Expectation Formation*

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Abstract

We use novel survey panel data to estimate how personal experiences affect expectations about aggregate economic outcomes in housing and labor markets. We exploit cross-sectional and time series variation in differences in locally experienced house prices to show that respondents systematically extrapolate from personally experienced home prices when asked for their expectations about US house price development. In addition, higher volatility of locally experienced house prices causes respondents to report a wider distribution over expected future national house price movements. We find similar results for labor market expectations, where we exploit within-individual variation in labor market status to estimate the effect of own experience on national labor market expectations. Personally experiencing unemployment leads respondents to be significantly more pessimistic about future nationwide unemployment. Extrapolation from personal experiences is more pronounced for less sophisticated individuals for both housing and unemployment expectations. Our results have implications for the modeling of expectations.

1 Introduction

Expectations play a key role in economic models of decision-making under uncertainty. The benchmark approach of assuming that individuals form expectations by accurately processing all available information and updating their beliefs accordingly has found little support in the data [see Manski, 2004, for an overview]. Recent work has turned to

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empirical measures of expectations to inform modelling assumptions that deviate from the rational expectations benchmark (see Barberis et al. [Forthcoming]). We contribute to this research effort by empirically analyzing how personal experiences affect expectations about aggregate economic outcomes, and as such provide guidance on modelling the expectation-formation process.

We focus on expectations about national house prices and unemployment rates, both of which are crucial for understanding economic activity. House price expectations have been argued to play an important role in understanding housing booms and busts, including the recent financial crisis.[Piazzesi and Schneider, 2009, Goetzmann et al., 2012, Glaeser et al., 2013, Burnside et al., 2014, Glaeser and Nathanson, 2015]. Employment expectations matter for economic recovery after recessions, and can influence households' job search behavior [see, for instance, Carroll and Dunn, 1997, Tortorice, 2011]. In addition, house prices and unemployment offer a rich empirical setting to understand the effect of experience on expectations more generally.

We use data from the Survey of Consumer Expectations (SCE), an original and recent monthly survey fielded by the Federal Reserve Bank of New York since 2012. The SCE is a nationally representative, internet-based survey of a rotating panel of approximately 1,200 US household heads. It elicits consumer expectations on various economic outcomes, including house price development and labor market outcomes, as well as respondents' personal background and current situation.

We first exploit variation in locally experienced house prices to estimate the effect of past experience on expectations. Since house price development has differed substantially across the US in the last decade, there is substantial geographic variation in the house price development experienced by different individuals over many years [1]. We use the entire history of such locally experienced past house price returns to proxy for each individual's experience. We find that past locally experienced house price development significantly affects expectations about future changes in US house prices. For instance, respondents in ZIP codes with a 1 percentage point higher change in house prices in the previous year expect the increase in US house prices to be .124 percentage points higher. Furthermore, consistent with Malmendier and Nagel [2013] in the case of inflation expectations, we find that more recently experienced house price changes have a substantially stronger effect than earlier ones.

[1] For instance, Arizona experienced large increases in house prices in the recent boom, with annual increases of up to 30% in 2005, followed by deep drops of over 25% in 2008. On the other hand, house prices in Indiana have been very stable over the same time horizon with average changes of less than 1% per year.

The Survey of Consumer Expectations elicts not only respondents' point estimate of the expected change in house prices, but also a distribution of expected house price changes. This allows us to estimate whether past experiences affect the width of the distribution over expected future national house price movements. We find that respondents who experience more volatile house prices locally indeed report a wider distribution over expected future national house price movements. For instance, the standard devation of expected house price changes is .114 percentage points higher for respondents who experienced a 1 percentage point higher standard deviation in past house price changes since living in their current ZIP code.

Next, we turn to the effect of unemployment experience on US unemployment expectations. During the year respondents stay in the survey, locally experienced house prices do not change enough to estimate how respondents update their expectations as their experiences change. Analysing unemployment expectations, however, allows us to focus on individuals who experience job transitions (for example, were previously employed and lose their jobs, or who were unemployed and find a new job) during the panel and to exploit this *within-individual* variation in experiences to estimate the effect on expectations. This is only possible because of the rich panel component of the survey, something that is absent from most other consumer surveys of expectations.[2] We find that experiencing unemployment leads respondents to be significantly more pessimistic about future US unemployment: when unemployed respondents believe the likelihood of increasing US unemployment over the next twelve months to be 4.5 percentage points higher than when employed (on a base average likelihood of 39 percent).

We further explore which mechanisms are consistent with how personal experiences affect expectations. First, while experiencing unemployment significantly affects expectations about US unemployment, it does not affect expectations about other economic outcomes, such as stock prices, interest rates, inflation or house prices. Therefore, respondents do not appear to become more pessimistic or optimistic in general due to changes in their employment situation. Similarly, past house prices are not related to expectations about these other outcomes.

Second, we study which respondents are more likely to extrapolate from their experiences when forming expectations. Respondents with lower numeracy skills, as measured by a battery of questions in the survey, appear to extrapolate the most from personally

[2]Previous studies, largely due to data limitations, have mostly overlooked the panel dimension of survey expectations (see Keane and Runkle, 1990, and Madeira and Zafar, 2014, for an exception), and instead have studied the aggregate evolution of beliefs in repeated cross-sections; this complicates the interpretation of previous work on learning in expectation updating.

experienced unemployment or house prices. The effect of having a college education on the extent of extrapolation from past experience is mixed and we do not find a relationship to age or household income.

Third, we analyze whether respondents extrapolate more from personal experiences when these experiences are likely to be more informative. For respondents with higher income pre- or post-job loss and for respondents in areas of low unemployment, unemployment is less likely to be influenced by aggregate economic conditions and more likely due to idiosyncratic factors. Nevertheless, we find no evidence that unemployment affects national unemployment expectations differently for these respondents. To justify the 4.5 percentage points higher likelihood of US unemployment rate reported by unemployed respondents, a back-of-the-envelope exercise indicates that respondents would need to be about 19% more likely to lose their job if unemployment were truly going up than they would if it were not- an arguably large gap.

While our results indicate that respondents are not fully incorporating all publicly available information to form expectations about aggregate outcomes, we cannot tell with certainty whether respondents rely heavily on their own experience because they do not know other relevant information or because they overweigh their personal experiences when incorporating them into expectations. Our results are therefore broadly consistent with models of adaptive and experience-based learning, but also lend support to models of expectation formation in which individuals form expectations subject to information constraints [Coibion and Gorodnichenko, 2012a,b]. In this case, however, we are unable to say if these information constraints arise because of rational inattention (as in Sims [2003], Gabaix [2014]) or costly information acquisition [Reis, 2006].

How individuals form expectations about aggregate outcomes has important implications for the conclusions drawn from models in economics and finance.[3] Heterogeneity in consumers' expectations can generate over-investment in real assets (Sims, 2009), cause financial speculative behavior [Nimark, 2010], and impact the economy's vulnerability to shocks [Badarinza and Buchmann, 2011]. In housing markets, overoptimistic beliefs are often cited as major contributors to the run up of house prices prior to the recent financial crisis (see, for instance, Piazzesi and Schneider [2009], Goetzmann et al. [2012], Burnside et al. [2014] and Glaeser and Nathanson [2015]). Consistent with this literature, our findings suggest that increases in house prices in the early 2000s could

[3] 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".

have led consumers to extrapolate based on their recent experiences, which would then have led them to become overly optimistic. Similarly, our findings that individuals extrapolate from local house prices to US wide house prices suggest an explanation for why out-of-town buyers, especially those from areas with higher past price appreciation, may be overly optimistic about home prices as argued by Chinco and Mayer [2014]. Similarly, extrapolation from recent experiences can lead unemployment expectations to be systematically biased at the beginning and end of recessions, as argued by Tortorice [2011]. During an economic downturn consumers who receive a bad labor market shock may therefore become overly pessimistic about labor market conditions leading them to invest less in job search or accept less suitable positions prolonging the effect of the initial shock.

Several papers have previously studied how past experiences affect consumers expectations about inflation and future returns in financial markets. Malmendier and Nagel [2013] show individuals' inflation expectations are influenced by the inflation experienced during an individual's lifetime.[4] Vissing-Jorgensen [2004] shows that young investors with little experience expected the highest stock returns during the stock market boom of the late 1990s,[5] and Amromin [2008] and Greenwood and Shleifer [2014] find that stock return expectations are highly correlated with past returns and the level of the stock market.

Compared to this previous work, our paper focuses on housing and unemployment expectations which merit interest in and of themselves. We also exploit different sources of variation in experience. For housing market expectations, we exploit geographic variation in locally experienced house prices rather than variation due to age or over time. In addition, we analyze the effect of experienced volatility on the width of the distribution of expected changes. For unemployment, we can observe how the same individual changes their expectations as their labor market experiences change while in the sample. This individual-level variation in experiences – which, to our knowledge, has not be exploited in any application – allows us to filter out confounding factors which could lead to differences in expectations across individuals. That both within- and across-

[4] While not studying expectations directly, several papers have shown how experiences affect subsequent investment decisions, possibly through expectations. For instance, Malmendier and Nagel [2011] show that bond and stock return experienced during an individual's life time affect risk taking and investment decisions. Kaustia and Knüpfer [2008] and Chiang et al. [2011] find that the returns investors experience in IPOs affect their decisions to invest in subsequent IPOs. Similarly, Koudijs and Voth [2014] find that having been exposed to potential losses leads lenders to lend more conservatively.

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

respondent variation in experiences in two very different applications lead to similar qualitative conclusions is reassuring and strengthens our implications for the modeling of consumer expectations. Our empirical findings therefore provide additional evidence for the growing literature exploring the implications of extrapolative expectation not just in housing markets or about unemployment, but also in other asset markets and macroeconomic models [see Barberis et al., Forthcoming, for a recent overview].

2 Data

Our data are from the Survey of Consumer Expectations (SCE), an original monthly survey fielded by the Federal Reserve Bank of New York since late 2012.[6] The SCE is a nationally representative, internet-based survey of a rotating panel of approximately 1,200 household heads. Respondents participate in the panel for up to twelve months, with a roughly equal number rotating in and out of the panel each month.

The monthly survey is conducted over the internet by the Demand Institute, a non-profit organization jointly operated by The Conference Board and Nielsen. The sampling frame for the SCE is based on that used for The Conference Board's Consumer Confidence Survey (CCS). Respondents to the CCS, itself based on a representative national sample drawn from mailing addresses, are invited to join the SCE internet panel. Each survey typically takes about fifteen to twenty minutes to complete. The response rate for first-time invitees hovers around 55%. The survey elicits consumer expectations on inflation, labor market outcomes, house price changes and several other economic indicators. When entering the survey, respondents answer additional background questions.

