MEASURING UNCERTAINTY BASED ON ROUNDING: NEW METHOD AND APPLICATION TO INFLATION EXPECTATIONS*

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Abstract

Although uncertainty plays an important role in many models of economic decisionmaking, empirical measures of individual agents' uncertainty are rare. A large literature on cognition and communication documents that people use round numbers to convey uncertainty. This paper introduces a method of quantifying the uncertainty associated with round number responses in survey data, which will allow economists to construct micro-level measures and time series indices of uncertainty from pre-existing data. To demonstrate the usefulness of this method, I construct a new measure of inflation uncertainty since 1978 that exploits consumers' tendency to round inflation forecasts to multiples of five on the Michigan Survey of Consumers. I document time series and cross-sectional properties of the measure and provide support for its validity. Mean inflation uncertainty is countercyclical and positively correlated with inflation disagreement, inflation volatility, and the Economic Policy Uncertainty Index. Inflation uncertainty varies more in the cross section than over time, and is lowest among high-income consumers, college graduates, males, and stock market investors. Cross-sectional and panel analysis reveals that more uncertain consumers are more reluctant to spend on durables, cars, and homes. I show that round number responses are common on a variety of other surveys, suggesting applications of this method for measuring uncertainty about income, gas prices, home prices, and other variables.

JEL codes: D80, D83, D84, E21, E31, C10
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1 Introduction

Most economic decisions are made under uncertainty. Uncertainty about macroeconomic conditions, policy, health, productivity, return on investments, and earnings all factor into the choices of firms, consumers, and policymakers. If an individual is to maximize her expected utility, for example, she must have in mind some probability distributions over future outcomes relevant to her decision. Uncertainty is a feature of these subjective beliefs, which econometricians have a limited ability to observe.[1]

The Great Recession has drawn increased attention to the potentially harmful macroeconomic consequences of heightened uncertainty, prompting new efforts to measure uncertainty. The New York Federal Reserve recently began conducting the Survey of Consumer Expectations (SCE), which elicits its respondents' subjective probability distributions over future inflation. They define an individual's inflation uncertainty as the interquartile range of her subjective probability distribution (Armantier et al., 2013). Surveys that directly elicit respondent's probabilistic expectations provide the most direct measure of uncertainty, but they are relatively uncommon and difficult to administer.[2] Most surveys of economic expectations simply ask respondents for their point forecasts of various outcomes, and Bruin et al. (2009) explain that "Surveys asking individuals for point predictions can at most convey some notion of the central tendency of their beliefs, and nothing about the uncertainty they feel when predicting outcomes."

Thus, most empirical research on economic uncertainty relies on proxies such as measures of disagreement or volatility.[3] The well-known Economic Policy Uncertainty (EPU) index, for example, is based on professional forecasters' disagreement about future government purchases and inflation, the number of federal tax code provisions set to expire in future years, and the frequency of mentions of uncertainty in newspapers (Baker et al., 2012). This line of research has made valuable inroads into understanding the role of uncertainty in the macroeconomy. A limitation of these uncertainty proxies is their lack of a micro-level dimension: they vary across time, but not across agents. Micro-level data and techniques often enable more rigorous analysis of macroeconomic relationships (Hsiao et al., 2005; Mian and Sufi, 2010). Given the well-documented heterogeneity of agent's economic expectations,[4] the value of micro-data is likely to be especially high in studies of the causes and consequences of uncertainty.

In this paper, I posit that in many cases, surveys asking for point predictions can in fact convey some indication of the respondents' uncertainty. Researchers in the fields of cognition, linguistics, and communication note that the use of a round number often signals more uncertainty than the use of a non-round number. In linguistics, this intuitive observation is named the *Round numbers suggest round interpretations (RNRI) principle* (Krifka, 2002). I review the multi-disciplinary literature that documents variants of the RNRI principle across numerous contexts. Building on this literature, I explain how rounding behavior can be exploited to construct quantitative, micro-level uncertainty

[1]In this paper, uncertainty refers to any measure of the spread (e.g. variance, interquartile range, or entropy) of an agent's subjective probability distribution over an outcome, as in Rich and Tracy (2010), Orlik and Veldkamp (2012), (Armantier et al., 2013), and others, and not in the sense of Knight (1921).

[2]To elicit probabilistic forecasts, the SCE asks consumers to provide probabilities, summing to 100%, that inflation will fall in various "bins" of width 2%. Also see van der Klaauw et al. (2008). The Philadelphia Federal Reserve's Survey of Professional Forecasters also elicits probabilistic forecasts of several macroeconomic variables.

[3]Uncertainty is conceptually distinct from disagreement, which measures the dispersion of beliefs *across* agents (Zarnowitz and Lambros, 1987). Orlik and Veldkamp (2012) clarifies the relationship and theoretical distinction between uncertainty and volatility.

[4]See e.g. Mankiw et al. (2004).

measures. I use inflation expectations data from the Michigan Survey of Consumers (MSC) as a demonstration since inflation uncertainty is of considerable and long-standing interest to economists and monetary policymakers,[5] and since I can compare the rounding-based measure to the SCE inflation uncertainty measure to test its validity.

MSC respondents report integer point forecasts of year-ahead inflation. About half of these forecasts are multiples of five. The RNRI principle suggests that the multiple-of-five (i.e. round number) responses indicate more uncertainty, on average, than non-multiple-of-five responses. If a consumer reports that her inflation expectation is 10%, this potentially signals less precision than a response of 9% or 11%, for example. A dummy variable that is positive if a respondent's forecast is a multiple of five could serve as a micro-level proxy for uncertainty. However, this rough proxy should be refined, since the association between rounding and uncertainty may vary over time, and different round numbers may indicate different levels of uncertainty.

Hence, instead of a dummy variable, I construct a continuous measure of uncertainty taking values between zero and one. I assume that consumers that are sufficiently uncertain about their inflation forecast round to a multiple of five when responding to the survey; call these "type h," for high uncertainty. Less uncertain consumers ("type l") report their forecast to the nearest integer, which may or may not be a multiple of five. If a consumer provides a multiple-of-five response, we do not know for sure whether she is type h or l. Responses in a given month come from a mixture of two distributions: one distribution of type-h responses whose support is multiples of five, and another of type-l responses whose support is integers. The mixture weight is the fraction of type-h consumers. For each month, I estimate the parameters of each distribution and the mixture weight via maximum likelihood. These estimates allow me to compute the *probability* that a consumer is type h given her response and the survey date. This probability is a proxy for her uncertainty.

I document basic properties of the inflation uncertainty proxy and provide evidence in support of its validity. For example, more uncertain consumers make larger forecast errors and revisions. The proxy displays similar demographic patterns as found by the New York Fed's SCE in 2013. Namely, inflation uncertainty is lower for more educated, higher-income consumers. Uncertainty is also lower among people with investments in the stock market. Mean inflation uncertainty is countercyclical and is positively correlated with alternative time-series proxies for uncertainty, including inflation disagreement, inflation volatility, and the EPU.

A major benefit of this new inflation uncertainty measure is its micro-level dimension and rotating panel structure, which allows for cross-sectional and panel analysis of the relationship between inflation uncertainty and economic activity. For instance, I link individual consumers' inflation uncertainty to their reported attitudes toward spending on cars, homes, and other durable goods, and find that more uncertain consumers express less favorable spending attitudes. Another benefit is that the measure uses pre-existing data, allowing historical analysis of inflation uncertainty with 432 months of data. This rich dataset has a number of applications to inflation forecasting, monetary policy, and tests of models of information rigidities and expectations formation.[6]

The paper is organized as follows. Section 2 discusses the association between round numbers and

[5]The Nobel lecture of Milton Friedman (1977) spurred interest in the relationship between the level of inflation, inflation uncertainty, and real economic activity. Ball (1992) hypothesizes that high inflation causes high inflation uncertainty. Inflation uncertainty implies uncertainty about real income, which may reduce consumption through a precautionary savings channel. Inflation uncertainty also implies uncertainty about the real interest rate, which may result in a slow, "hump-shaped" response of consumption to monetary policy (Mackowiak and Wiederholt, 2011).

[6]Other applications of the inflation uncertainty measure appear in my doctoral dissertation, from which this paper is adapted.

uncertainty, and documents the prevalence of round number responses in MSC inflation expectations data. Section 3 details the framework for constructing the new micro-level measure of uncertainty. Section 4 describes summary statistics and properties of the inflation uncertainty measure and establishes its validity. Section 5 explores the link between inflation uncertainty and consumption of cars, homes, and other durables. Section 6 describes other applications of the inflation uncertainty measure and of the method of estimating uncertainty based on rounding and concludes.

2 Round Numbers and the Expression of Uncertainty

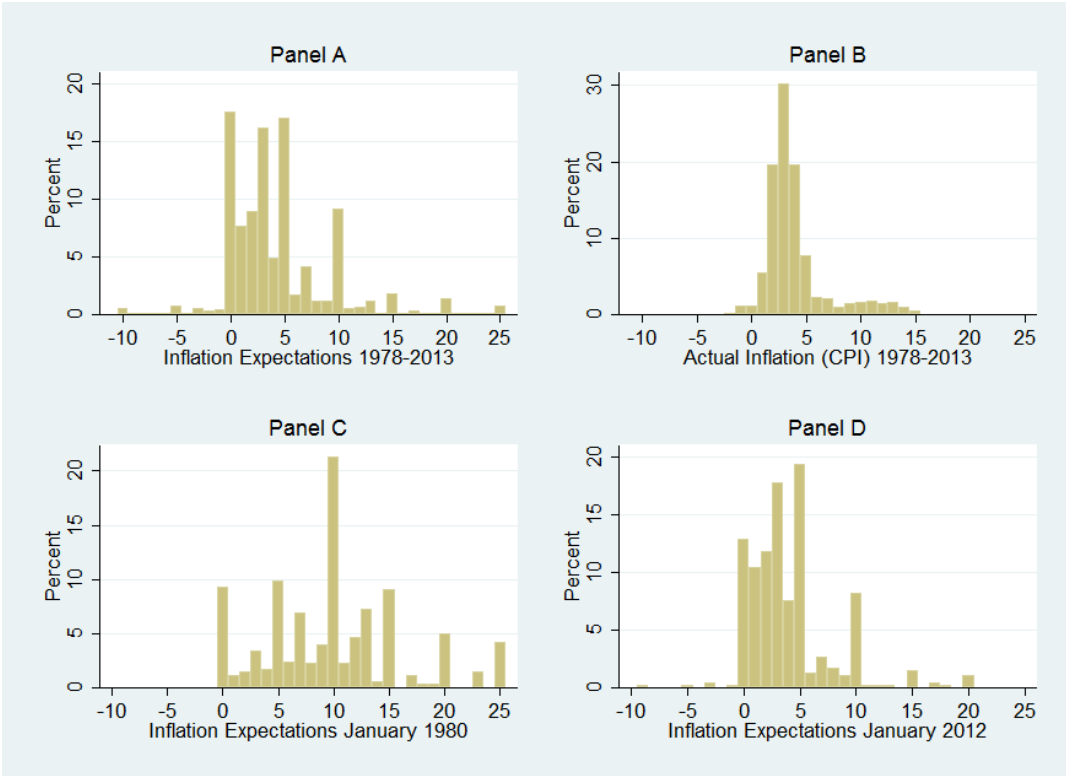
The method of measuring uncertainty introduced in this paper exploits a well-documented association between round numbers and uncertainty. Round numbers play a prominent role in communication and cognition (Albers and Albers, 1983). According to communication and linguistic theory, round numbers—typically multiples of five or of a power of ten, depending on context— are frequently used to convey that a quantitative expression should be interpreted as imprecise (Sigurd, 1988; Dehaene and Mehler, 1992; Jansen and Pollmann, 2001; Krifka, 2002). If a headline reports that 500 people attended a rally, this is interpreted as some number in the vicinity of 500. If the headline reports that 497 attended, this is interpreted as exactly 497. Likewise, someone who says she weighs 150 pounds may just have a rough idea; if she says 151 pounds, she has probably stepped on a scale recently. Indeed, self-reported body weight on the National Health and Nutrition Examination Survey is less accurate for adults who report round numbers than for those who do not (Rowland, 1990). This is the intuition behind the *Round Numbers Suggest Round Interpretation* (RNRI) principle (Krifka, 2009).

Experimental studies asking subjects to report quantitative estimates confirm that round responses are associated with imprecise estimates, or "The rounder the number, the less is known about the subject matter" (Selten, 2002, p. 25). Baird et al. (1970) ask subjects to estimate the ratios of visually presented lengths or areas. Most estimates are multiples of five and ten, even though the true ratios do not favor round numbers. Huttenlocher et al. (1990) find that, when asked to estimate the days elapsed since an event occurred, subjects have a tendency to report round numbers, especially for events remembered with less precision.

In the finance literature, Harris (1991) finds that stock traders' bids and offers are clustered at round numbers, especially when market volatility is high. Similarly, Zhao et al. (2012) find that cognitive limitations lead to limit order clustering at round prices in the Taiwanese stock exchange. Investors who round have worse performance. Herrmann and Thomas (2005) find that analysts' forecasts of earnings per share disproportionately occur in nickel intervals, especially for less-informed forecasters. Shiller (2000) and Westerhoff (2003) claim that market participants with limited knowledge anchor on round numbers when estimating fundamental values. Dechow and You (2012) explain that financial analysts tend to round to the nearest nickel because "humans will round a digit when they are uncertain... rounding implicitly signals the lack of precision (p. 1)."

Rounding is documented in surveys of earnings, age, and other variables. On the expectations module of the 2006 Health and Retirement Study, the majority of responses to questions about the subjective probability of a future event are multiples of five. Manski and Molinari (2010, p. 220) note that "a response of '30 percent' could mean that a respondent believes that the percent chance of the event is in the range [25, 35] but feels incapable of providing finer resolution." Schweitzer and Severance-Lossin (1996) show that the systematic nature of rounding on reported earnings on the Current Population Survey affects commonly-calculated statistics such as median earnings and measures of earnings inequality. Pudney (2008) finds that households' reported energy expenditures

Figure 1: Histograms of inflation expectations and realized inflation.



Notes: Panel A shows Michigan Survey inflation expectations pooled across all months. Panel B shows monthly year-over-year CPI inflation, and Panels C and D show Michigan Survey responses in two particular months.

are heaped at round responses. Economic historians and demographers find that self-reported ages in survey data exhibit heaping at multiples of five, particularly when respondents have low numeracy and are therefore uncertain about their precise age (Zelnick, 1961; A'Hearn and Baten, 2009).

2.1 Rounding in Surveys of Inflation Expectations

Round numbers are prevalent in the inflation expectations reported on the Michigan Survey of Consumers (MSC), a nationally-representative telephone survey. Each monthly sample of around 500 households consists of approximately 60% new respondents and 40% repeat respondents surveyed six months previously. Microdata is available since 1978. Respondents answer questions about their personal and financial characteristics and expectations, including, "By about what percent do you expect prices to go (up/down) on the average, during the next 12 months?" Respondents may give any integer response or a "don't know" response (see Appendix A for more details.)

