects. A one percentage point increase in actual house price changes increases recalled changes in the previous year by .26 percentage points and recalled changes over the previous five years by .72 percentage points. This suggests that respondents know the change in house prices in their local area reasonably well even though recall is not perfect (as would be indicated by an estimated coefficient on actual price changes of exactly 1).

When estimating the effect of local house price experience on expectations, we measure respondents' past experience by actual house price changes, though respondents rely on what they believe prior house price changes to be.[31] Table A5 shows that the estimated coefficient on recalled changes is highly statistically significant and larger than the corresponding coefficient on actual house price changes shown in Table 3.[32] In addition, reducing the influence of outliers in recalled house price changes by winsorizing at the 1 or 5 percent levels further increases the estimated effect.

D Robustness - Informativeness of Own Experience

Appendix Figure A1 shows estimates of the specification reported in Table 4 where we group by the coefficient and correlation between local and national home price changes estimated over the past 10, 15 and 20 years instead of over the whole sample period since 1976 as in the baseline. The magnitude of the effect of past local prices and their informativeness in the data are similar irrespective of the horizon used. The point estimates of the effect of locally experienced house price changes on expectations varies across the different time horizons,

[30] For instance, Weinstein (1980) documents that college students systematically underestimate the likelihood that something bad, such as losing their job, will happen to them.

[31] Cavallo et al. (2014) find in a field experiment that past recalled price changes are more predictive of expected inflation rates than actual past price changes.

[32] In unreported regressions we estimate the effect of both recalled and actual price changes, for the same sample of respondents. This reduces our sample size further since we now also require ZIP code level house price indices to be available. The effect of recalled price changes is similar to the effect in Table A5, but the effect of actual house price changes for this sample is smaller than in Table 3.

but the qualitative results remain very much the same. A t-test confirms no statistically different effect between areas with low and high predictiveness in the real data.

E Assessing Informativeness of Own Unemployment

Assuming that respondents are Baysion updaters, the difference in expectations between an individual who lost her job and one who is still employed should be:

$$
\begin{aligned}
&P(high|unemployed) - P(high|employed) = \\
&\frac{P(jobloss|nothigher) * x * P(high)}{P(jobloss|nothigher) * x * P(high) + P(jobloss|nothigher)(1 - P(high))} \\
-&\frac{(1 - P(jobloss|nothigher)x)P(high)}{(1 - P(jobloss|nothigher)x)P(high) + (1 - P(jobloss|nothigher))(1 - P(high))}
\end{aligned}
$$

We make the following assumptions about individuals priors:

- $P(high)$ is 38% (the average expectation of all respondents in our sample)
- $P(jobloss|nothigher) =$ is 5.6% (the average local unemployment rate in our sample)

We also assume the probability of job loss is higher by factor x if unemployment was going to increase relative to if unemployment was not going to increase, that is, $P(jobloss|high) = x * P(jobloss|nothigher)$.

Substituting in our assumptions, $P(high) = 38\%$ and $P(jobloss|nothigher) = 5.6\%$, and our estimated difference in expectations, $P(high|unemployed) - P(high|employed) = .0144$, yields $x = 1.06$. That is, respondents would need to be about 6% more likely to lose their job if unemployment were truly going up than they would be if unemployment were not going to increase to justify the estimated difference in posterior beliefs of 1.44 percentage points.

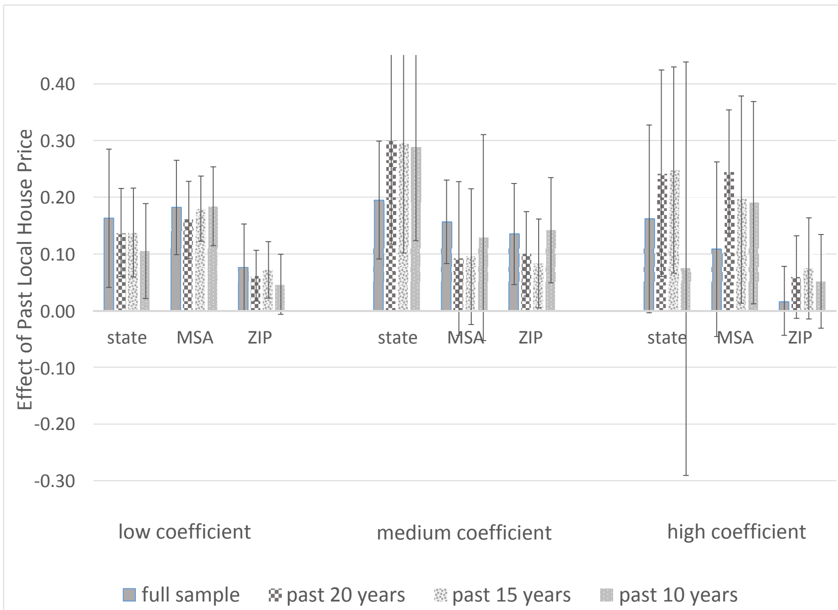


Figure A1: House Price Changes and Expectations by Magnitude of Effect in Data - Different Horizons

