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JEL classification: C82, E01, D80

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Abstract

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1 Introduction

Economic statistics, in particular important measures of economic activity such as real GDP growth, are subject to data revisions. GDP revisions seek to improve the accuracy of initial estimates by incorporating new information not available at time of the earlier data release and can include methodological improvements. More broadly, data revisions are one manifestation of "data uncertainty", with Manski (2015) distinguishing between "transitory", "permanent" and "conceptual" data uncertainties. This veil of uncertainty implies that agents need to consider how future data revisions affect their assessments of current economic conditions. Indeed, uncertainty about current estimates of economic activity and inflation has been used to explain how cautious, smooth changes in monetary policy can be optimal (e.g. see Aoki, 2003). Data uncertainty can also lead to disagreement among private agents about the current state of the economy, even after the first estimate of GDP growth is released; this can result in strategic uncertainties that can cause business cycles due to waves of optimism and pessimism as in Angeletos et al. (2018).

Although there is strong evidence that the unreliability of initial releases of economic statistics affects policy-making (e.g. see Orphanides, 2001; Croushore, 2011), statistical offices and policy-makers do not usually release measures of data uncertainty to accompany initial data releases.[1] The Bank of England and the Riksbank in their "Monetary Policy Reports" are exceptions.[2] They provide their own (quantitative) estimates of data uncertainty for historical real GDP growth values, evidencing a direct link between data uncertainty and monetary policy decisions. However, in general statistical offices continue to present headline GDP estimates as point estimates, arguably conveying a misleading degree of reliability in these data. This type of communication is common across national statistical offices - as emphasised by Manski (2015, 2018) and van der Bles et al. (2019).[3]

This paper evaluates if and how different methods of communicating GDP data uncertainty

[1] The Office for National Statistics (ONS) in the UK, for example, currently publish their first release estimates of GDP around 40 days after the end of the reference quarter. Via supporting documentation, available from the ONS website, users can learn that the data content of the ONS's first GDP estimate is 80% (measured by the output approach), 40% (income approach) and 60% (expenditure approach) see https://www.ons.gov.uk/economy/grossdomesticproductgdp/articles/introducinganewpublicationmodelforgdp/2018-04-27.

[2] Prior to November 2019 the Bank of England published its fan charts for historical GDP growth in their "Inflation Report".

[3] This communication practice runs counter to the fact that economic statisticians have long been aware of the importance of quantifying and communicating the uncertainties associated with economic statistics; see Kuznets (1948) and Morgenstern (1950). van der Bles et al. (2019) do note, however, that some statistical offices do regularly communicate sampling errors for labour market statistics, including aggregate employment and unemployment data.

affect the public's perceptions of current GDP values, their understanding of data uncertainty and their trust in the statistical office. Following a recent literature evaluating the impact of monetary policy communication on the public's expectations of inflation (Haldane and McMahon, 2018; Coibion et al., 2019) and on their trust and understanding of policy messages (Bholat et al., 2019), we employ a randomised controlled trial.

Clements and Galvao (2017) and Galvao and Mitchell (2019) consider how professional forecasters and policymakers quantify data uncertainties, specifically due to data revisions. But there is no empirical evidence as to whether, arguably, less *sophisticated* users of economic statistics, like households and businesses, are able to evaluate the likely impact of data revisions on their real-time assessments of the current state of the economy. Given that statistical offices do not communicate quantitative measures of uncertainty in their GDP press releases, the public may take early GDP point estimates at face-value. Or they may infer their own error magnitudes around the numbers presented to them. We do not know.

This paper firstly seeks to fill this information gap by using a randomised trial, conducted online, to assess if and how the UK public interpret and understand GDP data uncertainty.[4] We randomly sample more than 3,000 (nationally representative) adults. The GDP data are communicated to individuals in the trial control group in a format that mimics recent Office for National Statistics (ONS) press releases. We then take a further step by evaluating how different ways of communicating and visualising data uncertainty may affect user comprehension and interpretation of data uncertainty. This last step is implemented by measuring the effects of a set of randomised GDP data uncertainty communication *treatments* on a set of *outcomes*. These outcomes include the public's understanding of the causes of data revisions and their trust in the data producer.

We complement our empirical evidence with a separate survey of professionals (many of whom are economists), working mainly in government institutions, industry and academia. Comparison with the public survey is instructive both in identifying if and how heterogeneities across users affect understanding and, in turn, whether there are differing implications for how data uncertainty should be communicated to different audiences. This so-called "expert" survey also affords us the possibility of asking broader, more open-ended qualitative questions about data uncertainty and its communication.

This paper therefore picks up Manski's (2015, 2018) call for empirical studies on how communication of uncertainties associated with economic statistics affects users. Similar calls have been

[4] Our focus is written communication; we do not consider oral news reports, such as radio.

made by Spiegelhalter et al. (2011) and van der Bles et al. (2019) in wider inter-disciplinary contexts. Using examples across different fields, Spiegelhalter et al. (2011) show that probabilities (even when known) are notoriously hard to communicate whether via words, numbers or graphs. Empirical evidence is needed to establish what is understood and by whom.

We find that the majority of the public understand that there is uncertainty inherent in GDP numbers as typically communicated to them; but communicating uncertainty information improves the public's understanding of why data revisions happen. It encourages them not to take GDP point estimates at face-value, but does not decrease trust in the data. Our evidence suggests that it is especially helpful to communicate uncertainty information quantitatively using intervals, density strips and bell curves.

The plan of the remainder of this paper is as follows. Section 2 details the three main measured responses or outcomes of both the public and expert surveys. It motivates our survey questions, including with reference to the small but growing literature on uncertainty communication outside economic statistics, especially meteorology. In addition, Section 2 explains how we measure GDP data uncertainty, due to data revisions; and it sets out our six candidate ways of communicating this uncertainty - our *communication tools*. These (with one constituting the control) form the five treatments that are then randomised in the public trial.

Section 3 then analyses the common results from the public and the expert surveys. It first provides some summary statistics from both surveys, before considering how the survey results let us address the significance of average treatment effects on the outcome choices of interest. Section 4 analyses those questions specifically designed for the expert survey. Section 5 concludes. Appendices (online) contain supplementary material. Appendix A lists the two survey questionnaires and provides some summary statistics. Appendix B provides a more detailed qualitative discussion of the more open-ended questions from the expert survey, as summarised in the main paper; and provides additional results referred to in the main paper but not reported (for space reasons).

2 Data And Survey Design

In this section, we describe and motivate the design of both the public and the expert surveys.

The public survey was conducted online as a randomised controlled experiment. It was designed to assess how the public react to uncertainty information, if and when communicated to them in different ways. To keep our surveys manageable, and without much larger sample sizes, we focus on five candidate ways of communicating and visualising uncertainty, two of which are qualitative and three quantitative. These communication tools are detailed in Table 1; and discussed further in section 2.3.2.

The effects of these five communication tools on the public's understanding of data uncertainty will be contrasted with the effects of communicating, in effect, the current ONS headline press release to a *control* group. There is no (explicit) mention of uncertainty in this press release. Our sample size of about 3,000 respondents means that around 500 respondents are in each of our six groups. Respondents are randomly allocated into one of these six groups - the *control* group (presented with no uncertainty information) and five *treatment* groups (presented with uncertainty information). This randomisation lets us identify the causal effects of different ways of communicating uncertainty information (e.g., see Stock and Watson, 2014, ch. 13). The public survey, implemented by Dynata, takes a representative sample of the UK population (across age, gender and region using a quota sample).[5]

In contrast, the expert survey (run separately to the public survey) follows a non-probability sampling method. This was aimed at maximising the number of respondents across a range of expert user groups (industry, government institutions and academia), rather than ensuring representativeness. Unlike the public survey, sample sizes are insufficient to apply different communication treatments by allocating survey respondents into groups. As such, analysis of it does not claim to make any generalisations to the wider population of economic statistics users nor does it facilitate causal inference. Rather, the aim is to identify and discuss common themes, and identify the range and diversity of views. Nevertheless, the overlapping questions in the public and the expert survey allow us to assess whether more experienced users of economic data understand data uncertainty differently to the public. The expert survey also included more technical and broader questions about the communication of uncertainty both to the public and to (more regular) users of economic statistics.

The next section delineates the three main measured responses or outcomes evaluated in both the 19-question public survey and the 26-question expert survey. The survey questionnaires are listed in full in Appendix A. We then describe the data uncertainty communication tools subsequently evaluated by randomising the treatment in the public survey.

[5] Dynata (formerly Research Now, when the survey was run) is a global online sampling and digital data collection company. Invites are randomised and a survey router is used to support randomisation. The samples are taken from the actively-managed online panels maintained by Dynata and draw on a mixture of sources (invitation only, online partnerships and online sites). Dynata follow the ESOMAR guidelines https://www.esomar.org/what-we-do/code-guidelines.

2.1 Survey Outcomes

2.1.1 Perception Of Uncertainty In GDP Numbers

Our first outcomes relate to how people interpret or react to economic data when presented to them as point estimates (i.e. when no uncertainty information is presented). Thereby we evaluate (both the public's and experts') perceptions of single-valued GDP numbers. For the public survey, this involves comparison of outcomes against the five *treatment* groups that are presented with uncertainty information via one of our *communication tools*. Here we focus on qualitative perceptions of accuracy instead of more quantitative perceptions, considered in section 2.1.2 below.

Previous experiments, designed with similar aims, are to be found in the weather forecasting communication literature. Weather forecasting communication studies have found that where uncertainty information is not shown, people tend to make their own assumptions (see Joslyn and Savelli (2010) and Morss et al. (2010)) and can tend to over-estimate uncertainty.

Accordingly, a range of questions ask about qualitative and quantitative perceptions of single-valued GDP numbers as commonly emphasised in headline statistical press releases.[6] Specifically, having been told that the ONS's latest GDP growth estimate is a given number (1.5% was the latest number at the time we ran the surveys), respondents are first asked (question 11 in the public survey, question 7 in the expert survey): "`How accurate do you think the first estimate of GDP growth of 1.5% is likely to be?`" (possible replies: `very accurate`, `fairly inaccurate`, `not very accurate` and `very inaccurate`). Follow-on questions then probe further. They ask about respondents' qualitative expectations that GDP numbers are revised (e.g. question 14 in the public survey, question 10 in the expert survey): "`How surprised would you be if ONS issued a statement 3 months later which corrected the estimate for GDP growth to 2%?`" (possible replies: `very surprised`, `fairly surprised`, `not that surprised` and `not at all surprised`). And the respondents are asked about their confidence that the economy really grew at the specific rate of 1.5% indicated by the point estimate in the (mock) data press release.