Histograms of consumers' inflation expectations show heaping at multiples of five.[7] Panel A of Figure 1 displays the distribution of 219,181 forecasts between -10% and 25% from January 1978 to December 2013.[8] Panel B shows that inflation realizations (year-over-year percent changes in the

[7]For professional forecasters, response heaping does not occur at multiples of 5%, but does occur at multiples of 0.05% (Engelberg et al., 2009).

[8]Less than 1.5% of respondents choose a value outside the range of -10% to 25%; these extreme value responses are

Consumer Price Index) do not clump around multiples of five. In an average month, 48% of numeric survey responses are a multiple of 5, although only 10% of inflation realizations are a multiple of 5. Quantitative tools for detecting digit preferences confirm that heaping occurs at multiples of five and not at other values (see Appendix B.)

Panels C and D show the distribution of forecasts in one high inflation month and one low inflation month. In January 1980, when the most accurate forecast would have been 12%, the most common response was 10%. More consumers chose 5% and 15% than any nonround values. In January 2012, the most accurate forecast would have been 2%, but the most common was 5%.

The literature on rounding suggests that round responses are more likely to indicate higher imprecision or uncertainty. Examination of forecast errors and revisions supports this. More uncertain forecasts should be associated with larger ex-post errors and larger revisions on average.[9] Table 1 shows that round forecasts are indeed associated with significantly larger ex-post errors and revisions. Moreover, comparing round number forecasts to nearest non-round number forecasts, so magnitudes are similar, the multiple of five responses are less accurate than neighboring responses: 4% and 6% forecasts have smaller mean squared errors than 5% forecasts, etc. Multiples of five are unique in this regard; for example, 3% forecasts are not more inaccurate than 2% and 4% responses.

Table 1: Forecast errors and revisions for round and non-round forecasts.

	Non-round	**Round**	***t*-statistic for difference**
Mean absolute error (percentage pts)	2.4	4.6	54
Root mean squared error (percentage pts)	3.5	6.1	46
Mean absolute revision (percentage pts)	2.5	3.9	43
"Don't know" on second survey	4.0%	6.6%	15

Notes: Round forecasts are multiples of five while non-round forecasts are other integers. Forecast error is the difference between realized one-year-ahead CPI inflation and the respondent's inflation forecast. For a respondent who takes the Michigan Survey twice at a 6-month interval, the forecast revision is the difference between her second survey response and her first survey response. t-statistics computed using standard errors clustered by time period.

Survey respondents may give a "don't know" (DK) response, which is also indicative of uncertainty (Curtin, 2007; Blanchflower and Kelly, 2008). The final row of Table 1 shows that people who choose a round response the first time they take the survey are more likely than non-rounders to choose DK the second time. Similarly, of people who choose DK and a numerical response on the second survey, 60.0% choose a round number, compared to 45.9% of people who choose a numerical response on both surveys (t-stat 22.5, clustered by time). That rounding and providing DK responses are related behaviors provides further evidence of an association between rounding and uncertainty. These indications that round responses are associated with uncertainty are consistent with the literature and motivate the framework for quantifying uncertainty in the next section.

recoded as "don't know" responses as they likely indicate that respondent did not understand the question or the concept of percent. Results are insensitive to choice of trimming procedure.

[9]Bayes' Rule suggests that the magnitude of a forecast revision conditional on new information is inversely proportional to the precision of the prior.

3 Construction of Uncertainty Proxy

Michigan Survey of Consumers respondents provide integer forecasts for inflation and frequently choose responses that are a multiple of five (M5). As discussed in Section 2, M5 responses are likely associated with higher uncertainty than non-M5 responses. A dummy variable for M5 responses could provide a simple proxy for inflation uncertainty. However, this proxy can be refined: not all M5 forecasts are always equally likely to indicate uncertainty.

Suppose that each consumer i has a subjective probability distribution over future inflation with mean f_{it} and variance v_{it}. Consumers with sufficiently high uncertainty—say, v_{it} above some threshold V—provide a survey response R_{it} that is the nearest multiple of five to f_{it}. Call these consumers type h, for high uncertainty. Consumers with lower uncertainty provide a response R_{it} that is the nearest integer to R_{it}, which may or may not be a multiple of five. Call these type l, for low uncertainty.[10]

If we observe a non-M5 response, we know that $v_{it} < V$, and the respondent is type l. If we observe an M5 response, we don't know whether the respondent is type l or type h. We can, however, estimate the probability that she is type h. This estimated probability, ζ_{it}, provides a proxy for consumer i's inflation uncertainty.

The probability ζ_{it} that i is type h can be estimated via maximum likelihood. Note that the cross-sectional distribution of survey responses R_{it} in a given month is a mixture of two probability mass functions (pmfs). One pmf is the responses R_{it} from the type-l consumers, whose support is integers. The other pmf is the responses R_{it} from the type-h consumers, whose support is multiples of five. The mixture weight is the share of type-h consumers. I obtain maximum likelihood estimates of the mixture weight and the parameters of the two pmfs, and use these estimates to compute the probability ζ_{it} that a respondent is type h.

Suppose that the cross section of forecasts f_{it} from the type-h consumers is distributed $N(\mu_{ht}, \sigma^2_{ht})$ and from the type-l consumers $N(\mu_{lt}, \sigma^2_{lt})$. Then the pmfs ϕ^h_t and ϕ^l_t of the cross section of responses for types h and l are discretized normal distributions:[11]

$$\phi^l_t = P(R_{it} = j | i \text{ is type } l) = \int_{j-.5}^{j+.5} \frac{1}{\sigma_{lt}\sqrt{2\pi}} e^{\frac{(x-\mu_{lt})^2}{2\sigma^2_{lt}}} dx, \; j = ... -1, 0, 1, ... \quad (1)$$

$$\phi^h_t = P(R_{it} = j | i \text{ is type } h) = \int_{j-2.5}^{j+2.5} \frac{1}{\sigma_{ht}\sqrt{2\pi}} e^{\frac{(x-\mu_{ht})^2}{2\sigma^2_{rt}}} dx, \; j = .. -5, 0, 5, ... \quad (2)$$

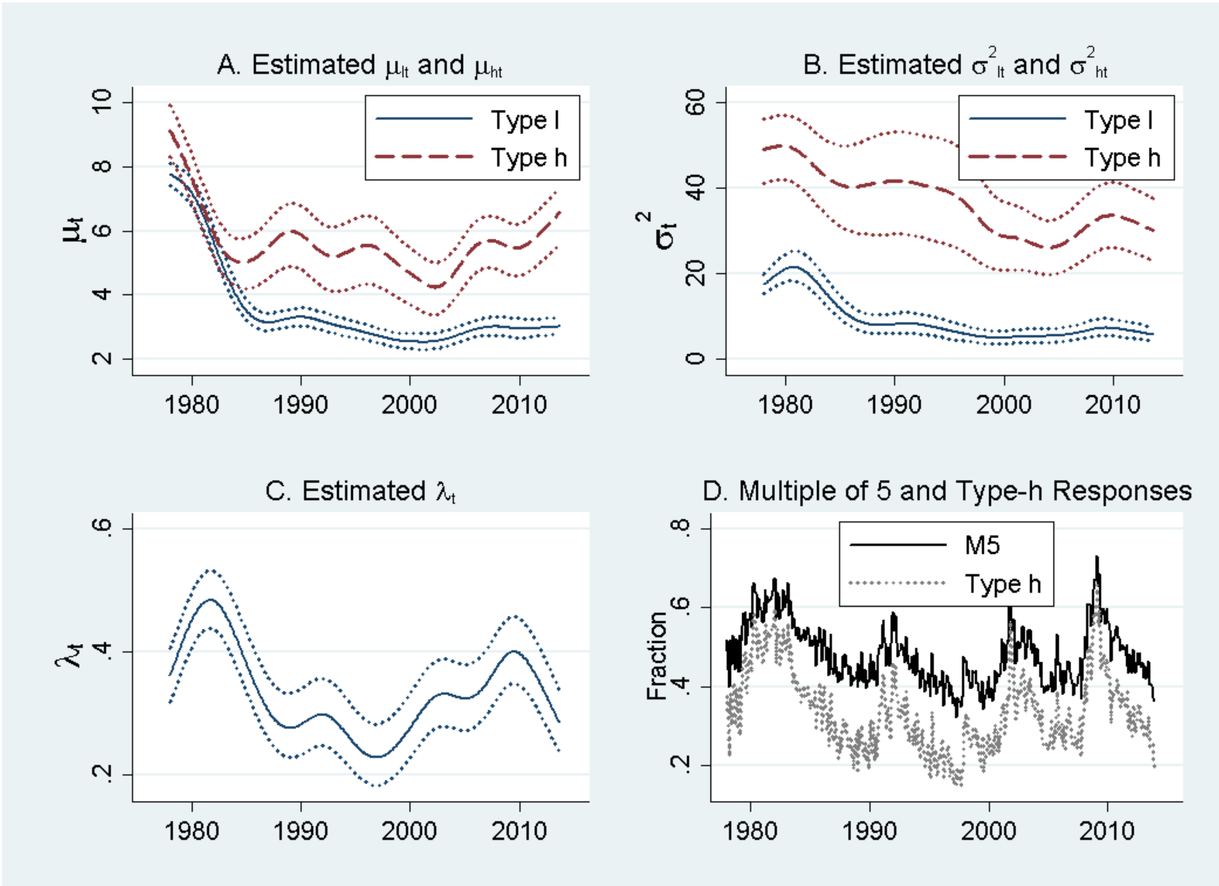
In each month t, survey responses come from a mixture of the two pmfs, $\phi_t = \lambda_t \phi^h_t + (1 - \lambda_t)\phi^l_t$, where the mixture weight λ_t is the fraction of numerical responses from type-h consumers. Suppose there are N^τ_t consumers of each type τ. We observe the total number of numerical responses $N_t = N^h_t + N^l_t$, but N^l_t and N^l_t are unknown, since M5 responses may come from either type. Thus $\lambda_t = \frac{N^h_t}{N^h_t + N^l_t}$ is unknown. The five unknown parameters of ϕ_t are λ_t, μ_{lt}, μ_{ht}, σ_{lt}, and σ_{ht}. For responses $\{R_{it}\}_{i=1}^{N^l_t + N^h_t}$, the likelihood is:

$$L(\{R_{it}\}_{i=1}^{N^l_t+N^h_t} | \lambda_t, \mu_{lt}, \mu_{ht}, \sigma_{lt}, \sigma_{ht}) = \Pi_{j=1}^{N^l_t+N^h_t} \phi_t(R_{it} | \lambda_t, \mu_{lt}, \mu_{ht}, \sigma_{ht}, \sigma_{lt}). \quad (3)$$

[10] In other applications, as I discuss in Section 6, a model with more than two agent types may be appropriate, and agents may round to multiples of values other than 5. For example, when forecasting future income, some respondents may round to the nearest $1000 and others to the nearest $10,000. This model can easily be adapted to such situations.

[11] Alternative distributions for the cross section of responses may be used instead of the normal distribution if appropriate to the survey data being used. In Appendix C.1 I instead use a distribution with fatter tails. Resulting inflation uncertainty estimates are not highly sensitive to the normality assumption.

Figure 2: Maximum likelihood estimates of mixture distribution parameters



Notes: Panels A, B, and C show maximum likelihood estimates of $\mu_{lt}, \mu_{ht}, \sigma^2_{lt}, \sigma^2_{ht}$, and λ_t with bootstrapped 95% confidence intervals. See Equation (3). For visual clarity, estimates and confidence bands are HP-filtered with smoothing parameter 14,400 and the trends are shown. Panel D plots λ_t, the share of responses from type-h consumers, with the share of M5 responses.

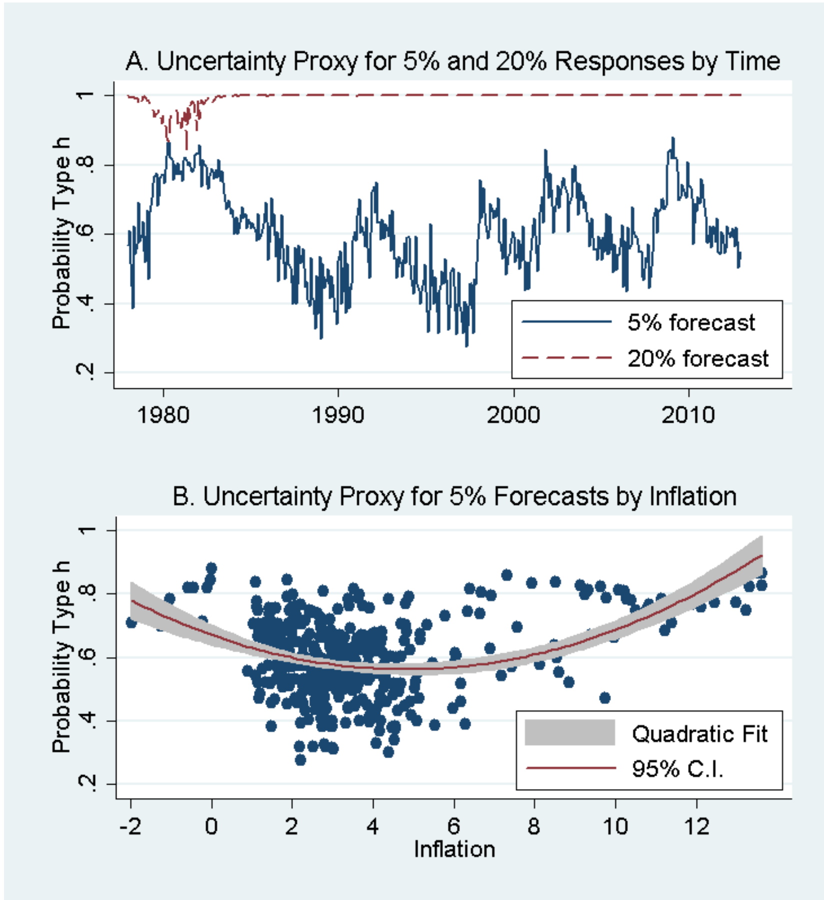
Figure 2 displays the maximum likelihood estimates with bootstrapped 95% confidence intervals. The likelihood ratio test confirms that the five-parameter mixture distribution fits the data significantly better than a two-parameter non-mixture distribution.[12] Panel D plots λ_t, the share of responses coming from type-h consumers, with the share of M5 responses. The two series have a correlation coefficient of 0.98, but λ_t is lower than the share of M5 responses, with a mean of 0.34 versus 0.48, since not all M5 responses indicate high uncertainty.

