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Personal Experiences and Expectations about Aggregate Outcomes

THERESA KUCHLER and BASIT ZAFAR*

ABSTRACT

Using novel survey data, we 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 U.S. house price changes and higher experienced house price volatility causes respondents to report a wider distribution over expected U.S. house price movements. When we exploit within-individual variation in employment status, we find 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, is inconsistent with risk adjustment, and is more pronounced for less sophisticated individuals.

EXPECTATIONS PLAY A KEY ROLE IN ECONOMIC models of decision-making under uncertainty. Recent work explores empirical measures of expectations to inform the modeling of the expectation formation process (see Barberis et al., 2015; Fuster, Laibson, and Mendel, 2010). This work shows that personal experiences have a substantial effect on expectations of aggregate economic outcomes (see, e.g., Malmendier and Nagel, 2011, 2016; Malmendier, Nagel, and Yan, 2017). Little is known, however, about what exactly constitutes the relevant set of "personal experiences." For instance, local house price movements can differ substantially across the United States.[1] But do differences in these

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[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.

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locally experienced house prices lead individuals to have different expectations about aggregate price changes despite witnessing the same aggregate price movements? Similarly, unemployment rates rose during the financial crisis throughout the United States, but does personally experiencing unemployment—rather than simply witnessing times of high unemployment—affect individuals' expectations about the aggregate unemployment rate? Further, do the answers to these questions depend on individual characteristics? And what do the answers to these questions have to say about the expectation formation process?

In this paper, we address the above questions in order 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 types of personal experiences affect expectations and whether their effects vary with 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, Peng, and Yen, 2012; Glaeser, Gottlieb, and Gyourko, 2012; Burnside, Eichenbaum, and Rebelo, 2016; Glaeser and Nathanson, 2017; Case, Shiller, and Thompson, 2012; Bailey et al., 2018), while employment expectations affect the speed of economic recovery after recessions, and can influence households' job search behavior (see Carroll and Dunn, 1997; Tortorice, 2011; Hendren, 2017). Our results therefore shed light on how expectations about these two key aggregate outcomes are formed while also providing insights 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 U.S. 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 and labor market changes, and 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 that tracks the same individuals monthly for up to 12 months. Second, the data contain respondents' ZIP code information, 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, and find that past locally experienced house prices significantly affect expectations about future changes in U.S. house prices.[2] For instance, respondents in ZIP codes with a 1-percentage-point higher change in house prices in the previous year expect the one-year-ahead increase in U.S. house prices to be 0.1 percentage points higher. We find that this reliance on

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

local experiences increases the cross-sectional dispersion in expectations by nearly 9%. 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: respondents who experienced a 1-percentage-point higher standard deviation in ZIP code- or metro-level house price changes in the past five years expect the standard deviation of one-year-ahead expected house price changes to be 0.045 and 0.27 percentage points higher, respectively.

Turning to the effect of personal unemployment experiences on U.S. unemployment expectations, we leverage the rich panel component of the survey to focus on individuals who experience job transitions (individuals who were previously employed and lose their jobs, or who were unemployed and find a new job) and exploit this *within-individual* variation in personal experiences to estimate their effect on expectations about aggregate unemployment.[3] We find that experiencing unemployment leads respondents to become significantly more pessimistic about future U.S. unemployment: they expect the likelihood of U.S. unemployment increasing in the next year to be 1.44 percentage points higher than when employed (relative to the average stated likelihood of 37%).[4]

We next explore potential mechanisms consistent with the observed extrapolation from personal experiences to aggregate outcomes, and the resulting implications for understanding how individuals form expectations.[5] First, the effect of personal experiences on expectations about aggregate outcomes suggests that respondents either do not know or do not optimally use all relevant publicly available information. All respondents in our sample are forming expectations about the same aggregate outcome—in our case, the change in U.S. house prices or nationwide unemployment. Therefore, the optimal weighting of any piece of public information should be the same for each respondent, irrespective of whether this information happens to be local or not. This is not what we find. Second, we 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. We find, however, that

[3] Few previous studies (Keane and Runkle, 1990; Madeira and Zafar, 2015) have used the panel dimension of survey expectations, largely as a result of data limitations.

[4] The stated expectations in our survey data are predictive of actual outcomes: Respondents who believe that they are more likely to lose their job are indeed more likely to subsequently do so. Expectations about future house price changes are related to whether respondents consider housing a good investment.

[5] We follow the literature that takes extrapolation to be "the formation of expected returns ... based on past returns" (Barberis et al., 2018). The psychology literature suggests several underlying biases that can contribute to such extrapolation.

the ability of local house price changes to predict aggregate price changes in the past is not associated with differences in the extent of extrapolation from locally experienced house prices. Thus, the optimal use of limited information is unlikely to explain our results.

Third, we examine 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, which implies that risk adjustment is unlikely to drive our results. While past price increases are good for homeowners, they are bad for renters. As a result, risk adjustment by homeowners 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 the 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, Laibson, and Mendel, 2010; Greenwood and Shleifer, 2014). To further understand the role of experiences in the expectation formation process, we investigate 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, one's own unemployment has no significant effect on most of these other expectations. These results indicate that respondents rely on their own experiences in a given domain when forming expectations about that particular domain, but experiences in one domain do not affect expectations about other outcomes.

We see our paper as making two contributions. First, our findings contribute to a large literature on how individuals form expectations about various outcomes. Several prior papers document 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 (2003) shows that young investors with little experience expected the highest stock

[6] While not studying expectations directly, several papers show 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, Rantapuska, and Sarvimäki (2017) show that labor market experiences during the Finnish Great Depression affect portfolio choices. Kaustia and

returns during the stock market boom of the late 1990s, and Amromin (2009) and Greenwood and Shleifer (2014) find that stock return expectations are highly correlated with past returns and the level of the stock market.[7] Compared to this work, we exploit the substantial cross-sectional and individual variation in house prices and employment experiences 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 standard deviation of the distribution of expected future price changes. To our knowledge, this extrapolation of both first and second moments has not been previously documented in the literature.[8] Our empirical approach to exploit geographic variation in locally experienced house prices in the cross-section is closely related to Bailey et al. (2018) who show that locally experienced house prices of an individual's friends influence her expectations about local house price changes. As such, their findings are complementary to ours, suggesting that both, an individual's own locally experienced house price changes, as well as those of her friends, affect expectations. Indeed, Armona, Fuster, and Zafar (2019) show that the impact of own local experiences on attitudes toward housing seems to be of a similar magnitude as that of friends' imputed experiences on housing attitudes. Bailey et al. (2018, forthcoming) also show that, by affecting expectations, friends' 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 on aggregate dynamics in the housing and labor markets.[9] Overly optimistic beliefs are often cited as major contributors to the run-up in house prices prior to the recent financial crisis (see, e.g., Piazzesi and Schneider, 2009; Goetzmann, Peng, and Yen, 2012; Burnside, Eichenbaum, and Rebelo, 2016; Case, Shiller, and Thompson, 2012; Glaeser and Nathanson, 2017). Our findings of extrapolation from recent personal experiences provide a plausible foundation for such overly optimistic

Knüpfer (2008) and Chiang et al. (2011) find that the returns investors experience in IPOs affect their decisions as to whether to invest in subsequent IPOs. Similarly, Koudijs and Voth (2016) 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] Using the Survey of Consumer Finances (SCF), Appendino (2013) 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, however, is based on suggestive evidence since the SCF does not contain data on subjective beliefs. Likewise, Armona, Fuster, and Zafar (2019) 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.

[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."

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 U.S.-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 heterogeneous 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, 2010; Scheinkman and Xiong, 2003; Simsek, 2013; Brunnermeier, Simsek, and Xiong, 2014).

For unemployment, we can observe how a given individual's expectations change as her labor market experiences vary 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 to accept less suitable positions, thereby prolonging the effect of the initial shock. Importantly, extrapolation from own employment experiences to aggregate employment conditions can also lead individuals to be unaware of the vastly different employment prospects across the United States, preventing them from relocating to areas with better employment prospects or reentering the labor market after a local shock has subsided. Our results therefore point to expectations as a possible channel explaining the persistent effects of differences in local unemployment shocks long after the Great Recession, as shown by Yagan (forthcoming).

The paper proceeds as follows. Section I describes our data and Section II the empirical strategy. Section III presents results on experiences and house price expectations, and Section IV on experiences and unemployment expectations. Section V presents results by respondent characteristics. Section VI explores the relationship between experiences and expectations about other outcomes, and Section VII investigates the link between expectations and actual outcomes. Section VIII concludes.

I. Data

Our data come from the SCE, a monthly survey of a rotating panel of approximately 1,200 household heads fielded by the Federal Reserve Bank of New York since late 2012.[10] Respondents participate in the panel for up to

[10] See Armantier et al. (2017) for additional information. The monthly survey is conducted over the Internet by the Demand Institute, a nonprofit organization jointly operated by The Conference

12 months, with a roughly equal number rotating in and out of the panel each month. Each survey typically takes about 15 to 20 minutes to complete and elicits consumer expectations on house price changes, labor market outcomes, and several other economic indicators. When entering the survey, respondents answer additional background questions.

A. Expectations about Aggregate House Price Changes and Unemployment Rates

Each month, respondents answer a set of questions about expected U.S. house price changes. First, respondents are asked whether they believe U.S. 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 one-year-ahead change in home prices. Second, the survey elicits a distribution of expected house price changes over the same 12-month horizon. 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%. The range of possible house price changes starts with a decrease of more than 12%, and then proceeds in steps of 2 to 4 percentage points: −12% to −8%, −8% to −4%, −4% to −2%, and −2% to 0%, etc., up to an increase of more than 12%. Internet Appendix A shows the exact phrasing of the question.[11] Using the midpoint of these bins and the individual-specific probability assigned to each bin, we compute the standard deviation of 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 response to this question is the focus of our analysis of unemployment expectations. Respondents are also asked about their current employment situation, which we use to classify respondents into five categories: employed (either full or part time), searching for work (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. Internet Appendix B shows the exact phrasing of these questions.

