Unemployment Expectations and the Business Cycle*

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Abstract

I compare unemployment expectations from the Michigan Survey of Consumers to VAR forecastable movements in unemployment. I document three key facts. First, one-half to one-third of the population expects unemployment to rise when it is falling at the end of a recession even though the VAR predicts the fall in unemployment. Second, more people expect unemployment to rise when it is falling at the end of a recession than expect it to rise when it is rising at the beginning of a recession even though the VAR predicts these changes. Finally, the lag change in unemployment is almost as important as the VAR forecast in predicting the fraction of the population that expects unemployment to rise. Professional forecasters do not exhibit these discrepancies. Least squares learning or real time expectations do little to help explain these facts. However, delayed updating of expectations can explain some of these facts and extrapolative expectations explains these facts best. Individuals with higher income or education are only slightly less likely to have expectations which differ from the VAR and those whose expect more unemployment when the VAR predicts otherwise are 8-10 percent less likely to believe it is a good time to make a major purchase.

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1 Introduction

In modern macroeconomic theory, expectations about the future drive current economic activity. In general, models assume rational expectations: agents know the true model and use it to form expectations. However, this assumption is not without controversy. Sargent (2001) and Evans & Honkapohja (2001) advocate models where agents learn the true model over time. Mankiw & Reis (2002) argue for models with agents who use outdated information to form their expectations. Given this plurality of views, work testing models with micro-level expectations data can provide important insight into the formation of expectations.

Consequently, I provide a detailed analysis of unemployment expectations from the Survey of Consumers conducted by the University of Michigan Survey Research Center. The measurement of unemployment expectations stems from the following question: "How about people out of work during the coming 12 months – do you think that there will be more unemployment than now, about the same, or less?"

I compare the sign of the unemployment change that the respondents expect with forecastable movements in unemployment (predicted by a four variable VAR). There are important differences between the consumers' expectations and forecastable movements in unemployment. The three key discrepancies are: 1. In the six months after a recession's end–when unemployment is falling–one-half to one-third of the population expects unemployment to *rise* even though the VAR predicts the *fall* in unemployment. 2. At a recession's beginning–when unemployment is rising–fewer people expected unemployment to rise than at the recession's end – when unemployment is falling– even though the VAR predicts the rise and fall of unemployment. 3. Controlling for the predictions of the VAR, the lag change in unemployment is almost as important as the VAR forecast of the future unemployment change in predicting the percent of the population that expects unemployment to rise.

Given the discrepancies between household expectations and VAR forecasts, I examine the ability of various models of expectations to match these facts. A least squares learning model and a model that uses real time data fail to explain these facts. A model with

delayed updating of expectations can help explain why there are so few pessimists (defined as individuals who expect unemployment to rise) at the beginning of a recession but not why there are so many pessimists at the end of a recession. An extrapolative expectations model where some agents form expectations by extrapolating current trends into the future can explain all the facts. I also show that even a univariate forecasting rule correctly predicts the sign of unemployment changes and that professional forecasters' expectations are much more consistent with the VAR than those of households.

Additionally, those with more education or a higher income are less likely to have expectations which differ from the VAR: however the difference is not economically significant. Expectational discrepancies are not confined to an economically unimportant fraction of the population, but evenly distributed across income and education groups. These expectational discrepancies affect attitudes concerning whether it is a good time to make a major purchases, e.g.: a house, a car, or a durable good. Specifically, when an individual expects unemployment to rise when in fact the VAR predicts it will fall, she is 8-10% less likely to think that it is a good time to make a major purchase.

Carroll (2003) and Mankiw *et al.* (2003) use the Michigan data to evaluate models of expectations. However, these papers test only one expectations model, where individuals infrequently update their information set. Additionally, these papers mainly study inflation expectations. While the highest quality data available are for inflation expectations, there are serious limitations of focusing on inflation expectations. First, inflation expectations are most important in models of price setting. Since this is a firm's decision, it is not clear that the populations they study correspond to individuals choosing prices in macroeconomic models[1]. Second, for the survey population where expectational errors are most likely and empirically are most significant, households from the Michigan survey, macroeconomic models suggest that expectations about future consumption, or the future state of the economy, are more important in determining household decisions than expectations about inflation.

[1] They study households from the Michigan Survey of Consumers, professional forecasters from the Livingston Survey, and professional forecasters from the Survey of Professional Forecasters

Souleles (2004) analyzes the survey's questions concerning expectations of future business conditions, financial positions, and household income and finds the forecast errors exhibit excess sensitivity, do not average out to zero over the twenty year sample period, and are correlated with demographic variables. My paper differs from the work of Souleles by focusing on unemployment expectations and business cycle induced changes in unemployment.

Carroll (2003) focuses on inflation expectations but also studies the Michigan unemployment expectations index: the percent of individuals who expect less unemployment minus the percent that expect more unemployment. He shows the dynamics of the index are well modeled by an equation that puts one-third of its weight on the professional forecast and two-thirds weight on the lag value of the index. Curtin (2003) shows that the same index is correlated with future unemployment changes. However, when he regresses the unemployment change on changes in the index, he finds the residuals are autocorrelated.

Like Carroll and Curtin I find evidence suggestive of serial correlation in the expectational errors of household though my work differs from theirs in substantial ways. First, the facts concerning excessive pessimism at the end of a recession and insufficient pessimism at the beginning of a recession are new. Second, I test the ability of a large number of theories to account for these facts. Third, I use the methodology of Carlson & Parkin (1975) to provide a rigorous mapping from models of expectation formation to equations that relate macro aggregates to aggregates of qualitative expectations like the indexes in the work of Caroll and Curtin. This methodology generates important insights. I show that expectations based solely on a distribution around the VAR expectation underestimate by a factor of 50 the importance of lag unemployment in predicting the fraction of people who expect unemployment to rise. Finally, contrary to Carroll, I find features of the data unaccounted for by the delay model: for example the large number of individuals expecting unemployment to rise at the end of a recession. Due to the mean reverting nature of unemployment, the delay model generates very few pessimistic predictions of the recovery even based on outdated information while extrapolation results in these predictions.

Finally, while some of the analysis uses the whole time series of expectations, much of the analysis focuses on expectations around recessions. There are important reasons for doing so. Firstly, recessions are key macroeconomic events and focusing on expectations around recessions allows us to analyze key drivers of economic behavior during recessions. Subsequently, we have the potential to unlock important causes of recessions and important factors which contribute to the persistence of recessions. Secondly, extrapolation, or insufficient understanding of mean reversion, has been show to be relevant in many important contexts: financial markets, housing markets and macroeconomic forecasting (see Fuster *et al.* (2010) for a survey). By focusing on recessions, when unemployment begins to revert to its mean, I am able to directly analyze the ability of agents to anticipate this mean reversion.

The rest of the paper proceeds as follows. Section 2 discusses the data while section 3 establishes the three key empirical facts outlined above. Section 4 examines the ability of four different models of expectation formation to address these facts. Section 5 examines data from simulated, heterogenous, structural expectations models. Section 6 shows that a univariate forecast can correctly predict the sign of unemployment changes and that professional forecasters forecast unemployment much better than households do. Section 7 examines the ability of individual characteristics to predict expectational errors and the influence of expectations on buying attitudes. Section 8 concludes.

2 Data

The data come from the Survey of Consumers conducted by the University of Michigan Survey Research Center. It is a monthly survey used to calculate the index of consumer sentiment. Observations begin in 1978 and end in July of 2010. There are about 500 respondents per month. The survey asks about respondents' demographic characteristics, expectations of inflation, unemployment and interest rates, views on the current economic state, and attitudes towards the purchase of economically significant items.

I study answers to the following question: "How about people out of work during the coming 12 months – do you think that there will be more unemployment than now, about the same, or less?" On average, almost half expect unemployment to stay the same, 36% expect it to get worse, while only 16% are optimistic and expect less unemployment. (Full summary statistics for the data are available in the appendix: table 1A)

This question is not ideal. It is not quantitative. Additionally, the meaning of "about the same" may differ among respondents and it is not clear what measure of unemployment the respondent will use in her answer. However the question does refer to a precise forecast window. Additionally, two of the responses reveal the sign of the respondent's unemployment expectation making it possible to test the accuracy of their prediction about the sign of future unemployment changes. This analysis is the paper's primary concern.

The data contain information on the respondent's: sex, age, education, marital status, income and race. Mean household income in year 2000 dollars is 46,169. The mean age is 47, mean education is 13 years, and 32% have graduated college. The percent of the sample that gave a valid answer to the questions is high, ranging from 93% for income to 99% for if the respondent was a college graduate, which speaks to the reliability of these data. Additionally, the appendix reports deciles of the income and education distribution which are consistent with that of the U.S. population as a whole. Finally, 84% of the sample is White, 9% Black, 5% Hispanic, 1% Asian, and 1% Native American.

The survey asks the respondents about economically significant purchases: if they think it is a good time to by a house, a car or a durable good. In general, individuals have upbeat buying attitudes. They think it is a good time to make a major purchase about two-thirds of the time.

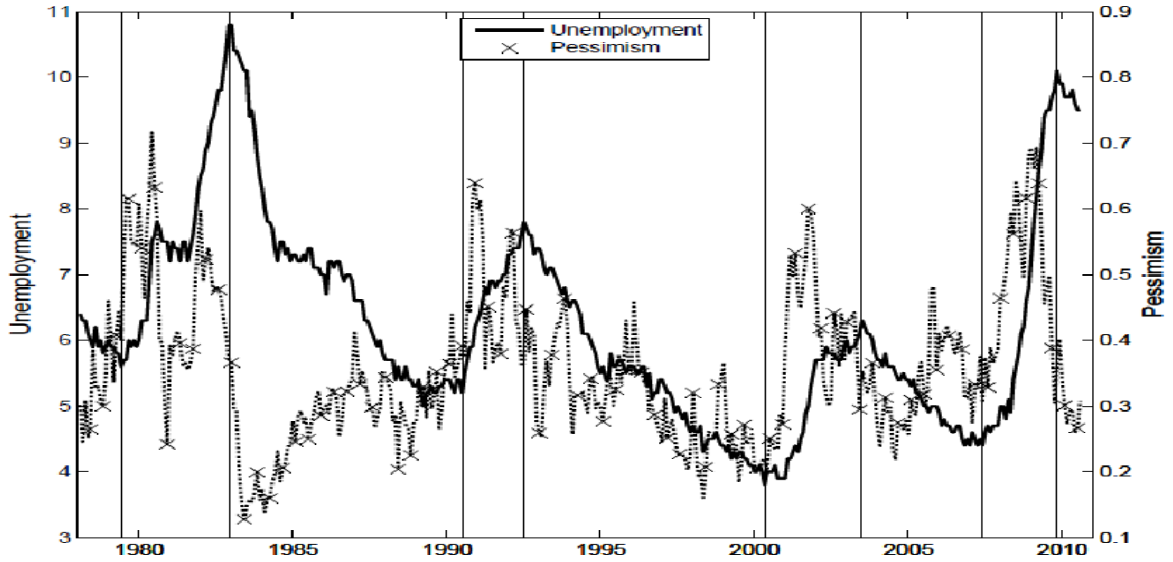

Figure 1: Unemployment versus Pessimism

Unemployment (solid line) versus Pessimism – the fraction of individuals who expect unemployment to rise – (x). Vertical lines mark peaks and troughs of unemployment.

3 Empirical Facts

Figure 1 plots the unemployment rate and pessimism (the fraction of people who expect unemployment to rise over the next year). Vertical lines mark the peak and trough of unemployment. At the peaks, around 35% of the population expects unemployment to rise, even though it is about to *fall* sharply. At the troughs a similar percent of the population expects unemployment to rise, even though it is about to *rise* sharply. During the recession of 2000, pessimism was 10 percentage points lower at the trough than at the peak of unemployment.

If unemployment changes were not forecastable then pessimism should not be sensitive to the level of unemployment. However, unemployment is strongly mean reverting and we would expect future unemployment changes to be forecastable. This plot then suggests that, relative to a statistical forecast, pessimism levels may be too high at the end of a recession and too low at the beginning of a recession. It also suggests that individual expectations may be overly-influenced by past changes. This section establishes these facts more formally.