The probability ζ_{it} that consumer i is type h at time t depends on her response and the parameters $\lambda_t, \mu^l_t, \mu^h_t, \sigma^l_t$,, and σ^h_t. If R_{it} is not a multiple of five, then $\zeta_t(R_{it}) = 0$. If R_{it} is a multiple of five, then ζ_{it} is some value between zero and one, given by Bayes' rule:

$$\zeta_{it} = \zeta_t(R_{it}) = P(\text{type } h|R_{it}) = \frac{P(\text{type } h)P(R_{it}|\text{type } h)}{P(R_{it})} = \frac{\lambda_t \phi^h_t(R_{it})}{\lambda_t \phi^h_t(R_{it}) + (1-\lambda_t)\phi^l_t(R_{it})}. \quad (4)$$

[12]The mean log likelihood for the mixture distribution is -1290 compared to -1468 for the two-parameter discretized normal distribution.

Figure 3: Estimates of uncertainty proxy ζ_{it}



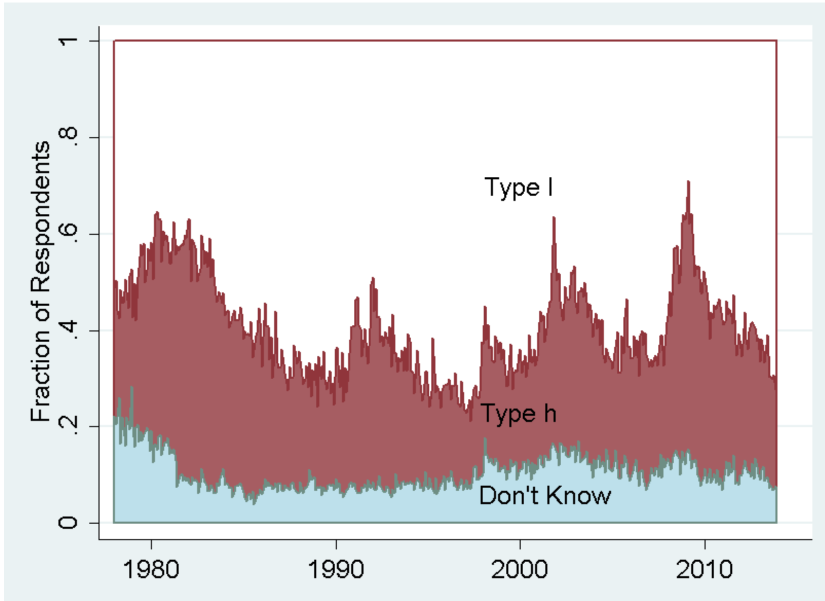
Notes: Panel A plots the inflation uncertainty proxy for 5% and 20% responses over time: $\zeta_t(5)$ is the probability that a consumer giving a 5% inflation forecast at time t is the highly uncertain type (type h), and $\zeta_t(20)$ is the probability that a consumer giving a 20% forecast is type h. Panel B plots $\zeta_t(5)$ against CPI inflation at time t, with quadratic fit and 95% confidence interval.

Figure 3 displays some of estimates of the uncertainty proxy ζ_{it}. In Panel A, values of ζ_{it} for responses $R_{it} = 5$ and $R_{it} = 20$ are plotted over time. Panel B plots $\zeta_t(5)$ against inflation π_t. When inflation is much higher or lower than 5%, $\zeta_t(5)$ tends to be higher, meaning that responses of 5% are more likely to come from the high-uncertainty type. A similar pattern appears for other values of R_{it}; $\zeta_t(10)$ is lower when inflation is near 10%, for example.

Note that construction of the proxy does not require any assumptions about V, the variance threshold above which agents round to a multiple of five. I estimate the probability that each agent is the highly uncertain type, without the need for arbitrary restrictions on the relative forecast variances of the high- and low-uncertainty types. In Appendix D, I show that under additional assumptions, the disagreement of each group can be used to estimate the mean uncertainty of each group following Lahiri and Sheng (2010). These estimates imply that the average forecast variance of type-h consumers is about four times greater than that of type-l consumers.

We have computed the uncertainty proxy ζ_{it} for consumers who provide a numerical response to the inflation expectations question. Some number N_t^{DK} of respondents decline to give a numerical

Figure 4: Inflation uncertainty index



Notes: The inflation uncertainty index is the sum of the shares of highly uncertain (type-h) consumers and consumers giving a "don't know" response. See Equation (5).

response to the inflation expectations question, and instead say they don't know, which, similar to rounding, indicates a high degree of uncertainty (see Curtin (2007)). For these respondents, let $\zeta_{it} = 1$. Let DK_t be the share of don't know responses at time t, which has mean 10.5% and standard deviation 3.7%. Figure 4 plots DK_t and the share of numerical resposes coming from types h and l.

The mean of ζ_{it} at time t is the sum of the shares of "don't know" responses and type-h responses. Call this the *inflation uncertainty index* U_t:

$$U_t = \frac{1}{N_t^h + N_t^l + N_t^{DK}} \sum_{i=1}^{N_t} \zeta_{it} = (1 - DK_t)\lambda_t + DK_t. \tag{5}$$

The next section describes properties of both ζ_{it} and U_t.

4 Properties and Validity of Inflation Uncertainty Measure

This section describes summary statistics and properties of the inflation uncertainty measure and provides support for its validity. Higher inflation uncertainty is associated with larger mean squared errors and forecast revisions. Demographic groups that tend to be more financially literate—high-income, highly-educated, males, and stock market investors—have lower average uncertainty, in line with findings from the New York Fed's Survey of Consumer Expectations (SCE). I also document time series properties of the inflation uncertainty index, which is countercyclical and is positively correlated with the Economic Policy Uncertainty index, inflation volatility, and inflation disagreement. While aggregate inflation uncertainty was strongly positively correlated with the level of inflation in higher-inflation decades, this relationship breaks down in recent years.

4.1 Micro-Level Summary Statistics and Demographic Patterns

The inflation uncertainty proxy (ζ_{it}) has mean 0.42 and standard deviation 0.41 over 245,946 observations. A regression of ζ_{it} on time fixed effects has an R^2 of 0.06, indicating that time series variation accounts for a relatively small share of the overall variation in uncertainty. The majority of the variation comes from the cross section.

A valid proxy for uncertainty should exhibit several properties. More uncertain individuals should on average make larger forecast revisions and errors. Uncertainty should also be persistent for individuals who take the survey twice, since individuals with better access to information or more precise models of the inflation process should continue to have lower uncertainty from one survey round to the next. Lahiri and Liu (2006) and van der Klaauw et al. (2008) document individual-level persistence in inflation uncertainty in other surveys. Table 2 verifies that ζ_{it} has these traits. The first two columns show that more uncertain consumers make significantly larger errors and revisions, while the third shows that uncertainty is persistent. When an individual takes the survey twice, her initial uncertainty is predictive of her uncertainty six months later.

Table 2: Properties of inflation uncertainty proxy ζ_{it}

	(1) Sq. Error	(2) Abs. Revision	(3) $\zeta_{i,t+6}$
ζ_{it}	55.66***	3.18***	0.32***
	(1.19)	(0.06)	(0.00)
Constant	5.10***	2.10***	0.25***
	(0.55)	(0.04)	(0.00)
Observations	216381	75797	88553
R^2	0.15	0.09	0.10

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust, time-clustered standard errors in parentheses. Sq. error is the squared difference between realized CPI inflation and the respondent's inflation forecast R_{it}. Abs. revision is the absolute forecast revision of a respondent who takes the survey twice at a six-month interval, $|R_{i,t+6} - R_{it}|$. With time fixed effects, the R^2 for columns (1) through (3) are 0.18, 0.10, and 0.14, and the coefficients on ζ_{it} are 54.0, 2.6, and 28.5.

Recent studies elicit individual consumers' expectations about future inflation in the form of subjective probability distributions, or density forecasts. Density forecasts allow direct computation of each respondent's inflation uncertainty, typically defined as the interquartile range of the respondent's density forecast. Comparison of the properties of ζ_{it} with measures of uncertainty derived from density forecasts provides further support of the validity of ζ_{it}.[13] Two projects at the New York Federal Reserve have collected consumers' density forecasts of inflation: the Household Inflation Expectations Project (HIEP) in 2007-2008, and the SCE since June 2013. The HIEP and the SCE compare inflation uncertainty by demographic group and find that it decrease with income and education (van der Klaauw et al., 2008; Armantier et al., 2013). HIEP results also show that uncertainty is higher for females than for males, higher for singles than for married people, lower for respondents who are responsible for their household's investments, and decreasing in financial literacy.

Demographic patterns in uncertainty revealed by the HIEP and SCE are shared by ζ_{it}. Table 3 summarizes differences in expectations, rounding, and ζ_{it} across demographic groups. The first two

[13]In Appendix D, I compare the magnitude of inflation uncertainty implied by the SCE and by the estimates in this paper, and find that the magnitudes are similar and are highly correlated over time.

columns display the fraction of multiple of five responses and "don't know" (DK) responses by group. The third and fourth columns display the mean error and root mean squared error for each group, and the fifth is the mean of ζ_{it}, or the share of type-h and DK respondents. The mean of ζ_{it} is lower for people with higher income and education and for males. Uncertainty varies non-monotonically by age, with youngest and oldest respondents most uncertain. Though the MSC does not test financial literacy, questions about stock market investments and homeownership added in 1990 are correlated with financial literacy (Rooij et al., 2011). Large-scale investors (in the top decile) are most certain, followed by smaller-scale and non-investors. Uncertainty is also lower among homeowners.

To formally test for differences in ζ_{it} between demographic groups, in Table 4, ζ_{it} is regressed on demographic variables and time fixed effects. Income, education, gender, marital status, geographic region, and race are all statistically significant. Coefficients on income, education, gender, and marital status are of the sign suggested by HIEP and SCE findings. The positive coefficient on the female dummy variable is also in line with findings that women are less knowledgeable about inflation than men on average (Lusardi, 2008). Coefficients on the linear and quadratic age terms imply that uncertainty is minimized at age 42, near prime working age.

The regression includes a married*female interaction term. The positive coefficient on the interaction term implies that while married men have lower inflation uncertainty than single men, married women have higher inflation uncertainty than single women. Since married women are less likely than single women to be primary financial decision-makers in their household (Ameriprise Financial Services, Inc., 2014), this is consistent with the HIEP finding that inflation uncertainty is lower for respondents who are primarily responsible for their household's investments.

The regression in Table 4 also includes a government opinion variable that takes values 1, 0, or -1 if the respondent's opinion of government policy is favorable, neutral, or negative. The negative coefficient implies that consumers with less trust in the government have higher inflation uncertainty, perhaps because they have less confidence in policymakers' ability or desire to stabilize inflation. Good news and bad news dummy variables that are positive if the respondent reports hearing good or bad news about business conditions both have negative coefficients. Consumers who hear any news about business conditions may be more informed about or attentive to economic statistics, and hence less uncertain about inflation.

These results supplement a larger literature on how the inflation expectations formation process varies across demographic groups (Bryan and Venkatu, 2001; Souleles, 2004; Bruin et al., 2010) and how access to information and the ability to process information vary with socioeconomic and demographic characteristics (Pfajfar and Santoro, 2008).

4.2 Time Series Properties and Correlations

The inflation uncertainty index U_t has mean 0.41, standard deviation 0.10, and autocorrelation coefficient is 0.91 over 432 months of data. Uncertainty was high in the recession of 1981-82, when inflation averaged 7.6% and the index averaged 0.57. Uncertainty declined during the Volcker disinflation, but rose slightly during the early 1990s recession. Newspapers from that period describe inflation uncertainty caused by the recession and the possible implications of the Gulf War on oil prices.[14] The index declined after the war. The minimum value, 0.21, occurred in May 1997, when

[14]The Wall Street Journal, for example, reported that "if the war is short and successful, there is likely to be a bounce-back in the economy when the uncertainty ends. If the Fed in the meantime has tried to drown out the downturn with easy monetary policy, the central bank may face a new inflation threat." ("War or Recession, the Fed Won't Panic," January 23, 1991, p. A12.) A Washington Post article titled "How Long? How Deep?" captured the uncertainty surrounding the war,

Table 3: Expectations and uncertainty by demographic group

	Mult. 5	DK	Error	RMSE	ζ	Observations
All	44%	11%	0.33	4.9	0.42	245,946
Bottom Income Tercile	46%	16%	1.19	5.5	0.49	56,975
Middle Income Tercile	45%	8%	0.77	4.8	0.39	69,812
Top Income Tercile	43%	5%	0.29	4.2	0.34	82,710
Non College Grad	45%	13%	0.31	5.3	0.45	85,139
College Grad	41%	6%	0.38	4.2	0.34	157,539
Male	40%	6%	-0.04	4.4	0.34	109,920
Female	46%	15%	0.66	5.4	0.48	135,355
Age 18-29	47%	8%	0.18	5.3	0.42	46,286
Age 30-64	43%	9%	0.38	4.8	0.39	151,704
Age 65-97	43%	19%	0.32	5.1	0.49	47,956
No Investments	43%	18%	1.57	4.9	0.49	38,891
Small or Medium Investor	42%	6%	0.98	4.2	0.35	41,800
Large Investor (Top Decile)	36%	4%	0.37	3.4	0.28	5,190
Non Homeowner	42%	14%	1.30	4.7	0.43	32,070
Homeowner	41%	10%	1.05	4.3	0.37	102,067

Notes: Mult. 5 and DK are the percent of respondents giving multiple of five or *don't know* responses, respectively. Error is the mean forecast error, RMSE the root mean squared forecast error, and ζ is the mean of the uncertainty proxy ζ_{it}.

inflation and unemployment had been low and steady for months. Uncertainty rose sharply in the 2001 and 2007-2009 recessions, reaching highs of 0.64 in November 2001 and 0.71 in February 2009.

The convergent validity of a measure is the degree to which it is related to other measures to which theory suggests it should be related, and can be established using correlation coefficients (Campbell and Fiske, 1959). Figure 5 plots U_t with related series. Correlation coefficients are of the sign suggested by theory. Panel A plots U_t with the level of inflation. Ball (1992) hypothesizes that when inflation is low, the public knows that policymakers would like to keep it low, so uncertainty is also low. When inflation is high, the public does not how willing policymakers will be to disinflate at the risk of causing a recession, thus uncertainty is high. Low inflation means maintaining the status quo, while high inflation means possible policy action. Inflation uncertainty and inflation were high in the late 1970s and early 1980s. The positive correlation between inflation uncertainty and inflation, with Granger-causality from inflation to inflation uncertainty,[15] is in line with the Ball hypothesis.