B. Past House Price Changes

We rely on the CoreLogic Home Price Index (HPI) to construct individual-level house price experiences. Crucially, for our purposes, the index is

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%.

[11] The Internet Appendix may be found in the online version of this article.

geographically comprehensive, with separate series at the ZIP code, metropolitan statistical area (MSA), and state levels. The data set goes back to 1976, which allows 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 are available for ZIP codes covering 59% of the U.S. population. Our analysis uses 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 each month to filter out seasonal effects.

C. Sample Description and Summary Statistics

Our sample contains all respondents who answer questions about expected house price changes and expected unemployment changes, who provide basic demographic information, and who are at least 25 years old. Our sample period spans from December 2012 until April 2017. The final sample contains 8,104 respondents. In our cross-sectional analyses, we focus on the most recent observation for each respondent, but all results are robust to choosing different observations. Table I reports sample summary statistics. Respondents in our sample are on average 51 years old, 55% went to college, and the average yearly household income is $81,000. Our sample therefore has higher education and higher income than the U.S. household population overall. While most of the analysis reported in the paper does not use weights to make the sample representative of the U.S. population, the weighted results are qualitatively similar—and, if anything, stronger.

In addition to basic demographic information, respondents are asked five questions based on Lipkus, Samsa, and Rimer (2001) and Lusardi (2009), which are used to construct an individual-specific measure of numeracy. Respondents, on average, answer 80% of the questions correctly, and at least a quarter answer all of the questions 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.

In the coming year, the average expected change in house prices is 5.5% on average and 5% at the median, which is also the most common answer. There is a wide variety of answers around the mean point estimate, as indicated by the standard deviation of over 8 percentage points and the distribution of all expected house price changes shown in Internet Appendix Figure IA.1. 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%. Table I also shows that past house prices in respondents' ZIP codes, MSAs, and states vary substantially. Prices increased by 6% on average in the past year, though by only 2.5% for respondents in the 25th percentile and by almost 9% for respondents in the

Table I

Summary Statistics

The table reports summary statistics of the characteristics, house price expectations, and past house price experience of respondents to the Survey of Consumer Expectations (SCE) used throughout the paper.

	N	Mean	*SD*	25th Percentile	50th Percentile	75th Percentile
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 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 two 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
Unemployment Experience						
Transitions from employment to unemployment	8,104	0.03	0.20	0	0	0
Transitions from unemployment to employment	8,104	0.04	0.22	0	0	0
Unemployment Expectations						
Expected likelihood of higher unemployment						
All	8,104	36.54	23.05	20.00	35.00	50.00

(*Continued*)

Table I—*Continued*

	N	Mean	SD	25th Percentile	50th Percentile	75th Percentile
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 U.S. unemployment	4,896	22.08	27.34	5.00	20.00	40.00

75th percentile.[12] Data on past house price changes at the ZIP code level are available for 6,032 of the 8,104 respondents and for everyone at the state level.

On average, respondents experience 0.03 transitions from employment to unemployment, resulting in a total of 271 instances in which respondents lose their previous employment. Similarly, there are 0.04 transitions per respondent from unemployment to employment for a total of 323 instances in which respondents find a new job out of unemployment. Below, we exploit these within-individual changes in employment experiences to estimate their effect on expectations. Internet Appendix Table IA.I shows the full set of each respondent's current and previous employment status in each monthly module. Employed respondents in our sample expect unemployment to go up with a likelihood of 37% on average. Unemployed respondents are substantially less optimistic, expecting unemployment to rise with a probability of 43.5%.

II. Understanding the Effect of Experiences on Expectations

A. Estimating the Effect of Experiences on Expectations

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

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

where $expectation_{it}^{d}$ is respondent i's expectation about aggregate outcome d at time t, $experience_{it}^{d}$ 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

[12] Internet Appendix Table IA.II reports additional summary statistics on the history and variability of past house price changes over different time horizons, confirming the substantial heterogeneity.

individual, such as the values of other aggregate outcomes. The parameter of interest is β. To estimate the effect of experience on expected house price changes, $expectation_{it}^{d}$ is the expected one-year-ahead or the expected two-year-ahead change in U.S. house prices, and $experience_{it}^{d}$ is the past local house price change where the respondent currently lives. To estimate the effect of own unemployment experience on unemployment expectations, $expectation_{it}^{d}$ is the percentage chance that U.S. 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.

B. 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, we lay out basic assumptions about the data-generating process and individuals' expectation formation. We then describe the implications.

B.1. Data-Generating Process

We assume that next period's value of aggregate outcome A depends on past outcomes in locations l in the previous 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

$$A_{t+1} = \sum_{s=0}^{S} \sum_{l} b_{s,l} L_{t-s,l} + \gamma G_t + \eta_{t+1}.$$

B.2. Full Information

First, we assess the joint hypothesis of whether respondents weight own experiences correctly and know all relevant public information, as captured by the following null hypothesis.

Hypothesis 1. Individuals know all relevant public information and weight all information correctly, including their own.

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

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

That is, individuals believe the weight on each past outcome at time $t - s$ in location l, $b_{s,l}$, to be $\hat{b}_{s,l}$. The term $f(\mathbf{X_i})$ captures the effect of individual characteristics. Under the null hypothesis that individuals know all relevant public information and weight it correctly, that is, that $\hat{b}_{s,l} = b_{s,l}$, an individual's expectation can be written as

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

where $L_{t-s,i}$ is the outcome in i's status or location in year $t-s$. Under the null hypothesis, $\sum_l \sum_{s=0}^{S} b_{s,l} w_l L_{t-s,l} + \gamma G_t$ 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, $b_{s,i}^{\text{miss}} = \hat{b}_{s,i} - b_{s,i}$, should be zero. This is true irrespective of the actual weights $b_{s,l}$ on past local experiences. Hence, we can test the null hypothesis without making any assumptions on the true data-generating process (beyond additivity). No matter how we weight past experiences, a nonzero coefficient indicates that individuals either do not know all relevant public information or do not weight this information correctly.

B.3. Limited Information

Rather than assuming full information, we 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:

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

Note that the optimal weight, $c_{s,i}$, on own past experiences likely differs from the corresponding optimal weight when other information is also available. Respondents believe the best predictor to be

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

We want to know whether respondents use their own experiences optimally, given their knowledge. That is, whether $\hat{c}_{s,i} = c_{s,i}$, as in the following null hypothesis.

Hypothesis 2. Given limited information about other variables, individuals weight their own experiences optimally.

To assess this hypothesis, we face two challenges. First, estimating separate $\hat{c}_{s,i}$ and $c_{s,i}$ for each past year and location is far beyond the scope of our data, as well as that of most other data sets. For instance, when estimating the effect of past ZIP-level house price changes, this would require estimating more than 144,000 separate parameters given the 37 years of house price data in the more than 3,900 ZIP codes our respondents live in. Second, even if we could estimate separate $\hat{c}_{s,i}$ and $c_{s,i}$, it would be difficult to interpret differences between the estimated $\hat{c}_{s,i}$ and $c_{s,i}$ without making additional assumptions. Specifically, we would not be able to say whether respondents systematically over- or underweight local information or whether differences are due to respondents incorrectly weighting early versus recent experiences.

We therefore assume that any incorrect weighting of early versus recent experiences does not differ across locations. That is, we assume that $\hat{c}_{s,i} = \hat{d}_s * \hat{v}_{own,i}$. This allows us to evaluate the weighting of local experiences separately from the weighting of different past outcomes. Using this assumption, we can rewrite respondents' expectations of aggregate outcome A_{t+1} as

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

We can then make assumptions about what respondents believe about the data-generating process and hence the weighting of past data, $\hat{d}_s$. Based on these assumptions, we can construct $\sum_{s=0}^{S} \hat{d}_s L_{t-s,i}$ and estimate $\hat{v}_{own,i}$. We can also estimate the true informativeness of this measure of own experiences in the data, $v_{own,i}$, and compare the two to determine whether respondents weight local experiences in accordance with the true informativeness of these experiences. We make two different assumptions about the weighting of past experiences. First, we assume that only the most recent experiences matter, that is, $\hat{d}_s > 0$ for $s = 0$ and $\hat{d}_s = 0$ for all $s > 0$. We can apply this approach to both of our settings: house prices and unemployment. Since we observe individual employment status only during the time in our sample, we cannot estimate the effect of an individual's entire employment status history. This is not the case for past local house prices, however, so in a second approach, we follow Malmendier and Nagel (2011). Specifically, we assume exponential weighting of past experiences and estimate both the weighting parameter and the time horizon over which past experiences matter from the data. Section III.D 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. For instance, it allows individuals to 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. In addition, in Appendix B we use lasso estimation to nonparametrically estimate the weights on past local house price experiences.

Given our two assumptions about how individuals weight past data, we estimate $\hat{v}_{own,i}$, the effect of our measure of experiences, $\sum_{s=0}^{S} \hat{d}_s L_{t-s,i}$, on expected aggregate outcomes, $E[A_{t+1}|t, i]$. We then estimate the effect of this experience variable on actual outcomes in the past, $v_{own,i}$. Comparing these two estimates allows us to assess whether respondents use local experiences in line with their informational content. Under the null hypothesis of optimal use of limited information, the reliance on local experiences should depend on its actual informativeness. That is, extrapolation from local experiences, $\hat{v}_{own,i}$, should be greater in areas where these experiences are objectively more informative about national aggregates, (higher $v_{own,i}$), compared to areas where local experiences are less informative. Whether this is the case then tells us whether optimal use of local information can explain our findings or whether other explanations are needed.

