Do Actions Speak Louder Than Words? Household Expectations of Inflation Based on Micro Consumption Data

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Abstract

Survey data on household expectations of inflation are routinely used in economic analysis, yet it is not clear how accurately households are able to articulate their expectations in survey interviews. We propose an alternative approach to recovering households' expectations of inflation from their consumption expenditures. We show that these expectations measures have predictive power for CPI inflation. They are better predictors of CPI inflation than household survey responses and more highly correlated with professional inflation forecasts, except for highly educated consumers, consistent with the view that more educated consumers are better able to articulate their expectations. We also document that households' inflation expectations respond to inflation news, as measured by the unpredictable component of inflation predictions in the survey of professional forecasters. The response to inflation news tends to increase with households' level of education, consistent with the existence of constraints on household's ability to process this information.

JEL Classification Codes: D12, D84, E31.

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1 Introduction

Survey data on household inflation expectations are routinely used in economic analysis (see, e.g., Thomas 1999; Carroll 2003; Mankiw, Reis and Wolfers 2003; Souleles 2004), yet there is reason to be skeptical of the reliability of survey data. We provide evidence that households have difficulty articulating their views about future inflation in response to survey questions. Given this evidence, we propose an alternative approach to measuring household inflation expectations based on household consumption expenditure data. The central idea is that by trading off future consumption against current consumption, households effectively take a stand on inflation expectations, even if they cannot articulate these expectations. Thus, by observing household consumption growth and by assuming that households, controlling for demographic characteristics, on average optimize their consumption decisions, we should be able to construct an implicit measure of households inflation expectations, provided that we are willing to take a stand on the interest rate faced by households, on the functional form of their utility function and on their intertemporal elasticity of substitution. Whether this model-based implicit measure of inflation expectations is a useful alternative to the standard Michigan survey measure is an empirical question to be addressed in this paper.

Our empirical analysis is based on household expenditure data from the Consumer Expenditure Survey (CEX) conducted by the BLS. We construct proxies for household consumption of nondurables and services, building on the work of Lusardi (1996). Based on these data, we construct estimates of consumers' implicit inflation expectations both at the aggregate level and controlling for educational status as a proxy for households' ability to articulate inflation expectations. The estimates we obtain are robust to alternative estimation approaches. We show that qualitatively similar results are obtained whether the inflation expectations are estimated implicitly under the assumption of rational expectations or explicitly based on regression models.

The first question addressed in the paper is whether the implicit measure of household inflation expectations contains useful information about CPI inflation beyond the information conveyed by standard survey measures. As the benchmark, we use the median of the inflation expectations in the Michigan Survey of Consumers. The median is more robust against outliers than the mean, and it has performed well in recent forecast accuracy comparisons. As Ang, Bekaert and Wei (2007) show, the median survey response is more accurate than both term structure models and regression-based forecasts of inflation, making it the most credible competitor of the implicit expectations measure.

One set of results pertains to aggregate measures of inflation without controlling for educational status. We show that the implicit measure of inflation expectations is a slightly more accurate predictor of the realizations of CPI inflation than the Michigan survey expectation of inflation. In the baseline model, the reduction in the root prediction mean-squared error (RPMSE) is 3.4 percentage points whether using quarterly Michigan survey data or Michigan survey data for the last month of the quarter. While these gains in accuracy are not large, they are obtained against the leading alternative of measuring inflation expectations.

The aggregate results provide a useful benchmark, but there is reason to expect consumers' ability to articulate expectations in response to survey questions to be correlated with their educational attainment. A natural conjecture is that the predictive power of the implicit measure of inflation expectations will be stronger relative to the survey measure for consumers with lower levels of education. Such a pattern would be consistent with the view that consumers with less education are less able to articulate the beliefs that they base their consumption decisions on. It would not be consistent with the explanation that households at low levels of education merely lack the information to form accurate inflation expectations (or the ability to process that information) because in the latter case the implicit expectations revealed by households' consumption choices could not be any more accurate than the household survey data.

We show that this conjecture is broadly supported by the data. Our conclusions are based on estimating separate models for each of several levels of education. Specifically, for consumers with at most a high school degree, the reduction in RPMSE from using the implicit measure instead of the median of the quarterly Michigan survey measure for that group of consumers ranges from 5.1 to 5.9 percentage points in the baseline model. For consumers with some college experience, this number drops to 3.3 percentage points. For consumers with a college degree the reduction diminishes to 2.2 percentage points and for consumers with graduate degrees to 1.5 percentage points. Moreover, formal model selection criteria suggest that there is strong statistical evidence that the implicit measure has higher predictive power for CPI inflation than the survey measure for consumers with low levels of education. For all consumers with less than a college degree, the Schwarz Information Criterion (SIC) selects the forecasting model based on the implicit expectations. For consumers with at least a college degree, the ranking is reversed in favor of the Michigan survey measure. Similar results are obtained using Michigan survey data for the last month of the preceding quarter. The RPMSE gains relative to the Michigan survey measure range from 6.2 percentage points for consumers with at most a high school degree and 4.3 percent for consumers with some college experience, to 1.9 percentage points for college graduates. The SIC favors the implicit measure for all but the highest educational group. In addition, we evaluate the correlation of the implicit expectations measures with other expectations measures. The correlation of the implicit measure with the household survey measure is shown to increase in the level of education, again consistent with the view that less educated households are less able to articulate their inflation expectations. Another useful benchmark are professional survey forecasts of inflation. These forecasts can be shown to be more accurate than household survey forecasts. We find that the implicit household expectations measure is more highly correlated with professional inflation forecasts than the household survey measure at all but the highest levels of education. Our results demonstrate that the model-based expectations measure is a reasonable alternative to measures based on household surveys.

An obvious concern is to what extent the predictive information in the implicit measure simply reflects information already contained in lagged inflation. We address this question by testing whether the new implicit measure of inflation expectations proposed in this paper contains useful information about future CPI inflation beyond the information contained in lagged CPI inflation. We confirm that the aggregate measure has marginal predictive value for CPI inflation at the one-quarter horizon, although not as much as the Survey of Professional Forecasters (SPF) or the Michigan survey forecast. Again there are important differences across educational groups. We find that, for all but the highest levels of education, the implicit measure has higher marginal predictive power than the Michigan survey measure (or for that matter a linear combination of both measures).

We conclude that actions indeed speak louder than words, especially for agents with low levels of education. This finding is consistent with the conjecture that only the most highly educated consumers are able to articulate accurately their inflation expectations in response to survey questions. Having controlled for household's inability to articulate inflation expectations by constructing the implicit expectations measure, in the last part of the paper, we use this measure of inflation expectations to assess how households' access to information about inflation or their ability to process news about inflation varies with the level of education. A natural measure of inflation news is the linearly unpredictable component of the inflation forecasts reported in the Survey of Professional Forecasters. A positive innovation to expected inflation should raise households' inflation expectations. Using structural impulse response analysis, we find strong evidence that household inflation expectations are driven by news about inflation, and that the aggregate response has the expected positive sign. If constraints on information or information processing were relatively more important at low levels of education, one would expect that more educated consumers should respond more strongly to inflation news from the Survey of Professional Forecasters. We find evidence supporting that view. Impulse response estimates show that the responsiveness of household expectations to SPF surprises is systematically higher for well-educated households, consistent with economic models that stress the transmission of news as a source of frictions in the macroeconomy (see, e.g., Carroll 2003).

The remainder of the paper is organized as follows. In section 2 we present evidence that casts doubt on the reliability of the Michigan survey measure of inflation expectations and motivates our alternative approach. Section 3 introduces the model of consumption behavior underlying the econometric analysis. We show how that model motivates regressions that allow us to recover households' implicit inflation expectations. The data are described in section 4. Section 5 contains the analysis of implicit inflation expectations at the aggregate level as well as disaggregated by consumers' educational status. Section 6 discusses alternative explicit measures of inflation expectations. In section 7, we assess the evidence for differences in households' ability to obtain or process inflation news. We conclude in section 8 with a discussion of possible alternative explanations of our results.

2 How Reliable are the Michigan Survey Expectations?

Our objective in this paper is to design a new measure of household inflation expectations and to compare its accuracy with that of more conventional inflation expectations measures based on household surveys. This benchmark is not a straw man. Ang, Bekaert and Wei (2007) show that the median of survey expectations of inflation tends to be more accurate than term structure forecasts and regression-based forecasting methods including Phillips curve models. Despite this evidence, there is reason to be skeptical about the accuracy of these household survey expectations, however. For example, it is widely accepted that household inflation expectations, while superior to regression-based forecasts, are inferior to professional inflation forecasts. That observation is also confirmed by our analysis below. Moreover, it is well known that household survey expectations of inflation may differ systematically from actual consumer price inflation rates. For example, Souleles (2004) documents that households tend to make systematic mistakes in forecasting inflation, resulting in inflated RPMSEs.

One possible explanation of this forecast bias is that households are simply not acting rationally, which has prompted tests of the rationality of household inflation expectations (see, e.g., de Menil and Bhalla 1975; Fackler and Stanhouse 1977; Gramlich 1983; Bryan and Gavin 1986; Rich 1989; Grant and Thomas 1999; Mehra 2002; Souleles 2004). Such tests will be biased in favor of rejecting forecast rationality, however, when the loss function used by the econometrician differs from that used by the household, making it difficult to interpret the test results (see Elliott, Komunjer, and Timmermann 2008). Our paper considers an alternative explanation of the bias of survey measures of household inflation forecasts and their lower accuracy compared with professional forecasts. We explore the possibility that some households are unable to communicate accurately their expectations in response to survey questions.

The prima facie evidence for this alternative explanation is strong. The Michigan survey of consumers elicits consumers' inflation expectations in two steps: The first question relates to the direction of future inflation: *'During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?'*. Respondents are then confronted with a more specific question: *'By what percent do you expect prices to go up, on the average, during the next 12 months?'.* The first row of Table 1 shows that on average more than 1% of the respondents to the Michigan survey of consumers are unable to answer the first question. An additional 7% of consumers are able to determine the likely direction of future inflation, but fail to answer the second question because they cannot articulate the expected value of the future inflation rate.

If our alternative explanation were true, one would expect that more highly educated consumers would be better able to articulate their inflation expectations. Indeed Table 1 shows that a systematic decline in the fraction of nonrespondents, as the educational status of the household improves. Whereas 3.12% of the respondents without a high school diploma were completely unable to answer question 1, that fractions falls to 1% for high school graduates, 0.69% for consumers with some college education, 0.67% for respondents with a college degree and 0.66% for respondents with a graduate degree. Similarly, the fraction of respondents who cannot answer the second survey question drops from 16.12% for consumers without high school diplomas, to 7.74% for high school graduates, 5.31% for consumers with some college experience, 4.34% for college graduates and 4.31% for consumers with graduate degrees.

