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Understanding Expectations Formation for Hand-to-Mouth Households: Lessons from the Financial Crisis

Tufan Ekici, Martin Geiger and Marios Zachariadis

Department of Economics, University of Cyprus, P.O. Box 20537, 1678 Nicosia, Cyprus
www.ucy.ac.cy/econ/?lang=en

Understanding Expectations Formation for Hand-to-Mouth Households: Lessons from the Financial Crisis*

Tufan Ekici †   Martin Geiger ‡   Marios Zachariadis §

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Abstract

We study how poor hand-to-mouth and wealthy hand-to-mouth households form their expectations as compared to wealthy liquid households in the United States, using monthly microeconomic survey data for the period from 2005:2 to 2013:6. Utilizing a timeline of financial crisis events along with changes in stock-market values and uncertainty around those events, we assess the responses of these households' expectations regarding inflation, unemployment, and the interest rate. Our estimates imply differences in the formation of expectations for liquidity constrained households relative to unconstrained ones. While adverse financial crisis events that lower future inflation do not affect inflation expectations for all households, wealthy hand-to-mouth households tend to revise their inflation expectations downwards substantially. This suggests they decipher these financial events' noisy signal regarding lower future inflation more accurately than other types of households, in line with having a greater incentive to do so.

Keywords: liquidity constraints, inflation expectations, unemployment expectations, interest rate expectations, financial shocks.

JEL Classification: D84, E30, E70, G01, G51

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†Anisfield School of Business, Ramapo College of New Jersey, USA. E-mail: tekici@ramapo.edu

‡Corresponding author. Liechtenstein Institute, Gamprin, Liechtenstein, and University of Innsbruck. E-mail: martin.geiger@liechtenstein-institut.li

§Department of Economics, University of Cyprus, Nicosia, Cyprus. E-mail: zachariadis.marios@ucy.ac.cy

1 Introduction

Liquidity constraints might limit an agent's discretion to take consumption-saving decisions based on expectations, thus reducing the incentive for such agents to pay attention and form accurate expectations to begin with. On the other hand, liquidity constraints might also serve to raise the stakes for households thus inducing them to pay more attention and form more accurate expectations. Our work investigates whether there exists heterogeneity in the formation of expectations between constrained and unconstrained agents, and across different types of liquidity-constrained agents.

More specifically, we study the role of liquidity constraints in the formation of expectations using a unique microeconomic dataset that includes information on expectations regarding inflation, unemployment, and interest rates as well as individual financial and other characteristics for US households at monthly frequency over the period 2005:2-2013:6 encompassing the financial crisis. The survey includes the specific day of the month during which each respondent was interviewed, allowing us to match each response to financial events within a precise window, e.g., from the day before each interview to the day following it. The detailed information available to us makes it possible to apply the well-established classification by Kaplan et al. (2014) distinguishing between poor hand-to-mouth (HtM) households, wealthy HtM, and other wealthy households not facing liquidity constraints.

The presence of liquidity constraints has important implications for macroeconomic models. For example, Farhi and Werning (2016) and Kara and Sin (2018) show that fiscal multipliers can be much larger in the presence of liquidity constrained agents, while Klein (2017) and Klein et al. (2022) provide empirical evidence in support of the importance of private debt for the size of the fiscal multiplier. The importance of liquidity-constrained agents underlined by the latter papers and by Kaplan et al. (2014) among others, makes it important to incorporate heterogeneous agents with different HTM status in macroeconomic models that consider the efficacy of fiscal policies for example. Differences in the formation of expectations between constrained and unconstrained agents such as the ones we explore here, would further suggest that it could be important to model this additional form of heterogeneity in macroeconomic models more broadly.

The financial crisis period which is a focal point of our study, provides a unique setting wherein to study liquidity constraints. The supply of credit was restrictive during this period rendering liquidity constraints more relevant. Thus, considering this sub-period along with the adjacent periods before and after the financial crisis, provides useful variation over time and across individuals that can help uncover potential differences in expectations formation between HtM versus unconstrained individuals. Importantly, the financial crisis provides a setting during which the stakes were potentially higher for liquidity constrained households, allowing us to examine their attentiveness as compared to other households.

One key advantage of the Consumer Finance Monthly Survey (CFMS) dataset we utilize here is the availability of information on the exact date of each individual interview over the course of each month, which allows us to look at the variation in responses over the chronology of the financial crisis during our sample period in a high-frequency setup. This allows us to gauge the direct effect of these events on expectations versus the indirect reaction to these events through their implied impact on macroeconomic outcomes, as macroeconomic variables move and are published with a delay. We use the Federal Reserve Bank of St. Louis' Financial Crisis Timeline which dates events associated with the financial crisis, in order to construct a novel instrument for financial crisis shocks which varies across individuals according to their interview dates. To quantify these events, we utilize their immediate effects on daily asset prices, namely the SP500 and the VIX. We consider changes in the SP500 and the VIX from the day before the interview to the day following it, and select events associated with large adverse reactions of the stock market where the SP500 drops or the VIX increases by more than one standard deviation.

Our main result is that wealthy HtM households revise inflation expectations downward substantially in the face of adverse financial events that lower future inflation, while these events do not affect inflation expectations for poor HtM households and for the unconstrained. Given that the future inflation rate actually goes down following these adverse financial events, wealthy HtM households appear to form their current expectations of the future in a manner that more accurately predicts this future movement as compared to other households. These findings can be understood by delving deeper into the features that characterize different types of liquidity constrained versus unconstrained households.[1]

Wealthy HtM households are much more likely to have a mortgage as compared to poor HtM (53% as compared to 19%) and since 92% of mortgages in the US have a fixed interest rate (see Chiang and Dueholm (2024) using Survey of Consumer Finances (SCF) data), this implies that a fall in inflation would be undesirable for this group as it would raise their real interest rate relative to what they would be facing in the absence of such a fall.[2] Hence, an adverse financial event which lowers future inflation would have a greater impact on the dynamic path of the wealthy HtM households' real debt burden and their ability to pay in the future, providing them with an incentive to pay attention to such adverse events in the first place. Therefore, wealthy HtM individuals have a greater incentive to pay attention and to more accurately decipher this noisy signal regarding lower inflation in the future, as compared to poor HtM households. As compared to wealthy unconstrained households, wealthy HtM have considerably lower liquid assets ($2987 as compared to $268,101) and this makes debt repayment a bigger issue for them. Thus, wealthy HtM individuals have a greater incentive than unconstrained ones to pay attention and to more accurately decipher this noisy signal regarding lower inflation in the future.

Based on the above, adverse financial events appear to alarm wealthy HtM households about the possibility of lower inflation in the future inducing them to adjust their inflation expectations downwards in the same direction as future inflation realizations, whereas wealthy unconstrained households and poor HtM ones with lower incentives to pay attention, appear inattentive. This greater responsiveness and more accurate formation of inflation expectations by those who have a greater incentive to pay attention to adverse financial shocks that lower future inflation, is consistent with models such as those in Sims (2010) or Mackowiak

[1] Table A12 shows some characteristics intrinsically related to liquidity constraints. Such aspects of liquidity constraints include a measure of liquid assets used for determining HtM status in section 2.1, the percentage with a mortgage for each type of household where having a mortgage is a typical reason wealthy households can become HtM, and tenure at current job given that not being able to keep a steady job is a typical reason for becoming a poor HtM.

[2] Wealthy HtM households would instead reasonably wish for debt erosion associated with higher inflation.

and Wiederholt (2009), where individuals can be rationally inattentive depending on their specific circumstances. This same evidence is inconsistent with noisy-information models that assume a fixed amount of capacity allocated to monitoring economic variables.

Furthermore, we find that inflation expectations are generally higher for poor and wealthy HtM households relative to wealthy unconstrained ones and this persists net of household income and education levels suggesting that liquidity constraints have a direct separate effect on the formation of expectations. Moreover, HtM households are more likely to expect higher unemployment as compared to unconstrained ones. This persists net of household income and education, suggesting again that liquidity constraints matter directly for the formation of expectations separately from household income and education. Additionally, poor HtM households are typically more likely to expect higher unemployment as compared to wealthy HtM. These differences are consistent with the length of time people state they have worked at their current job, with the mean values for poor HtM, wealthy HtM and unconstrained wealthy households respectively equal to 2.8, 6 and 8.2 years. Longer tenure might make people feel more job security and households' unemployment expectations reflect that.

Following adverse financial crisis events, however, while all households are more likely to expect higher unemployment, wealthy unconstrained households expect even higher future unemployment than HtM ones. As wealthy liquid households are more likely to be directly exposed to the financial sector,[3] their unemployment expectations go up by more in response to adverse financial sector events. The future unemployment rate goes up following such adverse financial events and different types of households appear to form their unemployment expectations in a manner that incorporates this signal to a different degree depending on their specific circumstances.

Finally, we find that adverse financial crisis shocks increase the cross-sectional standard deviation of inflation expectations among wealthy HtM households. This increased dispersion among these households in response to financial shocks is consistent with noisy information

[3]Such direct exposure would involve, e.g., a greater fear of losing one's job in the financial sector. Moreover, as shown in Table A12, these households also have a greater exposure to the financial sector as reflected in their stock holdings, so that it might be easier for them to perceive these financial events.

models that incorporate heterogeneity in signal-to-noise ratios and with sticky information models such as Mankiw and Reis (2002) that imply a positive association between disagreement and any shock, but inconsistent with basic noisy information models.

In the next section, we describe our dataset and the construction of our variables, and present some preliminary analysis of these. We then present the empirical model and our estimates, and briefly conclude in the last section of the paper.

2 Variables construction and preliminary data analysis

2.1 A household-level dataset of expectations and financial characteristics

In this subsection, we describe the household level dataset that allows to classify respondents according to the standard HtM classification according to Kaplan et al. (2014) and at the same time contains expectations about inflation, unemployment, and interest rates. This is the CFMS dataset generated at the Center for Human Resource Research of The Ohio State University by Lucia Dunn and her collaborators. The survey data comes from a monthly national random telephone survey of the representative US households (Dunn and Olsen (2014)). It includes expectations regarding inflation, unemployment and the interest rate, along with individual financial and other characteristics of households across the United States, available monthly during the period from 2005:2 to 2013:6 with a total sample size of more than 25,000 observations over this period, and an average monthly sample size of 335 observations with a median of 278.

Researchers focusing on household finances usually utilize SCF survey data released by the Federal Reserve Board. Information on household balance sheet in CFMS data has been shown to track SCF data fairly closely (Olsen and Dunn (2010)). SCF data is normally conducted triennially which does not allow for the analysis we undertake in this study as opposed to CFMS data which is available at a monthly frequency.[4]

Another advantage of the CFMS dataset is the availability of information on the exact date of the interview. This allows us to look at variation in responses over specific days of the period covered. This information is key for the high-frequency identification of financial shock events which we explain in detail in Section 2.2.

In our application, we utilize the following household characteristics in order to construct the shares of HtM households and to construct a number of explanatory variables for our different regression specifications: First, HtM status of the households is determined by using the specifications of Kaplan et al. (2014) (their equations 8 to 11). Specifically, poor-HtM households are those who hold little or no liquid wealth and no illiquid wealth, whereas wealthy-HtM households have significant amounts of illiquid assets. In order to be comparable to Kaplan et al. (2014), we follow their sample selection criteria deleting households with negative labor income or when all income is coming from self-employment, and where the age of the respondent is not between 22-79. We also consider an additional selection criterion, deleting outliers with zero monthly income or where this is greater than $100,000.

Our key financial measures are constructed as follows: The household's monthly income is the sum of net business income, labor income and other sources of income of the respondent and the spouse, if any. Liquid assets includes the sum of money in savings/checking accounts as well as cash holdings, mutual funds, stocks and bonds. Contrary to Kaplan et al. (2014) who did not have information on cash holdings, the CFMS dataset we utilize here includes a question that collects information on "Cash or certificate of deposits". Liquid debt is the sum of credit card debt (after the most recent payment), student loan debt, and any debt left on bank loans, payday loans and other loans. Liquid wealth is simply the difference between liquid assets and liquid debt. Illiquid Wealth includes the value of housing and other properties net of mortgages, net business equity, value of life insurance, retirement accounts,

[4] SCF conducted a follow-up survey in 2009 by contacting the sample from the regularly conducted 2007 survey in order to analyze aftermath of the pandemic on household finances. However, even that panel aspect does not provide us with the information we need to carry out the analysis in this paper.

IRAs, and Savings and Bonds. Utilizing the above measures, we create the HtM categories following Kaplan et al. (2014) who define poor hand-to-mouth households as those who hold little liquid wealth and no illiquid wealth[5], and wealthy hand-to-mouth households as having similar liquid wealth holdings as their poor counterparts but positive illiquid wealth. The share of HtM households in our dataset is around 35% which is comparable to Kaplan et al. (2014).[6] Finally, households with positive illiquid wealth and sufficient liquid wealth, greater than half of their monthly income, are categorized as unconstrained.

Table A12 presents the above constructed measures along with net worth, the fraction of households that own stock (implying different rates of participation in financial markets), and some other characteristics for poor HTM, wealthy HTM and unconstrained households described in footnote 1. As we can see in Table A12, there are large differences in liquid assets, liquid debt, liquid wealth, illiquid wealth and monthly income between households reflected in our Kaplan et al. (2014)-based categorization into poor HtM, wealthy HtM and unconstrained households.

