Balance of Risks and the Anchoring of Consumer Inflation Expectations

Jane Ryngaert*†
Wake Forest University

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Abstract

This paper shows that expected inflation risks pose threats to the anchoring of expectations. I propose a new method for fitting subjective probability distributions to density forecasts that allows for asymmetric beliefs over inflation outcomes. Using data from the Federal Reserve Bank of New York's Survey of Consumer Expectations, I show that medium-run expectations move in the direction of perceived short-run risks. I introduce a diffusion index of consumers' perceived balance of risks to inflation and show that movements in the short-run index predict movements in the medium-run expectations and in the medium-run index. I conclude with a new measure of aggregate expectations for consumers that incorporates asymmetry in individual subjective probability distributions.

JEL Classification: E31, D83, D84
Keywords: inflation expectations, uncertainty, survey data, consumers

*Wake Forest University, Department of Economics, Box 7505, Winston-Salem, NC 27109; (e-mail: ryngaertjm@wfu.edu)

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1 Introduction

Monetary policy makers have as a critical goal the anchoring of inflation expectaitons because theory predicts that stable expectations lead to stable inflation. Central banks therefore devote considerable attention to monitoring these expectations and the extent to which they are anchored (or de-anchored). Research has defined well-anchored expectations as close to the central bank's inflation target, unresponsive to short-term fluctuations, and having minimal cross-sectional disagreement and subjective uncertainty(Afrouzi, Coibion, Gorodnichenko, and Kumar (2015)). Recent work has also considered the cross-sectional skewness of expectations as an indicator of de-anchoring. Reis (2021) shows that a thickening of the right tail of the cross-sectional inflation distribution is among the first sign of upside de-anchoring. Natoli and Sigalotti (2018) shows that the negative tail of the options-implied short-run inflation expectation distribution is associated with lower long-run beliefs.

What is missing from our current understanding of de-anchoring risk is a discussion of expected risks. Monetary policy makers often speak in terms of risk to the inflation outlook and particularly in terms of *unbalanced risk*.[1] In a recent speech, Vice Chair of the Federal Reserve Richard Clarida said of the expectations of FOMC participants, "there is no presumption that the subjective distributions—or, for that matter, observed empirical distributions—for [inflation] are symmetric." This highlighting of the potential for asymmetry in subjective distributions accompanies the addition of historical values of the diffusion index of participants' inflation risk weightings to the Summary of Economic Projections (SEP).[2] In its communication with the public, the Federal Reserve projects that they view price stability and expectations monitoring with an eye towards the direction of risks. Their goal is to keep tail risks to inflation from becoming realized in inflation itself.[3] Preventing perceived tail risks from moving into long-run expectations is a complementary goal.

The availability of density inflation forecasts allows us to further consider how the risks implied by an individual's subjective probability distribution over inflation signal threats to anchoring. Using data from the Federal Reserve Bank of New York's Survey of Consumer Expectations, this paper considers how consumers' perceived upside and downside risks to short-run inflation feed into longer-run expectations. I find that up-

[1] "I am attentive to the risk that inflation pressures could broaden or prove persistent, perhaps as a result of wage pressures, persistent increases in rent, or businesses passing on a larger fraction of cost increases rather than reducing markups, as in recent recoveries. There are risks on both sides of the outlook. There are upside risks to consumption spending associated with the high level of households' savings. There are downside risks associated with the Delta variant." Lael Brainard, July 2021

[2] The historical values of diffusion indexes for the change in real GDP, the unemployment rate, and PCE and core PCE inflation appeared first in the December 2020 SEP. The value of diffusion index is given by the share of participants who respond that risk weighting around their projection is "Weighted to the Upside" minus the share that respond "Weighted to the Downside."

[3] "Monetary policy responded first in the summer of 2012 by acting to defuse the sovereign debt crisis, which had evolved from a tail risk for inflation into a material threat to price stability." Speech by Mario Draghi, President of the European Central Bank, at the ECB Forum on Central Banking, Sintra, 18 June 2019.

side (downside) tail risk in the subjective distribution of year-ahead inflation moves the central tendency of the expected medium-run distribution up (down). This implies that consumers believe inflation will move in the direction of their perceived risk, suggesting that monetary policymakers should consider monitoring tail risks in expectations and potentially structuring communication to manage these risks and prevent de-anchoring.

I further construct a diffusion index of consumers' perceived balance of risks to near-term inflation paralleling the SEP diffusion index for FOMC participants. This index subtracts the share of consumers with negatively-skewed distributions from the share of positively-skewed distributions. In a given period, the index will increase as more consumers perceive inflationary risk and decrease as more consumers perceive disinflationary or deflationary risk. I find that changes in this index are positively associated with changes in the median central tendency of expected medium-run inflation. The consensus measure of medium-run expectations thus moves in the direction of the predominantly anticipated short-run risk. This result parallels that of Andrade, Ghysels, and Idier (2012), who introduced measures of the asymmetry of subjective probability distributions in the United States Survey of Professional Forecasters and showed that aggregated measures of the direction of risk were useful in forecasting inflation.[4] Furthermore, the medium-run diffusion index positively correlates with the short-run diffusion index. This means that asymmetry in short-run risks translates to asymmetry in medium-run risks. If consumers predominantly anticipate upside risk in the near term, they will anticipate upside risk in the medium term. Should theses risks transmit to long-run expectations, this asymmetry is a potential indicator of de-anchoring.

The Federal Reserve has recently signaled the importance of asymmetry in risks around the projections of SEP members. As a final contribution, I construct a time-series of aggregate expected inflation for the Survey of Consumer Expectations that allows for asymmetry in private forecasts. I introduce a method of fitting subjective distributions that incorporates a respondent's point forecast as the mode of their subjective distribution. This produces individual distributions that have similar interpretations as the SEP projections and assessed balance of risks. The central tendency of the distribution is close to the *most likely* perceived outcome, while the skewness gives the risk weighting around this projection. The New York Fed publishes a measure of expected inflation derived from probablistic forecasts. Their current method for fitting subjective probability forecasts produces symmetric distributions by construction for roughly 30% of responses, attenuating the measurement of asymmetry in subjective distributions over future inflation. Given the Federal Reserve's recent emphasis on the asymmetry of its public forecasts, measures of private expectations should allow for such asymmetry, as the measure I propose does.