This evidence, although indicative, is likely to understate the problem. It stands to reason that there must be consumers who arbitrarily indicate some range of inflation rather than admit their inability to complete the survey. In addition, there will be respondents who are unable to report their views accurately despite their best intentions. This view is supported by the prevalence of some extreme views of survey respondents that seem at odds with the actual inflation experience over the same sample period. For example, overall, on average 3.2% of respondents expect implausibly high inflation in excess of 15% and an additional 16.1% of respondents on average expect no inflation at all, of which a quarter goes as far as expecting consumer prices to fall. There also are interesting contrasts between households of different levels of education. For example, the fraction of households expecting inflation in excess of 15% rises from 1.2% at the highest level of education to 5.2% at the lowest level.[1] Thus, the reliability of survey data on inflation expectations, especially at low levels of education, cannot be taken for granted. This view is also consistent with evidence that the *RPMSE* of the household survey inflation expectations monotonically improves with the level of education.

Another metric of how sensible the Michigan household survey expectations of inflation are, is their correlation with the inflation forecasts in the Survey of Professional Forecasters, which are consistently more accurate predictors of inflation than household survey measures, as discussed in section 5.2. Table 2 shows that the correlation of the median survey measure of expectations with the professional measure is steadily increasing in the level of educational attainment. It starts at 35% for households with less than a high-school degree, jumps to 62% for households with a high-school degree and 75% for households with some college training. It further rises to 81% for households with a college degree and peaks at 87% for households with graduate degrees. Clearly, the inflation expectations data provided by more educated households are of much higher quality than those obtained from less educated consumers.

The evidence above suggests that Michigan household survey responses about inflation expectations tend to be less accurate at low levels of education than at high levels of education. In this paper we investigate two complementary explanations of

[1] Interestingly, extreme views prevail even at times of low and stable inflation rates. For example, in 1997.II 10.7% of consumers with less than a high school degree expected at least 15% of inflation, when actual CPI inflation was near 1%. Another example is 1984.IV, when actual CPI inflation was near 3%. Nevertheless, a surprising 6.5% of consumers with less than a high school degree expected deflation and 21.7% expected no inflation at all.

this pattern. One is that the low quality of household inflation expectations at low levels of education reflects differences in household's ability to obtain or process information; the other is that this pattern reflects inherent differences in households' ability to articulate their inflation expectations. Clearly, if constraints on households' ability to obtain or process information were the *only* factor that undermines the accuracy of household inflation expectations at low levels of education, the implicit measure of these households' expectations could not be a more accurate predictor of future inflation than their Michigan survey responses. In section 5, we show the implicit measure of these households' inflation expectations tends to be more accurate, so there must be limits to relatively uneducated households' ability to articulate their views in response to survey questions. We also show that the correlation of the implicit measure of inflation expectations with the Michigan survey measure increases with the level of education, consistent with that same interpretation.

This interpretation of course hinges on the credibility of the implicit expectations measure. An alternative explanation of the higher predictive accuracy of the implicit expectations measure in many cases is that our estimates may be contaminated to a certain extent by the use of future real consumption growth (and hence implicitly inflation outcomes) in its construction, notwithstanding the arguments against this explanation discussed in section 5.1. Hence, in section 6, we verify the robustness of our results to alternative estimation approaches that do not rely on ex post realized data. We show that qualitatively similar predictive accuracy results would be obtained if we estimated household inflation expectations explicitly based on lagged observables.

Having controlled for households' inability to articulate their expectations by constructing the implicit expectations measure, we use the implicit measure of expectations in section 7 to assess how households' ability to receive and process news about inflation varies with the level of education. We focus on inflation news in the form of unpredictable shifts in professional inflation forecasts. If information constraints did not matter, we would expect the implicit inflation expectations to exhibit the same response to these news at all levels of education. Alternatively, if they do matter, we would expect households at higher levels of education to be less constrained, resulting in larger responses of the implicit expectations measure.

3 Model

Our starting point is the standard partial equilibrium model of consumption. Suppose that household i maximizes

$$E_0\left(\sum_{t=0}^{\infty}\beta^t u(c_{i,t})\right)$$

with respect to consumption $c_{i,t}$ subject to a sequence of budget constraints where β is a discount factor. The utility function embodies the commonly used assumption of constant relative risk aversion:

$$u(c_{i,t}) \;=\; \frac{1}{1-\rho}c_{i,t}^{1-\rho}\exp(\gamma' x_{i,t}+\eta_i),$$

where $1/\rho$ denotes the intertemporal elasticity of substitution, η_i is a fixed-effect preference shifter and $x_{i,t}$ is a vector of time-varying demographic variables that are assumed to be exogenous. Intertemporal optimization yields the Euler equation:

$$c_{i,t}^{-\rho}e^{\gamma' x_{i,t}+\eta_i} \;=\; \beta E_t\left[(1+r_{t+1})c_{i,t+1}^{-\rho}e^{\gamma' x_{i,t+1}+\eta_i}\right], \tag{1}$$

where r_{t+1} denotes the real interest rate prevailing in period t. The standard linear approximation to the Euler equation yields

$$E_t(\Delta ln c_{i,t+1}) \;=\; \frac{ln\beta}{\rho}+\frac{1}{\rho}E_t(r_{t+1})+\frac{\gamma'}{\rho}\Delta x_{i,t+1}, \tag{2}$$

We make the assumption that $E_t(r_{t+1})$ can be equated with the cross-sectional mean of the households' expectations of the real interest rate, r^e_{t+1}. That assumption would be implied by complete markets, for example, and is also needed to defend the use of linear approximations to the Euler equation. It allows us to estimate $(1/\rho)E_t(r_{t+1})$ by dummy variables.[2] Although we have no reason to suspect that this assumption holds literally, we will proceed as if it does. This approach is consistent with the view that in

[2] For a related approach see Beaudry and van Wincoop (1996).

generating expectations (or forecasts) imposing incorrect structure may still be helpful in reducing out-of-sample prediction errors.

In practice, we will proceed as follows: First we estimate the time dummy coefficients $\{\delta_s\}_{s=1}^T$ in

$$\Delta lnc_{i,t+1} \ = \sum_{s=1}^{T} \delta_s 1(s = t+1) + \gamma' \Delta x_{i,t+1} + u_{i,t+1} \tag{3}$$

by least-squares (LS), where $1(\cdot)$ is an indicator variable chosen such that $1(A) = 1$ if event A is true and $1(A) = 0$ otherwise. The estimates of $\{\delta_s\}_{s=1}^T$ are intended to capture the real interest expectations. In practice, these estimates may be contaminated by aggregate shocks that affect all households equally. That possibility will be addressed in section 5. To facilitate the exposition we will abstract from aggregate shocks for now.

We do not include an intercept in (3) because neither the location nor the scale of the expected real interest rate is identified. The expected real interest rate will be an affine transformation of the estimates of the dummy coefficients. This fact does not affect our subsequent statistical analysis because we are only interested in the linear effects of changes in expectations. Equation (3) can be estimated by LS because there are no endogenous regressors and the regression disturbance is orthogonal to lagged variables. To the extent that there is an omitted moving average (MA) component in the regression error, the LS estimates will be inefficient, but consistent, so the presence of an MA component in the regression error would not impair our analysis.

Given estimates of $\{\delta_s\}_{s=1}^T$, our affine measure of household inflation expectations is defined by

$$\pi^e_{t+1|t} \ = \ i_{t+1} - \rho\widehat{\delta}_{t+1}. \tag{4}$$

where i_{t+1} is the nominal interest faced by consumers in quarter t. This rate can be observed in principle. In the empirical analysis, we follow the convention in the literature of using the 3-month Treasury bill rate. The regressor $\hat{\delta}_{t+1}$ is a generated regressor, the estimation uncertainty of which vanishes as the cross-sectional dimension of the panel increases. This uncertainty can be treated as negligible in practice, allowing standard inference. Given a value for ρ, this relationship implies the date t expectation of inflation from period t to period $t + 1$.

As Carroll (2001) points out, it is not clear how reliable regression estimates of ρ are in general. Many empirical tests of the usefulness of the implicit expectations measure (such as predictive accuracy tests) can be conducted by simply regressing the variable of interest on i_{t+1} and $\hat{\delta}_{t+1}$. The advantage of focusing on unrestricted linear combinations is that one does not require an explicit choice of ρ. Where we do construct an explicit time series for the expectation of inflation in section 7, we will consider a range of alternative values of ρ. One approach to estimating ρ is based on independent survey evidence. Barsky, Kimball, Juster and Shapiro (1997) elicit estimates of the intertemporal elasticity of substitution from households' survey responses to hypothetical situations. The midrange of their elasticity estimates is about 0.2. Since the intertemporal elasticity of substitution is $1/\rho$, this midrange estimate implies $\rho = 5$, which is also consistent with the regression estimates in Hall (1988). Other authors have obtained somewhat lower regression estimates of ρ. For example, Basu and Kimball (2002) arrive at a value of $\rho = 2$. Given the potential imprecision of these estimates, in section 7 we compute results for a grid of values, encompassing estimates implied by independent survey evidence as well as regression estimates. Our qualitative findings are unaffected by the choice of ρ.

4 CEX Data

The estimation of equation (3) requires household data on consumption expenditures. In this paper, we will use expenditure data from the Consumer Expenditure Survey (CEX).[3] We follow Lusardi (1996) in focusing on *consumption of nondurables and services* as defined in the NIPA. That measure includes expenditures on food, alcoholic beverages, tobacco, utilities, personal care, household operations, public trans-

[3]Unlike the Panel Study on Income Dynamics (PSID), the CEX contains not only food consumption data, but also other relevant household consumption expenditures along with the characteristics of the households. The CEX data set contains data from two different types of surveys: an interview survey and a diary survey. We will use the interview survey data only, since the diary survey does not allow construction of time series of expenditures for specific households at quarterly frequency.

portation, gas and motor oil, apparel, health, education, reading, and miscellaneous expenses. Our main empirical results are robust to defining consumption as total expenditures less expenditures on education, medical care and housing. For a similar definition of consumption see Gourinchas and Parker (2002). Qualitatively, similar results would also be obtained based on the definition of *strictly nondurable consumption* in Lusardi (1996).

The estimation period is 1983.QIV-2004.QIV. We discard the observation for 1986.QI due to missing survey data, resulting in a pseudo panel with 83 time series observations after accounting for pre-sample observations. In sections 5, 6, and 7, we will present results at the aggregate level as well as by educational status. The CEX data as well as the quarterly Michigan survey data allow us to assign each survey respondent to one of five educational groups: (1) Less than a High School Degree, (2) High School Graduate, (3) Some College, (4) College Graduate, (5) Graduate School. When comparing our results to Michigan survey data for the last month of the quarter, we are restricted to the groups: (1) At Most High School Degree, (2) Some College, (3) At Least College Degree. We allow for heterogeneity across educational groups by fitting separate regressions for each level of education.

