Measuring Inflation Uncertainty in Turkey

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May 2019

Working Paper No: 19/12

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Abstract

Measuring and monitoring inflation uncertainty is an essential ingredient of monetary policy analysis. This study constructs survey measures of inflation uncertainty for the Turkish economy. Using density and point inflation forecasts in the CBRT Survey of Expectations, we derive various uncertainty measures through standard deviation, entropy, and disagreement among forecasters. Our results suggest that survey-based inflation uncertainty measures are broadly consistent with market-implied indicators of inflation risk. Moreover, we find that an increase in observed inflation is associated with higher inflation uncertainty across all empirical specifications.

Keywords: Inflation uncertainty; Inflation; Survey data; Density forecasts; Disagreement.
JEL Codes: C53; E31; E37; E58.

[1] We would like to thank Tayyar Büyükbaşaran for useful comments and suggestions. The views expressed in this paper are those of the authors' and do not necessarily represent the official views of the Central Bank of the Republic of Turkey.

Non-technical Summary

Measuring and monitoring inflation uncertainty is an essential element of monetary policy analysis. Heightened inflation uncertainty is undesirable from a policy and welfare perspective, as it is often associated with a deterioration in pricing behavior, higher interest rate uncertainty, and a delay of productive investments. Tracking movements in inflation uncertainty is even more important for economies like Turkey where price stability is yet to be established.

This paper constructs a broad range of inflation uncertainty measures for Turkey based on survey information. We assess the cross-consistency of these measures with quasi-market based indicators and evaluate their information content by studying the relationship between inflation uncertainty and macroeconomic variables.

A key strength of our study is to exploit individual-level density forecasts provided by the "Survey of Expectations" of the Central Bank of the Republic of Turkey (CBRT). We derive measures of inflation uncertainty by computing mean standard deviation of micro-level density forecasts and cross-sectional dispersion (disagreement) among survey respondents. As an alternative to these variance-based indicators, we also construct an entropy-based measure. As a cross-check for the relevance of our survey based indicators, we use a quasi-market-based measure of inflation uncertainty by combining survey information with breakeven inflation from inflation-indexed treasury securities. Our results suggest that survey-based measures are broadly consistent with its market-based counterpart.

Having constructed measures of inflation uncertainty, we also explore factors that co-move with uncertainty indicators. Our findings reveal that all measures of inflation uncertainty are positively and significantly associated with the level of inflation across all specifications. Most inflation uncertainty measures are also associated with sovereign risk premium and inflation surprises.

This paper is the first to construct and analyze direct measures of inflation uncertainty from density forecasts for an emerging market economy. Previous literature is concentrated on some advanced countries because of data limitations. Inflation uncertainty in emerging economies may have different dynamics due to imperfect credibility of institutions and diverse range of shocks leading to frequent shifts in the country risk premium. In that sense, our paper offers some complementary perspective to the existing studies, both in terms of understanding the relation of direct inflation uncertainty measures with key macro variables and assessing the interplay between different uncertainty indicators. Our results suggest that, contrary to the findings of the existing literature, disagreement among forecasters is a reasonable measure of inflation uncertainty in terms of tracking market-based indicators of inflation risk.

From a policy perspective, the paper aims to contribute to enriching the information set of the policy-making framework in Turkey by calculating timely, direct, and simple measures of inflation uncertainty. Our uncertainty measures reflect perceptions of inflation uncertainty at the individual level and they are available right after the publication of the expectation survey—without any lag, thus offering valuable information to policy makers.

1. Introduction

Measuring and monitoring inflation uncertainty is an essential element of monetary policy analysis. Changes in inflation uncertainty can reveal signals regarding the credibility of policy actions. Heightened inflation uncertainty is undesirable from a policy and welfare perspective, as it is often associated with a deterioration in pricing behavior, higher interest rate uncertainty, and a delay of productive investments. Tracking movements in inflation uncertainty is even more important for economies like Turkey where price stability is not fully established.

The literature proposes various measures of inflation uncertainty, which can be classified broadly under two categories.[2] The first group uses empirical time series models to extract indirect uncertainty measures, based on conditional variance (e.g., via estimating GARCH-type models) or ex-post forecast errors. The second group, which our paper belongs to, exploits the information embedded in expectation surveys to extract direct measures of inflation uncertainty. This paper constructs a broad range of inflation uncertainty measures for Turkey based on survey information. We assess the cross-consistency of these measures with quasi-market based indicators and evaluate their information content by studying the relationship between inflation uncertainty and macroeconomic variables.

A key strength of our study is to exploit individual-level density forecasts provided by the "Survey of Expectations" of the Central Bank of the Republic of Turkey (CBRT). Improving upon the majority of related literature –which in general uses point forecasts, we construct subjective uncertainty measures at the micro level, i.e., the degree of confidence that forecasters attach to their point forecasts.

Using the CBRT Survey of Expectations and employing the approach by Giordani and Soderlind (2003) and Boero et al. (2008), we derive measures of inflation uncertainty by computing mean standard deviation of micro-level density forecasts and cross-sectional dispersion (disagreement) among survey respondents. As an alternative to variance-based indicators, we also construct an entropy-based measure as in Wallis (2006) and Rich and Tracy (2010). We show that all uncertainty indicators move closely with each other. As a cross-check for the relevance of survey based indicators, we use a quasi-market-based measure of inflation uncertainty by combining survey information with breakeven inflation from inflation-indexed treasury securities. Our results suggest that survey-based measures are broadly consistent with its market-based counterpart.

Having constructed measures of inflation uncertainty, we also explore factors that co-move with uncertainty indicators. Our findings reveal that all measures of inflation uncertainty are positively and significantly associated with the level of inflation across all specifications. This result holds even with a level-independent uncertainty measure based on the notion of entropy. Most inflation uncertainty measures are also associated with sovereign risk premium and inflation surprises.

This paper is the first to construct and analyze direct measures of inflation uncertainty from density forecasts for an emerging market economy. Existing studies that use density forecasts are confined to some advanced countries because of data limitations.[3] Inflation uncertainty in emerging economies may have different dynamics due to imperfect credibility of institutions and diverse range of shocks leading to frequent shifts in the country risk premium. In that sense, our paper offers some complementary perspective to the existing literature, especially in understanding the relationship between direct inflation uncertainty measures and key macro variables. We show that some of the

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[2] Grimme et al. (2014) provide a survey of alternative methods in measuring inflation uncertainty as well as a comprehensive set of references.

[3] As documented in Rich and Tracy (2018), existing papers that use density forecasts are largely based on the ECB-Survey of Professional Forecasters (SPF), U.S. SPF, the Bank of England Survey of External Forecasters and the Federal Reserve Bank of New York Survey of Consumer Expectations.

findings of the literature may not be valid in an alternative context. For example, previous literature using density forecasts, which mainly focus on advanced economies, argue that the dispersion among professional forecasters are not found to be a good proxy for uncertainty as it has shown to exhibit relatively weak correlation with individual inflation uncertainty measures.[4] Our results suggest that, in an emerging market economy context such as the Turkish case, disagreement among forecasters exhibits significant correlation with individual level subjective uncertainty and appears to be a reasonable measure in terms of tracking market-based indicators of uncertainty. One possible explanation is relatively more volatile inflation environment and lower degree of anchoring in inflation expectations, which might lead to higher correlation between disagreement and uncertainty.