III. Experiences and U.S. House Price Expectations

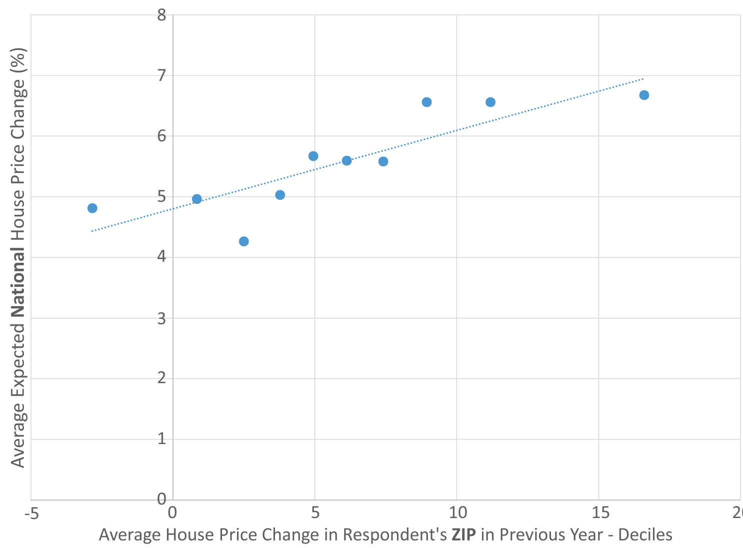
We start with the relationship between house price expectations and locally experienced house price changes over the past year. We then construct a measure of experiences that captures the total effect of house price dynamics over many years.

A. *Prior-Year Local Experiences and U.S. House Price Expectations*

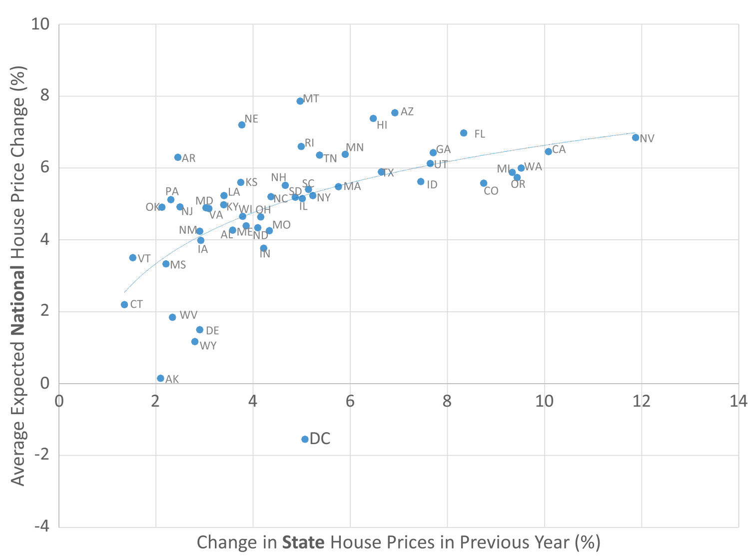
Figure 1 provides a first look at the relationship between locally experienced house price changes and expectations about aggregate house price changes. Panel A sorts respondents into deciles based on the prior year's change in house prices in the respondent's ZIP code. On average, respondents in ZIP codes with higher price changes over the past year expect one-year-ahead U.S. 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 U.S. 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 II, 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 one-year-ahead house price change, as well as the expected house price change in two years. The estimates confirm that past local experiences significantly affect expectations about U.S. house prices both in the coming year and further in the future. The effect is of similar magnitude irrespective of whether ZIP-, MSA-, or state-level house prices are used: a 1-percentage-point increase in past local house prices increases expected house price changes by between 0.1 and 0.2 percentage points.[13] Weighting our estimates so that the sample is representative of the U.S. population yields similar conclusions (and if anything, larger estimates). This is because less sophisticated respondents are underrepresented in our sample but rely more strongly on their own experiences, as we show below.

[13] Internet Appendix Table IA.III shows that the coefficients are stable as we add controls step by step. In addition, the fit of our model, as measured by the R^2, is in line with other papers studying the determinants of individual-level expectations, such as Das, Kuhnen, and Nagel (2017), Malmendier, Nagel, and Yan (2017), or Armona, Fuster, and Zafar (2019).



Panel A. ZIP-Level House Price Change



Panel B. State-Level House Price Change

Figure 1. Local house price experience and national house price expectation. 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 equivalent for each state. (Color figure can be viewed at wileyonlinelibrary.com)

Table II

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 local house price change is the year-over-year change in the ZIP code (column (1)), MSA (column (2)), or state (column (3)) in which the respondent lives. Standard errors are clustered at the state level. Time fixed effects are included for each survey month. Demographics include indicators for household income categories, respondents' age and age squared, and indicators for employment status and whether respondents own their home, are male, married, went to college, and are white or black. For the "Effect of 1 std when weighted," we use weights based on the American Community Survey (ACS) to make our sample representative of the U.S. population with respect to income, age, education, and region. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ZIP	(2) MSA	(3) State
Panel A: Expected One-Year Change in U.S. 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^2	0.0436	0.0388	0.0367
Panel B: Expected One-Year Change in U.S. House Prices in Two 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^2	0.0602	0.0496	0.0494

While house price changes vary substantially in the cross-section and over longer time horizons, they vary much less from month to month. In addition, they are measured more noisily, attenuating any estimates. Nevertheless, in Internet Appendix Table IA.IV, we estimate the equivalent of equation (1) in the full panel with individual fixed effects. Due to the rotating nature of the panel and the fact that respondents are in the panel for only a short period (at most one year), the individual fixed effects absorb both cross-sectional variation and differences in house price changes over time. This leaves us with very little statistical power. We do not find significant effects on the one-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-level house prices.

As outlined in Section II.B.2, the fact that we find a significant effect of local experiences 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 similar magnitude irrespective of whether respondents are asked about U.S. house prices in the coming one or two years. The actual predictiveness of past house prices, however, varies substantially by horizon: because of momentum and a certain degree of comovement across U.S. localities, past local house prices are somewhat predictive of one-year-ahead U.S. house prices, while house prices display medium-term reversal, with the prior year's local house prices virtually unrelated to U.S. house price movements between two and three years in the future.[14] However, respondents 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 evidence is a first indication 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. Specifically, we construct predicted values of the regression model in column (1) of Table II 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. We find that relying on locally experienced house prices at the ZIP code level increases the dispersion in expectations as measured by the standard deviation by 8.8%. Estimates are slightly larger using our MSA- or state-level results.

B. 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 II.B.3, whether this is the case allows us to determine 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 relationship between past local and U.S. house price changes, or how much they move with each other. The R^2 of the regression captures the goodness of fit or what fraction of U.S. house prices can be explained by variation in local house prices. We then divide locations into terciles based on the magnitude of the regression coefficients.

[14] For the localities of our survey respondents, a regression of national house price changes on prior-year local house price changes yields a coefficient estimate ranging from 0.35 (for ZIP-level house prices) to 0.46 (for state-level house prices). The coefficient on house price changes three years prior is essentially zero.

Table III

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 local house price change is the year-over-year change in the ZIP code (column (1)), MSA (column (2)), or state (column (3)) in which the respondent lives. Time fixed effects are included for each survey month. Demographics include indicators for household income categories, respondents' age and age squared, and indicators for employment status and 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. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Expected One-Year Change in U.S. House Prices		
	(1) ZIP	(2) MSA	(3) State
Local house price change * Low comovement with U.S. house prices	0.0760*	0.182***	0.163**
	(0.0391)	(0.0425)	(0.0626)
Local house price change * Medium comovement with U.S. house prices	0.135***	0.156***	0.195***
	(0.0456)	(0.0386)	(0.0532)
Local house price change * High comovement with U.S. house prices	0.0173	0.108	0.161*
	(0.0310)	(0.0787)	(0.0839)
Time Fixed Effects	Y	Y	Y
Demographics	Y	Y	Y
Low vs. high comovement	−0.0587	−0.0747	−0.00150
	(0.0482)	(0.0887)	(0.0877)
Number of observations	5,163	5,911	6,945
R^2	0.0447	0.0413	0.0374

Table III shows that there is no differential effect of past local prices on one-year-ahead expectations by the magnitude of the true effect.[15] 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 states 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: by the magnitude of the coefficient on local house prices as in Table III, and by the fit of the regression, as captured by the correlation between local and national house prices (or the R^2 of the regression). Figure 2 shows the estimated effect of past local house prices on national house price expectations. Again,

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

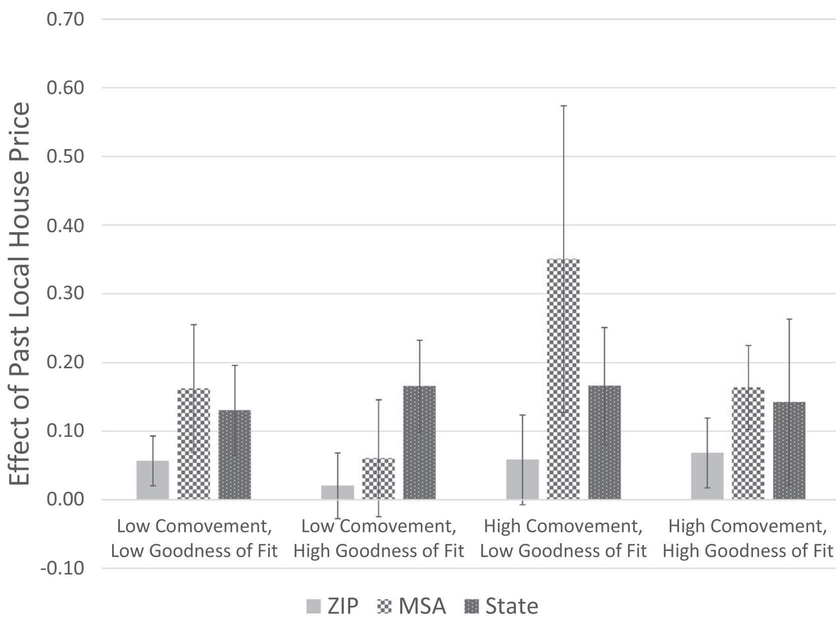


Figure 2. House price changes and expectations by magnitude and informativeness of effect in data. The figure shows the effect of prior-year local house price changes on expectations about national house price changes in regression estimates of equation (1). Standard errors are clustered at the state level. The dependent variable is the expected change in one-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 wherein the respondent lives, as labeled. Time fixed effects are included for each survey month. Demographics include indicators for household income categories, respondents' age and age squared, and indicators for employment status and 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.

we find no systematic differences using either dimension.[16] As discussed in Section II.B.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.