To examine pessimism at the recession's end, when unemployment is falling, and the extent to which these movements are predictable, I calculate the average of these variables across recessions using the following three regressions[2]:

$$Y_{it} = X_t\beta + \varepsilon_{it} \tag{1}$$

Y_{it} equals P_{it}, ΔU_t, or $E\Delta U_t$. P_{it} is one if the individual expects there to be more unemployment at time $t-12$ and zero otherwise[3], ΔU_t, the change in the unemployment rate, is $u_t - u_{t-12}$[4] and $E\Delta U_t$ is the VAR prediction of ΔU_t as I describe below.

To forecast unemployment I use the following four-variable, four-lag VAR:

$$z_t = A + B_1 z_{t-1} + B_2 z_{t-2} + B_3 z_{t-3} + B_4 z_{t-4} + \varepsilon_t \qquad E_{t-1}\varepsilon_t = 0 \tag{2}$$

where $z_t = \{y_t, \pi_t, i_t, u_t\}$. y_t is log GDP, π_t is CPI inflation, i_t is the fed funds rate, and u_t is the unemployment rate. I estimate the VAR on the full sample of data beginning in 1954:Q3 and ending in 2011:Q3[5]. To calculate the forecast of the unemployment change I forecast future unemployment using the VAR and set $E\Delta U_t = E_{t-12}[u_t - u_{t-12}]$ [6].

[2] This regression is related to the analysis of inflation expectations in Coibion & Gorodnichenko (2008). They draw conclusions concerning different expectations models from the response of inflation expectations to various shocks. I show that the level of pessimism that exists after a recession is also useful for drawing conclusions concerning different expectational models.

[3] The first regression is weighted using the survey's household weights. Estimating the first equation by collapsing the cross section into a single estimate for the percent of pessimists and using the resulting time series gave similar results.

[4] It is possible that the survey question elicits expectations not about the strict change in unemployment but the average level of unemployment over the next 12 months minus the current level of unemployment. Repeating the analysis in the paper with this definition did not change the main conclusions.

[5] More complicated VARs could be considered. But I will show that even this simple VAR is able to predict unemployment changes and individuals perform much more poorly than this simplistic, potentially misspecified, VAR. Additionally, a univariate forecast using only unemployment correctly forecasts the sign of unemployment changes.

[6] GDP is available only quarterly and the unemployment expectations are measured monthly. I require a procedure to impute monthly expectations from the quarterly VAR. Figure 1A in the appendix explains how I do this. The procedure results in VAR based expectations that are slightly lagged. Since I find that individuals look as if they are forecasting lagged unemployment changes relative to the unemployment changes they are asked to forecast, this procedure pushes the VAR closer to the data and strengthens the conclusion that the VAR does not fully represent the expectations contained in the data. Section 6 examines the impact of this assignment procedure and finds it to not be significant. Also, I have replicated the forecasts

X_t is a vector of twelve dummy variables each indicating a date corresponding to a specific number of months (zero to eleven) after the first time ΔU_t is negative at the end of a recession. (Since future unemployment changes become negative before the unemployment peak, these dates correspond to unemployment changes beginning a few periods before the unemployment peak dates.) I have data on expectations beginning in 1978, and treat the two recessions of the 1980s as one recession[7], so each of these dummy variables equals one at exactly four dates. The first dummy variable equals one the first time ΔU_t is negative at the end of each recession and is zero otherwise, the second dummy variable equals one for the next month in each recession and is zero otherwise, and so on. The coefficients on X_t give the mean level of the dependent variable across these four dates[8].

I repeat these regressions to estimate the levels of pessimism, actual unemployment changes, and average forecasts before the recession as well, when unemployment begins to rise. For this calculation, I replace X_t with a vector of dummy variables that mark months after unemployment begins to rise at the beginning of a recession[9].

Figure 2 plots the coefficients from the pessimism regressions. (Full regression results with standard errors are given in tables 2A and 3A in the appendix.) The solid line gives the average level of pessimism when unemployment begins to fall (month 0) up until 11 months into the recovery. The dashed line gives the average level of pessimism when unemployment begins to rise (month 0) up until 11 months into the recession. The levels of pessimism when unemployment begins to fall are high. One half to one third of the population is expecting unemployment to rise, when in fact it is falling. On the other hand, only a third of the population expects unemployment to rise when it is actually rising, at the beginning of the

using monthly industrial production– however I choose to use GDP because it covers the whole economy and because of the well known link between GDP growth and unemployment.

[7] I do this because there is no sustained unemployment recovery from the first recession of the 1980s.

[8] The starting points for where ΔU_t is first negative are: 1983 month 7, 1993 month 2, 2003 month 12 and 2010 month 8. The first element of X_t equals one for these dates and zero otherwise. The second element of X_t equals one on the dates 1983 month 8, 1993 month 3, 2004 month 1 and 2010 month 9 zero otherwise, an so on.

[9] The starting points for when ΔU_t is first positive are: 1980 month 1, 1990 month 7 and 2001 month 1 and 2007 month 9.

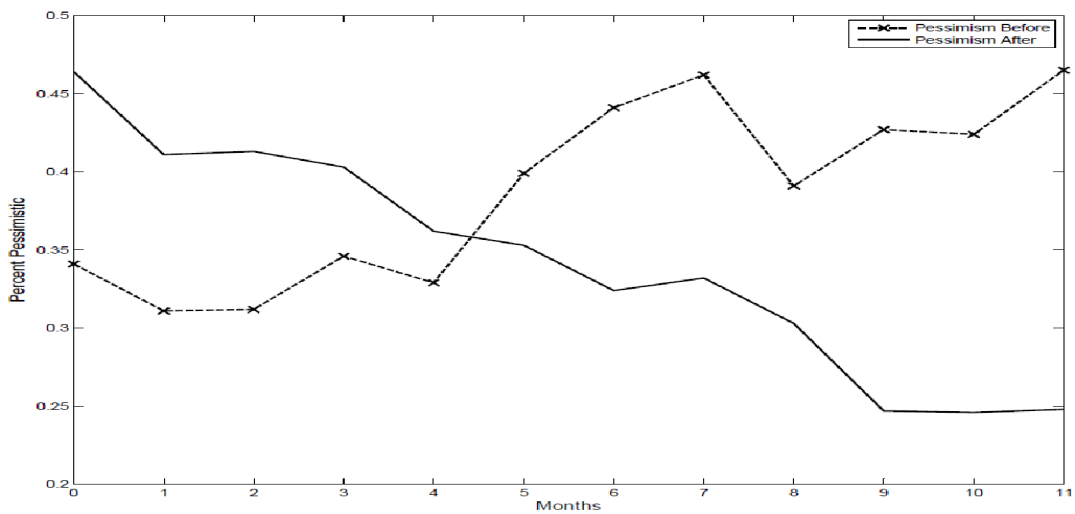

Figure 2: Pessimsim Before and After Recession

This solid line plots the average fraction of pessimists at the end of the recession when unemployment begins to fall. 0 denotes the first month unemployment begins to fall, 1 the second, and so on. The dashed line with X markers plots the average fraction of pessimists at the beginning of the recession when unemployment begins to rise. 0 denotes the first month, 1 the second month and so on.

recession. In fact, there is substantially more pessimism at the end of the recession (when unemployment is falling) than at the beginning of the recession (when unemployment is rising).

Figure 3 plots the coefficients for the actual unemployment change (solid and dashed lines) and VAR forecasted unemployment change (solid and dashed lines with x) regressions. The coefficients at the beginning of the recession are the dashed lines above zero, indicating that unemployment is rising and the VAR correctly forecasts the sign of these changes. The coefficients at the end of the recession are the solid lines below zero indicating that unemployment is falling and the VAR forecasts these changes as well.

To test the statistical significance of these results I estimate the following three regressions: $Y_{it} = X_t\beta + Y_t\gamma + \varepsilon_{it}$ where $Y_{it} = \{P_{it}, \Delta U_t, E\Delta U_t\}$, X_t is a vector of dummy variables indicating zero months to five months after unemployment begins to fall at the end of a recession, and Y_t is a vector of dummy variables indicating zero months to five months after

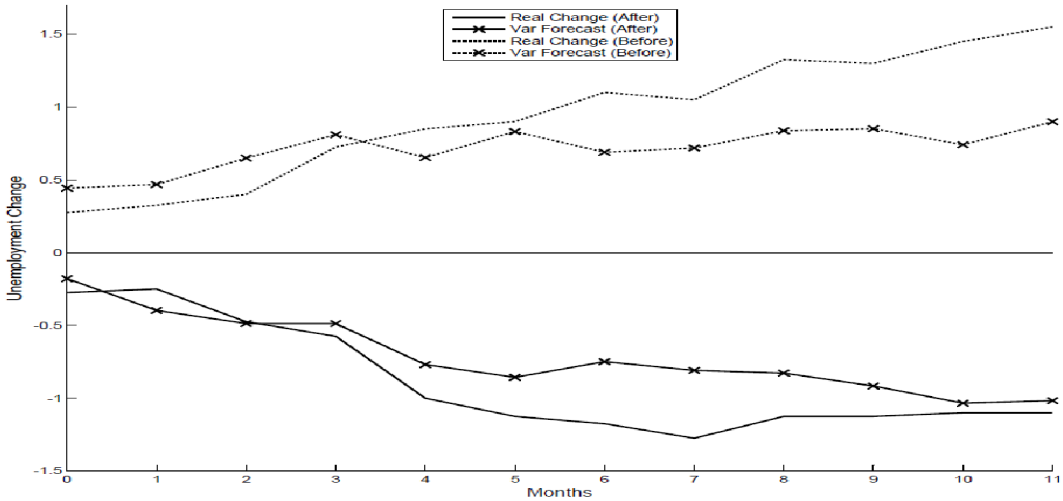

Figure 3: Unemployment Changes and VAR Forecasts

The line without (x) is the average actual unemployment change (across recessions). For the solid line, 0 denotes the first month unemployment begins to fall, 1 the second, and so on. For the dashed line, 0 denotes the first month unemployment begins to rise, 1 the second month and so on. The line with x marks the average VAR forecast of these changes.

unemployment begins to rise at the beginning of a recession. This regression, results in Table 1, shows the pattern of more pessimism during the recovery than during the recession's beginning while the signs of the VAR prediction would have us expect the opposite.

This table tests if the coefficients are significantly different from each other. For the pessimism regression, the first three coefficients on X_t are significantly different from the corresponding coefficients on Y_t indicating statistically significantly more pessimism after the recession than during the beginning of the recession. Even the results for month four and five are puzzling. We see a statistically significant, 1.3 to 1.7 percentage point difference in unemployment forecasts but no statistically significant difference in the levels of pessimism. The actual unemployment changes and VAR forecasts before the recession are all significantly different than their counterparts after the recession.[10]

Expectations around recession turning points appear partially backward looking. To

[10] I have omitted results for optimism – the percent of the population that expects unemployment to fall – but they support the main results here. There is three times as much pessimism than optimism at the end of a recession and the levels of optimism at the beginning and end of a recession are similar.

see if lag unemployment changes influence expectations across the whole sample I run the following regression:

$$P_t = \alpha + \beta E_t(u_{t+12} - u_t) + \gamma(u_t - u_{t-12}) + \varepsilon_t \tag{3}$$

P_t is the fraction of the population at time t that expects unemployment to rise. $E_t(u_{t+12} - u_t)$ is the VAR forecast of the future unemployment change and $u_t - u_{t-12}$ is the lag change in unemployment. Table 2 contains the results from this regression[11]. The coefficient on the VAR prediction is positive – when the VAR predicts unemployment will rise more, more people expect unemployment to rise. Nevertheless, controlling for the VAR prediction, the coefficient on the lag change in unemployment is positive and significant. Indeed, it is almost as large as the coefficient on the VAR expectation. The lagged unemployment change is almost as important as the VAR prediction in predicting the number of people who expect unemployment to rise at a given time.

If the VAR is an imperfect forecast then the lag unemployment rate may be correlated with actual unemployment changes even controlling for the VAR. Households may use the lag change to refine the VAR expectation. To see if this is the case, I run the regression above including the actual change in unemployment. If lagged unemployment changes are correlated with actual unemployment changes even conditional on the VAR expectation, the coefficient on lagged unemployment should fall. However, the coefficient on lagged unemployment does not change.

Now it is difficult to relate a point forecast of unemployment to a population distribution of expectations. In section 5, I will consider a model with an explicit distribution of expectations around the VAR forecast. I show that there is a direct mapping in this model between the VAR forecast and the predicted fraction of pessimists. However, this model underestimates the coefficient on lagged unemployment changes by a factor of 50, failing to

[11] I correct the OLS standard errors for autocorrelation in the residuals using a Newey-West procedure (Newey & West (1987)).

explain the influence of lagged unemployment on the number of pessimists.