2.1 Information on Housing and House Price Expectations

Each month, respondents in the Survey of Consumer Expectations are ask about their expectation for changes in house prices. First, respondents are asked whether they believe home prices nationwide to increase or decrease over the next 12 months and by about what percent. Figure 1 shows the distribution of expected house price changes.

Second, the survey elicits a distribution of expected house price changes. Specifically, respondents are asked to assign a probability to a range of possible house price changes such that the total of all probabilities adds up to 100 percent. The ranges of possible house prices changes start with a decrease of more than 12 percentage points, then

[6] See www.newyorkfed.org/microeconomics/sce.html for additional information.

proceeds in steps of two to four percentage points - 12 - 8 percentage points, 8 to 4 percentage points, 4 to 2 percentage points and 2 to 0 percentage points - up until an increase of more than 12 percentage points. Respondents also provide information about where they currently live, how long they have lived there and how long they have lived in their current state and whether they own or rent their current residence. Table 1 shows summary statistics of the expected house price changes, as well as past experienced house price changes of respondents.

2.2 Information on Own Employment and Unemployment Expectations

Each month, respondents in the Survey of Consumer Expectations are asked about their expectation for US unemployment a year later. Specifically, respondents are asked "What do you think is the percent chance that 12 months from now the unemployment rate in the U.S. will be higher than it is now?". In response, respondents state the percentage chance between 0 and 100. Respondents are also asked about their current employment situation based on which we classify respondents into five categories: employed (either full or part-time), searching for work (that is, the unemployed), retired, student and 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. Employed respondents are asked about the likelihood of loosing their current job within the next year and how likely they would find a new job within 3 months should they loose their current one.[7] Respondents currently not working are asked about the likelihood of finding a job within the next 3 and 12 months.[8]

We restrict our sample to respondents who answer at least two survey modules, state their employment status and answer the question about aggregate unemployment. Starting in December 2012, our sample contains 4,227 respondents who answer on average 6 survey modules, for a total of 25,764 respondent-month observations.

Table 2 shows each respondent's current and previous employment status every month. Respondents are employed in 69% of survey responses and currently looking

[7]The two questions are elicited as follows: "What do you think is the percent chance that you will lose your current job during the next 12 months?" and "Suppose you were to lose your job this month. What do you think is the percent chance that within the following 3 months, you will find a job that you will accept, considering the pay and type of work?"

[8]The former, for example, is elicited as follows: "And looking at the more immediate future, what do you think is the percent chance that within the coming 3 months, you will find a job that you will accept, considering the pay and type of work?"

for work (unemployed) in 5%. The remaining respondents are either students, retired or out of the labor force for other reasons.

While in the panel, several respondents experience changes in their employment status. Of special interest for us are the 132 instances in which respondents loose their previous employment and 172 instances where respondents find a new job out of unemployment, since we can exploit these within-individual changes in employment experiences to estimate their effect on expectations.

Table 3 shows additional summary statistics on the characteristics of respondents, their employment situation and employment expectations. The SCE provides weights to obtain nationally representative averages. However, our sample is not weighted and response rates and internet coverage may vary across demographics leading some demographic groups to be overrepresented in our sample. The average respondent in our sample is 50 years old. 87% of respondents are white and 8% black. Most respondents, 69%, are married and slightly more than half 55% are men. 56% of respondents went to college and the average yearly household income is $81,000. Our sample has respondents with higher income and higher educational attainment than the US population overall. As mentioned earlier, this may partly reflect differential internet access and computer literacy across various demographics.

Two of the respondent characteristics require additional explanation. Respondents were asked a series of either five or six questions, based on Lipkus et al. [2001] and Lusardi [2009], that provides an individual-specific measure of numeracy. Respondents, on average, answer 43% of the questions correclty, with at least a quarter of respondents answerning none of them correctly, and at least a quarter answering all of them correctly. As another measure of respondents' literacy, we asked: "On a scale of 1 to 7, how well would you say you understand what "inflation" means?", where 7 meant "I know exactly what "inflation" means". We see that 38% of respondents report they fully understand what inflation means.

Moving to observation-level characteristics, we see that respondents who are unemployed are more likely to live in areas with higher local unemployment (7.3%, on average, versus 6.9% for those who are employed). We therefore include controls for the local unemployment rate throughout.

3 Estimating Effect of Own Experience on Expectation

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

3.1 Estimating Effect of Local House Price Development on US Home Price Expectations

To estimate the effect of experience on expectations about house prices, we estimate equation 3.1 where $expectation^d_{it}$ is the expected change in average US house prices, as stated by respondent i at time t. We proxy for experienced house prices, $experience^d_{it}$, by the local house price development where the respondent currently lives. We face two main challenges in measuring local house price experience: constructing a measure that captures the total effect of house price development over many years and determining when respondents start to experience house prices.

Capturing house price development by including separate variables for each experienced annual return would make it hard to obtain precisely estimated coefficients, especially since house prices are serially correlated and therefore highly co-linear. We therefore follow the approach of Malmendier and Nagel [2011] to capture the history of past prices in one experience variable. Each person's house price experience is calculated as the weighted average of all experienced house price returns, R_t. The weights are determined by the parameter λ which allows the weights to increase, decrease or be constant over time. Specifically, each respondent i's house price experience in year t is measured by A_{it}, calculated as follows:

$$A_{it} = \sum_{k=1}^{horizon_{it}-1} w_{it}(k, \lambda) R_{t-k} \tag{1}$$

where

$$w_{it}(k, \lambda) = \frac{(horizon_{it} - k)^{\lambda}}{\sum_{k=0}^{horizon_{it}-1} (horizon_{it} - k)^{\lambda}}. \tag{2}$$

R_{t-k} is the change in local house prices in year $t-k$. The weights depend on the experience horizon of the individual, $horizon_{it}$, when the home price return was realized (k), and on the parameter λ. Note that in the case where $\lambda = 0$, A_{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 more recent experienced changes. We estimate λ later in the paper.

To filter out seasonal effects, we use year on year changes in home prices. Therefore, respondent's house price experience does not vary during the year they spend in the panel and we focus on only one house price expectation per respondent. The effect of house price experience on expectations is therefore identified in the cross-section by differences in the local house price history. In our main specification we use zip code level house prices, but also show results using MSA or state level house prices. Figure 6 in the appendix illustrates how geographic variation in house price changes leads to differences in the weighted housing experience variable for respondents with different experience horizons.

Finally, we need to determine when respondents start to *experience* local house prices, captured by the experience horizon $horizon_{it}$, especially for respondents who have previously lived in other areas. First, zip code level house prices are only available since 1976, so this is the earliest year respondents can start experiencing house prices. For each respondent, the survey collects data on how long respondents have lived in their current zip code and in the current state. Unfortunately, we do not know where respondents lived before they moved to their current zip code or state. We therefore consider three different horizons for when (after 1967) a respondent starts experiencing local house prices. The first assumption is that respondents' experience horizon starts a year before moving to their current zip code. This takes into account that respondents search for housing and are likely to experience local house price conditions shortly before an actual move. However, it assumes that respondents do not learn about prior local house price development in their current zip code, either by having lived near by or by researching prior house price development in the process of moving and searching for housing. To address this, we consider two longer horizons. The time the respondent lived in the current state addresses learning about house prices in nearby areas. An experience horizon since age 13 allows for the possibility that respondents research previous house price development before moving to an area or learn about it from their neighbors and friends and end up with the same house price experience as if they had grown up and always lived in their current zip code. As we show later, our choice of horizon has little impact on our qualitative conclusions.

$$expectation_{it}^{d} = \alpha + \beta experience_{it}^{d} + \gamma X_{it} + \epsilon_{it}, \tag{3}$$

where $expectation_{it}^{d}$ is respondent i's expectation about aggregate outcome d reported at time t and $experience_{it}^{d}$ is an individual's own experience related to outcome d. X_{it} are control variables, including time fixed effects and, in some specifications, individual fixed effects. We focus on respondents' experiences and their effect on expectations regarding US unemployment and nationwide house prices.

3.2 Estimating Effect of Own Employment on US Unemployment Expectations

To estimate the effect of own unemployment experience on unemployment expectations we estimate equation 3.1 where $expectation_{it}^{d}$ is the percentage chance that US unemployment will be higher a year later, as stated by respondent i in month t; the lower panel of Table 3 shows that the mean probability of this expectation over the sample period for the full sample is 39.2%. Unemployed individuals report a substantially higher average likelihood of this outcome (47.5% versus 39.2% for the employed; statisticlaly different at the xxx level). $experience_{it}^{d}$ is an individual's reported own employment status in month t.

Transitions in the respondent's employment situation during the panel, of which we showed evidence in Table 2, enable us to include individual fixed effects. This allows us to exploit within-individual variation in employment experience to identify the effect of experience on expectations.

We use two proxies for each individual's employment experience: the respondent's current employment status, as well as their beliefs about their employment prospects. Employment prospects are captured by respondents' beliefs about the likelihood of losing their job within the next 3 months and of finding a job within 3 months should they lose their job. Unlike employment status, employment expectations are based on both experiences and private information, such as job security, which is otherwise hard to assess. Table 3 shows that the for the employed respondents, the mean likelihood of loosing their job over the next months is 15.7 percent, with substantial heterogeneity across respondents as indicated by the large standard deviation. The average likelihood of finding a job within 3 months were the individual to lose their job is 52.3%.

It should be pointed out that respondents seem to understand the distinction between the likelihood of national unemployment rate going up, and the likelihood of they, themselves, losing their job over the next 3 months. The last row of Table 3 shows the average difference between these two variables. Employed respondents, on average, assign a 23.5 percentage point higher likelihood to the former outcome.

4 Local House Prices and House Price Expectations

Figure 2 gives a first look at the relationship between locally experienced past house prices and expectations. Panel A sorts respondents into deciles based on the change in house prices in 2013 relative to 2012. On average, respondents in ZIP codes with higher price changes expect house prices nationwide to increase more in the following year. Similarly, panel B shows that respondents in states with higher increases in house prices in 2013 on average expect house prices to be higher in the coming year. These graphs indeed suggest that respondents are influenced by local house price experiences when forming expectations about nationwide home prices.

4.1 Effect of Local House Prices on US House Price Expectations - Regression Analysis

Figure 2 suggests a relationship between local price development and nationwide house price expectations. We now turn to estimating the effect of past house price experience on expectation based on equation 3.1 controlling for respondent characteristics and measuring past house price experience by the whole history of past price development rather than just the previous year's house price change. Figure 3 shows the estimated effect. The dependent variable is each respondent's expected change in US wide house prices. Experience is measured by the weighted average of past local house price changes calculated according to equation 1 and outlined in section 3.1. The figure shows the estimated effect of past experience for different weighting parameters λ. At $\lambda = 0$ all experienced house prices are weighted equally whereas more recent experiences are over weighted as λ increases.