My paper fits most closely with the literature on risks in inflation expectations. These include Andrade, Ghysels, and Idier (2012) and Andrade, Fourel, Ghysels, and Idier (2000) that derive measures of inflation risk for professional forecasters in the U.S. and Eurozone, respectively. García and Manzanares (2007) fit a skewed-normal distribution to probabilistic forecasts from the U.S. Survey of Professional Forecasters to allow for

[4] Andrade, Fourel, Ghysels, and Idier (2000) showed that such measures of inflation risk for the ECB Survey of Professional Forecasters respond to past realizations of financial indicators in the Eurozone.

asymmetry in these forecasts. Ruge-Murcia (2003) considers a central banker's utility under deviations from the inflation target, with the potential for asymmetric preferences over the direction of risks. Killian and Manganelli (2003) model a central banker as a risk manager who must manage the risks of inflation falling outside the range of a targeting zone, with the potential for asymmetric risk aversion in upside and downside risks. Galati, Moessner, and van Rooji (2020) show that long-run inflation expectations of Dutch households are poorly anchored, largely due to household's placing large probability on inflation outcomes above the central bank's target.

I also contribute to the literature on fitting subjective distributions to probabilistic forecasts. D'Amico and Orphanides (2008) fits a normal distribution to density forecasts. Engelberg, Manski, and Williams (2009) proposes a method fitting triangular distribution to histograms where the respondent fills one or two bins and a parametric generalized beta distribution when the respondent fills three or more bins. The SCE uses this same method with the modification that they assume a uniform distribution for respondents filling a single bin (Armantier, Topa, van der Klaauw, and Zafar 2016). I modify the Engelberg, Manski, and Williams (2009) method by pinning the mode of a consumer's subjective probability distribution to her point forecast.

The paper proceeds as follows, Section 2 describes the data as well as my proposed method for fitting subjective distributions. Section 3 discusses how individual's perceived tail risks in short run inflation affect their medium-run expectations. Section 4 discusses the diffusion index for SCE respondents as an aggregate measure of asymmetry in expectations. Section 5 describes the measure I propose for calculating the aggregate expectation in the consumer data. Section 6 concludes with an application to the present.

2 Data

I use inflation expectations data from from the Federal Reserve Bank of New York's Survey of Consumer Expectations. Households provide their inflation expectations in two formats, first as a point estimate and then as probabilities that inflation may fall in a set of ranges. They are first asked:

What do you expect the rate of [inflation/deflation] to be ***over the next 12 months****?*[5] *Please give your best guess.*

Respondents provide this answer as a percentage. Many consumers repond with particularly high values of inflation. As such, the Federal Reserve Bank of New York elicits density forecasts of inflation and calculates the mean implied by a probability distribution fitted to the resulting histogram. The density forecast question asks consumers to consider several possible outcomes for inflation.

Now we would like you to think about the different things that may happen to inflation over the ***next 12 months****. We realize that this question may take a little more effort.*

[5] This selection of inflation or deflation is based on the answer to a previous question.

In your view, what would you say is the percent chance that, ***over the next 12 months...***

The respondent is then presented with a set of ranges for the rate of inflation or deflation, where deflation is defined for them as the opposite of inflation. The ranges are a rate of inflation 12% or higher, between 8% and 12%, between 4% and 8%, between 2% and 4%, between 0% and 2%, and the same set of bins for the rate of deflation. The questions eliciting point estimates and subjective distributions are repeated for the agent's expectations of inflation over the 12 month period from 24 months from the survey period to 36 months after the survey period. I refer to the expecations over the next 12 months as short-run inflation expectations and expectations over the period from 24 to 26 months from the survey date as medium-run inflation expectations.

Considered together, the point and density forecasts can provide information about the shape of an individual's subjective probability distribution. Including the point estimate rather than fitting a subjective distribution without it allows for the expression of additional heterogeneity (across and within) forecasters that provide identical histogram forecasts. Define a *unique histogram forecast* as a set of answers for each of the bins for either short-run or medium-run inflation. A *unique forecast* refers to a given unique histogram forecast coupled with a point forecast. Across all household-date observations in the survey, there are roughly 1.5 times as many unique forecasts as unique histogram forecasts.[6] This reveals considerable heterogeneity across households that report the same unique histogram forecast. Households will also repeat the same unique histogram forecast multiple times with different point estimates. In fact, among these forecasts repeated by the same household, only roughly 39% include the same point estimate across all repetitions. This means that a given household's expectations may be moving even as the histogram forecast remains stable.

The data suggests that households make point estimates consistent with the modes of their subjective distribution. Define a modal forecast as a point estimate that falls in the bin in which a households places maximum probability.[7] The majority of consumers give point forecasts consistent with the modal definition; 78.48% of short-run forecasts and 77.77% of medium-run ahead forecasts are modal forecasts. This contrasts with 68.12% of short-run and 68.91% of medium-run forecasts that fall in the same bin as the distribution implied mean calculated by the SCE.

I fit subjective probability distributions closely paralleling the method of Engelberg, Manski, and Williams (2009). They construct subjective distributions by fitting isoceles triangles to the histograms of respondents placing positive probability in one or two bins and generalized beta distributions to the histograms of respondents filling three or more bins. My method pins the mode of the distribution to the consumer's point estimate and fits a scalene triangle to one- and two-bin forecasts and a generalized beta with a fixed mode to forecasts with positive probability in three or more bins. This method is described in detail in Online Appendix A.

[6] There are 32,665 and 30,615 unique histogram forecasts and 48,154 and 46,687 unique forecasts for short-run and medium-run ahead inflation, respectively.

[7] In the case that a forecaster places the same maximum probability in multiple bins, a modal point forecast can fall in the range of any of these bins.