Taken together these facts show that individuals' expectations differ in important ways from the predictions of a VAR. They tempt us to ask what type of models can explain these beliefs. Answering this question is the aim of the next sections. First I consider different models of expectation formation then I consider models with an explicit distribution of expectations around the different model forecasts.

4 Alternative Models of Expectation Formation

4.1 Least Squares Learning

In the previous section I calculated the VAR on the full data sample. (This assumption mimics a rational expectations assumption where the agent knows the true model and calculates her expectations according to that model.) An alternative approach, is 'least squares learning' (Sargent (2001) and Evans & Honkapohja (2001)). Here the agent does not have access to the estimated VAR on all of the data, instead at each date she estimates the VAR on the data up until that date and uses this equation to forecast unemployment.

Figure 4 reports the forecasts of the least squares learning model. The least squares learning (LSL) model line (solid and dashed lines) is calculated in the same manner as the VAR line in figure 3 except the VAR forecast is replaced with the least squares learning forecast in the regression (1). To obtain this forecast, I use the same VAR as before (2) to calculate $E_{t-12}[u_t - u_{t-12}]$ except when forecasting the unemployment rate beginning at time t the VAR coefficients are estimated using data only through time $t-1$.

After the recession, during the recovery, a least squares learner would expect unemployment to fall. In fact, the prediction is on average more negative than the prediction of the VAR. This result is not surprising. Recall, the actual unemployment recovery from the recessions of 1991 and 2001 was much slower than would have been predicted based on past data alone. Therefore, the least squares learner expects more of a recovery than an individ-

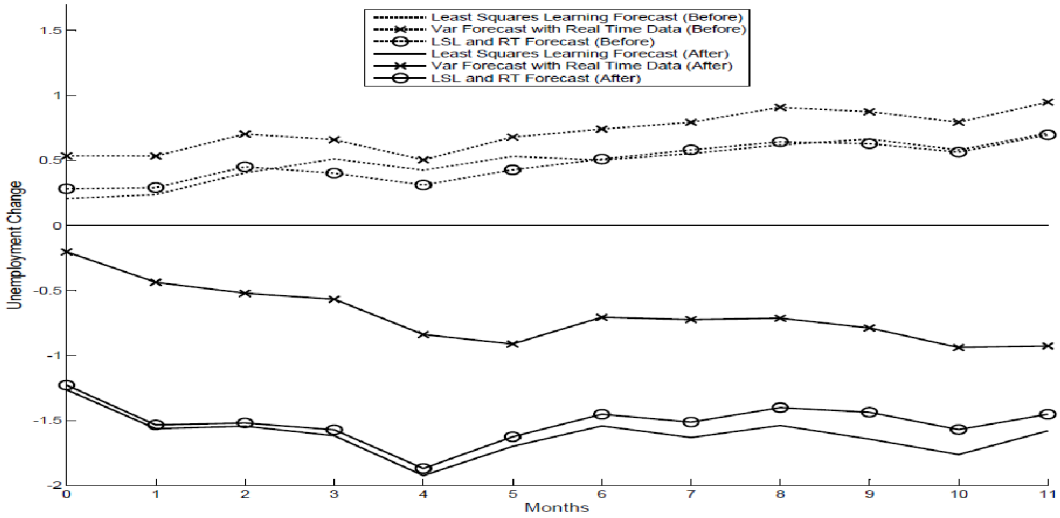

Figure 4: Least Squares Learning, Real Time and LSL and RT Forecasts

The line without (x) is the average least squares learning forecast of the unemployment change. For the solid line, 0 denotes the first month unemployment begins to fall, 1 the second, and so on. For the dashed line, 0 denotes the first month unemployment begins to rise, 1 the second month and so on. The lines marked with x are the average forecast from the VAR using real time data. The lines market with O are the least squares learning with real time data forecasts.

ual who uses the VAR equation. Figure 4 also shows the least squares learning expectation before the recession. The least squares learner, on average, expects unemployment to rise. It appears then that least squares learning does not explain the facts outlined in the previous section, especially the large level of pessimism at the end of the recession.

4.2 Real Time Data

In approximating expectations with the VAR, I assume agents have access to future data revisions. Instead, for the most recent data, they have access to only the first or second release, not the final revision. As argued by Orphanides (2001) and Orphanides & van Norden (2002) the use of real time data can change measurements of output gaps and the optimal choice of monetary policy. Inflation (measured with the CPI), the fed funds rate and unemployment are subject to only minor revisions, but GDP is often substantially revised. To explore this issue, I make use of the real time data set available from the Federal Reserve

Bank of Philadelphia (Croushore & Stark (1999)). I first assume that individuals have access to the VAR equation (2) estimated on the whole sample, but only have access to GDP data available at the time when they made their expectation[12]. Hence, if their expectation is formed at time t, they use the estimate of GDP available at time t and not the final revision.

Figure 4 contains the results. The real time line of figure 4 (solid and dashed lines with x) is calculated like the VAR line of figure 3 except the VAR forecasts are replaced with the real time data forecasts in the regressions. The use of real time data does not help to address the puzzles previously outlined. The expectations are similar to, and most importantly, of the same sign as the VAR. Therefore, it appears that neither the use of least squares learning nor real time data is fully responsible for the observed pattern of pessimism.

Now I consider and agent that only has access to the real time data when she makes her expectation, and also must learn about the parameters of the VAR Equation (2) using least squares learning as in the previous section. The expectations from this model (solid and dashed lines with O) are given in figure 4. The forecasts are quite similar to the least squares learning forecasts using the revised data. Combining, least squares learning and the use of real time data does not explain the observed pattern of pessimism.

4.3 Delayed Updating of Expectations

Several authors including Reis (2004), Mankiw & Reis (2002), Gabaix & Laibson (2001) and Carroll (2003) argue it is unreasonable to expect that consumers update their information instantaneously. They argue that to do so requires a cognitive cost and therefore, to economize on this cost, the agent will update his information infrequently.

I examine the ability of this model to account for the observed facts. Following Mankiw

[12] To implement this procedure the data used to estimate the VAR must be in the same units as the real time data. As in the real time data I use, as the measure of output, GNP before 1992 and GDP afterwards. I convert the full sample output data to 1960 dollars using the appropriate deflator. I then create a real time price index using the ratio of real time nominal output to real time real output and use this price index to convert the real time nominal output measure to 1960 dollars. (Note: When I consider least squares learning and the use of real time data, this procedure is no longer necessary because the real time data is used directly to calculate the VAR.)

& Reis (2002) and Carroll (2003), I assume that each agent has a fixed probability λ of updating her expectation in any given period. Therefore the percent of the population that has expectations based on information n periods old is:

$$\lambda(1-\lambda)^n$$

This formula implies that $\lambda(1-\lambda)^n$ percent of the population has expectations that come from the following expression: $E_{t-n}[u_{t+12}-u_t]$. Here the forecasting equation is the VAR equation (2) estimated on the whole sample and the expectation is calculated using information only through time $t-n$.[13] Importantly, this expression involves forecasting not only the future rate of unemployment but also the time t rate of unemployment when information is not completely up to date.

Since the delay model will only tell me the respondent's prediction for the change in unemployment, I need a procedure to assign the quantitative prediction to the qualitative categories "more" "less" and "stay the same." To do this I calculate c_l the lower cutoff, the point at which if the individual expects unemployment to fall by more than c_l they are classified as an optimist (expecting less unemployment) and c_u the upper cutoff, the point at which if the individual expects unemployment to rise by more than c_u they are classified as a pessimist (expecting more unemployment). Everyone else is classified as expecting unemployment to be about the same. Therefore the percent of pessimists in the population at time is given by:[14]

$$\%Pess_t = \sum_{n=0}^{\infty} \lambda(1-\lambda)^n * 1(E_{t-n}[u_{t+12}-u_t] > c_u)$$

where $1(E_{t-n}[u_{t+12}-u_t] > c_u)$ is an indicator function that equals one if $E_{t-n}[u_{t+12}-u_t] > c_u$

[13] Again the procedure in Figure 1a shows how I assign monthly expectations using the quaterly VAR.

[14] To implement this theory empirically, I assume that information is at most N periods old. I then rescale the percent of the population with information n periods old (so that they sum to one) using the following formula: $\frac{\lambda(1-\lambda)^n}{1-(1-\lambda)^{N+1}}$. N is chosen so that $(1-\lambda)^{N+1}$ (the percent of the population that would have information more than N periods old) is less than 5%.

and zero otherwise.

To calibrate λ, c_u and c_l I solve the following problem: $\min_{\lambda} x'Wx$, where x is a vector of two observations per month for every month in the data set: the survey estimates of the percent of people who respond that they expect unemployment to rise (pessimists) and the survey estimates of the percent that expect unemployment to fall (optimists); each percent is subtracted from the model's prediction for these variables. W is a diagonal weighting matrix. For the weights I use the inverse of the variance (i.e. the squared standard error) of the survey estimates of the monthly population percentages of pessimists and optimists.[15]

I solve the minimization problem multiple times, each time for a different pair of c_u and c_l. To find the overall minimum I take the minimum across the solutions to the minimization problem at these different pairs of cutoffs.[16]

The minimization occurs at an upper cutoff of 0.2, a lower cutoff of -0.4, and a value of λ of 0.0578. A value of 0.0578 implies that the agent updates her expectation roughly once every 17 quarters or once almost every four years. This is considerably more delay than is assumed, or estimated, in the literature. Carroll (2003) estimates and Mankiw & Reis (2002) take λ to be 0.25. This implies that the agent updates her expectations once every year. However more recent work, Reis (2004) has found optimal updating to be every 8 quarters. Note also that the data want to make it comparatively easier to be pessimistic (the upper cutoff is 0.2) than optimistic (the lower cutoff is -0.4). This fact is due to the tendency of respondents, on average, to more likely respond with pessimism than optimism.

Figure 5 contains the prediction of the delay model for the average number of pessimists. The model does a good job predicting the number of pessimists at the beginning of the recession, the prediction of the model (dashed line with x) is quite close to the data (dashed

[15] If we let $P_{i,t} = 1$ if the individual expects unemployment to rise, and zero otherwise then percent who are pessimistic is given by $\frac{\frac{1}{N}\sum w_i P_i}{\frac{1}{N}\sum w_i}$ and the variance of the sample mean is given by $\frac{\sum w_i^2 Var(P_i)}{[\sum w_i]^2}$ where w_i are the survey weights.

[16] It would be better to minimize over the three paramters, lambda and the two cutoffs, simultaneously. However, without adding noise, the function is not sufficiently well behaved in the cutoffs to make this a simple task. Because I want to first focus on the endogenous heterogenity of the model, not exogenous heterogenity from noise, I omit noise and therefore, I use the two step procedure described. In section 5, I explore estimation with noise.

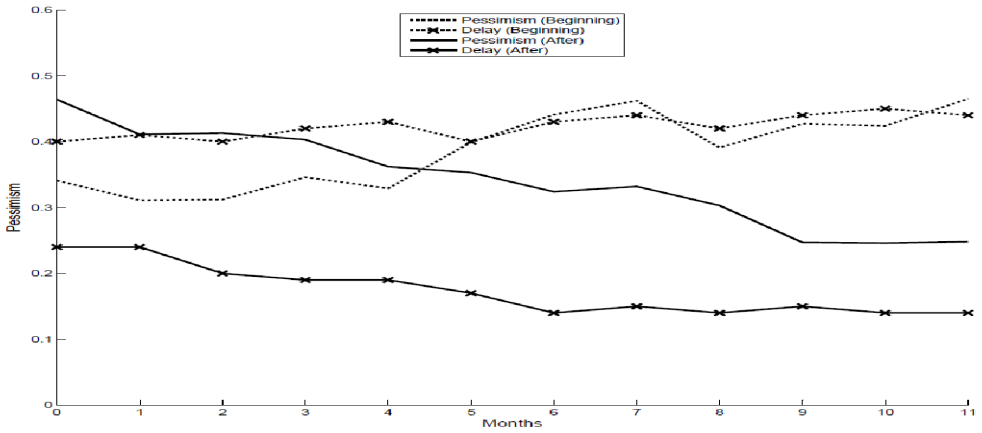

Figure 5: Predictions of the Delay Model

The solid line plots the average fraction of pessimists at the end of the recession when unemployment begins to fall. 0 denotes the first month unemployment begins to fall, 1 the second, and so on. The dashed line plots the average fraction of pessimists at the beginning of the recession when unemployment begins to rise. 0 denotes the first month, 1 the second month and so on. The predictions of the delay model are plotted in the same way as the data except they are marked with an x.

line). By having some agents base their expectations on old information, a substantial number of agents do not predict that unemployment will rise more that the pessimism cutoff (0.2 percentage points). Turning to the model prediction at the end of the recession (solid line with x), the model substantially underestimates the fraction of pessimism. Relatively few individuals expect unemployment to rise, and that number quickly dies out to zero. One more virtue of the delay model is evident though. It creates a fairly smooth endogenous distribution of expectations. One can see that the number of pessimists varies fairly smoothly from month to month.