Panel A of figure 3 shows the estimated coefficient of local house price experience (β in equation 3.1) on US house price expectations with 95% confidence bounds for the three different experience horizons considers with experience starting the year before the respondent moved to the current zip code, when he moved to his current state or at age 13. Local house prices are captured by ZIP code level prices (solid lines), as well as state level prices (dotted lines). ZIP code level house prices vary more than state level house prices, so Panel B shows the effect of a one standard deviation change in experience to allow to compare magnitudes. The figure shows that local house price experience significantly affects US house price expectations for a wide range of weighting parameters λ. The estimated influence of local house prices is similar for state and ZIP code level prices, as well as across the different experience horizons, as shown in Panel B.

Figure 4 shows the fit of the regression measured by R^2 when using ZIP code level house prices in Panel A and state level house prices in Panel B. In addition to the regression fit when experience is measured by the weighted average of past experience, the dotted line shows the fit of a regression including only the house price return in the previous year as a measure of past experience. Throughout all specifications, the highest R squared is obtained when experience is measured only by the most recent yearly house price change. Consistently, R^2 increases as λ increases since over weighing recent experience comes closest to the most recent year being weighted the most. The results therefore indicate not only that experienced house price returns significantly affect house price expectations, but that recently experienced returns have the most influence.

Table 4 therefore shows regression results of equation 3.1 when experience is only measured by the previous year's house price return in the state (column 1), ZIP code (column 2) and MSA (column 3) where the respondent lives. The estimates confirm that past local experience significantly affects expectation about US house prices. The effect is similar irrespective of whether state, ZIP code or MSA level house prices are included.

4.2 Effect of Local House Prices by Respondent Characteristics and on Other Outcomes

Table 4 shows the effect of local house prices on expectations about US house prices separately for owners and renters and college and non-college graduates. There is no significant difference between homeowners and renters in the influence of the prior year house price returns on expectations about US house prices. On average, homeowners, however, are less optimistic about US house prices than renters. College graduates, on average are more optimistic about US house prices, but extrapolate less from their local price experience. The point estimates are largest and only significant when past state prices proxy for local experience.

Table 6 analyzes whether a respondent's math score is related to the extent in which local house prices influence expectations about US house prices. Respondents with higher math scores extrapolate less from local house prices. The effect is statistically significant only when state level house prices are used to measure local house price experience. This result is consistent with our earlier finding that the labor market expectations of respondents with lower math scores are more affected by their current employment status than those of respondents with higher math scores.

Finally, table 7 shows that local house price changes are not systematically related to expectations about other economic outcome variables.

4.3 Effect of Local House Prices Variation on Expected Price Variation

Table 8 analyzes whether respondents who have experienced more volatile house prices where they live expect nationwide house prices to be more volatile. The dependent variable is the standard deviation of expected house prices elicited in the survey. The explanatory variables is the standard deviation of house prices in the respondent's zip code (column 1), state (column 2) and MSA (column 3). The standard deviation of past house prices is calculated over different horizons: since the respondent lived in the current zip code or state, since he was 13 and since the beginning of our data on local house prices in 1976. In all specifications we control for the previous year's return in house prices to account for different levels of house prices.

Table 8 shows that respondents in areas which experienced more volatile house prices indeed expect nationwide house prices to be more volatile. The estimated coefficient increases with the time horizon, but the standard deviation of the regressor decreases with time horizon. The overall effect of past house price variation on expected variation is therefore similar irrespective of horizon: A one standard deviation increase in the standard deviation of experienced house prices since moving to the current ZIP code (4.2 according to table 1) increases the standard deviation of expected house prices by almost half a percentage point (4.2*.115 = .483). The same increase in the standard devation of house prices since the beginning of our data increases the standard deviation of expected house prices by .32 (1.34*.239=.32). The estimated effects are similar when using state level house prices. MSA level house prices yield a slightly smaller and more noisyly estimated effect.

5 Own Employment Experience and US Unemployment Expectation

5.1 Employment Status and Unemployment Expectations

Figure 5 shows average national unemployment expectations by employed and unemployed respondents over our sample period. Both employed and unemployed adapt their expectations to changes in economic conditions. In December 2013, employed respondents believe unemployment to be higher with probability of just under 50% which drops to well below 40% in late 2014. At every point in time, however, respondents looking for work consider an increase in unemployment to be on average more than 7 percentage points more likely than than their employed counterparts.

Table 10 formally estimates this difference in nationwide unemployment expectations between employed and unemployed respondents. The estimation includes time fixed effects to absorb changes in economic conditions over time and isolate the effect of employment status. Relative to employed respondents (omitted category), those searching for work are 8 percentage points more pessimistic about nationwide unemployment. Retired respondents are more optimistic than others and those out of the labor force are slightly more pessimistic. Controlling for demographics and local unemployment rates, in the second column, reduces the difference between employed and unemployed respondents to 6.7 percentage points indicating that differences in characteristics partially explain differences in expectations. Column 3, which flexibly controls for local unemployment rates, yields estimates similar to those in the second column.

The last two columns of Table 10 include individual fixed effects which absorb any remaining differences in characteristics. The resulting estimates capture how much respondents adjust their expectations when their own employment status changes. Respondents become 4.5 percentage points more pessimistic (optimistic) when they become unemployed (find a new job out of unemployment).

Whether this implies that individuals are overly reliant on their personal experience depends on how informative their personal job loss is for nationwide unemployment. Assume that all respondents are Bayesian updaters and agree that the unconditional probability of national unemployment increasing is 40% (the average expectation of all respondents) and that the probability of job loss if unemployment was not going to increase is 7% (roughly the average unemployment rate in the US over our sample period). Let $P(high)$ be the (unconditional) probability of unemployment being higher a year from now based on publicly available information. Let $P(high|unemployed)$ and $P(high|employed)$ be the probability of unemployment being higher for respondents who have experienced a job loss and those who are still employed respectively. Assume that the likelihood of job loss if unemployment was not going to increase is $P(jobloss|nothigher)$ and that the probability of job loss is higher by x percent if unemployment was going to increase, that is, $P(jobloss|higher) = x * P(jobloss|nothigher)$. Then the differences in expectations by employed and unemployed respondents should be $P(high|unemployed) - P(high|employed) = \frac{P(jobloss|nothigher)xP(high)}{P(jobloss|nothigher)xP(high)+P(jobloss|nothigher)(1-P(high))} - \frac{(1-P(jobloss|nothigher)x)P(high)}{(1-P(jobloss|nothigher)x)P(high)+(1-P(jobloss|nothigher))(1-P(high))}$ Substituting in $P(high) = 40\%$, $P(jobloss|nothigher) = 7\%$ and $P(high|unemployed) - P(high|employed) = .0457$ yields $x = 19.1\%$. That is, respondents would need to be about 19% more likely to loose their job if unemployment was truly going up than they would be if unemployment was not going to increase to justify the estimated difference in posterior beliefs of 4.6 percentage points. [9]

5.2 Own Employment Prospects and Unemployment Expectations

Most respondents are employed and do not experience a job loss; however, their personal employment experience can still vary, for example through an increase in job uncertainty. For these respondents we proxy for such changes in experience by their self-assessed personal employment prospects and estimate the effect on their expectations for national unemployment. As mentioned earlier and shown in the lower panel of Table 3, respones to the two questions – likelihood of the national unemployment rate going up, and of the respondent themselves losing their job – are quite distinct, suggesting taht respondents are able to distinguish between the two.

While reassuring that respondents understand they are asked different questions, the large average difference of 23.5 percentage points in responses to the question about nationwide and personal unemployment is noteworthy. To a large extent job loss by employed respondents is what leads to higher nationwide unemployment. We would therefore expect the average probability of job loss to be similar in magnitude to the average expected increase in unemployment. The large average difference between the two, however, indicates that most respondents are much more optimistic regarding their

[9] For job loss rates, $P(jobloss|nothigher)$, between 1 and 20 percent and different unconditional probabilities the estimates vary but are of similar economic magnitude.

own employment prospects than they are about nationwide outcomes. This is consistent with prior evidence that respondents tend to overestimate their own ability,[10] and therefore their own employment prospects.

While respondents may be relatively optimistic about their own employment prospect, Table 11 shows that self-assessed employment prospects are still informative of future employment outcomes both in the cross-section, as well as within-respondent over time.[11] The dependent variable in the table is a dummy for whether the respondent actually loses her job over the specified horizon. Respondents who think they are more likely to loose their job when they first enter the panel are more likely to do so in the following months: Panel A of the table, which exploits cross-sectional variation, shows an increase of 10 percentage points in the reported likelihood of losing a job over the next 12 months is associated with a 0.016 increase (on a 0-1 scale) in the actual likelihood of losing a job over the next six months. Moreover, the lower panel of Table 11 shows that as respondents become more pessimistic about losing their job they are indeed at an increased risk of being laid off, in particular over a 1-month horizon. We take this as evidence of subjective expectations regarding own job loss capturing respondents' private information regarding their job stability.

Table 12 shows how self-assessed employment prospects affect expectations about US unemployment of employed respondents. As respondents become more pessimistic about losing their job, they also become more pessimistic about US unemployment. A one standard deviation increase in the self-assessed probability of job loss is associated with an increase of 2.3 percentage points in the expectations regarding an increase in the US unemployment rate.[12] Respondents' self-assessed likelihood of not finding a new job should they loose their current one, however, is negatively related with their assessment of US unemployment. The estimate is small in economic terms though: a one standard deviation increase in the likelihood of not finding a job is associated with a 0.6 decline in expectations regarding US unemployment being higher. The third column of the table shows that nationwide unemployment expectations are positively related with the likelihood of the respondent themselves being unemployed in 3 months, were they to lose their current job. These findings are generally consistent with respondents extrapolating

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

[11] Stephens Jr [2004] and Dickerson and Green [2012] also find that expectations of unemployment are predictive of future employment outcomes.

[12] The standard deviation of self-assessed job loss probability is 20.7 percentage points as shown in Table 3 which if multiplied with the coefficient of .110 yields the estimate of 2.3 percentage points.

from their own experience of increased likelihood of unemployment to an increasing US unemployment.

5.3 Effect of Employment Status on Other Outcomes

Do respondents extrapolate from their labor market experiences to expectations regarding other economic variables? Table 13 explores exactly this, and investigates whether respondents become more or less pessimistic not just about unemployment, but about other economic outcomes, as well. The first two columns of Table 13 show that unemployed respondents feel they are worse off than they were a year ago and also expect to be worse off a year later. This confirms that job loss is indeed a negative experience for respondents. The remaining columns estimate the effect of being unemployed on expectations about interest rates, US stock prices, inflation, government debt and house price development. We do not find an effect of employment status on expectations about these other variables. Unemployment therefore does not make respondents more or less pessimistic about economic conditions in general. Rather, respondents appear to consider their own employment experience to be informative only for aggregate unemployment. It is interesting to note that the estimate on “out of labor force” is qualitatively similar to that as the unemployed respondents. This would suggest that, the transition to out of the labor force, is partly driven in our sample by the same factors that lead respondents to become unemployed.

