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Measuring uncertainty based on rounding: New method and application to inflation expectations

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ABSTRACT

The 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 responses in pre-existing survey data. I construct micro-level and time series measures of inflation uncertainty since 1978. Inflation uncertainty is countercyclical and correlated with inflation disagreement, volatility, and the Economic Policy Uncertainty index. Inflation uncertainty is lowest among high-income consumers, college graduates, males, and stock market investors. More uncertain consumers are more reluctant to spend on durables, cars, and homes. Round responses are common on many surveys, suggesting numerous applications of this method.

1. Introduction

The Great Recession has drawn increased attention to the potentially harmful consequences of heightened uncertainty, prompting new measurement efforts. Surveys that elicit respondents' probabilistic expectations provide the most direct measure of uncertainty, but are relatively uncommon, as most surveys simply ask for point forecasts. Thus, most empirical research relies on time series uncertainty proxies that lack a micro-level dimension. This paper posits that surveys asking for point predictions can convey some indication of individual respondents' uncertainty. Researchers in cognition, linguistics, and communication note that the use of a round number often signals more uncertainty than the use of a non-round number. Krifka (2009) names this observation the *Round numbers suggest round interpretations (RNRI)* principle. Building on this principle, I develop a novel method of exploiting rounding behavior to construct micro-level uncertainty measures.

The association between rounding and uncertainty may vary over time and across contexts. The new methodology is flexible and based on the assumption that agents that are sufficiently uncertain about their forecast choose from a set of round numbers when responding to the survey; call these "type *h*," for high uncertainty. Less uncertain agents ("type *l*") choose from a larger set of possible responses. Responses in a given month come from a mixture of two distributions: one

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distribution of type-h responses with support on round numbers, and another of type-l responses with support on both round and non-round numbers. The mixture weight is the fraction of type-h consumers. For each survey date, maximum likelihood estimates of the parameters of each distribution and the mixture weight can be used 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, and estimates of the share of type-h agents at time t provide an uncertainty index.

This new method of measuring uncertainty has several major benefits. It provides a measure with a micro-level dimension, allowing cross-sectional and panel analyses that are impossible with many other uncertainty measures. Newer surveys that collect density forecasts do provide micro-level uncertainty measures, but it may be time consuming or mentally taxing for subjects to report their subjective probability distribution. The new method does not rely on assumptions about expectations *formation*, only about expectations *reporting*, and thus can be used to test and develop models of expectations formation. The method can be applied to *pre-existing* datasets containing point estimates or forecasts, allowing analysis of uncertainty even for time periods and variables for which we lack probabilistic survey data. The method is flexible enough to be used for many different types of survey data with prevalent round responses, such as surveys of health, time and energy use, and income and gas price expectations.

I use inflation expectations data as a proof-of-concept, since inflation uncertainty is of long-standing interest to economists and policymakers. A large share of respondents to the Michigan Survey of Consumers (MSC) and the Federal Reserve Bank of New York Survey of Consumer Expectations (SCE) report inflation forecasts that are a multiple of five. Since SCE respondents also provide density forecasts for inflation, I use the SCE data to validate that multiple-of-five point forecasts are indeed associated with larger density forecast interquartile ranges, and that the uncertainty measure constructed by my methodology is a stronger proxy for uncertainty than is a simple dummy variable indicating a multiple-of-five point forecast. Following this validation test, I construct micro-level and time series inflation uncertainty measures using the MSC data, which is available for a much longer time sample.

The inflation uncertainty index constructed from MSC data is countercyclical and was especially high in the early 1980s recession and the Great Recession. It is also high when inflation is either very high or very low. The inflation uncertainty index is positively correlated with alternative time-series proxies for uncertainty, including the Economic Policy Uncertainty index and, most strongly, with the Jurado et al. (2015) macro uncertainty index. It is positively correlated with inflation disagreement, but the correlation weakens after the Volcker disinflation. Inflation uncertainty varies more in the cross-section than over time and displays expected demographic patterns, with lower uncertainty for more educated and higher-income consumers, males, and people with investments in the stock market. More uncertain consumers also make larger forecast errors and revisions, and uncertainty is persistent at the individual level. Similar properties are exhibited by the SCE density forecast-based inflation uncertainty measure, providing further support for the validity of the rounding-based uncertainty proxy.

The new micro-level inflation uncertainty measure allows closer study of the link between uncertainty and reported behavior. Bachmann et al. (2015) find that MSC respondents with higher inflation expectations report less favorable attitudes toward spending on cars, homes, and other durable goods. Including the rounding-based uncertainty measure in similar regressions shows that more uncertain consumers also express less favorable spending attitudes, and the coefficient on expected inflation remains small and negative.

The paper is organized as follows. Section 2 discusses the association between round numbers and uncertainty. Section 3 details the methodology for constructing a micro-level measure of uncertainty. Section 4 applies this methodology to inflation expectations data, provides support its validity, and describes properties of the uncertainty measures. 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 (Dehaene and Mehler, 1992; Jansen and Pollmann, 2001; Sigurd, 1988). This is known as the *Round Numbers Suggest Round Interpretation* (RNRI) principle, and is quite intuitive (Krifka, 2009). 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 is less accurate for adults who report round numbers than for those who do not (Rowland, 1990). Experimental studies asking subjects to report quantitative estimates confirm that round responses are associated with imprecise estimates (Baird et al., 1970; Selten, 2002). 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, p. 1) 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."