2.1.2 Quantitative Perceptions Of Data Uncertainty

The weather forecasting literature suggests that the public's understanding of our quantitative uncertainty communication tools may relate to their ability to understand probabilities. For example, Handmer and Proudley (2007) use surveys to assess whether people's understanding of the uncer-

[6] See Appendix A and questions 11-19 in the public survey and questions 7-13 in the expert survey.

tainty in weather forecasts depends on how probability statements are communicated. They find that most lay users do understand probabilities, but that it can matter whether the uncertainty is communicated verbally or numerically. Joslyn and Savelli (2010) find, using an online survey, that the public understands that there is uncertainty inherent in point forecasts. And they argue that the provision of explicit uncertainty estimates may be necessary to overcome some of the anticipated forecast biases that may affect the usefulness of weather forecasts given their uncertainties. Complementing this, Joslyn and LeClerc (2013) find that providing uncertainty forecasts associated with weather forecasts increases trust in the forecast and gives people a helpful idea of the range of possible outcomes.

To measure our survey participants' understanding of data uncertainty, communicated via the tools described in section 2.3 below, we compare their own (subjective) quantitative assessments of GDP uncertainty with the (objective) measures of data uncertainty communicated to them; we describe how we measure *true* (from the perspective of the public) data uncertainty in section 2.3.1. Our approach is based on the general *desiderata* that the public's understanding and use of any uncertainty information should be consistent with how the data communicator should like them to use it. In other words, if the data communicator does have a specific variance in mind, say, that characterises uncertainty, then we should hope that this uncertainty information is communicated in such a way that aligns the public's understanding of uncertainty with this variance estimate.

Our surveys evaluate respondents' ability to interpret and quantify the uncertainty information provided by asking (questions 12 and 13 in the public survey, 8 and 9 in the expert survey): "`I would not be surprised if actual GDP growth was as high (or low) as: _ provide #`" and (questions 15 and 16 in the public survey; 11 and 12 in the expert survey): "`What do you think is the chance that GDP grew by exactly 1.5% [or between 1.2% and 1.8%]?`" (possible replies from `virtually certain - about a 99 in 100 chance (99%)`, through `very likely - about a 9 in 10 chance (90%)...` to `exceptionally unlikely - about a 1 in 100 chance (1%)`).

In posing these questions and communicating the uncertainty information via the communication tools, we deliberately use both words and numbers to describe the possibilities. This is because, as Spiegelhalter et al. (2011) emphasise, it can be hard to use words to convey precise probabilistic (uncertainty) information. One person's *very certain* may be different to another's. And if words are used, which ones: natural frequencies (e.g., one-in-ten) or probabilities (e.g., 0.1)? Textual or verbal uncertainty statements have been found to be interpreted differently by different people; e.g., experiments reported by Budescu et al. (2009) reveal large differences in the way people understand the verbal uncertainty phrases used by the Intergovernmental Panel on Climate Change. They recommend accordingly that both verbal terms and numerical values are used to communicate uncertainty - and we follow this practice.

A large literature in psychology and behavioural economics has found that people often make mistakes when making decisions in the face of uncertainty (see Kahneman and Tversky, 1979). As a consequence, it is of interest to assess how communication of uncertainty information affects users' decision-making. Empirical research in other disciplines has found that providing uncertainty information to users of uncertain data tends to help them make better decisions. This evidence often comes from running experiments on students or the public to see how uncertain weather *forecasts* are interpreted and used; e.g., see Joslyn and Savelli (2010), Marimo et al. (2013) and Roulston and Kaplan (2009). In particular, experiments evaluate whether people have different probabilistic thresholds (because of different loss functions and attitudes to risk) for taking 'action' given the uncertainty estimate; see Joslyn and Savelli (2010), Morss et al. (2010), Peachey et al. (2013) and Kox et al. (2015). But as Visschers et al. (2009) stress, in an inter-disciplinary review, the effects of different communication formats depend on the context.

In a macroeconomic policy decision-making context, the use of provisional data, that is, data subject to data revisions and other uncertainties, has been shown to affect monetary policy decisions in the models of Aoki (2003), Svensson and Woodford (2003) and Neri and Ropele (2014). In the context of our public survey, respondents may be "low stakes users" (as defined by Raftery (2016)), since their understanding of GDP data uncertainty may only have limited direct effects on their decision making. For example, macroeconomic conditions may well have an impact on household decisions to buy/sell a house. However, the quantitative links between GDP growth and house prices are themselves uncertain and not easily understood. As a consequence of the challenge of relating GDP data, and its uncertainty, to individual decisions made by members of the public, we focus on the decision-making effects of data uncertainty in our expert survey. We ask the experts how large the revision to the GDP estimate would have to be for them to reconsider their monetary policy advice (see q14, Appendix A1).[7] This question is therefore intended to mimic the sorts of questions used in surveys of users of weather forecasts (e.g. see Morss et al. 2010) in identifying

[7] Specifically, the experts are asked: "`Suppose you are regularly asked for your advice on UK monetary policy. Imagine that your latest advice is conditioned on this 1.5% GDP growth rate for the year to 2018Q3. Now imagine that the ONS does revise this 1.5% estimate upwards in the future. How big would the revision need to be for you to reconsider your advice?`".

thresholds for taking 'action' given uncertainties; see also Joslyn et al. (2007), Nadav-Greenberg and Joslyn (2009) and Joslyn and LeClerc (2012). It is also directly linked to the literature on the impact of data uncertainty on optimal monetary policy decisions (as, for example, modelled in Aoki, 2003).

The expert survey is also a means to understand how current and alternative uncertainty communication tools are perceived. Firstly, the experts are asked questions that reveal what they think of the public's understanding of uncertainty. They are asked to indicate their level of satisfaction with how uncertainty around economic statistics is communicated to the public by journalists and the media. Secondly, the experts are asked about how they and other (regular) users of economic statistics understand uncertainty; and about how satisfied they are with how uncertainty information is communicated to them by different agents, including the statistical office and the central bank. Thirdly, the experts are asked to rank and appraise the three contrasting visualisations of uncertainty presented to three of the groups in our public survey.

2.1.3 Trust And Attitudes To Data Revisions

There is sometimes believed to be a risk that communicating uncertainty information will erode trust in the data or indeed the data producer and/or communicator themselves. In turn, that trust may be affected by how the uncertainty information is communicated.[8] As a consequence, we also evaluate the impact of uncertainty communication tools both on trust in the statistical office and on the public's beliefs about the sources of data revisions.

Research outside economics has found that simple indicators of uncertainty can be preferable (cf. Intergovernmental Panel on Climate Change (IPCC) - see Budescu et al., 2009); it has found that communicating uncertainty information can, in fact, increase trust. For example, Joslyn and LeClerc (2013) find that including numerical uncertainty estimates with weather forecasts increases trust. But trust in the data producer might be related to how well uncertainty, and its sources, is understood.[9] It may well be that attitudes as well as trust affect how people interpret and react to uncertainty information. This has been found to be important when communicating climate change nowcasts and forecasts; e.g. see Visschers (2018).

[8] We do not pursue this here, but Raftery (2016) also considers how statistical calibration of the uncertainty estimate (of the sort studied in Galvao and Mitchell, 2019) may affect the confidence or trust in the forecast, with confidence and trust increasing as calibration improves.

[9] For example, people may not understand the process around data collection for economic data, and therefore misinterpret information communicated to them about economic data uncertainty as evidence that the ONS has made mistakes or been incompetent.

Our surveys therefore seek to capture aspects of trust in GDP numbers and if and how this relates to attitudes to and understanding of revisions to these numbers. Question 9 in the public surveys asks: "`Personally, how much trust do you have in economic statistics produced by the Office for National Statistics (ONS)? For example, on unemployment, inflation or economic growth?`". Then question 17 in the public survey (question 15 in the expert survey) goes onto ask: "`ONS regularly publishes revisions to their GDP estimates. Why do you think they do this?`". Respondents are invited to tick on seven possible reasons for revisions, including mistakes at the ONS and the availability of more information.

2.2 Survey Design: Additional Considerations

The public survey, in particular, was structured so that the respondents should not anticipate that the survey is about data uncertainty *per se*, at least until partially through the survey. This was to minimise the chances of framing responses. Respondents were not allowed to go back to previous questions in the survey, i.e. operationally the survey always moves forward, with the respondent retaining sight of the randomised communication tools (as shown in Table 1 and detailed in section 2.3.2 below).

Neither survey is intended to capture conceptual uncertainties associated with how GDP is or should be measured. To control for the fact that the public may not know what GDP measures, and that this may affect their responses, they were directly asked what they think GDP is (question 10): "`To the best of your knowledge, which option most accurately describes what GDP is?`". Respondents could then reply that GDP measures the increase in prices, how many people are in employment, the size of the economy, the difference between exports and imports, they have no clue or they have heard about GDP but are not sure what it is. After this question, if respondents either did not answer correctly (by agreeing that GDP measures the size of the economy) or did not answer the question, the survey provided these respondents with an explanation of what GDP does measure. They are reminded that "Gross domestic product (GDP) growth is the main indicator of economic performance" - a phrase taken directly from ONS's own GDP press release.

2.3 Communication Tools

2.3.1 Quantifying Data Uncertainty

To maximise realism, both surveys asked questions about the ONS's latest GDP estimates and headline press release. At the time of running the surveys, in late 2018/early 2019, this concerned the GDP estimate for 2018Q3 published by ONS on 9th November 2018. We present the year-on-year growth rate of 1.5%. This is based on the view that the public, arguably, are more familiar with year-on-year growth estimates presented over calendar years than quarterly growth rates. Our intention in this survey is not to test the public's ability to understand and interpret different change measures. So we chose to frame our questions around, we believe, the most widely understood measure of growth.