The paper also aims to contribute to the policy-making framework in Turkey. Studies on survey-based inflation uncertainty are limited for the Turkish economy. One exception is Hülagü and Şahinöz (2012), which was conducted before the launch of density forecasts. These authors calculate *indirect* measures of inflation uncertainty, using ex-post errors of the survey participants' point inflation forecasts. Their method computes uncertainty for a certain month only after the realization of inflation, which is observed with some lag. On the contrary, our uncertainty measures are available right after the publication of the expectation survey—without any lag, thus offering timely information to policy makers. Another novelty of our paper is that our measures reflect *direct* perceptions of inflation uncertainty for Turkey at the individual level, thanks to the availability of density forecasts since 2013.

Remaining of the paper is organized as follows: The next section introduces the survey and constructs various measures of uncertainty. The third section explores which macro variables are more closely associated with the uncertainty measures. The last section draws conclusions and final remarks.

2. Measures of Inflation Uncertainty

In this section, we introduce empirical measures for inflation uncertainty based on different approaches proposed in previous studies, which rely on distinct concepts and assumptions. The main goal is to construct direct measures of uncertainty as an input for policy analysis. To this end, we derive various survey-based measures using inflation expectations data compiled by the CBRT. We also propose a quasi-market based uncertainty measure by employing breakeven inflation from inflation-indexed bonds jointly with survey information, and use this metric as a cross check for our survey-based uncertainty measures.

Survey-Based Measures

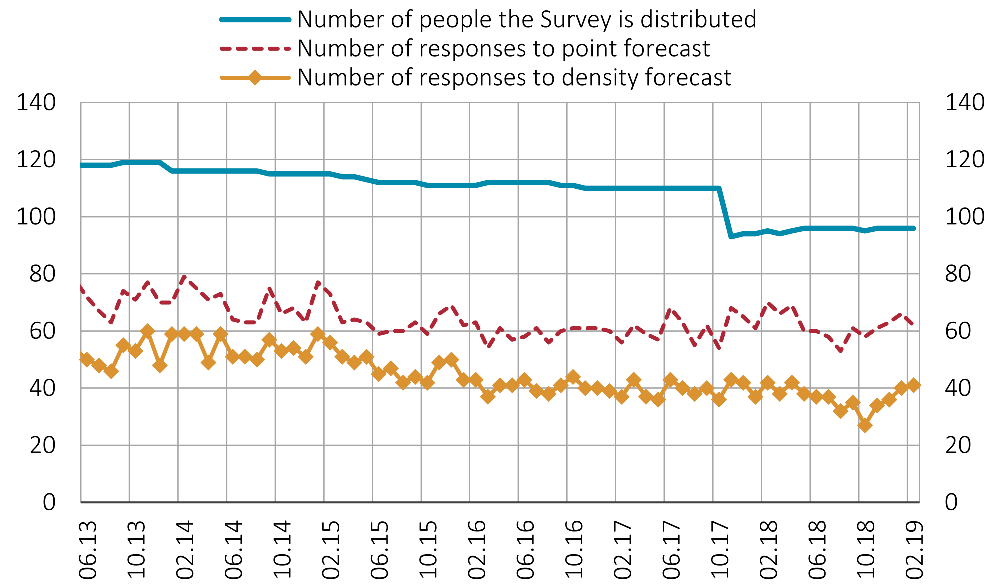
The literature proposes several alternatives for the construction of uncertainty indicators using survey data. These measures are generally calculated by either using cross sectional dispersion across participants' point forecasts or employing direct uncertainty measures from individual level density forecasts.[5] The former can be computed for all standard survey types, while the latter requires micro level probability distributions, which is not available in most surveys.

Our data set compiled by the CBRT provides a rich information set for constructing measures of inflation uncertainty. The CBRT "Survey of Expectations" (the Survey) collects forecasts from a group of external forecasters for their views on inflation, output growth, current account, interest rates and the Turkish lira exchange rate since 2001. Initially, the Survey was bi-monthly, but since January 2013 it is conducted once a month. The Survey is carried out typically the week before the Monetary Policy Committee meetings, and the summary of the survey results are published at the CBRT website. The participants covered in the sample include economists and analysists from banks, other financial

[4] See Rich and Tracy (2010) and the references therein.
[5] For example, see Boero et al. (2008) and the references therein.

institutions, academia, and large non-financial firms. Although most of the survey participants represent an institution, some of them are individual "professionals". The Survey is distributed to a fixed pool of around 100 participants during the second or third week of each month. The pool have remained broadly same in our sample period (since 2013) with minor revisions in November 2017.[6] Therefore, we have a nearly balanced panel. The response rate has been hovering around 60 percent for point forecasts and 40 percent for density forecasts. Figure 1 depicts the evolution of number of survey participants providing density and point forecasts over time.

Figure 1. Number of Responses in the Survey
(12-month ahead inflation expectations)

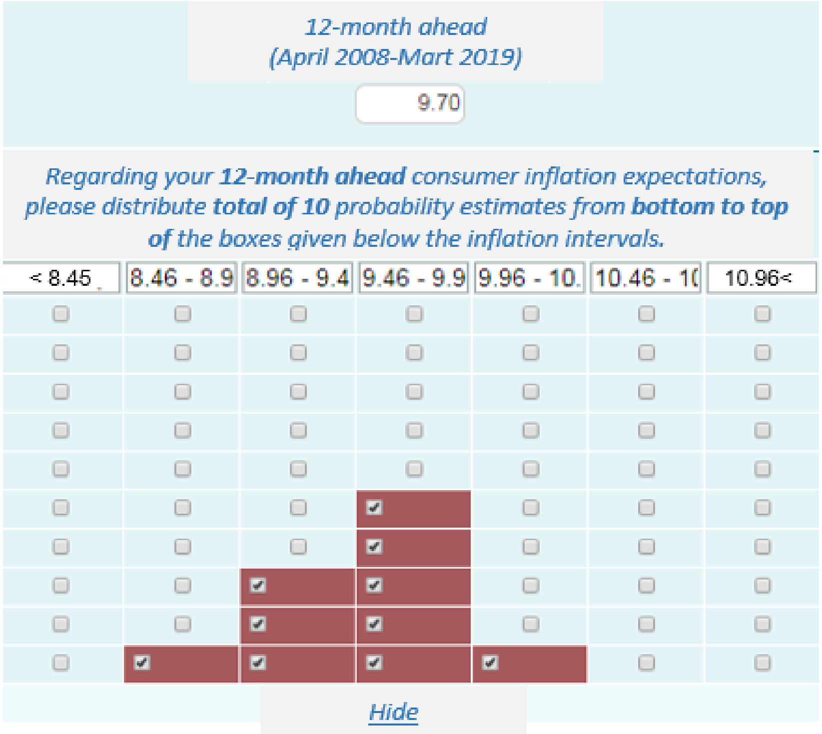


Source: CBRT.