Since the Great Moderation, the data suggest a modification of Ball's hypothesis. Very low inflation is also associated with high uncertainty. Ball's basic reasoning still applies. Inflation that is too low can be just as undesirable as inflation that is too high. When inflation is very low, policymakers will likely act, but the timing, type, and size of the action are sources of uncertainty. Around 1990, the idea that the Federal Reserve had an implicit 2% inflation target came into discussion (Taylor, 1993). The Federal Reserve made this goal explicit in January 2012. Inflation uncertainty is more strongly correlated with $|\pi_t - 2|$, the absolute deviation of inflation from 2%, than with the level of inflation

its effects on oil prices and inflation, and how aggressively the Fed would respond (January 27, 1981, p. H1.)

[15] A bivariate vector autoregression with three lags of inflation and the inflation uncertainty index finds that inflation Granger causes inflation uncertainty ($p = 0.01$). Lag order was selected by the AIC.

Table 4: Inflation uncertainty ζ_{it} regressed on demographic, opinion, and news variables

	(1) ζ_{it}	
log Real Income	-0.036***	(0.002)
Education	-0.013***	(0.000)
Female	0.096***	(0.003)
Married	-0.014***	(0.003)
Married Female	0.022***	(0.003)
Age	-0.004***	(0.0003)
Age Squared	0.00005***	(0.000003)
West Region	-0.009***	(0.003)
Northeast Region	0.020***	(0.002)
South Region	0.005**	(0.002)
White, non-Hispanic	-0.041***	(0.005)
African-American	-0.003	(0.006)
Hispanic	0.047***	(0.007)
Opinion of Government	-0.011***	(0.002)
Good News	-0.038***	(0.002)
Bad News	-0.011***	(0.002)
Observations	218066	
R^2	0.123	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust time-clustered standard errors in parentheses. Regression includes time fixed effects. Variable descriptions in Appendix Table A.2.

π_t. The correlation between $|\pi_t - 2|$ and U_t is 0.57, compared to 0.44 between π_t and U_t. Since 1990, the correlation between $|\pi_t - 2|$ and U_t is 0.20, compared to -0.27 between π_t and U_t. Deviations of inflation from its target level—either above *or* below—correspond to high uncertainty.

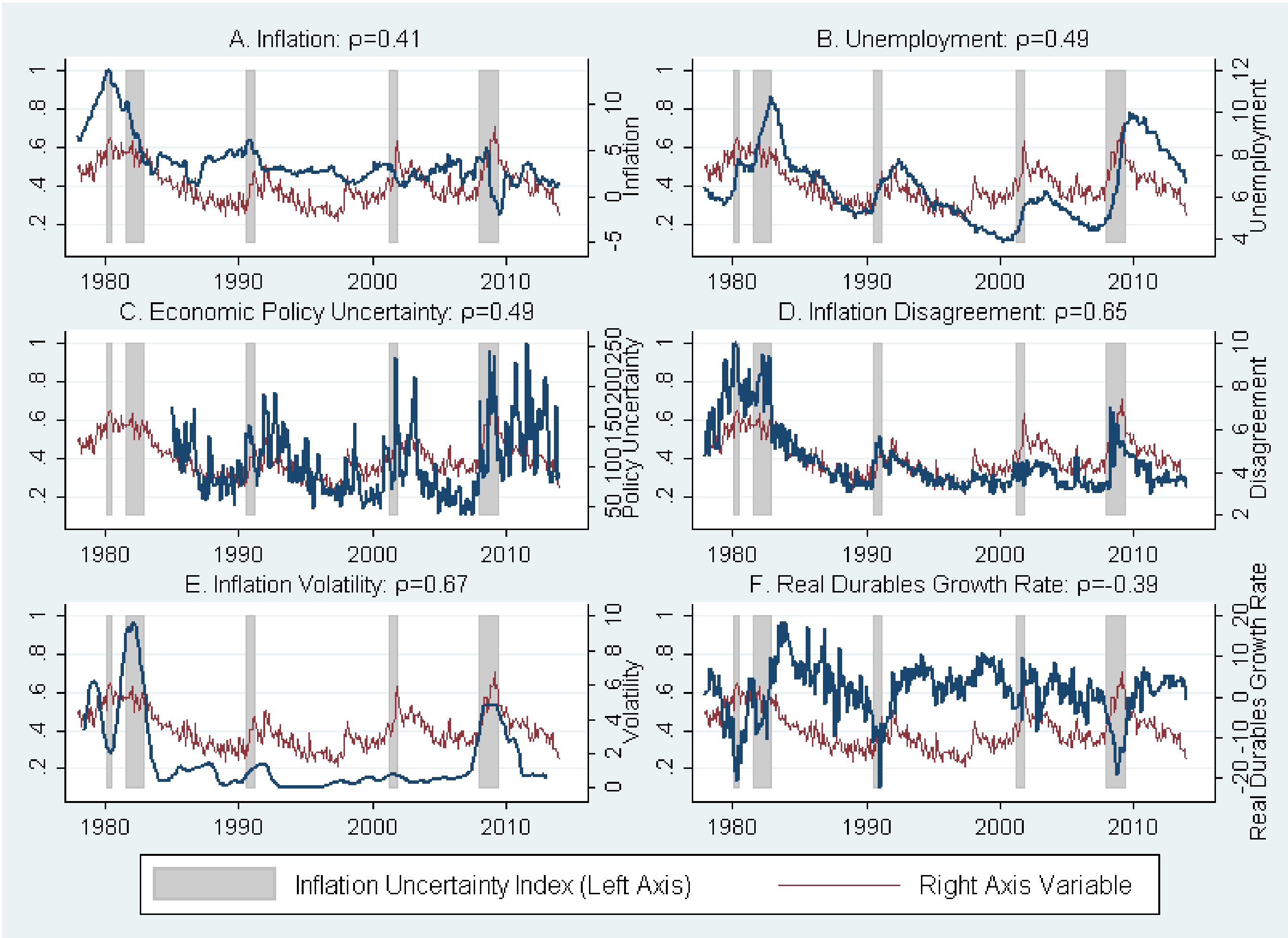
Panel B of Figure 5 plots the inflation uncertainty index with the unemployment rate. Inflation uncertainty is countercyclical, in line with theory. Bachmann and Moscarini (2012) hypothesize that recessions generate uncertainty by reducing the opportunity cost to firms of price mistakes, encouraging price experimentation, which raises the dispersion of price changes and increases uncertainty. The real options literature predicts countercyclical uncertainty with causation running in the reverse direction. With non-convex adjustment costs, uncertainty discourages irreversible investment and hiring (Bloom, 2009). Professional forecasters' uncertainty is also countercyclical (Rich et al., 2012).

The remaining panels plot the inflation uncertainty index U_t with commonly-used uncertainty proxies, beginning with the Economic Policy Uncertainty index (EPU) (Panel C). The EPU does not measure inflation uncertainty specifically, but does capture monetary policy-related uncertainty and forecaster inflation disagreement, so its positive correlation with U_t makes sense.[16]

Panel D shows that the index is strongly correlated with inflation disagreement, the cross sectional interquartile range of consumers' point forecasts. Uncertainty and disagreement are theoretically related, but distinct (Lahiri and Sheng, 2010). It is possible, for example, for consumers to provide

[16]The EPU is described in of Baker et al. (2012), with data and documentation available at http://www.policyuncertainty.com/us_monthly.html.

Figure 5: Inflation uncertainty index with related time series

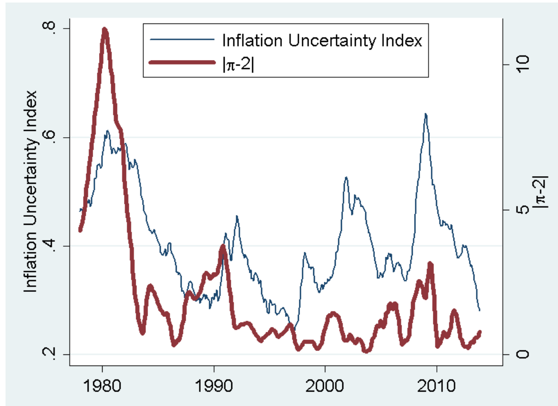


Notes: Correlation coefficients (ρ) in subtitles. Gray bars denote NBER recessions. Economic Policy Uncertainty Index from Baker et al. (2012). Disagreement is cross-sectional interquartile range of MSC inflation forecasts. Volatility is centered 3-year rolling variance of inflation.

similar point forecasts, so that disagreement is low, even while consumers are very uncertain about their individual point forecasts. Disagreement is an aggregate measure only, while at any given time, uncertainty may vary across consumers.[17] Researchers have used professional forecasters' density forecasts to study whether disagreement is a useful proxy for average uncertainty, with conflicting findings (Zarnowitz and Lambros, 1987; Lahiri and Liu, 2006; Boero et al., 2008; Rich and Tracy, 2010). Boero et al. (2014) find that for professional forecasters, disagreement is a useful proxy for average uncertainty in times of macroeconomic turbulence, when disagreement and uncertainty exhibit large fluctuations, but that low-level high-frequency movements in disagreement and average uncertainty are not strongly correlated. For consumers, similarly, inflation disagreement and mean uncertainty are positively correlated, but the correlation is weaker when disagreement is relatively low and stable. Before 1990, the correlation between the inflation uncertainty index and disagreement

[17] See Appendix D for more on the relationship between uncertainty and disagreement.

Figure 6: Inflation uncertainty and the absolute deviation of inflation from 2%



Notes: Both series shown as centered seven-month moving average.

is 0.91, while from 1990 to 2007 it is just 0.51. From 2008 to 2013 the correlation is 0.77.

The volatility or conditional volatility of inflation is another common proxy for inflation uncertainty (Fountas and Karanasos, 2007). Orlik and Veldkamp (2012) explain that the variance of the innovations from a GARCH model woud be equivalent to uncertainty only if agents knew the true inflation process and its true parameters. Thus uncertainty and volatility are likely to be correlated, but are distinct concepts. U_t is positively correlated with inflation volatility (Panel E).[18]

The countercyclicality of the inflation uncertainty index and its correlation with the EPU, inflation disagreement, and inflation volatility support the convergent validity of the proxy. A significant advantage of the rounding-based uncertainty proxy compared to existing proxies is its micro-level dimension which is useful for empirical analysis of the role of uncertainty in the economy. For example, Panel F shows a negative correlation between the inflation uncertainty index and real durables expenditures. The next section uses the micro-level uncertainty proxy to investigate the negative association between inflation uncertainty and consumption in more detail.

5 Inflation Uncertainty and Consumption

The links between inflation uncertainty and real economic activity are, in general, theoretically ambiguous (Cecchetti, 1993; Berument et al., 2005; Grier and Grier, 2006). Empirical studies relying on time series uncertainty proxies typically find a negative association between inflation uncertainty and real activity (Jansen, 1989; Evans and Wachtel, 1993; Davis and Kanago, 1996; Grier and Perry, 2000; Elder, 2004). The empirical evidence is mixed, however, with some studies finding a positive or negligible relationship (McTaggart, 1992; Clark, 1997; Barro, 1998).

Inflation uncertainty may influence consumers' intertemporal decisions. Inflation uncertainty implies uncertainty about real income and about the real rate of return on saving, which have opposite effects on intertemporal allocation (Kantor, 1983). The precautionary savings literature predicts that higher uncertainty about future income increases buffer-stock saving and reduces consumption (Leland, 1968; Kimball, 1990; Lusardi, 1998; Carroll, 2004). In contrast, uncertainty about the real rate

[18]In the figure, inflation volatility is defined as the three-year rolling variance of inflation, but positive correlations are also found for alternative definitions of volatility, including conditional volatility.

of return makes saving less attractive for risk averse consumers. A simple model in Appendix E clarifies how the coefficient of relative risk aversion determines whether saving increases or decreases with inflation uncertainty. In a neoclassical growth model in which money is introduced with a cash-in-advance constraint, Dotsey and Sarte (2000) show that inflation uncertainty increases saving.

Durable consumption is particularly sensitive to households' uncertainty (Romer, 1990; Bertola et al., 2005; Knotek and Khan, 2011). Durable purchases are costly to reverse because of the lemons problem and transaction costs (Akerlof, 1970; Mishkin, 1976; Knotek and Khan, 2011). Uncertainty increases the real option value of waiting to make a decision that is costly to reverse (Bernanke, 1983; Dixit and Pindyck, 1993; Bloom et al., 2007; Baker et al., 2012; Leduc and Liu, 2012; Bloom et al., 2013). The effects of inflation uncertainty on housing are especially complex because of particular features of mortgage financing (Lessard and Modigliani, 1975; MacDonald and Winson-Geideman, 2012; Piazzesi and Schneider, 2012).

Greater understanding of the relationship between uncertainty and consumption of durables is important because durable consumption is volatile and procyclical, and large declines in durable consumption may prolong recessions (Petev and Pistaferri, 2012). Mankiw (1985, pg. 353) notes that "Understanding fluctuations in consumer purchases of durables is vital for understanding economic fluctuations generally." As seen in Figure 5, U_t is negatively correlated with expenditures on real durables. The index is also negatively correlated with purchases of cars and homes (Table 5).

Table 5: Correlation between inflation uncertainty index U_t and aggregate spending series

	Correlation with U_t
Real Durables Growth Rate	-0.40
Car Sales	-0.52
Home Sales	-0.24

Notes: Monthly time series with 432 observations. Variable descriptions in Table A.1.

The MSC asks, "About the big things people buy for their homes–such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or a bad time for people to buy major household items?" Questions about cars and homes are similar (see Appendix A). Dummy variables DUR_{it}, CAR_{it}, and HOM_{it} take value 1 if consumer i says it is a good time to buy durables, cars, or homes, respectively. All have means of about two-thirds (Table 6, Part A).

Bachmann et al. (2013) show that consumers' responses to these spending attitude questions are positively correlated with actual expenditures. They use probit models to investigate the relationship between inflation expectations and spending attitudes and find a small negative coefficient on expected inflation. Since spending attitudes are theoretically related to not only the level of expected inflation, but also to inflation uncertainty, I include the inflation uncertainty proxy ζ_{it} in similar probit models.

First, to quantify the relationship between mean reported spending attitudes (DUR_t, CAR_t, and HOM_t) and actual aggregate spending on cars, home, and durables, I regress aggregate spending on mean spending attitudes and a time trend:

$$\ln(\text{Durables Spending}_t) = \alpha + \beta DUR_t + \gamma t, \tag{6}$$

and similarly for cars and homes (data descriptions in Appendix Table A.1). The estimated coefficients $\hat{\beta}$ are positive and highly statistically significant (Table 6, Part B).