[16] We also estimate the coefficient between local and national home price changes over the past 10, 15, and 20 years instead of over the entire 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. Internet Appendix Figure IA.3 shows that the exact estimates for the specification reported in Table III 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.

C. Different Levels of Local House Price Experiences

So far, we have shown that respondents overweight local experiences, but not what the most relevant "local" level of experiences is—the hyperlocal ZIP code, the MSA, the state, or a combination of the three. Table AI includes all three past house price experiences (ZIP code, MSA, and state) in one regression. The first six columns replicate the results in Table II for the sample of respondents for whom all three measures of house price changes are available. The results for this subsample are very comparable to those in Table II irrespective of whether or not we use weights to make our sample representative. Columns (7) and (8) of Table AI include all three past house prices in one regression. The magnitude of the estimated coefficients and their statistical significance varies by whether we look at one-year- or two-year-ahead expected house price changes and whether the sample is weighted. Given these results, what can we learn about the relative importance of different levels of "local" experiences?

Analysis of this question is complicated by two factors. First, past house price changes in a given ZIP code and the corresponding MSA and state are highly correlated.[17] Second, past house price changes are measured with error and this measurement error is plausibly more severe, the smaller the geographic region.

In Appendix A, we simulate expected house price changes for respondents in our data assuming that hyper local (ZIP code), state-level, or both types of local experiences matter for expectation formation. We estimate the equivalent of equation (1) on this simulated data, varying the extent of measurement error. For reasonable levels of measurement error, we do not find a statistically significant effect of either level of local house price experiences when they do not truly affect expectations in the simulated model. That is, we do not get false positives. However, with any level of measurement error, we also cannot recover the relative importance of experiences at different local levels for expectation formation. To further help interpret the coefficient estimates in Table II, recall that the coefficient estimate in a basic regression of Y on X is $\frac{\mathrm{Cov}(X,Y)}{\mathrm{Var}(X)}$. If two variables have similar covariance with the outcome, the estimated coefficient will be lower for the variable with higher variance, but the effect of a one-standard-deviation change will be of similar magnitude. This is exactly what we find: the standard deviation of past house price returns is substantially higher at the ZIP code level than at the MSA or state level (Table I), and Tables II and AI show that the estimated effect of a one-standard-deviation change in the dependent variable is very similar for all three levels of house price changes despite the different coefficient estimates. Taken together, our results indicate that local experiences at all levels—ZIP code, MSA, and state—play some role when respondents form expectations about aggregate outcomes. Given the likelihood of measurement error in past house price changes, however, our results do not provide reliable information about the relative importance of local experiences at different levels.

[17] In our sample, the correlation between ZIP code and MSA house price changes in the past year is 75%, that between ZIP- and state-level house price changes is 63%, and that between MSA- and state-level house prices is 84%.

D. History of Local House Prices and U.S. 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 how earlier experiences factor into the expectation formation process.

D.1. Weighted Average of Past House Price Changes as an Experience Measure

As noted in Section II.B.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, measured by H_{it}, is calculated as

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

where

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

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 in which $\lambda = 0$, 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. Finally, we need to determine when respondents start to experience local house prices, captured by the experience horizon (S_i). Our ZIP-level house price data are available 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 three or five 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 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 report results for all of these possible horizons and let the estimates inform us about which one yields the best fit in our data.

(a) House Price Changes Over Time

(b) Arizona - Weighted Experience

(c) New York - Weighted Experience

(d) Indiana - Weighted Experience

Figure 3. House prices and 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 according to equation (2). (Color figure can be viewed at wileyonlinelibrary.com)

Figure 3 illustrates how 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, New York, and Indiana. 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 recent decades. 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.

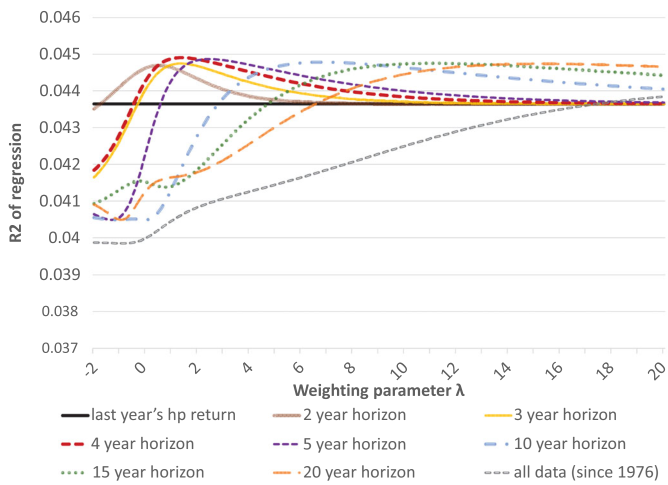
In particular, respondents with a 5- or 10-year experience horizon who heavily overweight recent experiences (i.e., $\lambda > 1$) tend to have large positive weighted home price experiences, since home price increases in the recovery after the crisis receive more weight. Weighted home price experiences also increase as early experiences are overweighted (i.e., $\lambda < 0$) 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.

D.2. History of Past House Prices and Expectations

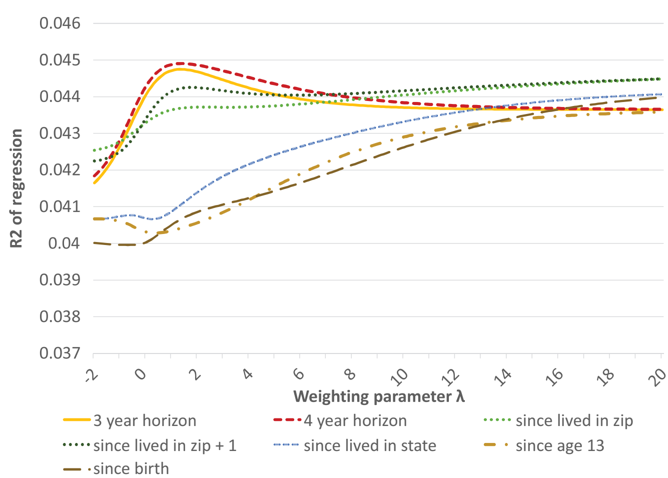
We consider values of the weighting parameter λ ranging from -2 to 20 in intervals of 0.1. For each λ on this grid, we calculate the weighted average of past house price changes and use it as our measure of past experiences to estimate equation (1). We then compare the R^2s of these regressions to determine which values of λ and experience horizon S_i yield the best fit for our data.

Figure 4 plots the fit of the regression, as measured by the R^2, along the range of weighting parameters λ for each experience horizon considered. Local experience is captured by ZIP-level house prices. Panel A shows 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 shows the fit of the regression when only using the previous year's house price change. Panel B shows results for horizons that 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 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, whereas 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 IV reports 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 0.63 to 0.67 percentage points for fixed-year horizons. For each specification, Figure 5 illustrates the weights on each year's house price return implied by best-fit values of λ as shown in Table IV. The best-fit weighting



Panel A. Fixed-Year Horizons (All Respondents)



Panel B. Individual-Specific Horizons (Respondents with Years Lived in ZIP Available)

Figure 4. Weighted average of ZIP code house prices and expectation. 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). (Color figure can be viewed at wileyonlinelibrary.com)

parameter λ is higher, the longer the horizon over which experiences are calculated, as shown in Table IV. 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

Table IV
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 one standard deviation of the experience variable on the expected house price change.

	Best Fit Parameters for Weighted Past Experiences				
Horizon	R^2 (1)	λ (2)	Coefficient (3)	Standard Error of Coefficient (4)	Effect of 1 Standard Deviation (5)
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				

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, house price changes in the most recent years receive the most weight. 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.[18] To see whether our results are influenced by the functional form assumption of exponential weighting, in Appendix B we instead use lasso estimation to estimate the effect of past house price changes on expectations. The results are very similar: the most recent years receive the most weight for explaining house price expectations.

Table V reports equivalent results as the analysis in Table III but with the history of past house prices rather than just the previous year's house price change as our measure of experiences. For each horizon, we use the optimal value of the weighting parameter λ as shown in Table IV and split respondents by how much this measure moves with U.S. house price changes in the data. Again, we find that the effect of local house price experiences on expected U.S. house price changes does not vary with how well-aligned these experiences are with U.S. house price changes in the actual data. This result confirms that

[18] Internet Appendix Table IA.V replicates the analysis of this section using state- and MSA-level house price changes instead of ZIP-level changes. The results are very similar.