5.4 Heterogeneity

Table 14 explores which respondents react most to their own experience when forming expectations. We estimate whether the effect of unemployment varies by whether respondents have a college degree (column 1), how well they did on the numeracy test (column 2), whether they say they perfectly understand what inflation means (column 3), age groups (column 4), local unemployment rate (column 5), and household income (column 6). The first three variables can be viewed as proxies for the respondent’s sophistication. We would, arguably, expect such individuals to be less prone to overweight idiosyncratic factors when reporting expectations for national outcomes. Local unemployment rate and with household income could both proxy for how informative own unemployment is for nationwide unemployment. Specifically, areas with low unemployment are generally doing well economically and are therefore better equipped to weather aggregate fluctuations without substantial layoffs. An individual is therefore more likely to loose their job because of idiosyncratic factors rather than aggregate shocks. Similarly, higher household income before a layoff or after finding a new job indicates that respondents work in well paying and highly qualified professions which are generally less sensitive to aggregate labor market conditions.

The estimates suggest that there are no significant differences in the effect of experiencing unemployment for college graduates, respondents who say they understand inflation perfectly or by age. Our point estimates suggest that unemployment has the largest effect, an increase of almost 8 percentage points, on expectations for respondents with numeracy in the lowest quintile, though the difference from respondents with higher numeracy scores is not statistically significant. We also do not find evidence that the effect of experiencing unemployment varies with how informative it is, at least in so far as local unemployment or household income are reasonable proxies for how informative own employment is about aggregate unemployment.

5.5 Unemployment Expectations Robustness Checks

In this section, we report a series of robustness checks. In our baseline model, reported in Table 10, the effects of own labor market experiences on nationwide unemployment expectations is restricted to be symmetric. We relax this in Table 15, which explores 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 the first column, we see that expectations of respondents who recently found a new job do not differ significantly from those of respondents who have been employed throughout the sample period. Respondents who lost their job or entered the sample looking for a job are substantially more pessimistic. When including individual fixed effects in column (2) of the table, however, we find no significant difference between recent job losers and employed respondents. Respondents who found a new job out of unemployment, however, are 5 percentage points more optimistic than those who are employed throughout the sample period.

We next investigate whether the effect of job loss or finding a job out of unemployment varies by the length of unemployment. Table 16 splits the indicator for being unemployed into separate indicators for each quintile of unemployment length. Respondents who have been unemployed longer are more pessimistic than the most recent job losers, but there is no clear monotonic relationship with the length of unemployment beyond the first quintile.

Finally, Table 17 shows that we obtain results very similar to our main results presented in table 10 when restricting the estimation to subsamples of our data which are less likely to be affected by potentially confounding factors. Column one excludes respondents who stated that they were leaving their job before becoming unemployed and starting to search for work. These respondents are likely to have anticipated their job loss or left voluntarily, possibly confounding the results. Column two restricts to respondents who only had one change from employment to unemployment or vice versa during the sample period, and no other changes in employment status. This excludes respondents who transitioned between employment and unemployment more than once during the sample period or who made additional transitions, such as retiring out of unemployment or becoming a student. The estimated effect of unemployment on employment expectations of 4.8 and 4.5 percentage points respectively is of similar magnitude and significance to our baseline estimate of 4.5 in Table 10, indicating that our baseline results are robust so such concerns.

6 Conclusion

This paper documents that recent personal experience affects expectations about aggregate unemployment and house price development. Experiencing unemployment leads respondents to be significantly more pessimistic about nationwide unemployment and house price development in the prior year significantly affects expectations about US house prices. Experiencing unemployment does not affect expectations about other economic outcomes, such as interest rates, stock prices, government debt or inflation. The results therefore suggest that respondents extrapolate from their own recent experience in the given domain when forming expectations about aggregates.

Our findings have important implications for understanding aggregate fluctuations in labor and housing markets. For instance, our results illustrate how house price increases can lead households to expect high house price returns to persist in the future. Such expectations have been argued to play an important role in understanding housing booms and busts, including the recent financial crisis.[Piazzesi and Schneider, 2009, Burnside et al., 2014, Goetzmann et al., 2012]. Moreover, our results offer further support for theories exploring the implications of extrapolative expectations in areas other than unemployment or housing markets. For instance, Barberis et al. [Forthcoming] outline the implications of extrapolative expectations in the asset markets.

A Variation in House Prices and Weighted Experience

Table 6 illustrates the geographic variation in house prices and how it 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 hours price development: 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 1980ies. Prices also increased in the early 2000s and declined afterwards, though both the increase and subsequent decline were substantially smaller than in Arizona. House prices in Indiana were relatively stable over the last decades with neither small declines nor large increases. The weighted house price experience in Indiana is therefore very similar for respondents of all experience horizons and irrespective of whether recent or earlier experiences are weighted more.

In Arizona and New York, weighted experience varies substantially with experience horizon, as well as weighting parameter λ. Respondents who experienced only the last 5 or 10 years average experienced house price changes increases as the recent years, the recovery after the crisis gains more weight. It also increases as early experiences or overweighted since for respondents with 10 year horizons, these overweigh the run-up in prices in the early 2000s. In New York, unlike in Arizona, respondents with a very long horizon also have high weighted house price experiences when early experiences receive higher weights since these capture the 1980s when New York, but not Arizona experienced large increases in house prices.

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Figure 1: Distribution of Expected House Price Changes

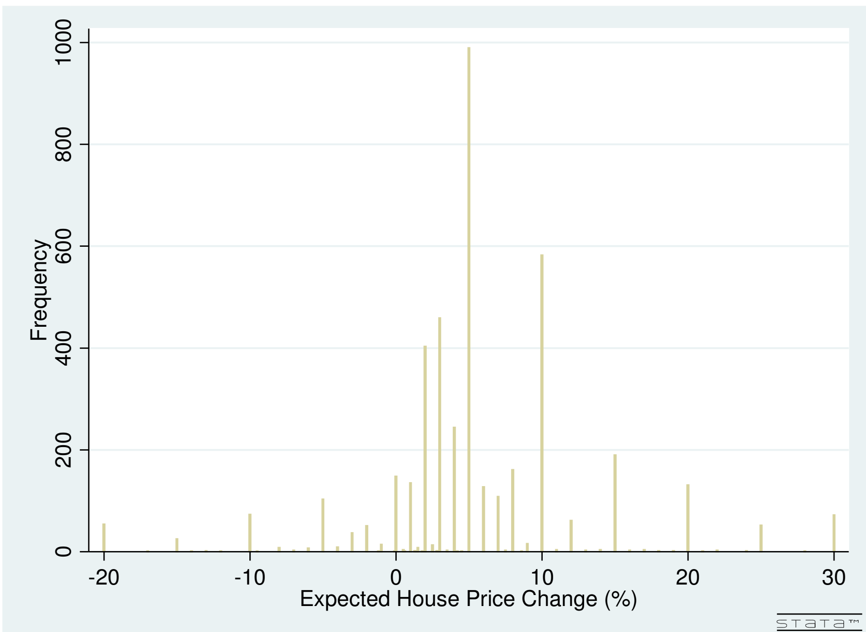
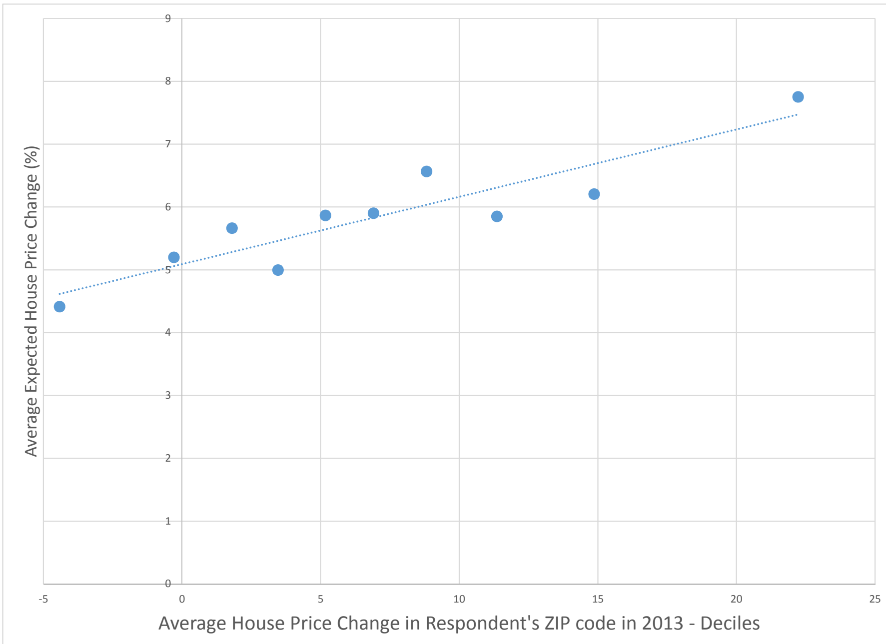
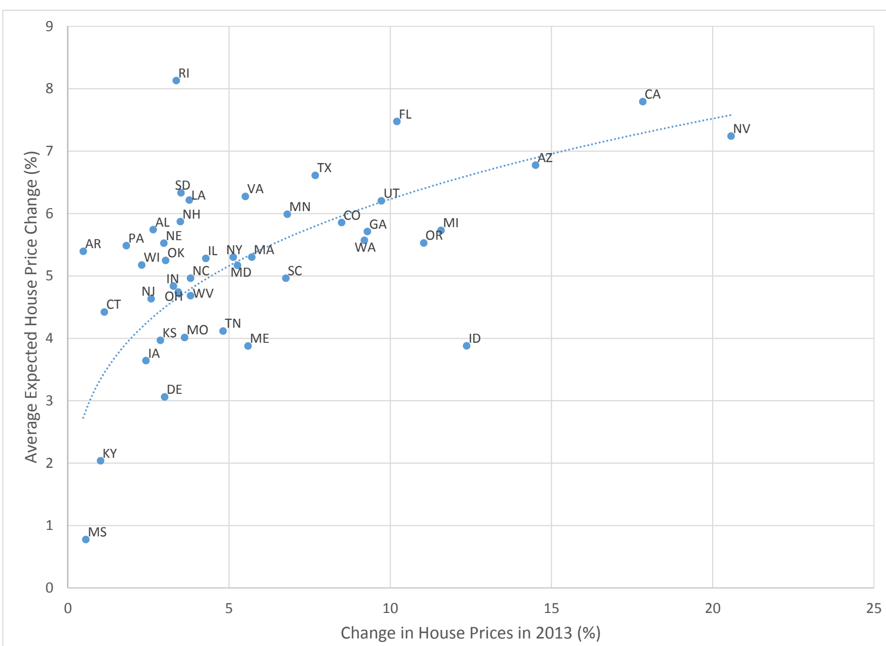