Next, I run probit regressions of CAR_{it}, HOM_{it}, and DUR_{it} on inflation uncertainty ζ_{it}, inflation point forecasts π^e_{it}, and a vector X_{it} of controls.[19] Let Φ denote the cumulative distribution function of the standard normal distribution. The probit model takes the form:

$$Pr(DUR_{it} = 1|\zeta_{it}, \pi^e_{it}, X_{it}) = \Phi(\beta_0\zeta_{it} + \beta_1\pi^e_{it} + X'_{it}\beta_2) \tag{7}$$

In Bachmann et al.'s baseline specification, the vector of control variables X_{it} includes demographic variables, macroeconomic variables (such as inflation, unemployment, and a zero lower bound dummy variable), and idiosyncratic expectations/attitude variables from MSC questions that ask consumers about their personal financial situation, income expectations, interest rate and unemployment expectations, and opinion of government policy. I use similar variables, listed in Appendix Table A.2, in my baseline specification. Estimation results are summarized in Table 6, Part C. Coefficients on both inflation uncertainty and expected inflation are negative and statistically significant. The reported marginal effects are the change in probability of having a favorable spending outlook for a one unit increase in inflation uncertainty or a one percentage point increase in expected inflation.

Using the coefficients β from the regression in Equation 6, the marginal effects of ζ_{it} on spending attitudes can be translated into back-of-the-envelop estimates of the decline in spending on cars, home, and durables associated with an increase in inflation uncertainty. If all agents were the low uncertainty type, the mean of DUR would be 3.1 percentage points lower compared to if all agents were the high uncertainty type. Correspondingly, real durable expenditures would be about 2.2% lower. Similarly, car sales and home sales would be about 2.0% and 4.8% lower, respectively. These figures, while non-negligible, are relatively small. For example, in January through Novemer 2007, prior to the start of the Great Recession, the mean of ζ was 0.38, and car sales averaged 16.1 million per year. During the recession, the mean of ζ was 0.63, and car sales averaged 12.0 million per year. In an accounting sense, the increase in inflation uncertainty accounts for roughly 2% of the decline in auto sales, and similarly small contributions to durables and home sales.

I conduct a variety of alternative specifications and robustness checks, detailed in Appendix F. Results are robust to restricting the time sample to exclude the early 1980s or the Great Recession, omitting all or some of the control variables in X_{it}, including gas price expectations as a control variable, omitting π^e_{it} from the regression, or using a linear probability model. These have minimal impact on the marginal effect of ζ_{it}, which remains negative and statistically significant. In another specification, I use respondents' reported desire to buy in advance of rising prices as a dependent variable. The desire to buy in advance of rising prices *does* increase with expected inflation, and decreases with inflation uncertainty. A consumer who expects high inflation with high certainty is most likely to report a desire to buy in advance of rising prices.

Inflation uncertainty may dampen the effects of monetary policy on the consumption of cars, homes, and other durables. Consumer spending on durables is quite interest-rate sensitive (Bernanke and Gertler, 1995; Erceg and Levin, 2002; Taylor, 2007). The sensitivity of durables spending and and business investment to interest rates facilitates the ability of monetary policy to influence real activity, but in the recent recovery, reduced sensitivity to interest rates has weakened the effectiveness of the Federal Reserve's accommodative policy stance (Zandweghe and Braxton, 2013). Macroeconomic uncertainty has been posited as a reason for this diminished interest sensitivity. Bloom (2013) notes that the interest-elasticity of investment is smaller in times of high uncertainty, making monetary and fiscal stabilization tools less effective. Bloom (2009) also notes that in times of high uncertainty, firms require a large reduction in interest rates to leave their marginal investment decisions unchanged since uncertainty increases the value of postponing decisions that are costly to reverse. For consumers,

[19] The regressions include generated regressors. Under the null hypothesis that the coefficient on a generated regressor is zero, standard errors do not need to be adjusted for generated regressors (Pagan, 1984).

Table 6: Spending attitudes, aggregate spending, and inflation uncertainty

	DUR	**CAR**	**HOM**
A. Mean spending attitudes			
Percent favorable responses	71%	64%	67%
B. Spending attitudes and aggregate spending: Equation (6)			
Coefficient $\hat{\beta}$	0.71***	1.01***	1.03***
	(0.03)	(0.07)	(0.12)
Observations	432	432	432
R^2	0.90	0.40	0.15
C. Spending attitudes, inflation uncertainty, and expected inflation: Equation (7)			
Marginal Effect of Inflation uncertainty	-3.1%***	-2.0%***	-4.7%***
	(0.37%)	(0.34%)	(0.37%)
Marginal Effect of Expected inflation	-0.02%	-0.29%***	-0.16%***
	(0.03%)	(0.03%)	(0.03%)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust, time-clustered standard errors in parentheses. The marginal effect is the change in probability (in percentage points) of having a favorable spending outlook for a one unit increase in inflation uncertainty or a one percentage point expected inflation, with remaining variables set to their means. Complete regression output in Appendix F.

similarly, since durables purchases are costly to reverse, a highly-uncertain consumer may be less rate-sensitive and require a larger reduction in interest rates in order to prompt a major purchase.[20] The uncertainty proxy allows me to study interest rate sensitivity under uncertainty empirically. In Appendix F.1, I show that the spending attitudes of more uncertain consumers are less sensitive to changes in interest rates and to monetary policy shocks. While the direct relationship between inflation uncertainty and durables spending attitudes appears small, uncertainty and spending attitudes are indirectly linked through interest rate sensitivity.

6 Conclusion and Additional Applications

This paper has introduced a method of measuring the uncertainty associated with survey responses based on an association between rounding and uncertainty. The cognition and communication literature documents a human tendency to use round numbers when reporting quantitative expressions with high imprecision or uncertainty. This tendency, manifested in response heaping at round numbers, enables construction of a micro-level uncertainty measures from point estimates in survey data. I demonstrate the value of this method by constructing an uncertainty measure using inflation expectations data from the MSC. To construct the measure, I assume that consumers with sufficiently high uncertainty report their inflation forecast to the nearest multiple of five, while consumers with less uncertainty report their forecast to the nearest integer. In a given month, survey responses come from a mixture of two distributions, one of which is positive only at multiples of five, and the other at

[20]Mackowiak and Wiederholt (2011) show that if consumers are more uncertain about the real interest rate, the response of consumption to monetary policy is slower. Since uncertainty about inflation implies uncertainty about the real interest rate, the response of consumption to monetary policy should be muted for consumers with high inflation uncertainty.

integers. I estimate the parameters of the mixture distribution by maximum likelihood. This allows me to compute the probability ζ_{it} that respondent i in month t is a highly-uncertain consumer; this probability is a measure of her inflation uncertainty.

Properties of the measure support its validity. Namely, higher values of ζ_{it} are associated with larger forecast errors and revisions, and ζ_{it} is persistent at the individual level. The New York Federal Reserve's new Survey of Consumer Expectations has collected probabilistic inflation forecasts from consumers since 2013, and documents certain demographic patterns in inflation uncertainty, which ζ_{it} also exhibits. Time series properties of the mean of the measure, which I call the inflation uncertainty index, also point to the measure's validity. The index is elevated when inflation is very high or very low, and is countercyclical, in line with other theoretical and empirical results about macroeconomic uncertainty in recessions. The index is positively correlated with other time-series proxies for uncertainty, including disagreement, inflation volatility, and the Economic Policy Uncertainty index.

Since inflation expectations and inflation uncertainty are the subject of a huge literature, the new micro-level inflation uncertainty measure has a variety of applications for economic analysis. Uncertainty varies more in the cross section than over time, and I use this heterogeneity in uncertainty across consumers to study the role of inflation uncertainty in the real economy. MSC respondents are asked whether they think it is a good time to buy durables, cars, or homes. Probit regressions find a small negative association between inflation uncertainty and spending attitudes spending.

The micro-level measure of inflation uncertainty holds promise for studying the formation of inflation expectations. The work of Mankiw and Reis (2002), Sims (2003), and others has renewed interest in the expectations formation process and the implications of frictions in information acquisition and processing for aggregate dynamics. Coibion and Gorodnichenko (2012) and Pfajfar and Santoro (2012) use micro-level survey data on inflation expectations to test the predictions of various models of information rigidities and expectations formation. Coibion and Gorodnichenko show how the impulse responses of mean forecast errors and disagreement among agents after exogenous structural shocks can be used to differentiate between models of informational rigidities. Similarly, different models of informational rigidities have different implications for inflation uncertainty that can be tested using the new measure ζ_{it}. The rotating panel structure of the data, which shows changes over time in individual agents' inflation uncertainty, should be particularly useful for this purpose.

Several other applications of the inflation uncertainty measure appear in Binder (2015), including an application to inflation dynamics.[21] In the Phillips curve framework, inflation depends on the expectations of the economy's price setters. Since no quantitative surveys of price setters' inflation expectations exist for the United States, professional forecasters' expectations are commonly used as a proxy. Coibion and Gorodnichenko (2013) suggest that it is preferable to use the mean inflation forecast from the MSC as a proxy for price setters' expectations. However, price setters may be more informed about inflation than the average consumer. The maximum likelihood framework of Section 3 estimated the mean inflation forecasts of the highly-uncertain and less-uncertain consumers (μ_h and μ_l, respectively). Using μ_l in Phillips curve estimation better replicates inflation dynamics since the Great Recession compared to using average consumers' or professional forecasters' expectations.

The MSC asks consumers not only about their one-year-ahead inflation expectations but also about their inflation expectations at the five- to ten-year horizon. Binder (2015) uses the same maximum likelihood method to construct a proxy for inflation uncertainty an the five- to ten-year horizon. Longer-horizon inflation uncertainty provides an indicator of the degree to which inflation expecta-

[21] This paper is adapted from Binder (2015), my doctoral dissertation, and I am in the process of adapting other portions into a companion paper.

tions are anchored. Inflation uncertainty at longer horizons is a gauge of central bank credibility and communications effectiveness (Cukierman, 1992; Mishkin, 2008; van der Klaauw et al., 2008). If the public believes that the central bank is committed to price stability in the long run—in particular, if inflation expectations are firmly-anchored around a long-run target— then long-run inflation uncertainty should be low, and inflation uncertainty should decrease with forecast horizon (Beechey et al., 2011). Short- and long-horizon uncertainty were similar until the late 1980s. Since then, long-horizon inflation uncertainty has been lower than short-horizon uncertainty and has not returned to the high levels of the early 1980s. In the last two decades, however, long-horizon uncertainty displays no downward trend, despite monetary policymakers' efforts to enhance communication and transparency.

The maximum likelihood estimation framework of Section 3 can be adapted to other survey data for which response heaping occurs at different round values, such as multiples of 0.5, 50, 100, 1000, etc. depending on the context. Response heaping can be detected by calculating a Whipple Index (see Appendix B) or by visual inspection of a histogram of responses. Instead of two types of agents (l and h), a larger number m of types can be used. Then the mixture distribution ϕ will be a mixture of m pmfs, and the likelihood function in (3) will be a function of $3m - 1$ parameters (the mean and variance of m pmfs and $m - 1$ mixture weights).[22] For example, the MSC asks consumers about their expectation of the change in gas prices (in cents per gallon) over the next 12 months and five years. Most expect gas prices to rise in multiples of 5 cents, with multiples of 25 cents more prevalent than other multiples of 5 cents. This motivates a model with three types of consumers, those who round to the nearest 1 cent, 5 cents, and 25 cents.

The MSC asks consumers about their quantitative expectations of several other economic variables, including percent change in family income over the next 12 months and percent change in the price of "homes like yours in your community" over the next 12 months and five years. Response heaping at round numbers is very prevalent in each of these questions. Among respondents who expect family income to rise, 18% report an expectation of a 5% rise, the most common response.

This method need not only be used with survey questions about expectations of the future. Measuring the uncertainty associated with responses about current or past values of variables could also provide interesting insights into attention and memory, informing models of rule-of-thumb behavior or rational inattention (Campbell and Mankiw, 1989; Sims, 2003). Rounding behavior on surveys such as the Federal Reserve Board's Survey of Consumer Finances or the British Household Panel Survey[23] could reveal how precisely consumers monitor their income, debts, assets, and expenditures.

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[22]When there is doubt about the appropriate number m of agents to use with a particular dataset, a likelihood ratio test can be used to compare the fit of models with different numbers of agents. When there are $m > 2$ agent types, the relative uncertainties of each type can be estimated using the approach in Appendix D.

[23]Pudney (2008) documents response heaping at round numbers for questions about consumption expenditures on the British Household Panel Survey. He is primarily interested in how rounding behaviors introduce measurement errors that distort inferences about changes in living standards over time.

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Appendix A Data Descriptions

The expectations and attitude questions from the MSC used in this research are:
A2. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?

A3. Now looking ahead—do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?

A7. And how about a year from now, do you expect that in the country as a whole business conditions will be better, or worse than they are at present, or just about the same?

A9. As to the economic policy of the government—I mean steps taken to fight inflation or unemployment—would you say the government is doing a good job, only fair, or a poor job?

A10. How about people out of work during the coming 12 months—do you think that there will be more unemployment than now, about the same, or less?

A11. No one can say for sure, but what do you think will happen to interest rates for borrowing money during the next 12 months—will they go up, stay the same, or go down?

A12b. By about what percent do you expect prices to go (up/down) on the average, during the next 12 months?

A13b. By about what percent per year do you expect prices to go (up/down) on the average, during the next 5 to 10 years?

A15a. By about what percent do you expect your (family) income to (increase/decrease) during the next 12 months?

A16. Generally speaking, do you think now is a good time or a bad time to buy a house? (A16a. Why do you say so?)

A18. About the big things people buy for their homes–such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or a bad time for people to buy major household items? (A18a. Why do you say so?)

A19. Speaking now of the automobile market–do you think the next 12 months or so will be a good time or a bad time to buy a vehicle, such as a car, pickup, van or sport utility vehicle? (A19a. Why do you say so?)

A20c. About how many cents per gallon do you think gasoline prices will (increase/decrease) during the next twelve months compared to now?

A25. [Introduced September 1999] The next questions are about investments in the stock market. First, do you (or any member of your family living there) have any investments in the stock market, including any publicly traded stock that is directly owned, stocks in mutual funds, stocks in any of your retirement accounts, including 401(K)s, IRAs, or Keogh accounts?

A26. [Introduced September 1999] Considering all of your (family's) investments in the stock market, overall about how much would your investments be worth today?

Table A.1: Spending attitude and aggregate expenditure variables

Variable	Code	Description
Spending Attitude Variables		
HOM	A16	Dummy: Good time to buy a house
DUR	A18	Dummy: Good time to buy durables
CAR	A19	Dummy: Good time to buy a car
HOM_BA	A16a	Dummy: Buy home in advance of rising prices
DUR_BA	A18a	Dummy: Buy durables in advance of rising prices
CAR_BA	A19a	Dummy: Buy car in advance of rising prices
BA	A16a, A18a, A19a	DUR_BA+CAR_BA+HOM_BA
LowR	A16a, A18a, A19a	Dummy: Mentions low rates as reason for spending attitude
HighR	A16a, A18a, A19a	Dummy: Mentions high rates as reason for spending attitude
MentionsR	A16a, A18a, A19a	Dummy: LowR==1 or HighR==1
Aggregate Expenditure Variables (with FRED codes)		
Real Durables Expenditures	PCEDG	Personal consumption expenditures on durable goods, divided by CPI and multiplied by CPI in 2000
Car Sales	ALTSALES	Lightweight vehicle sales, millions of units, seasonally adjusted
Home Sales	HSN1F	New one family houses sold, thousands of units, seasonally adjusted

Notes: MSC data from University of Michigan and Thomson Reuters. Other data from Federal Reserve Economic Data (FRED).