4.1 Household Selection

We classify households based on their consumer unit identification number (NEWID), interview month (QINTRVMO), and interview year (QINTRVYR). Since we are interested in constructing household-level observations for quarterly consumption growth, we only retain households who participated in enough consecutive interviews to allow us to compute their consumption growth for a given quarter. Since the CEX data do not necessarily line up with calendar quarters, it is important to make sure that the consumption growth variables are correctly timed. We drop households with missing data and households with negative or zero total consumption expenditures.

4.2 Controls

In estimating equation (3) we control for the demographic characteristics, x_{it}, of each household. The following data from the Consumer Unit Characteristics and Income (FMLY) file are used as controls: family size (FAM_SIZE), number of males age 16 and over (AS_COMP1), number of females age 16 and over (AS_COMP2), number of males age 2 through 15 (AS_COMP3), number of females age 2 through 15 (AS_COMP4), number of members under 2 (AS_COMP5), number of children less than 18 (PERSLT18), number of persons over 64 (PERSOT64), age of reference person (AGE_REF).

5 Empirical Results: Implicit Expectation Estimates

In the model evaluation exercise, we focus on expectations one quarter ahead. Although in principle our regression approach could be used for longer horizons, the CEX data are not suitable for estimating inflation expectations at horizons longer than one quarter. The reason is that few households remain in the survey for enough consecutive interviews to construct household consumption growth across several quarters. The implicit expectations data have to be matched with the corresponding survey expectations data with careful attention to the timing of each survey. Ideally, we would like the survey expectations to be for the same one-quarter horizon. Among the quarterly inflation forecast data available in the Survey of Professional Forecasters we therefore select the forecast for the one-quarter horizon. In contrast, the Michigan Consumer Survey expectation of inflation, while available quarterly, is recorded for a horizon of one year. No data for the one-quarter horizon are available. We therefore follow the approach of Roberts (1997) of using a suitably scaled version of the survey expectations data as a proxy for the one-quarter ahead expectations. We also present the corresponding results based on Michigan survey data for the last month of the quarter.

The predictions of the Michigan survey, the Survey of Professional Forecasters, and of the implicit expectations measure obtained from the Euler equation are compared with CPI inflation outcomes. Since the CEX consumption data are not seasonally adjusted, we use seasonally unadjusted CPI inflation rates, π_t, for all urban consumers from the Federal Reserve Bank of St. Louis data base, suitably converted to quarterly frequency. Note that an inherent difference between the Michigan survey measure and the Survey of Professional Forecasters is that the Michigan Survey question about inflation expectations does not specifically inquire about consumer price inflation, which may explain in part the superior accuracy of the professional forecasts.

5.1 Model Specification Issues

We begin by addressing some potential concerns regarding the reliability of our implicit expectations measure. One concern is that our expectations measure is based on regressions that implicitly involve ex post realizations of π_{t+1}. Since real consumption growth is constructed as the log difference of nominal consumption growth and consumer price inflation, in the limiting case, if nominal consumption growth were constant, all the variation in the regressand would be due to changes in future inflation. In that situation, one would expect the time dummy regressors to mimic the variation in future inflation by construction, overstating their true predictive accuracy. While nominal consumption growth is not constant in practice, lack of variation in nominal consumption growth would still undermine the credibility of our expectations measure. There are three points that can be made in defense of our approach. First, the standard deviation of the time series of cross-sectional averages of nominal consumption growth adjusted for demographics is more than seven times larger than that of consumer price inflation over the same period. Whereas the former standard deviation is 0.0385, the latter is only 0.0053.[4] Second, if our expectations measure were simply picking up variation in future CPI inflation, its time series properties should be the same across educational groups rather than varying systematically with educational status, as our evidence below suggests. Moreover, in section 7, we show that the implicit expectations

[4] See Slesnick (1992) for a comparison of the CEX consumer expenditures data with the aggregate consumption data in the National Income and Product Accounts (NIPA).

respond differently to inflation news at different levels of education in ways that are economically interpretable. Third, as discussed in section 6, similar improvements in predictive accuracy may be obtained using panel regressions on lagged observables to estimate household inflation expectations. The latter approach is not without its own shortcomings, however, so the results are best viewed as complementary.

A second concern is that our econometric model does not allow us to distinguish between aggregate shocks that affect consumption across all households on the one hand and shifts in real interest rate expectations on the other. Both would be picked up by the time dummies. This point has been discussed by Deaton (1992, pp. 146-148) and Mariger and Shaw (1993), among others. We address this concern by constructing proxies for aggregate shocks and removing their effect on the estimated time dummies. More formally, if the aggregate shocks enter additively, we can decompose the error term in equation (3)

$$u_{i,t+1} = a_{t+1} + \varepsilon_{it+1}$$

into an aggregate component (a_{t+1}) and an idiosyncratic component (ε_{it+1}), where the aggregate component a_{t+1} may be thought of as a weighted average of j aggregate shocks. The aggregate shocks are proxied for by forecast errors constructed from linear autoregressions for observable real variables that are likely to impact consumption:

$$a_{t+1} = \sum_j \alpha_j (y_{j,t+1} - y_{j,t+1|t})$$

This model suggests that we regress $\widehat{\delta}_{t+1}$ on a constant and a_{t+1} and define the real interest rate expectation as the residual of that regression, denoted by $\widetilde{\delta}_{t+1}$. In practice, we include five proxies for aggregate shocks: the commonly used net increase measure of real oil price shocks (see Hamilton 2003; Kilian 2008) and forecast errors from autoregressive models of real S&P500 stock returns, real disposable income growth, the Chicago Fed principal components index of real economic activity ($CFNAI$), and the real 3-month Treasury bill rate obtained by subtracting CPI inflation from the nominal rate. The real oil price shock variable is based on data in Kilian

(2008). The CFNAI business cycle index is available at http://www.chicagofed.org/economic_research_and_data/cfnai.cfm. The data on real disposable personal income growth are from the BEA. The S&P500 index series has been deflated by the CPI. The lag orders of the forecasting models are selected based on the SIC (see Inoue and Kilian 2006). The SIC suggests a random walk model for real stock returns, AR(1) models for real disposable income growth and for the $CFNAI$, and an AR(4) model for the real Treasury bill rate. No model is needed for the real oil price shock series. All shock measures considered are in real terms, as consumers would not be expected to respond to nominal shocks, unless these shocks are reflected in unanticipated changes in real variables.

Table 3 shows that in the baseline model these variables jointly account for about 20% of the variation in the aggregate $\widehat{\delta}_{t+1}$. At the disaggregate level, the R^2 ranges from 8% to 18%. Table 3 also shows ordinary LS point estimates for each aggregate shock and standard errors that account for the generated regressor problem (see Newey and McFadden 1994, pp. 2182-2184). Note that the α_j parameters are estimated separately for each educational group, allowing aggregate shocks to affect each group differently. The distinction between $\widetilde{\delta}_{t+1}$ and $\widehat{\delta}_{t+1}$ matters. In general, controlling for aggregate shocks lowers the predictive power of the implicit measure of expectations in the regression models reported in section 5. In the remainder of the paper we therefore employ $\widetilde{\delta}_{t+1}$ rather than $\widehat{\delta}_{t+1}$ as our measure of real interest rate expectations.

Our baseline specification will be appropriate if the permanent income hypothesis holds. We also considered the possibility that households' consumption growth may be related to household income growth, as would be expected in the presence of liquidity constraints. The standard response to this problem has been to find a proxy for household income growth to be included as an additional regressor in the linearized Euler equation. Given the well-known limitations of the CEX income data, the conventional approach has been to impute CEX household income growth data from PSID data. Of course, the households contained in those two surveys differ and the actual income growth for household i in period t in the CEX survey is not observable. Hence, it is common to substitute the conditional expectation of a given household's income growth, controlling for the demographic characteristics of the household in question (see, e.g. Lusardi 1996). There is no obvious alternative to this approach when testing whether consumption growth is sensitive to income growth as in Lusardi (1996). In our context, it is not necessary to appeal to such approximations. Income growth consists of an aggregate component that is common to all households and an idiosyncratic component specific to each household. Since we average across households in constructing the implicit expectations measure, idiosyncratic variation in income growth will average out by construction and need not be modelled. Aggregate income growth, however, is readily observable and can be explicitly controlled for when constructing $\widetilde{\delta}_{t+1}$. We therefore also estimated the baseline model with NIPA income growth included among the controls in constructing $\widetilde{\delta}_{t+1}$. While this first robustness check allows for the model coefficients to differ by educational level, it abstracts from differences in income growth rates across educational groups. Hence, we conducted a further robustness check based on measures of the growth of average household income in the CEX data constructed for each level of educational attainment and for the full sample.

Another implicit assumption in the baseline specification is that household preferences are separable in consumption and leisure. Without separability, the right-hand side of equation (2) would include expected hours growth as an additional term. We address this possibility by augmenting the baseline model with hours growth.[5] Finally, we considered liquidity constraints and nonseparable preferences in conjunction, resulting in a total of six alternative models to be considered.

5.2 Predictive Power for CPI Inflation

5.2.1 Overall Predictive Power

Aggregate Results: Baseline Model A simple first test of the ability of alternative expectations measures to explain future CPI inflation is provided in Table 4. Column 1 focuses on the RPMSE of predictive regressions of CPI inflation on a constant and the expectations measure for the same quarter. For the Michigan survey

[5] The data for quarterly hours growth were constructed from a seasonally adjusted monthly index of aggregate weekly hours obtained from nonfarm payrolls.

measure we report the RPMSE of the regression

$$\pi_{t+1} = \alpha_0 + \alpha_1 Michigan_{t+1|t} + v_{t+1}. \tag{5}$$

where $Michigan_{t+1|t}$ denotes the median survey expectation of inflation reported in the Michigan Survey of Consumers as of quarter t. We also experimented with imposing the restrictions that $\alpha_0 = 0$ (unbiasedness) and $\alpha_1 = 1$ (proportionality). These results are not reported because using these restrictions (one at a time or in conjunction) did not systematically improve the RPMSE of the Michigan survey measure and in several cases raised it compared to the unrestricted model. For the implicit expectations measure we report the RPMSE of the regression

$$\pi_{t+1} = \alpha_0 + \alpha_1 i_{t+1} + \alpha_2 \widetilde{\delta}_{t+1} + v_{t+1} \tag{6}$$

where we do not impose any restrictions on α_0, α_1 and α_2. The advantage of this regression is that we can assess the predictive accuracy of the implicit expectations measure without taking a stand on the value of ρ. Whereas the magnitude of α_1 and α_2 has no intrinsic meaning, the sign does. We find that all our estimates have a positive sign for the nominal interest rate coefficient and a negative sign for $\widetilde{\delta}_{t+1}$, as would be expected.