Figure 2: Local House Price Experience and Expectation

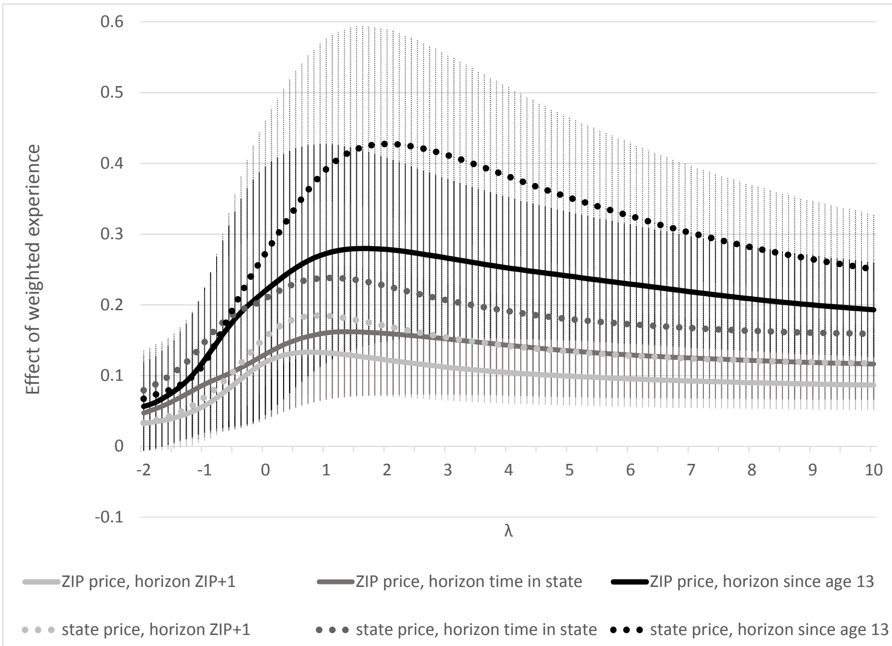


(a) ZIP Level House Price Change

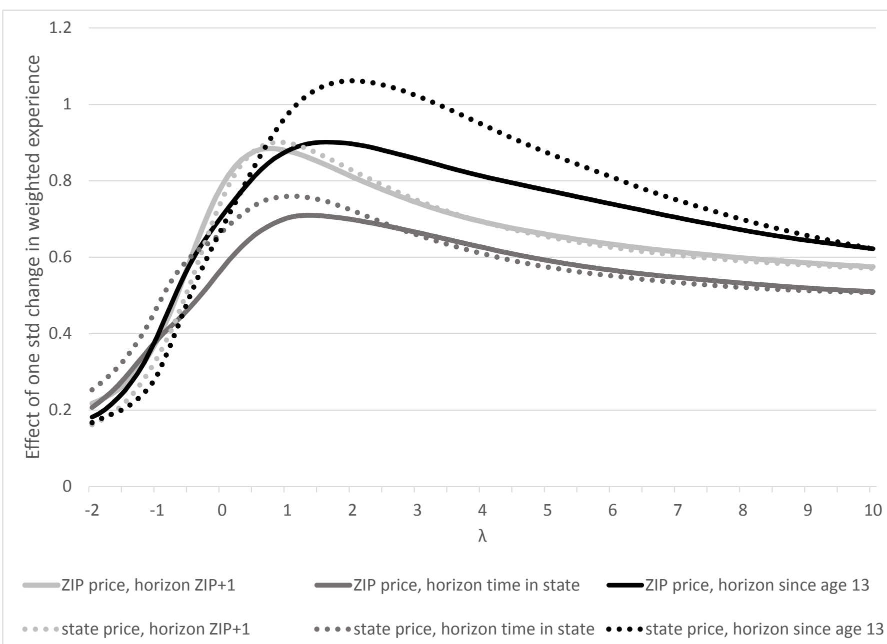


(b) State Level House Price Change

Figure 3: Local House Price Experience and Expectation - Estimated Influence

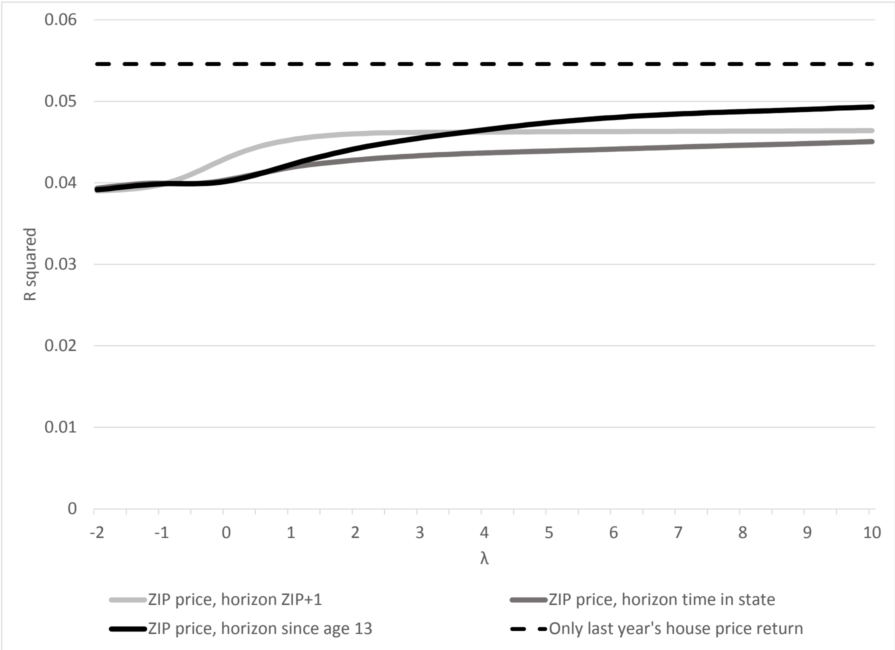


(a) Coefficient on weighted experience

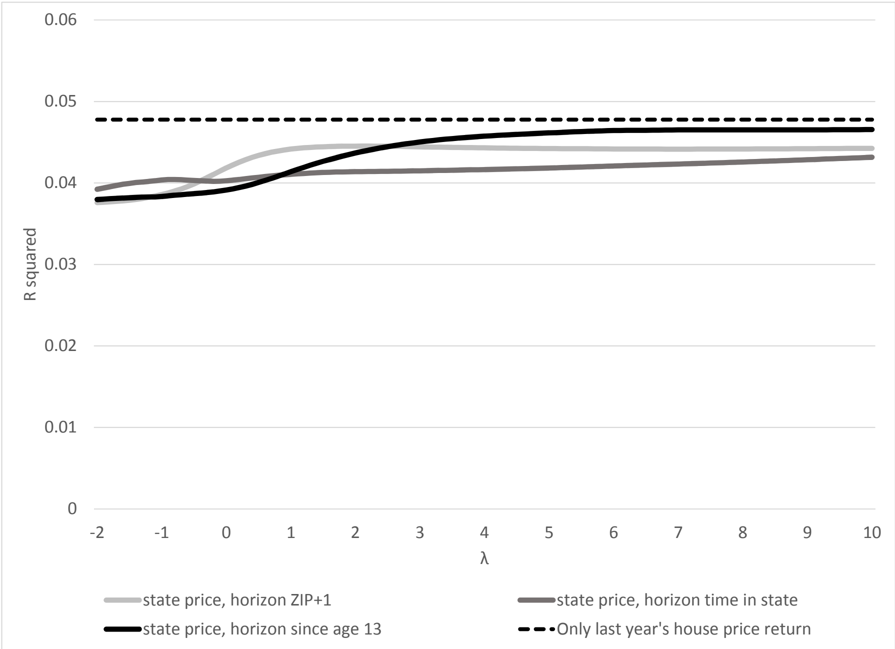


(b) Effect of one std change in weighted experience

Figure 4: Local House Price Experience and Expectation - Goodness of Fit



(a) Regression Fit - ZIP code level house prices



(b) Regression Fit - state level house prices

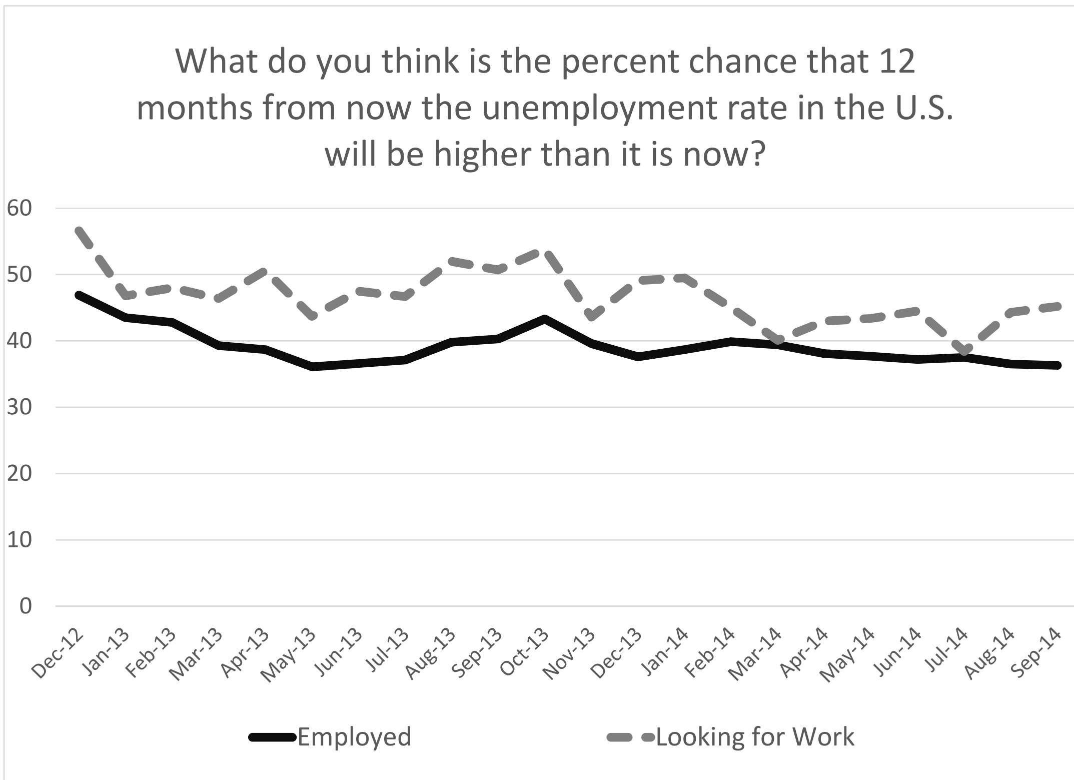
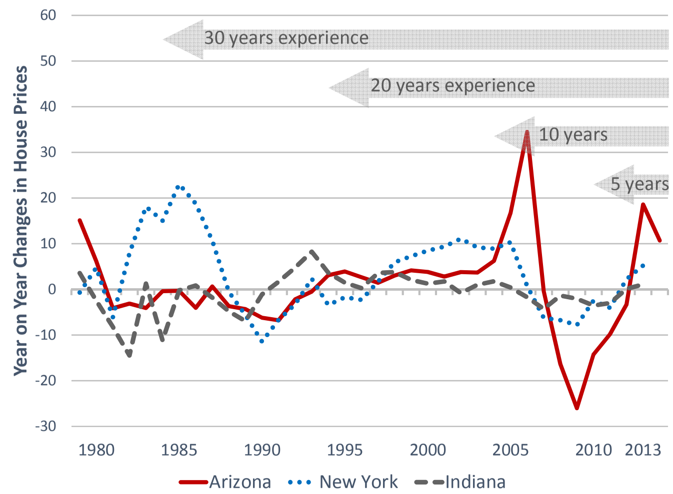