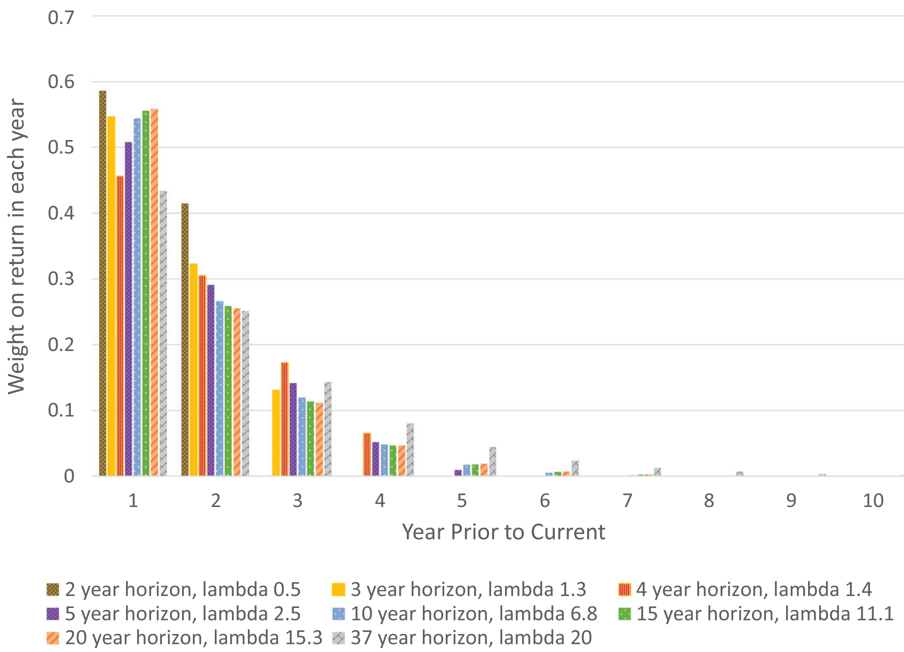


Figure 5. Weights implied by optimal weighting parameter—ZIP code house prices. The figure shows the weights on the house price changes in the past 10 years implied by the optimal weighting parameters corresponding to the specifications with the highest R^2 as shown in Table IV. (Color figure can be viewed at wileyonlinelibrary.com)

the extrapolation from local experiences that we observe is inconsistent with optimal use of limited information.

Do our results also inform us about whether respondents use past house price changes optimally? Unfortunately, without making additional assumptions on what respondents believe about the data-generating process, we cannot judge whether they use past realizations optimally. Our results indicate that the most recent years receive the most weight when explaining expectations. This could be due to respondents suboptimally using only the most recent house price changes to form expectations. However, it could also be the case that, based on past local house price changes, respondents have concluded that house price changes follow a short autoregressive process, such as an AR(1), in which case recent realizations receive the most weight in forming expectations, even though prior observations were used to learn about the data-generating process.

E. 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

Table V

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 one-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. Demographics include indicators for household income categories, respondents' age and age squared, and indicators for employment status and 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 IV. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Expected One-Year Change in U.S. House Prices: Weighted Past House Price Changes Over				
	2 Years (1)	3 Years (2)	5 Years (3)	10 Years (4)	15 Years (5)
Past house price changes * Low comovement with U.S. house prices	0.157*** (0.0325)	0.147*** (0.0349)	0.171*** (0.0352)	0.170*** (0.0331)	0.173*** (0.0322)
Past house price changes * Medium comovement with U.S. house prices	0.114*** (0.0349)	0.140*** (0.0408)	0.130*** (0.0459)	0.136*** (0.0471)	0.132*** (0.0427)
Past house price changes * High comovement with U.S. house prices	0.137*** (0.0376)	0.159*** (0.0379)	0.158*** (0.0545)	0.146*** (0.0416)	0.158*** (0.0500)
Time fixed effects	Y	Y	Y	Y	Y
Demographics	Y	Y	Y	Y	Y
Low vs. high comovement	−0.0200 (0.0540)	0.0113 (0.0522)	−0.0134 (0.0661)	−0.0241 (0.0590)	−0.0147 (0.0594)
Number of observations	6,032	6,032	6,032	6,032	6,032
R^2	0.0452	0.0450	0.0455	0.0458	0.0454

whether the effect of past experiences on expectations extends to the second moment. That is, we estimate whether respondents who have experienced more volatile house price changes locally report a distribution of expected one-year-ahead U.S. 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 VI 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)), calculated over the past 5, 10, and 20 years, as well as since the beginning of our CoreLogic data on local house prices in 1976.[19] For each horizon and house price measure, the

[19] When analyzing the effect of the level of past price changes, we compute exponentially weighted averages of past house price changes. The equivalent weighting is difficult to implement

Table VI
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 one-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 prices in the ZIP code (column (1)), MSA (column (2)), and state (column (3)) in which the respondent lives. Standard errors are clustered at the state level. Time fixed effects are included for each survey month. Demographics include indicators for household income categories, respondents' age and age squared, and indicators for employment status and whether respondents own their home, are male, married, went to college, and are white or black. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Std of Expected House Price Change		
	ZIP (1)	MSA (2)	State (3)
Std of house price changes since			
5 years ago	0.0489***	0.0125	0.0268
	(0.0159)	(0.0133)	(0.0218)
10 years ago	0.0307***	0.0236**	0.0143
	(0.0103)	(0.0109)	(0.0104)
20 years ago	0.0370***	0.0250**	0.0179
	(0.00847)	(0.0101)	(0.0109)
1976 (all available data)	0.0391***	0.0168	0.0157
	(0.0138)	(0.0152)	(0.0131)
Last year's house price change	Y	Y	Y
Demographics	Y	Y	Y
Number of observations	5,830	6,693	7,835

various cells in Table VI present the estimated coefficient and corresponding standard error on locally experienced volatility. In all specifications, we control for the level of past house price changes, as well as respondent demographics and survey date fixed effects.

Table VI shows that respondents in areas that experienced more volatile house price changes report a wider distribution of expected one-year-ahead house prices. A 1-percentage-point increase in the experienced standard deviation in the respondent's ZIP code increases the expected standard deviation by 0.03 to 0.049 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 Internet Appendix Table IA.II) increases the standard deviation of expected house price changes by 0.117 percentage points ($3.82 \times 0.0307 = 0.117$). The estimated effects are slightly smaller but of comparable magnitude when using

in the context of past standard deviations since the standard deviation can be calculated only over a handful of nonoverlapping horizons in our data and the analysis would be very sensitive to the number and length of nonoverlapping horizons chosen.

MSA- or state-level house price measures but are not statistically significant for state-level variables where we have much less variation. Our results indicate that respondents rely not only on the levels of past house price changes but also on their volatility when forming expectations about U.S. house price changes.

F. 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. Table CI 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 24% of respondents give almost the same answer, indicating that they understand they are being asked about different outcomes.[20] In addition, Internet Appendix Table IA.VII. shows 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.

Table CII shows that respondents have decent if imperfect recall of past local house price changes. A 1-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 II yields highly significant estimates that are comparable in magnitude to our baseline estimates (if anything, they are larger). Including both recalled and actual local house price changes, the coefficient on recalled house price changes remains highly significant and of similar magnitude. Actual house price changes on any local level are not statistically significant once we include recalled ZIP code house price changes. In cases in which actual and recalled local house prices differ, respondents therefore rely on what they remember local house price changes to be when forming expectations.[21]

[20] Separately, Table I 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% to losing their job, but believe that unemployment will be higher with a probability of 37%—a substantial difference.

[21] Consistent with our finding, Cavallo, Cruces, and Perez-Truglia (2017) find in a field experiment that past recalled price changes are more predictive of expected inflation rates than actual past price changes.

IV. Own Experiences and U.S. Unemployment Expectation

A. Employment Status Changes and Expectations

Losing a job or finding a new job out of unemployment are discrete, notable, and substantial changes in an individual's own employment experience. In this section, we focus on individuals who experience such job transitions while in our panel. This allows us to use *within-individual* variation to estimate the effect of own employment experiences on expected aggregate unemployment.

Table VII reports estimates of equation (1) for unemployment expectations and experiences.[22] The estimation includes time fixed effects to absorb changes in economic conditions over time and isolate the effect of own employment status. The first column shows that, in the cross-section, the unemployed are 6.7 percentage points more pessimistic about nationwide one-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 column (2) reduces the difference between employed and unemployed respondents to 5.5 percentage points, indicating that differences in observed characteristics partially explain differences in expectations. To address the concern that further differences in unobserved characteristics explain the remaining differences in expectations, columns (3) and (4) of Table VII include individual fixed effects, which absorb any potential differences in fixed 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. 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 respondents who are in and out of jobs over our sample period.

Finally, the last two columns of Table VII 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 (5), respondents who were employed throughout (the omitted category) and respondents who became employed only recently have similar expectations

[22] Internet Appendix Figure IA.2 shows average national unemployment expectations for employed and unemployed respondents during our sample period. All respondents adapt their expectations over time to changes in economic conditions. At each 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.

[23] In Internet Appendix Table IA.IX, we investigate whether the effect of job loss or finding a job out of unemployment varies with the length of unemployment and find no evidence for a systematic effect of unemployment length.