A special and valuable characteristic of the Survey is the availability of individual-level density forecasts in the form of histograms since 2013, which is a unique feature for an emerging economy. In order to understand the information content of our data set, let us have a more detailed look at the corresponding granular data. Survey participants provide density forecasts in two steps. First, on-line survey asks the respondents to provide their point forecasts for 12-month ahead and 24-month ahead inflation in a digital menu. Once the point forecast is received, the system automatically creates fixed intervals and asks participants to attach a discretized probability to each interval. Figure 2 shows an example of the screen shot that shows the density forecast filled out by a hypothetic participant whose point estimation is 9.7 percent for one-year ahead inflation.

[6] In November 2017, participants who have shown no response for a reasonably long period have been removed from the Survey pool, which have not affected the number of active respondents, as shown in Figure 1.

Figure 2: An Example of the Screen Shot



Source: CBRT.

As shown in Figure 2, range for intervals are set symmetrically around point forecasts,[7] and the whole range is divided into seven intervals. In notational form, let π_i^e denote survey respondent *i*'s point forecast for 12-month ahead inflation. Seven bins are automatically constructed around π_i^e as in Table 1. Then, respondents are asked to distribute probabilities as the multiples of 10% for each bin, which constitutes the density forecast.[8]

Table 1: Intervals for Estimating the Probability Distribution of the 12-month ahead Inflation with Point Forecast π_i^e

Bin	Intervals
#1	<(π_i^e-1.25)
#2	[(π_i^e-1.24), (π_i^e-0.75)]
#3	[(π_i^e-0.74), (π_i^e-0.25)]
#4	[(π_i^e-0.24), (π_i^e+0.25)]
#5	[(π_i^e+0.26), (π_i^e+0.75)]
#6	[(π_i^e+0.76), (π_i^e+1.25)]
#7	≥ (π_i^e+1.26)

[7] Until November 2017, intervals and bins for estimating the probability distribution for 24-month ahead inflation, were predetermined and fixed (<3.50, 3.50-4.49, 4.50-5.49, 5.50-6.49, 6.50-7.49, ≥7.50). Since November 2017, intervals are centered automatically around the point forecast of each respondent, as in 12-month ahead inflation. The structural shift due to methodological change shortens the timespan significantly for 24-month inflation expectations. Therefore, in this study we construct uncertainty measures only for 12-month horizon.

[8] It may be worthwhile to note some consequences of the particular survey design in creating bins for density forecasts: Having predetermined fixed-width intervals makes density forecasts—and thus uncertainty measures, less dependent on the level of inflation. On the other hand, relatively narrow and fixed intervals with limited number of bins constrain the distribution, for example, by lowering the chance of providing multi-modal density forecasts.

Using the Survey information, we construct several alternative measures of inflation uncertainty. We construct and present uncertainty measures only using the 12-month ahead inflation expectations, because changes in the parameters of density forecasts in November 2017 shortens our timespan significantly for 24-month inflation expectations (see also footnote 7).

Our first group of indicators employ standard deviations of density and point forecasts as a measure of uncertainty along the lines suggested by Zarnowitz and Lambros (1987), Giordani and Soderlind (2003), and Rich and Tracy (2010). These studies distinguish between individual uncertainty, cross-sectional dispersion, and aggregate uncertainty. To this end, we compute the following measures:

(i) average standard deviation of individual density forecasts (individual uncertainty),

(ii) cross-sectional standard deviation of point forecasts (disagreement), and

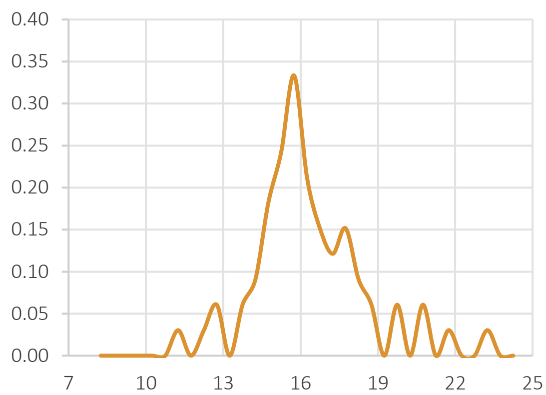
(iii) standard deviation of aggregated histogram of density forecasts (aggregate uncertainty).

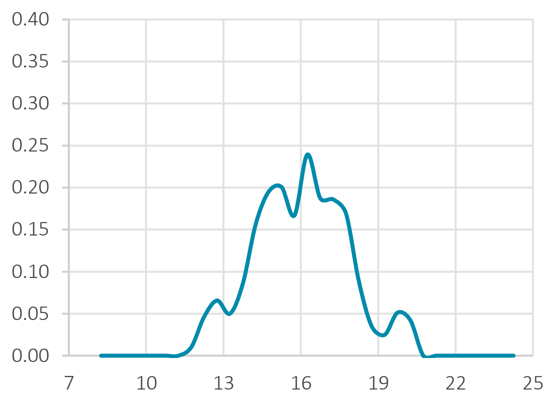
The particular design of the Survey published by the CBRT allows for a proper construction of all of the three measures.

The first measure employs density forecasts (shown representatively in Figure 2) by taking standard deviation of each individual distribution and averaging over all respondents. The second and third measures are computed by taking standard deviations of cross-sectional point forecasts and aggregated density forecasts, respectively. To provide some idea about how the latter distributions look like in the data, Figure 3 depicts the histograms for cross-sectional point forecasts and aggregated density forecasts for one-year ahead inflation expectations in January 2019. It is clear that the range of these distributions are typically wider than the range of individual density forecasts depicted in Figure 3 because of the non-constrained nature of point forecasts.

Figure 3: Histograms for Cross Sectional Point Forecasts and Aggregated Density Forecasts (January 2019 Expectations Survey)

3.a: Cross-Sectional Point Forecasts **3.b: Aggregated Density Forecasts**





Source: CBRT and authors' calculations.

Each of the three measures has its own merits and limitations. Average standard deviation of individual histograms reflects subjective uncertainty perceived by individual respondents. Because of its theoretical appeal, this measure is used as a benchmark for uncertainty in some studies.[9] However, underlying distribution forecasts are not available in most surveys. Moreover, this measure leaves out the information content of the dispersion among forecasters, which may be an important signal of

[9] See, for example, Rich and Tracy (2010).

uncertainty when expectations are not well anchored. Disagreement on the point forecasts has the advantage of capturing the information embedded in cross-sectional distribution. Yet, this indicator ignores perceived uncertainty at the individual level.[10] Moreover, heterogeneity in the frequency of official forecast updates by institutions may amplify the observed disagreement measures especially after significant inflation shocks. The third measure, which is the standard deviation of the aggregate histogram, is a hybrid indicator, which incorporates both individual-level uncertainty and disagreement among forecasters.[11]

We construct density-based measures of uncertainty by computing standard deviation of the histograms without assuming any specific continuous distribution for the probabilistic beliefs. As pointed in D'Amico and Orphanides (2008), computing the variances in this case requires two assumptions. First, since the first and last bins are open-ended, an assumption is needed about the range over which the individual histograms are defined. Following Zarnowitz and Lambros (1987), we assume that the first and last bins are closed and have the same width as that of others. The second assumption is related to the concentration of the probability mass within each bin. We assume that the probability is concentrated at the midpoint of each bin.