In the absence of official information, from the ONS, quantifying GDP data uncertainty in the UK[10], we assume a distributional form for the uncertainty around the ONS GDP point estimates. Specifically, we use estimates from Galvao and Mitchell (2019), based on a recent revisions analysis of ONS GDP estimates, to quantify "transitory" data uncertainty. Other sources of data uncertainty, for example due to limitations of the survey methodology, are not represented; and methodological work on measuring non-sampling errors continues (e.g. see Manski, 2016).[11]

We characterise GDP data uncertainty via a Gaussian density, centered on the ONS first-release point estimate, with standard deviation equal to the historical standard deviation of revisions to this first estimate over the subsequent four years. After four years, GDP growth estimates in the UK have gone through at least four annual (*Blue Book*) revisions; and revisions beyond this point tend not to reflect the arrival of additional survey information but methodological changes. The standard deviation of these revisions in the 20-year window between 1993Q2 and 2013Q1 is 0.8% and the mean absolute revision is 0.7%.[12] We assume zero mean revisions, i.e. we assume the first release is an unbiased estimate of the revised estimate. This assumption, as shown in Galvao

[10] To quote the ONS: "The estimate of GDP ... is currently constructed from a wide variety of data sources, some of which are not based on random samples or do not have published sampling and non-sampling errors available. As such it is very difficult to measure both error aspects and their impact on GDP. While development work continues in this area, like all other G7 national statistical institutes, we don't publish a measure of the sampling error or non-sampling error associated with GDP". See https://www.ons.gov.uk/economy/grossdomesticproductgdp/methodologies/grossdomesticproductgdpqmi

[11] Although ONS do report and analyse data revisions, they note explicitly at https://www.ons.gov.uk/economy/grossdomesticproductgdp/methodologies/grossdomesticproductgdpqmi that "there is no simple way of measuring the accuracy of GDP" and go onto emphasise that while revisions tell us something about "reliability" "there are other aspects to accuracy, which revisions analysis cannot attempt to measure" (e.g. if a lower response rate than normal is received the estimates are more uncertain even if they are not subsequently revised).

[12] We continue to consider year-on-year growth rates.

and Mitchell (2019), holds better for more recent ONS data. The Bank of England also assume that historical GDP data uncertainty is characterised by a Gaussian density. Their estimates of the standard deviation to first release estimates of GDP growth have tended to increase since first published in 2007: they have fluctuated between 0.6% and 1.1%. Accordingly, to be broadly consistent both with the real-time data evidence in Galvao and Mitchell (2019) and practice at the Bank of England, we use a standard deviation estimate of 0.8% when quantifying GDP data uncertainty.[13] Based on these standard deviation estimates and the assumption of Gaussianity and mean zero revisions, the 90% confidence interval around a point estimate of 1.5% is 0.2% to 2.8%.

Based on these estimates, we pose questions (particularly q16 in the public survey and q12 in the expert survey) to test how well the public do at inferring this uncertainty; and, if communicated to them in different ways, how well they understand it. Our surveys assume the true data density has a mean of 1.5% and is such that the probability of GDP growing between 1.2% and 1.8% is about 30%. As already explained in section 2.1.2, the *better* the uncertainty information is communicated, the more the public's understanding of uncertainty should align with our assumed "true" density estimate.[14]

2.3.2 Data Uncertainty Communication Tools

In principle, for a given quantification of uncertainty, we might follow van der Bles et al. (2019) and delineate nine candidate ways of communicating this uncertainty: (i) a full explicit probability distribution (e.g., a fan chart); (ii) a summary of a distribution; (iii) a rounded number, range or an order-of-magnitude assessment; (iv) a predefined categorisation of uncertainty; (v) a qualifying verbal statement; (vi) a list of possibilities or scenarios; (vii) informally mentioning the existence of uncertainty; (viii) no mention of uncertainty; (ix) explicit denial that uncertainty exists. The list follows a scale from the most comprehensive communication device, (i), to the narrowest one, (vii), including no communication of uncertainty and indeed denial of its existence (viii and ix).

In turn, for each of these nine communication options, there are different ways of communicating and visualising the uncertainty. Experimental evidence outside economic statistics has begun to investigate how different visualisations of uncertainty and indeed the uncertainty of visualisation

[13] We refer the reader to Galvao and Mitchell (2019) for further analysis of UK data revisions and evidence that the nature of data revisions in the UK has changed over time and that data revisions in the UK have both "news" and "noise" components.

[14] One might suspect that the public's reaction to and interpretation of uncertainty information is not independent of the business cycle or the state of the economy. Because our experiment was run during a period of high policy uncertainty, due to Brexit, it is not clear if and how our results extend to periods of low(er) economic uncertainty. This is a topic for future research.

matter; see Joslyn and LeClerc (2013), Nadav-Greenberg et al. (2008), Tak et al. (2015), Correll and Gleicher (2014) and Padilla et al. (2015). See Brodie et al. (2012) for a review. In an investment context, Driver et al. (2010) investigate whether using a pictorial presentation of risk, in the form of a synthetic *risk reward* indicator, helps people make better investment choices. Again they use an experimental approach, which allows them to assess the impact of different designs after controlling for differences in the sample of people seeing the different designs.

Even when not presented with a full probability density function to represent the uncertainty (like (i) on the nine-point scale above), users may still try to infer the underlying density function from the incomplete uncertainty information that they are provided. Tak et al. (2015) and Dieckmann et al. (2015, 2017) find that when presented with range estimates (like (iii) on the scale above) users in their experiments still seek to impose their underlying (subjective) density function on these range estimates; and this is again affected by the motivations of the user of the uncertainty estimates.

Each group in our public survey is presented with a statement based on the GDP growth estimate of 1.5% published by ONS on 9th November 2018. Specifically, after ten introductory questions (see Appendix A1) that identify individual characteristics and the test and reminder of what GDP measures, the survey informs the respondents that:

> *The Office for National Statistics (ONS) publishes estimates of GDP growth. You will be asked a number of questions about this, so please take time to read the ONS statement below.*

Then each of the randomised six groups is presented with a different GDP communication tool. These tools are shown in Table 1. The control group are presented with something that closely resembles the current ONS headline press release. Groups 2 and 3 are presented with a qualitative, qualifying verbal statement. Groups 4 to 6 are presented with a quantitative impression of GDP data uncertainty. For the expert survey (classified as Group 7 in Table 1), we use the main statement from the current ONS press release.

These statements and the allotted data uncertainty communication tool are kept in front of the respondents throughout the survey. So as the respondents move through the survey questions they can always see their randomly allocated GDP communication treatment. We do not wish to test a respondent's memory.

In choosing how to communicate uncertainty to survey participants we made some choices in the interests of parsimony. For example, while the colour of an uncertainty graph may well matter, we just use a common colour across treatments - to avoid this affecting cross-group behaviour.[15] The quantitative measurements of uncertainty presented to Groups 4 to 6 use knowledge we as survey designers have (but the survey respondent does not) on what the *true* data density is assumed to be given our quantification of uncertainty (as explained in section 2.3.1 above).

The control group, Group 1, are therefore not presented, directly, with any uncertainty information beyond the textual reference to uncertainty, given that the ONS do refer to their GDP numbers as "estimates". Group 2 respondents are warned explicitly that the number is approximate. This communication tool is deliberately only a minor tweak on the baseline stimulus above, in that it now also includes *about*. We are therefore following in the spirit of the IPCC (see Budescu et al. (2009)) in providing a textual confidence indicator. For Group 3, what is added is that we are now warning respondents that the number is both approximate but also providing more textual information on the fact that the values are subject to revisions and that the 1.5% number is likely to change.

Three different visualisations of data uncertainty, as quantified in section 2.3.1, are communicated to Groups 4 to 6. The amount of uncertainty information communicated increases from Group 4 to Group 6. For Group 4, in addition to the qualitative information presented to Group 3, we present a 60% confidence interval. We also include some details on how to interpret the probabilistic information communicated.[16] Group 5 are then presented with a density strip that provides additional information on how the probability mass is allocated across three 30% probability bands. Finally, Group 6 are provided with a distributional form for this uncertainty; this involves presenting Group 6 with a bell curve. It is shaded like a fan chart, following recent practice at the ONS.[17] In turn, this builds on the Bank of England's pioneering approach to the communication of both historical and future uncertainty via its fan charts.

Finally, the communication tool applied to the expert group (recall this survey is run separately to the randomised trial) follows current ONS press releases in informally informing experts of the existence of uncertainty (like (vii) in the scale above) by using the word "estimate". This is a longer,

[15] As Spiegelhalter et al. (2011) discuss, there are in fact a broader set of candidate ways of representing the uncertainty about continuous quantities like GDP growth, including interactive web-based and infographic formats that we do not explore in this paper. We also had to decide what if any textual uncertainty information to publish alongside the graph.

[16] There was a typo in one instance of the online public survey that meant Group 4 were told there was a 3 in 10 chance that GDP growth fell outside the blue line, not a 4 in 10 chance.

[17] For example, see https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/internationalmigration/bulletins/migrationstatisticsquarterlyreport/july2018revisedfrommaycoveringtheperiodtodecember2017

more detailed, version of the communication tool applied to the control group in our public survey. We also ask experts to rank the three quantitative communication tools presented to Groups 4 to 6 in the public survey.

3 Survey Results

3.1 Summary Statistics

A total of 3,045 respondents from the UK public were recruited by Dynata, who implemented our public survey as detailed in Appendix A1. The survey was carried out using their online platform in the second week of December 2018. The summary statistics in Appendix A1 indicate that our sample is, as it should be by construction, representative of the UK population. The survey respondents are from all UK regions, cover all age brackets from 18, with varied educational levels and employment status.

Appendix A1 lists the 21 survey questions and summarises the public's responses by reporting the percentages that gave each answer. Some summary statistics that we mention upfront are: 50% of respondents claimed some knowledge of economics and correctly stated what GDP measures (question 10). 50% of the respondents had heard of the ONS before this survey; and only 15% do not trust the ONS.[18]

Before looking for treatment effects, we confirmed statistically that the split into six groups is indeed random.[19] This means that treatment is not correlated with individual characteristics; and we can therefore infer causal effects for the different uncertainty communication treatments by comparison against the control group (Group 1).

3.1.1 Expert Survey

The online expert survey was disseminated through the ESCoE (Economic Statistics Centre of Excellence) emailing list, social media particularly Twitter and emailing personal contacts and

[18] This is consistent with independent survey evidence. The 2019 *Public Confidence in Official Statistics* report, produced by the National Centre for Social Research (NatCen) on behalf of the UK Statistics Authority, similarly finds that 85% of people who gave a view trusted the statistics produced by ONS; see https://www.statisticsauthority.gov.uk/news/pcos-2019/

[19] To test random allocation, we take the answers to questions 1 to 10 as individual characteristics. We then use probit models to test whether individuals in each treatment group are statistically different from those in the control group. Reassuringly, we find no evidence of lack of randomness of the treatment (results not shown, available upon request). The only exception was for that group of respondents with a postgraduate degree (a Masters or PhD), where we found some statistical evidence that postgraduates were disproportionately allocated to some of the treatment groups. As a consequence, among our controls, we do include measures of educational achievement.

asking them to forward to colleagues. The recruitment period lasted for four weeks, between 18 February and 17 March 2019. The survey received 136 responses in total, of which 109 were fully completed. Respondents spent, on average, 15 minutes to complete the survey.