Denote the implied means of the short-run and medium-run distributions as $E_{it}[\pi^{SR}]$ and $E_{it}[\pi^{MR}]$, respectively. I use the interquartile range, IQR_{it} as a measure of the second moment and solve for Bowley (1920)'s measure of skewness for each individual distribution:

$$Skewness_{it} = \frac{p75_{it} + p25_{it} - (2 \times p50_{it})}{p75_{it} - p25_{it}}. \tag{1}$$

where $p75$ denotes the 75th percentile and the other percentiles are similarly notated. I use this measure for the asymmetry of risks in the distribution.

I quantify tail risks in either direction by defining the left and right tails as the difference between percentiles:

$$LT_{it} = p25_{it} - p5_{it}, \tag{2}$$

$$RT_{it} = p95_{it} - p75_{it}. \tag{3}$$

These give measures of how far the extremes of the distribution go. The left tail tells us how far beyond the 25th percentile the distribution extends to downside outcomes. The right tail captures the range of upside outcomes beyond the 75th percentile. Measures of inflation-at-risk or expected inflation-at-risk, such as those discussed in Andrade, Ghysels, and Idier (2012) and López-Salido and Loria (2020), measure risk by value of the 25th or 75th percentile. The tails as I have defined them give a sense of how far a consumer thinks inflation can go in either direction conditional on reaching an already high or low level. The right(left) tail will increase in length as rare perceived outcomes are weighted more to the upside(downside). A tail will decrease in length if the mode of the distribution is close to the relevant bound of the support of the consumer's subjective distribution.

The survey-weighted average implied mean for both short-run and medium-run is roughly 3.8. The average IQR is roughly 5.5 and the the average left and right tails roughly 3.0 and 2.8, respectively. These numbers are large compared to a series that is targeted to 2 % for the entirety of the sample period. We should keep these magnitudes in mind when considering how components of the short-run distribution will impact medium run-expectations. The average distribution is symmetric indicating an approximate balance of consumers consumers having positively- and negatively-skewed distributions. However, this balace that changes from period to period, as will be discussed in Section 4.

3 Short Run Risks and Medium Run Expectations

Well-anchored long-run expectations should remain stable and insensitive to movements in short-run expectations. While short-run expectations may move with macroeconomic shocks, well-anchored long-run expectations should remain firmly fixed by the central bank's target. I propose that well-anchored longer-run expectations should be uncorrelated with perceived short-run risks. If long-run expectations always return to the inflation target, they should not drift towards the tails of the short-run distribution.

Afrouzi, Coibion, Gorodnichenko, and Kumar (2015) refers to long-run expectations as *increasingly anchored* if they are not influenced by fluctuations in short-run beliefs. They propose regressing long-run forecasts on short run forecasts. If expectations are well-anchored, the coefficient on short run expectations should be equal to zero. I extend this regression to include measures of asymmetry and risk in subjective short-run distributions. I estimate the following spefication, regression the implied mean of the medium-run distribution, $E_{it}[\pi^{MR}]$ on the implied mean of the short-run distribution, $E_{it}[\pi^{SR}]$, as well as the skewness, left and right tails, and the interquartile range (IQR) of the short-run distribution. I include individual and period fixed effects:

$$E_{it}[\pi^{MR}] = \beta_1 E_{it}[\pi^{SR}] + \beta_2 IQR_{it}^{SR} + \beta_2 RT_{it}^{SR} + \beta_3 LT_{it}^{SR} + \beta_4 Skewness_{it}^{SR} + u_i + e_i + \epsilon_{it}$$

If expectations are well anchored, we would expect all of the coefficients to be equal to 0. The estimated values are:

$$\begin{aligned} E_{it}[\pi^{MR}] = {} & 0.555^{***} E_{it}[\pi^{SR}] - 0.051^{***} IQR_{it}^{SR} + 0.09^{***} RT_{it}^{SR} - 0.03^{***} LT_{it}^{SR} \\ & - 0.15 Skewness_{it}^{SR} \quad [R^2 = 0.481]. \end{aligned}$$

The short-run mean, both tails, and the interquartile range all have statistically significant coefficients, meaning than fluctuations in the subjective probability distribution influence longer-run expected inflation. Noteably, the coefficient on skewness is negative, meaning that the medium run $E_{it}[\pi^{MR}]$ moves in the opposite direction of the consumer's predominant risk. This coefficient is, however, not statistically significant. Increased length in the tails draws $E_{it}[\pi^{MR}]$ in the direction of the tail. This means that as consumers' perceived tail risks range a broader set of high inflation outcomes, their longer-run expectations will increase.

4 A Diffusion Index for Consumers

This section introduces a diffusion index of the risk weightings of consumers in the Survey of Consumer Expectations. This parallels the public reports of SEP and gives a measure of the aggregate asymmetry in consumer expectations.

The skewness calculated in Equation 1 can be interpreted in terms of the risk weighting FOMC participants report about their inflation projections. Positively-skewed distributions correspond with a belief that risks are weighted to the upside; negatively-skewed distributions indicate a belief that risks are weighted to the downside. The index over the balance of risks is then given by:

$$DI_t^{BoR} = Share[Skewness^{+}] - Share[Skewness^{-}] \tag{4}$$

where the shares are survey-weighted. This number will increase as the share of positively skewed increases and will decrease as the share of negatively skewed distributions increases. It is bounded between [-1 and 1], with -1 meaning *all* respondents expect predominantly downside risk and 1 meaning all respondents weight risk to the upside. Positive values mean relatively more respondents anticipate inflationary risk while negative values mean more respondents anticipate deflationary risks. I derive this index for both short run and medium run expectations: $DI^{BoR,SR}$, $DI^{BoR,MR}$.

Figure 1 shows the three-month moving averages of these two series plotted over time. Also highlighted is the x-axis as a diffusion index of 0 indicates a that the survey is evenly weighted between those with positively- and negatively-skewed distributions. Throughout the sample period, the short-run index shows greater upside risk while the medium-run series is more likely to indicate dominant downside risk. The series largely move together, with a correlation of 0.51. A notable exception to their comovement is in the COVID period, when aggregate short-run risk perceptions swung to the upside while medium-run risk perceptions moved to the downside. Consumers may anticipate higher inflation in response to the pandemic as Binder (2020) finds, but expect short-run inflation to revert back to long-run mean levels, which would indicate anchoring.