Rounding is documented in surveys of earnings, age, and other variables. Self-reported ages exhibit heaping at multiples of five, particularly when respondents are uncertain about their precise age (A'Hearn and Baten, 2009; Zelnick, 1961). Pudney (2008) finds that households' reported energy expenditures are heaped at round responses. 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. On the Health and Retirement Study, the majority of responses concerning 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." Responses of 0%, 50%, and 100% are especially common, and are interpreted as representing high uncertainty (Fischhoff and de Bruin, 1999; Hudomiet and Willis, 2013; Kezdi and Willis, 2003; Lillard and Willis, 2001).

For variables of considerable interest to economists, such as inflation expectations, rounding occurs at values other than 0%, 50%, and 100%, and the uncertainty associated with different round responses may vary across responses and over time. The next section proposes a methodology for constructing a continuous uncertainty proxy based on rounding behavior.

3. Methodology for construction of uncertainty proxy

Suppose that each agent i has a subjective probability distribution with mean f_{it} and variance v_{it} over the realization of a variable. There are two types of agents: type l, the lower uncertainty type, and type h, the higher uncertainty type. For $\tau \in \{l, h\}$, type-τ agents provide a survey response R_{it} from a set S_τ, where $S_h \subset S_l$. For example, S_h may be the set of multiples of 5 and S_l the integers. The response R_{it} is the element of S_τ nearest to f_{it}. The implicit assumption is that type-h agents choose "rounder" responses, or responses from a coarser set, because they tend to have higher values of v_{it}, or greater uncertainty. If we observe a response $R_{it} \notin S_h$, we know that respondent i is type l. If $R_{it} \in S_h$, we do not know whether i is type l or type h, but can estimate the probability ζ_{it} that she is type h, which provides a proxy for her inflation uncertainty.

Note that the cross-sectional distribution of survey responses R_{it} in a given month is a mixture of two probability mass functions (pmfs). The pmf ϕ_t^l of responses from the type-l agents has support S_l, and the pmf ϕ_t^h of responses from the type-h agents has support S_h. Suppose that the cross section of forecasts f_{it} from the type-l agents is has probability density function $p_l(x)$, and from the type-h agents $p_h(x)$. Then ϕ_t^h and ϕ_t^l are discretized versions of these distributions:

$$\phi_t^l = P(R_{it} = j | i \text{ is type } l) = \int_{f_{\min}^l(j)}^{f_{\max}^l(j)} p_l(x)dx, \quad j \in S_l \tag{1}$$

$$\phi_t^h = P(R_{it} = j | i \text{ is type } h) = \int_{f_{\min}^h(j)}^{f_{\max}^h(j)} p_h(x)dx, \quad j \in S_h, \tag{2}$$

where $f_{\min}^\tau(j)$ and $f_{\max}^\tau(j)$ are, respectively, the minimum and maximum values of f_{it} that are rounded to $j \in S_\tau$ for respondents of type $\tau \in \{l, h\}$.

In month t, survey responses come from the pmf $\phi_t = \lambda_t \phi_t^h + (1 - \lambda_t)\phi_t^l$, where the mixture weight λ_t is the fraction of numerical responses from type-h consumers. We observe the total number of numerical responses, but the numbers of responses N_t^l and N_t^h from the low-uncertainty and high-uncertainty type, respectively, are unknown, since responses from S_h may come from either type. Thus $\lambda_t = \frac{N_t^h}{N_t^h + N_t^l}$ is unknown, but λ_t and the parameters of ϕ_t^h and ϕ_t^l can be estimated by maximum likelihood estimation. The probability ζ_{it} that consumer i is type h depends on R_{it}, λ_t, and the parameters of ϕ_t^h and ϕ_t^l. If $R_{it} \notin S_h$, then $\zeta_{it} = 0$. If $R_{it} \in S_h$, then by Bayes' rule:

$$\zeta_{it} = \frac{P(\text{type } h)P(R_{it}|\text{type } h)}{P(R_{it})} = \frac{\lambda_t \phi_t^h(R_{it})}{\lambda_t \phi_t^h(R_{it}) + (1 - \lambda_t)\phi_t^l(R_{it})}. \tag{3}$$

In addition to this micro-level uncertainty proxy ζ_{it}, we can construct a time series uncertainty index U_t that estimates the share of type-h respondents at time t. If all respondents provided a numerical forecast, this share would simply be λ_t. But suppose, as is common with survey data, that some number N_t^{DK} of respondents decline to give a numerical response and instead say they don't know. The DK response may indicate a high degree of uncertainty (Blanchflower and Kelly, 2008; Curtin, 2007), or may reflect ambiguity or unwillingness to express inflation expectations quantitatively for other reasons. One option is to drop these respondents from the analysis. This would be appropriate if respondents give the DK response for reasons totally orthogonal to their uncertainty, so fluctuations in the share of DK responses are uninformative about

Table 1
Validation of uncertainty proxy with FRBNY SCE data.