The figure shows effect of prior year local house price changes on expectations about national house prices changes in regression estimates of Equation 1 when grouped by the magnitude of the effect in the data over various horizons. Standard errors are clustered at the state level. The dependent variable is the expected change in year-ahead house prices in percentage points as stated by the respondent. Past house price change is the change in the previous calendar year in the ZIP code, MSA or state where the respondent lives, as labeled. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey, respondents' age and age squared and indicators for whether respondents own their home, are male, married, went to college and are white or black. Respondents are grouped into three groups based on the coefficient on prior local house price changes in a regression of national house price changes on prior year local price changes.

	N	Mean	Std. Dev.	25th pctile	50th pctile	75th pctile
Past House Price Experience - Average Changes						
Mean change of **ZIP code** level house prices						
past 3 years	6131	5.09	3.43	2.75	5.05	7.22
past 5 years	6131	5.99	3.72	3.09	5.70	8.64
past 10 years	6131	0.40	1.91	-0.88	0.36	1.58
since respondent lived in ZIP	5335	3.88	3.37	1.70	3.53	5.75
since respondent lived in state	5988	3.87	2.10	2.71	3.68	4.95
since respondent was age 13	6131	3.81	1.53	2.85	3.67	4.74
since 1976 (beginning of data series)	6131	4.05	1.31	3.08	3.82	4.84
Mean change of **MSA** level house prices						
past 3 years	7038	4.85	2.62	2.93	4.86	6.93
past 5 years	7038	5.64	3.22	3.19	4.92	8.46
past 10 years	7038	0.44	1.47	-0.52	0.30	1.27
since respondent lived in ZIP	6171	3.69	2.66	1.89	3.38	5.34
since respondent lived in state	6882	3.74	1.74	2.80	3.58	4.67
since respondent was age 13	7038	3.65	1.30	2.88	3.57	4.43
since 1976 (beginning of data series)	7038	3.88	1.06	3.17	3.74	4.60
Mean change of **state** level house prices						
past 3 years	8234	5.01	2.11	3.61	4.86	6.80
past 5 years	8234	5.87	2.78	3.62	5.37	8.45
past 10 years	8234	0.48	1.21	-0.33	0.59	1.31
since respondent lived in ZIP	7244	3.86	2.42	2.17	3.64	5.47
since respondent lived in state	8056	3.89	1.66	2.88	3.65	4.95
since respondent was age 13	8234	3.82	1.31	2.99	3.65	4.53
since 1976 (beginning of data series)	8234	4.07	1.16	3.30	3.82	4.95
Past House Price Experience - Variation						
Standard devations in the past 10 years in						
ZIP code	6131	8.07	3.82	5.15	7.10	10.64
MSA	8234	6.98	3.61	4.53	5.25	8.90
state	7038	6.93	3.84	4.24	5.79	9.32

Table A1: House Price History Summary Statistics

The table shows mean, standard deviation and the 25$^{\text{th}}$, 50$^{\text{th}}$ and 75$^{\text{th}}$ percentile of house price experiences of respondents of the Survey of Consumer Expectations (SCE) used throughout the paper.

	I	II	III	IV
Past House Price Change in	**Expected Change in US House Prices - Next Year**			
ZIP	0.103***			0.0373
	(0.0188)			(0.0396)
MSA		0.181***		0.0471
		(0.0304)		(0.0557)
State			0.245***	0.164**
			(0.0476)	(0.0692)
Time Fixed Effects	Y	Y	Y	Y
Demographics	Y	Y	Y	Y
Effect of 1 std	0.559	0.733	0.855	
Effect when weighted	0.798	0.954	1.062	
Number of observations	5,398	5,398	5,398	5,398
R squared	0.0457	0.0471	0.0478	0.0485
Past House Price Change in	**Expected 1 Year Change in US House Prices in 2 Years**			
ZIP	0.103***			0.0740**
	(0.0173)			(0.0349)
MSA		0.138***		-0.0251
		(0.0270)		(0.0534)
State			0.196***	0.149**
			(0.0408)	(0.0596)
Time Fixed Effects	Y	Y	Y	Y
Demographics	Y	Y	Y	Y
Effect of 1 std	0.562	0.558	0.689	
Effect when weighted	0.789	0.712	0.739	
Number of observations	5,267	5,267	5,267	5,267
R squared	0.061	0.06	0.0611	0.0626