Table A.2: Control variables in spending attitudes regressions

Variable	Code	Description
Demographic Control Variables from Michigan Survey of Consumers		
Log Real Income		Natural log of real income
Education		Highest grade of education completed
Female		Dummy: Female
Married		Dummy: Married
Married*Female		Dummy: Interaction of Female and Married
Age		Age in years
Age Squared		Age in years, squared
Region		Dummies: West, Northeast, and South
Race		Dummies: White, African-American, and Hispanic
Investment quintile*	A25-26	Stock investments: none (0), lowest (1),...,top (5)
Attitude and Expectation Control Variables from Michigan Survey of Consumers		
PAGO	A2	Personal finances better (1), same (0), or worse (-1) than last year
PEXP	A3	Personal finances will be better (1), same (0), or worse (-1) next year
BEXP	A7	Business conditions will be better (1), same (0), or worse (-1) next year
GOVT	A9	Opinion of government economic policy is favorable (1), neutral (0), or unfavorable (-1)
UNEMP	A10	Expect unemployment rate to rise (1), stay same (0), or fall (-1)
RATEX	A11	Expect interest rates to rise (1), stay same (0), or fall (-1)
π^e	A12b	Expected % change in prices in next 12 mos.
INEX	A15a	Expected % change in family income in next 12 mos.
GAS*	A20c	Expected change in gas prices in next 12 mos. (cents)
Macroeconomic Control Variables (with FRED codes)		
Unemployment	UNRATE	Civilian unemployment rate
Fed funds rate	FEDFUNDS	Federal funds rate
Inflation	CPIAUCSL	CPI inflation rate, year-over-year
ZLB	FEDFUNDS	Dummy: Fed funds rate $\leq 0.25\%$

Notes: MSC data from University of Michigan and Thomson Reuters. Other data from Federal Reserve Economic Data (FRED). *Denotes variables not included in regressions unless specified.

Appendix B Identifying Heaping with Whipple Indices

Demographer George Whipple developed the Whipple Index to quantify the prevalence of heaping at multiples of five in self-reported age data. The index is five times the number of multiple-of-five responses divided by the total number of responses. For inflation expectations data, let N_j be the number of responses of value j. The Whipple Index is:

$$W = \frac{N_{-10} + N_{-5} + N_0 + ... + N_{25}}{N_{-10} + N_{-9} + ... + N_{24} + N_{25}} * 5, \tag{8}$$

Values of W above 1.75 indicate very prevalent heaping (United Nations, 2012). For the Michigan Survey inflation expectations data, W is 2.45.

Modifications of the Whipple Index, including the Myers' Blended Index and the digit-specific Whipple Index, are designed to identify heaping at any value, not just multiples of five. The index involves comparison of the frequencies of reported values to frequencies that would occur under the population distribution of true values, under some assumptions about the true distribution. Existing modified Whipple indices are designed specifically for use with age data as they assume true ages should be uniformly distributed on certain ranges. I modify the Myers' Blended Index to be used with inflation data. Suppose we have T observations of realized inflation. Let M_j be the number of inflation realizations in $[j - 0.5, j + 0.5)$, the integer bin centered at j. Then the modified Whipple Index for j is:

$$\hat{W}_j = \frac{N_j}{N_{-10} + N_{-9} + ... + N_{24} + N_{25}} \frac{T}{M_j} \tag{9}$$

The highest values of $\hat{W}_j$ occur at $j = 0, 5, 10,$ and 15 (see Table B.1). $\hat{W}_j$ is undefined for $j < -2$ or $j > 15$ since $M_j = 0$ for such j. Notably, $\hat{W}_1$, $\hat{W}_2$, and $\hat{W}_3$ are less than or equal to one, indicating no heaping at these values.

Table B.1: Inflation forecasts and inflation realizations

Inflation (%)	Responses (%)	Realizations (%)	Ratio
-10	0.5	0.0	.
-9 to -6	0.2	0.0	.
-5	0.7	0.0	.
-4	0.1	0.0	.
-3	0.4	0.0	.
-2	0.3	0.2	1.5
-1	0.4	1.1	0.3
0	15.0	1.1	13.5
1	7.1	7.1	1.0
2	8.3	21.1	0.4
3	14.7	29.3	0.5
4	4.4	17.1	0.3
5	14.8	6.7	2.2
6	1.4	2.4	0.6
7	3.2	1.8	1.8
8	0.9	0.9	1.0
9	0.8	1.8	0.4
10	7.4	2.0	3.7
11 to 14	1.7	4.0	0.4
15	1.4	0.0	.
16 to 19	0.3	0.0	.
20	1.1	0.0	.
21 to 24	0.1	0.0	.
25	0.6	0.0	.
All multiples of 5	41.4	9.8	4.2

Notes: This table compares the distribution of MSC inflation expectations to the distribution of inflation realizations rounded to the nearest integer. Last column shows the ratio of responses to realizations in each bin.

Appendix C Non-Normal Distributional Assumptions

In Section 3, I assume that the cross sectional distribution of forecasts from consumers of type $\tau \in \{l, h\}$ is normal with mean $\mu_{\tau t}$ and variance $\sigma^2_{\tau t}$. Estimates are not particularly sensitive to this normality assumption. The logistic distribution has heavier tails (higher kurtosis) than the normal distribution, with probability density function:

$$f(x; \mu, s) = \frac{e^{=\frac{x-\mu}{s}}}{s(1+e^{-\frac{x-\mu}{s}})^2}, \tag{10}$$

where the mean is μ and the variance is $\sigma^2 = s^2\pi^2/3$.

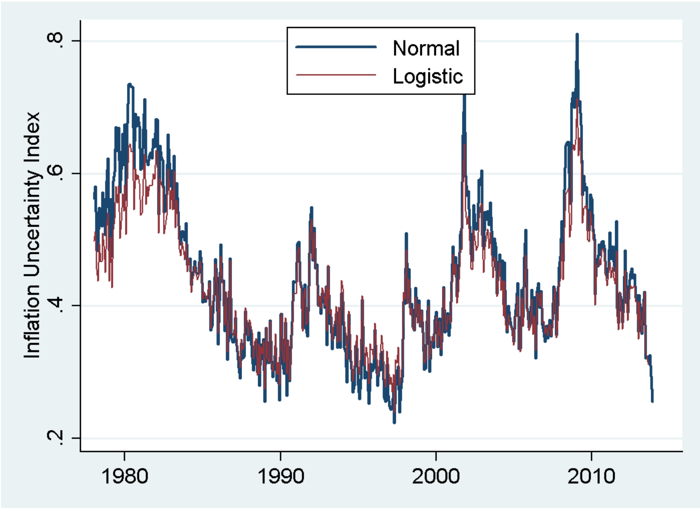
Table C.1 compares the maximum likelihood estimates and inflation uncertainty index under the assumptions of normal and logistic cross-sectional distributions, and Figure C.1 plots the index under both distributional assumptions. Results are quite similar in each case.

Table C.1: Maximum likelihood estimates with normal and logistic errors

Estimate	Mean with normal distribution	Mean with logistic distribution	Correlation between normal and logistic
λ	0.34	0.36	0.998
μ_l	3.52	3.36	0.999
μ_h	5.60	5.05	0.995
σ_l	2.88	2.70	0.988
σ_h	5.79	5.53	0.956
U_t	0.44	0.42	0.990

Notes: Estimates from Section 3 are computed under alternative assumptions on the cross-sectional distributions of forecasts by type. Last column shows correlation coefficient between resulting estimates.

Figure C.1: Inflation uncertainty index with normal and logistic error distributions



Notes: Inflation uncertainty index estimated as in Section 3 under assumption that the cross section of forecasts from each consumer type is normally or logistically distributed.

Appendix D Disagreement and Uncertainty

The uncertainty proxy ζ_{it} constructed in Section 3 estimates the probability that consumer i is the "high uncertainty" type given her response R_{it}. I assumed that each consumer i has a subjective probability distribution over inflation with mean f_{it} and variance v_{it}, and that consumers round f_{it} to the nearest multiple of five if v_{it} is sufficiently high, say above some threshold V. We know that v_{it} is higher for type-h than for type-l consumers, but how much higher? Let v_{ht} and v_{lt} be the average uncertainty of type-h and type-l consumers, respectively, at time t.

Disagreement, the cross-sectional variance of point forecasts, is often used as an estimate of average uncertainty. For professional forecasters, who provide density forecasts for inflation, disagreement and average uncertainty are similar. Lahiri and Sheng (2010) derive a relationship between disagreement and the average uncertainty of a group of forecasters by assuming that each forecaster's error $e_{it} = f_{it} - \pi_{t+12}$ is the sum of a common component ν_t and an idiosyncratic component ϵ_{it}:

$$e_{it} = u_t + \epsilon_{it}. \tag{11}$$

They make these assumptions: $E[u_t] = E[\epsilon_{it}] = 0$, $var(u_t) = \sigma^2_{ut}$, $var(\epsilon_{it}) = \sigma^2_{\epsilon it}$,$E(u_t u_{t-k}) = 0$ for any $k \neq 0$, $E(\epsilon_{it}\epsilon_{jt}) = 0$ for any $i \neq j$, and $E[\epsilon_{it}u_{t-k}] = 0$ for any i, k. Using this decomposition of forecast errors, Lahiri and Sheng show that the average uncertainty of a group g of forecasters is:

$$v_{gt} = \sigma^2_{ut} + D_{gt}, \tag{12}$$

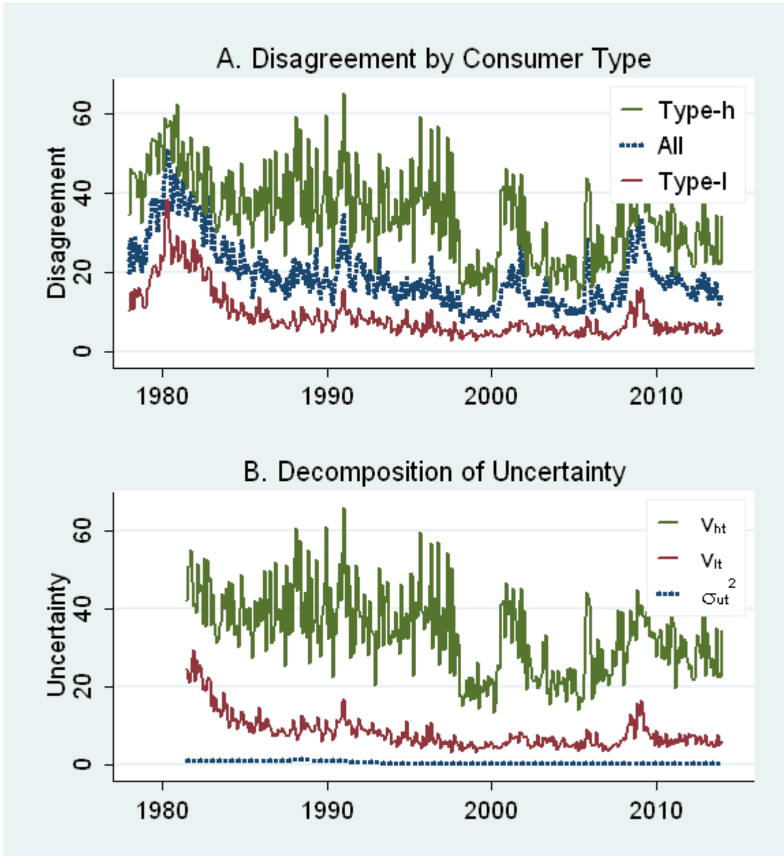
where D_{gt} is disagreement, given by the cross-sectional variance of point forecasts. Recall that disagreement among type-h consumers is σ^2_{ht} and among type-l consumers is σ^2_{lt}, both of which were estimated by maximum likelihood in Section 3. Panel A of Figure D.1 plots disagreement among all consumers, among type-l consumers, and among type-h consumers. Type-h disagreement is about four times higher than that of type-l consumers. Using Equation (12), we can use σ^2_{lt} and σ^2_{ht} to compute v_{lt} and v_{ht}. For $\tau \in \{l, h\}$, $v_{\tau t} = \sigma^2_{ut} + \sigma^2_{\tau t}$.

All that remains is to estimate σ^2_{ut}. Lahiri and Sheng suggest using probabilistic forecast data from the Survey of Professional Forecasters (SPF). SPF respondents assign probabilities summing to 100% that inflation will fall in different bins. From each forecaster j's density forecast, the variance can be computed. Let $v_{SPF,t}$ be the mean forecast variance across professional forecasters and $D_{SPF,t}$ be disagreement among professional forecasters. By Equation (12), we can compute $\sigma^2_{ut} = v_{SPF,t} - D_{SPF,t}$. Panel B of Figure D.1 plots σ^2_{ut}, v_{lt}, and v_{ht}. The mean of σ^2_{ut} is 0.65, which is an order of magnitude smaller than the disagreement D_{lt} or D_{ht} of either group of consumers.[24] Thus, mean uncertainty $v_{\tau t}$ is only slightly greater than disagreement $D_{\tau t}$ for consumers of type $\tau \in \{l, h\}$. If consumer i has probability ζ_{it} of being type h, then an estimate of her forecast variance v_{it} is $v_{it} = \zeta_{it}v_{ht} + (1 - \zeta_{it})v_{lt}$.

The Survey of Consumer Expectations (SCE) reports the median forecast interquartile range from probabilistic forecasts as a measure of uncertainty. For comparability, I transform v_{it} to the corresponding interquartile range, $1.349\sqrt{v_{it}}$. SCE and MSC uncertainty measures are both available from June through December 2013, when both average 3.2% with correlation coefficient 0.82 (Figure D.2). If we had not treated responses as coming from high and low uncertainty consumers, but had in-

[24]The SPF is a quarterly survey conducted by the Philadelphia Federal Reserve. Forecasters provide fixed-horizon probabilistic forecasts of annual-average over annual-average GDP price level growth beginning in 1981Q3. See documentation at http://www.phil.frb.org/research-and-data/real-time-center/survey-of-professional-forecasters/spf-documentation.pdf, page 24. Because of the noise inherent in this data, I HP-filter the estimated σ^2_{ut} series, then linearly interpolate to convert the quarterly series into a monthly series.