For well-anchored inflation expectations, a change in the aggregate asymmetry of short-run risks should not affect the central tendency of aggregate medium-run expectations. Consumers might expect, however, that longer-run outcomes will tend in the direction of short-run risks. In this case, changes in the diffusion index will move aggregate expectations in the direction of the change in risk perception. I test this with the following regression:

$$Med_t[E_{it}[\pi^{MR}]] = 1.03^{***} + 0.65^{***} Med_{t-1}[E_{it-1}[\pi^{MR}]] + 0.59^{*} \Delta DI_t^{BoR,SR} \;\; [R^2 = 0.429].$$

I use the survey-interpolated median across forecasters in a period to avoid sensitivity of the central tendency to outliers. I further exclude years before 2016 as the medium-run expectation was on a downward trend from the beginning of the survey to late 2015, perhaps due to increased credibility of the 2% target.This target was announced on January 25, 2012. This regression shows that the aggregate expectation is persistent, but also responds to changes to the diffusion index. As the balance of risk moves to the upside for more consumers, ($\Delta DI_t^{BoR,SR} > 0$), the median medium-run inflation expectation increases.

The filtering of short-term risk assessments into medium-term risk assessments is another de-anchoring risk. $DI_t^{BoR,SR}$ and $DI_t^{BoR,MR}$ are positively correlated. Furthermore, the following regression shows that the diffusion index for short-run expectations is a significant predictor of the diffusion index for medium-run expectations, even after controlling for the past value of $DI^{BoR,MR}$.

$$DI_t^{BoR,MR} = -0.01^{**} + 0.47^{***} DI_t^{BoR,SR} + 0.24^{***} DI_{t-1}^{BoR,MR} [R^2 = 0.329] \tag{5}$$

This shows that the predominantly anticipated risks to short-run inflation move with the predominantly anticipated risks to medium-run inflation. If medium-run risks feed into long-run expectations the way that short-run risks feed into medium-run expectations, changes in the aggregate risk outlook are indicative of de-anchoring pressure.

5 A New Measure of Expected Inflation

I propose as a measure of aggregate consumer expectations the medians of the means implied by each individual distribution.[8] The distributions are fit using the method described briefly in Section 2 and in detail in Appendix A. The method allows for asymmetry in the subjective distributions by pinning the mode of the distribution to the consumer's point estimate of inflation.

Figure 2 plots these medians over time for short-run and medium-run expectations. Both series trend downwards for the first two years of the survey, potentially reflecting growing public understanding of the Federal Reserve's inflation target. Towards the end of the sample, into the COVID period, the medians increase, reflecting the public perception that the pandemic would increase inflation as found in Binder (2020).

Figure 3 plots the measures of cross-sectional disagreement and subjective uncertainty for short-run and medium-run expectations. The dispersion is calculated as the difference in the interquartile range across the individual implied means in a period. An individual's subjective uncertainty is defined as the interquartile range of the individual subjective distribution. The measure presented in the figure is the interpolated median across individuals' IQRs. Uncertainty is generally larger than disagreement, support the empirical findings of D'Amico and Orphanides (2008), Rich and Tracy (2015), Rich, Song, and Tracy (2012), and Coibion, Gorodnichenko, Kumar, and Ryngaert (2021) that disagreement is an imperfect proxy for subjective uncertainty. Both disagreement and uncertainty have decreased over the survey period until increasing in March 2020 and remaining high, a potential sign of de-anchoring. The increase in medium-run disagreement and uncertainty was slightly more modest than that in short-run disagreement and uncertainty.

5.1 Comparison to the SCE Measure

The Survey of Consumer Expectations currently publishes a similar measure of aggregate expectations using the means implied from the subjective distributions fit using the method of Engelberg, Manski, and Williams (2009) as described in Armantier, Topa, van der Klaauw, and Zafar (2016). This method assumes symmetry for respondents with probability distributions filling one or two bins. In comparison, the method I propose allows for the asymmetry that Federal Reserve Vice Chair Clarida emphasized in his recent speech. Roughly 30% of respondents fill one or two bins, so the assumption of symmetry will impact a large number of observations and consequently, any aggregate measure derived from these distributions.

[8]The median is interpolated according to Cox (2009). The SCE currently publishes medians rather than means to avoid the influence of outliers and I follow this.

Figure 4 shows the difference in the subjective probability distributions generated by the different methods. The mode assumption allows for heterogeneity in implied central tendency and uncertainty across households that have the same subjective forecast putting all probability in a single bin. It also moves the mean of the subjective distribution closer to the respondent's point estimate, which is especially useful if a respondent's point forecast is more likely to fall to one side of the interval than the other. Consider, for example, the bins placing inflation between 2% and 4% Of the 4080 respondents who assign probability only to this bin 1246 also report a point estimate of at or below 2% while only 774 report a point estimate at or above 4%. Panels 4a and 4c show the fitted subjective probability distribution for these two cases. Under my proposed fitting method, these two forecasts differ both in implied mean and in the direction of the risk to the outlook. There is a meaningful difference in the subjective distributions of a consumer who thinks that inflation will be 2% or higher (up to 4%) and a consumer who thinks that inflation will be 4% or lower (down to 2%).

The second column compares several forecasts with positive probability in the bins 0% to 2% and 2% to 4% and report a point forecast of 2% inflation. In the case where the respondent assigns equal probability to the two bins, depicted in Panel 4d, the point estimate falls at the exact midpoint of the interval and the two methods produce the same distribution. As the probability in the rightmost bin decreases, as shown in Panels 4e and 4f, the distribution fitted by the SCE and Engelberg, Manski, and Williams (2009) remains an isoceles triangle with the peak moving away from the point estimate at 2. In contrast, my method keeps the peak of the triangular distribution at 2 and moves the right endpoint to form a scalene triangle. This method concentrates subjective density near the point estimate, with implications for measures of uncertainty, asymmetry, and tail risk.