	(1) Short horizon	(2) Short horizon	(3) Long horizon	(4) Long horizon
M5	3.25***		2.98***	
	(0.05)		(0.05)	
ζ_{it}		5.66***		5.48***
		(0.08)		(0.08)
Constant	2.70***	2.61***	2.81***	2.67***
	(0.02)	(0.02)	(0.02)	(0.02)
Observations	34,645	34,645	34,618	34,618
R^2	0.14	0.22	0.12	0.22

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Dependent variable is IQR of density forecast for inflation on the FRBNY SCE. M5 indicates that the point forecast is a multiple of five, and ζ_{it} is the rounding-based uncertainty proxy.

fluctuations in uncertainty. Another option is to let $\zeta_{it} = 1$ for all DK respondents or for some share of them. To nest these options, let $\theta \in [0, 1]$ and define:

$$U_t = \frac{\lambda_t N_t + \theta N_t^{DK}}{N_t + \theta N_t^{DK}} \tag{4}$$

Note that for $\theta = 0$, U_t is equal to λ_t. For $\theta = 1$, the numerator and denominator include all DK responses, which are assumed to indicate high uncertainty.

4. Inflation uncertainty measure: validation, comparisons, and properties

Round numbers are prevalent in the inflation expectations reported on consumer surveys, including the long-running Michigan Survey of Consumers (MSC) and the newer Federal Reserve Bank of New York Survey of Consumer Expectations (FRBNY SCE). The MSC is 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. 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” (DK) response. Online Appendix A documents the prevalence of response heaping at multiples of 5% (M5).

The SCE provides not only point forecasts, but also density forecasts, of inflation at the 1-year and 2- to 3-year horizons from June 2013 through September 2015.[1] At both horizons, almost a third of point forecasts are M5. The FRBNY researchers fit a beta distribution to each density forecast and provide the interquartile range (IQR) as a measure of uncertainty. The SCE data can be used to verify that consumers who provide M5 point forecasts also provide density forecasts with larger IQRs. I also use the SCE point forecasts to construct the uncertainty proxy ζ_{it} via the methodology of the previous section and check that it is a stronger proxy for the density forecast IQR than a dummy variable indicating an M5 response. After this validation check, the uncertainty proxy is constructed using the MSC data, for which point forecasts are available since 1978.

For the SCE estimates and the benchmark estimates with the MSC data, $p_h(x)$ and $p_l(x)$ are assumed to be normal distributions, so $f_{it} \sim N(\mu_{lt}, \sigma_{lt}^2)$ if i is type l and $f_{it} \sim N(\mu_{ht}, \sigma_{ht}^2)$ if i is type h. Type-l respondents provide integer forecasts ($S_l = \mathbb{Z}$) and type-h respondents provide multiple-of-five (M5) forecasts ($S_h = M5$). For the benchmark inflation uncertainty index with the MSC data, $\theta = 1$: all DK respondents are treated as type h. I show that estimates are not very sensitive to these assumptions, and document the measures’ properties and external validity.

4.1. Validation with survey of consumer expectations

In Table 1, the IQR of each SCE respondent’s density forecast is regressed on either a dummy variable indicating an M5 point forecast or on the uncertainty proxy ζ_{it} constructed via the methodology of the previous section. The positive coefficient on the M5 dummy indicates that an M5 point forecast is associated with an IQR twice as large as that of a non-M5 forecast. The coefficient on ζ_{it} is also positive and statistically significant, and the regressions with ζ_{it} have a higher R^2 than the regressions with the M5 dummy.[2] Coefficient estimates indicate that the low uncertainty type has an average forecast IQR of about 2.6% and the high uncertainty type of about 8.3%.

[1] The SCE asks respondents to provide probabilities, summing to 100%, that inflation will fall in various “bins” of width 2% (Armantier et al., 2013).

[2] The density forecast IQR is itself a potentially noisy measure of uncertainty, as the bin width for the probabilistic forecasts is fairly large, and estimating the IQR relies on assuming a beta distribution.