All RPMSE results in Table 4 are presented as ratios that normalize the RPMSE of the implicit expectations measure relative to that of the Michigan survey measure. A ratio below unity indicates that the implicit inflation expectation measure is a more accurate predictor of actual CPI inflation than the median of the Michigan survey measure. Table 4 shows an improvement in the RPMSE by 3.4 percentage points in the baseline model. While this gain in accuracy is not large and not statistically significant, it is obtained relative to a measure of inflation expectations that has been shown to dominate a wide range of alternative predictors.[6]

[6] The statistical significance of the RPMSE gains in table 4 was assessed using a variation of the test proposed in Diebold and Mariano (1995). That test does not allow us to reject the Michigan survey measure in favor of the implicit expectations measure or, for that matter, the implicit expectations measure in favor of the Michigan survey measure.

The reduction in the RPMSE does not necessarily mean that the implicit expectations measure can be expected to be a better predictor out-of-sample because the regression model (6) contains one more regressor than model (5). A common approach to choosing between competing forecasting models is to rank models by an information criterion that involves a penalty term for parameter profligacy. As shown in Inoue and Kilian (2006), under weak assumptions the Schwarz Information Criterion (SIC) will consistently select the best out-of-sample forecasting model among any finite set of nested or nonnested models.[7] This property is not shared by alternative methods of ranking forecasting models such as the recursive RPMSE criterion. Moreover, the recursive method can be shown to be asymptotically equivalent to the Akaike Information Criterion (AIC). Since the SIC favors more parsimonious models than the AIC, our approach biases the results in favor of the Michigan survey. The lower the SIC value, the more accurate is the forecasting model expected to be out-of-sample. Table 4 shows that the implicit expectations measure has a strictly lower SIC value (-10.456) than the Michigan survey measure (-10.439), despite the greater parsimony of the latter forecasting model. That conclusion is robust to imposing unbiasedness and/or proportionality restrictions on equation (5). It is worth pointing out that neither the implicit measure nor the Michigan household survey measure of inflation expectations is as accurate as the Survey of Professional Forecasters whose SIC value is -10.504. This result is consistent with the view that professionals are better at predicting inflation than households.

Although evaluations of predictive accuracy provide a stringent test of the validity of the proposed measure of household inflation expectations, note that we do not advocate the use of these expectations measures for real-time forecasting. Not only are the CEX data available only with a considerable delay, but our expectations measure is based on data for $c_{i,t+1}$ and $x_{i,t+1}$that are not available at date t. Rather the point is to show ex post what household expectations at that point in time must have been, given households' consumption choices. The type of expectations measure constructed in this

[7] An exception is the comparison of two nonnested regression models with different degrees of parsimony, but exactly identical PMSEs in population. For further discussion see Inoue and Kilian (2006). We abstract from this possibility which seems remote in practice.

paper is useful for studying the expectations formation of households. Evaluations of predictive performance simply provide a useful check on the realism of the implications of our model-based approach to measuring expectations.

Results by Educational Status: Baseline Model While the aggregate results in the first row of Table 4 provide a useful benchmark, the consumers' educational attainment can be expected to be correlated with their ability to articulate accurately their expectations in response to survey questions. A natural conjecture is that the predictive power of the implicit measure of inflation expectations will be stronger relative to the survey measure for consumers with lower levels of education. Such a pattern would be consistent with the view that consumers with less education are less able to articulate the beliefs that they base their consumption decisions on.

Both the Michigan survey expectations data and the CEX consumption data are recorded separately for each of the five educational groups listed at the beginning of this section. This allows us to use our model-based approach to construct measures of expected inflation for each educational group and to compare these implicit inflation expectations to the Michigan survey expectation for the same educational group. The remaining results shown in Table 4 have been obtained by re-estimating all regressions separately for each educational group, thus controlling for possible heterogeneity across groups.

The first column shows the reductions in RPMSEs from using the implicit expectations measure by educational status. We find that the greatest gains tend to accrue at lower levels of education, consistent with the view that consumers with low educational attainment are unable to articulate their expectations, allowing even crude proxies based on their consumption choices to improve forecast accuracy. The implicit expectations cannot improve on the accuracy of the median survey response for highly educated consumers with no difficulty in accurately responding to survey questions. Table 4 shows a reduction of between 5.1% and 5.9% in RPMSE for consumers without college experience; these gains shrink to 3.3% for households with some college training, to 2.2% for college graduates and to 1.5% for consumers with a graduate degree. The SIC ranking favors the implicit measure for all consumers but those with at least a college degree.

Another way of judging the improved accuracy of the implicit expectations measure is to focus on its correlation with inflation outcomes. For the full sample, that correlation is 30% (compared with 23% for the Michigan survey measure). The implicit measure has higher correlations with inflation outcomes for all households but those with a graduate degree. The relative gains in fit are highest at low levels of education and monotonically decline with rising levels of education. For high levels of education, the correlations are quite similar.

Results for Alternative Regression Specifications Table 4 also provides the corresponding results for five alternative regression specifications that allow for liquidity constraints and nonseparable utility functions. Allowing for income growth or hours growth to enter as an additional regressor in the construction of $\widetilde{\delta}_{t+1}$ (or for that matter allowing both income growth and hours growth to enter) produces no change in the qualitative patterns of results and only very minor quantitative changes. Hence, for the remainder of the paper we focus on the results from the baseline model, noting that qualitatively similar results would be obtained with any of these alternative specifications.

5.2.2 Correlation with Survey Measures

Whereas so far we have focused on the ability of the implicit expectations measure to improve on the accuracy of the Michigan survey measure as a predictor of inflation outcomes, an alternative metric for evaluating the fit of the model is provided by the correlation of the implicit measure of inflation expectations with other expectations measures. A direct implication of our hypothesis that households become increasingly more articulate with higher levels of education is that the implicit expectations measure should be more highly correlated with the Michigan survey measure at high levels of education than at low levels. The first column of Table 5 supports this hypothesis. Whereas the correlation is only 30% for households with less than a high school degree, it rises to 42% for households with a high school degree, 55% for households with some college, 64% for households with a college degree and 69% for households with graduate training.

Moreover, the second and third column of Table 5 show that at low levels of education the implicit measure is much more highly correlated with the expert forecasts in the Survey of Professional Forecasters than the Michigan survey measure. For example, for households without a high school degree the correlation is 78% using the implicit expectations measure rather than 35% using the Michigan survey. In contrast, for households with at least a college degree, the implicit measure is less highly correlated with the Survey of Professional Forecasters than the Michigan survey expectations. This evidence is consistent with the view that it is not access to information (or the inability to process that information) that undermines the accuracy of the Michigan survey forecasts at low levels of education but rather the inability of households to articulate their views. Extracting this information is not costless, as the structural economic model we use in estimating these household expectations involves many approximations and noisy estimates. Thus one would not expect our approach to work well when the Michigan survey expectations are already quite accurate, as for highly educated consumers. In fact, one would expect our estimates to be inferior to model-free measures of expectations. At low levels of education, however, the Michigan survey forecasts are so poor that approximation error and estimation noise become a secondary concern.

5.2.3 Marginal Predictive Power

Aggregate Results The *SIC* results in Table 4 constitute strong evidence that even a crude version of our model-based approach to inferring inflation expectations is useful as a predictor of CPI inflation at the quarterly horizon. A closely related question is whether the new implicit measure of inflation expectations proposed in this paper contains useful information about future CPI inflation beyond the information contained in lagged CPI inflation (and for that matter beyond the information already contained in other expectations measures). Table 6a summarizes the results of several alternative predictive regressions. The dependent variable is always one-quarter-ahead CPI inflation, π_{t+1}. The baseline model is:

$$\pi_{t+1} = \alpha_0 + \alpha_1 \pi_t + v_{t+1}. \tag{7}$$

In addition, we consider models with the following sets of additional regressors involving expectations as of date t:

$$\begin{aligned}
\pi_{t+1} &= \alpha_0 + \alpha_1 \pi_t + \alpha_2 SPF_{t+1|t} + v_{t+1} && (8)\\
\pi_{t+1} &= \alpha_0 + \alpha_1 \pi_t + \alpha_2 Michigan_{t+1|t} + v_{t+1} && (9)\\
\pi_{t+1} &= \alpha_0 + \alpha_1 \pi_t + \alpha_2 i_{t+1} + \alpha_3 \widetilde{\delta}_{t+1} + v_{t+1} && (10)\\
\pi_{t+1} &= \alpha_0 + \alpha_1 \pi_t + \alpha_2 SPF_{t+1|t} + \alpha_3 Michigan_{t+1|t} + v_{t+1} && (11)\\
\pi_{t+1} &= \alpha_0 + \alpha_1 \pi_t + \alpha_2 SPF_{t+1|t} + \alpha_3 i_{t+1} + \alpha_4 \widetilde{\delta}_{t+1} + v_{t+1} && (12)\\
\pi_{t+1} &= \alpha_0 + \alpha_1 \pi_t + \alpha_2 Michigan_{t+1|t} + \alpha_3 i_{t+1} + \alpha_4 \widetilde{\delta}_{t+1} + v_{t+1}, && (13)
\end{aligned}$$

where $SPF_{t+1|t}$ denotes the inflation forecast from the Survey of Professional Forecasters, available from the Philadelphia Fed, and $Michigan_{t+1|t}$ denotes the median survey expectation of inflation reported in the Michigan Survey of Consumers. The predictive value of each of the two survey measures can be assessed by a one-sided t-test. The predictive value of the implicit expectations measure can be tested by conducting a Wald test of the null hypothesis that the regression coefficients of $\widetilde{\delta}_{t+1}$ and i_{t+1} are both zero. Note that this test does not require us to take a stand on the value of ρ. The results of this Wald test will be reported in Tables 6a under the column label *Implicit*. p-values based on suitable standard error estimates that account for the generated regressor problem and possible heteroskedasticity are reported in parentheses.

For all regressions in Table 6a the Breusch-Godfrey (BG) test results are consistent with the absence of serial correlation in the regression error. This is true in particular for the lagged inflation-only benchmark model.[8] While we do not show individual

[8] Alternatively, one could use the SIC with an upper bound of 5 lags to select the lag order of the AR

regression estimates for i_{t+1} and $\widetilde{\delta}_{t+1}$, we note that in all cases the estimate of the nominal interest rate coefficient is positive and that of $\widetilde{\delta}_{t+1}$ is negative. Table 6a shows that the implicit measure of inflation expectations is highly significant, as are the Michigan survey measure and the SPF measure. These test results establish conclusively the marginal predictive content of our expectations measure for CPI inflation at the 5% level. The individual statistical significance of the implicit measure is lost, when the implicit measure is combined in the same regression with the Michigan survey measure or with the SPF measure. The same is true for the Michigan survey measure when it is combined with other measures. In contrast, the SPF measure remains significant at the 5% level when combined with other predictors.