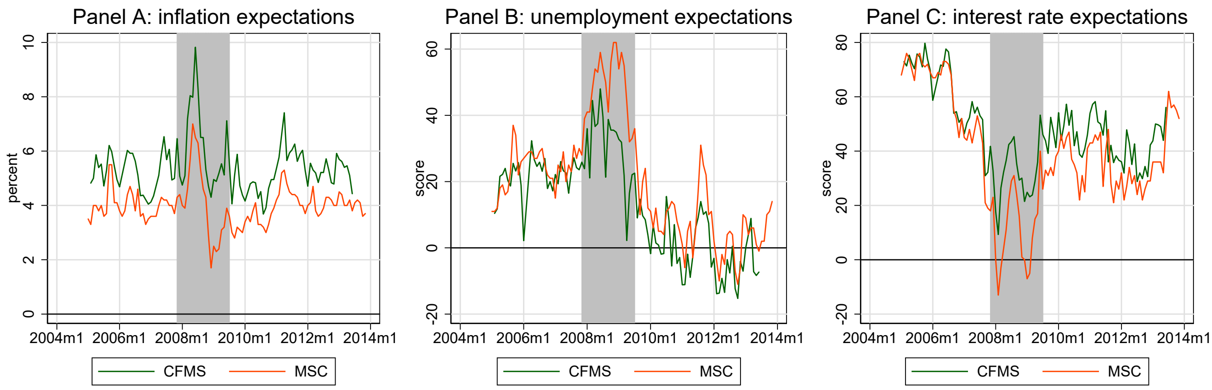
Our dependent variables are measures of economic expectations. There are several variables that capture a household's economic expectations in the CFMS dataset. The question that measures inflation expectations is especially important since it allows for a continuous response option. Interest rate and unemployment expectations allow only for a discrete (Up/Down/Same) choice. Finally, we consider control variables for respondent's gender, race, age, and education. We also use self-reported gross household income in the previous year as a control variable in some of our specifications.

Figure 1 shows aggregate time series of the CFMS expectations measures we are interested in. Aggregate inflation expectations are average point estimates while we show balance scores for unemployment and interest rate expectations. In the latter case we subtract the share of respondents who indicate an expected decrease from those who indicate an expected increase. The financial crisis recession as classified according to the NBER's Business Cycle

[5]More specifically, poor HTM status occurs when average balances of liquid wealth are positive but less than half of household income during a pay period, while illiquid wealth is less than or equal to zero.

[6]They use two different samples. HtM share in Survey of Consumer Finances (SCF) is 31% (p. 101), whereas it is 46% in the Panel Study of Income Dynamics (PSID) sample (p. 123).

Figure 1: Aggregate CFMS expectations together with MSC expectations



Notes: Inflation expectations are average point estimates whereas aggregate unemployment expectations and interest rate expectations are balance scores.

Dating Committee is indicated by the shaded area. We see that relatively more respondents expect higher unemployment and more people expect lower interest rates as the financial crisis sets in. With respect to inflation expectations the revision in expectation due to the financial crisis is less clear. Inflation expectations tend to increase initially at the onset of the crisis, while they gradually decrease in the course of the recession. Overall, revision in expectations tends to be consistent with predominant demand-side effects pertaining to the financial crisis.

Moreover, in Figure 1 we can see that CFMS movements over time are comparable to the Michigan Survey of Consumers (MSC). The contemporaneous correlation of the CFMS with the respective MSC series is .78 for inflation expectations, .86 for unemployment expectations, and .94 for interest rate expectations. However, we do observe level differences that can be large in certain cases such as at the onset of the Financial Crisis for inflation and interest rate expectations and during 2009 for unemployment expectations. This is perhaps not surprising given the smaller number of households surveyed by the CFMS as compared to the MSC for each unit of time.[7]

2.2 Constructing a financial shock measure

Our point of departure to construct a financial crisis shock measure is an official timeline of the financial crisis put together by the Federal Reserve Bank of St. Louis. The timeline spans from February 27, 2007, to April 13, 2011, and documents 305 events. To capture the effectiveness of those events, we select and quantify meaningful events based on daily changes in the SP500 and the VIX precipitated by financial crisis events.

The idea to identify shocks exploiting high frequency changes in asset prices is motivated by the high-frequency identification of monetary policy shocks, originating with Kuttner (2001), Faust et al. (2004), and Gürkaynak et al. (2005a,b). The intuition there was to identify monetary policy surprises from price changes in a time window around monetary policy announcements. We apply the same idea to financial crisis-related events. Similar to our study, which applies the logic of high-frequency identification in a different context, Geiger and Güntner (2024) exploit an official timeline of the exit of the UK from the EU, along with changes in UK stock prices, the Pound Sterling exchange rate and an index of economic policy uncertainty, to characterize Brexit shocks. Känzig (2021) exploits price changes in crude oil futures and carbon emission certificates in response to announcements of changes in OPEC production quotas to gauge the effects of oil supply news. Bahaj (2020), for example, draws on euro crisis events to identify sovereign spread shocks using high frequency data. Lastly, Piffer and Podstawski (2018) identify uncertainty shocks using intra-day changes in the price of gold around geopolitical events.

Given the large number of listed events — more than one event per week on average — we select and quantify them according to their immediate effects on daily asset prices to isolate meaningful events that might plausibly be noticed by different types of individuals. In this

[7] Consistent with the CFMS, the MSC asks "By about what percent do you expect prices to go (up/down) on the average, during the next 12 months?". Respondents in the MSC are chosen to reflect a random sample of the population. A minimum of 500 persons is interviewed each month by telephone. We show the preprocessed survey aggregates provided by the MSC survey center. In the case of the CFMS, we discard respondents providing inflation forecasts outside a range of -10 to 30 percent to not distort mean forecasts (see also Curtin, 1996), given the much smaller sample we have at hand for each period.

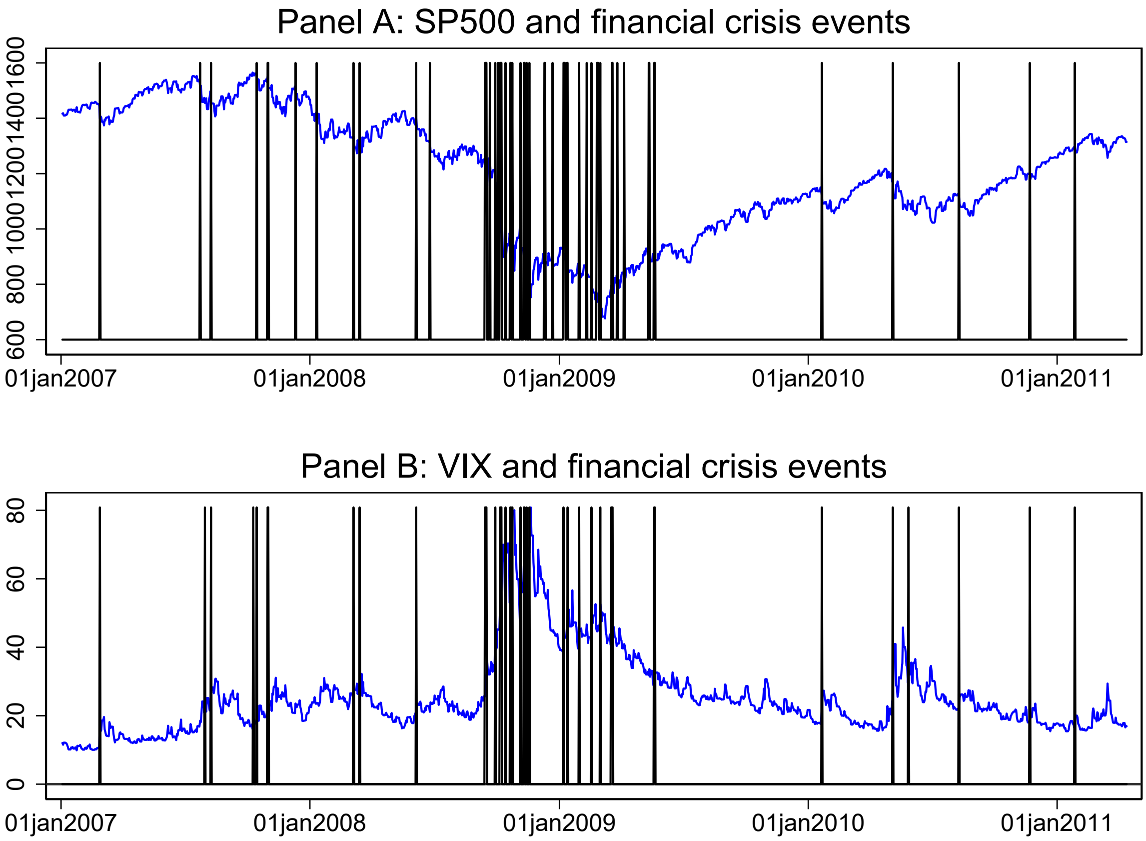
context, any inattention result regarding certain types of households would be particularly informative. Specifically, we only consider events pertaining to adverse reactions of the stock market, i.e. where the SP500 drops or the VIX increases by more than one standard deviation. These provides us with 58 SP500-based events and 42 VIX-based events.

In the regressions below, we consider changes in the SP500 and the VIX from the day before the interview to the day following the interview. Depending on the chronological coincidence of the interview and the financial crisis events, we use a flexible event window of up to three days in order to sharply identify the financial crisis shock: a respondent is associated with a non-zero financial crisis shock if a meaningful financial crisis event happened on the day of the interview, the day before the interview, or the two days before it. As interview dates vary across individuals over the course of each month, exploiting the exact timing of the individual interview dates in relation to events that happen right before, renders these shocks specific to those individuals interviewed shortly after a financial event occurs.

Figure 2 shows the evolution of the stock market indexes together with selected financial crisis events. Specifically, Panel A plots the SP500 together with vertical lines indicating financial crisis events that coincided with a drop in the stock market from $t-1$ to $t+1$ that exceeded one standard deviation of the first differences.[8] Analogously, Panel B plots the VIX together with financial crisis events that precipitated an upswing of more than one standard deviation. Consistent with the chronology of the Great Financial crisis, most financial crisis events materialized in the fourth quarter of 2008 and the first quarter of 2009. It appears that the majority of large movements in the indices is associated with the financial crisis. Notably, we see that while most events selected based on the SP500 and the VIX coincide, there are exceptions (the correlation between the two series is 0.77). This indicates that the financial crisis events tend to precipitate first and second moment movements in the stock market.

[8]Note that in the micro-level regression below, the event window is specific to each respondent depending on the interview date. However, We also estimate a version with a fixed event window from $t-1$ to $t+1$ in a robustness check.

Figure 2: Stock market developments together with selected financial crisis events

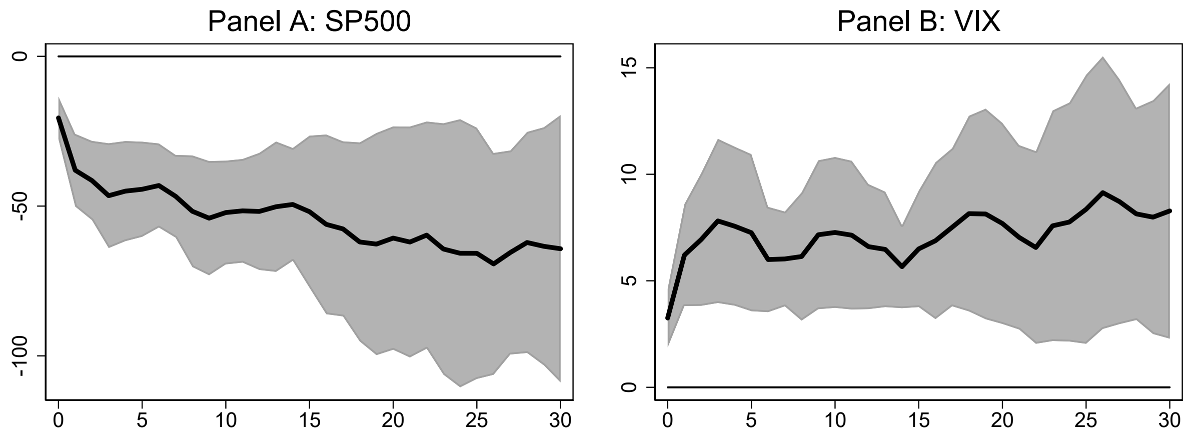


Notes: Vertical lines indicate selected financial crisis events that pertain to an adverse change in the stock market measures above a one-standard-deviation threshold.

To illustrate how the selected financial crisis events affect the indices, we plot the dynamic response in daily frequency in Figure 3. Unsurprisingly, as the events are selected based on the adverse change from $t-1$ to $t+1$, we see a pronounced market reaction on impact. Interestingly, the events have a persistent effect on the stock-market during the month following a financial event, with a drop in the SP500 of more than 50 index points and an increase in the VIX of more than 5 index points.

Before we turn to the effects of the events on individual survey responses, we assess the macroeconomic impact of the financial crisis shocks on macroeconomic outcomes. The actual macroeconomic effects of the financial crisis instrument serve as a benchmark against which we can compare the revision in the survey responses due to the event-induced changes in the

Figure 3: Stock market developments together with selected financial crisis events



Notes: The figure shows the dynamic response of the indices to dummies indicating selected financial crisis events estimated in the form of local projections. Specifically, the indices are regressed on the respective dummies in addition to the lagged dependent variable up to a lag order of 5 (i.e. a business week) as well as a linear and quadratic trend. The grey shaded areas indicate the 95 percent confidence intervals based on Newey-West standard errors. The x-axes is in days.