Appendix A2 lists the 27 survey questions and provides some summary statistics across experts' responses. It shows that most experts are regular users of GDP statistics. 74% used GDP and national account statistics during the past 12 months. Most experts use GDP statistics either quarterly (23%), monthly (25%) or weekly (18%). Again the expert survey covers all age brackets from 18, but with only 29% of the sample identifying as female compared with 51% in the public survey. The most represented employment sectors are academia and research (32%), ONS and Bank of England (17%), Government departments (15%) and private business (10%).

3.2 Measuring Treatment Effects On Individual Choices

To understand what influences the outcomes evaluated in the surveys, we model the respondents' choices to each question using probit models. We define binary outcomes by aggregating the ordinal choices for each question into two. For example, for question 11 (in the public survey) that asks for views about the accuracy of the GDP point estimate, the ordinal answers range from "very accurate" through "fairly accurate" and then "fairly inaccurate" to "very inaccurate": we set the outcome variable (y_i), for individual i, equal to 1 for the "very" and "fairly" accurate responses, 0 otherwise. Analysis (available upon request) based on ordered probit models, not discretising the responses, delivered very similar results; so, for ease of interpretation, we present results here using the binary choice models.

A set of control variables, to capture the individual characteristics, are also included in the probit models.[20] Note, however, that these controls do not measure causal/treatment effects; they provide information on the (partial) correlations between these control variables and the outcomes. We will defer discussing these individual characteristics further until we have looked at the treatment effects. We emphasise that for the public survey the estimated treatment effects with and without the controls are very similar; this is as might be expected, given that the treatments are random. But, as Gail et al. (1984) show, even in randomised experiments estimates of the treatment effect can be biased in nonlinear models with omitted explanatory variables. Hence our preference to run models with the controls included.

[20] We do not report results for specifications that include as controls separate dummies for the regions of the UK, as these were statistically insignificant and their inclusion did not affect inference.

In summary, we use the following probit model to test for statistically significant effects of treatment on the outcome variable:

$$Prob(y_i = 1) = \Phi\left(\alpha + \sum_{j=2}^{6} \beta_j D_i^j + W_i'\gamma\right) \text{ for } i = 1, ..., N, \tag{1}$$

($N = 3045$ for the 6 group public survey), where $\Phi(.)$ is the cumulative density function of the Gaussian distribution, $D_i^j = 1$ (0 otherwise) if individual i was randomly allocated to Group j (where $j = 1$ is the control group) and W_i is a $k \times 1$ vector of control variables with associated coefficient vector γ. Rejection of the null hypothesis that $\beta_j = 0$ indicates that communication tool j has a statistically significant effect on the probability of choosing $y_i = 1$. Because of randomisation, the average treatment effect can be measured as the difference in outcomes between the five groups presented with uncertainty information and the control group, only told that the GDP value is an estimate. This is measured by the marginal effects of D^j (for $j = 2, ..., 6$) on $Prob(y_i = 1)$, computed analytically at the sample average of all the regressors.[21] We can also assess the significance and estimate the marginal effects of the control variables via the estimates for γ. Note that the control variables are also binary variables.

We also use probit models to evaluate if and how the expert group differs from the control group. We estimate a probit model between the outcomes that are common across the public and expert surveys by including a seventh dummy variable for those respondents from the expert survey. As we did not collect as much individual data for the experts, this model is estimated without the controls. The probit model estimated to obtain estimates of β_7, that is, the difference in outcomes between the experts and the control group, is:

$$Prob(y_i = 1) = \Phi\left(\alpha + \sum_{j=2}^{7} \beta_j D_i^j\right) \text{ for } i = 1, ..., 3154, \tag{2}$$

and involves merging outcome choices that are common across both surveys. Results for the effect of expertise are presented as "G7: Expert" (when available) in Tables 2 to 4.

[21] These marginal effects are computed in Stata following Williams (2012), and they look at discrete changes of the binary regressors.

3.3 Qualitative Perceptions Of Uncertainty In GDP Numbers

Our analysis starts by evaluating survey respondents' qualitative assessments about the accuracy and uncertainty of GDP numbers.

A large proportion of the public control group (82%) and the expert survey respondents (86%) viewed the GDP point estimate, of 1.5%, as either "fairly or very accurate" (question 11 in the public survey; question 7 in the expert survey). Around half of respondents then said they would not be surprised if this estimate was revised to 2% during the next three months: 48% of the public control group and 68% of the expert respondents said they would either be "not that" or "not at all" surprised if this happened (question 14 in the public survey; question 10 in the expert survey). Consistent with this awareness of revisions, 65% of control group respondents also stated that they were not that surprised ("not that" or "not at all" surprised) that estimates of GDP are regularly revised (question 18 in the public survey).

To look beyond these averages, we estimate the probit models, in eqs. (1) and (2), to see how responses are affected by the different communication tools. In Table 2 we evaluate the effects of our different uncertainty communication treatments on three different survey outcomes (questions, denoted "q#"). These outcomes relate to the perceived qualitative accuracy of GDP estimates (q11) and to whether data revisions are surprising (q14 and q18). For each of these three outcomes, in the first column of Table 2 we present a t-statistic for whether the treatment is statistically significant compared to the control group (and for whether the control variables are statistically significant). Values in bold indicate statistical significance at the 10% level. In the second column, the marginal effects (at the mean of the other variables) measure the effect of the regressor of interest on the probability of a particular outcome. We present these marginal effects in percentage points. The bottom row of Table 2, denoted "G1 average", reports the percentage of respondents in Group 1 (the control group) that replied saying GDP estimates are accurate (q11), that a revision from 1.5% to 2% would not be surprising (q14) and that regular data revisions are surprising (q18).

Table 2 shows that some of the treatments affect the public's qualitative perceptions of the accuracy of GDP estimates (see q11). By contrast, the experts' perceptions of accuracy are statistically no different from the control group. Two specific ways of communicating data uncertainty are found to have statistically significant effects (at 10%) on how the public perceive the accuracy of the initial GDP estimate: (i) adding "about" (Group 2) and (ii) presenting a 60% confidence interval (Group 4). These statistically significant marginal effects indicate that these methods of communicating data uncertainty lead the public to believe that the GDP point estimate is less accurate than if they were not presented with this uncertainty information. They are 4 to 5 percentage points less likely to view the GDP estimate of 1.5% as "very" or "fairly" accurate, than in the control group where 82% of respondents viewed the GDP estimate as at least fairly accurate.

In contrast, looking at q18, respondents are less surprised that the GDP data are revised if they received the qualitative communication that GDP is subject to revisions (Group 3) or if uncertainty is quantified via the density strip (Group 5). Respondents allocated to these groups are 6 percentage points less likely to say that they are surprised that the GDP estimate of 1.5% is revised than in the control group, where 35% of respondents were surprised. However, an inspection of the results for the outcome of q14 reveals that none of the different communication tools - or treatments - affect how surprised the public is that GDP estimates are revised to the specific value of 2%: the t-statistics indicate no significant effects. The results in Table 2, therefore, suggest that some ways of communicating data uncertainty lead to lower perceptions of the accuracy of initial data releases. But both qualitative and quantitative uncertainty information, when communicated, reduces the surprise element that GDP data are revised.

3.4 Quantitative Perceptions Of GDP Uncertainty

We now test, in Table 3, whether the different communication tools affect whether the public are able to make more accurate quantitative assessments of GDP data uncertainty.

We first use the probit models, in eqs. (1) and (2), to assess the effect of the treatments on the individuals' probabilistic perceptions that GDP grew at exactly 1.5% (q15 in Table 3). We expect that those individuals who understand that GDP estimates are uncertain, including because of revisions, are more likely to give a lower probability to this specific event (a more "unlikely" answer). The binary outcome in the probit models is set equal to 1 (0 otherwise) for respondents that ticked one of the three boxes - from "virtually certain" through "very likely" to "quite likely" - indicating a greater than 60% chance that GDP grew by exactly 1.5%. This means that, if the communication tools are effective, we should expect to observe statistically negative coefficients on the treatment dummies seen in the first set of two columns in Table 3.

We do indeed find statistically significant negative effects when communicating uncertainty via either the predictive interval (Group 4) or the bell curve (Group 6). Compared with the control group, where 45% of individuals attribute greater than a 60% chance that GDP grew at exactly 1.5%, individuals *treated* with the bell curve are 8 percentage points less likely to do so. While this cannot be identified as causal, the experts also differ statistically from the control group. They are 24 percentage points less likely to attribute a greater than 60% chance to GDP growing at exactly 1.5%. They too expect data revisions.[22]

The second outcome evaluated in Table 3 (q16) is whether respondents can infer that "`the chance that GDP grew between 1.2% and 1.8%`" is about 30% - recall this is the correct answer, given our quantitative estimates of uncertainty in section 2.3. The summary statistics in Appendix A1 (and the bottom row of Table 3) show that, across treatment groups, only 12% of the public clicked on this answer (and 10% for control group respondents). They also confirm the impression that the majority of the public do not take the 1.5% estimate at face-value: as fewer than 23% of the public (and 25% of control group respondents) think it is "very likely" or "virtually certain" that GDP, in fact, grew somewhere between 1.2% and 1.8% (Appendix A1, q16). By contrast, 40% of experts believed this to be the case (Appendix A2, q12), indicating that they perceive less GDP data uncertainty than the public.

Table 3 reports the estimates from a probit model estimated with an observed outcome equal to 1 if the individual answered q16 correctly, 0 otherwise. The estimates in Table 3 suggest that, as before, the quantitative communication strategies improve the likelihood of a correct answer. That is, the predictive interval (Group 4) and the bell curve (Group 6) communication tools lead to individuals being 3 to 4 percentage points more likely to answer question 16 correctly. Interestingly, on this occasion, the experts do no better than the control group. However, given they were presented with the same type of communication tool as the control group, this is perhaps forgivable.