Even if there is evidence that expectations measures help predict CPI inflation in population relative to models including only lagged CPI inflation, the existence of predictability in population does not guarantee that these regressors also have predictive value out-of-sample. We again assess the out-of-sample predictive power of each regression based on the SIC. The lower the value of the SIC, the higher the predictive power of the regression model for CPI inflation. Table 6a shows that both household expectations measures improve on models with lagged inflation only (-10.394). Adding the implicit inflation expectations raises the predictive power of the forecasting model (-10.446) as does adding the Michigan survey measure of inflation expectations (-10.456) or adding the SPF forecast (-10.508). The relative gain is greatest with the SPF measure, a fact that (in conjunction with the superior unconditional predictive ability of the SPF discussed in the context of Table 4) will help motivate the impulse response analysis further below. Unlike in Table 4, the Michigan survey measure ranks ahead of the implicit measure when combined with lagged inflation. Combinations of SPF and the Michigan measure have essentially the same SIC value as the Michigan survey measure alone. There are no gains from combining the implicit measure with

benchmark model for inflation. The upper bound of 5 is implied by the seasonal-multiplicative model of Box, Jenkins and Reinsel (1994) for quarterly data. The SIC selects a lag order of zero, which is consistent with the fact that the first-order lag of inflation in Table 6a is not statistically different from zero. We nevertheless include the first lag of inflation in the inflation-only benchmark model in Table 6a since we are interested in the marginal predictive ability of the expectations measures. If we dropped this lag, we would revert to the unconditional results in the top panel of Table 4.

either of the other measures.

Results by Educational Status Table 6b studies the marginal predictive content of alternative household expectations measures by educational group. There is no evidence of serial correlation with the exception of a marginal rejection at the 10% level for one of the models for consumers with graduate degrees. As in the aggregate analysis, the implicit expectations predictor individually is highly significant for each educational group. So is the Michigan survey measure with the exception of consumers without a high school degree. Combining both measures results in both predictors being insignificant at low levels of education; at higher levels of education the Michigan survey measure tends to retain its statistical significance, whereas the implicit measure does not.

Based on the SIC, the implicit measure has higher out-of-sample predictive power for CPI inflation than the Michigan survey measure for all consumers who have not earned at least a college degree. For each of these groups, the SIC favors the implicit measure. For consumers with higher education, the SIC ranking is reversed in favor of the survey measure. Specifically, for college and university graduates the Michigan survey measure is the more accurate marginal predictor. This evidence once again confirms the potential for implicit expectations measures to measure more accurately the inflation expectations of relatively uneducated consumers who have difficulty articulating their inflation expectations. Combinations of expectations measures are generally suboptimal predictors, reflecting the unfavorable bias-variance trade-off, although for the lowest levels of education they still are more accurate than using the Michigan survey alone.

5.3 Sensitivity Analysis: How Important is the Timing of the Michigan Survey Data?

The Michigan survey in addition to quarterly data also includes data for the last month of each quarter. These data have advantages as well as disadvantages compared with the quarterly data we used for the baseline analysis. The disadvantage is that the monthly expectations data provided by the Michigan survey offer less detailed information about consumers' educational status. The breakdown available is: (1) at most a high school degree, (2) some college experience, or (3) at least a college degree. The advantage of monthly data is that the last month of the preceding quarter is likely to be a more accurate measure of the household inflation expectations for the current quarter than the quarterly Michigan survey data.

The predictive analysis using these alternative data yields results broadly similar to those reported in Tables 4 and 6. Starting with the direct comparison of the Michigan survey measure and the implicit measure in Table 7, we find that the implicit measure reduces the RPMSE ratio by 3.4 percentage points in the aggregate. For consumers with at most a high school degree, the estimated reduction is 6.2 percentage points, for consumers with some college training 4.3 percentage points and for the most educated 1.9 percentage points. Like in Table 4, the SIC ranks the implicit measure ahead of the Michigan survey measure for the aggregate and for all educational groups but consumers with at least a college degree. Table 8a shows that the implicit measure based on aggregate data has marginal predictive power over and above the information contained in lagged inflation, but less so than the survey-based measures. This result mirrors the evidence in Table 6a. Broken down by educational status in Table 8b, the implicit measure is preferred to the Michigan survey forecast for all groups but consumers with at least a college degree, consistent with the results in Table 6b. We conclude that our results are robust to the timing of the Michigan survey data.

6 Empirical Results: Explicit Expectations Estimates

As discussed in section 5, one potential concern with the estimates of households' implicit expectations is that we use future real consumption growth (and hence implicitly inflation outcomes) in their construction. Although we already presented several arguments that the degree of contamination from the implicit use of inflation outcomes is likely to be small, it is useful to verify the robustness of our results to alternative estimation approaches that do not reply on ex post realized data. This section shows that qualitatively similar results would be obtained if we estimated household inflation expectations explicitly.

The proposal is to estimate first the regression

$$\Delta c_{i,t+1} \; = \; \beta_0 + \beta' z_t + \gamma' \Delta x_{i,t+1} + v_{i,t+1}, \tag{14}$$

where z_t is a vector of time t macroeconomic variables used in Table 3: real disposable personal income growth, CFNAI, real S&P500 returns, real T-bill rate and real oil price shock. Since $E_t\left(r_{t+1}\right) \propto \beta' z_t$, an affine transformation of the real interest rate expectation may be constructed as

$$\tilde{\delta}_{t+1} \; = \; \hat{\beta}' z_t,$$

where $\hat{\beta}$ is the least-squares estimate of β in equation (14). We do not attempt to estimate β recursively since we are not interested in real time inflation forecasting, but in the best possible ex-post estimate of this parameter. Moreover, we would not expect recursive estimates to be reliable given the small sample size.

It might have seemed natural to include $\Delta c_{i,t}$ in generating predictions of household consumption growth. This is not feasible for two reasons. First, in the presence of fixed effects, η_i, of the type postulated in our theoretical model, the estimator of panel models in first differences is consistent only in the absence of lagged dependent variables in the regression model. While this problem could potentially be overcome with instrumental variable estimators, the use of lagged individual data as instruments would reduce our panel sample size to the point of making this exercise uninteresting. Second, as discussed earlier, unlike the demographic information in the CEX survey, individual consumption growth data are highly variable and likely to suffer from severe measurement error. That measurement error will bias the regression estimates and raise or lower the RPMSE in ways that are unpredictable. For that reason we only include demographic characteristics and aggregate predictors.

The first two panels of Table 9 contrast the predictive accuracy of the explicit expectations estimates with that of survey data for the last quarter and for the last month of the quarter. The results are reassuring in that the qualitative pattern of results matches exactly the results in Tables 4 and 7. So do the results for marginal predictive content by level of education (not shown to conserve space). In addition, the correlation of the explicit expectations measure with the Michigan survey is increasing in the level of education, as was the case for the implicit measure, and it is more highly correlated with the survey of professional forecasters than the Michigan survey for low levels of education, consistent with the earlier results.

One concern with explicit expectations estimates that does not arise in the estimation of implicit expectations measures is that households may not have access to the predictors in z_t in real time. If so, the results in the first two panels of Table 9 may overstate households ability to predict inflation. Indeed, although the qualitative pattern is similar, the RPMSE reductions reported in Table 9 are much larger than in Table 4. While the construction of a real-time data set for z_t is beyond the scope of this paper, we can construct a crude proxy for $z_t^{\text{real}\,time}$as follows: We postulate that only lagged values of growth in real disposable income and of the real oil price shock are known in real time. Nominal interest rates and stock returns are available in real time. In proxying real returns and interest rates at date t, we postulate that households rely on last period's inflation rate. Finally, for the CFNAI index, the publication lag is one month, which suggests using last month's indicator instead. After replacing z_t by this proxy for $z_t^{\text{real}\,time}$ in the regression model above, we obtain the results in the last two panels of Table 9. As expected, the magnitudes of the RPMSE gains are now more similar to those reported in Tables 4 and 7. Although the RPMSE ranking is not quite monotonic, it shows systematic differences between low and high levels of education, consistent with the earlier results, and the SIC ranking is the same as in Tables 4 and 7. Moreover, the results for marginal predictive content are qualitatively unchanged when using real-time data, as are the correlation patterns. While the results using real-time data are necessarily tentative, we conclude that our main qualitative results are robust to whether inflation expectations are estimated implicitly from realized data under the assumption of rational expectations or explicitly using regressions on observable lagged data.

This does not mean that implicit and explicit expectations measures are highly correlated. In fact, based on the real-time data results, their full-sample correlation is only 38% Clearly, parametric estimates of household expectations are potentially highly sensitive to the omission of relevant predictors, be it at the household or the aggregate level. We know very little about how households form inflation expectations. For that reason, we prefer the nonparametric approach underlying the implicit expectations measures developed in section 5. The results in this section merely serve to illustrate the plausibility of the improved predictive accuracy from using CEX household expenditures we documented in section 5.

7 The Response of Household Inflation Expectations to Inflation News

7.1 Aggregate Results

Having controlled for household's inability to articulate inflation expectations by constructing the implicit expectations measure, in this section we use this measure of inflation expectations to assess how households' access to information about inflation or their ability to process news about inflation varies with the level of education. Very similar results would be obtained with the real-time measure of explicit expectations discussed in section 6. As our analysis in Table 6a demonstrated, SPF forecasts of inflation contain additional information beyond household expectations data. This result suggests that we treat linearly unpredictable changes in SPF forecasts of inflation as a proxy for news about future inflation. One would expect that a surprise increase in professional forecasts of inflation would induce consumers to raise their expectations as well. This question may be addressed in the context of a trivariate vector autoregressive (VAR) model with intercept for professional forecasts of inflation ($SPF_{t+1|t}$), the nominal interest rate (i_{t+1}) and households' real interest rate expectations ($\widetilde{\delta}_{t+1}$). Note that i_{t+1} is assumed to be observed at the beginning of period t. In other words, households form real interest rate expectations $\hat{\delta}_{t+1}$, having observed i_{t+1}. In contrast, SPF forecasts for $t+1$ are formed before i_{t+1} is set (reflecting their release date in the middle of the preceding quarter). The lag order of the VAR is set to one.

By our timing conventions, SPF forecasts cannot respond to innovations in i_{t+1} within the quarter. In addition, we make the following identifying assumptions: First, we impose the assumption that SPF forecasts of inflation do not respond within the same quarter to innovations in household expectations of inflation. Given the delayed availability of CEX data, this assumption seems reasonable. Our second identifying assumption is that i_{t+1} does not respond to $\widetilde{\delta}_{t+1}$ within the same quarter, which again may be motivated by the delayed availability of the CEX data. Third, we impose the assumption that the implicit household expectations do not respond to SPF innovations within the same quarter. This assumption is less obvious since SPF forecasts are released in the middle of the second month of each quarter, leaving households some time to adjust consumption.