An Alternative Measure of Inflation Uncertainty: Entropy

Survey based uncertainty indicators presented so far uses the notion of standard deviation. On the other hand, some studies employ the concept of "entropy" to derive uncertainty measures from survey data. Entropy is a reasonable candidate as an alternative uncertainty indicator since it measures the degree of concentration of a probability distribution without any direct dependence on the level of expectations. The advantage of this measure is that it provides more robust results than the standard deviation metric when the individual probability distributions are non-normal. Therefore, as a fourth measure, we adopt an alternative approach drawing on the concept of entropy from information theory as proposed in Wallis (2006), and Rich and Tracy (2010). The entropy measure takes the following form:[12]

$$\tau_{\pi,t} = -\left(\sum_{b=1}^{n_b} p_{b,t}\left[\ln\left(p_{b,t}\right)\right]\right). \qquad \textbf{(1)}$$

where $p_{b,t}$ shows the probability assigned to the b^{th} interval at time t, and n_b shows the total number of intervals in frequency distribution.

The entropy indicator provides additional information compared to variance based measures: First, given a certain standard deviation, entropy changes with the shape of the histogram. Second, entropy reflects whether probability is concentrated on a few points or dispersed over many points, which may dampen the relative weight of tail concentrations compared to variance based measures. Given a fixed number of bins and a constant bin width as in our case, the histogram-based entropy is maximized if the forecasts are distributed equally among all bins. Therefore, the concept of entropy may be more appropriate for bi-modal distributions, which may arise during times of heightened uncertainty and structural breaks.

[10] See Mankiw et al. (2003) for a discussion.

[11] A formal representation of the uncertainty measures for a generic distribution are provided in the Appendix.

[12] Wallis (2006) shows that equation (1) can be interpreted as a histogram-based approximation to the entropy of a continuous random variable.

We construct the entropy measure only for aggregated density forecasts. An alternative approach would be to compute entropy for each individual and average over all survey respondents as in Rich and Tracy (2010). However, the variation of the entropy measure can be too limited if there are few intervals in the probability distribution, as in our case due to particular design of the survey (fixed narrow range with small number of bins). In fact, a comparison of the right panel of Figure 3 with Figure 2 reveals that the aggregated density forecasts display a wider range of distribution compared to individual level density forecasts. Accordingly, we use aggregated density forecasts instead of individual density forecasts for entropy calculation.

Comovement of Uncertainty Indicators

After calculating the entropy indicator, we now have four different survey-based measures of uncertainty. Table 2 shows cross correlation of these indicators. While all four variables are highly correlated within each other across the sample, the correlation of average individual level uncertainty with other indicators is relatively lower. This may result from the fact that all indicators other than average individual uncertainty are sensitive to cross-sectional dispersion by construction and individual forecast distribution exhibits lower variance than the cross-sectional distribution due to relatively narrow pre-fixed range of individual histograms.

It is interesting to observe that inflation uncertainty measures based on density forecasts (uncertainty) are highly correlated with inflation uncertainty measure based on cross-sectional dispersion (disagreement). Previous studies—all on advanced economies—have explored the relationship between disagreement and uncertainty. The evidence from the US and ECB Survey of Professional Forecasters has been mixed. For the case of US, Zarnowitz and Lambros (1987) report a modest positive association between disagreement and uncertainty; Giordani and Soderlind (2003) find a positive and significant correlation between the two indicators; Rich and Tracy (2010) report a very weak relationship between disagreement and uncertainty. Boero et al. (2008) and Abel et al. (2016) find little support on the use of disagreement as proxy for uncertainty for the Bank of England and ECB surveys, respectively.

Contrary to the literature on advanced economies, we find a strong and statistically significant association between uncertainty and disagreement. This contrast might be due to more volatile and thus uncertain inflation environment in Turkey than its advanced counterparts. Indeed, by developing a Bayesian learning model, Lahiri and Sheng (2010) show that the disagreement-uncertainty relationship may be inversely related to the volatility of the forecasting environment.

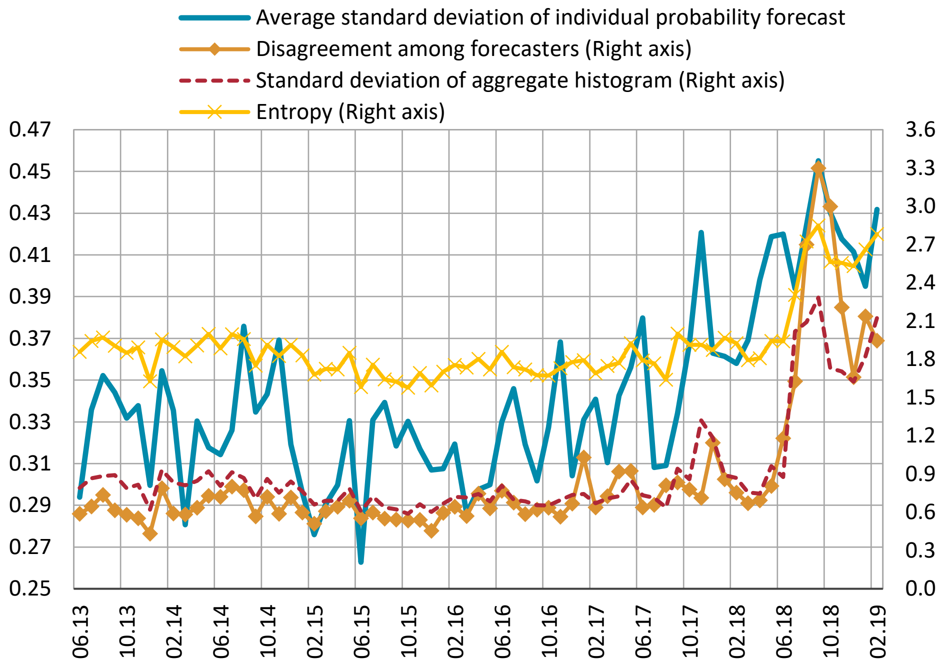
Table 2: Cross Correlation of Inflation Uncertainty Measures Constructed Using Survey Data

Sample Period:	June 2013 - February 2019			
	Average standard deviation of individual probability forecast ($\overline{\sigma}_t$)	Disagreement among forecasters ($\sigma_{\pi,t}$)	Standard deviation of aggregate histogram ($\sigma_{A,t}$)	Entropy of the aggregate histogram ($\tau_{\pi,t}$)
$\overline{\sigma}_t$	1	0.71***	0.74***	0.74***
$\sigma_{\pi,t}$		1	0.91***	0.91***
$\sigma_{A,t}$			1	0.96***
$\tau_{\pi,t}$				1

Notes: Number of observations is 69. (*), (**) and (***) represent statistical significance at levels of 10, 5 and 1 percent, respectively.