Why does the delay model fail to match the percent of pessimists at the end of the recession? To answer this question I examined forecasts of unemployment changes at each point in time based on information which gets progressively older. (Table 4A in the appendix gives the details of this calculation.) The calculation showed that even with outdated information the forecast of the unemployment change at the recession's end are usually negative, and if positive, rarely larger than the pessimism cutoff of 0.2. To understand the intuition for this

result it is useful to think about two cases.

First, consider a situation where the agent has only slightly old information. For example, the agent knows that unemployment has risen a few periods ago and does not know what happened since. An agent using a statistical forecast would not expect past unemployment changes to persist indefinitely into the future, since he knows that unemployment declines eventually flatten out and then become negative as unemployment returns to its mean. Therefore, when forecasting what happens at the end of the recession he expects a slight fall as unemployment returns to its mean. I did find a few slightly positive forecasts based on old information, hence some pessimism at the end of the recession, but they were small, and quickly went to zero.

Second think about a situation where the agent has very old information. He would predict more or less no change in the unemployment rate. This is intuitive. Most economists would not have an expectation about the change in the unemployment rate six years into the future from five years into the future. They would predict more or less no change in unemployment. As the age of the information used for the forecast increases, the forecast of the unemployment change goes towards zero. These individuals will not be pessimistic – which makes it hard for the model to generate a large number of pessimists.

It is instructive to contrast this case with the case of forecasting inflation. Since inflation is close to a random walk, a forecast of inflation today, based on information from two years ago, will not differ much from the level of inflation two years ago. In this case, an agent will look fairly extrapolative, using past inflation rates to forecast today's inflation. However, unemployment *changes* are certainly not a random walk. And forecasts of unemployment changes today, based on old information, are not the same as unemployment changes from a few periods in the past.

4.4 Extrapolative Expectations

Next I consider a model where a fraction of consumers forecast unemployment with the VAR and the rest form their expectations by taking a weighted average of past changes. These agents form expectations according to:

$$\widehat{E}_t\left[u_{t+12}-u_t\right]=\sum_{n=0}^{N}\frac{\lambda(1-\lambda)^n}{1-(1-\lambda)^{N+1}}\left[u_{t-n}-u_{t-n-12}\right] \tag{4}$$

where u_t is the unemployment rate at time t and λ is a parameter that controls how much the recent past is weighted relative to the less recent past[17]. Therefore the percent of pessimists at time t is given by

$$\%Pess_t = e*1(\widehat{E}_t\left[u_{t+12}-u_t\right]>c_u)+(1-e)*1(E_t\left[u_{t+12}-u_t\right]>c_u)$$

where e is the percent of the population that are extrapolators, c_u is the upper cutoff, the point at which if the individual expects unemployment to rise by more than c_u they are classified as a pessimist, 1 is the indicator function, and $E_t\left[u_{t+12}-u_t\right]$ is the expectation from the VAR (2).

To choose the percent of extrapolators, e, I solve the following problem: $\min_e \; x'Wx$ where, as in the previous section, x is a vector of two observations per year: the percent of people who respond that they expect unemployment to rise and the percent that expect unemployment to fall; each percent is subtracted from the model's prediction for these variables. W is a diagonal weighting matrix with the inverse of the variance of the data estimates on the diagonal (as in the previous section). I calibrate $\lambda = 0.5$. The estimate of e and the model's predictions were not very sensitive to the choice of λ. Again, the model's prediction depends on what cutoffs constitute unemployment staying the same, rising, and falling so I calculated e for different values of these cutoffs and then choose the overall minimum. The objective function is minimized at the values $e = 0.495$, the upper cutoff $= 0.5$ and the lower cutoff

[17] $N = 20*12-1$ representing 20 years.

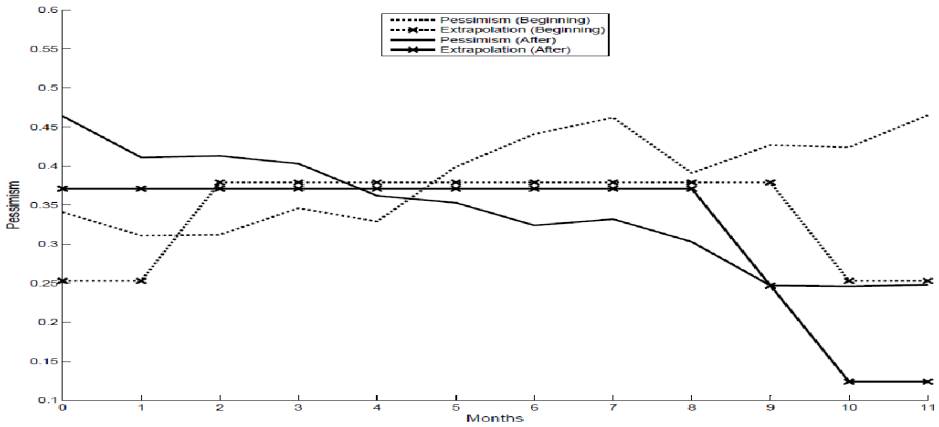

Figure 6: Predictions of Extrapolation Model

This solid line plots the average fraction of pessimists at the end of the recession when unemployment begins to fall. 0 denotes the first month unemployment begins to fall, 1 the second, and so on. The dashed line plots the average fraction of pessimists at the beginning of the recession when unemployment begins to rise. 0 denotes the first month, 1 the second month and so on. The predictions of the extrapolation model are plotted in the same way as the data except they are marked with an x.

$= -1.8$.

Figure 6 shows the model's prediction for the average number of pessimists. Extrapolation captures two features that the other models have not. First, the model predicts the large and lasting pessimistic predictions of the recovery (solid line). The extrapolators are pessimistic at the end of the recession. Though pessimism falls as the lag changes in unemployment become smaller. Secondly, it matches the fact that there is more pessimism after the recession than at the beginning of the recession. Before the recession we have increasing pessimism from the rational agents but no pessimism from the extrapolators. (The level of pessimism does not equal 0.495 for all months because sometimes the rational forecast is slightly below the upper cutoff of 0.5 to be pessimist.)

5 Heterogeneity

In this section I relate a point forecast of an unemployment change to a distribution of unemployment expectations. I estimate models where there is a distribution of expectations around the predictions of the different expectational models.

I show that estimation of the VAR, least squares learning, and real time expectations models leads to a large variance of the distribution and unreasonable cutoffs for assigning individuals into the optimist or pessimist categories. Estimates of the delay parameter indicate substantial delay and estimates of the percent of extrapolators indicate significant extrapolation. Finally, only the extrapolation model comes close to explaining why the lag unemployment change helps predict the number of pessimists (table 2) and why there is more pessimism after the recession than before the recession (figure 2).

For the VAR model, the least squares learning model, and the real time data models I assume that at every point in time the distribution of expectations in the population are given by:

$$Exp_t \sim N(\mu_t, \sigma^2) \tag{5}$$

where μ_t is $E_t[u_{t+12-}u_t]$ from the VAR equation (2), or the least squares learning model, or the real time data models, and with variance σ^2 which is a parameter to be estimated[18]. One interpretation is that individuals observe the VAR forecast with noise and the noise has variance σ^2. Furthermore, I estimate c_l the lower cutoff, the point at which if the individual expects unemployment to fall by more than c_l they are classified as an optimist and c_u the upper cutoff, the point at which if the individual expects unemployment to rise by more than c_u they are classified as a pessimist. Otherwise, they are classified as expecting

[18] Another method would follow the approach of Howrey (2001) and calculate the probability of unemployment rising at each point in time by sampling from the VAR residuals. I could use this probability to predict the percentage of pessimists at each point in time. I do not follow his approach for two reasons: 1) It is unclear why some individuals would expect a certain path of VAR residuals when they have an expected value of zero and 2) this method puts a restriction on the variance of the distribution around the VAR expectation. I prefer to make the variance a free parameter to give the model the best chance of matching the data. Even then I will find severe limitations of the VAR model.

unemployment to stay the same. Therefore the fraction of the population that is pessimistic at time t is given by

$$\%Pess_t = 1 - \Phi(c_u, \mu_t, \sigma^2)$$

where Φ is the normal cumulative distribution function evaluated at c_u for mean μ_t and variance σ^2. To estimate the parameters of the model I solve the following problem:

$$\min_{\sigma, c_u, c_l} x'Wx \tag{6}$$

where x is a vector of two observations per month for every month in the data set: the percent of people who respond that they expect unemployment to rise and the percent that expect unemployment to fall each subtracted from the model's prediction for these variables and W is a diagonal weighting matrix with the inverse of the variance of the data estimates on the diagonal (see section 4.3).

For the delay model, the estimation procedure is similar. First the population is broken up into individuals who base their expectations on information n periods old, for $n = 0, ...N$ ($N = 86$). The percent of the population in each group is given by the same formula as in section 4.3. Then within these groups the expectations are given by

$$Exp_t \sim N(\mu_t^n, \sigma^2)$$

with μ_t^n equal to $E_{t-n}[u_{t+12} - u_t]$ (as in section 4.3) and variance σ^2 which is estimated along with the upper and lower cutoffs. Then the model's prediction for the percent of the population that is pessimistic at time t is:

$$\%Pess_t = \sum_{n=0}^{N} \frac{\lambda(1-\lambda)^n}{1-(1-\lambda)^{N+1}} \left[1 - \Phi(c_u, \mu_t^n, \sigma^2)\right]$$

The exact problem solved is (6) with the predictions of the delay model replacing the predictions of the VAR model and also optimizing over the delay parameter λ.

Finally, for the extrapolation model, I assume that at each point in time a fraction $1-e$ of the population has expectations which are given by (5) and another fraction, e of the population has expectations given by

$$Exp_t \sim N(\mu_t^e, \sigma^2)$$

where μ_t^e is given by the extrapolation equation (4). Therefore the percent of the population that is pessimistic at time t is given by:

$$\%Pess_t = e * \left[1 - \Phi(c_u, \mu_t^e, \sigma^2)\right] + (1-e) * \left[1 - \Phi(c_u, \mu_t, \sigma^2)\right]$$

Note that I assume extrapolators and rational agents have the same value of σ^2. To estimate the parameters I solve (6) optimizing over e and λ from equation (4) as well as σ and the cutoffs.

Table 3 displays the estimated parameters. The models all need a large σ to match the data. The large σ is needed because at every point in time, even when the VAR expectation is significantly positive or negative, there are a substantial number of pessimists and optimists. The standard deviation is 3.8 for the VAR and real time models and above nine for the learning model and the learning model with real time data. It is about 2.2 for the delay model and 2.5 for the extrapolation model.

In addition, as shown in Table 1A, since there are many people who answer "about the same" to the unemployment question the large standard deviation forces the upper and lower cutoffs to be fairly large. For example in the VAR model, an individual must expect unemployment to rise by more than 1.6 percentage points before they will answer "more unemployment" as opposed to about the same. This seems unreasonable; who would think that an increase in unemployment by 1.6 percentage points is unemployment being "about the same"? This discrepancy is more dramatic for the lower cutoffs since people are unconditionally much more likely to be pessimistic than optimistic. The lower cutoffs are:

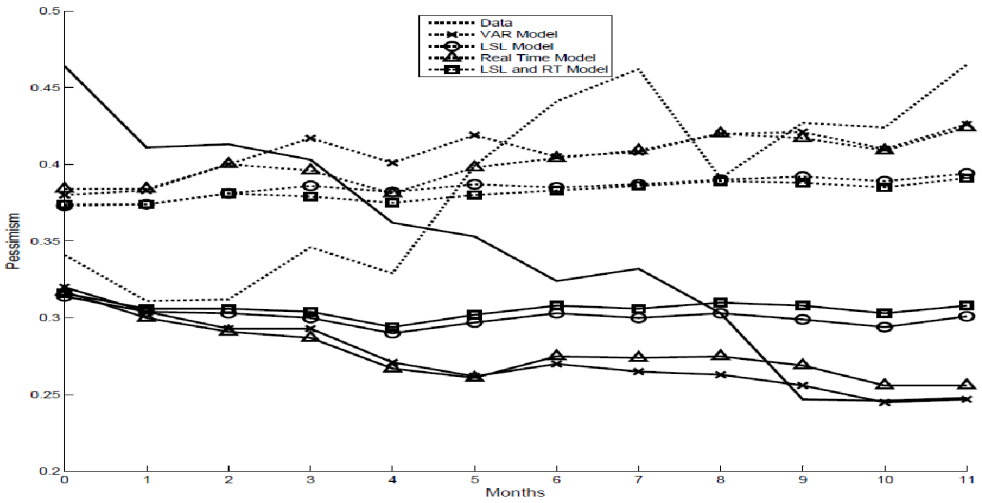

Figure 7: VAR, LSL, Real Time, and LSL and RT Models

The solid line plots the actual level of pessimism after the recession, the dashed line plots the actual level of pessimism at the beginning of the recession. Along with these series I plot the prediction of the VAR model (x), the LSL model (o), and the Real Time Data model (triangle), and the LSL with Real Time Data Model (square).