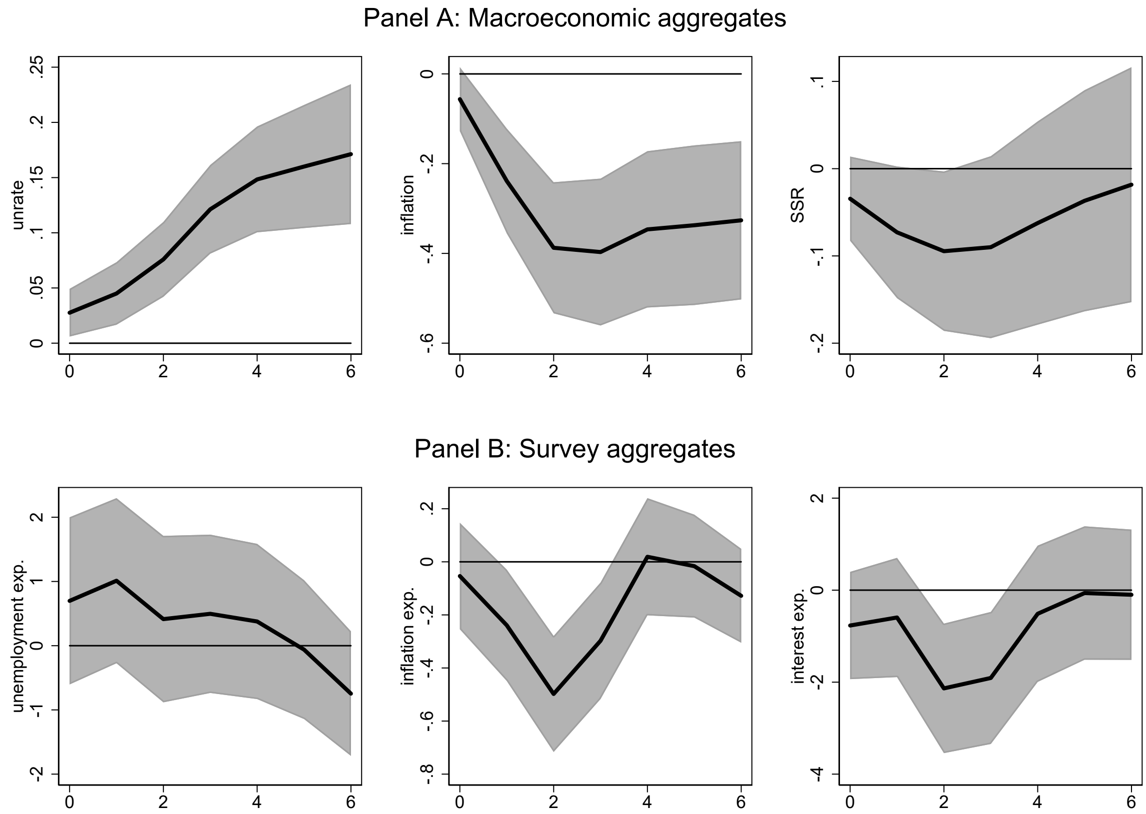
SP500 and the VIX. To do so, we aggregate the daily instrument to the monthly frequency by adding it up.

To trace the macroeconomic impact of the financial crisis events, we fit VAR-models to the financial crisis shock instrument, the CPI inflation rate, the unemployment rate, and the Shadow Short Rate (SSR) by Krippner (2015) as a measure of the stance of monetary policy in an environment where the zero lower bound effectively constraints monetary policy. The reduced-form representation of the structural VAR model is given by

$$x_t = c + \sum_{l=1}^{p} B_l x_{t-l} + e_t, \tag{1}$$

where c denotes the vector of reduced-form intercept terms, B_l the matrix of reduced-form coefficients at lag l, and e_t a vector of possibly contemporaneously correlated residuals with covariance matrix $\Sigma_e = E(e_t e_t')$. Plagborg-Møller and Wolf (2021) show that a block-recursive identification scheme with the instrument ordered first yields consistent impulse response functions even in the presence of measurement error. Along these lines, and given

Figure 4: Effects of financial crisis shocks on macroeconomic aggregates and aggregate survey measures



Notes: The figure shows the dynamic response of macroeconomic aggregates to financial crisis shocks measured as monthly aggregates of changes in the SP500 together with 90 percent confidence intervals. The x-axes is in months. Unemployment and interest rate expectations enter the VAR as balance scores while the remaining variables are in percent.

the high-frequency nature of the financial crisis instrument, we evaluate the financial crisis measure as an internal instrument and order it first.

We evaluate the effects of the financial crisis instrument constructed from the SP500 in Figure 4 as well as from the VIX index in Figure A1 in the appendix. In Panel A of Figure 4 we see that the financial crisis shocks have significant negative effects on the US macroeconomy in line with previous literature using other identification approaches to isolate financial shocks (Caldara et al., 2016; Furlanetto et al., 2017). A one-standard-deviation shock in the instrument precipitates an increase in the unemployment rate of approximately

0.3 percentage points over six months after the shock. The inflation rate decreases by similar orders of magnitude. Thus, the financial crisis shocks move the economy along the Phillips curve. In line with these dominant demand effects, the interest rate decreases. The responses of macroeconomic aggregates to the financial crisis shocks provide a benchmark against which we can compare the responses of expectations.

Panel B of Figure 4 depicts the effects of the financial crisis shocks on the survey aggregates shown above in Figure 1. Overall, the responses of the aggregated survey expectations are more short-lived than the respective macro-variables responses but qualitatively resemble those of their respective macroeconomic counterparts. In line with the macroeconomic response of the unemployment rate, relatively more respondents tend to expect higher unemployment, although responses are not significant at the 90 percent confidence interval. Inflation expectations decrease by slightly less than .5 percentage points over two months, moving in the same direction and by a similar order of magnitude as the actual inflation rate shown in Panel A. Consistent with the forecasting lead, responses of expected inflation are short-lived compared to their macroeconomic counterpart. Finally, we observe that relatively more respondents expect interest rates to go down, moving in the same direction as the actual short-run interest rate shown in Panel A of Figure 4. How aggregate survey expectations are affected by the financial crisis shocks is consistent with the effects of general aggregate demand shocks as discussed in Geiger and Scharler (2021), who estimate the effects of these shocks on survey expectations from the MSC.

While this aggregate analysis already provides a first indication of how the financial shocks affect expectations, identification of the events is not as tight in this case as the chronological coincidence of events and interview dates is complicated by monthly aggregation, and thus fails to exploit the individual-level interview dates in relation to events that happen right before. In particular, we cannot effectively distinguish between the direct reaction of households to the financial crisis events versus the indirect reaction to these events through their implied impact on macroeconomic outcomes. The micro data allow for a sharper identification since we can tightly relate the daily events to the individual interview dates.

Furthermore, the micro-level information also allows us to take account of individual characteristics in the formation of expectations. We thus turn to the micro-level data next.

3 Estimation and results

3.1 Household-level regressions

In what follows, we estimate the following regression equation:

$$y_{it} = \alpha_0 + \alpha_1 x_{1it} + \alpha_2 x_{2it} + \alpha_3 x_{3it} + \alpha_4 z_{it} + \epsilon_{it} \tag{2}$$

where y stands for the economic expectations variable (namely, inflation expectations, unemployment expectations or interest rate expectations), x_1 includes dummy variables for poor and wealthy HtM status (the comparison group being wealthy non-HtM households), x_2 includes financial shock measures, x_3 includes interactions between the financial shock measures and HtM status, and z are the control variables which include income and education variables as well as age, sex, and race of the respondent. We also control for four census regions (Northeast, Midwest, South, West) in our baseline regressions.

As the responses for unemployment and interest rate expectations are discrete, an ordered discrete choice model is warranted in this case and we thus used an ordered logit specification in our baseline when the dependent variable is one of these two expectations variables. For the specification with inflation expectations as the dependent variable we simply used pooled Ordinary Least Squares in the baseline.

Next, we present estimates pertaining to the formation of expectations for individual households belonging in different HtM categories.

3.2 Baseline Results

We begin with our estimates pertaining to inflation expectations formation which are shown in Table 1 below. The estimates for poor HtM households (HtM=P) are presented in the first row of Table 1 and all tables of results that follow, and the estimates for wealthy HtM households (HtM=W) are presented in the second row. These estimates are relative to the unconstrained wealthy households in each case.

We can see that inflation expectations are higher for poor and wealthy HtMs relative to wealthy unconstrained households. As shown in columns 3 and 6 of Table 1, this finding persists net of household income and education levels suggesting that liquidity constraints matter directly for the formation of expectations separately than household income and education. The latter are associated with lower inflation expectations. In Table 1, we can also see that poor HtM households typically have higher inflation expectations than wealthy ones, but this difference is not always significant.

From Table 1, we also see that adverse financial crisis events do not affect inflation expectations for every type of household. Wealthy HtMs, however, tend to revise inflation expectations downwards in the face of adverse events that lower the value of the stock market or increase stockmarket-related uncertainty. Looking at the interaction term, we see that an average financial crisis shock in our sample lowers inflation expectations of wealthy HtM individuals substantially, by approximately 2 percentage points through the liquidity status channel.[9] Since wealthy HtM are much more likely to have a mortgage as compared to the poor and mortgages are predominantly fixed rate, lower inflation rates would be undesirable for this group as it would raise their real interest rate relative to what that would be in the absence of such a fall. Thus, following an adverse financial event that lowers future inflation rates, there would be a greater impact on the dynamic path of the wealthy HtM's real debt burden and their ability to pay in the future. This provides the wealthy HtM with a greater incentive to pay attention to such events.[10] As shown in Panel A of Figure 4, the inflation rate goes down following adverse financial sector events and wealthy HtM households appear

[9]An average shock that lowers the SP500 more than the one-stadard-deviation cutoff amounts to 43.72 index points, so that inflation expectations decrease by $43.72 \times 0.06 = 2.62$ percentage points for the wealthy HtM. Analogously, an average event-induced hike in the VIX which amounts to 6.60, lowers inflation expectations by $0.04 \times 6.60 = 2.24$ percentage points for wealthy HtM households.

[10]Wealthy HtM might also find it easier to observe these financial events' signal as compared to poor HtM which do no participate as much in financial markets (a mere 14% of them owns stock as compared to 53% for the wealthy HtM), so that wealthy HtM may have a lower cost of paying attention to these financial events as compared to poor HtM households.

to form their current expectations of the future so that they more accurately predict this future movement as compared to the poor. This is in line with wealthy HtM individuals having a greater incentive to pay attention and to more accurately decipher these financial events' noisy signal regarding lower future inflation. As compared to wealthy unconstrained households, the considerably lower liquid assets of the wealthy HtM raise their incentive to pay attention to such events, which again rationalizes the latter's response as compared to the lack of response by the former.[11,12]

Turning our attention to the other covariates, we observe that male status lowers inflation expectations, and the same goes for whites relative to other groups.

Table 2 shows our estimates pertaining to unemployment expectations formation. As we can see in the first two rows of Table 2, HtM households are more likely to expect higher unemployment as compared to unconstrained ones. As can be seen in the 3rd and 6th columns of Table 2, this effect persists net of the income and education levels of the household. Higher education and income lead to lower unemployment expectations revisions. Moreover, poor HtM households are typically less likely to expect higher unemployment as compared to wealthy ones but this difference in expectations between poor and wealthy HtM households is not always significant.

[11] A reflection of their greater incentive to pay attention is that these HtM households are at least three times more likely to worry "all of the time" or "most of the time" about debt as compared to unconstrained households as shown in Table A13 in the Appendix.

[12] Although the wealthy liquid households' greater participation in financial markets (89% own stock) might make it easier for them to observe these financial events' signal, the fact that these households are not liquidity constrained apparently reduces their incentive to decipher this noisy signal by so much that they do not decipher this even though it should be relatively easier for them to do so.

TABLE 1: Inflation Expectations Formation

HtM=P	4.422***	3.492***	2.327***	4.365***	3.408***	2.248***
	(8.46)	(6.71)	(3.71)	(8.51)	(6.67)	(3.63)
HtM=W	2.823***	2.254***	2.042***	2.774***	2.192***	1.976***
	(9.97)	(7.88)	(5.74)	(9.85)	(7.71)	(5.59)
Shock	0.00932	0.00719	0.00868	0.0712	0.0543	0.0611
	(0.88)	(0.68)	(0.72)	(0.88)	(0.67)	(0.67)
HtM=P × Shock	-0.0475	-0.0474	0.00620	-0.320	-0.353	0.225
	(-1.05)	(-1.02)	(0.08)	(-1.25)	(-1.27)	(0.54)
HtM=W × Shock	-0.0552***	-0.0587***	-0.0605***	-0.365***	-0.369***	-0.335**
	(-3.05)	(-3.21)	(-2.86)	(-3.19)	(-3.19)	(-2.56)
25-39		0.615	-0.371		0.138	-1.169
		(0.48)	(-0.20)		(0.10)	(-0.56)
40-54		1.459	0.346		0.946	-0.482
		(1.15)	(0.19)		(0.69)	(-0.23)
55-69		1.645	0.164		1.113	-0.700
		(1.30)	(0.09)		(0.81)	(-0.34)
70+		0.573	-0.763		0.0746	-1.545
		(0.45)	(-0.41)		(0.05)	(-0.74)
Some College		-0.820**	-0.663		-0.772**	-0.551
		(-2.45)	(-1.62)		(-2.33)	(-1.36)
College Degree		-2.501***	-2.027***		-2.478***	-1.997***
		(-7.89)	(-4.97)		(-7.87)	(-4.93)
College and More		-2.778***	-2.151***		-2.736***	-2.082***
		(-8.84)	(-5.39)		(-8.76)	(-5.24)
male		-1.520***	-1.297***		-1.553***	-1.354***
		(-7.27)	(-5.09)		(-7.54)	(-5.46)
white		-0.880**	-0.602		-0.952**	-0.671
		(-2.33)	(-1.35)		(-2.51)	(-1.50)
Log Hshld Income			-0.895***			-0.888***
			(-5.47)			(-5.49)
Constant	5.508***	7.375***	17.98***	5.523***	7.953***	18.77***
	(29.82)	(5.46)	(7.07)	(30.28)	(5.49)	(6.97)
Shock Measure	SP	SP	SP	VIX	VIX	VIX
Regional Dummies	YES	YES	YES	YES	YES	YES
Observations	12314	12295	8579	12177	12159	8470

Notes: t-statistics in parentheses; *, **, and *** indicate significance at the 10, 5, and 1 percent level.

Following financial crisis events that lower stock-market values or increase stock-market volatility, while all households are more likely to expect higher unemployment as shown in row 3 of Table 2, wealthy liquid households expect higher future unemployment than HtM ones as indicated by the negative estimated interaction effects of financial crisis events with HtM status shown in rows 4 and 5. As wealthy unconstrained households are more likely to be directly exposed to the financial sector and have greater exposure to it as reflected in their stock holdings, they react more to adverse financial sector events that raise future unemployment. As shown in Panel A of Figure 4, the unemployment rate goes up following such adverse financial sector events and different types of households form their expectations in a manner that incorporates this signal to a differing degree depending on their specific circumstances.