6 Conclusion : Are Expectations De-Anchoring?

The question of anchoring is particularly relevant in the current inflation environment. U.S. inflation has reached levels not seen in decades following supply chain disruptions and fiscal stimulus brought on by the coronavirus pandemic. The U.S. adopted an inflation targeting strategy of monetary policy in 2012, modified to average inflation targeting in 2020. For such monetary policies to work, longer-run expectations need to remain anchored amid short-run fluctuations. Are expectations showing signs of upside deanchoring or are the fluctuations localized to short-term expectations?

This paper has presented the tools to study this using the tails of one-year ahead and three-year ahead subjective inflation distributions. The SCE data has been collected through October 2021 but the New York Fed disseminates aggregated data in real time and microdata at a 9-month lag. Currently, the data is available through December 2020. The published aggregates show that the SCE's headline measure of inflation expectations experienced a modest increase at the outset of the pandemic in March of 2020, but started to increase more dramatically in April 2021 and continuing from there.

I am working on teaming up with someone there to gain early access to the data.

Failing that, I anticipate having data into the summer months of 2021 by spring 2022.

References

Afrouzi, Hassan, Olivier Coibion, Yuriy Gorodnichenko, and Saten Kumar (2015). “Inflation Targeting Does Not Anchor Inflation Expectations: Evidence From Firms in New Zealand”. In: *Brookings Papers on Economic Activity*, pp. 151–225.

Andrade, Philippe, Valáre Fourel, Eric Ghysels, and Julien Idier (2000). “Inflation Zone Targeting”. In: *European Economic Review* 44.7, pp. 1351–1387.

Andrade, Philippe, Eric Ghysels, and Julien Idier (2012). “Tails of Inflation Forecasts and Tales of Monetary Policy”.

Armantier, Olivier, Giorgio Topa, Wilbert van der Klaauw, and Basit Zafar (2016). “An Overview of the Survey of Consumer Expectations”. In: *Federal Reserve Bank of New York Staff Report* 800.

Binder, Carola (2020). “Coronavirus Fears and Macroeconomic Expectations”. In: *The Review of Economics and Statistics* 102.2, pp. 721–730.

Bowley, Arthur L. (1920). *Elements of Statistics*. New York: Charles Scribner’s Sons.

Coibion, Olivier, Yuriy Gorodnichenko, Saten Kumar, and Jane Ryngaert (Aug. 2021). “Do You Know That I Know That You Know?: Higher Order Beliefs in Survey Data”. In: *Quarterly Journal of Economics* 136 (3), pp. 1387 –1446.

Cox, Nicholas (2009). “IQUANTILE: Stata module to calculate interpolated quantiles”.

D’Amico, Stephania and Athanasios Orphanides (2008). “Uncertainty and Disagreement in Economic Forecasting”. In: *Divisions of Research and Statistics and Monetary Affairs, Federal Reserve Board* 56.

Engelberg, Joseph, Charles Manski, and Jared Williams (2009). “Macroeconomic Expectations of Households and Professional Forecasters”. In: *Journal of Business and Economic Statistics* 27.1, pp. 30 –41.

Galati, Gabriele, Richhild Moessner, and Maarten van Rooji (2020). “The Anchoring of Long-Term Inflation Expectations of Consumers”. In: *De Nederland Bank Working Paper* 688.

García, Juan Angel and Andrés Manzanares (2007). “What Can Probability Forecasts Tell Us About Inflation Risks?” In: *European Central Bank Working Paper Series* 825.

Killian, Lutz and Simone Manganelli (2003). “The Central Bank as a Risk Manager: Quantifying and Forecasting Inflation Risks”.

López-Salido, David and Francesca Loria (2020). “Inflation at Risk”.

Natoli, Filippo and Laura Sigalotti (2018). “Tail Co-movement in Inflation Expectations as an Indicator of Anchoring”. In: *International Journal of Central Banking* 14.1, pp. 35–71.

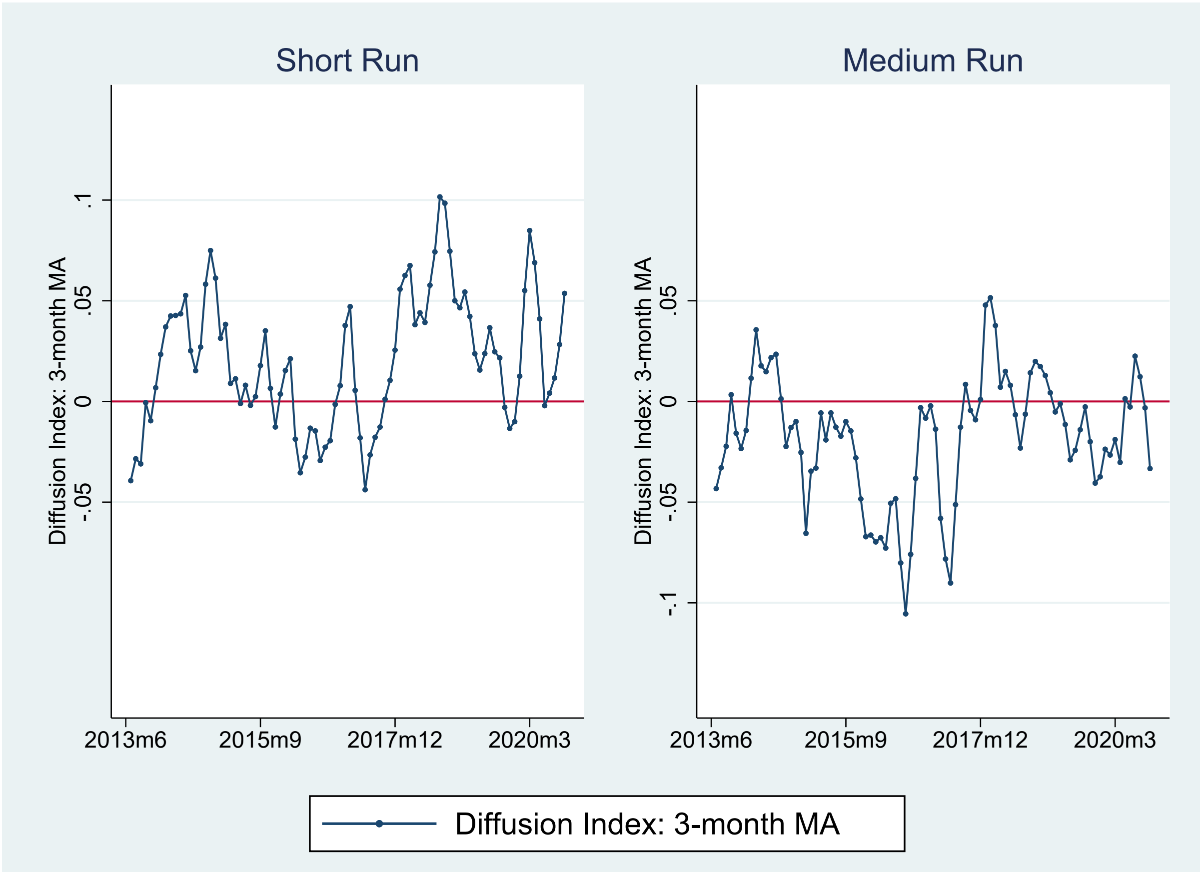
Reis, Ricardo (2021). “Losing the Inflation Anchor”. In: *Brookings Papers on Economic Activity*.