Figure 4 provides a graphical presentation of the four alternative uncertainty measures constructed so far using survey data. A cursory look at the series suggest that all the measures tend to show an upward trend after 2017, displaying a sharp movement until September 2018. Although inflation uncertainty indicators in general declined after September, most of them remained at elevated levels compared to historical averages. A closer look at the behavior of indicators reveal some important differences. For example, the measure calculated from the individual density forecasts, which captures the direct perception of uncertainty, shows a slow but continuous decline after September 2018. On the other hand, the entropy indicator, which measures the concentration across intervals, has not shown any significant improvement during this period. This specific episode confirms that the notion of individual uncertainty, disagreement, and entropy have distinct features. From a policy perspective, it may be important to evaluate the information content of each indicator carefully, assessing which measures are moving in what direction and at what speed at the micro level.

Figure 4: Measures of Inflation Uncertainty



Source: Authors' calculations.

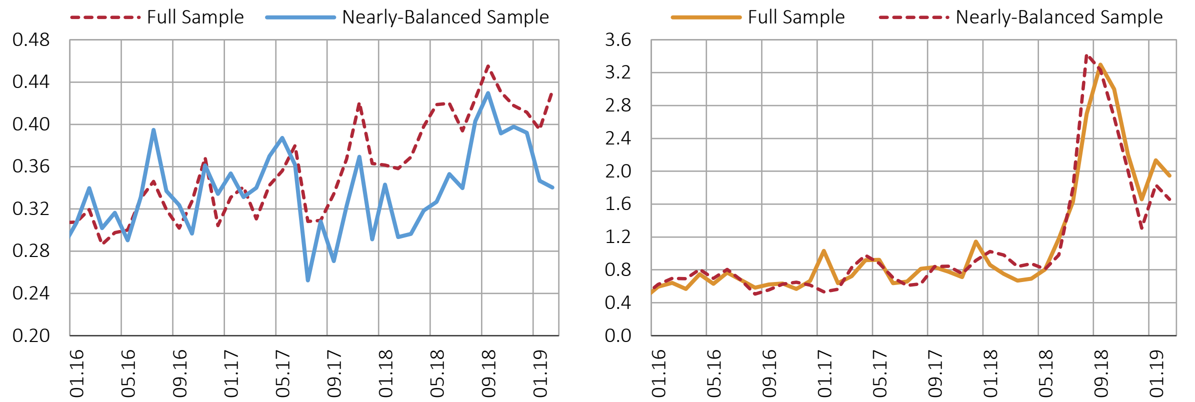
Robustness Analysis for Survey Based Indicators

Note that, not all the participants respond to the Survey every month, leading to missing observations as implied in Figure 1. Using simple averaging or standard deviation in the computation of indices, especially with too many missing observations, might increase the volatility in the indicators and undermine the information content of the uncertainty measures. Therefore, one natural question for robustness purposes is whether missing observations affect our uncertainty measures in a significant way. In order to address this issue, we adopt two alternative approaches. First, we calculate the uncertainty measures with a "nearly-balanced" panel of respondents and compare them with the full sample estimates. To this end, we form a subsample by including participants with more than 90 percent response since 2016. This means at least 36 responses out of 38 months for January 2016 – February 2019. The number of participants who fulfill this requirement is 15 for density forecasts and 24 for point forecasts.

Figure 5 compares the results of near-fixed subsamples with the whole sample for some of our inflation uncertainty measures. Although there are some differences between the indicators constructed using two samples, main trends display a similar path.

Figure 5: "Full Sample" vs. "Nearly-Balanced Sample" Estimates of Survey-based Inflation Uncertainty Measures

5.a: Average s.d. of individual probability forecast ($\overline{\sigma}_t$) | 5.b: Disagreement among forecasters ($\sigma_{\pi,t}$)

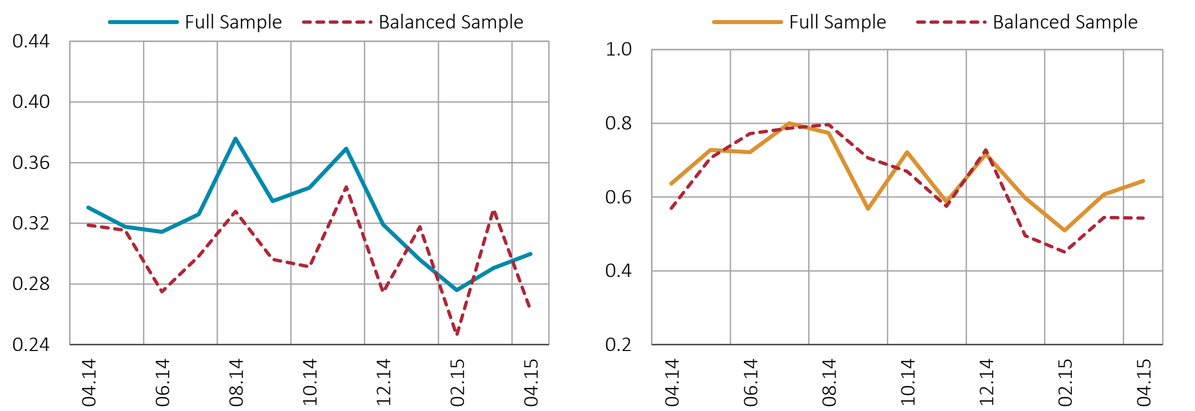


Source: Authors' calculations.

Second, we search for a fully balanced panel for a continuous window. It is not possible to find a fully balanced panel for the entire period but we are able to detect some windows with reasonable number of participants responding fully to the Survey. For example, we find that between the period April 2014 and April 2015, 19 participants for density forecasts and 27 for point forecasts have fully responded without missing any survey. After calculating uncertainty indices for this subsample, we compare them with the full number of participants for the same window. The results are shown in Figure 6. Again, there are some differences between the indicators at high frequencies; however, main trends do not exhibit a major divergence. Overall, we conclude that our uncertainty measures are broadly robust against missing observations.

Figure 6: "Full Sample" vs. "Balanced Sample" Estimates of Survey-based Inflation Uncertainty Measures (Comparison Period: April 2014-April 2015)

6.a: Average s.d. of individual probability forecast ($\overline{\sigma}_t$) | 6.b: Disagreement among forecasters ($\sigma_{\pi,t}$)



Source: Authors' calculations.

A Quasi-Market Based Measure of Inflation Uncertainty

Up to this point, we have used survey information to construct inflation uncertainty measures. However, part of the literature argues that information content of survey-based measures may be limited because of reputational constraints, representativeness of the survey sample, lack of "skin in the game", and low incentives.[13] Moreover, uncertainty is a latent variable and thus cannot be observed or verified directly using a true benchmark. In that sense, assessing the comovement between alternative uncertainty measures may help provide some insight into the relevance of our analysis. This subsection provides an alternative measure of uncertainty using a quasi-market based indicator, which would help conduct cross check analysis. To this end, we employ the concept of "breakeven inflation" jointly with mean survey forecast to derive a proxy for inflation risk.