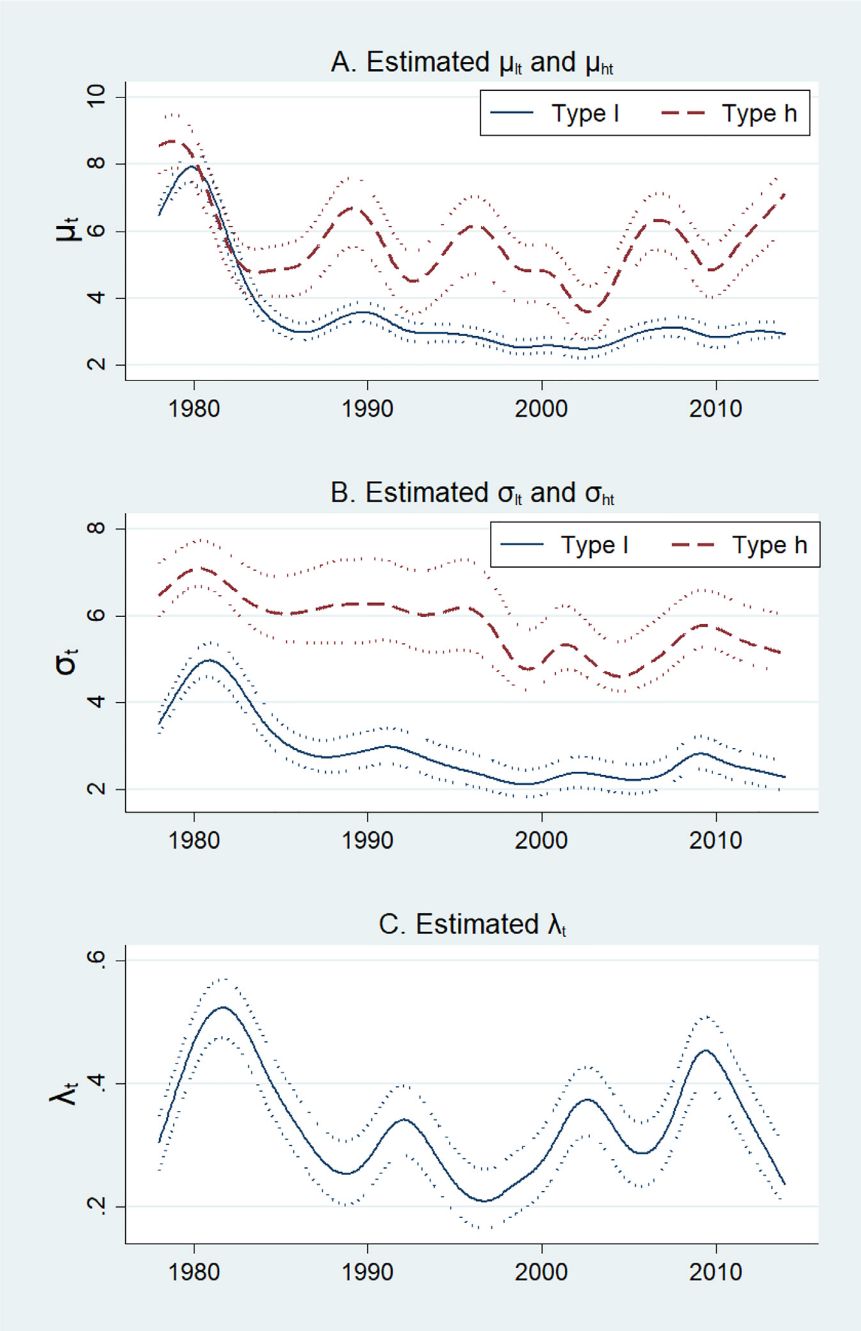

Fig. 1. Maximum likelihood estimates. **Notes:** For visual clarity, maximum likelihood estimates of μ_{lt}, μ_{ht}, σ_{lt}, σ_{ht}, and λ_t with bootstrapped 95% confidence intervals are HP-filtered with smoothing parameter 14,400.

4.2. Michigan survey inflation uncertainty estimates

The same methodology is used to construct inflation uncertainty measures using MSC data for which many years of point forecasts, but no density forecasts, are available. Fig. 1 displays the maximum likelihood estimates of λ_t, μ_{lt}, μ_{ht}, σ_{lt}, and σ_{ht} with bootstrapped 95% confidence intervals.[3]

[3] The likelihood ratio test confirms that the five-parameter mixture distribution fits the data better than a two-parameter discretized normal distribution, with mean log likelihood −1290 compared to −1468.