-4, -10, -4, and -10 for the VAR, LSL, real-time data and LSL with real-time data models respectively. The upper cutoffs are more reasonable for the delay and extrapolation model: 0.9 and 1.1 respectively. The lower cutoffs for these models are -2.3 and -2.7 respectively.

The delay parameter, λ, is estimated to be 0.1586 and the percent of extrapolators is estimated to be 0.35. We can rank models by the minimum of the objective (6) that is obtained. The extrapolation model does best, followed by the delay model then the VAR model, the real time data model, the LSL model, and finally the LSL model with real time data.

Figures 7-9 redo the analysis of figure 2 with the simulated fraction of pessimists. (Full regression results are available in the appendix: Tables 5A and 6A.) First, the simulated models come fairly close to the actual percent of pessimists in the data. They do this however with a large estimate of sigma and therefore by making the percent pessimists and optimist fairly insensitive to the mean of the distribution, the expectational forecast. All

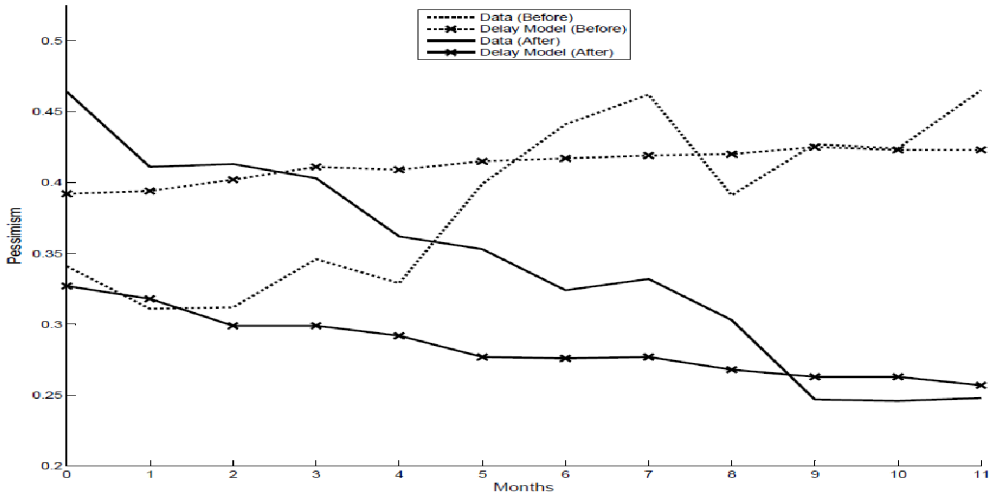

Figure 8: Predictions of the Delay Model

The solid line plots the actual level of pessimism after the recession; the dashed line plots the actual level of pessimism at the beginning of the recession. Along with these series I plot the prediction of the delay model (x).

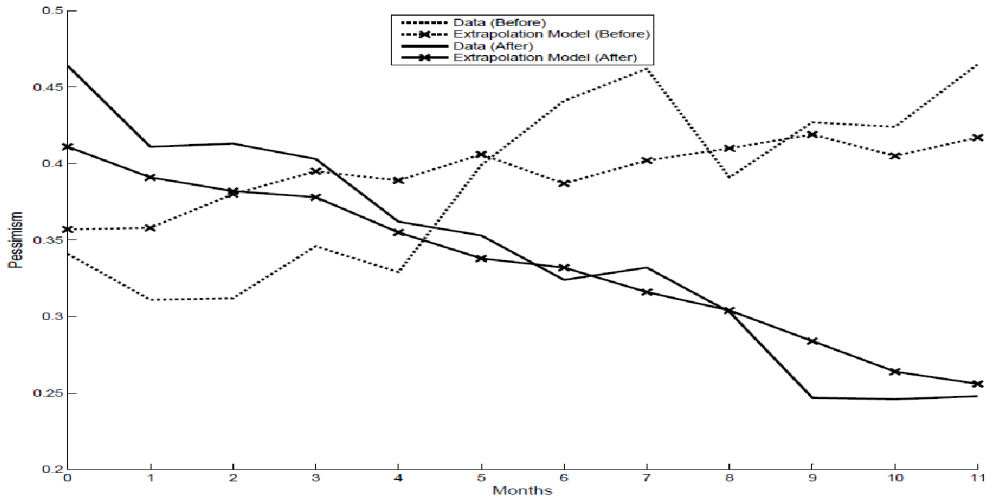

Figure 9: Predictions of Extrapolation Model

The solid line plots the actual level of pessimism after the recession; the dashed line plots the actual level of pessimism at the beginning of the recession. Along with these series I plot the prediction of the extrapolation model (x).

models underestimate the level of pessimism at end of the recession. The extrapolation model comes the closest to matching the data. It underestimates the level of pessimism by only 5 percentage points while the other models are off by at least 12 percentage points. One of the important facts in this paper was that the level of pessimism was higher after the recession than at the beginning of the recession. Only the extrapolation model matches this fact. All other models predict lower levels of pessimism at the end of a recession (solid line) than at the beginning of the recession (dashed line).

Table 4 regresses the simulated fraction of pessimists on the VAR forecast and the lag change in unemployment to see if the models can replicate the relationship outlined in table 2. In the data, for this regression, the lag change coefficient was 75% the VAR forecast coefficient. The extrapolation model comes closest to matching this fact: the coefficient on the lag change is 57% the coefficient on the VAR forecast. For the delay model, the lag coefficient is 12% the VAR coefficient. The rational models fair poorly. The VAR, LSL, real-time data, and real-time data with learning model predict the lag change coefficient should be essentially zero.

6 Extensions

6.1 Univariate Forecasting

If mean reversion in unemployment is a key feature of the VAR's ability to forecast unemployment than one should be able to obtain similar results with just a univariate forecast of unemployment. To see if a univariate forecasting rule can explain the patterns of pessimism I repeat the regression (1) for before and after the recession but instead of using the VAR forecast I use the univariate forecast from regressing unemployment on four lags of unemployment.

Figure 10 contains the results. The univariate forecasts are generally smaller in magnitude than those of the VAR. However the univariate forecasts are of the same sign as the VAR

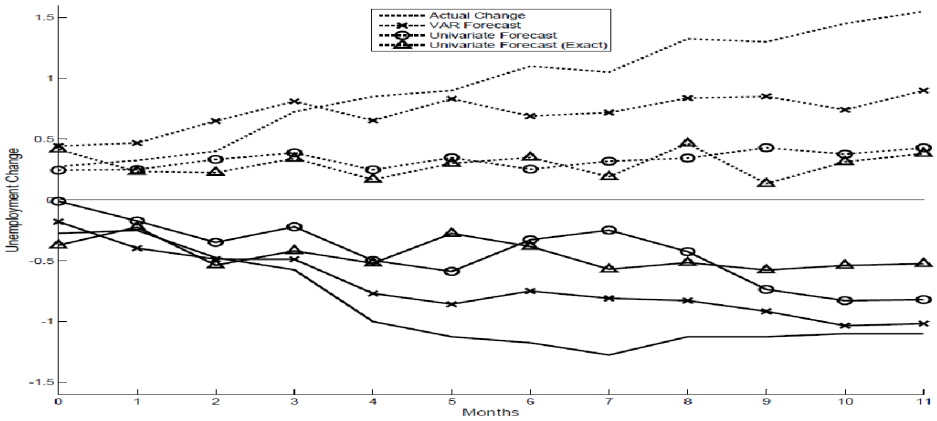

Figure 10: Univariate Forecasts

The line without a marker is the average actual unemployment change (across recessions). For the solid line, 0 denotes the first month unemployment begins to fall, 1 the second, and so on. For the dashed line, 0 denotes the first month unemployment begins to rise, 1 the second month and so on. The lines with x are the average VAR forecast of these changes. The lines with -o- are the average univariate forecast of these changes. The lines with -(triangle)- are the average univariate forecast of these changes without the quarterly assignment procedure.

forecasts. This test reveals how puzzling these pessimistic expectations really are. Even a naive and simple forecasting technique, ignoring all information in the economy except the past rates of unemployment is able, on average, to correctly predict the sign of future unemployment changes. This achievement, however, is a task many households in the survey are unable to perform.

This analysis is related to the work of Ball (2000). He argues that the true structural model is one in which agents make univariate forecasts of inflation as opposed to naive adaptive expectations. He shows his model is consistent with observed expectations in pre-war versus post-war data. However, in this case, it appears a univariate unemployment forecast does not capture important features of individual unemployment expectations.

Finally, figure 10 displays the exact univariate forecast. Recall that since GDP is available quarterly, I needed to use the procedure described in figure 1A (in the appendix) to assign monthly expectations from the quarterly VAR. With monthly unemployment I can drop this assumption– which was used to calculate the univariate forecast–and use the exact

unemployment expectation from the univariate unemployment forecast to calculate the univariate forecast (exact) line. As one can see the two univariate forecasts are similar – in fact the exact forecast is more negative at the beginning of the recovery and more positive at the beginning of the recession deepening the inconsistency – and indicate that the assignment procedure does not drive the results. I also obtained similar forecasts using a monthly VAR with industrial production in place of GDP as an additional check.

6.2 Survey of Professional Forecasters

In this paper I ask if individual expectations are consistent with forecastable movements in unemployment. A related question is whether the expectations of professional forecasters differ importantly from household expectations. Or, in other words, do professional forecasters make the same mistakes households do? To examine this question I use data from the Survey of Professional Forecasters (SPF) conducted by the Federal Reserve Bank of Philadelphia.[19] I have data on the unemployment expectations for individual forecasters from 1978 through 2011. I calculate the percent who expect unemployment to rise each month and plot this fraction of pessimism along with the fraction of pessimists from the Michigan data.[20]

The results, in Figure 11 show that professional forecasters exhibit more pessimism at the beginning of a recession than at the end and levels of pessimism among professional forecasters at the end of a recession die out quickly. They are much more accurate than household expectations. In table 4 I show the result of regressing the fraction of pessimism in the SPF on the VAR prediction of the unemployment change and the lag change in unemployment. For households the coefficient on the lag change is 75% the coefficient on the VAR. For professional forecasters this factor is only 39%.

[19] Data and documentation are available at: http://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/

[20] I classify the professional forecasters as pessimistic if they expect unemployment to rise by at least 0.2. Results are robust to different cutoffs. Since data are available only quarterly, I assign expectations to the months as in Figure 1A.

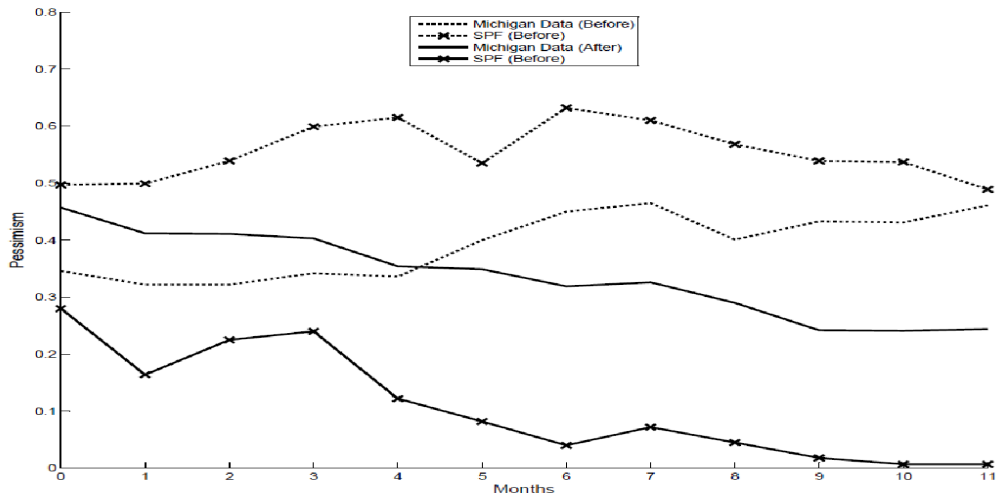

Figure 11: Professional Forecasters

The solid line plots the actual level of pessimism after the recession; the dashed line plots the actual level of pessimism at the beginning of the recession. Along with these series I plot the fraction of professional forecasters that expect unemployment to rise by at least 0.2 points (x).