Table A2: Previous Year's House Price Change and House Price Expectations - Same Sample

The table shows regression estimates of Equation 1. The dependent variable is the expected change in house prices in percentage points as stated by the respondent. Past house price change is the change in the previous calendar year in the ZIP code (column 1), MSA (column 2) or state (column 3) where the respondent lives. Standard errors are clustered at the state level. Time fixed effects are included for each survey month. Demographics include indicators for each of the 11 possible categories eliciting household income in the survey, respondents' age and age squared and indicators for whether respondents own their home, are male, married, went to college and are white or black.

	ZIP Code Level House Prices			MSA Level House Prices			State Level House Prices		
Horizon	R2	λ	effect of 1 standard deviation	R2	λ	effect of 1 standard deviation	R2	λ	effect of 1 standard deviation
2 years	4.470%	0.5	0.626	3.905%	1.7	0.735	3.706%	1.2	0.804
3 years	4.475%	1.3	0.638	3.911%	2.5	0.749	3.729%	1.4	0.850
4 years	4.490%	1.4	0.668	3.914%	3.3	0.757	3.736%	2	0.864
5 years	4.487%	2.5	0.654	3.916%	4.3	0.760	3.737%	3	0.859
10 years	4.478%	6.8	0.641	3.917%	10.1	0.758	3.736%	7.6	0.855
15 years	4.475%	11.1	0.636	3.917%	16	0.757	3.736%	12.1	0.854
20 years	4.474%	15.3	0.634	3.916%	20	0.761	3.736%	16.7	0.852
all data	4.385%	20	0.642	3.713%	20	0.759	3.561%	20	0.889
Number of Individuals	6,032			6,925			8,104		

Table A3: Best Fit Parameters for Weighted Past Prices as Experience Measure - ZIP Code, MSA and State Home Prices

For each horizon, the table shows the parameters of the specifications with the highest R^2 in Equation 2 where past house price experiences are measured by a weighted average of past house price changes according to equation 2. The first three columns use ZIP code level house prices, the three middle columns MSA level house prices and the last three state level house prices.

	N	Mean	Std. Dev.	25th pctile
Difference between US and ZIP code expected house price change				
Difference (in percentage points)	3,684	1.084	9.623	-2
Absolute difference (in percentage points)	3,684	5.503	7.967	1
Same national and ZIP code expected price change	919	0.200	0.400	0
Difference of 1 percentage points or less	3,684	0.240	0.427	0
Difference of 2 percentage point or less	3,684	0.404	0.491	0

Table A4: Difference between US and ZIP Code Level House Price Expectations

The table shows mean, standard deviation and the 25^{th}, 50^{th} and 75^{th} percentile for the difference between respondents' expectations of house price changes nationwide and in their current ZIP code.

	Recalled change in ZIP code house prices in				Expected change in US house prices		
	I	II	III	IV	V	VI	VII
	Last year		Last 5 years				
Actual Change in ZIP	0.296***	0.263***	0.622***	0.720***			
	(0.0363)	(0.0385)	(0.132)	(0.102)			
Recalled Change in ZIP							
Actual					0.159***		
					(0.0317)		
Winsorized 1%						0.202***	
						(0.0347)	
Winsorized 5%							0.313***
							(0.0402)
Time Fixed Effects	N	Y	N	Y	Y	Y	Y
Demographics	N	Y	N	Y	Y	Y	Y
Number of observations	2730	2730	2726	2726	3630	3630	3630

Table A5: Actual and Recalled Changes of Past House Prices and Expectations

Columns (I) to (IV) show the relationship between the actual house price changes in a respondent's ZIP code and the house price changes as perceived by the respondent. A coefficient equal to 1 would indicate perfect recall of past prices by respondents. Columns (V) to (VII) show regression estimates of Equation 1 with recalled past price changes in the respondent's ZIP code instead of actual past prices changes as the explanatory variable. The dependent variable is the expected change in year-ahead house prices in percentage points as stated by the respondent. Demographics include indicators for each of the 11 possible categories eliciting household income in the survey, respondents' age and age squared and indicators for whether respondents own their home, are male, married, went to college and are white or black.