The third outcome assessed in Table 3 takes the answers from questions 12 and 13 (in the public survey) which asked for respondents to provide a high and a low number which they would not be surprised if actual GDP growth were. For each respondent, we compute the range between these high and low numbers. As shown in Appendix A1, about 35% of respondents did not provide answers to these questions, perhaps suggesting an inability or reluctance to quantify GDP data uncertainty. Moreover, 11% of all respondents provided not only an interval but the interval was of exactly 1 percentage point. In Table 3, we apply a linear regression model to evaluate whether the communication tools affect the individual estimates for the width of this interval. We find no significant effects.

The results in Table 3 are therefore on balance positive, in the sense that providing the public

[22] On average only about 20% of experts think there is more than a 60% that GDP grew by exactly 1.5% (see Appendix A2, q11).

with quantitative expressions of data uncertainty encourages them both to view GDP estimates as subject to revisions but also to quantify this uncertainty in a helpful (correct) manner. When we consider that a large proportion of the public are neither sure what GDP measures nor what the ONS does, it is perhaps encouraging that we are able to find statistically significant improvements in terms of how the public understand data uncertainty when quantitative impressions of data uncertainty are communicated to them.

The last outcome evaluated in Table 3 refers to question 19; it is set equal to 1 if respondents answered either "none at all" or "very little" when asked whether they think they received enough information about GDP data uncertainty. The estimated coefficients from the probit model confirm (as we should hope) that the communication of uncertainty is perceived to be more informative (statistically significant) when either a qualifying verbal assessment of data uncertainty (Group 3) or a quantitative impression of uncertainty (Groups 4 to 6) is provided. The negative sign of these estimates suggests that these treatments caused more respondents to answer "a lot/some" than in the control group (where 36% of respondents gave one of these two answers). The marginal effects indicate that respondents treated with the bell curve (Group 6) are 30 percentage points less likely to say that they were not given much uncertainty information than the control group. Respondents treated with the alternative quantitative communication statements (Groups 4 and 5) are 25 percentage points less likely. Interestingly, respondents subject only to qualitative uncertainty information are sensitive to whether they are given the extra sentence emphasising why revisions happen; as for Group 3 there is an increase of 20 percentage points in the probability of perceiving informational content.

We can conclude, looking across Tables 2 and 3, that while the public agrees that the amount of uncertainty information provided to them increases with the group number - so uncertainty communication does matter for treatments (Group 2 to 6) - this only affects the degree of surprise that GDP estimates are revised for Groups 3 and 5. And more uncertainty information does cause them to view the GDP point estimate of 1.5% as less accurate, but only for treatment Groups 2 and 4.

3.4.1 Experts' Quantitative Uncertainty Assessments And Views On Uncertainty Communication

The experts were independently asked to quantify their probabilities that GDP would grow between specific ranges. 90% of experts answered this quantitative question. On average, these experts attribute a 66% chance to GDP growing between 1% and 2% - and a small probability (4%) to GDP either contracting or growing by more than 3% (see Appendix A2, q13). This assessment suggests that, on average, the experts saw slightly less uncertainty than we quantified in section 2.3 (and also presented to the experts in a later question; Appendix A2, q25). Recall, we assume 0.8% and 2.2% to be the limits of the 60% (central) probability interval. This is consistent with the aforementioned evidence suggesting that experts, on average, appear to under-estimate GDP data uncertainty.

We also asked experts to imagine themselves in a decision-making context: we asked them to identify the size of the GDP revision that would lead them to change their monetary policy advice if the 1.5% GDP growth estimate, on which they were asked to base their initial advice, were revised. Results suggest that a threshold revision is 0.3 percentage points (see Appendix A2, q14). This is because 90% of experts (who provided a quantitative answer for this question) did not imagine changing their advice about monetary policy if the 1.5% GDP growth estimate were revised by just 0.1 or 0.2 percentage points. This again supports the view that experts expect data uncertainty and condition their putative monetary advice on this basis. But, consistent with inter-disciplinary evidence (e.g. Morss et al. (2010)), we find that experts have different probabilistic thresholds for taking 'action', i.e. there is heterogeneity across the experts. This is seen by the fact that nearly 50% of experts said they would not change their advice unless the revision were greater than or equal to 0.5 percentage points (see Appendix A2, q14). Experts' own quantitative assessments of data uncertainty assign, on average across experts, a probability of 15% to data revisions raising GDP growth to 2% (Appendix A2, q13). This suggests that these experts only foresee a small chance that they would change their monetary policy advice because of data revisions.

The experts were also asked to rank the three graphical representations of uncertainty presented to Groups 4, 5 and 6 in the public survey. The bell curve was ranked as most effective by almost half of the experts, though more than a fifth ranked it the least effective (see Appendix A2, q25). The confidence interval was ranked least effective by the majority (60% of experts), with the density strip scored in the middle by 55% of experts.

Additional analysis of those questions designed specifically for the expert survey is deferred to Section 4.

3.5 Trust And Sources Of Data Revisions

Towards the end of both surveys, respondents were asked why they think the ONS revises its GDP estimates. Recall that all our communication tools, with the exception of the control group (Group 1), Group 2 (who were simply told GDP is "about" 1.5%) and the experts, contain the phrase "but this estimate is likely to be revised as updated information becomes available".

Table 4 present estimates for three sets of probit models, as in eq. (1) and eq. (2), where the outcome variable is a binary variable equal to 1 (0 otherwise) when the respondent felt that revisions were explained by: "vested interests", defined as either the ONS or the Government having vested interests in data production and collection; mistakes at the ONS; or when they identify that revisions are due to more information becoming available. As Table 4 and Appendix A show, 31% of the control group and 4% of the experts believe vested interests are at work; 10% of the control group and 32% of the experts think ONS mistakes are to blame; and 50% of the control group in the public survey and 84% of the experts understood (in general, correctly) that revisions are explained by updated information. Respondents were able to identify multiple sources of revisions, if they so wished.

The t-statistics in all three columns of Table 4 confirm that the experts' understanding of the causes of revisions is statistically different from the control group in the public survey. Experts are 22 percentage points more likely to think that revisions are not explained by vested interests. And they are 33 percentage points more likely to believe that revisions are explained by updated information arriving. However, experts are also 21 percentage points more likely to think that mistakes at the ONS are to blame for revisions.

While the different communication treatments do not cause the public to change their view as to whether revisions are due to vested interests or to mistakes at the ONS, both the density strip (Group 5) and the bell curve (Group 6) do have a causal effect. The public are 7 to 8 percentage points more likely to understand that data revisions do, in general, occur due to updated information if they see a density strip or bell curve that quantifies the data revision uncertainties than if they are simply told that GDP is an estimate. 50% of respondents in this control group viewed data revisions as due to updated information.

As a consequence, we conclude that communicating uncertainty about early releases of GDP by providing quantitative information alongside the point estimate (as in the density strip and bell curve) improves the public's quantitative perceptions of why data revisions happen. But these treatments do not affect public trust in the statistical office. They do not lead to individuals thinking that data revisions are because of vested interests at the ONS or the Government.

3.5.1 Trust In The ONS And The Public's Understanding Of Data Uncertainty and Of GDP

Of all the controls included in the models estimated in Tables 2-4, the binary variable for trust in the ONS stands out as the most important. It tends to have the highest t-values and the largest marginal effects. The results in Tables 2 and 3 suggest that trust in the ONS is strongly related to qualitative and quantitative perceptions of data accuracy and the degree to which the public take the 1.5% point estimate at face value (and consequently do not view the estimate probabilistically).

More specifically, trust in the ONS is strongly associated with: (a) a stronger belief in the accuracy of the first GDP estimate (q11 in Table 2); (b) increased surprise if GDP is subsequently revised to 2% (q14 in Table 2); (c) a stronger belief that the first estimate of GDP is exactly 1.5% (q15 in Table 3); and (d) a lower chance that GDP uncertainty is correctly quantified and interpreted (q16 in Table 3). That is, trust in the ONS is associated with a lower tendency to view the GDP estimate probabilistically. But, on the flip side, Table 4 shows that trust in the ONS is associated with a greater tendency to view data revisions as not due to vested interests or mistakes at the ONS. Trust in the ONS is associated with a 23 percentage points increase in the chance that revisions are believed to be because of improvements in data availability (q17_2 in Table 3). Other factors that are associated with this, and have similarly sized marginal effects, are education and age. The educated and older are more likely to understand that a factor explaining revisions is improvements in data availability.

The other control variable we look at more closely is the dummy variable capturing whether individuals know or understand what GDP measures (as captured by q10 in the public survey). The estimated signs on these dummies in Tables 2-4 are not always easy to interpret. For example, relative to those individuals who either do not have an idea of what GDP measures or who have not heard of GDP, both correctly and *incorrectly* understanding GDP is associated with higher assessments of data accuracy but then less surprise that GDP data are revised.[23] To investigate whether the communication treatments have differential effects on people who understand GDP we experiment with extended versions of the probit models in Tables 2-4. These

[23] In Tables 2-4 we identify those who incorrectly understand GDP as those respondents who *guessed* (incorrectly) by stating that GDP measures employment, prices or the trade balance.

extended models are identical to those specifications seen in Tables 2-4 but include additional interaction dummies. Specifically, they interact the "know GDP concept" dummy with the five treatment dummies. In general, these interaction effects are statistically insignificant (at the 10% significance level); and estimation results are very similar to those reported in Tables 2-4 (so we do not separately report them here). But there is some evidence that the effects of the communication treatments are stronger on those individuals who do understand what GDP measures. In particular, for q19 (`Thinking back to the ONS statement about GDP growth, how much information did it give that the 1.5% estimate may be uncertain?`) we find that the effect of the treatment is stronger (in a statistically significant manner) on those people who do understand GDP. And similarly for question 18 (`Are you surprised that estimates of GDP growth are regularly revised?`) and for question q17_2 (`More information coming available explains GDP revisions`) we find that the effects of the bell curve treatment (Group 6) and density strip (Group 5), respectively, are stronger on those individuals who do understand GDP.

We repeat that one should not make policy recommendations based on interpretation of these controls, since they do not measure causal effects.

4 Additional Views On Uncertainty Communication From The Expert Survey

The experts were also asked to provide more detailed, open-ended feedback on the proposed ways of presenting data uncertainty. In addition, they were invited to provide their own suggestions on how to convey data uncertainty. 46 experts answered, and their responses are discussed qualitatively in Appendix B1. While views were quite varied, we draw out here two main takeaways. First, different ways of communicating the same uncertainty information likely have benefits, given heterogeneities among the user groups. Some users may prefer simpler verbal communication methods, others more involved quantitative communication via the fan chart. Secondly, not all experts agreed that reporting uncertainty information should be a priority, with some believing it may obscure and confuse the public. This appears to contrast the aforementioned evidence from our public survey, given we have found that communicating uncertainty information improves both the public's perceptions of data uncertainty and their understanding of why data revisions happen.