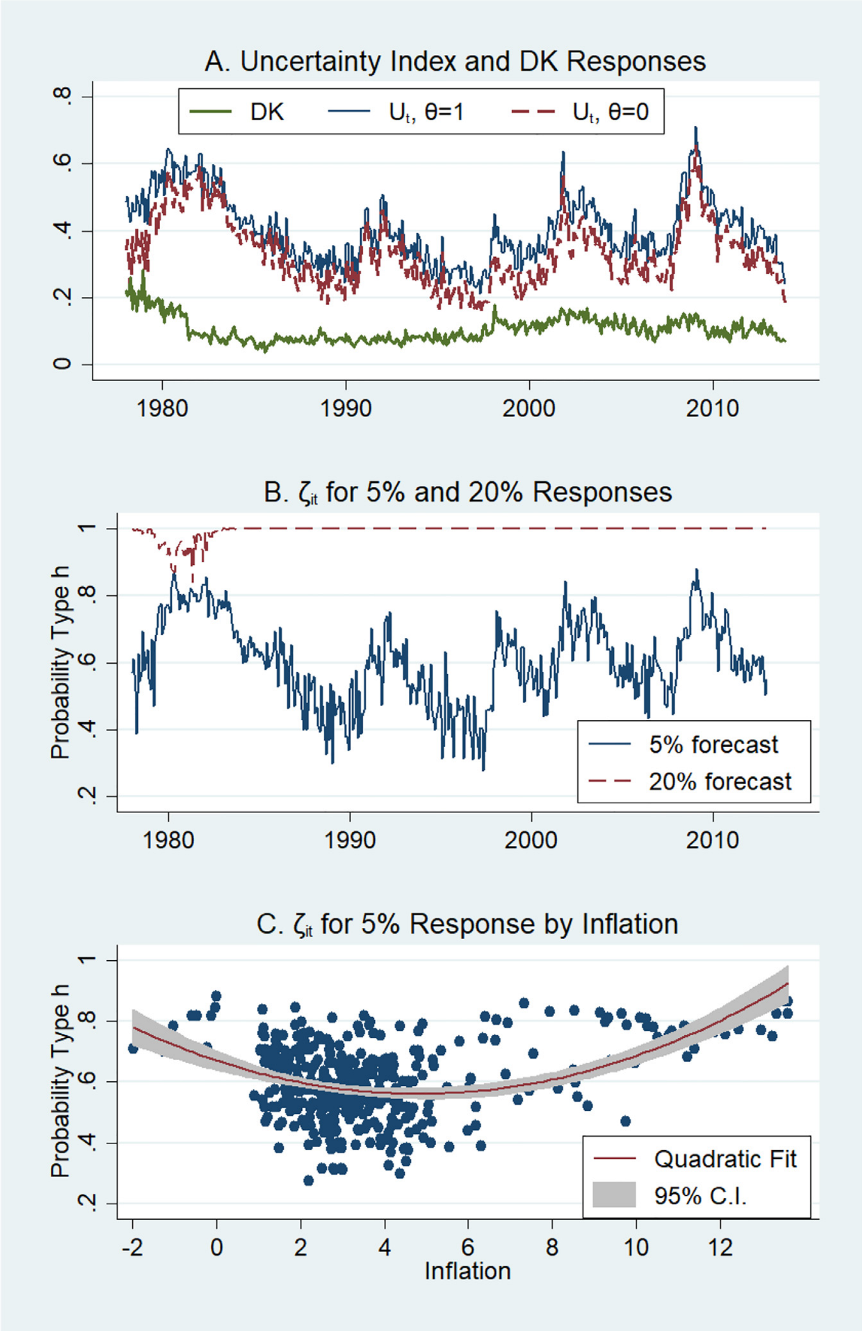

Fig. 2. Inflation uncertainty estimates. **Notes:** DK is the share of "don't know" responses and U_t is the inflation uncertainty index; ζ_{it} is the probability that consumer i is the high uncertainty type, given her inflation forecast at time t.

Fig. 2 plots the share of DK responses, which has mean 10.5% and standard deviation 3.7%, and shows how the uncertainty index U_t depends on how the DK responses are treated. For $\theta = 0$, all DK responses are excluded, so $U_t = \lambda_t$. For $\theta = 1$, DK responses are treated as type h. The resulting U_t is not highly sensitive to θ: the correlation coefficient for the benchmark estimates with $\theta = 1$ and the estimates with $\theta = 0$ is 0.97. For any other θ, U_t lies between the two series shown, and the correlation coefficient with the baseline estimates is greater than 0.97. For any θ, U_t has standard

Table 2
Maximum likelihood estimates with normal, logistic, and extreme value distributions.

	Normal	Logistic		Extreme value	
Estimate	Mean	Mean	Corr.	Mean	Corr.
λ_t	0.33	0.36	0.99	0.35	0.98
μ_{lt}	3.5	3.3	0.997	3.9	0.998
μ_{ht}	5.6	5.1	0.97	5.3	0.96
σ_{lt}	2.9	2.7	0.99	3.2	0.98
σ_{ht}	5.8	5.5	0.95	6.0	0.88
Skew_l	–	–	–	0.70	–
Skew_l	–	–	–	1.9	–
U_t	0.40	0.42	0.99	0.41	0.99

Notes: Estimates computed with MSC data under alternative assumptions about $p_h(x)$ and $p_l(x)$. Corr. is the correlation of the estimates using logistic or extreme value distributions with the baseline estimates using normal distributions. Normal and logistic distributions have zero skewness.

deviation 0.10 and mean between 0.33 (when $\theta = 0$) and 0.40 (when $\theta = 1$).[4] In Panel B of Fig. 2, values of ζ_{it} for responses $R_{it} = 5$ and $R_{it} = 20$ are plotted over time. Except in the early 1980s, when inflation was highest, 20% responses almost certainly come from type-h consumers. For 5% responses, the likelihood that the respondent is type-h is lower and more time varying. Panel C plots ζ_{it} for 5% responses against inflation. When inflation is much higher or lower than 5%, responses of 5% are more likely to come from the high-uncertainty type, as should be expected.

The maximum likelihood estimates and uncertainty index are not very sensitive to the normality assumption. Estimates using normal and logistic distributional assumptions are almost perfectly correlated (Table 2) with similar goodness-of-fit.[5] Note that $p_h(x)$ and $p_l(x)$ need not be symmetric and need not have two parameters. If $p_h(x)$ and $p_l(x)$ are generalized extreme value distributions (with three parameters), the resulting estimates of λ_t and U_t are still almost perfectly correlated with those estimated under assumption of normality. The remainder of this paper uses the benchmark inflation uncertainty estimates constructed with the MSC data, normal distributions for $p_h(x)$ and $p_l(x)$, and $\theta = 1$.