Our identifying assumptions thus can be summarized as follows. Let ε_t denote the vector of structural innovations of the VAR model. Then, suppressing the lagged regressors, the structural VAR model may be written as:

$$\begin{pmatrix} SPF_{t+1|t} \\ i_{t+1} \\ \widetilde{\delta}_{t+1} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ 0 & a_{32} & a_{33} \end{bmatrix} \times \begin{pmatrix} \varepsilon_t^{SPF} \\ \varepsilon_t^{i} \\ \varepsilon_t^{\delta} \end{pmatrix} + \ ... \tag{15}$$

where a_{ij} denotes parameters in the impact multiplier matrix that are to be estimated. The overidentifying restriction that $a_{31} = 0$ can be tested. A J-test of this restriction does not reject at conventional significance levels.

Given the responses of i_{t+1} and $\widetilde{\delta}_{t+1}$, equation (3) allows us to construct the implied responses of the implicit inflation expectations to a one-standard deviation surprise increase in the SPF forecast of inflation for any choice of ρ. We consider values of $\rho \epsilon \{1, 2, 5\}$. The overall shape of the response is unaffected by the choice of ρ. The main difference is in the scale of the response, which is of little interest here. We therefore impose $\rho = 2$ in the results shown below. A natural question is whether inflation expectations respond to SPF news. The answer is affirmative. The left panel of Figure 1 shows a sharp peak in the response of aggregate inflation expectations after one quarter, followed by decline that gradually levels off. This evidence is consistent with the view that households adjust their expectations in response to inflation news.

7.2 Results by Educational Status

By analogy to the aggregate analysis, we can compute the effect of innovations to the SPF forecast of inflation on household inflation expectations for each educational group. A natural conjecture is that the degree of adjustment in response to news about inflation should increase with the level of education. Such a pattern would arise if households with low levels of education lacked access to information about inflation or (more plausibly) were less capable of processing that information. By using the implicit expectations measure we are able to test this hypothesis separately from the question of households' ability to articulate their inflation expectations.

The second panel of Figure 1 broadly confirms this hypothesis. We again focus on the results for $\rho = 2$, noting that our qualitative results are robust to alternative choices of ρ. There is a distinct difference between the responses for consumers with a college degree or a graduate degree on the one hand and consumers without a college degree on the other. All responses peak in quarter 1, but the responses of consumers without a college degree are much smaller than for consumers with university degrees. Consumers with a a college degree respond almost three times as much after one quarter as consumers with only some college experience. Consumers with graduate degrees respond almost six times as much as consumers with only some college experience. Since we expect that agents with better education are better able to process news about inflation, this differential response is consistent with models that stress the transmission of news as an important source of frictions in the macroeconomy.

While these differences seem large, it is unclear to what extent they merely reflect sampling error. Given the generated regressor nature of the $\widetilde{\delta}_{t+1}$ and the high persistence of i_{t+1}, it is not straightforward to compute confidence intervals for the responses in Figure 1. One way of reducing sampling error is to aggregate across educational groups. The last panel of Figure 1 shows analogous results for consumers with at most a high school degree, for consumers with some college experience, and for consumers with at least a college degree. The response for consumers with at least a college degree is more than three times as large as the response of consumers without a college degree. In contrast, the difference between the responses of households without a college degrees is minor. We conclude that there is robust evidence that consumers with lower levels of education do not incorporate news about future inflation to the same extent as highly educated consumers. This fact is supportive of models that stress the transmission of news as a source of frictions in the macroeconomy (see, e.g., Carroll 2003).

8 Conclusion

We developed a new methodology for measuring household inflation expectations that does not rely on households' ability to communicate their inflation expectations accurately. Rather than using survey data on inflation expectations, we relied on survey data on CEX consumer expenditures. With the help of economic theory, we inferred households' inflation expectations from their consumption choices. Our evidence showed that this approach can provide an effective tool for measuring household inflation expectations, at least for households with low levels of education. The expectations data we derived complement existing measures of inflation expectations from the Michigan Survey of Consumers. We showed that this new expectations measure contains useful information about future CPI inflation beyond the information contained in current inflation or in consumer survey measures. This finding is remarkable in that the latter survey measures have been shown in the literature to be more accurate than term structure models as well as regression based forecasts. Our results are qualitatively robust to estimating these expectations from realized data under the assumption of rational expectations or estimating them explicitly from regressions on lagged observables.

We conclude that actions indeed may speak louder than words. The gains in accuracy compared with median inflation expectations in the Michigan Survey of Consumers were more pronounced for consumers with low levels of education, but tended to vanish for consumers with high levels of education. This result is consistent with the conjecture that only the most highly educated consumers are able to articulate accurately their inflation expectations in response to survey questions. Moreover, the higher the level of education, the higher the positive correlation between the implicit expectations and the household survey expectations. We also showed that the implicit measure is more highly correlated with professional inflation forecasts than the household survey measure, except for households with the highest levels of education.

It may seem that the pattern of results we present could simply arise from unobserved differences across educational groups, for example, in the composition of the consumption baskets or in household preferences. Neither of these conjectures is plausible. The first alternative explanation is based on the premise that the consumption basket underlying the CPI inflation measure is more representative of the consumption patterns of highly educated (and typically wealthier) consumers than of the consumption patterns of less educated consumers. This would certainly help explain the superior accuracy of the median survey response of highly educated consumers.

Indeed, data from the CEX show some differences in consumption baskets across educational groups (see U.S. Department of Labor 2006). For example, data for 2004 show that the expenditure shares for food and for tobacco tend to be higher, the lower the level of education. Whereas consumers with less than a high school degree spend 16.8% on food, college graduates spend only 12.1%. The share of expenditures on personal insurance and pensions increases in the level of education from about 8% for consumers with less than a high school degree to near 13% for college graduates. That pattern is not universal, however. Some of the most important expenditure shares are remarkably stable across levels of education. For example, consumers with less than a high school degree attribute 34.3% of their spending to housing; college graduates spend 32.2%. The corresponding expenditure shares for transportation are 17.6% and 17.1%; those for apparel are 4.2% and 4.3%, respectively. What sheds further doubt on this explanation is that there is no evidence that the consumption basket of highly educated consumers is systematically closer to the national average than the baskets of the other groups.

In any case, some of our empirical results are at odds with this alternative explanation. Whereas differences in consumption baskets could in principle account for the fact that more educated consumers tend to have more accurate expectations (as measured by the RPMSE of the Michigan survey expectations), they do not help to explain the disproportionately larger improvements in accuracy from using the implicit expectations measure for less educated consumers (as measured by the RPMSE or the SIC value relative to the Michigan survey expectation). The latter pattern, however, is consistent with the evidence we presented that consumers with low levels of education are disproportionately inarticulate, when it comes to expressing their expectations of inflation.

The second alternative explanation attributes our results to differences in preference parameters across different levels of education. This explanation also lacks support. Differences in preferences may arise in the form of differences in the intertemporal elasticity of substitution (and hence ρ) or in the discount factor β. Since our predictive accuracy comparisons are based on affine transformations, changes in ρ do not affect our regression estimates and hence cannot explain the fit of the model. Differences in β across educational groups are captured by the intercept and do not affect the definition of the implicit expectations measure. Hence, we conclude that our results are unlikely to be a mere statistical artifact of unobserved heterogeneity in preferences across educational groups.

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References

1. Ang, A., Bekaert, G., and M. Wei (2007) “Do Macro Variables, Asset Markets, or Surveys Forecast Inflation Better?” *Journal of Monetary Economics*, 54, 1163-1212.

2. Barsky, R.B., Kimball, M., Juster, T., and M.D. Shapiro (1997), “Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Survey ,” *Quarterly Journal of Economics*, 112, 537-579.

3. Basu, S., and M. Kimball (2002), “Long-Run Labor Supply and the Elasticity of Intertemporal Substitution for Consumption,” mimeo, Department of Economics, University of Michigan.

4. Beaudry, P. and . van Wincoop (1996), “The Intertemporal Elasticity of Substitution: An Exploration using a US Panel of State Data,” *Economica,* 63, 495-512.

5. Box, G.E.P, G.M. Jenkins and G.C. Reinsel (1994), *Time Series Analysis: Forecasting and Control*, 3^{rd} ed., Prentice Hall: Englewood Cliffs, NJ.

6. Bryan, M.F., and W.T. Gavin (1986), “Models of Inflation Expectations Formation: A Comparison of Household and Economist Forecasts. Comment,” *Journal of Money, Credit and Banking*, 18, 539–544.

7. Carroll, C.D. (2001), “Death to the Log-Linearized Consumption Euler Equation! (And Very Poor Health to the Second-Order Approximation),” *Advances in Macroeconomics* 1, Article 6.

8. Carroll, C.D. (2003), “Macroeconomic Expectations of Households and Professional Forecasters,” *Quarterly Journal of Economics*, 118, 269-298.

9. Deaton, Angus (1992), *Understanding Consumption,* Oxford University Press: Oxford, UK.

10. Diebold, F.X., and R.S. Mariano (1995), “Comparing Predictive Accuracy,” *Journal of Business and Economic Statistics*, 13, 253-263.

11. Elliott, G., Komunjer, I., and A. Timmermann (2008), ”Biases in Macroeconomic Forecasts: Irrationality or Asymmetric Loss?”, *Journal of the European Economic*

Association, 6, 122-157.

12. Fackler, J., and B. Stanhouse (1977), "Rationality of the Michigan Price Expectations Data," *Journal of Money, Credit and Banking*, 9, 662–666.

13. Gourinchas, P.O., and J.A. Parker (2002), "Consumption Over the Life Cycle," *Econometrica*, 70, 47-89.

14. Gramlich, E.M. (1983), "Models of Inflation Expectations Formation: A Comparison of Household and Economist Forecasts," *Journal of Money, Credit and Banking*, 15, 155–173.

15. Grant, A.P., and L.B. Thomas (1999), "Inflation Expectations and Rationality Revisited" *Economics Letters*, 62, 331-338.

16. Hall, R.E. (1988), "Intertemporal Elasticity of Substitution," *Journal of Political Economy*, 96, 971-989.

17. Hamilton, J.D. (2003), "What is an Oil Shock?" *Journal of Econometrics*, 113, 363-398.

18. Inoue, A., and L. Kilian (2006), "On the Selection of Forecasting Models," *Journal of Econometrics*, 130, 273-306.

19. Kilian, L. (2008), "Exogenous Oil Supply Shocks: How Big Are They and How Much Do They Matter for the U.S. Economy?" *Review of Economics and Statistics*, 90, 216-240.

20. Lusardi, A. (1996), "Permanent Income, Current Income, and Consumption: Evidence from Two Panel Data Sets," *Journal of Business and Economic Statistics*, 14, 81-90.