4.1 Confidence In Interpreting Uncertainty Information

Experts were more confident about their own ability to interpret uncertainty than the average user of economic statistics (see q20 and q21 in Appendix A2). This may reflect the fact that the experts are more experienced and frequent users of economic statistics than the *average* user. It may also reflect a well-known tendency of an "illusory superiority bias", in which people think they are better than the average person. Although, the Dunning-Kruger effect stipulates that people with high cognitive abilities tend to view themselves as less competent than people with lower abilities. Simple cross-tabulations (reported for space reasons in Appendix B2) suggest that while most experts showed a high degree of confidence, those who use GDP statistics more frequently expressed more confidence in interpreting uncertainty.

4.2 How Uncertainty Information Is Communicated To The Public By The Media

Experts were also asked about their satisfaction with how uncertainty around economic statistics is communicated to the public by the media. Overall, almost 65% of experts expressed a negative opinion, with 25% neutral; see Appendix A2 (q22). This was also reflected in experts' poor assessment of the public's understanding of the uncertainty around economic estimates, with fewer than 3% of experts believing that the general public have a good understanding (q16 in Appendix A2).

The experts were also asked two open-ended questions about how journalists and the media discuss and present uncertainty around economic statistics, both what they do well and what they could improve. The questions received 44 and 55 responses, respectively, and are discussed qualitatively in Appendix B3. While views were again quite varied, we summarise here three main takeaways. First, experts said that only a few journalists discuss uncertainty around economic statistics well. They called for more discussion of uncertainties and their causes. Secondly, experts often argued that the media should focus less on small changes and on short-term fluctuations that are often within the bands of uncertainty, and instead emphasise longer-term trends. This focus should be accompanied by contextual information and explanations to provide a narrative to the data. Thirdly, some experts believed that conceptual uncertainties (about GDP) overshadow data uncertainty.

4.3 Experts' Views On How Uncertainty Is Communicated To Them

The majority of experts were satisfied with how the ONS and the Bank of England communicate uncertainty (see Appendix A2, q22). But a smaller proportion of experts were satisfied with how the Government more generally and also the media communicate uncertainty information (Appendix A2, q22).

Two more open-ended questions were also asked of the experts, about how well the Government, the ONS, the Bank of England and economists and researchers in general present economic uncertainty, and what they could improve. The questions received 41 and 42 responses, respectively, and are discussed qualitatively in Appendix B4. We draw out here four main conclusions. First, the Bank of England's fan charts were frequently praised as a means of emphasising uncertainties, even if, it was claimed, subsequent discussions lost sight of these uncertainties and reverted to focus on the point estimates. Secondly, the Government and politicians were criticised by some experts for their cynical use of economic data, for suppressing or highlighting data uncertainties when it suited them. Some experts believed organisations like the ONS and the Office for Budget Responsibility (that provides independent economic forecasts and independent analysis of the UK public finances) should hold Government to account for misleading or selective interpretation of economic data. Thirdly, similarly to responses about how the media communicate uncertainty to the public, a common theme was to focus more on long-term trends - the *bigger picture* - rather than smaller short-term changes. Fourthly, experts typically argued that researchers and Government economists need to be and should be better informed about the sources of data revisions.

5 Conclusions

This paper reports results from a randomised controlled experiment of over 3,000 members of the public, supplemented with a targeted but smaller survey of expert users, to assess the effects of a range of uncertainty communication tools on perceptions of GDP data uncertainty and trust in the data producer.

We first find that the public, like experts, do not take GDP point estimates at face value. The majority, whether asked about this qualitatively or quantitatively, expect data uncertainty. They are not surprised when GDP data are revised.

Importantly, we then find that if and how uncertainty information is communicated to the public matters. Communicating uncertainty information alongside the GDP point estimate improves the public's understanding of why data revisions happen. It encourages more of the public to view the point estimate as just that, a point within a range of possible outcomes. The experiments indicate, in particular, that it is especially helpful to communicate uncertainty information quantitatively using intervals, density strips and bell curves. Quantitative communication of uncertainty information is, in general, preferable to textual descriptions and certainly better than no communication at all, beyond referring to GDP as an "estimate". It decreases the chance that the public misinterprets the uncertainty information given to them, and does not reduce trust in the statistical office or encourage the view that data revisions are due to vested interests at the ONS or the Government.

Our results for economic statistics are, therefore, consistent with emerging inter-disciplinary evidence that providing quantitative uncertainty information leads to a better understanding of the range of possible outcomes and to better decisions by non-experts, but need not erode trust in the data (see Joslyn and LeClerc, 2013). They are also consistent with the view that, given differences between people (which were also found to explain the public's understanding of uncertainty information), it is crucial to communicate uncertainty information in a general form (like the bell curve). The public can then use and make decisions in the face of uncertainty in their own way. They can extract from the bell curve information of specific interest to them. The majority of experts we surveyed also favoured use of the bell curve, although they were more critical of how the media than the statistical office communicates data uncertainty.

This paper focuses on GDP "data uncertainty" in the UK. Future research could carry out similar experiments for other countries and consider estimates for other economic variables. As van der Bles et al. (2019) review, some statistical offices do compute sampling error estimates for some economic variables, such as unemployment; these error estimates might be exploited when testing the public's understanding of uncertainty information when conveyed to them in different ways. Similarly, empirical evidence assessing alternative ways of communicating economic forecast uncertainty would be a natural extension of the experimental approach suggested in this paper.

6 References

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Table 1: Data Uncertainty Communication Tools

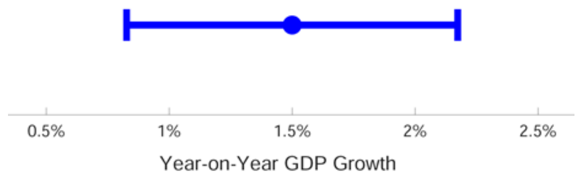
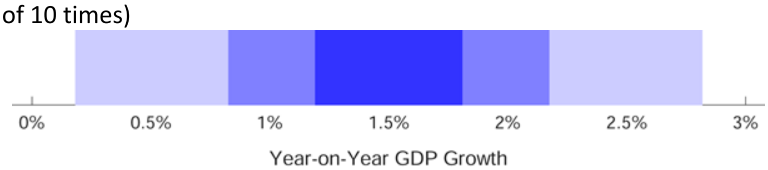
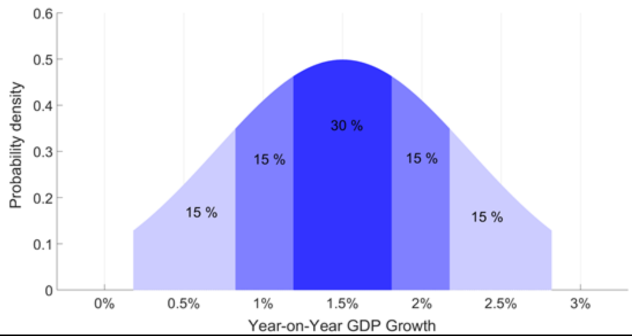
Group	Uncertainty Communicated	Tool
G1	Qualitative. GDP is a statistic ('estimate')	"GDP is estimated to have increased by 1.5% during the last year."
G2	Qualitative. Includes also a confidence attribute ("about")	"GDP is estimated to have increased by about 1.5% during the last year."
G3	Qualitative. GDP is a statistic subject to revisions.	"GDP is estimated to have increased by about 1.5% during the last year. But this estimate is likely to be revised as updated information becomes available."
G4	Qualitative and Quantitative. Information that GDP is a statistic subject to revisions. Likely quantitative impact of revisions using words and predictive interval.	G3 phrase above **+** " - When this happens, it is still quite likely that GDP growth will be somewhere on the blue line between 0.8% and 2.2% (a 6 in 10 chance, or 60%). And it is less likely that GDP growth will be outside the blue line (a 4 in 10 chance, or 40%)." 
G5	Qualitative and Quantitative. Information that GDP is a statistic subject to revisions. Likely quantitative impact of revisions using words and density strip.	G3 phrase above **+** " - When this happens, ONS estimates that GDP growth is most likely to be in the dark blue area (3 out of 10 times) and within each pair of lighter blue areas on a further 3 out of 10 occasions. ONS are very confident that GDP growth is somewhere in the total blue area, and will fall outside very rarely (1 out of 10 times)  The shading around the central estimate of 1.5% represents the uncertainty of the GDP estimates based on historical revisions, with 30%, 60% and 90% confidence intervals shown. The highlighted central estimate is the most likely value, while the values towards the upper and lower limit are possible but less likely. Other sources of uncertainty, for example due to limitations of the survey methodology, are not represented."
G6	Qualitative and Quantitative. Information that GDP is a statistic subject to revisions. Likely quantitative impact of revisions using words and fan chart.	G3 phrase above **+** " - When this happens, ONS estimates that GDP growth is most likely to be somewhere around 1.5% (where the graph is highest) but there is also a chance that GDP growth will be different. GDP growth is most likely to be in the dark blue area (3 out of 10 times), and within each pair of lighter blue areas on a further 3 out of 10 occasions. ONS are very confident that GDP growth is somewhere in the total blue area, and will fall outside very rarely (1 out of 10 times)." 
G7	Qualitative. As in the current ONS press release. (Expert Survey only)	"UK gross domestic product (GDP) in volume terms is estimated to have increased by 0.6% between Quarter 2 (Apr to June) and Quarter 3 (July to Sept) 2018. Compared with the same quarter a year ago, the UK economy has grown by 1.5%."