4.3. Time series properties and comparisons with other uncertainty indices

Most uncertainty proxies have only a time series dimension, and can be compared to the inflation uncertainty index U_t. The first panel of Fig. 3 plots U_t with the Economic Policy Uncertainty index (EPU), which does not specifically aim to measure inflation uncertainty, but is based on professional forecasters' disagreement about future government purchases and inflation, the number of federal tax code provisions set to expire, and mentions of uncertainty in newspapers (Baker et al., 2016). The correlation of the EPU and U_t is 0.5. The EPU is more volatile, and spikes in the EPU associated with the September 2001 terrorist attacks and 2011 debt-ceiling disputes are not matched by corresponding spikes in inflation uncertainty. See Binder (2017) for extensive comparison of U_t and subcomponents of the EPU. The inflation uncertainty index has a stronger correlation (0.76) with the one-year-horizon macro uncertainty index of Jurado et al. (2015), which measures the common variation in uncertainty across a large number of series, where the uncertainty of a series is defined as the conditional volatility of the unforecastable component of the series. U_t is also correlated with other measures of volatility and conditional volatility; the correlation with the three-year rolling variance of inflation is 0.67, for example.

Each of these uncertainty measures is countercyclical. 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). The correlation of U_t and the unemployment rate is 0.49 (Fig. 3, Panel C); for the EPU and the macro uncertainty index, correlations with the unemployment rate are 0.57 and 0.27, respectively. Like the macro uncertainty index, U_t rose most in the early 1980s and in the Great Recession, but fell quickly as macroeconomic conditions improved. The EPU, in contrast, remained elevated longer following the Great Recession. Inflation uncertainty averaged 0.57, or 1.7 standard deviations above its mean, in the recession of 1981-82. Uncertainty declined during the Volcker disinflation, but rose slightly during the early 1990s recession. Newspapers from that period describe inflation uncertainty caused by the

[4] Suggestive evidence that DK responses may reflect high uncertainty comes from the rotating panel of respondents. Respondents who provide a round number forecast the first time they take the survey are 65% more likely than respondents who provide a non-round forecast to provide a DK response the second time.

[5] The log likelihood with the logistic distribution has mean −1260 and standard deviation 370, and with the normal distribution has mean −1280 and standard deviation 365. There is no statistically significant difference in goodness-of-fit. The logistic distribution has heavier tails than the normal distribution: $p(x; \mu, s) = \frac{e^{= \frac{x-\mu}{s}}}{s(1+e^{-\frac{x-\mu}{s}})^2}$, where the mean is μ and the variance is $\sigma^2 = s^2\pi^2/3$.

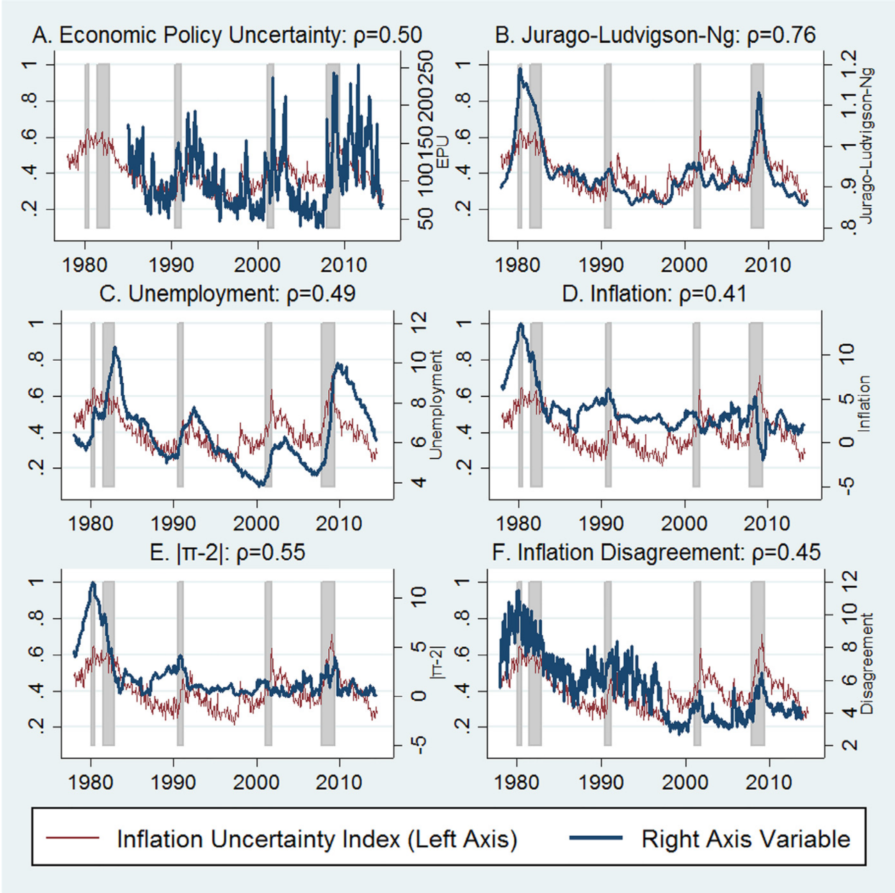

Fig. 3. Inflation uncertainty index with related time series. **Notes:** Correlation coefficients (ρ) in subtitles. Gray bars denote NBER recessions.

recession and the possible implications of the Gulf War on oil prices. The minimum value, 0.21, occurred in May 1997. Uncertainty rose sharply in the 2001 and 2007–2009 recessions, reaching highs of 0.64 in November 2001 and 0.71 (3 standard deviations above mean) in February 2009.