7 Who Make These Errors and Does it Matter?

The previous sections of the paper have argued that individual's unemployment expectations contain predictable deviations from statistical forecasts across the business cycle, namely insufficient pessimism at the beginning of recessions and excessive pessimism during recoveries. Now, I use the survey data to examine characteristics associated with those whose expectations differ from the VAR and the impact these deviations have on buying attitudes.

This section makes two points to demonstrate the importance of this paper's results. Firstly, these deviations are consistent across the population and not confined to an economically unimportant group. Second, these deviations, especially pessimistic errors are associated with large changes in buying attitudes.

7.1 Characteristics Associated with Expectational Errors

To examine whose expectations are more likely to deviate from the VAR, I estimate the following regressions: $Y_{it} = F(\alpha + X_{it}\beta + Z_t\gamma) + \varepsilon_{it}$. Here Y_{it} = either $Error_{it}$ which

equals one if the individual's response differs from the VAR forecast and is zero otherwise[21] or $PessimisticError_{it}$ which equals one if the individual expects unemployment to rise and the VAR predicts it will not rise and it is equal to zero otherwise. X_{it} is a vector of individual characteristics and Z_t contains the lag unemployment rate and year fixed effects.[22] I estimate the model both by OLS ($F(x) = x$) and probit (F = standard normal cdf).

Table 5 contains the regression results. The first column contains the OLS results; the second column contains the marginal effects (evaluated at the means) from the probit model. I find that men are 1% less likely to make expectational errors. I find a non-monotonic effect of age. Though the best and worst by age differ only by about three percent. An additional grade of education reduces the probability you make an error by 0.4 percent and college graduates are 0.3 percent less likely to make an error. Taken together these estimates imply education does little to mitigate these errors. Comparing a college graduate (with 16 years of education) with a individual with a 6th grade education, the college graduate is only 4.3% less likely to make an error in his unemployment expectations. Similarly, income has only a small impact on the probability of making an expectational error. The coefficient on income is -0.000044. Since income is measured in *thousands* of year 2000 dollars, an individual with an annual income that is 100,000 dollars greater is only 0.44% less likely to make an error[23]. Finally, an individual being optimistic about his own finances has a small effect on the probability of making an error as does the individual's race.

Second, still in table 5, we turn to the characteristics associated with making a pessimistic error, expecting unemployment to rise when the VAR predicts otherwise. The coefficient on being male is again -1%. The age coefficients imply that the best and worst by age differ by about 4%. Being a college graduate has an insignificant affect on the probability of making a pessimistic error, and the difference in the probability of making a pessimistic error between

[21] Here I use upper and lower cutoffs of .2 and -.2 to classify responses into about the same, more unemployment and less unemployment. Results were robust to other choices for the cutoffs.

[22] While the data allow me to control for many individual characteristics, including the individual's own assessment of his finances, it is not a panel survey and I can not control for unobserved heterogeneity with individual fixed effects.

[23] Using income in logs did not change the estimates of the income effect significantly.

a college graduate and an individual with a 6th grade education is only 4%. The effect of income on the probability of making a pessimistic error is larger: an individual with an annual income that is 100,000 dollars greater is 2% less likely to make an error. Taken with the results on income, the results on education imply that these errors are not made solely by an economically unimportant fraction of the population but are made fairly evenly across the income and education distributions.

7.2 The Effect of Errors on Buying Attitudes

Next I examine the effect of unemployment expectations on buying attitudes. The survey asks the following three questions: 1."Generally speaking, do you think now is a good time or a bad time to buy a house?" 2."Speaking now of the automobile market, do you think the next 12 months or so will be a good time or a bad time to buy a car?" and 3."About the big things people buy for their homes, such as furniture, a refrigerator stove, television, and things like that. Generally speaking, do you think now is a good or a bad time for people to buy major household items?" For each item I run the following regressions:

$$BadBuy_{it} = F(\alpha + \beta Pessimist_{it} + \gamma X_{it} + \delta Z_t) + \varepsilon_{it} \quad (7)$$

$$BadBuy_{it} = F(\alpha + \beta PessError_{it} + \gamma X_{it} + \delta Z_t) + \varepsilon_{it} \quad (8)$$

where $BadBuy_{it}$ indicates the individual believes it to be a bad time to buy the item mentioned in the question above, $Pessimist_{it}$ equals one if the individual expects unemployment to rise and is zero otherwise, $PessError_{it}$ equals one if the individual expects unemployment to rise contrary to the VAR and is zero otherwise, X_{it} is a vector of individual characteristics as in the previous section and Z_t contains the lag unemployment rate and year fixed effects. Importantly, I am able to control for the individual's optimism or pessimism about his own finances. The model is estimated by OLS ($F(x) = x$) and probit (F = standard normal cdf). We would expect both β coefficients to be positive, being pessimistic about the future

is correlated with thinking that it is a bad time to make a large purchase.

Table 6 shows the results, suppressing the control variable coefficients. Both being pessimistic about future unemployment changes and making a pessimistic error has important effects on buying attitudes. Being pessimistic or making a pessimistic error results in being 8% less likely to think it is a good time to buy a house, 10% less likely to think it is a good time to buy a car, and 8% less likely to think it is a good time to purchase of a durable good.

8 Conclusion

I have compared household unemployment expectations, measured by the Michigan Survey of Consumers, with the predictions of a four variable VAR containing GDP, the unemployment rate, the inflation rate, and the fed funds rate. Three important facts emerged. First, concerning the fall in unemployment at the end of the recession, there are above average levels of pessimism with half to one-third of the population expecting unemployment to *rise* even though the VAR predicts the fall in unemployment. Second, concerning the rise in unemployment at the beginning of a recession, fewer people had expected unemployment to rise than at the end of a recession when unemployment is falling even though the VAR predicted these changes. Finally, when regressing the percent of the population that expects unemployment to rise on the VAR prediction of the future unemployment change and the lag unemployment change, the lag change coefficient was the same magnitude as the VAR prediction coefficient. A model with a random expectations distribution around the VAR expectation underestimated the lag change coefficient by a factor of 50.

I then examined the ability of other expectation models to match these facts. This pattern of expectations was not due to the unavailability of revised data. Least squares learning had an even harder time than the VAR explaining pessimism at the end of the recession. Similarly, delayed updating of expectations helped explain why there are few pessimists at the beginning of a recession but not why there are many pessimists at the end

of a recession. An extrapolative expectations model where agents partially form expectations by extrapolating current trends into the future, explained both insufficient pessimism at the beginning of the recession and excessive pessimism at the end of the recession. In its fifth section, the paper demonstrated that among data simulated from the different expectational models, only data from the extrapolation model could match the facts outlined previously and the sixth section showed that even a simple univariate forecast could forecast the sign of unemployment changes. In addition, professional forecasters' expectations do not depart so dramatically from the VAR forecasts as households do.

While those with more education or greater income are less likely to make expectational errors (i.e. differing from the VAR) the effect is almost negligible; therefore expectational errors are not confined to an economically insignificant fraction of the population. Finally, when an individual expects unemployment to rise when in fact the VAR predicts it will fall, they are 8%-10% less likely to think it is a good time to make a major purchase.

Standard rational expectations models assume that individuals know the true model and make their expectations according to that model. In this paper I have tried to approximate the true model for unemployment using statistical forecasts – a VAR and a univariate forecast of unemployment changes. I have argued that individual forecasts vary substantially from these statistical forecasts and vary in a way that is predictable. Namely after an extended period of falling unemployment they are less likely to predict unemployment will rise than after an extended period of rising unemployment. However, a statistical forecast does the opposite – because of the mean reverting nature of unemployment. Most models of expectations: least squares learning, real time data and delayed updating of expectations can not explain these patterns. However a model in which some agents extrapolate past changes to form their expectations can. While it would be easier to tie expectations data to the predictions of theoretical models if we had better survey data (i.e. quantitative, and clearer definition of unemployment), the data quality does not appear to drive the results. Firstly, the data are poorly approximated by a random distribution around the VAR expec-

tations suggesting that the discrepancies in expectations is more than measurement error. Secondly, expecting more unemployment gives a clear prediction of the sign of the future unemployment change and this prediction can be tested, and is tested in this paper.

The results in this paper suggest many avenues for further research. For one, the extrapolation model is quite ad hoc. Perhaps more complicated learning based models could provide a better foundation for the usefulness of extrapolation. Second, the results suggest that extrapolating agents could be used in macroeconomic models to potentially explaining various phenomenon: e.g. financial market participation, the persistence of recessions, and large changes in equity and housing prices. Finally, the results suggest that expectational errors, or undue pessimism may have important affects on consumption through their effects on buying attitudes. These consumption effects warrant further study.

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Table 1: Pessimism at the Beginning and After Recession

Months	Pessimist	RealUrateChange	ExpUrateChange	Pvalue Pessimist	Pvalue RealUrateChange	Pvalue ExpUrateChange
Beginning 0	0.464***	-0.275***	-0.179	0.015	<.001	0.015
	[0.030]	[0.055]	[0.218]			
1	0.411***	-0.250***	-0.397	0.01	<.001	0.06
	[0.030]	[0.057]	[0.441]			
2	0.413***	-0.475***	-0.487	0.0184	<.001	<.001
	[0.015]	[0.126]	[0.305]			
3	0.403***	-0.575*	-0.488	0.2457	<.001	<.001
	[0.013]	[0.312]	[0.304]			
4	0.362***	-1.000**	-0.769*	0.4224	<.001	<.001
	[0.007]	[0.388]	[0.404]			
5	0.353***	-1.125***	-0.857**	0.4837	<.001	<.001
	[0.029]	[0.407]	[0.363]			
After 0	0.341***	0.275***	0.442***			
	[0.040]	[0.042]	[0.130]			
1	0.311***	0.325***	0.468***			
	[0.023]	[0.075]	[0.147]			
2	0.312***	0.400***	0.649***			
	[0.040]	[0.080]	[0.103]			
3	0.346***	0.725***	0.810***			
	[0.047]	[0.110]	[0.167]			
4	0.329***	0.850***	0.653***			
	[0.041]	[0.322]	[0.110]			
5	0.399***	0.900***	0.831***			
	[0.059]	[0.313]	[0.198]			
Observations	209,127	391	391			

The table contains the results of regressing, on a vector of variables indicating months since unemployment began to rise and months since it began to fall, if the individual expects unemployment to rise, the actual change in unemployment, and the VAR prediction of the change. Column one uses the survey's household weights. The rightmost columns contain the p-values of the test that the before and after coefficients are equal (by month). Standard errors are corrected for within month correlation in the first column and autocorrelation in the others using Newey-West with 3 lags. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 2: Pessimism and Lag Unemployment Changes

	Pessimist	Pessimist
ExpectedUrateChange	0.078***	0.050***
	[0.010]	[0.011]
LagRealUrateChange	0.057***	0.051***
	[0.006]	[0.005]
RealUrateChange		0.031***
		[0.006]
Constant	0.340***	0.341***
	[0.006]	[0.006]
Observations	391	391
R-squared	0.523	0.579

This table contains the results from regressing the percent of the population who expect unemployment to rise on a VAR prediction of the unemployment change and the lag unemployment change. The second column adds the actual unemployment change as a regressor. Standard errors are corrected for autocorrelation using a Newey-West procedure with 3 lags. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: Estimates of the Parameters of the Heterogenous Expectations Models