Table 2: How uncertainty communication affects *qualitative* perceptions of the accuracy of GDP estimates

	Accuracy of first estimate (q11)		Surprise about a revision to 2% (q14)		Surprised GDP is revised (q18)	
Choices:	Very accurate and fairly accurate		Not that surprised and not at all surprised		Very surprised and fairly surprised	
	t-stats	ME at Mean (p.p.)	t-stats	ME at Mean (p.p.)	t-stats	ME at Mean (p.p.)
Treatments:						
G2: textual 'about'	**-1.86**	-4.4	0.57	1.8	-1.23	-3.8
G3: likely revised	-0.68	-1.6	1.46	4.6	**-1.82**	-5.6
G4: interval	**-1.68**	-4.1	0.91	2.9	-1.19	-3.6
G5: density strip	0.17	0.0	0.42	1.3	**-2.17**	-6.6
G6: bell curve	-0.36	-0.8	0.20	0.6	-0.48	-1.5
G7: Expert*	1.05	3.6	1.53	7.6	-	-
Controls:						
Know GDP concept	**2.78**	5.6	**-3.63**	-10.1	**-7.79**	-19.6
Guess GDP concept	**3.16**	6.7	**-6.19**	-17.9	0.03	0.0
Trust ONS	**13.95**	24.9	**-1.97**	-5.2	0.23	0.5
No view on ONS	**4.40**	9.3	**2.29**	7.5	**3.17**	9.3
Heard of ONS	**-4.37**	-7.6	0.02	0.4	**-3.38**	-7.0
Postgraduate	-0.97	-3.2	-1.10	-4.9	**-3.62**	-14.5
Graduate	-0.12	-0.3	0.49	1.8	**-5.57**	-20.0
A levels	-0.15	0.3	0.05	0.0	**-4.07**	-13.6
Age: 25-34	**2.27**	6.4	**-2.85**	-10.4	**9.37**	32.5
Age: 35-44	1.04	2.6	**-5.53**	-18.8	**10.63**	34.2
Age: 45-54	0.33	0.7	**-2.19**	-7.5	**7.40**	24.2
Age: 55-64	0.54	1.3	**-1.78**	-5.9	**4.29**	13.8
Age: 65+	-0.36	-0.8	-0.17	0.1	0.38	1.2
Full time job	-1.14	-1.8	-1.48	-3.1	**2.52**	5.0
Don't know Econ	**-3.45**	-5.2	**2.54**	5.1	**-1.72**	-3.3
Don't listen to news	**-2.23**	-3.7	**1.78**	4.1	**2.63**	5.5
G1 average	**82%**		**48%**		**35%**	

Notes: Estimates from probit models, =1 for the choice indicated. For each model, the first column shows t-statistics for significance of the independent variable; and the second column shows the marginal effect at the mean in percentage points (p.p.). Values in bold indicate statistical significance at the 10% level with robust standard errors. G2 to G6 indicate the second to sixth (treatment) Groups, each randomly presented with a different way of communicating the uncertainty information. G7 is the (non-random) expert Group. N=3045 for the 6 group model; N=3172 for the pooled 7 group model. * indicates that the coefficient on G7 is from the 7 Group model without controls. For q18 15% of respondents replied "I had never thought about it before doing this survey"; their responses are added to the "very surprised" outcomes. "G1 average" denotes the percentage of respondents in Group 1 (the control group) that replied with one of the Choices indicated.

Table 3: How uncertainty communication affects *quantitative* perceptions of the accuracy of GDP estimates and assessments of how much uncertainty information was provided

	GDP is 1.5% (q15)		Chance between 1.2% and 1.6% (q16)		Range interval (q12-q13)	Informational content of original statement (q19)	
Choices:	Virtually certain, very likely, quite likely		Quite unlikely (30%)		high-low (int)	None at all and very little	
	t-stats	ME at Mean (p.p.)	t-stats	ME at Mean (p.p.)	OLS t-stats	t-stats	ME at Mean (p.p.)
Treatments:							
G2: textual ‘about’	-0.71	-2.3	-0.34	-0.6	0.15	-0.30	-0.9
G3: likely revised	-0.03	-0.0	0.20	0.4	-0.44	**-6.00**	-19.1
G4: interval	**-1.71**	-5.4	**1.93**	3.9	-0.63	**-7.64**	-24.5
G5: density strip	-0.68	-2.2	1.36	2.7	0.01	**-7.59**	-24.3
G6: bell curve	**-2.61**	-8.3	**1.70**	3.4	0.37	**-9.63**	-30.7
G7: Expert*	**-5.40**	-23.2	-0.81	-2.2	0.18	-	-
Controls:							
Know GDP concept	**4.28**	12.0	0.28	0.4	**-2.23**	0.21	0.5
Guess GDP concept	**6.46**	18.8	-1.18	-2.2	**-2.33**	0.96	2.7
Trust ONS	**9.46**	25.9	**-3.04**	-4.8	0.01	**-3.38**	-9.1
No view on ONS	1.11	3.8	-1.37	-2.7	-1.62	**-3.53**	-11.7
Heard of ONS	**-2.69**	-6.1	1.29	1.8	**-2.73**	**-4.00**	-8.9
Postgraduate	**-2.34**	-10.4	0.46	1.2	0.88	-1.37	-6.2
Graduate	**-2.03**	-7.8	0.58	1.3	1.59	-1.20	-4.7
A levels	**-1.87**	-6.8	-0.13	-0.3	1.37	-1.15	-4.3
Age: 25-34	**4.16**	15.2	0.18	0.3	**-4.88**	**4.38**	16.0
Age: 35-44	**4.69**	15.8	-1.62	-3.4	**-3.65**	**2.87**	9.6
Age: 45-54	**2.96**	10.0	-0.30	-0.6	**-2.51**	1.27	4.3
Age: 55-64	1.58	5.2	-1.23	-2.5	1.32	1.16	3.7
Age: 25-34	-1.66	-5.4	0.17	0.3	0.58	-1.17	-3.7
Full time job	0.09	0.1	0.80	1.0	0.99	**2.58**	5.5
Don’t know Econ	**-4.58**	-9.2	1.03	1.3	-0.17	-0.84	-1.7
Don’t listen to news	-1.19	-2.8	1.14	1.7	0.20	0.66	1.5
G1 average	**45%**		**10%**		**1.08**	**63%**	

Notes: Estimates from probit and linear regression model (for outcome of q12 and q13). Probit models =1 for the choice indicated. The first column shows t-statistics for significance of the regressor; and the second column indicates marginal effects at the mean in percentage points (p.p.). Values in bold indicate statistical significance at the 10% level with robust standard errors. G2 to G6 indicate the second to sixth (treatment) Groups, each randomly presented with a different way of communicating the uncertainty information. G7 is the (non-random) expert Group. N=3045 for the 6 group probit models; N=3172 for the pooled 7 group probit models. For (q12-q13) N=1546 for the 6 groups and N=1660 for the 7 groups. * indicates that the coefficient on G7 is from the 7 Group model without controls. “G1 average” denotes the percentage of respondents in Group 1 (the control group) that replied with the Choice(s) indicated.

Table 4: How uncertainty communication affects the public's understanding of the causes of data revisions

Explanation for revisions:	Vested Interests (q17_3+q17_4)		Mistakes (q17_1)		Additional information (q17_2)	
	t-stat	ME at Mean (p.p.)	t-stat	ME at Mean (p.p.)	t-stat	ME at Mean (p.p.)
Treatments:						
G2: textual 'about'	-0.17	-0.5	-0.83	-1.4	-0.60	-2.0
G3: likely revised	-0.22	-0.6	-1.39	-2.3	1.39	4.7
G4: interval	-0.64	-1.8	-0.29	-0.5	0.88	2.9
G5: density strip	-1.06	-2.9	-0.72	-1.3	**2.09**	7.0
G6: bell curve	-1.05	-2.9	-0.61	-1.1	**2.36**	7.8
G7: Expert*	**-8.28**	-22.0	**4.89**	20.5	**8.54**	33.3
Controls:						
Know GDP concept	0.76	1.9	**2.88**	4.3	**4.87**	14.0
Guess GDP concept	**4.61**	11.5	**3.37**	5.2	-1.04	-3.2
Trust ONS	**-5.41**	-11.9	**-4.21**	-5.2	**8.22**	23.2
No view on ONS	**-5.83**	-16.3	**-5.78**	-10.0	**1.74**	6.0
Heard of ONS	-0.78	-1.5	-0.08	-0.1	**6.34**	14.5
Postgraduate	-0.41	-1.6	-0.31	-0.7	**4.59**	21.0
Graduate	-0.58	-2.0	-0.85	-1.7	**5.21**	20.6
A levels	-0.23	-0.7	-1.02	-2.0	**3.93**	14.5
Age: 25-34	1.21	3.7	**2.89**	5.5	**-6.86**	-26.4
Age: 35-44	**2.24**	6.3	**3.84**	6.6	**-5.36**	-18.5
Age: 45-54	**2.27**	6.5	**2.59**	4.5	**-4.08**	-14.4
Age: 55-64	0.16	-0.4	0.88	1.5	-0.74	-2.5
Age: 25-34	-0.59	-1.6	0.66	-1.1	**2.09**	7.1
Full time job	0.36	0.6	0.51	0.6	**-2.73**	-6.2
Don't know Econ	**-3.52**	-5.9	-0.46	-0.5	**4.23**	9.0
Don't listen to news	**-1.98**	-4.0	0.11	0.1	**-2.64**	-6.4
G1 average	**31%**		**10%**		**50%**	

Notes: Estimates from probit models. The binary variable is equal to 1 if the survey respondent says, when answering question 17, that GDP revisions are explained by the factor(s) listed in the first row. The first column of each block has t-statistics for the significance of the regressor; and the second column has estimates of the marginal effect at the mean in percentage points (p.p.). G2 to G6 indicate the second to sixth (treatment) Groups, each randomly presented with a different way of communicating the uncertainty information. Values in bold indicate the regressor is statistically significant at the 10% level with robust standard errors. N=3179 for 7 groups. G7 is the (non-random) expert Group. N=3045 for the 6 group model; N=3172 for the pooled 7 group model. * indicates that the coefficient on G7 is from the 7 Group model without controls. "G1 average" denotes the percentage of respondents in Group 1 (the control group) that indicated revisions were explained by the factor(s) indicated.