Table VII

Effect of Employment Status on Unemployment Expectations

The table shows regression estimates of equation (1). Standard errors are clustered at the respondent level. Employment status is each respondent's self-reported current employment status. In columns (5) and (6), employed respondents who were not previously unemployed are classified as *Employed*. Respondents who are looking for work and were not previously employed are classified as *Unemployed*. 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 in which the respondent lives. Time fixed effects are included for each survey month. Demographics include indicators for each of the 11 possible categories of household income. When no individual fixed effects are included, demographics also include respondents' age, age squared, and indicators for whether respondents are male, married, went to college, and are white or black. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Percent Chance U.S. Unemployment Higher in a Year					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment status						
Employed			Omitted			
Unemployed	6.734***	5.514***	1.442**	1.447**		
	(0.942)	(0.948)	(0.655)	(0.655)		
Become employed					1.122	−2.153*
					(1.115)	(1.116)
Become unemployed					5.217***	−0.172
					(1.430)	(0.986)
Always unemployed					5.724***	0.897
					(1.205)	(1.102)
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

about aggregate unemployment. Unemployed respondents are substantially more pessimistic, irrespective of whether they entered the sample unemployed or only recently lost their job. When including individual fixed effects in column (6), however, we find the opposite: respondents who just lost their job do not become significantly more pessimistic, but respondents who find a new job out of unemployment become significantly more optimistic, about aggregate unemployment. This suggests that the effect in columns (3) and (4) is driven primarily by respondents who become more optimistic about nationwide unemployment when they find a new job after having been unemployed, rather than respondents who just lost a job.

B. Informativeness of Own Employment Status

We next assess whether the extent of respondents' updating of their expectations when they experience unemployment is plausibly consistent with its informational content. How informative about nationwide unemployment rates would own unemployment need to be to justify the observed difference in expectations between employed and unemployed respondents of 1.44 percentage points that we observe in the data? To address this question, we assume that respondents are Bayesian updaters, that all respondents agree that the unconditional probability of national unemployment increasing is 37% (the average expectation of all respondents in our sample), and that the probability of job loss is 3% if unemployment was not going to increase (the job loss rate fell from 3.5% at the beginning of the sample to 2.3% at the end). Internet Appendix Section III shows the calculation. Based on these assumptions, we find that respondents would need to be about 6% more likely to lose their job if unemployment were truly going up than if unemployment were not going to increase to justify the estimated difference in posterior beliefs of 1.44 percentage points.

V. Effects by Respondent Characteristics and Implications for Interpretation

A. Effects by Respondent Characteristics

Next, we explore how the effect of past experiences on expectations about nationwide outcomes varies with respondent characteristics. Specifically, we investigate whether results differ by proxies for sophistication (such as a college degree or the respondent's numeracy score), age, and home ownership (which allows us to assess whether reporting of risk-adjusted probabilities could explain our results). The extent of heterogeneity along these characteristics can shed further light on which factors may contribute to the observed extrapolation from local and personal experiences. We report results for the expected one-year-ahead house price change, but results are qualitatively similar when using the expected house price change in two years.

A college degree and higher numeracy can be viewed as proxies for the respondent's sophistication. If cognitive biases cause respondents to extrapolate from own experiences to aggregate outcomes, 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] Table VIII investigates this conjecture. Panel A shows that the effect of past ZIP-level house price changes on expected one-year-ahead house price changes for respondents with low numeracy is 0.14, whereas the estimate for respondents with high numeracy is 0.06—a difference of 0.08. The difference between low and high numeracy respondents is larger, at 0.17 and 0.16, and statistically significantly different from zero for MSA- and state-level house prices, respectively. Similarly, Panel B shows that past local house prices affect expectations about U.S. house price changes substantially more for respondents who did not go to college relative to those who did. 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 experiences on expectations should decrease with age, since younger respondents with a shorter prior experience history react more strongly to the most recent experience than older respondents. Panel A of Table IX shows that recent local house price changes affect expectations strongly for all respondents and that the magnitude of the estimates is very similar for all ages. The results control for ZIP code tenure and are very similar when restricting the sample to respondents who have moved to the ZIP code in the last 10 years (see Internet Appendix Table IA.VIII.), which indicates that this effect is not driven by older respondents living in their current ZIP code for a very long time. This result is consistent with our findings in Section III.D that the most recent experienced house price changes matter most for expected house price changes and that age-specific experience horizons do not improve the fit in the data.

A potential concern with our results is that instead of actual probabilities, respondents report risk-adjusted probabilities in the survey and 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, forthcoming), making them more risk-averse and increasing the risk adjustment contained in risk-adjusted expectations. Thus, while risk adjust-

[24] Less sophisticated individuals may have less accurate nonlocal 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 do not find to be the case in Section III.B

Table VIII

House Price Change and Expectations by Numeracy and College

The table shows estimates of equation (1). Standard errors are clustered at the state level. Past local house price change is the year-over-year change in the ZIP code (column (1)), MSA (column (2)), or state (column (3)) in which the respondent lives. Time fixed effects are included for each survey month. Demographics include indicators for household income categories, respondents' age and age squared, and indicators for employment status and whether respondents own their home, are male, married, went to college, and are white or black. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	Expected One-Year Change in U.S. House Prices		
	ZIP (1)	MSA (2)	State (3)
Panel A: 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 numeracy	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)
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	5,752	6,593	7,695
R^2	0.0479	0.0399	0.0377
Panel B: 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)
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	6,032	6,925	8,104
R^2	0.0438	0.0390	0.0369

ment should amplify any extrapolation from past experiences for homeowners, it should dampen extrapolation from past prices for renters. Panel B of Table IX shows, however, 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.

Table IX

House Price Change and Expectations by Age and 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 one-year-ahead house prices in percentage points as stated by the respondent. Past local house price change is the year-over-year change in the ZIP code (column (1)), MSA (column (2)), or state (column (3)) in which the respondent lives. Time fixed effects are included for each survey month. Demographics include indicators for household income categories, respondents' age and age squared, and indicators for employment status and 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. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	Expected One-Year Change in U.S. House Prices		
	ZIP (1)	MSA (2)	State (3)
Panel A: By Age			
Past local house price change * Age 25 to 39	0.0497	0.175***	0.157***
	(0.0507)	(0.0534)	(0.0535)
Past local house price change * Age 40 to 49	0.155***	0.207***	0.294***
	(0.0498)	(0.0693)	(0.0844)
Past local house price change * Age 50 to 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)
Time fixed effects	Y	Y	Y
Demographics	Y	Y	Y
Difference age 60 plus vs. 25 to 39	0.0653	−0.0300	0.0614
	(0.0540)	(0.0413)	(0.0595)
Number of observations	6,028	6,921	8,099
R^2	0.0449	0.0392	0.0377
Panel B: By Homeownership			
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)
Time fixed effects	Y	Y	Y
Demographics	Y	Y	Y
Difference nonhomeowner vs. homeowner	−0.0395	−0.0420	−0.0831
	(0.0547)	(0.0605)	(0.0715)
Number of observations	6,032	6,925	8,104
R^2	0.0438	0.0389	0.0369

Finally, in Internet Appendix Tables IA.X to IA.XIV, we also estimate whether the effect of locally experienced house prices differs by region and local characteristics, such as 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 X
Effect of Unemployment on Expectations by Respondent Characteristics

The table shows estimates of equation (1) with *Looking for work* interacted with numeracy, college, and age. Standard errors are clustered at the respondent level. Significance levels: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	Percent Chance U.S. Unemployment Higher in a Year		
	(1)	(2)	(3)
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	3,525	3,775	3,775
Number of individuals	424	432	432

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

B. Potential Underlying Biases

Overall, our results show strong evidence of extrapolation from own experiences to expectations about aggregate outcomes, which is substantially stronger for less sophisticated individuals. Our earlier results in Section III.B show 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. In the literature (e.g., Kahneman, Slovic, and Tversky, 1982; Shleifer, 2012), several underlying behavioral biases have been cited as contributing to extrapolation, which in the finance literature is often simply understood as "the formation of expected returns ... based on past returns" (Barberis et al., 2018). These biases include availability (overweighting of more easily available information), the representativeness heuristic (overestimating the likelihood of representative scenarios), or anchoring (the tendency to be influenced by initially presented values, even when seemingly irrelevant for the task at hand), though in the context of extrapolation, these biases are not necessarily mutually exclusive. Do our results speak to whether a particular bias leads individuals to rely on recent or personal information when forming expectations about aggregate outcomes? Respondents may extrapolate from recent local or personal experiences because these experiences are more readily available to them and easily come to mind when thinking about house price changes or unemployment. As such, our results are consistent with availability bias as an underlying psychological force that leads to extrapolation from recent local experiences. Anchoring suggests a disproportionate influence of an initially presented value but is generally not considered domain-specific. That is, whether the initially presented value is in the same domain or another domain should not matter. Hence, in the case of pure anchoring, we would expect that any initial value on which respondents anchor should affect expectations across domains. This is not what we find when investigating whether labor or housing market experiences affect expectations in other domains (see Section VI). Domain-specific anchoring within the domain of house prices or unemployment, however, would be consistent with our results. Overall, our results suggest extrapolation from recent local and personal experiences without pinpointing whether a specific underlying behavioral bias drives the observed extrapolation.