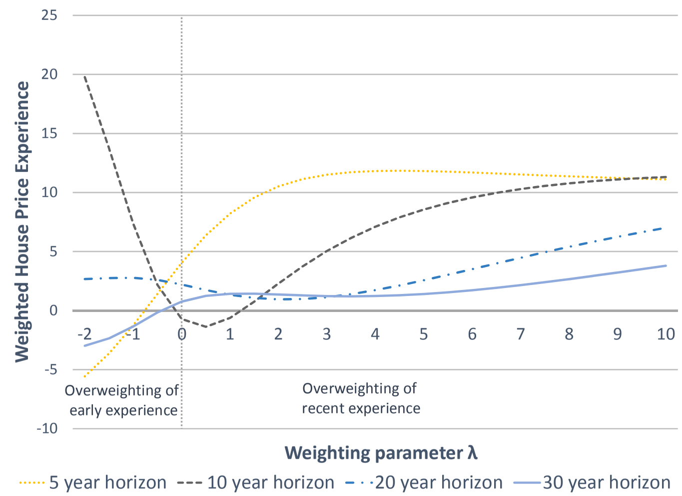
Figure 5: Employment Status and Unemployment Expectations Over Time

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

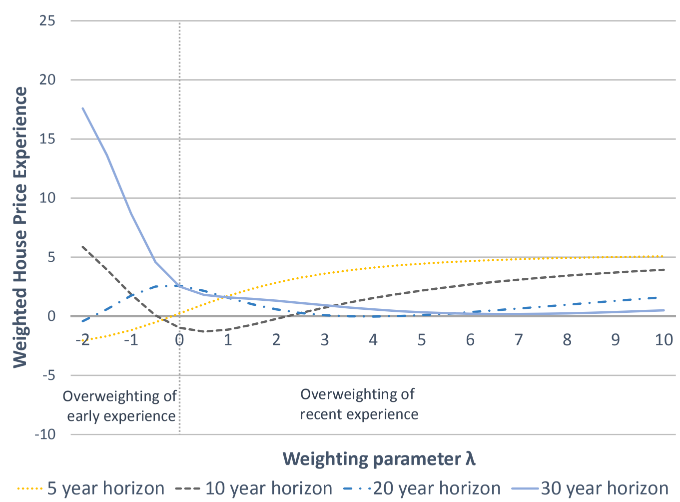
Figure 6: House Prices and Weighted Experience



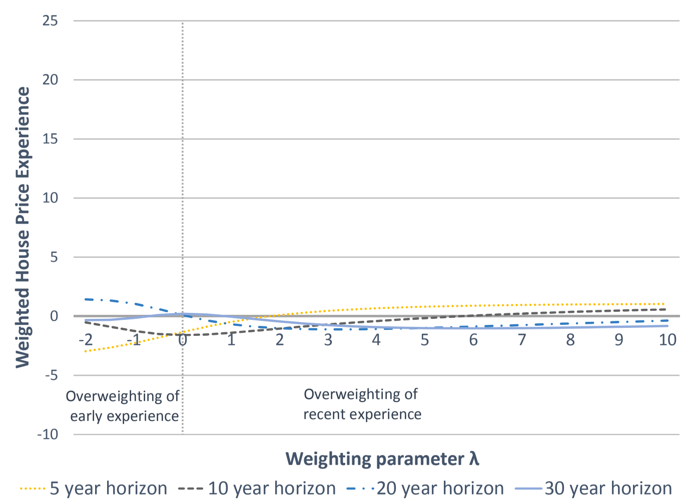
(a) House Price Changes Over Time



(b) Arizona - Weighted Experience



(c) New York - Weighted Experience



(d) Indiana - Weighted Experience

Panel A shows yearly changes in house prices in Arizona, Indiana and New York. The remaining panels show how the weighted house price experience of respondents with experience horizons of 5, 10, 20 and 30 years in Arizona (Panel B), New York (Panel C) and Indiana (Panel D) changes as the weighting parameter λ changes. λ equal to zero

	N	Mean	Std. Dev.	25th pctile	75th pctile
Expected House Price Changes					
Expected mean house price change	4,340	4.143	4.342	1.350	6.350
Expected standard devation of house price change		14.202	10.460	5.874	19.392
Expected probability of house price change > 12%		10.879	22.768	0.000	10.000
Past House Price Experience - Average Changes					
Mean change of **ZIP code** level house prices since					
respondent lived in ZIP		2.681	4.163	0.113	4.692
respondent lived in state		3.897	2.858	2.769	5.356
respondent was age 13		4.320	1.683	3.222	5.443
1976 (beginning of data series)		4.917	1.340	3.961	5.811
Mean change of **state** level house prices since					
respondent lived in ZIP		2.771	3.437	0.542	4.385
respondent lived in state		4.039	2.388	3.020	5.402
respondent was age 13		4.382	1.482	3.353	5.429
1976 (beginning of data series)		4.951	1.224	4.108	5.807
Mean change of **MSA** level house prices since					
respondent lived in ZIP		2.598	3.597	0.378	4.168
respondent lived in state		3.866	2.465	2.898	4.927
respondent was age 13		4.217	1.464	3.240	5.083
1976 (beginning of data series)		4.783	1.166	4.087	5.522
Past House Price Experience - Variation					
Mean change of **ZIP code** level house prices since					
respondent lived in ZIP		8.143	4.138	5.232	10.420
respondent lived in state		8.387	3.259	5.992	10.346
respondent was age 13		8.368	2.839	6.158	10.332
1976 (beginning of data series)		8.395	2.428	6.394	10.209
Standard deviation of **state** level house prices since					
respondent lived in ZIP		6.713	3.877	4.010	8.537
respondent lived in state		7.198	3.090	4.882	8.781
respondent was age 13		7.227	2.713	4.948	8.887
1976 (beginning of data series)		7.308	2.374	5.006	8.537
Standard deviation of **MSA** level house prices since					
respondent lived in ZIP		6.889	4.059	4.060	8.984
respondent lived in state		7.332	3.260	4.902	9.145
respondent was age 13		7.330	2.896	5.061	9.144
1976 (beginning of data series)		7.429	2.472	5.447	9.143

Table 1: House Price Summary Statistics

The table shows mean, standard deviation and 25^{th} and 75^{th} percentile for house price expectations and past house price experience of respondents of the Survey of Consumer Expectations (SCE) used throughout the paper.

Previous Employment Status			Current Employment Status					
			Employed	Looking for Work	Retired	Student	Out of Labor Force	Total
	Unknown	N	2,902	253	783	33	256	4,227
		% row	69	6	19	1	6	100
	Employed	N	14,443	132	94	30	41	14,740
		% row	98	1	1	0	0	100
	Looking for Work	N	172	733	65	13	48	1,031
		% row	17	71	6	1	5	100
	Retired	N	101	55	4,132	4	55	4,347
		% row	2	1	95	0	1	100
	Student	N	31	9	2	111	5	158
		% row	20	6	1	70	3	100
	Out of Labor Force	N	50	40	70	7	1,094	1,261
		% row	4	3	6	1	87	100
	Total	N	17,699	1,222	5,146	198	1,499	25,764
		% row	69	5	20	1	6	100

Table 2: Employment Status Transitions from Month to Month

The table shows the number of observations for each combination of current and previous employment status stated by respondents in the Survey of Consumer Expectations (SCE). Respondents' previous employment status is unknown when they first enter the survey and is the respondent's employment status in the previous survey module they participated in for later modules.

	N	Mean	Std. Dev.	25th pctile	75th pctile
Respondent Characteristics					
Age (when entering sample)	4,227	50.80	14.34	39	62
White	4,227	0.87	0.34	1	1
Black	4,227	0.08	0.26	0	0
Male	4,227	0.55	0.50	0	1
Married	4,227	0.69	0.46	0	1
College (when entering sample)	4,227	0.56	0.50	0	1
Income	4,227	81,344	51,978	45,000	125,000
understand inflation	2,566	0.38	0.48	0	1
math score (% correctly answered)	2,564	0.43	0.49	0	1
Employment Status Switches	4,457	0.25	0.73	0	0
Observations Level					
Local Unemployment					
all	25,764	7.0	1.9	5.7	8.1
only employed	17,699	6.9	1.9	5.6	8.0
only unemployed respondents	1,222	7.3	1.8	6.1	8.4
Employment Expectations					
all	25,764	39.2	23.7	20	50
only employed	17,699	39.2	23.3	20	50
only unemployed respondents	1,222	47.5	25.8	30	62
Own Employment Prospects - Employed					
Loose job	15,395	15.7	20.7	1	20
find new job within 3 months		52.3	32.3	25	80
difference between own and US unemployment		23.5	28.2	5	43

Table 3: Employment Summary Statistics

The table shows mean, standard deviation and 25^{th} and 75^{th} percentile for key characteristics of the sample of respondents of the Survey of Consumer Expectations (SCE) used throughout the paper. Included in the sample are respondents who state their employment status, their expectations about US unemployment, provide information about demographics and live in an area for which unemployment statistics are available. We do not require respondents to answer the questions on math, whether they understand inflation and about their own employment prospects to be included in the sample.