21. Mankiw, N.G., Reis, R., and J. Wolfers (2004), "Disagreement about Inflation Expectations," *NBER Macroeconomics Annual 2003*, 209-248.

22. Mariger, R.P., and K. Shaw (1993), "Unanticipated Aggregate Disturbances and Tests of the Life-Cycle Consumption Model Using Panel Data," *Review of Economics and Statistics*, 75, 48-56.

23. Mehra, Y.P. (2002), "Survey Measures of Expected Inflation: Revisiting the Issues of Predictive Content and Rationality," *Federal Reserve Bank of Richmond Economic Quarterly*, 88, 17-36.

24. Menil, G. de, and S. Bhalla (1975), "Direct Measurement of Popular Price Expectations," *American Economic Review*, 65, 169-180.

25. Newey, W.K., and D.L. McFadden (1994), "Large-Sample Estimation and Hypothesis Testing," in Engle, R.F., and D.L. McFadden (eds.), *Handbook of Econometrics*, Volume 4, Elsevier: Amsterdam, Netherlands, 2111-2245.

26. Rich, R., (1989), "Testing Rationality of Inflation Forecasts from Survey Data: Another Look at the SRC Expected Price Change Data," *Review of Economics and Statistics*, 71, 682–686.

27. Roberts, J.M. (1997), "Is Inflation Sticky?" *Journal of Monetary Economics*, 39, 173-196.

28. Slesnick, D.S. (1992), "Aggregate Consumption and Saving in the Postwar United States," *Review of Economics and Statistics*, 74, 585-597.

29. Souleles, N.S. (2004), "Expectations, Heterogeneous Forecast Errors, and Consumption: Micro Evidence from the Michigan Consumer Sentiment Surveys," *Journal of Money, Credit and Banking*, 36, 39-72.

30. Thomas, L.B. (1999), "Survey Measures of Expected U.S. Inflation," *Journal of Economic Perspectives*, 13, 125-144.

31. U.S. Department of Labor (2006), *Consumer Expenditures in 2004,* Report 992, U.S. Bureau of Labor Statistics.

Table 1. Education Group and Do-Not-Know Responses in Michigan Survey

Average Percentages by Education Level: 1983:Q4–2004:Q4

Education Level	Do Not Know; NA	Will Go Up By; Do Not Know How Much
Full Sample	1.12	6.99
Less than High School	3.12	16.12
High School	1.00	7.74
Some College	0.69	5.31
College Degree	0.67	4.34
Graduate Studies	0.66	4.31

Source: Michigan Survey of Consumers

Table 2. Correlation of Michigan Household Inflation Expectations with Inflation

Forecasts in Survey of Professional Forecasters

By Level of Education: 1983:Q4–2004:Q4

	Percent
Full Sample	80.99
Less Than High School	34.59
High School Graduate	62.25
Some College	74.71
College Graduate	81.12
Graduate School	87.16

Source: Michigan Survey of Consumers and Survey of Professional Forecasters.

Table 3. Explanatory Power of Aggregate Shocks for Time Dummies: Baseline Model

	Constant	Forecast errors				Real	R^2
		Real Disposable Personal Income Growth	CFNAI	Real S&P500 Returns	Real T-Bill Rate	Oil Price Shock	
Full Sample	0.011	0.344	0.006	-0.151	1.167	1.287	0.195
	(0.003)	(0.327)	(0.006)	(0.033)	(0.606)	(0.709)	
Less than High School	-0.047	-0.422	0.005	-1.791	-0.079	3.435	0.176
	(0.005)	(0.628)	(0.008)	(1.954)	(0.045)	(1.165)	
High School Graduate	0.000	-0.033	0.007	0.967	-0.108	1.631	0.141
	(0.004)	(0.447)	(0.007)	(1.006)	(0.037)	(0.639)	
Some College	0.021	0.723	0.004	0.904	-0.222	-0.055	0.179
	(0.005)	(0.421)	(0.008)	(1.271)	(0.041)	(0.872)	
College Graduate	0.060	0.883	0.014	2.460	-0.198	1.573	0.163
	(0.006)	(0.775)	(0.010)	(1.282)	(0.059)	(1.097)	
Graduate School	0.087	1.777	0.004	5.225	-1.131	0.100	0.076
	(0.008)	(1.048)	(0.012)	(2.035)	(0.089)	(1.793)	

Source: The forecasting models are described in the text. The numbers in parentheses in columns (2)-(7) are standard errors. The standard errors account for the generated regressor problem and possible heteroskedasticity. All regressions pass tests for zero serial correlation in the residuals.

Table 4. Predictive Accuracy of Implicit Expectations Measures for CPI Inflation Outcomes: Alternative Regression Specifications

	RPMSE Ratio Implicit/Michigan	*SIC* Michigan	*SIC* Implicit	*N*	*T*
		Baseline Model			
Full Sample	0.966	-10.439	**-10.456**	223283	83
Less Than High School	0.949	-10.394	**-10.445**	43773	83
High School Graduate	0.941	-10.400	**-10.468**	66794	83
Some College	0.967	-10.433	**-10.446**	56329	83
College Graduate	0.978	**-10.461**	-10.452	33197	83
Graduate School	0.985	**-10.486**	-10.462	23190	83
		Baseline Model with NIPA Income Growth			
Full Sample	0.965	-10.439	**-10.457**	223283	83
Less Than High School	0.949	-10.394	**-10.445**	43773	83
High School Graduate	0.941	-10.400	**-10.469**	66794	83
Some College	0.967	-10.433	**-10.446**	56329	83
College Graduate	0.978	**-10.461**	-10.453	33197	83
Graduate School	0.985	**-10.486**	-10.463	23190	83
		Baseline Model with Hours Growth			
Full Sample	0.964	-10.439	**-10.459**	223283	83
Less Than High School	0.949	-10.394	**-10.445**	43773	83
High School Graduate	0.938	-10.400	**-10.474**	66794	83
Some College	0.968	-10.433	**-10.445**	56329	83
College Graduate	0.976	**-10.461**	-10.456	33197	83
Graduate School	0.983	**-10.486**	-10.467	23190	83
		Baseline Model with NIPA Income Growth and Hours Growth			
Full Sample	0.964	-10.439	**-10.459**	223283	83
Less Than High School	0.949	-10.394	**-10.445**	43773	83
High School Graduate	0.938	-10.400	**-10.475**	66794	83
Some College	0.968	-10.433	**-10.445**	56329	83
College Graduate	0.976	**-10.461**	-10.456	33197	83
Graduate School	0.983	**-10.486**	-10.468	23190	83
		Baseline Model with CEX Income Growth			
Full Sample	0.972	-10.450	**-10.453**	99124	82
Less Than High School	0.948	-10.399	**-10.452**	19793	82
High School Graduate	0.952	-10.408	**-10.454**	29956	82
Some College	0.968	-10.442	**-10.453**	25271	82
College Graduate	0.983	**-10.471**	-10.452	14403	82
Graduate School	0.996	**-10.502**	-10.455	9701	82
		Baseline Model with CEX Income Growth and Hours Growth			
Full Sample	0.972	-10.450	**-10.453**	99124	82
Less Than High School	0.948	-10.399	**-10.452**	19793	82
High School Graduate	0.952	-10.408	**-10.454**	29956	82
Some College	0.968	-10.442	**-10.453**	25271	82
College Graduate	0.983	**-10.471**	-10.452	14403	82
Graduate School	0.996	**-10.502**	-10.457	9701	82

Notes: The RPMSEs for the implicit measure have been constructed based on regressions of actual inflation on a constant and the expectations measure in question. SIC stands for Schwarz Information Criterion. Boldface indicates the preferred predictor.

Table 5. Correlations of Selected Inflation Expectations Measures

By Level of Education: 1983:Q4–2004:Q4

	Correlation of implicit measure and Michigan survey Percent	Correlation of SPF and implicit measure Percent	Correlation of SPF and Michigan survey Percent
Full Sample	60.95	76.53	80.99
Less Than High School	29.76	77.89	34.59
High School Graduate	41.89	71.97	62.25
Some College	54.57	77.41	74.71
College Graduate	64.07	77.49	81.12
Graduate School	69.12	75.40	87.16

Source: Michigan Survey of Consumers, Survey of Professional Forecasters and estimates of baseline model.

Table 6a. Marginal Predictive Content of Implicit Expectations Measures for CPI Inflation: Baseline Model

Full Sample								
Constant	π_t	SPF	Michigan	Implicit	BG	*SIC*	*N*	*T*
0.008	-0.086				0.012	-10.394		83
(0.000)	(0.408)				(0.913)			
0.002	-0.232	0.948			2.171	**-10.508**		83
(0.317)	(0.042)	(0.000)			(0.141)			
-0.002	-0.295		1.569		1.841	-10.456		83
(0.617)	(0.021)		(0.001)		(0.175)			
0.005	-0.199			9.921	1.158	-10.446	223283	83
(0.012)	(0.070)			(0.006)	(0.282)			
0.000	-0.272		0.783	4.176	2.263	-10.413	223283	83
(0.870)	(0.039)		(0.074)	(0.103)	(0.133)			
0.001	-0.251	0.842	0.268		2.501	-10.456		83
(0.739)	(0.067)	(0.022)	(0.358)		(0.114)			
0.002	-0.232	0.596		1.685	2.781	-10.423	223283	83
(0.317)	(0.044)	(0.021)		(0.366)	(0.095)			

Notes: The numbers in parentheses in columns 1-6 are p-values. BG stands for the Breusch-Godfrey test for serial correlation and *SIC* for the Schwarz Information Criterion. Boldface indicates the preferred predictive model.