VI. 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 XI shows the effect of own employment status (Panel A) and past local house price experiences (Panel B) on expectations about other aggregate economic

Table XI

Own Experiences and Expectations about Other Economic Outcomes

The table shows estimates of equation (1) with the following dependent variables: whether the respondent believes that they will be better off a year later (column (1)) and are better off than a year ago (column (2)), both on a five-point scale; the percentage chance that interest rates on saving accounts (column (3)) and U.S. 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 U.S. home prices (column (8)); and likelihood of higher unemployment (column (9)). Fixed effects are included for each month. Demographics include indicators for household income categories, respondents' age and age squared, and indicators for employment status and whether respondents own their home, are male, married, went to college, and are white or black. Controls also include past house price changes in Panel A, column (8). Standard errors are clustered at the state level. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

			Percentage Chance That the Following Will Be Higher in a Year						
	Will Be Better Off in a Year	*Are* Better Off than Year Ago	Interest Rates on Savings	U.S. stock Prices	Inflation 1 Year	Inflation 3 Years	Government Debt	Home Prices	Unemploy-ment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Effect of Own Employment Status									
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	60,672	60,663	60,668	60,147	52,888	52,881	52,744	45,281	
Number of individuals	8,104	8,103	8,104	8,104	7,770	7,752	7,921	6,038	

(*Continued*)

Table XI—*Continued*

Panel B: Effect of Local House Price Change								
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	6,030	6,025	6,029	5,985	6,003	6,003	5,881	6,032

outcomes. The first two columns of Table XI show that unemployed respondents feel that they are worse off than they were a year ago and also expect to be worse off a year later. 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, since, unlike personal unemployment, local house prices are not major determinants of individual well-being. The remaining columns, columns (3) to (9), estimate the effect of experiencing unemployment (Panel A) and of past house prices (Panel B) on expectations about interest rates, U.S. 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 result also suggests that there are no other unobserved factors that are correlated with past house price growth that could be driving our results. Experiencing unemployment also has no effects on expectations about interest rates, stock prices, inflation, and government debt. We find a negative effect on expected house price growth, indicating that losing one's job may lead individuals to be more pessimistic about some aspects of the economy. However, any such general pessimism does not seem to be pervasive since other outcomes are not significantly affected. Alternatively, this result could be due to chance, given the multiple hypotheses being tested. 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 by experiences in the two other domains.[25]

VII. 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.

A. Labor Market Expectations and Realized Outcomes

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 XII analyzes the extent to which these self-assessed employment

[25] This is not to say that expectations about macroeconomic outcomes do not move with each other. Table IA.XIV in the Internet Appendix adds respondents' expectations about unemployment and house prices as explanatory variables and shows how they relate to expectations about the other macroeconomic outcomes considered. The results indicate that the comovement of expectations about aggregate outcomes is driven by factors other than own experiences that influence expectations about all of these outcomes.

Table XII

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 one, three, six, or nine months of the survey module. Pr*(job loss within 12 months)* is the percentage chance that the respondent will lose her job within the next 12 months as stated by the respondent (on a zero to one 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, and 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. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Panel A: Employment Prospects When Entering Sample

	Lose Job Within			
	One Month (1)	Three Months (2)	Six Months (3)	Nine Months (4)
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	4,865	4,696	4,463	4,225

Panel B: Within Individual Changes in Employment Prospects

	Lose Job Within			
	One Month (1)	Three Months (2)	Six Months (3)	Nine Months (4)
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	34,261	32,901	30,870	28,895
Number of individuals	4,988	4,809	4,568	4,324

Table XIII
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 household income categories, respondents' age and age squared, and indicators for employment status and whether respondents own their home, are male, married, went to college, and are white or black. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Housing in ZIP is a Good Investment		
	One-Year National Expectations (1)	One-Year ZIP Expectations (2)	Five-Year ZIP Expectations (3)
Expectations—first tercile		(omitted)	
Expectations—second tercile	0.290***	0.625***	0.400***
	(0.0709)	(0.0728)	(0.0752)
Expectations—third 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	3,744	3,670	3,662

prospects are indicative of actual future employment outcomes in the cross-section, as well as within-respondent over time. Respondents who think that 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, which exploits cross-sectional variation, shows that a 1-percentage-point increase in the reported likelihood of losing a job over the next twelve months is associated with a 0.14 percentage point increase in the actual likelihood of losing a job over the next six months. Moreover, Panel B 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]

B. House Price Expectations and Attitudes towards Housing

To evaluate implications of expected house price changes, we again turn to the subset of respondents who answered additional questions about housing mentioned in Section III.F. These respondents were also asked whether they considered buying a home in their ZIP code today a good investment. This allows us to evaluate whether respondents who are more optimistic about future

[26] Stephens (2004) and Dickerson and Green (2012) also find that expectations of unemployment are predictive of future employment outcomes, and Buchheim and Link (2017) find that firms' expectations are informative of their future business condition.

house prices are more likely to consider buying a home a good investment.[27] Table XIII shows that respondents who expect house prices to increase more, either nationally or in their current ZIP code, do indeed rate investing in real estate in their current ZIP code to be more attractive.

VIII. Conclusion

This paper documents that recent personal experiences affect expectations about aggregate house price changes and unemployment. We find that recent local house price dynamics significantly affect expectations of U.S. 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 house price changes also perceive future one-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 and personal experiences.

Our paper builds on the growing literature on experiences and expectations in at least three ways. First, we add to this literature by showing that the types of personal experiences that affect expectations are often local or truly personal and can differ from the aggregate outcomes that individuals have seen in their lifetime. Second, the rich data on respondents' demographics and circumstances allow us to investigate heterogeneity in expectation formation, which further helps 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. We find that labor and housing market experiences do not affect expectations about these other economic outcomes, suggesting that extrapolation from own experiences is domain-specific. Taken together, our results suggest that respondents naively extrapolate from their own recent experience in the given domain when forming expectations about aggregates. Our findings offer further support for theories that explore the implications of extrapolative expectations in areas other than unemployment or housing markets (Barberis et al., 2015; Fuster, Laibson, and Mendel, 2010). Beyond implications for the modeling of expectations, our results also have important implications for understanding aggregate fluctuations in labor and housing markets.

[27] Prior evidence suggests that expectations are indeed related to actual, as well as intended, future investment decisions. See Gennaioli, Ma, and Shleifer (2016) for the effect of expectations on actual investment and D'Acunto, Hoang, and Weber (2018) for intended purchases.

Our sample period coincides with a period in which home prices have 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 become available, it will be interesting to investigate what role, if any, the macroeconomic environment plays in how individuals form expectations about aggregate outcomes. Similarly, whether housing experts, like individual consumers as in this paper, exhibit a tendency to extrapolate from own experiences (as suggested by recent work such as Malmendier, Nagel, and Yan (2017)) would be an interesting question to explore.

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Appendix A: Different Levels of Local House Prices

A.1. ZIP-, MSA-, and State-Level Experiences in Same Regression

A.2. Simulation

To better understand the implications of the high correlation between different levels of local house price changes and potential measurement error, we simulate expected house price changes for respondents in our data. We then run the equivalent of our actual regressions on the simulated data and add various levels of measurement error to past house price changes. Specifically, for each respondent, we generate simulated national house price expectations according to

$$hp_i^{sim} = a + b_{zip} yhpc_i^{zip} + b_{msa} yhpc_i^{msa} + b_{state} yhpc_i^{state} + e_i,$$

where $yhpc_i^{zip}$, $yhpc_i^{msa}$, and $yhpc_i^{state}$ are the house price changes in the previous year in respondent i's ZIP code, MSA, and state, respectively. We choose three baseline scenarios and pick values for the coefficients based on our baseline estimates in Table II:

1. Only ZIP-level experiences affect expectations, that is, $b_{zip} = 0.1$ and $b_{msa} = b_{state} = 0$.
2. Only state-level experiences affect expectations, that is, $b_{state} = 0.2$ and $b_{zip} = b_{msa} = 0$.
3. ZIP- and state-level experiences affect expectations, that is, $b_{zip} = 0.1$, $b_{state} = 0.2$, and $b_{msa} = 0$.

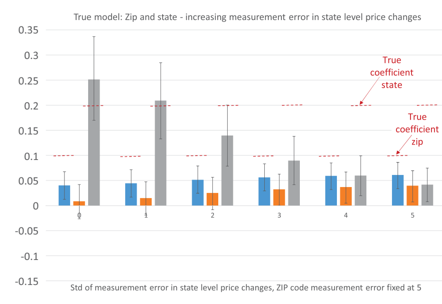
We then run the following equivalent to equation (1) on our simulated data:

$$\begin{aligned} hp_i^{sim} = a &+ \beta_{zip}(yhpc_i^{zip} + \eta_{zip}) + \beta_{msa}(yhpc_i^{msa} + \eta_{msa}) \\ &+ \beta_{state}(yhpc_i^{state} + \eta_{state}) + \epsilon_i. \end{aligned}$$

(a) True model: Zip only

(b) True model: State only

(c) True model: Zip and state - same measurement error



(d) True model: Zip and state - different measurement error

Figure A1. Simulation with varying measurement error of past local house price changes. The table shows regression estimates of equation (1) on simulated expectations under different assumptions about the true data-generating process and different amounts of measurement error. (Color figure can be viewed at wileyonlinelibrary.com)

This allows us to control the measurement error (η_{zip}, η_{msa}, and η_{state}) with which the econometrician observes local house price changes. The simulated measurement error terms are normally distributed and we vary the standard deviation from zero (no measurement error) to five, which is close to the standard deviation of past yearly ZIP-level house price changes in our sample. Figure A1 shows the results. The first set of bars in each panel shows that without measurement error in past house price changes, a regression including all three past house price changes recovers the true parameters of the model. With measurement error, however, this is no longer the case. As is well known, measurement error attenuates the estimates toward zero, which can be seen in the declining estimates as measurement error increases. Assuming the presence of measurement error, we are therefore interested in what we can still conclude from our estimates. Panels A and B show that when only ZIP code or state house price experiences matter in the true model, we underestimate the true effect of the level of past local house price changes that truly matter. The coefficients on past house price changes that do not matter in the true model become less precisely estimated as measurement noise increases—but they do not become statistically significant from zero. This finding suggests that the statistically significant coefficients that we obtain in Table AI indicate