	Expected Change in US House Prices		
	I	II	III
	State	ZIP	MSA
Past House Price Return	0.157***	0.124***	0.142***
	0.017	0.013	0.021
Time Fixed Effects	Y	Y	Y
Demographics	Y	Y	Y
Number of observations	4,168	2,972	3,522
R squared	0.047	0.054	0.051

Table 4: Previous Year's House Prices Change and House Price Expectations

The table shows regression estimates of equation 3.1 for different weighting parameters λ. The dependent variable is the expected change in house prices in percentage points as stated by the respondent. Past house price return is the weighted average of past house prices calculated according equation 1. Time fixed effects are included for each survey month. Demographics include indicators for each of the 11 possible categories eliciting household income in the survey, respondents' age and age squared and indicators for whether respondents own their home, are male, married, went to college and for whether they stated white or black as their race.

	Expected Change in US House Prices		
	I	II	III
	State	ZIP	MSA
		By ownership	
Past House Price Return	0.169***	0.154***	0.168***
	0.034	0.035	0.035
Past House Price Return * Own	-0.011	-0.035	-0.030
	0.038	0.047	0.050
Own	-0.934*	-0.556	-0.973*
	0.470	0.426	0.436
Time Fixed Effects	Y	Y	Y
Demographics	Y	Y	Y
Number of observations	4,102	2,928	3,467
R squared	0.047	0.056	0.051
		By college	
Past House Price Return	0.218***	0.155***	0.180***
	1.578	0.032	0.049
Past House Price Return * College	-0.101*	-0.054	-0.060
	0.042	0.043	0.054
College	0.797*	0.120	0.371
	0.371	0.349	0.354
Time Fixed Effects	Y	Y	Y
Demographics	Y	Y	Y
Number of observations	4,168	2,972	3,522
R squared	0.046	0.052	0.048

Table 5: Previous Year's House Prices Change and House Price Expectations by Homeownership and College

The table shows regression estimates of equation 3.1. Standard errors are clustered at the state level. The dependent variable is the expected change in house prices in percentage points as stated by the respondent. Past house price return is the return in the previous year in the state (column 1 and 3), ZIP code (column 2 and 4) or MSA (column 3 and 6) where the respondent lives. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey, respondents' age and age squared and indicators for whether respondents own their home, are male, married, went to college and for whether they stated white or black as their race.

	Expected Change in US House Prices		
	I	II	III
	State	ZIP	MSA
Past House Price Return	0.231***	0.153***	0.138***
	0.057	0.047	0.049
Past Return * Math 2nd quintile	-0.040	0.036	0.037
	0.081	0.066	0.071
Past Return * Math 3rd quintile	-0.076	0.002	0.055
	0.069	0.054	0.052
Past Return * Math 4th quintile	-0.121+	-0.106	-0.006
	0.066	0.066	0.077
Past Return * Math 5th quintile	-0.118*	-0.078	-0.056
	0.059	0.052	0.045
Math 2nd quintile	-0.295	-0.780	-0.516
	0.735	0.627	0.690
Math 3rd quintile	-0.109	-0.783	-1.073
	0.805	0.651	0.741
Math 4th quintile	-0.300	-0.718	-0.628
	0.692	0.594	0.635
Math 5th quintile	-0.753	-1.132*	-0.941
	0.686	0.551	0.590
Time Fixed Effects	Y	Y	Y
Demographics	Y	Y	Y
Number of observations	3,762	2,707	3,195
R squared	0.046	0.064	0.051

Table 6: revious Year's House Prices Change and House Price Expectations by Math Score

The table shows regression estimates of equation 3.1. Standard errors are clustered at the state level. The dependent variable is the expected change in house prices in percentage points as stated by the respondent. Past house price return is the return in the previous year in the state (column 1 and 3), ZIP code (column 2 and 4) or MSA (column 3 and 6) where the respondent lives. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey, respondents' age and age squared and indicators for whether respondents own their home, are male, married, went to college and for whether they stated white or black as their race.

			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	US stock prices	Inflation 1 year	Inflation 3 years	government debt	unemployment
Last Year's House Price Return	-0.00142	-0.00213	0.0399	0.0954	0.0258	0.0355	0.00699	-0.0835
(ZIP code level)	(0.00145)	(0.00209)	(0.0632)	(0.0717)	(0.0274)	(0.0338)	(0.0607)	(0.0817)
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	3040	3040	3039	2996	3026	3023	2937	3041

Table 7: Effect of Local House Prices on Expectations about Other Economic Outcomes

The table shows regression estimates of equation 3.1 with the following dependent variables: respondents' answer on a 5 point scale to whether they believe to be better off a year later (column 1) and whether they are better off than a year ago (column 2); the percentage chance that interest rates on saving accounts (column 3) and US stock prices (column 4) will be higher a year later; respondents best guess of the inflation rate 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 the expected change in US home prices (column 8). Time fixed effects are included for each survey month. Local unemployment is the unemployment rate in the ZIP code the respondent lives in. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey. Standard errors are cluster

	Std of expected house price change		
	I	II	III
	ZIP	State	MSA
Std of returns since			
lived in ZIP	0.114**	0.0923**	0.0997*
	(0.0445)	(0.0401)	(0.0512)
	2994	4228	3573
	0.0560	0.0567	0.0625
lived in state	0.125*	0.133**	0.122
	(0.0655)	(0.0508)	(0.0776)
	2995	4219	3564
	0.0537	0.0551	0.0604
age13	0.223**	0.194**	0.164
	(0.0891)	(0.0898)	(0.111)
	3050	4294	3629
	0.0549	0.0556	0.0610
all data	0.238**	0.206**	0.182
	(0.0974)	(0.0906)	(0.126)
	3050	4294	3629
	0.0545	0.0554	0.0609
Last year's house price return deciles	Y	Y	Y
Demographics	Y	Y	Y

Table 8: Past Variation in House Price and Expected Variation - Standard Deviation

The table shows regression estimates of equation 3.1. For each horizon, the table first shows the estimated coefficient on the standard deviation of experience returns with standard errors clustered at the state level in parentheses. Below each estimate are the number of observations and the R^2 of the regression. The dependent variable is the standard devation of expected change in house prices in percentage points as stated by the respondent. The standard deviation of past house price returns is based in house prices in the ZIP code (column 1), state (column 2) and MSA (column 3) where the respondent lives. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey, respondents' age and age squared and indicators for whether respondents own their home, are male, married, went to college and for whether they stated white or black as their race.

	Tail probability of expected house price change		
	I	II	III
	ZIP	State	MSA
Tail probability of returns since			
lived in ZIP	0.0886***	0.0331	0.101***
	(0.0285)	(0.0211)	(0.0297)
	2843	4004	3388
	0.0787	0.0711	0.0755
lived in state	0.0820***	0.0437*	0.0696**
	(0.0256)	(0.0237)	(0.0290)
	2843	3994	3378
	0.0783	0.0724	0.0739
age13	0.112***	0.0448	0.114***
	(0.0376)	(0.0452)	(0.0412)
	2897	4068	3442
	0.0763	0.0706	0.0735
all data	0.117***	0.0423	0.107**
	(0.0356)	(0.0487)	(0.0470)
	2897	4068	3442
	0.0759	0.0705	0.0727
Last year's house price return deciles	Y	Y	Y
Demographics	Y	Y	Y

Table 9: Past Variation in House Price and Expected Variation - Tail Probabilities

The table shows regression estimates of equation 3.1. For each horizon, the table first shows the estimated coefficient on the probability of expected (absolute) house price changes being greater than 12 percent with standard errors clustered at the state level in parentheses. Below each estimate are the number of observations and the R^2 of the regression. The dependent variable is the standard devation of expected change in house prices in percentage points as stated by the respondent. The standard deviation of past house price returns is based in house prices in the ZIP code (column 1), state (column 2) and MSA (column 3) where the respondent lives. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey, respondents' age and age squared and indicators for whether respondents own their home, are male, married, went to college and for whether they stated white or black as their race.

	Chance US Unemployment will be higher in a year				
	I	II	III	IV	V
Employment Status					
Employed			(omitted)		
Looking for Work	8.135***	6.655***	6.642***	4.539***	4.577***
	(1.319)	(1.300)	(1.300)	(1.029)	(1.031)
Retired	-3.089***	-3.539***	-3.517***	1.021	1.025
	(0.751)	(0.970)	(0.969)	(1.112)	(1.107)
Student	-0.272	-0.796	-0.806	2.382	2.332
	(2.663)	(2.499)	(2.496)	(2.141)	(2.136)
Out of Labor Force	3.885***	1.951	1.998	1.105	1.078
	(1.335)	(1.369)	(1.368)	(1.558)	(1.558)
Local Unemployment Rate		-9.179***		0.299	
		(1.529)		(0.260)	
Local Unemployment (Decile Indicators)			Y		Y
Time Fixed Effects	Y	Y	Y	Y	Y
Demographics		Y	Y	Y	Y
Individual Fixed Effects				Y	Y
Average of dependent variable	39.16	39.16	39.16	39.16	39.16
Number of observations	25,764	25,764	25,764	25,764	25,764
Number of individuals	4,227	4,227	4,227	4,227	4,227

Table 10: Effect of Employment Status on Unemployment Expectations

The table shows regression estimates of equation 3.1. Standard errors are clustered at the respondent level. The dependent variable is the percentage chance of US unemployment being higher a year later as stated by the respondent. Employment status is each respondent's self reported current employment status. Local unemployment is the unemployment rate in the ZIP code the respondent lives in. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey. When no individual fixed effects are included, demographics also include respondents' age and age squared, indicators for whether respondents are male, married, went to college and for whether they stated white or black as their race.