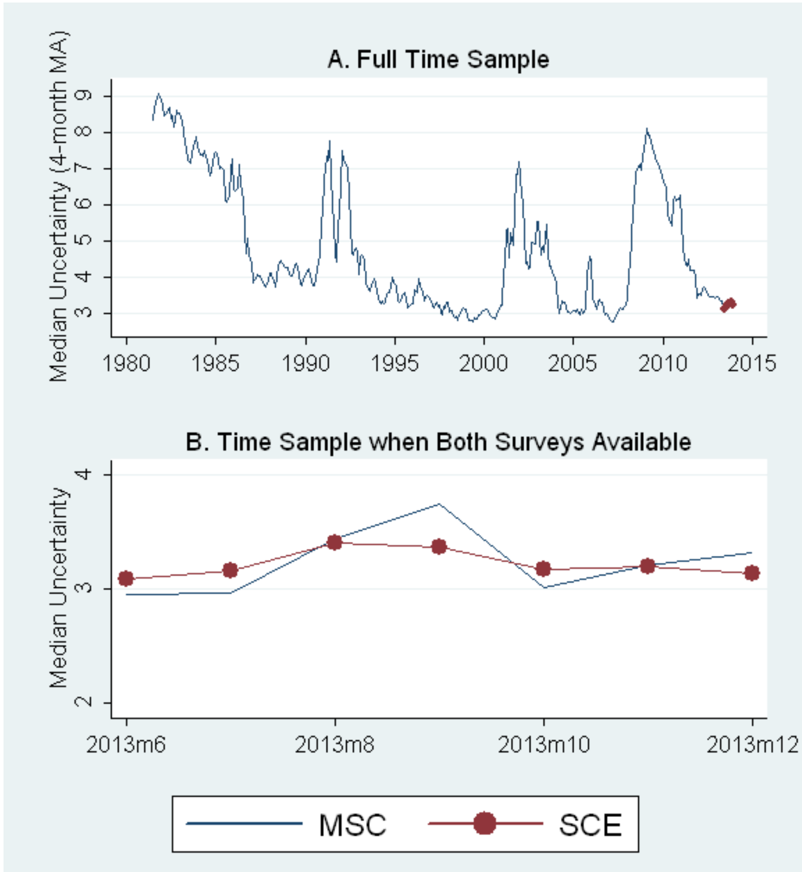
Figure D.1: Inflation disagreement and mean inflation uncertainty by consumer type



Notes: Disagreement is cross-sectional forecast variance. For Panel B, see Equation (12).

stead used disagreement of all consumers to compute mean uncertainty, the corresponding median interquartile range for June through December 2013 would average 3.6%, and would have a correlation of 0.62 with the SCE measure. Thus, using rounding behavior to distinguish between consumer types results in uncertainty estimates more comparable to those obtained by the SCE.

Figure D.2: Inflation uncertainty estimates compared to Survey of Consumer Expectations



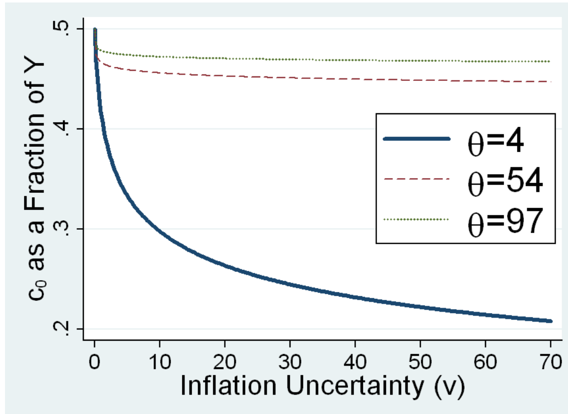
Notes: Inflation uncertainty in this figure is defined as the interquartile range of a respondent's inflation forecast. SCE series is inflation uncertainty as computed from probabilistic forecasts in the NY Fed's Survey of Consumer Expectations. MSC series is from this paper. Panel A shows entire time sample with four-month moving average filter. Panel B shows months for which both series exist.

Appendix E Model of Inflation Uncertainty and Intertemporal Allocation

This simple two-period model of an endowment economy with a single consumption good clarifies basic effects of inflation uncertainty on saving. The consumer's probability distribution over π, the rate of inflation from period 0 to 1, is $N(0, v)$. For simplicity, let the nominal interest rate be 0, so the real rate r is given by $1 + r = (1 + \pi)^{-1}$. Lifetime utility is $U = u(c_0) + u(c_1)$, where c_t is consumption in period t and $u(c) = \frac{c^{1-\theta}}{1-\theta}$. Suppose the consumer receives an endowment Y in period 0. Then her budget constraint is $c_0 + c_1(1 + \pi) = Y$. Expected utility as a function of c_0 is:

$$E[U(c_0)] = \frac{c_0^{1-\theta}}{1-\theta} + E[\frac{(Y - c_0)^{1-\theta}}{(1-\theta)(1+\pi)^{1-\theta}}] = \frac{c_0^{1-\theta}}{1-\theta} + \frac{(Y - c_0)^{1-\theta}}{1-\theta} E[(1+\pi)^{\theta-1}]. \tag{13}$$

Figure E.1: Consumption by inflation uncertainty



Notes: Graph shows fraction of endowment consumed in period 0 in a two-period model by inflation uncertainty v and coefficient of relative risk aversion θ. Estimates of θ from Gertner (1993), Sydnor (2006), and Cohen and Einav (2007).

The first-order condition in c_0 is:

$$c_0^{-\theta} = (Y - c_0)^{-\theta} E[(1+\pi)^{\theta-1}] \tag{14}$$

I take a second-order Taylor expansion of $(1+\pi)^{\theta-1}$ around $\pi = 0$:

$$(1+\pi)^{\theta-1} \approx 1 + \pi(\theta-1) + \frac{\pi^2}{2}(\theta-1)(\theta-2). \tag{15}$$

Then substituting this approximation into Equation (14) and rearranging,

$$c_0 \approx \frac{Y}{(1+\frac{v}{2}(\theta-1)(\theta-2))^{\frac{1}{\theta}} + 1} \tag{16}$$

Notice that if there is no inflation uncertainty ($v = 0$), optimal period 0 consumption is $c_0 = Y/2$. The consumer would simply smooth consumption across the two periods. If the consumer has log utility, so $\theta = 1$, then $c_0 = Y/2$ regardless of v. If $\theta \in (0,1)$ or $\theta > 2$, then c_0 is decreasing in v. If $\theta \in (1,2)$, then c_0 is increasing in v. Empirical studies find a range of estimates of the coefficient of relative risk aversion θ. Gertner (1993) estimates that the coefficient of relative risk aversion is around 5. Sydnor (2006) estimate that it is 54 and Cohen and Einav (2007) estimate that it is 97. Figure E.1 plots c_0/Y as a function of v for these three empirical estimates of θ. In each case, initial consumption is decreasing in inflation uncertainty. Higher inflation uncertainty means that the return on savings is riskier, which makes saving less attractive. But the desire to smooth consumption intertemporally increases saving in the presence of uncertainty.

Appendix F Inflation Uncertainty and Consumption

Table F.1 displays results from the baseline specification in which spending attitudes are regressed on the demographic, macroeconomic, and expectational control variables listed in Table A.2. The coefficients on the expectational control variables are of the expected sign. Consumers with favorable expectations of their future income and financial situation, business conditions, and unemployment, or with more positive opinions of government policy, are more ready to spend. Nearly all demographic control variables have significant coefficients. Higher income consumers are more eager to spend, and men, particularly if married, express more readiness to buy houses.

Table F.1: Spending attitudes, inflation uncertainty, and inflation expectations

	(1) DUR		(2) CAR		(3) HOM	
v	-5.1e-03***	(6.0e-04)	-2.8e-03***	(4.3e-04)	-5.0e-03***	(6.6e-04)
π^e	-2.0e-03**	(1.0e-03)	-9.1e-03***	(8.9e-04)	-8.2e-03***	(1.0e-03)
log Real Income	4.6e-02***	(6.0e-03)	1.1e-01***	(6.0e-03)	1.4e-01***	(7.2e-03)
Education	-2.4e-03	(1.8e-03)	1.8e-02***	(1.6e-03)	3.3e-02***	(2.1e-03)
Female	-6.3e-02***	(1.2e-02)	-1.1e-02	(1.2e-02)	-2.0e-02*	(1.2e-02)
Married	9.4e-03	(1.1e-02)	-4.0e-03	(1.1e-02)	5.5e-02***	(1.2e-02)
Married Female	-4.9e-02***	(1.6e-02)	-6.7e-02***	(1.4e-02)	-4.8e-02***	(1.4e-02)
Age	-1.0e-02***	(1.4e-03)	-9.1e-03***	(1.3e-03)	7.7e-03***	(1.4e-03)
Age Squared	9.9e-05***	(1.3e-05)	9.5e-05***	(1.3e-05)	-8.2e-05***	(1.4e-05)
West	-3.8e-02***	(1.2e-02)	-2.2e-02**	(1.1e-02)	-1.0e-01***	(1.3e-02)
Northeast	-2.2e-02*	(1.2e-02)	3.6e-03	(1.0e-02)	-1.6e-01***	(1.4e-02)
South	-2.3e-02**	(9.9e-03)	-9.8e-03	(9.2e-03)	-3.5e-02***	(1.0e-02)
White	1.2e-01***	(2.2e-02)	1.4e-01***	(2.2e-02)	2.5e-01***	(2.3e-02)
African-American	8.0e-02***	(2.5e-02)	4.1e-02	(2.5e-02)	6.1e-03	(2.6e-02)
Hispanic	-4.7e-03	(2.7e-02)	-1.2e-02	(2.6e-02)	7.0e-02**	(2.8e-02)
INEX	1.3e-03***	(2.2e-04)	1.8e-03***	(2.4e-04)	2.8e-03***	(2.4e-04)
PAGO	1.4e-01***	(5.0e-03)	7.7e-02***	(4.3e-03)	8.7e-02***	(4.9e-03)
PEXP	4.4e-02***	(5.9e-03)	6.8e-02***	(6.3e-03)	6.3e-02***	(6.7e-03)
BEXP	9.3e-02***	(6.7e-03)	1.3e-01***	(6.0e-03)	1.2e-01***	(7.0e-03)
RATEX	7.2e-02***	(5.9e-03)	-1.2e-02**	(5.4e-03)	-3.2e-03	(7.9e-03)
UNEMP	-1.5e-01***	(7.0e-03)	-1.1e-01***	(6.5e-03)	-1.2e-01***	(7.7e-03)
GOVT	1.4e-01***	(7.2e-03)	1.3e-01***	(6.0e-03)	1.2e-01***	(7.8e-03)
Unemployment	-9.9e-02***	(6.4e-03)	-1.7e-02***	(6.2e-03)	-2.5e-02**	(1.1e-02)
Fed Funds Rate	3.3e-02***	(4.6e-03)	-5.8e-03	(3.8e-03)	-6.4e-02***	(5.9e-03)
Inflation	-7.3e-02***	(8.7e-03)	-7.8e-02***	(7.2e-03)	-1.1e-01***	(1.2e-02)
ZLB	5.8e-02	(4.0e-02)	-1.5e-01***	(3.1e-02)	-2.5e-01***	(5.4e-02)
Observations	151671		152186		155841	
Pseudo R^2	0.07		0.05		0.12	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Probit regressions with robust, time-clustered standard errors in parentheses. Variable descriptions in Table A.2.

Table F.2 summarizes the marginal effects of inflation uncertainty and expected inflation on spending attitudes for durables, cars, and homes for the baseline specification and a variety of alternative specifications. In the baseline, if uncertainty ζ_{it} increases from 0 to 1, the probability that the respondent will say it is a good time to buy durables falls by 3%.

Table F.2: Marginal effects of inflation uncertainty on spending attitudes

	Specification	DUR		CAR		HOM	
		ζ	π^e	ζ	π^e	ζ	π^e
(1)	Baseline	-3.0	-0.02*	-2.0	-0.29	-4.7	-0.16
(2)	Year>1984	-2.6	0.09	-1.3	-0.33	-3.7	-0.25
(3)	Year<2008	-2.7	-0.02*	-1.7	-0.26	-4.7	-0.11
(4)	No π^e	-4.0		-3.8		-6.5	
(5)	No ζ		-0.03		-0.33		-0.26
(6)	Include GAS	-2.9	-0.10*	-2.3	-0.32	-4.6	-0.25
(7)	No expectation controls	-3.7	-0.19	-1.6	-0.55	-4.3	-0.36
(8)	No controls	-7.8	-0.4100	-5.1	-1.00	-9.9	-1.1
(9)	Linear probability model	-3.1	-0.03*	-2.0	-0.30	-4.4	-0.16
(10)	Ordered probit	-3.3	-0.01*	-2.0	-0.28	-4.7	-0.15
(11)	Control function	-12.3	-0.08*	-9.2	-0.28	-18.4	-0.19
(12)	Rotating panel	-1.7	-.09*	-1.4	-0.32	-2.9	-0.19
(13)	Buy in advance of rising prices	-2.8	0.49	-2.1	0.24	-1.5	0.2

Notes: The marginal effect is the change in probability (in percentage points) of having a favorable spending outlook for a one unit increase in ζ or a one percentage point increase in π^e. When calculating marginal effects, remaining variables are set to their means. All effects are statistically significant with $p < 0.01$ unless noted by *.

In rows 2 and 3 of Table F.2, I restrict the time sample to exclude either the high inflation of the early 1980s or the Great Recession. Neither greatly effects the coefficients on ζ and π^e. Row 4 omits π^e from the regression. The marginal effect of ζ is virtually unchanged from the baseline. Likewise if ζ is excluded and π^e is included, the marginal effect of π^e is similar to baseline (row 5).

Row 6 includes gas price expectations as a control. GAS_{it} is respondent i's expected change in gas prices, in cents, in the next year. Bachmann et al. (2013) include this variable in a robustness check in case some households primarily have gas prices in mind when reporting inflation expectations. The estimated coefficient on GAS is negative, and the marginal effect indicates that a $1 increase in gas price expectations is associated with about 5 percentage points lower probability of saying it's a good time to buy durables, a car, or a home.

In another specification, Bachmann et al. omit the idiosyncratic expectations/attitude variables, in case controlling for the expectations variables mops up general equilibrium effects. An increase in expected inflation might, for example, cause an increase in growth expectations, which in turn increases willingness to spend. Row 7 omits the expectations/attitude control variables, and row 8 omits all control variables. In both cases, the marginal effects of ζ and π^e are larger in magnitude. Row 9 shows results from a linear probability model instead of a probit model. These are regressions of the form: $DUR_{it} = \beta_0\zeta_{it} + \beta_1\pi^e_{it} + X'_{it}\beta_2$. Again, results do not differ notably from the baseline.