Turning to the covariates, we note that our finding that higher education makes people expect lower unemployment is not surprising given chronically higher unemployment rates for those without college education, and the same goes for the finding that whites expect lower unemployment as compared to other racial groups.

Table 3 shows our estimates pertaining to interest rate expectations. Interest rate expectations are revised downwards following adverse financial events like a fall in the value of the stockmarket or an increase in stockmarket-related uncertainty. As shown in Panel A of Figure 4, the interest rate goes down following such adverse financial sector events, and the revision of interest rate expectations is consistent with this downward movement.

Revisions in interest rate expectations also go down with income, education and age. Moreover, being male is associated with smaller revisions in interest rate expectations. Finally, we note that HtM status does not typically affect the formation of interest rate expectations. When significant, in columns 3 and 6 (1 and 4) of Table 3, downward (upward) revision in interest rate expectations of poor (wealthy) HtMs is more likely than for wealthy unconstrained households.

TABLE 2: Unemployment Expectations Formation

HtM=P	0.478***	0.328***	0.230***	0.481***	0.328***	0.219***
	(8.49)	(5.60)	(3.13)	(8.56)	(5.59)	(2.98)
HtM=W	0.255***	0.169***	0.139***	0.255***	0.169***	0.134***
	(6.33)	(4.10)	(2.73)	(6.35)	(4.10)	(2.65)
Shock	0.00958***	0.00963***	0.0108***	0.0604***	0.0602***	0.0644***
	(5.55)	(5.54)	(5.50)	(5.05)	(4.99)	(4.82)
HtM=P × Shock	-0.00725*	-0.00826**	-0.0102*	-0.0647**	-0.0743***	-0.0778*
	(-1.86)	(-2.07)	(-1.74)	(-2.51)	(-2.72)	(-1.85)
HtM=W × Shock	-0.00580*	-0.00576*	-0.00453	-0.0458**	-0.0459**	-0.0400*
	(-1.87)	(-1.82)	(-1.25)	(-2.25)	(-2.23)	(-1.75)
25-39		-0.00691	0.0642		0.0332	0.113
		(-0.04)	(0.27)		(0.18)	(0.45)
40-54		0.154	0.231		0.198	0.289
		(0.87)	(0.97)		(1.09)	(1.17)
55-69		0.0298	0.0882		0.0752	0.142
		(0.17)	(0.37)		(0.41)	(0.58)
70+		-0.146	-0.161		-0.0964	-0.0980
		(-0.81)	(-0.67)		(-0.52)	(-0.39)
Some College		-0.0954**	-0.0712		-0.0983**	-0.0709
		(-2.13)	(-1.33)		(-2.19)	(-1.31)
College Degree		-0.349***	-0.294***		-0.347***	-0.284***
		(-7.50)	(-5.14)		(-7.42)	(-4.94)
College and More		-0.412***	-0.412***		-0.408***	-0.397***
		(-8.47)	(-6.84)		(-8.33)	(-6.55)
male		-0.0361	0.0215		-0.0408	0.0159
		(-1.10)	(0.54)		(-1.24)	(0.40)
white		-0.223***	-0.203***		-0.238***	-0.218***
		(-4.49)	(-3.38)		(-4.75)	(-3.59)
Log Hshld Income			-0.110***			-0.118***
			(-4.92)			(-5.23)
Shock Measure	SP	SP	SP	VIX	VIX	VIX
Regional Dummies	YES	YES	YES	YES	YES	YES
Observations	13479	13458	9364	13320	13300	9243

Notes: t-statistics in parentheses; *, **, and *** indicate significance at the 10, 5, and 1 percent level.

TABLE 3: Interest Rate Expectations Formation

HtM=P	0.0467	-0.0679	-0.147*	0.0422	-0.0704	-0.161**
	(0.79)	(-1.10)	(-1.92)	(0.71)	(-1.14)	(-2.10)
HtM=W	0.128***	0.0550	0.0131	0.127***	0.0557	0.0118
	(2.96)	(1.24)	(0.24)	(2.95)	(1.25)	(0.22)
Shock	-0.00882***	-0.00865***	-0.00600***	-0.0395***	-0.0393***	-0.0225*
	(-4.94)	(-4.81)	(-2.96)	(-3.24)	(-3.21)	(-1.68)
HtM=P × Shock	0.00292	0.00136	-0.000617	0.0139	0.00552	0.0156
	(0.74)	(0.34)	(-0.10)	(0.53)	(0.20)	(0.38)
HtM=W × Shock	0.000583	0.000676	0.000314	0.00325	0.00567	0.00519
	(0.19)	(0.22)	(0.09)	(0.16)	(0.28)	(0.23)
25-39		-0.406*	0.0124		-0.372*	0.0805
		(-1.89)	(0.05)		(-1.71)	(0.30)
40-54		-0.594***	-0.160		-0.556***	-0.0797
		(-2.80)	(-0.61)		(-2.58)	(-0.30)
55-69		-0.693***	-0.220		-0.657***	-0.135
		(-3.27)	(-0.84)		(-3.05)	(-0.50)
70+		-0.681***	-0.204		-0.645***	-0.112
		(-3.17)	(-0.77)		(-2.95)	(-0.41)
Some College		-0.0995**	-0.0612		-0.0926*	-0.0519
		(-2.07)	(-1.07)		(-1.92)	(-0.90)
College Degree		-0.204***	-0.210***		-0.186***	-0.187***
		(-4.09)	(-3.48)		(-3.70)	(-3.09)
College and More		-0.218***	-0.169***		-0.214***	-0.160**
		(-4.23)	(-2.68)		(-4.12)	(-2.52)
male		-0.130***	-0.0986**		-0.136***	-0.105**
		(-3.73)	(-2.38)		(-3.87)	(-2.50)
white		0.0533	0.0448		0.0446	0.0187
		(1.03)	(0.73)		(0.86)	(0.30)
Log Hshld Income			-0.0994***			-0.102***
			(-4.19)			(-4.25)
Shock Measure	SP	SP	SP	VIX	VIX	VIX
Regional Dummies	YES	YES	YES	YES	YES	YES
Observations	13481	13460	9322	13322	13303	9200

Notes: *t*-statistics in parentheses; *, **, and *** indicate significance at the 10, 5, and 1 percent level.

3.3 Disagreement

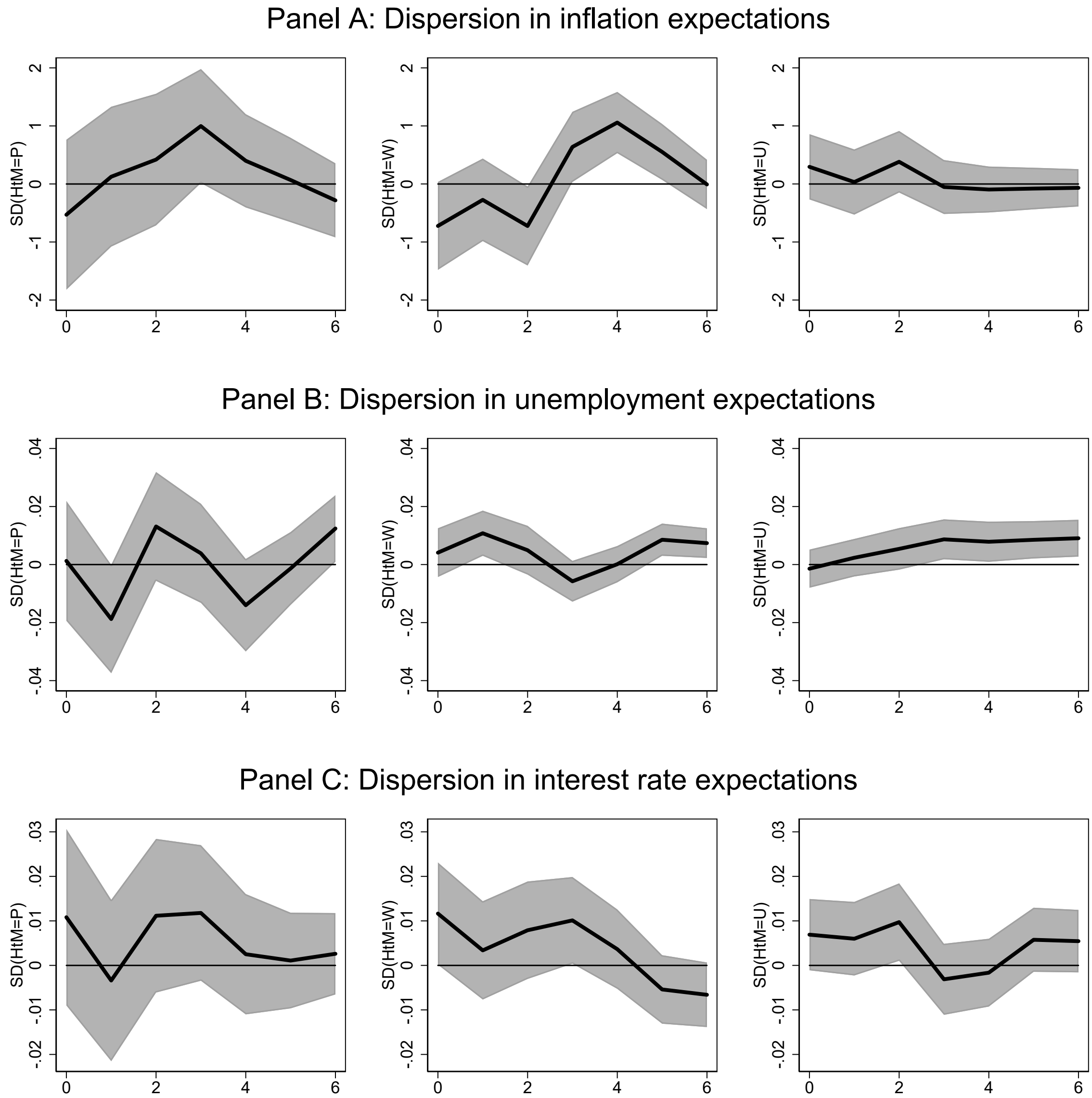
In this section, we consider specifications that explain the dispersion of the cross-sectional distribution of individual expectations at each point in time in an attempt to understand disagreement among respondents over time. The response of disagreement to shocks can help differentiate between different models of imperfect information and expectations formation. Moreover, using higher moments of the cross-sectional distribution effectively utilizes features of the cross-sectional distribution, retaining important aspects of the household-level information available in these data, while alleviating the noise present in the household-level regressions.

More specifically, we construct time series of cross-sectional standard deviations for each HtM-status category. We then evaluate these aggregate measures of second moment movements in the survey data within the VAR model presented in Section 2.2 and depicted in Figure 4. The results are presented below. The estimates for poor HtM households (HtM=P) are presented in the first column, for wealthy HtM (HtM=W) in the second column, and for wealthy unconstrained households (HtM=U) in the third column of each Panel.

Figure 5 shows the effects of the financial crisis shocks constructed from the SP500, while Figure A2 in the appendix shows comparable results for the variant constructed from the VIX. It appears that financial crisis shocks tend to increase uncertainty for some households as the cross-sectional standard deviation goes up for certain types of households in the face of such shocks. With respect to inflation expectations, we observe in Panel A of Figures 5 and A2, that the increase is most distinct for wealthy HtM households shown in the middle column of the Panel (and absent for wealthy unconstrained households shown in the last column of the Panel), reflecting the fact that, within this group, respondents update inflation expectations differently (similarly). The increased dispersion among wealthy HtM households in response to financial shocks is inconsistent with basic noisy information models but consistent with noisy information models that incorporate heterogeneity in signal-to-noise ratios and with sticky information models such as Mankiw and Reis (2002) that imply a positive association between disagreement and any shock.

With respect to unemployment expectations, it is remarkable that poor HtM households react relatively similarly to financial shocks. As we can see in the first column of Panel B in Figures 5 and A2, the cross-sectional standard deviation among poor HtM households does not react significantly, in spite of the fact that, on average, poor HtM update unemployment expectations significantly as we have seen in Table 2. This can perhaps be explained by poor households being affected relatively homogeneously by financial crisis shocks as suggested by the high business cycle vulnerability of this group (Hoynes et al., 2012). That disagreement among poor HtM households regarding their unemployment expectations does not go up in response to large financial shocks, is inconsistent with sticky information models that imply a positive association between disagreement and any shock. By contrast, disagreement among wealthy HtM households (and among wealthy unconstrained households) regarding their unemployment expectations tends to go up in response to these adverse financial shocks. Finally, as we can see in Panel C of Figures 5 and A2, dispersion in interest rate expectations among poor HtM households does not react to large financial shocks, which is again inconsistent with sticky information models.

Figure 5: Effects of financial crisis shocks constructed from the SP500 on economic expectations



Notes: The figure shows the dynamic response of cross-sectional standard deviations of economic expectations for poor HtM households in the first column, for wealthy HtM in the second column and for wealthy unconstrained households in the third column of each Panel. We note that inflation expectations are quantitative while unemployment and interest expectations are qualitative measures. The x-axes is in months.

3.4 Robustness

3.4.1 Using a Fixed Window to identify financial events

The next set of results presented in this section uses our Fixed Window definition of financial shocks where we consider changes in the SP500 and the VIX from the day before the interview to the day following the interview (as opposed to the Flexible window results presented in Section 3.2 which consider up to three days preceding the interview). Again, inflation expectations are estimated using OLS and the other two expectations using ordered logistic regressions.

As we can see in the first five rows of Table A1 in the appendix, the estimates for the impact of our main variables on inflation expectations based on the fixed window are qualitatively similar to those in our baseline Table 1. Moreover, as we can see in the first five rows of Table A2 in the appendix, the estimates for the impact of our main variables on unemployment expectations based on the fixed window are qualitatively similar to those for our baseline shown in Table 2: HtM status, the financial shock, and the interactions of the latter with the former retain their significance except for the interaction of the S&P500-based measure of the financial shock with poor HtM status which loses its significance as seen in the first three columns of Table A2. Finally, the estimates in Table A3 for the impact of our main variables on interest rate expectations based on the fixed window are qualitatively similar to those in our baseline in Table 3.