(A) Employment Prospects When Entering Sample

	Loose job within			
	1 month	3 months	6 months	9 months
Pr(job loss within 12 months)	0.0297**	0.0791***	0.159***	0.160***
	(0.013)	(0.022)	(0.031)	(0.034)
Local Unemployment (Indicators for Decile)	Y	Y	Y	Y
Demographics	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y
Individual Fixed Effects				
Number of observations	2,551	2,407	2,192	1,959

(B) Within Individual Changes in Employment Prospects

	Loose job within			
	1 month	3 months	6 months	9 months
Pr(job loss within 12 months)	0.0197**	0.021	(0.003)	-0.006
	(0.010)	(0.014)	(0.012)	(0.013)
Local Unemployment (Indicators for Decile)	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	14,211	12,945	11,161	9,300
Number of individuals	2,551	2,407	2,192	1,959

Table 11: Predictiveness of Own Employment Prospects

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

	Change US unemployment will be higher in a year			
	I	II	III	IV
Pr(job loss within 12 months)	0.110***			0.109***
	(0.0131)			(0.0130)
1-Pr(find job within 3 months)		-0.0180*		-0.0167*
		(0.00924)		(0.00929)
Pr(unemployed ≥ 3 months)			0.123***	
			(0.0197)	
Local Unemployment (Indicators for Decile)	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y
Demographics	Y	Y	Y	Y
Individual Fixed Effects	Y	Y	Y	Y
Mean of Dependent Variables	39.21	39.21	39.21	39.21
Number of observations	15,399	15,944	15,395	15,395
Number of individuals	2,808	2,891	2,808	2,808

Table 12: Effect of Own Employment Prospects on US Unemployment, for the Employed

The table shows regression estimates of equation 3.1. Standard errors are clustered at the respondent level. The dependent variable is the percentage chance of US unemployment being higher a year later as stated by the respondent. *Pr(job loss within 12 months)* is the percentage chance that the respondent will loose his or her job within the next 12 months and *1-Pr(find job within 3 months)* is the percentage chance that the respondent will not find a job within 3 months in case of job loss, both as stated by the respondent. *Pr(unemployed* $\geq$ *3 months)* is the probability that the respondent will be unemployed longer than 3 months calculated as *Pr(job loss within 12 months)* times *1-Pr(find job within 3 months)*. Local unemployment is the unemployment rate in the ZIP code the respondent lives in. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey. When no individual fixed effects are included, demographics also include respondents' age and age squared, indicators for whether respondents are male, married, went to college and for whether they stated white or black as their race.

	I	II	III	IV	V	VI	VII	VII
	Will be better off in a year	*Are* better off than year ago	interest rates on savings higher	US stock prices higher	Inflation 1 year	Inflation 3 years	government debt increase	home price increase
Employment Status								
Employed	(omitted)				(omitted)			
Looking for Work	-0.109**	-0.486***	1.301	0.104	0.0910	-0.0419	-0.486	-0.443
	(0.0431)	(0.0578)	(1.078)	(1.009)	(0.214)	(0.218)	(1.165)	(0.676)
Retired	-0.0975**	-0.247***	0.644	-0.428	-0.216	-0.0830	0.153	-0.0788
	(0.0460)	(0.0464)	(1.280)	(1.169)	(0.232)	(0.215)	(1.018)	(0.582)
Student	-0.113	-0.409***	-4.669**	-3.460**	-0.138	-0.639	-0.300	2.346*
	(0.105)	(0.0993)	(2.153)	(1.761)	(0.315)	(0.492)	(1.186)	(1.327)
Out of Labor Force	-0.184***	-0.337***	0.245	-0.799	-0.0150	-0.146	0.579	0.916
	(0.0612)	(0.0594)	(1.752)	(1.346)	(0.285)	(0.344)	(1.316)	(1.250)
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	25,752	25,757	25,743	25,209	22,920	23,084	21,622	18,222
Number of individuals	4,227	4,227	4,227	4,226	4,074	4,078	4,061	2,926

Table 13: Effect of Employment Status on Expectations about Other Economic Outcomes

The table shows regression estimates of equation 3.1 with the following dependent variables: respondents' answer on a 5 point scale to whether they believe to be better off a year later (column 1) and whether they are better off than a year ago (column 2); the percentage chance that interest rates on saving accounts (column 3) and US stock prices (column 4) will be higher a year later; respondents best guess of the inflation rate 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 the expected change in US home prices (column 8). Time fixed effects are included for each survey month. Local unemployment is the unemployment rate in the ZIP code the respondent lives in. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey. Standard errors are cluster

		Chance US Unemployment will be higher in a year								Chance US Unemployment will be higher in a year			
		college education		math score quintile		understand inflation		age		local unemployment		household income
Employed		(omitted)		(omitted)		(omitted)		(omitted)		(omitted)		(omitted)
Looking for work		4.759***		7.787***		3.652***		4.196		4.263		5.431**
		(1.459)		(2.564)		(1.399)		(2.827)		(2.598)		(2.344)
Looking for work	college	1.009	math score		understand	1.827	age		local unemployement		household income	
interacted with		(1.882)	2nd quintile	-4.624	inflation	(2.086)	35 to 50	2.314	2nd decile	3.468	$10k-20k	-0.492
				(3.640)				(3.336)		(3.034)		(3.045)
			3rd quintile	-4.806			50 to 65	-0.449	3rd decile	-0.295	$20k-30k	-2.529
				(3.485)				(3.049)		(2.977)		(3.617)
			4th quintile	-3.387					4th decile	0.658	$30k-40k	-3.633
				(4.419)						(3.133)		(3.492)
			5th quinitile	-3.664					5th decile	-0.361	$40k-50k	0.481
				(3.101)						(3.249)		(3.601)
									6th decile	2.327	$50k-60k	-1.945
										(3.525)		(3.829)
									7th decile	-0.990	$60k-75k	-0.445
										(3.231)		(3.499)
									8th decile	-0.212	$75k-100k	-0.111
										(3.134)		(3.655)
									9th decile	-0.460		
										(3.181)		
									10th decile	0.301		
										(3.419)		
Retired		1.009		-0.0341		0.153		0.799		0.992		1.025
		(1.111)		(1.240)		(1.251)		(1.129)		(1.110)		(1.109)
Student		2.397		3.093		2.854		2.406		2.400		2.458
		(2.145)		(2.248)		(2.186)		(2.121)		(2.130)		(2.146)
Out of Labor Force		1.097		1.309		1.261		1.070		1.041		1.107
		(1.560)		(1.744)		(1.726)		(1.562)		(1.558)		(1.575)
Time Fixed Effects		Y		Y		Y		Y		Y		Y
Demographics		Y		Y		Y		Y		Y		Y
Individual Fixed Effects		Y		Y		Y		Y		Y		Y
Number of observations		25764		20375		20380		25764		25,764		25,764
Number of individuals		4227		3812		3814		4227		4,227		4,227

Table 14: Effect of Unemployment on Expectations by Respondent Characteristics

The table shows regression estimates of equation 3.1 with the indicator for searching for work interacted with college, math score, whether the respondent claims to perfectly understand what inflation is and age, as well as local unemployment and household income . Standard errors are clustered at the respondent level. The dependent variable is the percentage chance of US unemployment being higher a year later as stated by the respondent. Employment status is each respondent's self reported current employment status. Local unemployment is the unemployment rate in the ZIP code the respondent lives in. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey. When no individual fixed effects are included, demographics also include respondents' age and age squared, indicators for whether respondents are male, married, went to college and for whether they stated white or black as their race.

	Chance US Unemployment will be higher in a year	
	I	II
Employment Status		
Employed	omitted	
Looking for Work	7.259***	2.639*
	(1.562)	(1.546)
Become Employed	0.199	-4.841***
	(1.712)	(1.617)
Became Unemployed	5.271**	1.253
	(2.236)	(1.690)
Retired	-3.514***	0.0296
	(0.972)	(1.133)
Student	-0.807	1.300
	(2.499)	(2.163)
Out of Labor Force	2.003	-0.168
	(1.369)	(1.561)
Local Unemployment (Indicators for Decile)	Y	Y
Demographics	Y	Y
Mean of dependent variable	39.16	39.16
Number of observations	25,764	25,764
Number of individuals	4,227	4,227

Table 15: Asymmetric Effect of Employment Status on Unemployment Expectations

The table shows regression estimates of equation 3.1. Standard errors are clustered at the respondent level. The dependent variable is the percentage chance of US unemployment being higher a year later as stated by the respondent. Respondents who are employed and were not previously unemployed during the sample are classified as *Employed*. Respondents who are looking for work and were not previously employed are classified as *Looking for Work*. Respondents who are currently employed but were unemployed in any previous survey module are classified as *Become Employed*. Respondents who are currently looking for work but were employed in any previous survey module are classified as *Become Unemployed*. Local unemployment is the unemployment rate in the ZIP code the respondent lives in. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey. When no individual fixed effects are included, demographics also include respondents' age and age squared, indicators for whether respondents are male, married, went to college and for whether they stated white or black as their race.

	Chance US Unemployment will be higher in a year	
	I	II
Employment Status		
Employed	omitted	
Looking for Work		
Unemployment Length - 1st quintile		
Unemployment Length - 2nd quintile	5.541***	2.489*
	(2.106)	(1.491)
Unemployment Length - 3rd quintile	12.43***	6.071***
	(2.530)	(1.744)
Unemployment Length - 4th quintile	6.674***	2.162
	(2.375)	(1.826)
Unemployment Length - 5th quintile	7.204**	4.221*
	(3.253)	(2.156)
Retired	-3.480***	0.453
	(0.938)	(1.035)
Student	0.138	1.226
	(2.288)	(2.154)
Out of Labor Force	1.820	-0.176
	(1.313)	(1.442)
Local Unemployment (Indicators for Decile)	Y	Y
Demographics	Y	Y
Time Fixed Effects	Y	Y
Individual Fixed Effects		Y
Mean of dependent variable	39.13	39.13
Number of observations	27,514	27,514
Number of individuals	4,457	4,457

Table 16: Effect of Unemployment Length on Unemployment Expectations

The table shows regression estimates of equation 3.1. Standard errors are clustered at the respondent level. The dependent variable is the percentage chance of US unemployment being higher a year later as stated by the respondent. Employment status is each respondent's self reported current employment status. For unemployed respondents, employment status is split into five categories based on the length of unemployment. Local unemployment is the unemployment rate in the ZIP code the respondent lives in. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey. When no individual fixed effects are included, demographics also include respondents' age and age squared, indicators for whether respondents are male, married, went to college and for whether they stated white or black as their race.

	not planning to leave job	one transition in/ out of employment
	Chance US Unemployment will be higher in a year	
Employment Status		
Employed	(omitted)	
Looking for Work	4.808***	4.531**
	(1.103)	(2.011)
Retired	0.902	
	(1.211)	
Student	2.857	
	(2.434)	
Out of Labor Force	1.083	
	(1.612)	
Local Unemployment (Decile Indicators)	Y	Y
Time Fixed Effects	Y	Y
Demographics	Y	Y
Individual Fixed Effects	Y	Y
Average of dependent variable	39.18	45.76
Number of observations	24,435	671
Number of individuals	4,037	105

Table 17: Employment Status on Unemployment Expectations in Subsamples

The table shows regression estimates of equation 3.1. Column 1 excludes respondents who stated they expected to leave their job with 100% probability. Column 2 only includes respondents with exactly one change between being employed and searching for a job. Standard errors are clustered at the respondent level. The dependent variable is the percentage chance of US unemployment being higher a year later as stated by the respondent. Employment status is each respondent's self reported current employment status. Local unemployment is the unemployment rate in the ZIP code the respondent lives in. Time fixed effects are included for each survey month. In all specifications, demographics include indicators for each of the 11 possible categories eliciting household income in the survey. When no individual fixed effects are included, demographics also include respondents' age and age squared, indicators for whether respondents are male, married, went to college and for whether they stated white or black as their race.