Respondents may give positive, negative, or neutral responses to the spending attitude questions. In row 10, in place of the dummy variables DUR, CAR, and HOM, we can define spending attitude variables that take value 1 for positive, 0 for neutral, and -1 for negative responses, and use an ordered probit model instead of a probit model. This makes almost no difference to the regression results. Since about two thirds of respondents give positive responses to the spending attitude questions, distinguishing between negative and neutral responses adds little useful variation.

In another robustness check, in place of ζ_{it}, I include a dummy variable $ROUND_{it}$ that takes value 1 if the respondent's inflation forecast is a multiple of five. Table F.3 reports estimated coefficients and marginal effects. I also define a "placebo" dummy variable $PLACEBO_{it}$ that takes value 1 if the respondent's inflation forecast plus one is a multiple of five, i.e. if the response is in $\{-6, -1, ..., 14, 19, 24\}$. If $PLACEBO_{it}$ is included as a regressor in place of $ROUND_{it}$, its coefficient is not statistically different from zero.

Table F.3: Spending attitudes, round number responses, and inflation expectations

		(1) DUR	(2) CAR	(3) HOM
ROUND	Coefficient	-3.7e-02***	-2.7e-02***	-6.8e-02***
	Std. Err.	(7.7e-03)	(6.4e-03)	(7.6e-03)
	Marginal Effect	-1.2%***	-0.97%***	-2.2%***
π^e	Coefficient	-2.2e-03**	-8.9e-03***	-7.0e-03***
	Std. Err.	(9.7e-04)	(8.6e-04)	(1.0e-03)
	Marginal Effect	-0.07%**	-0.32%***	-0.23%***
Observations		164621	165248	169258
Pseudo R^2		0.07	0.06	0.14

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Probit regressions with robust time-clustered standard errors in parentheses. Dummy variable ROUND takes value 1 if expected inflation is a multiple of five. Marginal effect is change in probability (in percentage points) of favorable spending attitude if ROUND increases from 0 to 1 or if π^e increases by one percentage point. Control variables from Table A.2 included.

Row 11 summarizes the marginal effects from a control function (CF) approach. Bachmann et al. (2013) use this approach to address two potential concerns with the baseline specification. The first is that an omitted variable may be relevant to both spending attitudes and expected inflation, biasing the coefficient on expected inflation. The second is that measurement error may bias the coefficient on expected inflation towards zero. Imbens and Wooldridge (2007) recommend the CF approach, which involves two stages. Restricting the sample to respondents who took the survey twice, in the first stage, Bachmann et al. regress expected inflation on the control variables X_{it} from the baseline and on expected inflation from the previous time the respondent took the survey. In the second stage, they estimate the baseline model but include the first stage residual as an additional control variable.

Similar concerns arise in my baseline specification with respect to inflation uncertainty, so I also use the CF approach (Table F.4). In the first stage, I regress inflation uncertainty ζ_{it} on lagged uncertainty $\zeta_{i,t-6}$ and the control variables from the baseline. In the second stage, I regress spending attitudes on inflation uncertainty, expected inflation, the same control variables, and the first stage residual. The marginal effects of ζ_{it} are negative, statistically significant, and larger in magnitude than in the baseline results. Bachmann et al. also find marginal effects that are larger in magnitude using the CF approach. This suggests that measurement error in π^e and ζ biases the coefficients of interest toward zero in the baseline.

The specification in row 12 also uses of the rotating panel. Suppose there is some unobserved time-invariant characteristic of individuals that makes them more or less willing to spend, that is also correlated with inflation expectations or uncertainty. Bachmann et al. (2013) refer to this as optimism

Table F.4: Control function approach

First Stage				
		ζ_{it}		
$\zeta_{i,t-6}$	Coefficient	0.242***		
	Std. Err.	0.0034		
Observations		74668		
R^2		0.14		
Std. Err. Of Residuals		0.36		
Second Stage				
		DUR	CAR	HOM
First stage residual	Coefficient	0.314***	0.236***	0.492***
	Std. Err.	0.062	0.060	0.064
ζ_{it}	Coefficient	-0.470***	-0.271***	-0.603***
	Std. Err.	0.0614	0.0608	0.0621
	Marginal Effect	-12.3***	-9.21***	-18.4***
π^e_{it}	Coefficient	-0.0027**	-0.0083	-0.0063
	Std. Err.	0.00137	0.00134	0.00142
	Marginal Effect	-0.082**	-0.283***	-0.194***
Observations		68235	68322	69835
Pseudo R^2		0.07	0.06	0.14

Notes: Marginal effect is change in probability of favorable spending outlook for one unit increase in uncertainty or one percentage point increase in expected inflation, with remaining variables set to means. In second stage, coefficient (marginal effect) is the standard coefficient (marginal effect) from probit regression divided by $(1 + (\text{coefficient on first stage residual})^2 * (\text{first stage std error of residual})^2)^{1/2}$, following Wooldridge (2002).

or pessimism, which could bias the coefficients on π^e_{it} and ζ^e_{it}. Using the rotating panel of respondents, and controlling for past spending attitudes, uncertainty, and expected inflation, while including both current and lagged values of the macroeconomic and expectational controls addresses this concern.

Row 13 summarizes a new that uses an alternative spending attitude variable. When asked to explain why they think it is a good or bad time to buy a house, car, or durables, MSC respondents commonly express a desire to buy in advance of rising prices. Let DUR_BA_{it} be a dummy variable that takes value 1 if the respondent says that it is a good time to buy durables because she desires to buy in advance of rising prices. Define CAR_BA_{it} and HOM_BA_{it} analogously for cars and homes. Let $BA_{it} = DUR\_BA_{it} + CAR\_BA_{it} + HOM\_BA_{it}$. The mean of BA_{it} is 0.31.

In Table F.5, I regress DUR_BA, CAR_BA, and HOM_BA on inflation uncertainty ζ_{it}, expected inflation π^e_{it}, and the usual set of demographic, macroeconomic, and expectational control variables. Row 12 of Table F.2 summarizes the marginal effects of ζ and π^e. The coefficients on ζ are negative. In contrast to the regression in Table F.1 and all specifications using DUR, CAR, and HOM as dependent variables, the coefficients on π^e are positive and statistically significant. Moreover, the marginal effects of π^e are larger in magnitude. Many respondents base their spending attitudes on factors unrelated to inflation expectations, such as opinions about safety features in cars, which may explain why Bachmann et al. find such a small coefficient on π^e. The variable CAR_BA is a more direct measure than CAR of spending attitudes related to expected inflation.

In Table F.6, the dependent variable is BA_{it}, which takes values 0, 1, 2, and 3. The control

Table F.5: Inflation uncertainty and the desire to buy in advance of rising prices

	(1) DUR_BA		(2) CAR_BA		(3) HOM_BA	
ζ	-1.5e-01***	(1.2e-02)	-1.6e-01***	(1.4e-02)	-1.2e-01***	(1.5e-02)
π^e	2.7e-02***	(1.0e-03)	1.8e-02***	(1.4e-03)	1.6e-02***	(1.5e-03)
Unemployment	1.1e-03	(6.8e-03)	-6.3e-03	(8.8e-03)	-7.0e-02***	(1.1e-02)
Fed Funds Rate	3.8e-02***	(5.2e-03)	4.4e-02***	(7.8e-03)	1.1e-02	(8.0e-03)
Inflation	4.6e-02***	(7.4e-03)	2.1e-02*	(1.2e-02)	6.8e-02***	(1.4e-02)
ZLB	-1.1e-01**	(4.7e-02)	-2.2e-01***	(5.6e-02)	4.4e-02	(7.4e-02)
Observations	164621		165248		169258	
Pseudo R^2	6.8e-02		5.6e-02		5.2e-02	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Probit regressions with robust, time-clustered standard errors in parentheses. Variable descriptions in Tables A.1 and A.2. Regressions include demographic and expectation controls.

variables from the baseline specification are included. Column (1) includes π^e_{it}, (2) includes π^e_{it} and ζ_{it}, and (3) includes π^e_{it}, ζ_{it}, and the interaction $\pi^e_{it} * \zeta_{it}$ as regressors. Notice that with the inclusion of ζ and $\pi^e * \zeta$, the estimated coefficient on π^e is larger, and the coefficient on the interaction term is negative and statistically significant.

Table F.6: Inflation uncertainty and the desire to buy in advance of rising prices

	(1) BA	(2) BA	(3) BA
π^e	2.0e-02***	2.4e-02***	2.9e-02***
	(1.0e-03)	(1.1e-03)	(2.3e-03)
ζ		-1.7e-01***	-1.3e-01***
		(1.1e-02)	(1.8e-02)
$\pi^e * \zeta$			-7.0e-03***
			(2.4e-03)
Observations	157872	157872	157872
Pseudo R^2	5.3e-02	5.4e-02	5.4e-02

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordered probit regressions with robust time-clustered standard errors in parentheses. BA_{it} measures desire to buy durables, cars, and homes in advance of rising prices. Control variables from Table A.2 included.

F.1 Uncertainty and Interest Rate Sensitivity

Inflation uncertainty may reduce consumers' sensitivity to interest rates. The uncertainty proxy allows me to study this. The MSC asks consumers to state *why* they think it is a good or bad time to spend on homes, cars, and durables. They commonly mention interest rates, especially for the homebuying question. Of those who say it is a good time to buy a home, 53% cite low interest rates. Of those who say it is a bad time to buy a home, 41% cite high rates. Overall, 57% of consumers mention interest rates in response to at least one of the spending questions. If a consumer mentions interest rates as a reason for her spending attitudes, this indicates that rates are salient to her spending decisions.

Consumers' mentions of interest rates vary with inflation uncertainty ζ_{it}. Most relevant to the recent recovery, consumers with high inflation uncertainty are less likely to mention low rates as a reason for favorable spending attitudes. Since 2009, the Federal Reserve has maintained very low rates, and 48% of consumers mention low interest rates in their explanations of spending attitudes. For consumers with $\zeta_{it} \leq 0.5$, 54% mention low rates, while for consumers with $\zeta_{it} > 0.5$, only 42% mention low rates.

Controlled probit regressions find that compared to a low-uncertainty consumer ($\zeta_{it} = 0$), a highly uncertain consumer ($\zeta_{it} = 1$) is 6.8 percentage points less likely to mention interest rates. Let $LowR_{it}$ and $HighR_{it}$ be dummy variables that take value 1 if consumer i mentions low or high interest rates, respectively, in her explanations for any of her spending attitudes. Let $MentionsR_{it}$ take value 1 if i mentions high or low interest rates, i.e. if $LowR_{it} + HighR_{it} > 0$. The means of $LowR_{it}$, $HighR_{it}$, and $MentionsR_{it}$ are 0.43, 0.17, and 0.57, respectively. I run probit regressions of the form:

$$Pr(LowR_{it} = 1|\zeta_{it}, X_{it}) = \Phi(\beta_0\zeta_{it} + X'_{it}\beta_1) \tag{17}$$

where X_{it} includes demographic control variables in Table A.2 and time fixed effects. The marginal effects of ζ_{it} in Table F.7 imply that a highly uncertain consumer ($\zeta_{it} = 1$) has an 8.3 percentage points lower probability of mentioning low rates and a 6.8 percentage points lower probability of mentioning rates compared to a less uncertain consumer ($\zeta_{it} = 0$).

Table F.7: Marginal effects of inflation uncertainty on interest rate mentions in spending attitudes

	LowR	**HighR**	**MentionsR**
Marginal Effect	-8.29***	0.124	-6.82***
Std. Err.	0.346	0.208	0.349
Observations	222284	222284	222284
Pseudo R^2	0.24	0.22	0.16

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Probit regressions from Equation (17) with robust, time-clustered standard errors. Dependent variables described in Table A.1. Time fixed effects and demographic control variables from Table A.2 included. The marginal effect is the change in probability (in percentage points) of mentioning low interest rates, high interest rates, or any interest rates, for a one unit increase in ζ, with remaining variables set to their means.

Another way to guage consumers' interest rate sensitivity is to use the rotating panel to observe changes in interest rate mentions when the interest rate changes. Let R_{it} be the sum of consumer i's mentions of high interest rates minus the sum of her mentions of low interest rates. R_{it} ranges from -3 to 3. For example, if i mentions low interest rates for cars and homes but makes no mention of interest rates for other durables, then $R_{it} = -2$. Let rate$_t$ be some measure of the interest rate at time t and consider a regression of the form:

$$\Delta R_{it} = \beta_0 + \beta_1 \Delta \text{rate}_t + \beta_2 \Delta \text{rate}_t * \zeta_{it} + \beta_3 \zeta_{it} \tag{18}$$

We expect β_1 to be positive: consumers should be more likely to mention high rates when rates increase and to mention low rates when rates decrease. If the coefficient β_2 on the interaction term is negative, then interest sensitivity is lower for more uncertain consumers.

The regression output in Table F.8 shows that this is indeed the case. I use three alternative interest

Table F.8: Inflation uncertainty and interest rate sensitivity

	(1)	(2)	(3)
	ΔR	ΔR	ΔR
ζ	0.004	-0.060***	-0.006
	(0.013)	(0.022)	(0.017)
Δ Fed funds rate	0.152***		
	(0.017)		
Δ Fed funds rate * ζ	-0.063***		
	(0.010)		
Δ Real rate		0.009***	
		(0.002)	
Δ Real rate * ζ		-0.011***	
		(0.002)	
MP Shock			0.199***
			(0.034)
MP Shock * ζ			-0.070***
			(0.027)
Observations	88553	75797	76763
R^2	0.024	0.001	0.007

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust time-clustered standard errors in parentheses. See Equation (18).

rates for rate$_t$. In the first column, rt_t is the federal funds rate. In Column (2), rate$_t$ is a measure of the real interest rate given by the federal funds rate minus expected inflation π^e_{it}. In Column (3), Δrate$_t$ is a monetary policy shock (MP shock), defined as the sum of six lags of the Romer and Romer (2004) monetary policy shock.[25] In Column (1), β_2 is nearly half the size of β_1, which implies that type-h ($\zeta_{it} = 1$) consumers are about half as sensitive as type-l ($\zeta_{it} = 0$) consumers to changes in the federal funds rate. The magnitudes of the coefficients in Column (2) imply that unlike type-l consumers, type-h consumers are not sensitive to changes in real interest rates. Coefficients in Column (3) imply that type-h consumers are about two-thirds as sensitive to monetary policy shocks as type-l consumers.

These results indicate that interest rates are less salient for consumers who are very uncertain about inflation when they make spending decisions. Monetary policy, therefore, may be less effective when consumer inflation uncertainty is high. To the extent that central bank efforts to improve communication, credibility, and well-anchored inflation expectations can reduce consumer uncertainty about inflation, they may help improve the ability of monetary policymakers to influence real activity through interest rate policy.

[25] Romer and Romer identify exogenous monetary policy shocks as innovations to the federal funds rate that are uncorrelated with the Fed's Greenbook forecasts generated prior to each FOMC meeting. The shock series is updated in Coibion et al. (2012)