Breakeven inflation is defined as the difference between the yield to maturity on nominal bond and inflation-indexed bonds with same maturities. This spread, which is widely used as an alternative measure of inflation expectation in the literature, is called breakeven inflation (or inflation compensation) because it is the rate of inflation that, if realized, would leave an investor indifferent between holding a nominal or an inflation-indexed security.

Given that inflation indexed bonds provide protection against unexpected inflation, breakeven inflation includes a risk premium term as an additional component.[14] In notational form:

$$Breakeven\ Inflation = Y^{nominal} - Y^{real} = \pi^e + RP \qquad \textbf{(2)}$$

where $Y^{nominal}$ is the yield to maturity on a nominal bond, Y^{real} is the real yield of the inflation indexed bond, π^e is the expected average future inflation over the whole term of the bond. The *RP* term includes the risk compensation for inflation, and thus it is reasonable to assume that it is directly related to inflation uncertainty. Although *RP* may include liquidity premium and other additional factors, we will assume that movements in inflation risk is the main driver of this component in an environment of highly volatile inflation during our sample period.

Equation (2) decomposes breakeven inflation into two components consisting of average inflation expectations and inflation risk premium. The breakeven inflation can be calculated at any time using the spread of observed yields on nominal and indexed bonds at the same maturity. In order to extract an indicator of inflation uncertainty (RP), we need a proxy for inflation expectations π^e. Following Shen (2006) and Söderlind (2011), we will take mean of survey expectations as a measure for π^e, and construct our alternative measure of inflation uncertainty by subtracting this term from breakeven inflation.

We obtain two-year breakeven inflation data directly from Bloomberg, which is calculated using fitted two-year nominal Treasury bond yield and the real yield on inflation-indexed securities with same maturity.[15] As a proxy for expected average annual inflation over the next two years, we take an average of two-year-ahead and one-year-ahead inflation expectations from the survey, which matches the terms of the bonds.

[13] For example, see Keane and Runkle (1990) and Manski (2004).

[14] See Gürkaynak et al. (2010) for a detailed exposition.

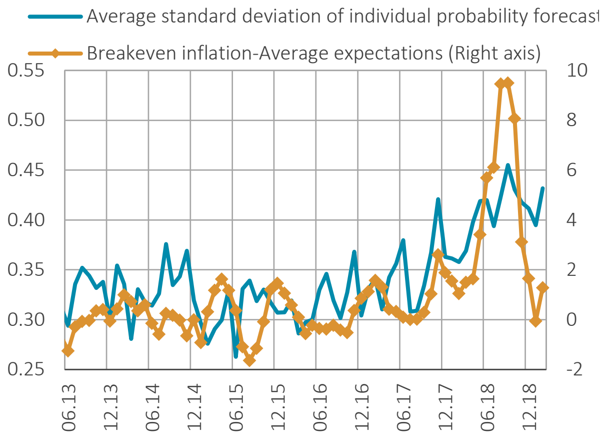
[15] For the ease of comparability with other indicators, ideal maturity to use for breakeven inflation would be one-year as our survey-based measures also have one-year horizon. However, historical data is not available for one-year maturity; therefore, we used two-year breakeven inflation.

Are survey-based measures consistent with market-based measures?

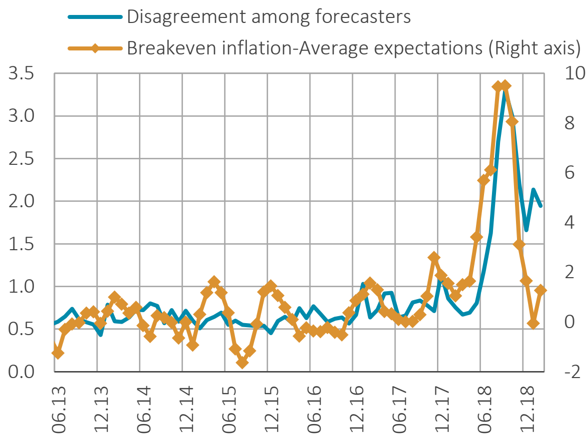
Now that we have an alternative measure of inflation uncertainty that is based on quasi-market indicators, it is possible to assess the consistency of our survey and market based measures as a cross-check analysis. Figure 7 compares each of the four survey inflation uncertainty measures with the market-based alternative constructed using breakeven inflation. All survey based uncertainty measures seem to move closely with the market-based measure. In particular, comovement between the disagreement indicator and market-perceived inflation risk appears to have strengthened during sharp movements in the second half of 2018.

Figure 7: Comparison of Survey-based Inflation Uncertainty Measures with Market-based Indicator

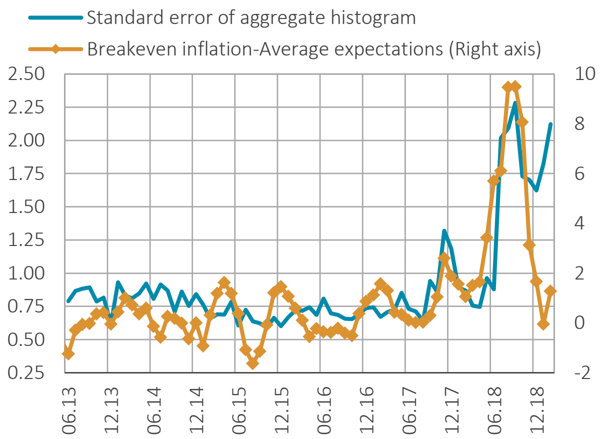
7.a: Average s.d. of individual probability forecast ($\overline{\sigma}_t$)



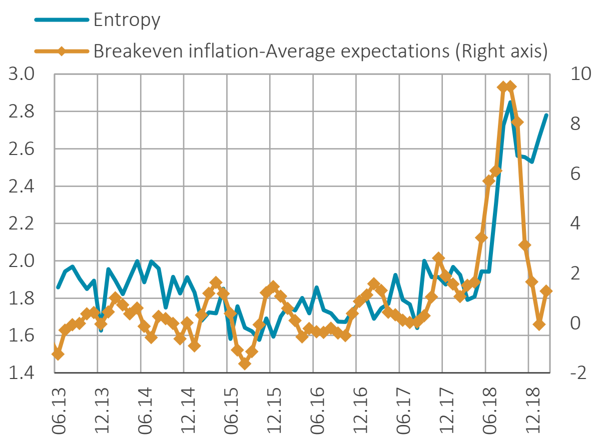
7.b: *Disagreement among forecasters* ($\sigma_{\pi,t}$)



7.c: Standard deviation of aggregate histogram ($\sigma_{A,t}$)



7.*d:* Entropy of the aggregate histogram ($\tau_{\pi,t}$)



Source: Authors' calculations.