3.4.2 Outliers and imputed values

Survey measures of inflation expectations of households can have outliers. For example, in our data set we have some households who expect as high as 500% inflation or 100% deflation in the USA. Such outliers are infrequent but still need some attention as discussed extensively early on by Curtin (1996) and more recently by Fofana et al. (2024). The distribution of inflation expectations in our data set is shown in Table 4 below.

Table 4. Inflation Expectations Bins in CFM

	Percent of CFM
$<=$ -20	.53
(-20,-10]	.87
(-10,0]	25.03
(0,10]	59.44
(10,20]	8.13
(20,30]	3.50
(30,40]	.57
(40,50]	1.20
More than 50%	.74
N	22284

One approach is to delete these outliers, but that might eliminate some useful information. Another approach, favored by Curtin (1996), is to truncate those at some pre-determined acceptable level. Here, we follow Curtin (1996) and choose the latter approach. We use two different cutoffs for inflation expectations values: -10 for the lower bound and 30 for the upper bound, and also try -10 and 50 respectively. As we can see in Table 4, adopting the wider range covers nearly the entire response distribution, with just over 2% of the distribution outside of this range as compared to about 1% for the Michigan Survey Data reported in Curtin (1996).

Another problem with survey data is missing observations. There are some households who say that prices will go up over the next year but do not provide a numeric value. Hence, these individuals cannot be used in our baseline models. Following again Curtin (1996), we impute the values for these respondents by using the mean expected inflation of all those who said prices will go up. The imputed inflation expectations are then truncated using the two specifications above. This raises our sample size and allows us to include households with potentially valuable information in our analysis.

Table 5 below shows the estimates obtained for inflation expectations when we apply truncation and imputation as described above. While the table shows only coefficient estimates for our key variables, all of the models include the same control variables as the ones in the third and sixth columns of Table 1. The first four columns do not consider imputation while the last four columns apply the imputation discussed above. Odd number columns consider the S&P 500 while even number columns present estimates for the VIX.

As can be seen, the estimates are comparable to those in our baseline, with the estimated impact and significance of coefficients not affected qualitatively by truncation nor imputation. Interestingly, however, we observe that truncation leads to distinctly smaller estimates across the board for all our variables (including for HtM status and its interaction with the financial shock) as compared to the baseline shown in columns 3 and 6 of Table 1. Moreover, relaxing somewhat the truncation rule to -10, 50 in columns 3, 4, 7 and 8 raises somewhat the estimates relative to the stricter truncation rule (-10, 30) adopted in columns 1, 2, 5, and 6.

We next experiment with the imputation of household income. In our earlier analysis, we ignored missing information on household income. However, there is a substantial number of observations with missing household income so that we would like to check the robustness of our results to utilizing this larger sample. We thus use mean imputation to replace those missing values. Table 6 shows the results when we use imputed income values. The first two columns of this table report the estimated impact on inflation expectations (comparable to columns 3 and 6 of Table 1). Columns 3 and 4 report the estimated impact on unemployment expectations (comparable to columns 3 and 6 of Table 2) and columns 5 and 6 report estimates of the impact on interest rate expectations (comparable to columns 3 and 6 of Table 3). Again, odd number columns consider the S&P 500 while even number columns pertain to the VIX. We use OLS for Inflation expectations and ordered logit model for the other two expectation measures. All the other control variables are the same as the ones we used in the 3rd and 6th columns of Tables 1, 2 and 3 for our baseline.

Table 5. Truncated Inflation Expectations

HtM=P	1.717***	1.719***	2.103***	2.121***	1.561***	1.559***	1.869***	1.880***
	(4.70)	(4.71)	(4.59)	(4.63)	(4.96)	(4.95)	(4.75)	(4.77)
HtM=W	1.559***	1.507***	1.864***	1.812***	1.442***	1.392***	1.714***	1.664***
	(7.03)	(6.83)	(6.72)	(6.56)	(7.23)	(7.02)	(6.89)	(6.72)
Shock	0.00503	0.0421	0.00990	0.0706	0.00411	0.0359	0.00870	0.0628
	(0.59)	(0.65)	(0.95)	(0.94)	(0.51)	(0.59)	(0.89)	(0.89)
HtM=P $\times$ Shock	0.0173	0.415	0.0274	0.471	0.0140	0.353	0.0227	0.404
	(0.42)	(1.60)	(0.56)	(1.59)	(0.40)	(1.52)	(0.55)	(1.54)
HtM=W $\times$ Shock	-0.0423***	-0.223**	-0.0526***	-0.289***	-0.0355**	-0.183**	-0.0451***	-0.243**
	(-2.66)	(-2.24)	(-2.84)	(-2.58)	(-2.51)	(-2.07)	(-2.74)	(-2.44)
Log Hshld Income	-0.648***	-0.648***	-0.826***	-0.824***	-0.630***	-0.629***	-0.776***	-0.772***
	(-6.74)	(-6.70)	(-6.78)	(-6.70)	(-7.36)	(-7.34)	(-7.20)	(-7.12)
Constant	14.34***	14.70***	17.34***	18.13***	14.50***	14.82***	16.92***	17.63***
	(8.40)	(8.18)	(7.66)	(7.43)	(10.04)	(9.63)	(8.88)	(8.49)
Shock Measure	SP	VIX	SP	VIX	SP	VIX	SP	VIX
Truncated Range	[-10,30]	[-10,30]	[-10,50]	[-10,50]	[-10,30]	[-10,30]	[-10,50]	[-10,50]
Imputation	NO	NO	NO	NO	YES	YES	YES	YES
Observations	8579	8470	8579	8470	9491	9371	9491	9371

Notes: t-statistics in parentheses; *, **, and *** indicate significance at the 10, 5, and 1 percent level.

Table 6. Using Imputed Household Income

HtM=P	2.870***	2.781***	0.265***	0.262***	-0.101	-0.106*
	(5.41)	(5.27)	(4.38)	(4.31)	(-1.57)	(-1.65)
HtM=W	2.022***	1.955***	0.147***	0.145***	0.0430	0.0425
	(7.13)	(6.94)	(3.51)	(3.48)	(0.96)	(0.95)
Shock	0.00607	0.0441	0.00955***	0.0594***	-0.00870***	-0.0398***
	(0.58)	(0.54)	(5.49)	(4.91)	(-4.83)	(-3.24)
HtM=P × Shock	-0.0424	-0.326	-0.00776*	-0.0716***	0.00163	0.00703
	(-0.91)	(-1.19)	(-1.95)	(-2.62)	(0.40)	(0.25)
HtM=W × Shock	-0.0577***	-0.367***	-0.00575*	-0.0464**	0.000736	0.00581
	(-3.13)	(-3.16)	(-1.82)	(-2.25)	(0.23)	(0.28)
Imputed Log Hshld Income	-0.823***	-0.834***	-0.0867***	-0.0925***	-0.0443**	-0.0480**
	(-5.03)	(-5.24)	(-4.16)	(-4.40)	(-2.01)	(-2.15)
Shock Measure	SP	VIX	SP	VIX	SP	VIX
Dependent Variable	INF	INF	UNEMP	UNEMP	INT	INT
Observations	12295	12159	13458	13300	13460	13303

Notes: *t*-statistics in parentheses; *, **, and *** indicate significance at the 10, 5, and 1 percent level.

As we can see in Table 6, the estimates based on imputed household income are qualitatively unchanged relative to our baseline. One notable difference as compared to the baseline estimates shown in columns 3 and 6 of Table 1, is that the estimated impact on inflation expectations of belonging in the poor HtM category (HtM=P) is now greater than before the imputation of income, while the estimates for wealthy HtM (HtM=W) status are almost unchanged relative to the baseline. This is consistent with poorer potentially constrained households being more likely not to report income so that our baseline which does not impute income tends to under-include these households and to underestimate the impact of poor HtM status on inflation expectations.

3.4.3 State-level conditions

In this section, we include additional variables at the state level. More specifically, we consider state-specific fixed effects and state-level time-varying macroeconomic conditions.

As the households in our dataset are sampled from all over the United States it is possible that they might face different, state-specific, economic conditions that might influence their expectations formation process. Thus, in another robustness test, we re-estimate our baseline models from Section 3.2 after adding state dummies (instead of regional dummies). Tables A4, A5 and A6 present the respective estimates for inflation, unemployment, and interest rate expectations as outcome variables. These tables show that using individual state dummies (not shown in the tables) leaves our estimates qualitatively but also quantitatively unchanged in this case relative to the baseline models in Tables 1, 2 and 3 of Section 3.2.

We then add the state-level unemployment rate to capture time-varying state-specific macroeconomic conditions as well as state-level gas prices which are widely thought to play a potentially important role in expectations' formation. The estimates are shown in Tables A7, A8 and A9. As we can see there, our main results from our baseline in section 3.2 remain intact.[13]

[13]This is the case even though sample size is greatly reduced due to unavailability of the state-level gas price data which are only available until February 2011. Regressions that include state-level unemployment but exclude gas prices to fully exploit our time-series sample produce similar results (not reported here). Including state dummies in addition to state-level gas prices and unemployment again gives similar results.

4 Conclusion

Using microeconomic survey data for 2005:2 to 2013:6 across the US and a timeline of financial crisis events, we have found differences in the formation of unemployment and inflation expectations of liquidity constrained households relative to unconstrained ones, which accord well with characteristics that are intrinsically related to liquidity constraints.

The financial crisis period provides a setting during which the stakes were potentially higher for liquidity constrained households, allowing us to examine their attentiveness as compared to other households. Importantly, we find that while financial crisis events do not affect inflation expectations for all types of households, wealthy HtM tend to revise inflation expectations downward relative to other households in the face of adverse events that reduce future inflation. Liquidity constraints apparently provide wealthy HtM with a greater incentive to pay attention and to more accurately decipher the financial events' noisy signal regarding lower future inflation as compared to wealthy unconstrained households. As compared to poor HtM, wealthy HtM are much more likely to have a mortgage and given that these are predominantly fixed rate, the latter would face a higher real interest rate following events that lower the inflation rate as compared to the higher-inflation scenario in the absence of such events. This provides them with a greater incentive to pay attention and to decipher the noisy signal from such events. Thus, wealthy HtM react distinctly to adverse financial events that appear to alarm them about the possibility of lower inflation in the future which would adversely affect the dynamic path of their real debt burden and their ability to pay in the future, while other households remain inattentive.

Greater responsiveness and more accurate formation of inflation expectations by those who have a greater incentive to pay attention to adverse financial shocks, is consistent with models such as those in Sims (2010) or Mackowiak and Wiederholt (2009), where individuals are rationally inattentive depending on their specific circumstances. Rational inattention models linking higher uncertainty with higher marginal returns from forming accurate forecasts imply that capacity is reallocated to allow increased accuracy when variability is higher. Instead, this is inconsistent with noisy-information models assuming a fixed amount of capacity allocated to monitoring economic variables given that individuals "cannot choose to pay more attention at certain times" (Mankiw and Reis, 2010).

Moreover, as shown in Coibion and Gorodnichenko (2012), our results regarding the response of the cross-sectional dispersion (i.e., disagreement) across households in expectations' formation following a financial shock, can be informative about the relevance of the sticky information model of Mankiw and Reis (2002) versus the basic noisy information model. In the basic noisy information model without heterogeneity in signal-to-noise ratios, disagreement across individuals does not respond to shocks. By contrast, the sticky information model predicts that disagreement responds to shocks. We find that disagreement in inflation expectations increases most distinctly for wealthy HtM households, reflecting the fact that within this group, respondents update inflation expectations relatively differently to each other. This increased dispersion among households in response to financial shocks is inconsistent with basic noisy information models but consistent with noisy information models that incorporate heterogeneity in signal-to-noise ratios and with sticky information models such as Mankiw and Reis (2002) that imply a positive association between disagreement and any shock. Interestingly, inconsistent with the latter model, disagreement among poor HtM households regarding their unemployment and interest rate expectations does not react to adverse financial shocks.

Our work has investigated whether there exists heterogeneity in the formation of expectations between constrained and unconstrained agents but also across different types of liquidity constrained agents. The differences we find suggest it could be important to model this type of heterogeneity in macroeconomic models, e.g., in contexts pertaining to the potentially heterogeneous formation of expectations in response to financial or monetary shocks. According to our empirical findings, noisy information models with heterogeneity in signal-to-noise ratios related to liquidity constraints would be a promising route for future theoretical exploration.

Appendix

In this Appendix to be published online after publication, we present tables of results with additional estimations that serve to check the robustness of our results. We first present tables of results (A1, A2 and A3) discussed in subsection 3.4.1 of the paper, pertaining to the fixed window identification of financial events. We next present tables of results pertaining to subsection 3.4.3. Tables A4, A5 and A6 introduce state dummies to our baseline specification, while Tables A7, A8 and A9 incorporate time-varying state-level unemployment rates and gas prices. All of these specifications are consistent with the main results from our baseline.

We note that Table A8 reports a surprising (negative) estimate for the impact of state-level unemployment on unemployment expectations. Further investigation into this has shown that this negative effect arises solely from the period following the collapse of Lehman Brothers. As the economy was in a recession during this period, we can hypothesize that a higher level of unemployment at the state-level could have induced people to believe that the recession was reaching its peak and that the economy would recover soon, as compared to states with lower current unemployment rates. Before that, the effect of state-level unemployment on unemployment expectations was positive in line with higher current unemployment at the state-level inducing people to expect a higher unemployment rate into the future.

Finally, we consider Probit instead of Logit estimation for Unemployment expectations and Interest rate expectations in Tables A10 and A11 respectively. As we can see there, this does not qualitatively change our estimates.