Table AI

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. Columns that report ACS (American Community Survey) weights make our sample representative of the U.S. population with respect to income, age, education, and region. Standard errors are clustered at the state level. Time fixed effects are included for each survey month. Demographics include indicators for household income categories, respondents' age and age squared, and indicators for employment status, whether respondents own their home, are male, married, went to college, and are white or black. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Expected Change in U.S. House Prices—Next Year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past house price change in								
ZIP	0.103***	0.146***					0.0373	0.0439
	(0.0188)	(0.0278)					(0.0396)	(0.0408)
MSA			0.181***	0.262***			0.0471	0.192**
			(0.0304)	(0.0473)			(0.0557)	(0.0865)
State					0.245***	0.273***	0.164**	0.0443
					(0.0476)	(0.0708)	(0.0692)	(0.116)
Weights	None	ACS	None	ACS	None	ACS	None	ACS
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Demographics	Y	Y	Y	Y	Y	Y	Y	Y
Effect of 1 std	0.559	0.798	0.733	1.062	0.855	0.954		
No. of observations	5,398	5,383	5,398	5,383	5,398	5,383	5,398	5,383
R^2	0.0457	0.0637	0.0471	0.0667	0.0478	0.0635	0.0485	0.0670

Panel B: Expected One-Year Change in U.S. House Prices in Two Years

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past house price change in								
ZIP	0.103***	0.144***					0.0740**	0.114*
	(0.0173)	(0.0375)					(0.0349)	(0.0576)
MSA			0.138***	0.182***			−0.0251	0.0287
			(0.0270)	(0.0459)			(0.0534)	(0.0781)
State					0.196***	0.203***	0.149**	0.0611
					(0.0408)	(0.0623)	(0.0596)	(0.108)
Weights	None	ACS	None	ACS	None	ACS	None	ACS
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Demographics	Y	Y	Y	Y	Y	Y	Y	Y
Effect of 1 std	0.562	0.789	0.558	0.739	0.689	0.712		
No. of observations	5,267	5,252	5,267	5,252	5,267	5,252	5,267	5,252
R^2	0.0610	0.0682	0.0600	0.0657	0.0611	0.0641	0.0626	0.0688

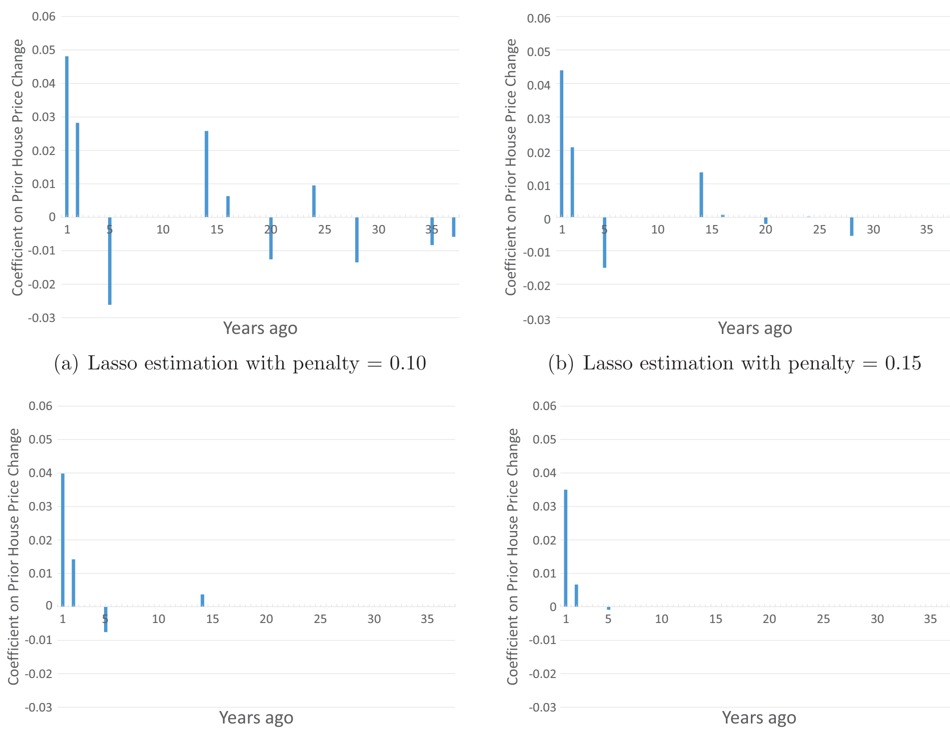
that both ZIP- and state-level house price experiences play a role in respondents expectation formation process. Panels C and D evaluate whether we can recover the relative importance of ZIP- and state-level house price experiences in a model in which both play a role. When both are measured with the same degree of error (Panel C), increasing measurement error leads us to overestimate the relative importance of ZIP-level experiences. In Panel D, we keep the measurement error for ZIP- and MSA-level house prices high (at five) and vary the measurement error of state-level house prices to reflect the fact that ZIP-level house prices are likely to be measured more noisily than state-level house prices. In this case, we overestimate the effect of state-level house prices when the measurement error of state-level house prices is small relative to that of ZIP-level house prices, and we overestimate the importance of ZIP-level prices as measurement error becomes more similar.

Appendix B: History of Local House Prices—Lasso Estimation

We estimate equation (1) including separate regressors for each local house price change in the prior 37 years (the beginning of our data) instead of using an exponentially weighted average as in Section III.D. House price changes are highly serially correlated, so estimating this equation via OLS is problematic. With many highly correlated regressors, OLS estimation often leads to large coefficient estimates of opposite signs for highly correlated regressors that are difficult to interpret. To prevent this issue, we use lasso estimation. Lasso estimation modifies OLS by adding a penalty term on the sum of absolute coefficients and therefore encourages the model to select the most important variables by assigning coefficients of zero to many potential explanatory variables. To make results comparable to our earlier results, we include the same fixed effects for date and respondent characteristics by de-meaning the data before applying the lasso estimation. Figure B1 shows the resulting estimates. From Panel A to D, we increase the penalty on large coefficients and force the model to select fewer nonzero coefficients. Panel A shows that the two most recent years receive the highest weights in the estimation. However, some of the characteristic wave patterns of opposite-sign coefficients assigned to highly correlated regressors remain. As we increase the penalty on large coefficients, fewer and fewer early observations receive nonzero coefficients and the most recent observations receive the most weight. In Panel D, the penalty is large enough that only three coefficients are nonnegative and the most recent year receives by far the largest weight. The results therefore confirm that the most recent local house price changes have the largest effect on expected future house prices as suggested in Section III.D.

Appendix C: Robustness—Local House Prices

Table CI compares respondents' expectations about ZIP code and national house price changes. Table CII analyzes the effect of recalled house price changes instead of actual house price changes. The first two columns show the relationship between recalled and actual house price changes. The next six columns show the effect of recalled ZIP-level house price changes on expectations. Internet Appendix Table IA.VI replicates the analysis for two-year-ahead house price expectations.



(a) Lasso estimation with penalty = 0.10

(b) Lasso estimation with penalty = 0.15

(c) Lasso estimation with penalty = 0.20

(d) Lasso estimation with penalty = 0.25

Figure B1. Lasso estimation of effect of history of past price changes. The graph shows the estimated coefficient on house price changes in prior years from a Lasso estimation of equation (1) with varying parameters. (Color figure can be viewed at wileyonlinelibrary.com)

Table CI

Difference between U.S. and ZIP Code Level House Price Expectations

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

	N	Mean	Std. Dev.	25th Percentile	50th Percentile	75th Percentile
Difference between U.S. and ZIP-level expected house price change						
Difference (in percentage points)	3,684	1.084	9.623	−2	1	4
Absolute difference (in percentage points)	3,684	5.503	7.967	1	3	6
Difference of 1 percentage points or less	3,684	0.240	0.427	0	0	0
Difference of 2 percentage point or less	3,684	0.404	0.491	0	0	1

Table CII

Actual and Recalled Changes of Past House Prices and Expectations

Columns (1) and (2) show the relationship between the actual house price changes in a respondent's ZIP code and those perceived by the respondent. A coefficient of 1 indicates perfect recall. Columns (3) to (8) show regression estimates of equation (1) with recalled past price changes in the respondent's ZIP code as the explanatory variable of interest. Demographics include indicators for household income categories, respondents' age and age squared, and indicators for employment status, whether respondents own their home, are male, married, went to college, and are white or black. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	Recalled Price Change in ZIP Code		Expected Change in U.S. House Prices					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Actual change in ZIP	0.297***	0.266***						
	(0.0366)	(0.0384)						
Recalled change in ZIP			0.0999***	0.122***	0.181***	0.0849**	0.105***	0.160***
			(0.0341)	(0.0375)	(0.0389)	(0.0344)	(0.0381)	(0.0401)
Actual change in								
ZIP						0.0270	0.0262	0.0242
						(0.0556)	(0.0555)	(0.0552)
MSA						0.0435	0.0340	0.0216
						(0.0982)	(0.0994)	(0.100)
State						0.106	0.107	0.105
						(0.0803)	(0.0801)	(0.0775)
Winsorized?	.	.	No	1%	5%	No	1%	5%
Time fixed effects	N	Y	Y	Y	Y	Y	Y	Y
Demographics	N	Y	Y	Y	Y	Y	Y	Y
Number of observations	2,727	2,727	2,462	2,462	2,462	2,462	2,462	2,462

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.