Rich, Robert, Joseph Song, and Joseph Tracy (2012). “The Measurement and Behavior of Uncertainty: Evidence from the ECB Survey of Professional Forecasters”. In: *Federal Reserve Bank of New York Staff Reports* 588.

Rich, Robert and Joseph Tracy (2015). “A Closer Look at the Behavior of Uncertainty and Disagreement: Micro Evidence from the Euro Area”. In: *American Economic Review* 105.3, pp. 1177–1216.

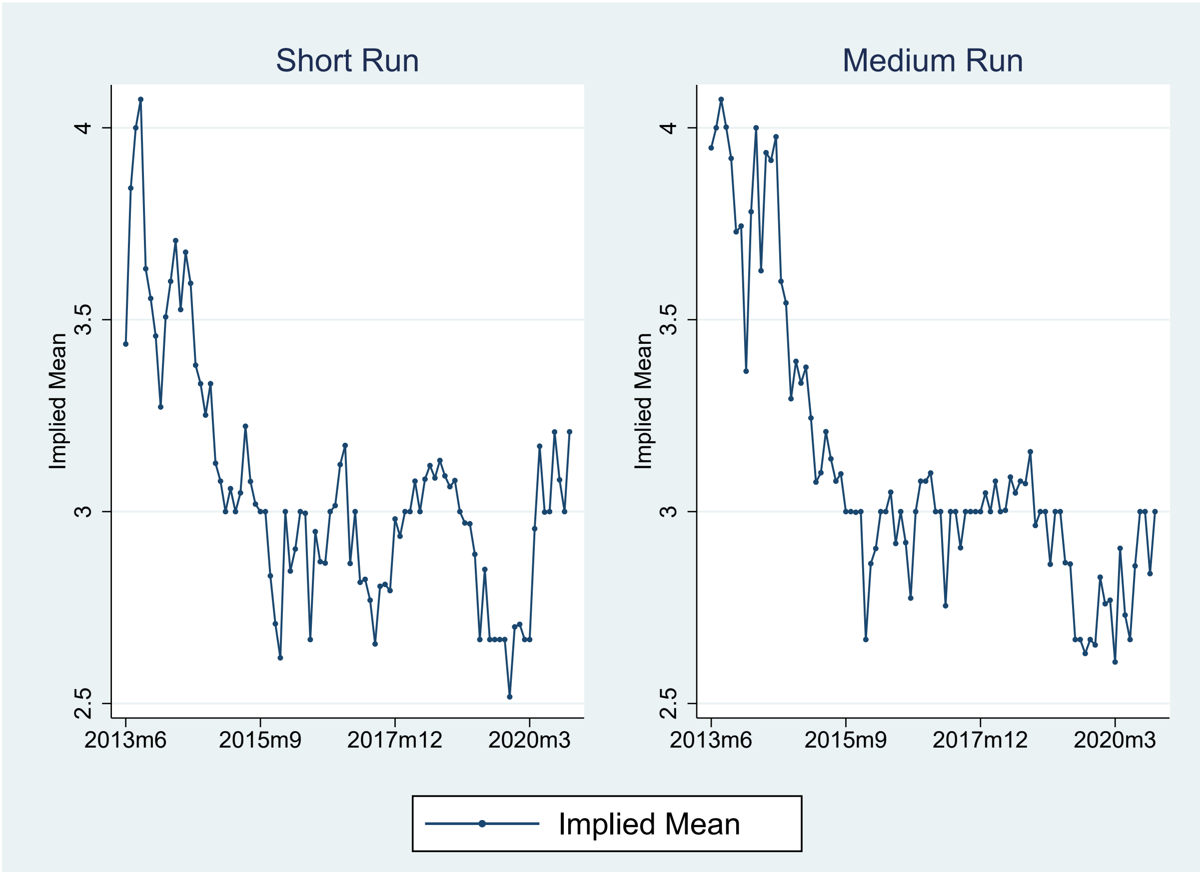
Ruge-Murcia, Francisco J. (2003). “Inflation Targeting under Asymmetric Preferences”. In: *Journal of Money, Credit, and Banking* 35.5, pp. 763–785.

Figure 1: Diffusion Indexes



Notes: The figure shows the diffusion indexes of the assessed risk weighting around short-run and medium-run projections. It is calculated by, for each month, subtracting the survey-weighted share of participants whose distributions are negatively skewed from the share of participants with positively skewed distributions.