TABLE A1: Inflation Expectations Formation using Fixed Window

HtM=P	4.491***	3.482***	2.271***	4.455***	3.437***	2.253***
	(9.02)	(7.02)	(3.84)	(9.08)	(7.04)	(3.84)
HtM=W	2.808***	2.197***	1.957***	2.787***	2.168***	1.906***
	(10.33)	(8.04)	(5.84)	(10.26)	(7.94)	(5.72)
Shock	-0.00480	-0.00572	-0.00623	0.00368	-0.00659	0.0199
	(-0.33)	(-0.40)	(-0.40)	(0.03)	(-0.06)	(0.18)
HtM=P × Shock	-0.0141	-0.00847	0.0877	-0.260	-0.272	0.525
	(-0.24)	(-0.14)	(0.99)	(-0.70)	(-0.72)	(1.17)
HtM=W × Shock	-0.0524**	-0.0581**	-0.0453*	-0.311**	-0.318**	-0.276*
	(-2.20)	(-2.48)	(-1.75)	(-2.07)	(-2.15)	(-1.73)
25-39		0.476	-0.560		0.359	-0.669
		(0.36)	(-0.29)		(0.27)	(-0.34)
40-54		1.230	0.0321		1.084	-0.0928
		(0.95)	(0.02)		(0.82)	(-0.05)
55-69		1.386	-0.193		1.209	-0.390
		(1.06)	(-0.10)		(0.92)	(-0.20)
70+		0.242	-1.230		0.156	-1.326
		(0.18)	(-0.64)		(0.12)	(-0.68)
Some College		-0.816**	-0.715*		-0.743**	-0.615
		(-2.52)	(-1.82)		(-2.32)	(-1.58)
College Degree		-2.539***	-2.079***		-2.478***	-1.998***
		(-8.22)	(-5.32)		(-8.07)	(-5.14)
College and More		-2.774***	-2.165***		-2.702***	-2.056***
		(-9.04)	(-5.63)		(-8.89)	(-5.39)
male		-1.535***	-1.346***		-1.621***	-1.436***
		(-7.58)	(-5.49)		(-8.12)	(-5.99)
white		-0.987***	-0.676		-1.041***	-0.720*
		(-2.72)	(-1.58)		(-2.86)	(-1.68)
Log Hshld Income			-0.945***			-0.958***
			(-6.02)			(-6.21)
Constant	5.458***	7.687***	18.94***	5.496***	7.906***	19.29***
	(30.44)	(5.58)	(7.48)	(30.79)	(5.67)	(7.56)
Shock Measure	SP	SP	SP	VIX	VIX	VIX
Regional Dummies	YES	YES	YES	YES	YES	YES
Observations	12846	12837	9121	12749	12741	9047

Notes: t-statistics in parentheses; *, **, and *** indicate significance at the 10, 5, and 1 percent level.

TABLE A2: Unemployment Expectations Formation using Fixed Window

HtM=P	0.467***	0.314***	0.228***	0.471***	0.320***	0.222***
	(8.63)	(5.56)	(3.24)	(8.69)	(5.65)	(3.15)
HtM=W	0.266***	0.181***	0.153***	0.266***	0.182***	0.151***
	(6.85)	(4.53)	(3.17)	(6.84)	(4.56)	(3.12)
Shock	0.0116***	0.0115***	0.0111***	0.0865***	0.0855***	0.0848***
	(4.52)	(4.43)	(3.95)	(4.39)	(4.32)	(3.78)
HtM=P × Shock	-0.00921	-0.00746	-0.00955	-0.130***	-0.122***	-0.133**
	(-1.64)	(-1.30)	(-1.29)	(-3.32)	(-2.97)	(-2.38)
HtM=W × Shock	-0.00872**	-0.00890**	-0.00726	-0.0801***	-0.0809***	-0.0783**
	(-1.98)	(-2.01)	(-1.47)	(-2.60)	(-2.61)	(-2.28)
25-39		0.00400	0.0928		0.0430	0.126
		(0.02)	(0.39)		(0.24)	(0.53)
40-54		0.155	0.247		0.193	0.283
		(0.88)	(1.06)		(1.08)	(1.20)
55-69		0.0331	0.106		0.0771	0.144
		(0.19)	(0.45)		(0.43)	(0.61)
70+		-0.139	-0.131		-0.0891	-0.0838
		(-0.77)	(-0.55)		(-0.49)	(-0.35)
Some College		-0.0892**	-0.0711		-0.0921**	-0.0697
		(-2.04)	(-1.37)		(-2.10)	(-1.33)
College Degree		-0.343***	-0.297***		-0.338***	-0.285***
		(-7.54)	(-5.36)		(-7.41)	(-5.12)
College and More		-0.400***	-0.402***		-0.395***	-0.389***
		(-8.40)	(-6.90)		(-8.27)	(-6.63)
male		-0.0305	0.0205		-0.0314	0.0162
		(-0.95)	(0.54)		(-0.98)	(0.42)
white		-0.232***	-0.215***		-0.235***	-0.215***
		(-4.78)	(-3.70)		(-4.81)	(-3.67)
Log Hshld Income			-0.104***			-0.109***
			(-4.83)			(-5.04)
Shock Measure	SP	SP	SP	VIX	VIX	VIX
Regional Dummies	YES	YES	YES	YES	YES	YES
Observations	14054	14044	9955	13944	13935	9873

Notes: *t*-statistics in parentheses; *, **, and *** indicate significance at the 10, 5, and 1 percent level.

Table A3: Interest Rate Expectations Formation using Fixed Window

HtM=P	0.0714	-0.0366	-0.120	0.0721	-0.0352	-0.123*
	(1.26)	(-0.61)	(-1.63)	(1.26)	(-0.59)	(-1.67)
HtM=W	0.110***	0.0414	-0.0103	0.108***	0.0388	-0.0176
	(2.66)	(0.97)	(-0.20)	(2.59)	(0.91)	(-0.34)
Shock	-0.00993***	-0.00982***	-0.00869***	-0.0301	-0.0305	-0.0253
	(-3.79)	(-3.71)	(-2.96)	(-1.52)	(-1.53)	(-1.12)
HtM=P $\times$ Shock	0.00506	0.00497	0.00934	0.00229	0.00856	0.0503
	(0.90)	(0.87)	(1.20)	(0.06)	(0.21)	(0.86)
HtM=W $\times$ Shock	0.0000789	-0.000242	0.000638	-0.00189	-0.00103	0.00759
	(0.02)	(-0.06)	(0.13)	(-0.06)	(-0.03)	(0.23)
25-39		-0.370*	0.100		-0.362*	0.114
		(-1.75)	(0.39)		(-1.69)	(0.44)
40-54		-0.571***	-0.0723		-0.562***	-0.0547
		(-2.73)	(-0.28)		(-2.65)	(-0.21)
55-69		-0.665***	-0.132		-0.658***	-0.116
		(-3.18)	(-0.52)		(-3.10)	(-0.45)
70+		-0.627***	-0.0974		-0.618***	-0.0763
		(-2.95)	(-0.38)		(-2.87)	(-0.29)
Some College		-0.0958**	-0.0466		-0.0861*	-0.0314
		(-2.04)	(-0.84)		(-1.83)	(-0.56)
College Degree		-0.183***	-0.164***		-0.176***	-0.154***
		(-3.76)	(-2.80)		(-3.59)	(-2.62)
College and More		-0.203***	-0.132**		-0.200***	-0.126**
		(-4.01)	(-2.15)		(-3.94)	(-2.04)
male		-0.130***	-0.102**		-0.132***	-0.0994**
		(-3.81)	(-2.54)		(-3.86)	(-2.46)
white		0.0538	0.0409		0.0557	0.0383
		(1.07)	(0.68)		(1.10)	(0.64)
Log Hshld Income			-0.109***			-0.113***
			(-4.73)			(-4.86)
Shock Measure	SP	SP	SP	VIX	VIX	VIX
Regional Dummies	YES	YES	YES	YES	YES	YES
Observations	14057	14046	9911	13946	13937	9828

Notes: *t*-statistics in parentheses; *, **, and *** indicate significance at the 10, 5, and 1 percent level.

Table A4: Inflation Expectations Formation with State Dummies

HtM=P	4.379***	3.486***	2.360***	4.322***	3.407***	2.286***
	(8.44)	(6.74)	(3.79)	(8.49)	(6.70)	(3.72)
HtM=W	2.741***	2.199***	1.999***	2.696***	2.143***	1.948***
	(9.69)	(7.68)	(5.62)	(9.56)	(7.50)	(5.50)
Shock	0.00701	0.00498	0.00555	0.0653	0.0492	0.0525
	(0.67)	(0.48)	(0.47)	(0.82)	(0.61)	(0.59)
HtM=P × Shock	-0.0494	-0.0487	0.00274	-0.348	-0.380	0.190
	(-1.09)	(-1.04)	(0.03)	(-1.36)	(-1.36)	(0.44)
HtM=W × Shock	-0.0544***	-0.0583***	-0.0586***	-0.374***	-0.380***	-0.342***
	(-3.07)	(-3.25)	(-2.84)	(-3.32)	(-3.34)	(-2.65)
25-39		0.735	-0.174		0.282	-0.929
		(0.57)	(-0.09)		(0.20)	(-0.44)
40-54		1.590	0.593		1.096	-0.194
		(1.24)	(0.31)		(0.79)	(-0.09)
55-69		1.720	0.375		1.208	-0.449
		(1.34)	(0.20)		(0.87)	(-0.21)
70+		0.678	-0.515		0.197	-1.261
		(0.53)	(-0.27)		(0.14)	(-0.59)
Some College		-0.788**	-0.664		-0.738**	-0.551
		(-2.34)	(-1.63)		(-2.21)	(-1.36)
College Degree		-2.443***	-2.000***		-2.419***	-1.964***
		(-7.70)	(-4.94)		(-7.69)	(-4.89)
College and More		-2.742***	-2.129***		-2.694***	-2.057***
		(-8.63)	(-5.27)		(-8.55)	(-5.12)
male		-1.480***	-1.262***		-1.512***	-1.321***
		(-7.19)	(-5.02)		(-7.46)	(-5.42)
white		-0.747*	-0.423		-0.812**	-0.485
		(-1.96)	(-0.93)		(-2.12)	(-1.06)
Log Hshld Income			-0.867***			-0.856***
			(-5.32)			(-5.30)
Constant	5.036***	6.580***	16.08***	5.042***	7.146***	16.80***
	(9.22)	(4.56)	(6.20)	(9.20)	(4.64)	(6.12)
Shock Measure	SP	SP	SP	VIX	VIX	VIX
State Dummies	YES	YES	YES	YES	YES	YES
Observations	12399	12380	8655	12262	12244	8546

Notes: t-statistics in parentheses; *, **, and *** indicate significance at the 10, 5, and 1 percent level.

A5: Unemployment Expectations Formation with State Dummies

HtM=P	0.473***	0.325***	0.218***	0.478***	0.327***	0.210***
	(8.39)	(5.54)	(2.96)	(8.49)	(5.57)	(2.85)
HtM=W	0.253***	0.169***	0.129**	0.255***	0.170***	0.125**
	(6.28)	(4.09)	(2.55)	(6.33)	(4.11)	(2.48)
Shock	0.00956***	0.00961***	0.0107***	0.0603***	0.0601***	0.0643***
	(5.53)	(5.51)	(5.42)	(5.03)	(4.96)	(4.79)
HtM=P × Shock	-0.00731*	-0.00828**	-0.0101*	-0.0657**	-0.0758***	-0.0791*
	(-1.88)	(-2.08)	(-1.72)	(-2.54)	(-2.76)	(-1.88)
HtM=W × Shock	-0.00602*	-0.00603*	-0.00476	-0.0478**	-0.0482**	-0.0428*
	(-1.94)	(-1.90)	(-1.31)	(-2.34)	(-2.33)	(-1.85)
25-39		-0.0143	0.0572		0.0165	0.0869
		(-0.08)	(0.24)		(0.09)	(0.34)
40-54		0.147	0.225		0.183	0.265
		(0.83)	(0.94)		(1.01)	(1.06)
55-69		0.0207	0.0750		0.0576	0.111
		(0.12)	(0.31)		(0.32)	(0.44)
70+		-0.143	-0.162		-0.103	-0.119
		(-0.79)	(-0.67)		(-0.55)	(-0.47)
Some College		-0.0909**	-0.0688		-0.0938**	-0.0692
		(-2.03)	(-1.28)		(-2.08)	(-1.28)
College Degree		-0.346***	-0.295***		-0.344***	-0.286***
		(-7.41)	(-5.14)		(-7.34)	(-4.96)
College and More		-0.418***	-0.423***		-0.413***	-0.409***
		(-8.54)	(-7.02)		(-8.39)	(-6.73)
male		-0.0379	0.0177		-0.0423	0.0126
		(-1.16)	(0.45)		(-1.28)	(0.32)
white		-0.211***	-0.191***		-0.225***	-0.205***
		(-4.21)	(-3.15)		(-4.46)	(-3.35)
Log Hshld Income			-0.112***			-0.120***
			(-5.00)			(-5.30)
Shock Measure	SP	SP	SP	VIX	VIX	VIX
State Dummies	YES	YES	YES	YES	YES	YES
Observations	13569	13548	9445	13410	13390	9324

Notes: t-statistics in parentheses; *, **, and *** indicate significance at the 10, 5, and 1 percent level.