Table 6b. Marginal Predictive Content of Implicit Expectations Measures for CPI Inflation by Educational Status of Household: Baseline Model

Constant	π_t	Michigan	Implicit	BG	*SIC*	*N*	*T*
			Less Than High School				
0.005	-0.210		12.087	0.195	**-10.440**	43773	83
(0.012)	(0.052)		(0.002)	(0.659)			
0.005	-0.121	0.406		0.235	-10.355		83
(0.096)	(0.284)	(0.140)		(0.627)			
0.004	-0.219	0.131	0.363	0.352	-10.388	43773	83
(0.046)	(0.059)	(0.363)	(0.132)	(0.553)			
			High School Graduate				
0.004	-0.196		11.012	0.960	**-10.457**	66794	83
(0.046)	(0.075)		(0.004)	(0.328)			
0.002	-0.187	0.966		1.167	-10.375		83
(0.505)	(0.122)	(0.016)		(0.280)			
0.003	-0.222	0.290	0.356	1.549	-10.407	66794	83
(0.505)	(0.081)	(0.247)	(0.126)	(0.213)			
			Some College				
0.005	-0.207		9.805	0.004	**-10.440**	56329	83
(0.012)	(0.065)		(0.007)	(0.951)			
-0.000	-0.256	1.307		0.581	-10.435		83
(0.870)	(0.033)	(0.000)		(0.446)			
0.001	-0.272	0.690	0.289	0.183	-10.409	56329	83
(0.739)	(0.027)	(0.037)	(0.124)	(0.668)			
			College Graduate				
0.004	-0.198		9.535	0.311	-10.443	33197	83
(0.046)	(0.066)		(0.008)	(0.577)			
0.001	-0.246	1.181		1.879	**-10.465**		83
(0.739)	(0.036)	(0.001)		(0.170)			
0.002	-0.246	0.614	0.253	0.836	-10.410	33197	83
(0.317)	(0.040)	(0.077)	(0.150)	(0.361)			
			Graduate School				
0.005	-0.194		9.251	0.582	-10.449	23190	83
(0.012)	(0.071)		(0.010)	(0.446)			
0.001	-0.295	1.162		2.831	**-10.514**		83
(0.617)	(0.012)	(0.001)		(0.092)			
0.001	-0.271	0.803	0.164	2.651	-10.438	23190	83
(0.617)	(0.021)	(0.018)	(0.172)	(0.104)			

Notes: The numbers in parentheses in columns 1-5 are p-values. Boldface indicates the preferred predictive model.

Table 7. Predictive Accuracy of Implicit Expectations Measures for CPI Inflation Outcomes: Baseline Model

Based on Michigan Survey Data for the Last Month of the Preceding Quarter

	RPMSE Ratio Implicit/Michigan	*SIC* Michigan	*SIC* Implicit
Full Sample	0.966	-10.441	**-10.456**
At Most High School	0.938	-10.387	**-10.461**
Some College	0.957	-10.411	**-10.446**
At Least College Degree	0.981	**-10.471**	-10.456

Notes: See Table 3. Boldface indicates the preferred predictor.

Table 8a. Marginal Predictive Content of Implicit Expectations Measures for CPI Inflation: Baseline Model

Based on Michigan Survey Data for the Last Month of the Preceding Quarter

Full Sample								
Constant	π_t	SPF	Michigan	Implicit	BG	*SIC*	*N*	*T*
0.008	-0.086				0.012	-10.394		83
(0.000)	(0.409)				(0.913)			
0.002	-0.232	0.948			2.171	**-10.508**		83
(0.317)	(0.042)	(0.000)			(0.141)			
-0.004	-0.334		1.876		0.968	-10.472		83
(0.317)	(0.014)		(0.000)		(0.325)			
0.005	-0.199			10.273	1.158	-10.446	223283	83
(0.012)	(0.070)			(0.006)	(0.282)			
-0.002	-0.315		1.144	4.428	1.532	-10.431	223283	83
(0.505)	(0.022)		(0.028)	(0.109)	(0.216)			
-0.001	-0.290	0.709	0.719		2.003	-10.464		83
(0.803)	(0.046)	(0.041)	(0.198)		(0.157)			
0.002	-0.232	0.596		2.011	2.781	-10.423	223283	83
(0.317)	(0.044)	(0.021)		(0.366)	(0.095)			

Notes: See Table 6a. Boldface indicates the preferred predictive model.

Table 8b. Marginal Predictive Content of Implicit Expectations Measures for CPI Inflation by Educational Status of Household: Baseline Model

Based on Michigan Survey Data for the Last Month of the Preceding Quarter

Constant	π_t	Michigan	Implicit	BG	*SIC*	*N*	*T*
At Most High School							
0.005	-0.201		13.877	0.892	**-10.452**	110567	83
(0.046)	(0.070)		(0.001)	(0.345)			
0.006	-0.130	0.373		0.153	-10.346		83
(0.046)	(0.283)	(0.212)		(0.696)			
0.004	-0.219	0.163	0.351	1.294	-10.400	110567	83
(0.317)	(0.085)	(0.346)	(0.122)	(0.255)			
Some College							
0.005	-0.207		9.805	0.004	**-10.440**	56329	83
(0.012)	(0.065)		(0.007)	(0.951)			
0.002	-0.223	0.992		0.001	-10.399		83
(0.505)	(0.057)	(0.004)		(0.981)			
0.001	-0.276	0.604	0.323	0.007	-10.409	56329	83
(0.739)	(0.021)	(0.064)	(0.120)	(0.936)			
At Least College Degree							
0.004	-0.198		9.426	0.421	-10.445	56387	83
(0.046)	(0.067)		(0.009)	(0.517)			
-0.000	-0.307	1.349		1.700	**-10.501**		83
(0.870)	(0.013)	(0.000)		(0.192)			
0.000	-0.287	0.916	0.191	1.549	-10.434	56387	83
(0.807)	(0.024)	(0.027)	(0.159)	(0.213)			

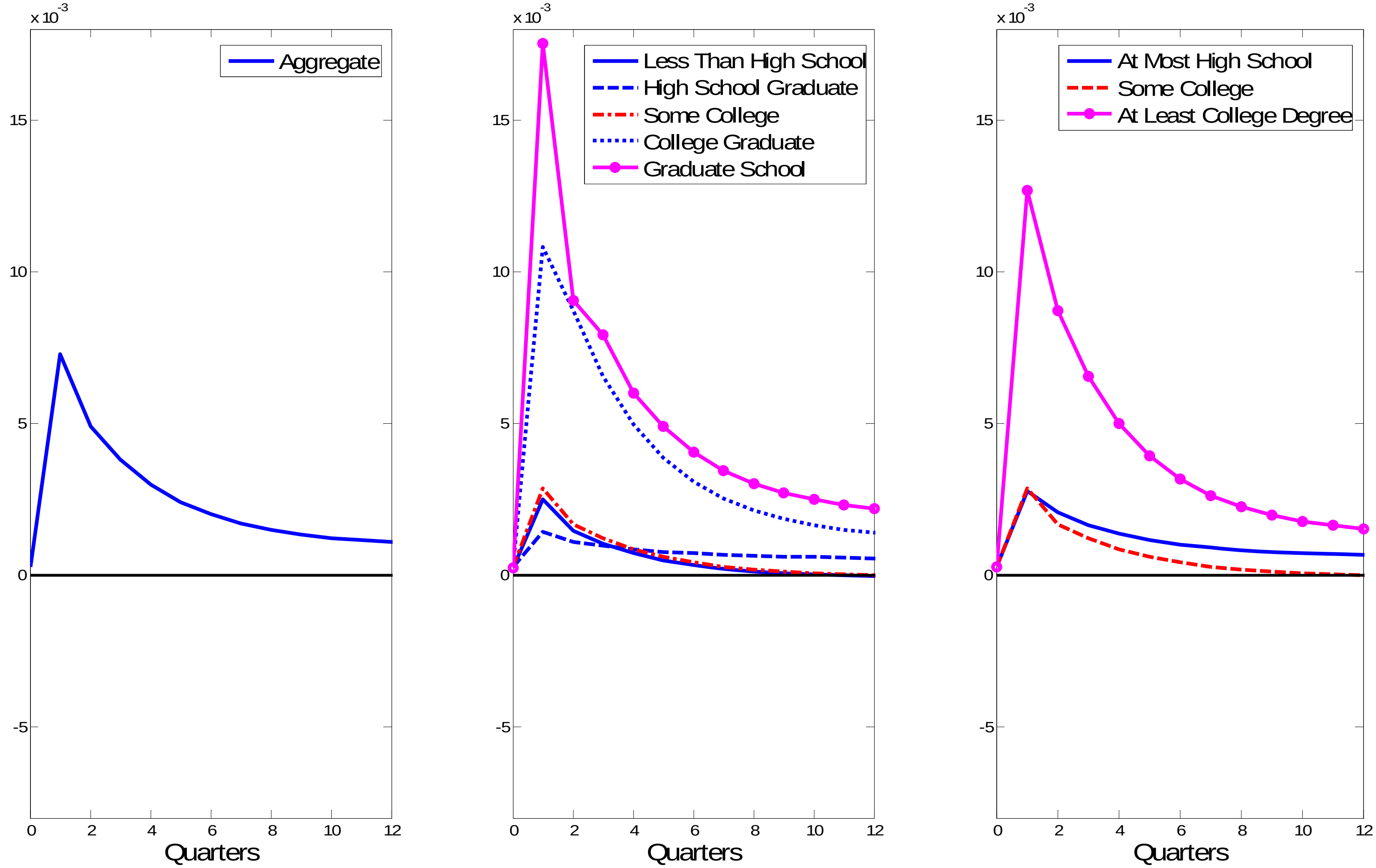
Notes: See Table 6b. Boldface indicates the preferred predictive model.

Table 9. Predictive Accuracy of Explicit Expectations Measures for CPI Inflation Outcomes

	RPMSE Ratio Explicit/Michigan	*SIC* Michigan	*SIC* Explicit	N	T
		Quarterly survey data: z_t			
Full Sample	0.922	-10.439	**-10.547**	223283	83
Less Than High School	0.889	-10.394	**-10.575**	43773	83
High School Graduate	0.923	-10.400	**-10.507**	66794	83
Some College	0.947	-10.433	**-10.488**	56329	83
College Graduate	0.978	**-10.461**	-10.452	33197	83
Graduate School	0.994	**-10.486**	-10.445	23190	83
		Last-month-of-quarter survey data: z_t			
Full Sample	0.923	-10.441	**-10.547**	223283	83
At Most High School	0.892	-10.387	**-10.563**	110567	83
Some College	0.937	-10.411	**-10.488**	56329	83
At Least College Degree	0.986	**-10.471**	-10.446	56387	83
		Quarterly survey data: $z_t^{\text{real}\,time}$			
Full Sample	0.959	-10.439	**-10.469**	223283	83
Less Than High School	0.946	-10.394	**-10.451**	43773	83
High School Graduate	0.951	-10.400	**-10.446**	66794	83
Some College	0.937	-10.433	**-10.509**	56329	83
College Graduate	0.976	**-10.461**	-10.456	33197	83
Graduate School	0.974	**-10.486**	-10.485	23190	83
		Last-month-of-quarter survey data: $z_t^{\text{real}\,time}$			
Full Sample	0.960	-10.441	**-10.469**	223283	83
At Most High School	0.946	-10.387	**-10.445**	110567	83
Some College	0.927	-10.411	**-10.509**	56329	83
At Least College Degree	0.975	**-10.471**	-10.468	56387	83

Notes: The RPMSEs for the explicit measure have been constructed analogously to Table 4. SIC stands for Schwarz Information Criterion. Boldface indicates the preferred predictor.

Figure 1: Responses of Implicit Household Inflation Expectations to an SPF Shock



NOTES: Based on structural VAR(1) for $SPF_{t+1|t}$, i_{t+1}, and $\tilde{\delta}_{t+1}$.