Figure 2: Measure of Consumer Expectations

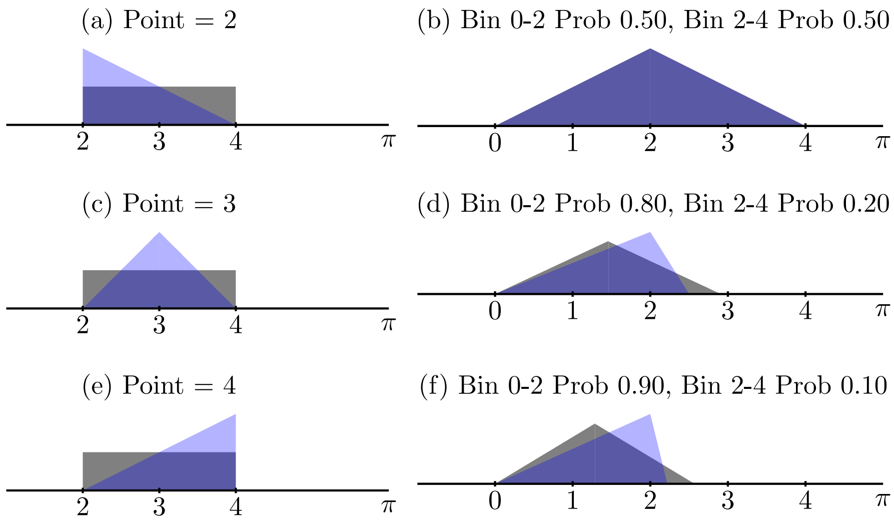


Notes: The figure shows the survey-interpolated medians of the distribution implied means for each short-run and medium-run inflation expectations. The means are calculated using the subjective probability distribution proposed in this paper.

Figure 3: Disagreement and Uncertainty

Notes: The figure shows measures of cross-sectional disagreement and subjective uncertainty for short-run and medium-run inflation expectations. The dispersion is calculated as the difference in the interquartile range across the individual implied means in a period. The subjective uncertainty measure is the interpolated median of the interquartile ranges of the individual subjective distributions.

Figure 4: Comparison of Methods: One Bin and Two Bins



Notes: This figure shows the fitting methods for respondents placing positive probability in one or two bins. The first column compares unique forecasts that share an identical one-bin histogram but that have different point estimates. The second column shows forecasts that all have the same point estimates but place differing probabilities across the same two bins. The Survey of Consumer Expectations distribution is shown in solid gray while the distribution fitted using the approach described in this paper is shown in partly transparent blue. The modified approach allows for asymmetric probability distributions in those who report probability in only two bins, in contrast to the approach of Engelberg, Manski, and Williams 2009 and Armantier, Topa, van der Klaauw, and Zafar 2016 who impose symmetry on these distributions. More than 30% of forecasters fill one or two bins for both one-year and three-year forecasts, meaning that the relaxation of the assumption of symmetry will impact a large number of observations.

APPENDICES

A Fitting Methods

This appendix describes my alternative method for deriving the implied mean and quartiles from each respondents subjective probability distribution. This method is designed to approximate the method the Survey of Consumer Expectations uses to fit subjective distributions to reported probabilities as closely as possible with one adjustment - using the point forecasts to pin down the mode of the distribution.

A-1 Case 1 - Consumer uses one interval.

When the respondent places all probability in a bounded interval, I fit a triangular distribution with endpoints given by the interval's endpoints rather than fitting a uniform distribution to the bin.[9] I allow the triangle to be scalene and for the highest point of the triangle to coincide with the consumer's point estimate. When this point estimate falls outside of the interval, I use the endpoint nearest to the point estimate as the mode of the distribution. Engelberg, Manski, and Williams (2009) assumes an isoceles triangle with the mode at the midpoint of the bin. My adjustment allows for asymmetric distributions even among forecasters who fill only one bin.

A-2 Case 2 - Consumer uses two intervals.

I fit triangular distributions for those respondents filling two adjacent intervals.[10] Again, I allow the distribution to be a scalene triangle with the mode of the distribution coinciding with the respondent's point estimate.[11] When fitting triangular distributions over two intervals, one of the endpoints of the distributions is fitted to either the rightmost point of the higher interval or the leftmost point of the lower interval. The other endpoint is determined from the restricted endpoint, the assumed mode of the distribution, and the probabilities placed in each bin. Denote the mode of the distribution as p and upper and lower bounds of the distribution as l and r, respectively. The height of the distribution is given by $h = \frac{2}{r-l}$. The subjective distribution for an individual is therefore given by:

$$f(x) = \begin{cases} \frac{2}{(r-l)(p-l)}(x-l) & l \leq x \leq p \\ \frac{2}{(r-l)(r-p)}(r-x) & p < x \leq r \end{cases}$$

[9]When a survey respondent places all probability in an unbounded interval, the SCE assumes bounds of -38 and 38. I follow this convention.

[10]Include number not doing this.

[11]The mode is, in certain cases, modified to allow the probabilities in each interval under the fitted distribution to match the probabilities that the consumer assigned to those intervals. In any situation where the mode differs from the reported point estimate, I choose the value of the mode that is both consistent with the reported probabilities and closest to the reported point estimate.

Two adjacent bins will have respective endpoints $[x_1, b]$ and $[b, x_2]$. Denote the consumer's point estimate as p. Denote the probability in the lower bin as δ. The restricted and fitted endpoints will be determined by a combination of the relative widths of the two bins, δ, and the position of p relative to b. To keep the probability under the subjective distribution in the bins to which the respondent assigned it, the mode is sometimes adjusted. In some cases, I attempt to fit the left endpoint and solve for the right endpoint only in the event that solutions for the left endpoint fall outside of the lower interval. In other cases, I attempt to fit the right endpoint first. Should the right endpoint fall outside the upper interval, I fit the left endpoint next.

A-2.1 Pin right endpoint $r = x_2$, solve for l

Cases in which I solve for the left endpoint first include:

- Lower bin has smaller probability, $\delta < 0.5$, bins are of equal width
- Lower bin has smaller probability, $\delta < 0.4$, lower bin is narrower, both bins are bounded
- Lower bin has smaller probability, $\delta < 0.5$, lower bin is wider, both bins are bounded
- Higher bin has smaller probability, $0.4 \leq \delta < 0.5$, lower bin is wider, both bins are bounded
- Even weight in two bins ($\delta = 0.5$), lower bin is wider, both bins are bounded
- Even weight in two bins ($\delta = 0.5$), bins are of equal width, point estimate falls in lower bin $p < b$
- Weight falls in lowest bin, which is unbounded

$p = b$ Call the probability in the leftmost bin δ. If the point estimate, p, falls at the breakpoint between the two bins.

$$l = \frac{b - \delta x_2}{1 - \delta} \tag{A-2}$$

$p > b$ When p falls above the point separating the two bins, l is the solution to the following quadratic that falls within $[x_1, b]$:

$$(1 - \delta)l^2 + [\delta(p + x_2) - 2b]l + (b^2 - \delta p x_2) = 0 \tag{A-3}$$

Such a case is shown in figure A-2.