Table A6: Interest Rate Expectations Formation with State Dummies

HtM=P	0.0517	-0.0598	-0.145*	0.0493	-0.0602	-0.157**
	(0.87)	(-0.97)	(-1.89)	(0.83)	(-0.97)	(-2.05)
HtM=W	0.121***	0.0507	0.0123	0.120***	0.0520	0.0114
	(2.78)	(1.14)	(0.23)	(2.79)	(1.17)	(0.21)
Shock	-0.00896***	-0.00880***	-0.00604***	-0.0405***	-0.0402***	-0.0228*
	(-5.00)	(-4.87)	(-2.96)	(-3.30)	(-3.25)	(-1.69)
HtM=P × Shock	0.00370	0.00224	-0.000347	0.0176	0.0100	0.0174
	(0.93)	(0.55)	(-0.06)	(0.66)	(0.36)	(0.42)
HtM=W × Shock	0.000807	0.000923	0.000407	0.00295	0.00547	0.00528
	(0.26)	(0.29)	(0.11)	(0.14)	(0.26)	(0.23)
25-39		-0.408*	0.0146		-0.371*	0.0844
		(-1.90)	(0.05)		(-1.70)	(0.31)
40-54		-0.586***	-0.147		-0.546**	-0.0674
		(-2.76)	(-0.56)		(-2.53)	(-0.25)
55-69		-0.684***	-0.208		-0.644***	-0.123
		(-3.22)	(-0.79)		(-2.98)	(-0.46)
70+		-0.681***	-0.197		-0.644***	-0.106
		(-3.16)	(-0.74)		(-2.94)	(-0.39)
Some College		-0.0977**	-0.0633		-0.0911*	-0.0535
		(-2.03)	(-1.10)		(-1.88)	(-0.93)
College Degree		-0.207***	-0.209***		-0.190***	-0.189***
		(-4.15)	(-3.47)		(-3.79)	(-3.11)
College and More		-0.224***	-0.175***		-0.218***	-0.164**
		(-4.31)	(-2.76)		(-4.19)	(-2.57)
male		-0.126***	-0.0909**		-0.132***	-0.0966**
		(-3.61)	(-2.19)		(-3.74)	(-2.32)
white		0.0735	0.0652		0.0644	0.0405
		(1.41)	(1.04)		(1.22)	(0.64)
Log Hshld Income			-0.101***			-0.104***
			(-4.27)			(-4.33)
Shock Measure	SP	SP	SP	VIX	VIX	VIX
State Dummies	YES	YES	YES	YES	YES	YES
Observations	13571	13550	9403	13412	13393	9281

Notes: t-statistics in parentheses; *, **, and *** indicate significance at the 10, 5, and 1 percent level.

A7: Inflation Expectations Formation with State-level macro variables

HtM=P	4.791***	3.929***	2.932***	4.681***	3.771***	2.777***
	(7.71)	(6.26)	(3.66)	(7.71)	(6.14)	(3.52)
HtM=W	2.935***	2.400***	2.230***	2.854***	2.295***	2.089***
	(8.54)	(6.76)	(4.65)	(8.35)	(6.52)	(4.40)
Shock	0.00214	0.00150	0.00951	0.0117	0.00420	0.0357
	(0.20)	(0.14)	(0.78)	(0.16)	(0.06)	(0.44)
HtM=P × Shock	-0.0505	-0.0496	0.0118	-0.273	-0.297	0.281
	(-1.11)	(-1.06)	(0.15)	(-1.00)	(-0.98)	(0.68)
HtM=W × Shock	-0.0448**	-0.0494***	-0.0522**	-0.300***	-0.310***	-0.275**
	(-2.39)	(-2.61)	(-2.34)	(-2.67)	(-2.73)	(-2.13)
State Avg Gas Price	2.920***	2.771***	3.205***	2.838***	2.691***	3.159***
	(9.06)	(8.65)	(8.30)	(8.56)	(8.17)	(7.85)
State Unemp Rate	-0.164***	-0.177***	-0.0858	-0.150**	-0.163***	-0.0683
	(-2.75)	(-2.97)	(-1.26)	(-2.51)	(-2.75)	(-1.02)
25-39		0.591	-0.739		0.0551	-1.659
		(0.44)	(-0.37)		(0.04)	(-0.73)
40-54		1.298	-0.0832		0.726	-1.024
		(0.99)	(-0.04)		(0.51)	(-0.46)
55-69		1.818	0.105		1.216	-0.907
		(1.37)	(0.05)		(0.85)	(-0.41)
70+		0.326	-1.171		-0.239	-2.063
		(0.24)	(-0.58)		(-0.17)	(-0.91)
some_college		-0.887**	-0.569		-0.835**	-0.422
		(-2.25)	(-1.11)		(-2.14)	(-0.84)
college_only		-2.323***	-1.626***		-2.314***	-1.598***
		(-6.02)	(-3.00)		(-6.04)	(-2.97)
college_plus		-2.629***	-1.906***		-2.586***	-1.798***
		(-6.88)	(-3.71)		(-6.83)	(-3.52)
male		-1.526***	-1.286***		-1.572***	-1.369***
		(-6.00)	(-3.82)		(-6.28)	(-4.20)
white		-1.113**	-0.942*		-1.223***	-1.072**
		(-2.56)	(-1.77)		(-2.79)	(-2.00)
Log Hshld Income			-0.890***			-0.898***
			(-4.23)			(-4.29)
Shock Measure	SP	SP	SP	VIX	VIX	VIX
Regional Dummies	YES	YES	YES	YES	YES	YES

Observations	9072	9053	5693	8936	8918	5585

Notes: t-statistics in parentheses; *, **, and *** indicate significance at the 10, 5, and 1 percent level.

A8: Unemployment Expectations Formation with State-level macro variables

HtM=P	0.510***	0.425***	0.374***	0.518***	0.430***	0.364***
	(7.77)	(6.20)	(4.16)	(7.89)	(6.26)	(4.04)
HtM=W	0.282***	0.233***	0.235***	0.284***	0.236***	0.231***
	(5.90)	(4.74)	(3.68)	(5.96)	(4.80)	(3.63)
Shock	0.00793***	0.00816***	0.00843***	0.0548***	0.0562***	0.0571***
	(4.45)	(4.54)	(4.17)	(4.47)	(4.56)	(4.20)
HtM=P × Shock	-0.00732*	-0.00825**	-0.00902	-0.0665**	-0.0763***	-0.0712*
	(-1.83)	(-2.02)	(-1.53)	(-2.54)	(-2.75)	(-1.68)
HtM=W × Shock	-0.00546*	-0.00559*	-0.00449	-0.0507**	-0.0523**	-0.0480**
	(-1.71)	(-1.73)	(-1.20)	(-2.44)	(-2.48)	(-2.06)
State Avg Gas Price	0.249***	0.230***	0.230***	0.278***	0.259***	0.282***
	(6.17)	(5.66)	(4.72)	(6.68)	(6.19)	(5.58)
State Unemp Rate	-0.0782***	-0.0781***	-0.0856***	-0.0825***	-0.0832***	-0.0904***
	(-8.88)	(-8.78)	(-8.42)	(-9.31)	(-9.29)	(-8.85)
25-39		0.0876	0.160		0.134	0.223
		(0.47)	(0.63)		(0.70)	(0.84)
40-54		0.345*	0.444*		0.402**	0.528**
		(1.87)	(1.78)		(2.13)	(2.02)
55-69		0.288	0.373		0.349*	0.453*
		(1.56)	(1.49)		(1.84)	(1.73)
70+		-0.0180	0.00424		0.0439	0.0943
		(-0.10)	(0.02)		(0.23)	(0.35)
some_college		-0.0623	-0.0452		-0.0652	-0.0395
		(-1.21)	(-0.70)		(-1.25)	(-0.60)
college_only		-0.261***	-0.209***		-0.256***	-0.189***
		(-4.78)	(-2.96)		(-4.66)	(-2.66)
college_plus		-0.197***	-0.224***		-0.188***	-0.196***
		(-3.42)	(-3.00)		(-3.23)	(-2.59)

male		-0.0413	0.0211		-0.0466	0.0143
		(-1.07)	(0.43)		(-1.20)	(0.29)
white		-0.248***	-0.267***		-0.269***	-0.291***
		(-4.36)	(-3.72)		(-4.69)	(-4.00)
Log Hshld Income			-0.0279			-0.0402
			(-1.03)			(-1.47)
Shock Measure	SP	SP	SP	VIX	VIX	VIX
Regional Dummies	YES	YES	YES	YES	YES	YES
Observations	9943	9922	6241	9785	9765	6121

Notes: t-statistics in parentheses; *, **, and *** indicate significance at the 10, 5, and 1 percent level.

A9: Interest rate Expectations Formation with State-level macro variables

HtM=P	0.0222	-0.0587	-0.171*	0.0153	-0.0623	-0.189**
	(0.32)	(-0.81)	(-1.84)	(0.22)	(-0.86)	(-2.04)
HtM=W	0.110**	0.0522	0.00776	0.107**	0.0519	0.00339
	(2.11)	(0.97)	(0.11)	(2.05)	(0.97)	(0.05)
Shock	-0.00994***	-0.00970***	-0.00746***	-0.0458***	-0.0449***	-0.0316**
	(-5.54)	(-5.36)	(-3.67)	(-3.73)	(-3.64)	(-2.35)
HtM=P × Shock	0.00317	0.00178	0.000998	0.0182	0.0101	0.0259
	(0.79)	(0.44)	(0.17)	(0.69)	(0.36)	(0.62)
HtM=W × Shock	0.000563	0.000716	0.000488	0.000656	0.00258	0.00390
	(0.18)	(0.23)	(0.14)	(0.03)	(0.12)	(0.17)
State Avg Gas Price	-0.209***	-0.207***	-0.102**	-0.251***	-0.250***	-0.149***
	(-4.89)	(-4.83)	(-2.01)	(-5.68)	(-5.64)	(-2.84)
State Unemp Rate	-0.0741***	-0.0705***	-0.0363***	-0.0728***	-0.0693***	-0.0343***
	(-8.14)	(-7.68)	(-3.45)	(-7.95)	(-7.50)	(-3.25)
25-39		-0.329	0.0672		-0.285	0.140
		(-1.46)	(0.24)		(-1.24)	(0.48)
40-54		-0.462**	-0.0838		-0.408*	0.0115
		(-2.08)	(-0.30)		(-1.80)	(0.04)
55-69		-0.519**	-0.136		-0.467**	-0.0365
		(-2.33)	(-0.49)		(-2.06)	(-0.13)

70+		-0.529**	-0.120		-0.477**	-0.00955
		(-2.33)	(-0.42)		(-2.07)	(-0.03)
some_college		-0.0696	-0.0292		-0.0586	-0.0132
		(-1.25)	(-0.42)		(-1.04)	(-0.19)
college_only		-0.129**	-0.184**		-0.103*	-0.150**
		(-2.18)	(-2.48)		(-1.71)	(-2.00)
college_plus		-0.138**	-0.135*		-0.132**	-0.124
		(-2.22)	(-1.72)		(-2.11)	(-1.56)
male		-0.165***	-0.142***		-0.175***	-0.153***
		(-3.96)	(-2.76)		(-4.16)	(-2.94)
white		0.0692	0.0473		0.0559	0.00748
		(1.17)	(0.65)		(0.94)	(0.10)
Log Hshld Income			-0.0766***			-0.0787***
			(-2.67)			(-2.71)
Shock Measure	SP	SP	SP	VIX	VIX	VIX
Regional Dummies	YES	YES	YES	YES	YES	YES
Observations	9958	9937	6223	9799	9780	6101

Notes: *t*-statistics in parentheses; *, **, and *** indicate significance at the 10, 5, and 1 percent level.

TABLE A10: Unemployment Expectations Formation using ordered probit

HtM=P	0.264***	0.174***	0.122***	0.266***	0.175***	0.115***
	(7.98)	(5.05)	(2.82)	(8.06)	(5.07)	(2.65)
HtM=W	0.146***	0.0958***	0.0786***	0.146***	0.0956***	0.0753**
	(6.09)	(3.89)	(2.59)	(6.12)	(3.89)	(2.49)
Shock	0.00562***	0.00566***	0.00632***	0.0352***	0.0351***	0.0375***
	(5.44)	(5.45)	(5.41)	(4.98)	(4.93)	(4.80)
HtM=P × Shock	-0.00419*	-0.00472**	-0.00608*	-0.0380**	-0.0436***	-0.0469*
	(-1.82)	(-2.01)	(-1.80)	(-2.52)	(-2.72)	(-1.95)
HtM=W × Shock	-0.00374**	-0.00376**	-0.00310	-0.0283**	-0.0282**	-0.0251*
	(-2.05)	(-2.04)	(-1.48)	(-2.37)	(-2.35)	(-1.89)
25-39		-0.00528	0.0366		0.0196	0.0705
		(-0.05)	(0.25)		(0.18)	(0.47)
40-54		0.0899	0.137		0.117	0.175
		(0.86)	(0.96)		(1.09)	(1.18)
55-69		0.0118	0.0474		0.0392	0.0831
		(0.11)	(0.33)		(0.37)	(0.56)
70+		-0.0909	-0.0987		-0.0610	-0.0577
		(-0.85)	(-0.68)		(-0.56)	(-0.39)
Some College		-0.0549**	-0.0414		-0.0569**	-0.0418
		(-2.06)	(-1.29)		(-2.12)	(-1.29)
College Degree		-0.206***	-0.177***		-0.205***	-0.171***
		(-7.43)	(-5.18)		(-7.36)	(-4.98)
College and More		-0.245***	-0.247***		-0.243***	-0.238***
		(-8.47)	(-6.87)		(-8.35)	(-6.59)
male		-0.0214	0.0131		-0.0242	0.0101
		(-1.10)	(0.56)		(-1.23)	(0.42)
white		-0.117***	-0.107***		-0.125***	-0.115***
		(-4.03)	(-3.04)		(-4.28)	(-3.22)
Log Hshld Income			-0.0632***			-0.0684***
			(-4.76)			(-5.11)
Shock Measure	SP	SP	SP	VIX	VIX	VIX
Regional Dummies	YES	YES	YES	YES	YES	YES
Observations	13479	13458	9364	13320	13300	9243

Notes: *t*-statistics in parentheses; *, **, and *** indicate significance at the 10, 5, and 1 percent level.