Volatility-based inflation uncertainty proxies are frequently used to test the association between inflation and inflation uncertainty posited by Friedman (1977) and formalized by Ball (1992), who 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 know how willing policymakers will be to disinflate, thus uncertainty is high. Grier and Perry (1998) and others find support for this hypothesis. Panel D plots U_t with the level of inflation. Inflation and U_t were both high in the early 1980s, but very low inflation is also associated with high uncertainty: U_t is more strongly correlated with the absolute deviation of inflation from 2% than with the level of inflation (Fig. 3, Panel E). Ball's basic reasoning may still apply, as low inflation may also prompt deviation from the status quo.

4.4. Uncertainty and disagreement

Disagreement refers to cross sectional dispersion (i.e. standard deviation) of point forecasts. Researchers have used density forecasts to study whether disagreement is a useful proxy for average uncertainty, with conflicting findings (Boero et al., 2008; Lahiri and Sheng, 2010; Rich and Tracy, 2010; Zarnowitz and Lambros, 1987).

For consumers, inflation disagreement and U_t have correlation coefficient 0.45 (Fig. 3, panel F). Disagreement has a more pronounced negative time trend than U_t: a regression of disagreement on a linear time trend has $R^2 = 0.61$, while a regression of U_t on a linear time trend has $R^2 = 0.05$. Disagreement is also less countercyclical and more strongly correlated with inflation itself than is U_t. For disagreement, the correlation coefficients with unemployment and inflation are 0.34 and 0.75, compared to 0.49 and 0.41 for U_t. Note that disagreement arises both between and within the two groups of consumers, types l and h. As Fig. 1 shows, the difference between group means (μ_{lt} and μ_{ht}) was negligible until late 1983, but has since widened, and disagreement within groups (σ_{lt} and σ_{ht}) has trended slightly downward for both groups. A variance decomposition shows that on average, 92% of disagreement is within-group variation.

Table 3
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	216,381	75,797	88,553
R^2	0.15	0.09	0.10
Comparison of beta coefficients on ζ_{it} (MSC) and IQR (SCE)			
MSC	0.38	0.31	0.32
SCE	0.41	0.36	0.59

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust, time-clustered standard errors in parentheses. The independent variable is inflation uncertainty at time t. Sq. error is squared difference between realized CPI inflation from period t to $t+12$ (corresponding to the time horizon of the forecast made at time t) and the respondent's inflation forecast made at time t. Abs. revision is the absolute forecast revision of a respondent who takes the survey twice at time t and $t+6$, $|R_{it+6} - R_{it}|$.

Boero et al. (2014) find that for professional forecasters, disagreement is a strong proxy for average uncertainty in times of macroeconomic turbulence, when disagreement and uncertainty exhibit large fluctuations, but high-frequency smaller movements in disagreement and uncertainty are not strongly correlated. For consumers, similarly, the strength of the correlation between uncertainty and disagreement varies over different time subsamples. Before 1988, uncertainty and disagreement strongly comove, rising with inflation and falling during the Volcker disinflation, with correlation coefficient 0.77. Since then, however, the correlation coefficient is −0.05. But if we limit the time sample to after 2006, when both series exhibit large fluctuations, the correlation is again strongly positive, at 0.87.

4.5. Micro-level properties

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 3 verifies that more uncertain consumers make significantly larger errors and revisions in the future and that when an individual takes the survey twice, her initial uncertainty is predictive of her uncertainty six months later. The table also shows that each of these properties is shared by the SCE density forecast interquartile range uncertainty measure.

The FRBNY Household Inflation Expectations Project (HIEP) collected density forecasts of inflation from 2007 to 2008, as the SCE has since June 2013. The associated measures of inflation uncertainty decrease with income, education, and financial literacy and are lower for males, married people, and those responsible for their household's investments (Armantier et al., 2013; van der Klaauw et al., 2008). Demographic patterns revealed by the HIEP and SCE are shared by ζ_{it}, as Table 4 shows. The mean of ζ_{it} is lower for people with higher income and education and for males, who also make smaller forecast errors and less frequently give "don't know" responses. 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 (van Rooij et al., 2011). Large-scale investors are most certain, followed by smaller-scale and non-investors. Uncertainty is also lower among homeowners.

5. Inflation uncertainty and consumption

The links between inflation uncertainty and real economic activity are theoretically ambiguous (Berument et al., 2005; Cecchetti, 1993). Empirical studies relying on time series uncertainty proxies typically find a negative association between inflation uncertainty and real activity (Davis and Kanago, 1996; Elder, 2004; Evans and Wachtel, 1993; Grier and Perry, 2000), but some find a positive or negligible relationship (Barro, 1998; Clark, 1997). Inflation uncertainty implies uncertainty about real income, which should increase precautionary saving, and about the real rate of return on saving, which makes saving less attractive for risk averse consumers (Kantor, 1983; Kimball, 1990; Lusardi, 1998); see model in Online Appendix D. Durable consumption, which is costly to reverse and highly volatile, is particularly sensitive to uncertainty (Bertola et al., 2005). The effects of inflation uncertainty on housing are complex because of particular features of mortgage financing

Table 4
Expectations and uncertainty by demographic group.