Table 3 shows cross correlations of breakeven-based inflation uncertainty measure with each survey-based measure. These findings complement the results depicted in Figure 7, indicating a highly significant correlation between all four types of survey-based uncertainty measures with the market-based measure. In other words, survey-based measures of uncertainty move closely with the inflation risk compensation implied by market yields. However, the correlations fall markedly when we exclude the second half of 2018 from the sample, during which inflation and uncertainty have displayed sharp movements. This observation suggests that movements in breakeven inflation might have been largely driven by inflation risk premium towards the end of the sample, whereas liquidity premium and other factors might have played a relatively more important role in the previous period.

Table 3: Correlations between Survey-based and Market-based Uncertainty Measures

Sample Period:	June 2013 - February 2019			
	Average s.d. of individual probability forecast ($\bar{\sigma}_t$)	Disagreement of point forecasts ($\sigma_{\pi,t}$)	Standard deviation of aggregate histogram ($\sigma_{A,t}$)	Entropy of the aggregate histogram ($\tau_{\pi,t}$)
Market Based Measure (Breakeven Inflation)	0.66***	0.79***	0.72***	0.65***
Sample Period:	June 2013-June 2018			
	0.50***	0.48***	0.37***	0.22***

Notes: Number of observations is 69 for June 2013-February 2019 and 61 for June 2013-June 2018. (*), (**) and (***) represent statistical significance at levels of 10, 5 and 1 percent, respectively.

These results indicate that monitoring alternative measures of inflation uncertainty and assessing their relative movements may provide useful input for policy analysis. Survey-based measures and market-based indicators may be complementary to each other in gauging perceived inflation risks by economic agents.

Which variables are related to inflation uncertainty?

As a final extension, we study which economic variables are closely associated with our uncertainty measures. The purpose is not to seek causal inference, but to gain some insight regarding the relevance of our measures in terms of their relationship with related variables. Note that all of our five alternative uncertainty measures are constructed in time series dimension for the ease of comparability. On the other hand, the survey also includes individual-specific density forecast data, which allows us to construct direct uncertainty measures at the micro level and use them in panel regressions. Therefore, to exploit the cross sectional dimension, we first conduct panel regressions with individual level uncertainty, and then turn to time series analysis for a comparison of all alternatives.

Table 4 shows panel regression results where the dependent variable is the individual level inflation uncertainty measure constructed using density forecasts. We employ four variables to explain uncertainty: (i) annual inflation, (ii) monthly change in sovereign credit risk[16] (EMBI spread, i.e., the average spread between yields on FX denominated bonds issued by the treasury and the corresponding risk free security), (iii) one-month ahead inflation forecast error (surprise inflation) at the individual level, and (iv) forecast error for end-of-month USD/TRY exchange rate at the individual level (surprise USD).

The lag structure of regressors reflects the information set available to the forecaster by the time of the survey. The results indicate that inflation uncertainty is associated with the level of inflation and changes in sovereign risk premium. These findings are similar to the empirical results by Carvalho and Minella (2012), where it is shown that, for the case of Brazil, variations in inflation uncertainty can be largely explained by the change in inflation and EMBI spread. These authors use disagreement among forecasters as a proxy for uncertainty and conduct a time series analysis, while we are able to construct forecaster-specific direct uncertainty measures and use them in panel regressions. Having cross

[16] The surveys are generally conducted around mid-month during our sample period. Thus, for the EMBI spread variable, we take month-over-month change in the first 10 days average to reflect the information set available to the forecasters by the time of the Survey.

sectional dimension allows us to employ surprise inflation at the individual level as an additional explanatory variable. Our findings show that, subjective perception of inflation uncertainty is significantly associated with inflation surprises in addition to level of inflation and changes in the risk premium.

Table 4: Which Variables are Related to Individual Level Uncertainty? (Sample Period: June 2013-February 2019)

Dependent Variable: Individual forecast error standard deviation ($\sigma_{i,t}$)				
	(I)	(II)	(III)	(IV)
$Inflation_{t-1}$	0.005***	0.005***	0.005***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)
$\Delta EMBI_t$		0.031***	0.037***	0.033**
		(0.011)	(0.013)	(0.016)
$\text{Surprise Inflation}_{i,t-1}$			0.012**	0.011**
			(0.005)	(0.005)
$\text{Surprise USD}_{i,t-1}$				0.075
				(0.114)
Observations	3,021	3,021	2,606	2,596
R^2	0.440	0.442	0.432	0.433

Notes: The Table reports panel estimates from ordinary least squares regressions. All estimations include survey respondent fixed effects to control for the time invariant individual characteristics. Standard errors (shown in parentheses) are clustered at the survey respondent level. (*), (**) and (***) represent statistical significance at levels of 10, 5 and 1 percent, respectively.

Next, using the statistically significant variables in Table 4,[17] we run similar OLS regressions with time series data using five alternative uncertainty measures constructed in the previous section. Each column in Table 5 involves a different uncertainty measure as the dependent variable. Recall that the variable in the first column is the average standard deviation of individual level distribution forecasts. Second column reflects disagreement, i.e. cross-sectional dispersion of individual point forecast. The third column is a combination of these two measures, incorporating both individual level subjective uncertainty and disagreement among forecasters. The fourth column employs the concept of entropy and the final column represents the market-based measure of inflation risk.

Table 5: Which Macro Variables are Related to Uncertainty? (Sample: June 2013 - February 2019)

Sample Period:	June 2013 - February 2019				
Dependent Variable:	Average s.d. of individual density forecast ($\bar{\sigma}_t$)	Disagreement among forecasters ($\sigma_{\pi,t}$)	Standard deviation of aggregate histogram ($\sigma_{A,t}$)	Entropy of the aggregate histogram ($\tau_{\pi,t}$)	Market Based Inflation Uncertainty Measure (RP)
$Inflation_{t-1}$	0.007***	0.121***	0.079***	0.059***	0.315***
	(0.001)	(0.016)	(0.009)	(0.006)	(0.072)
$\Delta EMBI_t$	0.054***	0.332	0.362***	0.193**	2.724**
	(0.012)	(0.231)	(0.136)	(0.093)	(1.075)
$\text{Surprise Inflation}_{i,t-1}$	0.013***	0.123**	0.051	0.004	1.287***
	(0.003)	(0.058)	(0.042)	(0.022)	(0.227)
Constant	0.263***	-0.390***	0.082	1.284***	-2.500***
	(0.007)	(0.142)	(0.083)	(0.058)	(0.648)
Observations	68	68	68	68	68
R^2	0.644	0.775	0.749	0.742	0.636

Notes: The table reports estimates from ordinary least squares regressions. Robust standard errors are in parentheses. (*), (**) and (***) represent statistical significance at levels of 10, 5 and 1 percent, respectively.

[17] Inflation surprise variable is now the *average* forecast error of all respondents, because regressions are in time series form.

The results suggest that all uncertainty measures are strongly associated with the level of inflation, which is in line with other studies. Inflation surprises and changes in sovereign credit risk have a significant relation with four of the five indicators. Overall, inflation variables and a measure of sovereign risk premium explain a sizable fraction of the variation in inflation uncertainty as depicted by high R^2 values.