	VAR Model	LS Learning Model	Real Time Model	LSL ad RT Model	Delay Model	Extrapolation Model
Sigma	3.82	9.11	4.03	9.59	2.19	2.54
	(0.07)	(0.27)	(0.08)	(0.31)	(0.08)	(0.05)
Upper Cutoff	1.61	3.17	1.72	3.4	0.943	1.1
	(0.03)	(0.11)	(0.03)	(0.13)	(0.03)	(0.02)
Lower Cutoff	-3.96	-10.3	-4.17	-10.8	-2.28	-2.7
	(0.08)	(0.29)	(0.09)	(0.33)	(0.08)	(0.04)
Lambda	--	--	--	--	0.1586	0.99
	--	--	--	--	(0.01)	(0.11)
Percent Extrapolators	--	--	--	--	--	0.35
	--	--	--	--	--	(0.0075)
Function Value	11380	14669	12164	15027	11061	8044

This table gives the estimates of the parameters of the expectational models. The distibution of expectations is assumed to be normally distributed with mean zero and variance sigma around the caclulated expectation of the model, the individual is assigned to expect unemployment to rise if they expect a change above the upper cutoff, to expect unemployment to fall if they expect unemployment to fall more than the lower cutoff. lambda is the probability of updating expectations in the delay model and the extrapolation parameter in the extrapolation model. Finally the percent of extrapolaters are the percent of individuals who form their expectation by extrapolating past unemployment rate changes. In parentheses are the square root of the appropriate diagonal entry of (1/N)(d'Wd')^-1(d'WSWd)(d'Wd)^-1 where d = $\partial (F_1 \ldots F_{2T}/\partial\beta)$, β is the model parameters, evaluated at the estimated parameters, where W is the (inverse variance) weighting matrix and $(F_1 \ldots F_N)$ are the predictions of the model, and S is the (by year month block diagonal) covariance matrix of $w_iP_i/w_{i,bar}$ and $w_iO_i/w_{i,bar}$, where P_i is a dummy variable for expecting more unemployment, O_i is a dummy variable for expecting less unemployment, w_i are the survey weights, $w_{i,bar}$ is the mean of the survey weights, and N is the number of observations in the month with the minimum number of observations.

Table 4: Simulated Pessimism and Lag Unemployment Changes

	Data	VarPessimists	LSLPessimists	LSL and RT Pessimists	RealTimePessimists	Delay Pessimists	Extrap Pessimists	SPF Pessimists
ExpectedUrateChange	0.078***	0.094***	0.054***	0.048***	0.084***	0.085***	0.088***	0.253***
	[0.010]	[0.001]	[0.005]	[0.005]	[0.002]	[0.002]	[0.002]	[0.029]
LagRealUrateChange	0.057***	0.001***	-0.003	-0.005*	-0.004**	0.010***	0.050***	0.098***
	[0.006]	[0.000]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	[0.022]
Constant	0.340***	0.339***	0.340***	0.341***	0.340***	0.341***	0.340***	0.283***
	[0.006]	[0.000]	[0.002]	[0.002]	[0.001]	[0.002]	[0.001]	[0.020]
Observations	391	391	391	391	391	391	391	391

This table repeats the first regression from table 2 but instead of using the actual number of pessimists it uses the number simulated from the different expectational models and from the Survey of Professional Forecasters. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Predictor of Expectational Errors and Pessimist Errors

	Prob. Make Error		Prob. Make Pessimistic Error	
	OLS	Probit	OLS	Probit
Male	-0.0109***	-0.0118***	-0.0112***	-0.0108***
	[0.0024]	[0.0025]	[0.0022]	[0.0022]
Age	-0.0028***	-0.0029***	0.0042***	0.0042***
	[0.0004]	[0.0005]	[0.0004]	[0.0004]
Age Squared	0.000028***	0.000029***	-0.000044***	-0.000043***
	[0.0000044]	[0.0000045]	[0.0000039]	[0.0000041]
Education	-0.0042***	-0.0043***	-0.0040***	-0.0036***
(Highest Grade Attained)	[0.0007]	[0.0007]	[0.0007]	[0.0006]
College	0.0025	0.0024	0.0023	0.0013
	[0.0037]	[0.0038]	[0.0034]	[0.0034]
Married	0.0033	0.0035	-0.0003	-0.0001
	[0.0027]	[0.0027]	[0.0024]	[0.0025]
Income (in thousands of	-0.000044	-0.000047	-0.0002***	-0.0002***
year 2000 Dollars)	[0.000028]	[0.000029]	[0.00002]	[0.0000]
Optimistic About Own Finances	0.0192***	0.0190***	-0.0552***	-0.0546***
	[0.0026]	[0.0027]	[0.0023]	[0.0023]
Black	-0.0141***	-0.0145***	0.0642***	0.0638***
	[0.0045]	[0.0046]	[0.0044]	[0.0045]
Hispanic	0.0009	0.0002	-0.0007	-0.0005
	[0.0060]	[0.0062]	[0.0053]	[0.0055]
Native American	-0.0135	-0.0139	0.0464***	0.0506***
	[0.0132]	[0.0135]	[0.0126]	[0.0136]
Asian	0.0273***	0.0271***	0.0024	0.0005
	[0.0095]	[0.0097]	[0.0083]	[0.0089]
Lag Unemployment Rate			0.0797***	0.0897***
			[0.0032]	[0.0035]
Constant	0.8287***		-0.3615***	
	[0.0149]		[0.0238]	
Observations	188,824	188,824	142,180	142,180
R-squared	0.0396		0.0748	

This table contains the results from regressing if the agent's response differs from the VAR (Error) and if the agent's response is "more unemployment" when the VAR predicts otherwise (Pessimistic Error) on individual characteristics. The first column, in each panel, gives OLS estimates the second column gives estimates of the marginal effects from a probit model. Regressions are weighted using the survey's household weights. Standard errors in brackets. The pessimistic error regression contains fixed effects for years. Observations fall in these regressions because I exclude years in which it is impossible for there to be a pessimistic error because the VAR predicts unemployment will rise. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Effects of Expectational Errors on Buying Attitudes

	Bad Time Buy Home		Bad Time Buy Car		Bad Time Buy Durables	
	OLS	Probit	OLS	Probit	OLS	Probit
Pessimist	0.088***	0.099***	0.099***	0.103***	0.089***	0.090***
	[0.002]	[0.003]	[0.003]	[0.003]	[0.002]	[0.002]
Observations	183,220	183,220	176,876	176,876	177,153	177,153
R-squared	0.166		0.075		0.081	
Pessimistic Error	0.079***	0.095***	0.101***	0.109***	0.076***	0.080***
	[0.003]	[0.004]	[0.004]	[0.004]	[0.003]	[0.004]
Observations	183,220	183,220	176,876	176,876	177,153	177,153
R-squared	0.161		0.07		0.075	

This table presents the results from regressing individual reponses to questions about their buying attitudes on if they expect unemployment to rise (pessimist), if they expect it to rise when the VAR predicts otherwise (pessimistic error) and on individual characteristics. The first column, in each pair, gives OLS estimates and the second columns gives the marginal effects from a probit model. All regression includes year fixed effects and all the control variables from the previous regressions in Table 5. Regressions are weighted using the survey's household weights. Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Table 1A: Summary Statistics

Table 1a: Unemployment Expectations	More Unemployment	About the Same	Less Unemployment
Number of Responses	75038	98745	32365
Percent Responding	36.4	47.9	15.7

Table 1b: Summary Statistics for Characteristics	N	Mean	Standard Deviation	Percent Responding
Income (In Year 2000 Dollars)	194694	46169	45023	92.9
Age	208004	47	17.2	99.2
Highest Grade Completed (1 to 17)	206777	13.2	2.73	98.6
College Graduate (Yes = 1)	206767	0.32	0.47	98.6

Table 1c: Percentiles for Income and Education	Income	Highest Grade Completed
10	11,287	10
20	17,782	12
30	23,753	12
40	30,669	12
50	37,433	13
60	44,969	14
70	54,580	15
80	66,320	16
90	83,375	17

Table 1d: Race	Number	Percent
White	171,485	83.8
African-American	18,213	8.9
Hispanic	10,027	4.9
Asian	3,274	1.6
Native American	184	0.09

Table 1e: Responses to Buying Attitudes Questions	Good	Pros and Cons	Bad
House	65.9	2.2	32.0
Car	63.2	3.3	33.5
Durable Good	71.0	5.0	24.0

This table gives summary statistics for the Survey of Consumers data. Table 1a tabulates responses to the question: "How about people out of work during the coming 12 months -- do you think that there will be more unemployment than now, about the same, or less?" and Table 1e tabulates responses to questions on whether or not they think it is a good time to buy a house, car or durable good. Calculations use the survey's household weights.

Appendix Table 2A: Pessimism After a Recession

Months After Unemp. Fall	Pessimist	Real Urate Change	VAR Urate Change	LSL Urate Change	Real Time Urate Change	LSL and RT Urate Change
0	0.464***	-0.275***	-0.179	-1.264***	-0.203	-1.228***
	[0.030]	[0.055]	[0.218]	[0.377]	[0.223]	[0.365]
1	0.411***	-0.250***	-0.397	-1.563**	-0.437	-1.534**
	[0.030]	[0.057]	[0.441]	[0.667]	[0.427]	[0.633]
2	0.413***	-0.475***	-0.487	-1.544***	-0.521	-1.519***
	[0.015]	[0.126]	[0.305]	[0.417]	[0.321]	[0.428]
3	0.403***	-0.575*	-0.488	-1.617***	-0.567*	-1.572***
	[0.013]	[0.312]	[0.304]	[0.377]	[0.325]	[0.402]
4	0.362***	-1.000**	-0.769*	-1.923***	-0.839**	-1.869***
	[0.007]	[0.388]	[0.404]	[0.561]	[0.415]	[0.566]
5	0.353***	-1.125***	-0.857**	-1.699***	-0.911**	-1.625***
	[0.029]	[0.407]	[0.363]	[0.312]	[0.423]	[0.293]
6	0.324***	-1.175***	-0.749***	-1.542***	-0.706**	-1.452***
	[0.021]	[0.360]	[0.258]	[0.206]	[0.290]	[0.181]
7	0.332***	-1.275***	-0.809***	-1.631***	-0.724**	-1.512***
	[0.025]	[0.391]	[0.258]	[0.331]	[0.308]	[0.295]
8	0.303***	-1.125***	-0.828***	-1.538***	-0.713**	-1.401***
	[0.037]	[0.407]	[0.266]	[0.242]	[0.290]	[0.204]
9	0.247***	-1.125***	-0.916***	-1.643***	-0.788***	-1.437***
	[0.036]	[0.407]	[0.277]	[0.181]	[0.295]	[0.159]
10	0.246***	-1.100**	-1.034***	-1.762***	-0.938***	-1.570***
	[0.046]	[0.482]	[0.227]	[0.214]	[0.251]	[0.203]
11	0.248***	-1.100**	-1.017***	-1.580***	-0.927***	-1.452***
	[0.037]	[0.531]	[0.206]	[0.121]	[0.180]	[0.091]
Observations	209,127	391	391	391	391	391

The table contains the results of regressing, on a vector of variables indicating months since unemployment began to fall at the end of a recession, if the individual expects unemployment to rise, the actual change in unemployment, the VAR prediction, the least squares learning prediction, and the real time data prediction of the change. Standard errors are corrected for within month correlation in the first two columns and autcorrelation in the other columns using a Newey-West procedure with 3 lags. * significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Table 3A: Pessimism At Beginning of A Recession

Mos After Unemp. Rises	Pessimist	Real Urate Change	VAR Urate Change	LSL Urate Change	Real Time Urate Change	LSL and RT Urate Change
0	0.341***	0.275***	0.442***	0.206	0.535***	0.283
	[0.040]	[0.042]	[0.130]	[0.218]	[0.102]	[0.201]
1	0.311***	0.325***	0.468***	0.238	0.534***	0.292
	[0.023]	[0.075]	[0.147]	[0.224]	[0.101]	[0.201]
2	0.312***	0.400***	0.649***	0.405	0.704***	0.452
	[0.040]	[0.080]	[0.103]	[0.304]	[0.083]	[0.288]
3	0.346***	0.725***	0.810***	0.512*	0.660***	0.402
	[0.047]	[0.110]	[0.167]	[0.299]	[0.175]	[0.329]
4	0.329***	0.850***	0.653***	0.426	0.505***	0.312
	[0.041]	[0.322]	[0.110]	[0.295]	[0.137]	[0.330]
5	0.399***	0.900***	0.831***	0.531	0.680***	0.428
	[0.059]	[0.313]	[0.198]	[0.397]	[0.197]	[0.423]
6	0.441***	1.100***	0.689***	0.503	0.741***	0.511
	[0.088]	[0.303]	[0.171]	[0.407]	[0.240]	[0.466]
7	0.462***	1.050***	0.718***	0.553	0.794***	0.582
	[0.080]	[0.250]	[0.172]	[0.402]	[0.229]	[0.455]
8	0.391***	1.325***	0.837***	0.62	0.909***	0.644
	[0.072]	[0.141]	[0.175]	[0.476]	[0.237]	[0.519]
9	0.427***	1.300***	0.851***	0.665	0.875***	0.629
	[0.059]	[0.095]	[0.186]	[0.496]	[0.203]	[0.475]
10	0.424***	1.450***	0.741***	0.581	0.795***	0.564
	[0.064]	[0.105]	[0.204]	[0.511]	[0.222]	[0.487]
11	0.465***	1.550***	0.899***	0.71	0.949***	0.697
	[0.057]	[0.116]	[0.244]	[0.593]	[0.250]	[0.574]
Observations	209,127	391	391	391	391	391