	M5	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	5190
Non Homeowner	42%	14%	1.30	4.7	0.43	32,070
Homeowner	41%	10%	1.05	4.3	0.37	102,067

Notes: M5 and DK are percent of respondents giving multiple-of-five or "don't know" responses. Error is the mean forecast error, RMSE the root mean squared forecast error, and ζ the mean of the ζ_{it}.

Table 5
Spending attitudes, aggregate spending, and inflation uncertainty.

	DUR	CAR	HOM
A. Spending attitudes and inflation uncertainty: Regression Eq. (5)			
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%)
B. Spending attitudes and aggregate spending: Regression Eq. (6)			
$\hat{\beta}$	0.71^{***}	1.01^{***}	1.03^{***}
	(0.03)	(0.07)	(0.12)
Observations	432	432	432
R^2	0.90	0.40	0.15

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust, time-clustered standard errors in parentheses. 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 one percentage point expected inflation, with remaining variables set to their means.

(MacDonald and Winson-Geideman, 2012). The index U_t is negatively correlated with the real durables growth rate, car sales, and home sales.[6]

The MSC asks several questions about respondents' spending attitudes. Let 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. Bachmann et al. (2015) show that consumers' responses to these questions are positively correlated with actual expenditures. In probit regressions of spending attitudes on expected inflation, they find a small negative coefficient on expected inflation. I include the inflation uncertainty proxy ζ_{it} in similar probit models of the form:

$$Pr(DUR_{it} = 1|\zeta_{it}, \pi^e_{it}, X_{it}) = \Phi(\beta_0\zeta_{it} + \beta_1\pi^e_{it} + X'_{it}\beta_2), \tag{5}$$

where π^e_{it} is i's inflation point forecast, Φ is the cumulative distribution function of the standard normal distribution, and X_{it} is a vector of demographic and macroeconomic controls and expectations and 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 (Online Appendix B). In the estimation results in Table 5, coefficients on both inflation uncertainty and expected inflation are negative and statistically significant.

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. Estimates of β are positive and highly statistically significant (Table 5, Part B). Using these estimates, 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

[6] Correlation coefficients are −0.40, −0.52, and −0.24, respectively; see variable descriptions in Online Appendix B.

the low uncertainty type, the mean of DUR would be 3.1 percentage points higher compared to if all agents were the high uncertainty type. Correspondingly, real durable expenditures would be about 2.2% higher. Similarly, car sales and home sales would be about 2.0% and 4.8% higher. In January through November 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, and keeping in mind that the relationship is not necessarily causal, the increase in inflation uncertainty accounts for roughly 2% of the decline in auto sales, and similarly small contributions to durables and home sales.

Alternative specifications and robustness checks appear in Online Appendix E. Results are robust to restricting the time sample to exclude the early 1980s or the Great Recession, omitting or adding control variables in X_{it}, 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 desire to buy in advance of rising prices. I also show that the spending attitudes of more uncertain consumers are less sensitive to changes in interest rates and to monetary policy shocks.

6. Discussion and conclusions

This paper has introduced a novel method of measuring the uncertainty associated with survey responses by exploiting the human tendency to use round numbers when reporting quantitative expressions with high uncertainty. This tendency is manifested in response heaping at round numbers. The nature of the response heaping can be quantified to construct micro-level uncertainty measures from point estimates in pre-existing survey data.

Using the new methodology, I construct a micro-level uncertainty measure and an inflation uncertainty index using inflation expectations data from the MSC. Properties of the measure support its validity. The inflation uncertainty index is positively correlated with other time-series proxies for uncertainty, including the EPU and the Jurado et al. macro uncertainty index. Uncertainty 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. At the micro level, higher values of the uncertainty measure are associated with larger forecast errors and revisions, the measure is persistent, and demographic patterns are consistent with the literature.

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. I find a small negative association between inflation uncertainty and spending attitudes. The micro-level measure of inflation uncertainty holds promise for studying the formation of inflation expectations, different models of informational rigidities have testable implications for inflation uncertainty. The rotating panel structure of the data should be particularly useful for this purpose.

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. Inflation uncertainty at longer horizons is an important gauge of central bank credibility and communications effectiveness (Mishkin, 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). Verbrugge and Binder (2016) construct and analyze the inflation uncertainty index for the five- to ten-year horizon. 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. Verbrugge and Binder also show that apparent fluctuations in mean or median household long-run inflation expectations are sometimes attributable to changes in rounding behavior, reflecting changes in inflation uncertainty, and suggest tracking the mean inflation expectations of high-uncertainty and low-uncertainty consumers separately.

The construction of rounding-based uncertainty measures 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. The MSC asks consumers for quantitative expectations of other economic variables, including percent change in family income, change in gas prices, and percent change in the price of "homes like yours in your community." Response heaping at round numbers is very prevalent in each of these questions. 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 insights into attention and memory, informing models of rule-of-thumb behavior or rational inattention. Rounding behavior on surveys such as the Federal Reserve Board's Survey of Consumer Finances or the British Household Panel Survey could reveal how precisely consumers monitor their income, debts, assets, and expenditures.

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Supplementary material

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