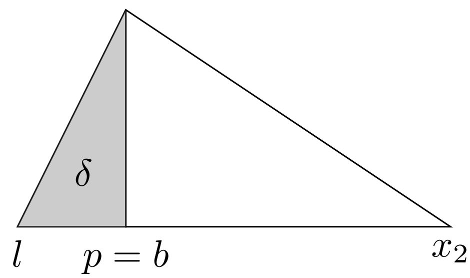


Figure A-1: Point Estimate at Bin Breakpoint

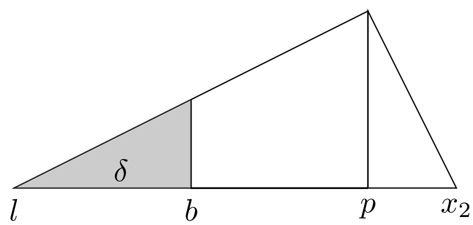


Figure A-2: Point Estimate in Higher Bin

$p < b$ If the point estimate falls in the lower bin, the left endpoint of the triangle is:

$$l = x2 - \frac{(x_2 - b)^2}{(x_2 - p)(1 - \delta)} \tag{A-4}$$

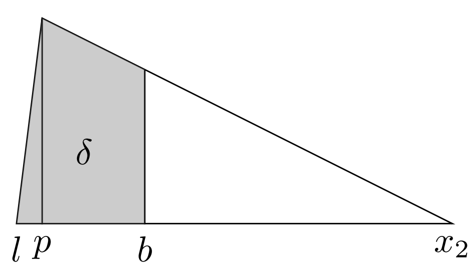


Figure A-3: Point Estimate in Lower Bin, Case 1

The exception to this is the case where the solution to l is greater than the point estimate (putting the point estimate outside of the fitted distribution). In this case, the left endpoint is given by:

$$l = x_2 - \frac{\sqrt{(l - \delta)^2(x_2^2 - 1) - (1 - \delta)(x_2 - b)^2}}{1 - \delta} \tag{A-5}$$

The first case is shown in A-3. The exception is shown in A-4.

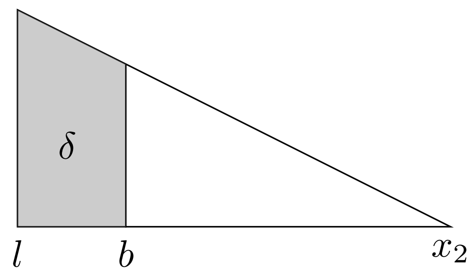


Figure A-4: Point Estimate in Lower Bin, Case 2

A-2.2 Pin left endpoint, $l = x_1$, solve for r

Cases in which I solve for the right endpoint first include:

- Higher bin has smaller probability, $\delta < 0.5$, bins are of equal width
- Higher bin has smaller probability, $\delta < 0.4$, higher bin is narrower, both bins are bounded
- Higher bin has smaller probability, $\delta < 0.5$, higher bin is wider, both bins are bounded
- Lower bin has smaller probability, $0.4 \leq \delta < 0.5$, higher bin is wider, both bins are bounded
- Even weight in two bins ($\delta = 0.5$), higher bin is wider, both bins are bounded
- Even weight in two bins ($\delta = 0.5$), bins are of equal width, point estimate falls in higher bin $p > b$
- Weight falls in highest bin, which is unbounded

1. $p = b$

   Call the probability in the rightmost bin δ. If the point estimate, p, falls at the breakpoint between the two bins, the right endpoint is given by:

$$r = \frac{b - \delta x_1}{1 - \delta} \tag{A-6}$$

2. $p < b$

   If the point estimate falls in the lower bin, r is the solution to the following quadratic that falls within $[b, x_2]$:

$$(1 - \delta)r^2 + [\delta(p + x_1) - 2b]l + (b^2 - \delta p x_1) = 0 \tag{A-7}$$

3. $p > b$

$$r = x_1 - \frac{(b - x_1)^2}{(p - x_1)(1 - \delta)} \tag{A-8}$$

A-3 Case 3 - Consumer uses three or more intervals.

When the consumer places positive probability to three or more intervals, I fit a generalized beta distribution with endpoints l and r and shape parameters α and β following Engelberg, Manski, and Williams (2009). As in Armantier, Topa, van der Klaauw, and Zafar (2016), I fix l and r to the minimum and maximum bounds of the intervals with positive probability.[12] The probability distribution is given by:

$$f(x) = \begin{cases} 0 & x < l \\ \frac{1}{B(\alpha,\beta)} \frac{(x-l)^{\alpha-l}(r-x)^{\beta-1}}{(r-l)^{\alpha+\beta-1}} & l \leq x \leq r \\ 0 & x > r \end{cases}$$

where $B(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha,\beta})$. I assume that the individual's point estimate is equal to the mode of their distribution, which given by $l + (r - l)\left(\frac{\alpha-1}{\alpha+\beta-1}\right)$. If the respondent's point estimate falls outside of the range l to r, I set p equal to the value of l or r closest to the reported point estimate. The imposition of the point estimate as the mode of the distribution creates a further relationship between α and β. Given these requirements, I fit the shape parameters (and bounds in the case of unbounded intervals) as in Armantier, Topa, van der Klaauw, and Zafar (2016), fitting a minimum distance estimator that minimizes the distance between the observed probability distribution and the probability distribution generated by the proposed parameter combinations.

[12] If the positive probability intervals include the unbounded intervals, I allow the relevant bound(s) to be estimated along with the shape parameters. Following Armantier, Topa, van der Klaauw, and Zafar (2016), I allow a maximum value of 38 for r and a minimum value of -38 for l .