Conclusion and Final Remarks

Using survey and market data, we have constructed various measures of inflation uncertainty for Turkey. Our focus is not to provide an exhaustive list of uncertainty indicators, but to present timely and intuitive direct measures that can be tracked and monitored regularly for practical policy analysis. To our knowledge, this is the first study constructing and analyzing direct measures of inflation uncertainty from density forecasts in an emerging market economy.

Uncertainty is an unobserved variable and hence it is not possible to assess the absolute signaling power of each measure by comparing it with a true benchmark. We lend support to the relevance of our measures by comparing survey-based indicators with a market-based measure and by evaluating their co-movement with related macroeconomic variables. Uncertainty measures seem to be consistent with the movements in relevant macro indicators. Moreover, survey-based measures exhibit high correlation with the market-based counterpart especially during sharp movements in inflation, suggesting that our indicators capture common movements in inflation uncertainty. Overall, the measures derived in this paper have the potential to be useful in assessing the risks to inflation outlook and pricing behavior.

In contrast with many studies in the literature, disagreement among forecasters in our case seem to offer complementary and useful information for gauging inflation uncertainty. Some previous research on survey-based measures of inflation uncertainty argue that the most relevant indicator of inflation uncertainty is obtained using density forecasts at the individual level.[18]Dispersion among professional forecasters are not found to be a good proxy for uncertainty, as it has shown to exhibit relatively weak correlation with direct measures of individual inflation uncertainty. However, in an emerging market economy context such as the Turkish case, disagreement among forecasters appears to be a reasonable measure in terms of tracking market-based indicators of uncertainty. One possible explanation is relatively more volatile inflation environment and lower degree of anchoring in inflation expectations, which might lead to high correlation between disagreement and uncertainty.[19]

Finally, our results also highlight the value of price stability from a welfare perspective. We find that all survey measures of inflation uncertainty are significantly associated with the level of observed inflation. This result holds even with a level-independent uncertainty measure such as the one calculated using the notion of entropy. Although causality is likely to run both ways, these results nevertheless underscore the traditional welfare-reducing role of inflation through higher uncertainty, and hence support the rationale for achieving price stability.

[18] See Rich and Tracy (2010) and the references therein.
[19] This finding is in line with the implications of the model presented in Lahiri and Sheng (2010).

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APPENDIX: Formal Representation of Inflation Uncertainty Measures

This section presents an analytical exposition of the standard deviation-based uncertainty measures used in the study and shows the relationship between them. For simplicity purposes, we assume that there are no missing observations and the number of panelist are fixed with n participants.

Let density forecast at time t be a random variable Π with a probability distribution of $f_{i,t}(\pi), i = 1, \dots, n$ for a survey of n individuals.[20] We assume that the individual point forecasts, $\pi_{i,t}^{e}$, are the means of individual forecast densities with individual variances $\sigma_{i,t}^{2}$ at time t. Intervals for each bin ($b = 1, \dots, 7$) to which the respondents attach a probability are defined as in Table 1. $M_{i,b,t}$ denotes the mid-point of bin b of respondent *i*'s probability distribution at time t. In order to calculate $\sigma_{i,t}^{2}$ we use the following formula:

$$\sigma_{i,t}^{2} = \sum_{b=1}^{7} (M_{i,b,t} - \pi_{i,t}^{e})^{2}\, p_{i,b,t} \qquad \textbf{(A.1)}$$

where $p_{i,b,t}$ shows the probability that the forecaster *i* assigns to the b^{th} interval at time t. Then we take the square root of $\sigma_{i,t}^{2}$ to get the standard deviation of individual histograms ($\sigma_{i,t}$). Lastly, we calculate the average standard deviation of individual histograms, which we denote by $\overline{\sigma_t}$, by taking the average of $\sigma_{i,t}$ across forecasters. That makes our first measure of uncertainty:

$$\overline{\sigma_t} = \frac{1}{n}\sum_{i=1}^{n} \sigma_{i,t} \qquad \textbf{(A.2)}$$

Our second inflation uncertainty measure is disagreement among forecasters. This measure is defined as the cross sectional dispersion across survey participants' point forecasts, which is basically the standard deviation of survey participants' point forecasts at time *t*, denoted by $\sigma_{\pi,t}$. Standard deviation is computed by taking the square root of the variance ($\sigma_{\pi,t}^{2}$) which is defined as follows:

$$\sigma_{\pi,t}^{2} = \frac{1}{n}\sum_{i=1}^{n}\left(\pi_{i,t}^{e} - \frac{1}{n}\sum_{i=1}^{n} \pi_{i,t}^{e} \right)^{2} \qquad \textbf{(A.3)}$$

The third measure of uncertainty is constructed using aggregated density forecasts by computing standard deviation of aggregate histogram, denoted by $\sigma_{A,t}$, which is derived by aggregating individual density forecasts (across n forecasters). In notational form, the aggregate density forecast is

$$f_{A,t}(\pi) = \frac{1}{n}\sum_{i=1}^{n} f_{i,t}(\pi) \qquad \textbf{(A.4)}$$

with the first moment (the average point forecast) and the second moment as

$$\mu_{1,t}' = \frac{1}{n}\sum_{i=1}^{n} \pi_{i,t}^{e} = \pi_{A,t}^{e} \qquad \mu_{2,t}' = \frac{1}{n}\sum_{i=1}^{n} ({\pi_{i,t}^{e}}^{2} + \sigma_{i,t}^{2}). \qquad \textbf{(A.5)}$$

Hence the variance of the aggregate density forecast is

[20] As the sample has missing observations, the variable *n* does not stay constant through time. That means *n* is time varying. However, we drop the time subscript on *n* for notational simplicity.

$$\sigma_{A,t}^2 = \frac{1}{n}\sum_{i=1}^{n}\sigma_{i,t}^2 + \frac{1}{n}\sum_{i=1}^{n}(\pi_{i,t}^e - \pi_{A,t}^e)^2 \qquad \textbf{(A.6)}$$

Equation A.6 states that the variance of the aggregate density $\sigma_{A,t}^2$ incorporates both individual level uncertainty (first term) and disagreement among forecasters (second term).[21] Therefore, this is a hybrid measure combining the information in individual density forecasts and cross sectional dispersion among point forecasts of participants. One drawback of this measure is the possibility that in some cases cross-sectional dispersion (second term in Eq. A.6) may dominate individual uncertainty (first term) because surveys may impose a fixed narrow range for individual probability distributions, while there is typically no boundary limit for point forecasts.

The standard deviation of the aggregate density $\sigma_{A,t}^2$ is computed using aggregated histogram, which is prepared by the CBRT Statistics Department and regularly published at the CBRT official website. Aggregated probability distributions of inflation expectations are reported in a tabular form, including upper and lower limits of the intervals with assigned probabilities. Although this does not reflect the exact aggregate distribution as defined in Equation A.4, it provides a reasonable approximation.

[21] See Giordani and Soderlind (2003) and Boero et al. (2008) for a more detailed discussion.

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