TABLE A11: Interest Rate Expectations Formation using ordered probit

HtM=P	-0.00408	-0.0673*	-0.104**	-0.00620	-0.0679*	-0.111**
	(-0.12)	(-1.85)	(-2.29)	(-0.18)	(-1.86)	(-2.44)
HtM=W	0.0657**	0.0250	-0.00109	0.0645**	0.0249	-0.00248
	(2.55)	(0.95)	(-0.03)	(2.51)	(0.94)	(-0.08)
Shock	-0.00562***	-0.00554***	-0.00411***	-0.0263***	-0.0263***	-0.0170**
	(-5.43)	(-5.32)	(-3.54)	(-3.72)	(-3.71)	(-2.20)
HtM=P × Shock	0.00214	0.00133	-0.000349	0.0110	0.00680	0.00900
	(0.92)	(0.56)	(-0.10)	(0.71)	(0.42)	(0.37)
HtM=W × Shock	0.000947	0.00101	0.000851	0.00557	0.00692	0.00702
	(0.51)	(0.54)	(0.40)	(0.46)	(0.57)	(0.52)
25-39		-0.230*	0.0162		-0.209*	0.0569
		(-1.88)	(0.10)		(-1.68)	(0.36)
40-54		-0.332***	-0.0795		-0.308**	-0.0319
		(-2.74)	(-0.52)		(-2.50)	(-0.20)
55-69		-0.391***	-0.112		-0.368***	-0.0611
		(-3.23)	(-0.73)		(-2.98)	(-0.39)
70+		-0.379***	-0.0973		-0.355***	-0.0418
		(-3.08)	(-0.62)		(-2.83)	(-0.26)
Some College		-0.0603**	-0.0375		-0.0566**	-0.0315
		(-2.12)	(-1.10)		(-1.97)	(-0.92)
College Degree		-0.118***	-0.122***		-0.107***	-0.108***
		(-3.96)	(-3.38)		(-3.59)	(-2.98)
College and More		-0.125***	-0.0967**		-0.122***	-0.0905**
		(-4.04)	(-2.56)		(-3.93)	(-2.38)
male		-0.0803***	-0.0615**		-0.0835***	-0.0647***
		(-3.85)	(-2.48)		(-3.98)	(-2.59)
white		0.0442	0.0448		0.0398	0.0295
		(1.45)	(1.23)		(1.29)	(0.80)
Log Hshld Income			-0.0518***			-0.0532***
			(-3.71)			(-3.78)
Shock Measure	SP	SP	SP	VIX	VIX	VIX
Regional Dummies	YES	YES	YES	YES	YES	YES
Observations	13481	13460	9322	13322	13303	9200

Notes: t-statistics in parentheses; *, **, and *** indicate significance at the 10, 5, and 1 percent level.

TABLE A12: Sample Statistics on key variables

	(1) Poor-HTM	(2) Wealthy-HTM	(3) Non-HTM
Liquid Assets	729.22	2986.68	268100.5
	(76.2)	(228.9)	(10028.4)
Liquid Debt	7598.12	12138.47	2915.73
	(481.67)	(547.97)	(125.54)
Liquid Wealth	-6841.79	-9151.79	265184.8
	(456.25)	(436.43)	(10028.72)
Illiquid Wealth	-12921.95	209098.9	449649.3
	(1146.6)	(16529.5)	(10089.9)
Monthly Income	2613.59	5108.74	7351.7
	(104.9)	(124.3)	(87.03)
Net Worth	2098.27	193251.08	707448.01
	(125696.8)	(966325.6)	(1715119.3)
Percent with a mortgage	0.19	0.53	0.55
	(0.395)	(0.499)	(0.498)
Tenure (yrs) at current job	2.76	6.00	8.23
	(6.201)	(9.137)	(10.56)
Percent stock owner	0.14	0.56	0.89
	(0.352)	(0.497)	(0.316)
Observations	1680	3543	9895

Notes: The table shows means with standard deviations in parentheses. Liquid assets are the sum of the amount in savings/checking account, cash holdings, mutual funds, stocks and bonds. Liquid debt is the sum of credit card debt (after the most recent payment), student loan debt, and any debt left on bank loans, payday loans and other loans. Liquid wealth is the difference between liquid assets and liquid debt. Illiquid Wealth includes the value of housing and other properties net of mortgages, net business equity, value of life insurance, retirement accounts, IRAs, and Savings and Bonds. Net Worth is the difference between total assets and liabilities. This is generated by the data provider and includes all assets/liabilities as opposed to our constructed measures that include a subset of those. Monthly income is the sum of net business income, labor income and other sources of income of the respondent and the spouse for each household. Percent stock owner reflects stock ownership defined as owning Mutual Funds, Retirement Accounts, IRAs, Stocks or Bonds.

SUBJECTIVE FINANCIAL DISTRESS

CFMS has a set of questions that ask respondents about their subjective financial distress levels and their subjective ability to manage the debt. The four questions have been asked in every survey since 2005:11. The questions (with their response categories in parenthesis) are provided below:

1) Overall, how often do you worry about the total amount you (and your spouse/partner) owe in overall debt? Would you say you worry all of the time (5), most of the time (4), some of the time (3), hardly ever (2), or not at all (1)?

2) How much stress does the total debt you (and your spouse/partner) are carrying cause to you? Is it a great deal of stress (5), quite a bit (4), some stress (3), not very much (2), or no stress at all (1)?

3) Now, thinking ahead over the next five years, how much of a problem, if any, will the total debt you (and your spouse/partner) have taken on be for you? Will it be an extreme problem (5), a large problem (4), medium problem (3), small problem (2), or no problem at all (1)?

4) How concerned are you that you (and your spouse/partner) never will be able to pay off these debts? Are you very much concerned (5), quite concerned (4), somewhat concerned (3), not very concerned (2), or not at all concerned (1)?

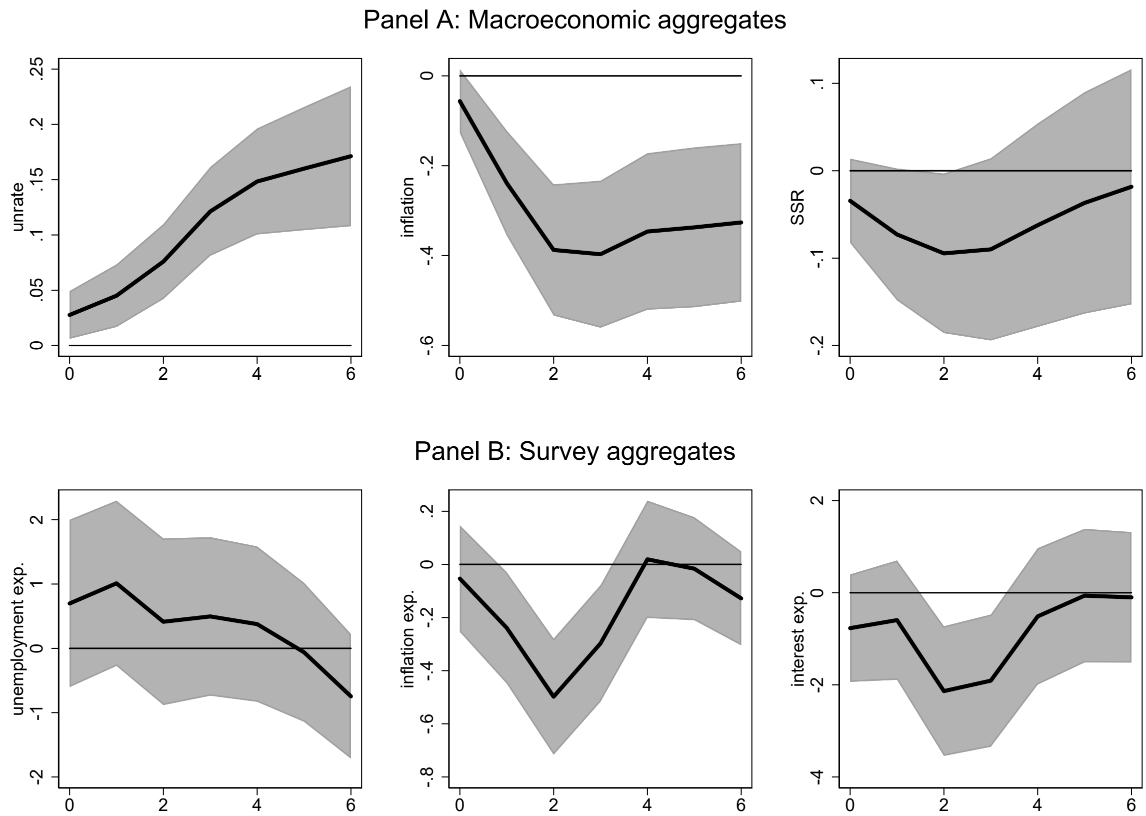
There are a small number of people who answered these questions by claiming that they don't have any debt even though they had some minor debt amounts. So we excluded these people and all other who have declared that they don't have any debt (there was a separate answer category for these people coded as 0) and calculated the percentage of people for each question who have chosen 4 or 5 (high financial distress or high concern). The percentages for each HtM category separately are shown in Table A13 below (Standard deviations are shown in parentheses).

The table shows that too few of the non-HtMs worry about their indebtedness as compared to HtMs. There is also some discrepancy among the HtMs, with wealthy HtMs less likely to worry about their current indebtedness or their ability to pay their debt off in the future.

TABLE A13: Subjective Financial Distress

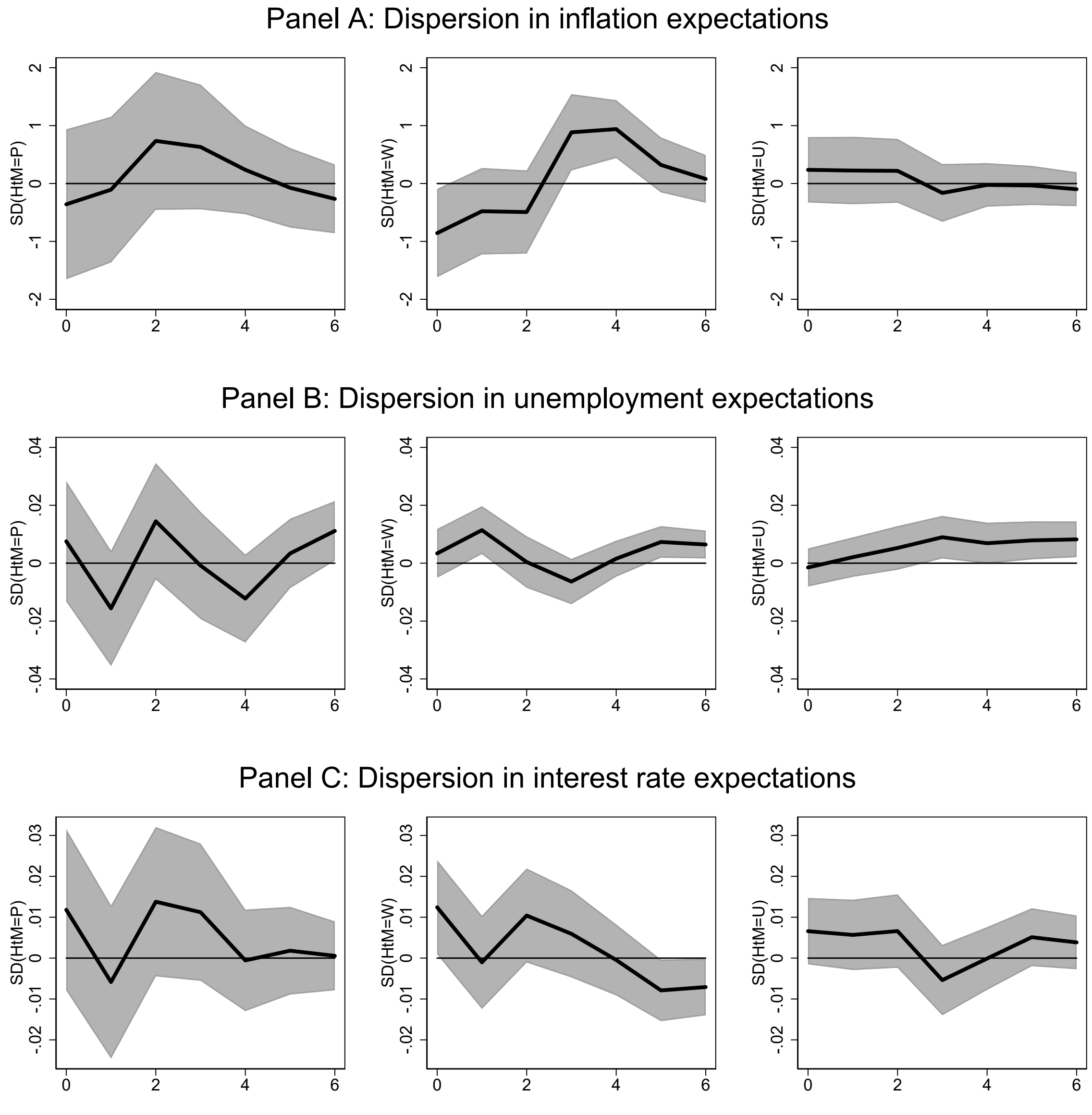
	(1) Poor-HTM	(2) Wealthy-HTM	(3) Non-HTM
worry debt	0.40	0.35	0.11
	(0.490)	(0.476)	(0.315)
stress debt	0.40	0.33	0.10
	(0.491)	(0.469)	(0.300)
problem debt	0.28	0.21	0.06
	(0.450)	(0.407)	(0.243)
concern debt	0.32	0.22	0.06
	(0.465)	(0.415)	(0.231)
Observations	1059	2588	7005

Figure A1: Effects of financial crisis shocks on macroeconomic aggregates and aggregate survey measures



Notes: The figure shows the dynamic response of macroeconomic aggregates to financial crisis shocks measured as monthly aggregates of changes in the VIX together with 90 percent confidence intervals. The x-axes is in months. Unemployment and interest rate expectations enter the VAR as balance scores while the remaining variables are in percent.

Figure A2: Effects of financial crisis shocks constructed from the VIX on macroeconomic aggregates



Notes: The figure shows the dynamic response of cross-sectional standard deviations of economic expectations for poor HtM households in the first column, for wealthy HtM in the second column and for wealthy unconstrained households in the third column of each Panel. We note that inflation expectations are quantitative while unemployment and interest expectations are qualitative. The x-axes is in months.

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