The table contains the results of regressing, on a vector of variables indicating months since unemployment began to rise at the beginning of a recession, if the individual expects unemployment to rise, the actual change in unemployment, the VAR prediction the least squares learning, and the real time data expectation of the change. Standard errors are corrected for within month correlation in the first column and autcorrelation in the other columns using a Newey-West procedure with 3 lags. * significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Table 4A: Why Delay Model Doesn't Match Pessimism Facts

End of a Recession -- Unemployment Falling

Lag/Months	0	1	2	3	4	5	6	7	8	9	10	11
0	-0.179	-0.397	-0.487	-0.488	-0.769	-0.857	-0.749	-0.809	-0.828	-0.916	-1.034	-1.017
1	-0.295	-0.467	-0.6	-0.583	-0.647	-0.758	-0.794	-0.711	-0.797	-0.851	-0.869	-0.962
2	-0.475	-0.587	-0.741	-0.666	-0.679	-0.766	-0.792	-0.795	-0.785	-0.795	-0.642	-0.736
3	-0.0624	-0.045	-0.443	-0.661	-0.655	-0.802	-0.795	-0.736	-0.764	-0.807	-0.775	-0.716
4	0.168	0.0472	-0.161	-0.123	-0.0542	-0.44	-0.666	-0.62	-0.74	-0.765	-0.665	-0.679
5	0.212	0.105	0.0477	0.103	0.0204	-0.174	-0.133	-0.0438	-0.388	-0.59	-0.518	-0.617
6	0.281	0.297	0.193	0.156	0.0736	0.0188	0.0623	0.00801	-0.154	-0.116	-0.0291	-0.312
7	0.17	0.1	0.0911	0.21	0.226	0.135	0.113	0.0544	0.00703	0.0388	0.00574	-0.123
8	0.0861	0.089	0.118	0.133	0.081	0.0735	0.153	0.166	0.0954	0.0834	0.0432	0.00403
9	0.154	0.132	0.123	0.0657	0.0682	0.0883	0.105	0.0674	0.0622	0.109	0.121	0.067
10	0.112	0.131	0.122	0.115	0.0983	0.09	0.05	0.0528	0.0659	0.085	0.0577	0.0534

Begining of a Recession -- Unemployment Rising

Lag/Months	0	1	2	3	4	5	6	7	8	9	10	11
0	0.442	0.468	0.649	0.81	0.653	0.831	0.689	0.718	0.837	0.851	0.741	0.899
1	0.537	0.543	0.665	0.633	0.679	0.795	0.775	0.747	0.744	0.732	0.762	0.774
2	0.57	0.573	0.663	0.666	0.671	0.694	0.736	0.764	0.8	0.733	0.699	0.633
3	0.509	0.496	0.44	0.637	0.67	0.659	0.681	0.682	0.653	0.753	0.761	0.718
4	0.394	0.47	0.433	0.429	0.417	0.355	0.602	0.65	0.606	0.632	0.633	0.57
5	0.291	0.291	0.264	0.344	0.409	0.365	0.343	0.331	0.282	0.537	0.587	0.518
6	0.288	0.31	0.268	0.252	0.251	0.223	0.29	0.342	0.301	0.271	0.261	0.224
7	0.138	0.153	0.136	0.238	0.257	0.221	0.215	0.213	0.19	0.241	0.279	0.245
8	0.096	0.106	0.0974	0.117	0.128	0.117	0.195	0.211	0.184	0.184	0.182	0.164
9	0.0498	0.0519	0.0574	0.0858	0.0931	0.0881	0.103	0.11	0.103	0.162	0.175	0.156
10	0.0706	0.0592	0.0669	0.0538	0.0553	0.0597	0.0789	0.0848	0.0819	0.0934	0.0976	0.093

The average expected unemployment change at n months (first row) into the recovery (top panel) or recession (bottom panel) based on information k periods old (first column).

Appendix Table 5A: Simulated Pessimism After a Recession

Mos After Fall	Pessimist	VarPess	LSLPess	LSL and RT Pess	RealTimePess	DelayPess	ExtrapPess	SPF Pess
0	0.464***	0.320***	0.314***	0.316***	0.317***	0.327***	0.411***	0.280*
	[0.030]	[0.020]	[0.015]	[0.014]	[0.019]	[0.010]	[0.032]	[0.163]
1	0.411***	0.304***	0.304***	0.306***	0.300***	0.318***	0.391***	0.164***
	[0.030]	[0.038]	[0.025]	[0.023]	[0.034]	[0.019]	[0.032]	[0.033]
2	0.413***	0.293***	0.303***	0.306***	0.291***	0.299***	0.382***	0.225*
	[0.015]	[0.027]	[0.016]	[0.015]	[0.026]	[0.019]	[0.018]	[0.131]
3	0.403***	0.293***	0.300***	0.304***	0.287***	0.299***	0.378***	0.240*
	[0.013]	[0.027]	[0.014]	[0.014]	[0.027]	[0.021]	[0.018]	[0.132]
4	0.362***	0.271***	0.290***	0.294***	0.267***	0.292***	0.355***	0.122***
	[0.007]	[0.034]	[0.021]	[0.020]	[0.032]	[0.023]	[0.022]	[0.043]
5	0.353***	0.262***	0.297***	0.302***	0.261***	0.277***	0.338***	0.082***
	[0.029]	[0.032]	[0.012]	[0.011]	[0.034]	[0.026]	[0.010]	[0.031]
6	0.324***	0.270***	0.303***	0.308***	0.275***	0.276***	0.332***	0.040***
	[0.021]	[0.023]	[0.008]	[0.007]	[0.023]	[0.025]	[0.013]	[0.015]
7	0.332***	0.265***	0.300***	0.306***	0.274***	0.277***	0.316***	0.072***
	[0.025]	[0.023]	[0.013]	[0.011]	[0.025]	[0.025]	[0.015]	[0.024]
8	0.303***	0.263***	0.303***	0.310***	0.275***	0.268***	0.304***	0.045
	[0.037]	[0.023]	[0.009]	[0.008]	[0.024]	[0.028]	[0.016]	[0.028]
9	0.247***	0.256***	0.299***	0.308***	0.269***	0.263***	0.284***	0.018*
	[0.036]	[0.024]	[0.007]	[0.006]	[0.024]	[0.030]	[0.021]	[0.010]
10	0.246***	0.245***	0.294***	0.303***	0.256***	0.263***	0.264***	0.007
	[0.046]	[0.019]	[0.008]	[0.007]	[0.020]	[0.026]	[0.017]	[0.006]
11	0.248***	0.247***	0.301***	0.308***	0.256***	0.257***	0.256***	0.007
	[0.037]	[0.017]	[0.005]	[0.003]	[0.014]	[0.027]	[0.010]	[0.006]
Observations	209,127	391	391	391	391	391	391	391

This table repeats the analysis of table 2A, replacing the actual number of pessimists in the data with the number calculated from the simulated expectational models and from the Survey of Professional Forecasters. * significant at 10%; ** significant at 5%; *** significant at 1%

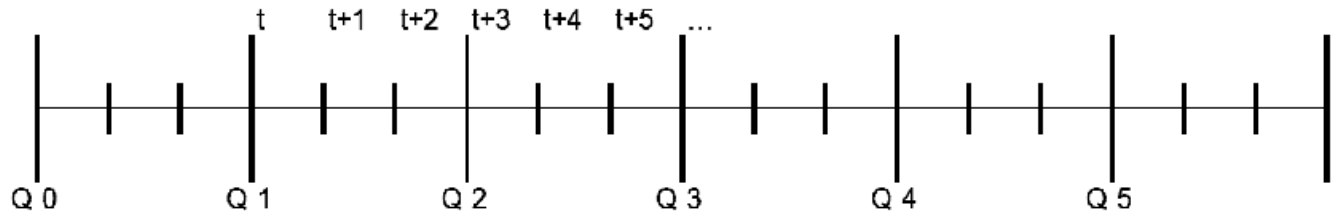
Appendix Table 6A: Simulated Pessimism At Beginning of A Recession

Mos After Unemp. Rises	Pessimist	VarPess	LSLPess	LSL and RT Pess	RealTimePess	DelayPess	ExtrapPess	SPF Pess
0	0.341***	0.380***	0.373***	0.374***	0.384***	0.392***	0.357***	0.497***
	[0.040]	[0.013]	[0.009]	[0.008]	[0.010]	[0.008]	[0.012]	[0.108]
1	0.311***	0.383***	0.374***	0.374***	0.384***	0.394***	0.358***	0.499***
	[0.023]	[0.015]	[0.009]	[0.008]	[0.010]	[0.010]	[0.012]	[0.108]
2	0.312***	0.400***	0.381***	0.381***	0.400***	0.402***	0.380***	0.539***
	[0.040]	[0.010]	[0.013]	[0.012]	[0.008]	[0.007]	[0.009]	[0.092]
3	0.346***	0.417***	0.386***	0.379***	0.396***	0.411***	0.395***	0.599***
	[0.047]	[0.017]	[0.013]	[0.013]	[0.017]	[0.008]	[0.015]	[0.154]
4	0.329***	0.401***	0.382***	0.375***	0.381***	0.409***	0.389***	0.615***
	[0.041]	[0.011]	[0.012]	[0.013]	[0.013]	[0.007]	[0.007]	[0.153]
5	0.399***	0.419***	0.387***	0.380***	0.398***	0.415***	0.406***	0.535***
	[0.059]	[0.020]	[0.017]	[0.017]	[0.019]	[0.009]	[0.018]	[0.087]
6	0.441***	0.405***	0.385***	0.383***	0.404***	0.417***	0.387***	0.632***
	[0.088]	[0.017]	[0.017]	[0.019]	[0.023]	[0.008]	[0.015]	[0.107]
7	0.462***	0.408***	0.387***	0.386***	0.409***	0.419***	0.402***	0.610***
	[0.080]	[0.017]	[0.017]	[0.018]	[0.022]	[0.008]	[0.019]	[0.109]
8	0.391***	0.420***	0.390***	0.389***	0.420***	0.420***	0.410***	0.568***
	[0.072]	[0.018]	[0.020]	[0.021]	[0.023]	[0.008]	[0.019]	[0.087]
9	0.427***	0.421***	0.392***	0.388***	0.417***	0.425***	0.419***	0.539***
	[0.059]	[0.019]	[0.021]	[0.019]	[0.020]	[0.014]	[0.019]	[0.132]
10	0.424***	0.410***	0.389***	0.385***	0.409***	0.423***	0.405***	0.537***
	[0.064]	[0.021]	[0.022]	[0.020]	[0.022]	[0.014]	[0.019]	[0.133]
11	0.465***	0.426***	0.394***	0.391***	0.424***	0.423***	0.417***	0.489***
	[0.057]	[0.025]	[0.025]	[0.023]	[0.024]	[0.015]	[0.025]	[0.143]
Observations	209,127	391	391	391	391	391	391	391

This table repeats the analysis of table 3A, replacing the actual number of pessimists in the data with the number calculated from the simulated expectational models and the Survey of Professional Forecasters. * significant at 10%; ** significant at 5%; *** significant at 1%

A Supplementary Figures and Tables

Figure 1A: Assignment of Expectations



The letter t indexes months and the quarters are marked.

For months t and t+1 I assign the unemployment expectation $E_{Q0}[U_{Q4}] - U_{Q0}$

For month t+2 I assign the unemployment expectation $E_{Q0}[U_{Q5}] - U_{Q1}$