Online Appendix A1: Public Online Survey Questions and Summary Statistics

		Total	
		Count	%
Q1. What is your gender?	Total	3045	100.0%
	Male	1490	48.9%
	Female	1548	50.8%
	Other (please specify)	3	0.1%
	Prefer not to state	4	0.1%

		Total	
		Count	%
Q2. What is your age?	Total	3045	100.0%
	Under 18	0	0.0%
	18-24	357	11.7%
	25-34	556	18.3%
	35-44	513	16.8%
	45-54	521	17.1%
	55-64	479	15.7%
	65 and above	619	20.3%

		Total	
		Count	%
Q3. Where do you live?	Total	3045	100.0%
	East of England	273	9.0%
	East Midlands	224	7.4%
	London	369	12.1%
	North East	125	4.1%
	North West	346	11.4%
	Northern Ireland	69	2.3%
	Scotland	246	8.1%
	South East	450	14.8%
	South West	264	8.7%
	Wales	150	4.9%
	West Midlands	265	8.7%
	Yorkshire & Humberside	264	8.7%

		Total	
		Count	%
Q4. What is your highest educational qualification?	Total	3045	100.0%
	PhD or equivalent doctoral level qualification	81	2.7%
	Masters or equivalent higher degree level qualification (MA, MSc, PGCE etc.)	294	9.7%
	Bachelors or equivalent degree level qualification (BA, BSc etc.)	680	22.3%
	Post-secondary below-degree level qualification	264	8.7%
	A Level / NVQ Level 3	708	23.3%
	GCSE / O Level / NVQ Level 1 / NVQ Level 2	769	25.3%
	CSE	74	2.4%
	Any other qualification	58	1.9%
	None of the above	117	3.8%

		Total	
		Count	%
Q5. What's your current employment status?	Total	3045	100.0%
	Employed full-time	1176	38.6%
	Employed part-time	448	14.7%
	Unemployed and currently looking for work	136	4.5%
	Unemployed and not currently looking for work	235	7.7%
	Student	135	4.4%
	Retired	671	22.0%
	Self-employed	113	3.7%
	Unable to work	131	4.3%

		Total	
		Count	%
Q6. In which, if any, have you ever studied economics?	Total	3045	100.0%
	Q6. In which, if any, have you ever studied economics? - At school	819	26.9%
	Q6. In which, if any, have you ever studied economics? - In higher education (e.g. university, college)	719	23.6%
	Q6. In which, if any, have you ever studied economics? -	186	6.1%

		Count	%
	Through self-directed study (books)		
	Q6. In which, if any, have you ever studied economics? - Self-motivated study (course)	186	6.1%
	Q6. In which, if any, have you ever studied economics? - Other – please specify:	26	0.9%
	Q6. In which, if any, have you ever studied economics? - Don't know / can't recall	97	3.2%
	Q6. In which, if any, have you ever studied economics? - No, I have never studied economics	1346	44.2%

		Total	
		Count	%
Q7. How frequently, if at all, do you read/watch/listen to news stories related to economics or the economy?	Total	3045	100.0%
	Never	227	7.5%
	Rarely	557	18.3%
	Monthly	292	9.6%
	Weekly	748	24.6%
	Almost every day	732	24.0%
	Every day	372	12.2%
	Not sure	117	3.8%

		Total	
		Count	%
Q8. The Office for National Statistics (ONS) is the UK's largest independent producer of official statistics and the recognised national statistical institute of the UK. Before answering this survey, had you ever heard of the ONS?	Total	3045	100.0%
	Yes, I had heard of them, and knew what they did	1480	48.6%
	Yes, I had heard of them, but didn't know what they did	797	26.2%
	No, I had never heard of them	598	19.6%
	Not sure / don't know	170	5.6%

		Total	
		Count	%
Q9. Personally, how much trust do you have in economic statistics produced by the Office for National Statistics (ONS)? For example, on unemployment, inflation or economic growth?	Total	3045	100.0%
	Trust them greatly	349	11.5%
	Tend to trust them	1566	51.4%
	Tend not to trust them	414	13.6%
	Distrust them greatly	65	2.1%
	Not sure / don't know	651	21.4%

		Total	
		Count	%
Q10. To the best of your knowledge, which option most accurately describes what GDP is?	Total	3045	100.0%
	GDP measures the increase in prices	247	8.1%
	GDP measures how many people are in employment	200	6.6%
	GDP measures the size of the economy	1405	46.1%
	GDP measures the difference between exports and imports	352	11.6%
	I don’t have a clue what GDP is	462	15.2%
	I have heard about GDP but not sure what it is	379	12.4%

		Total	
		Count	%
Random allocation into groups. Present each Group with its uncertainty information	Total	3045	100.0%
	GROUP1	507	16.7%
	GROUP2	508	16.7%
	GROUP3	508	16.7%
	GROUP4	506	16.6%
	GROUP5	507	16.7%
	GROUP6	509	16.7%

		Total	
		Count	%
Q11. How accurate do you think the first estimate of GDP growth of 1.5% is likely to be?	Total	3045	100.0%
	Very accurate	261	8.6%
	Fairly accurate	2205	72.4%
	Not very accurate	533	17.5%
	Very inaccurate	46	1.5%

		Total	
		Count	%
Q12. I would not be surprised if actual GDP growth was as high as: _ provide #	Total	3045	100.0%
	Not selected	2020	66.3%
	Don't know	1025	33.7%

		Total	
		Count	%
Q13. I would not be surprised if actual GDP growth was as low as: _ provide #	Total	3045	100.0%
	Not selected	1960	64.4%
	Don't know	1085	35.6%

		Total	
		Count	%
Q14. How surprised would you be if ONS issued a statement 3 months later which corrected the estimate for GDP growth to 2%?	Total	3045	100.0%
	Very surprised	444	14.6%
	Fairly surprised	1095	36.0%
	Not that surprised	1283	42.1%
	Not at all surprised	223	7.3%

		Total	
		Count	%
Q15. What do you think is the chance that GDP grew by exactly 1.5%?	Total	3045	100.0%
	Virtually certain – about a 99 in 100 chance (99%)	80	2.6%
	Very likely – about a 9 in 10 chance (90%)	399	13.1%
	Quite likely – about a 6 in 10 chance (60%)	808	26.5%
	Fifty-fifty – about a 1 in 2 chance (50%)	1018	33.4%
	Quite unlikely – about a 3 in 10 chance (30%)	474	15.6%
	Very unlikely – about a 1 in 10 chance (10%)	144	4.7%
	Exceptionally unlikely – about a 1 in 100 chance (1%)	122	4.0%

		Total	
		Count	%
Q16. What do you think is the chance that GDP grew by between 1.2% and 1.8%?	Total	3045	100.0%
	Virtually certain – about a 99 in 100 chance (99%)	152	5.0%
	Very likely – about a 9 in 10 chance (90%)	549	18.0%
	Quite likely – about a 6 in 10 chance (60%)	836	27.5%

	Fifty-fifty – about a 1 in 2 chance (50%)	941	30.9%
	Quite unlikely – about a 3 in 10 chance (30%)	360	11.8%
	Very unlikely – about a 1 in 10 chance (10%)	128	4.2%
	Exceptionally unlikely – about a 1 in 100 chance (1%)	79	2.6%

		Total	
		Count	%
Q17. ONS regularly publishes revisions to their GDP estimates. Why do you think they do this?	Total	3045	100.0%
	Q17_1. ONS regularly publishes revisions to their GDP estimates. Why do you think they do this? - Mistakes at the ONS	275	9.0%
	Q17_2. ONS regularly publishes revisions to their GDP estimates. Why do you think they do this? - More information becomes available	1617	53.1%
	Q17_3. ONS regularly publishes revisions to their GDP estimates. Why do you think they do this? - The ONS has vested interests in results / manipulates production or collection	280	9.2%
	Q17_4. ONS regularly publishes revisions to their GDP estimates. Why do you think they do this? - The Government has vested interests in the results / interferes in production or collection	606	19.9%
	Q17_5. ONS regularly publishes revisions to their GDP estimates. Why do you think they do this? - Limitations to the way GDP is measured	607	19.9%
	Q17_6. ONS regularly publishes revisions to their GDP estimates. Why do you think they do this? - Other [please write any other reasons]	25	0.8%
	Q17_7. ONS regularly publishes revisions to their GDP estimates. Why do you think they do this? - Don’t know / not sure	533	17.5%

		Total	
		Count	%
Q18. Are you surprised that estimates of GDP growth are regularly revised?	Total	3045	100.0%
	Very surprised	107	3.5%
	Fairly surprised	413	13.6%
	Not that surprised	1157	38.0%
	Not at all surprised	906	29.8%
	N/A. I had never thought about it before doing this survey	462	15.2%

		Total	
		Count	%
Q19. Thinking back to the ONS statement about GDP growth, how much information did it give that the 1.5% estimate may be uncertain?	Total	3045	100.0%
	None at all	259	8.5%
	Very little	1193	39.2%
	Some	1336	43.9%
	A lot	257	8.4%

Online Appendix A2: Expert Online Survey Questions and Summary Statistics

		Total	
		Count	%
Q1. In the last 12 months, which economic statistics have you used (Select all that apply)?	Total	136	100%
	Industry and business statistics	80	58.8%
	International trade and balance of payments	71	52.2%
	Public sector finance	40	29.4%
	Productivity	63	46.3%
	Inflation and price indices	71	52.2%
	GDP and national accounts	100	73.5%
	Regional and local economic statistics	69	50.7%
	Employment, wages and labour market	86	63.2%
	I haven't used ONS economic statistics in the last 12 months	3	2.2%
	Other (please specify)	15	11.0%

		Total	
		Count	%
Q2. How frequently do you use GDP statistics?	Total	136	100%
	Never	6	4.4%
	Annually	11	8.1%
	Quarterly	31	22.8%
	Monthly	34	25.0%
	Weekly	25	18.4%
	Almost every day	14	10.3%
	Every day	4	2.9%
	Not sure	11	8.1%

		Total	
		Count	%
Q3. What is your gender?	Total	130	100.0%
	Male	86	66.2%
	Female	37	28.5%
	Prefer not to say	7	5.4%
	Other (please specify)	0	0.0%

		Total	
		Count	%
Q4. What is your age?	Total	130	100%
	Under 18	1	0.8%
	18-24	3	2.3%
	25-34	39	30.0%
	35-44	27	20.8%
	45-54	24	18.4%
	55-64	20	15.4%
	65+	16	12.3%

		Total	
		Count	%
Q5. What is the name of your organisation? (optional)	Total	136	100.0%
	Selected	62	46.0%

		Total	
		Count	%
Q6. Which option best describes your organisation?	Total	3045	100.0%
	ONS or Bank of England	21	16.1%%
	Academia or research	41	31.5%
	Local or regional government	5	3.9%
	Central government department	20	15.4%
	Public organisation	1	0.8%
	Journalist/media	5	3.9%
	Voluntary sector or charity	4	3.1%
	Political party or organisation	0	0.0%
	International organisation	5	3.9%
	Private business	13	10.0%
	Private user	2	1.5%
	Trade association	1	0.8%
	Other (please specify)	12	9.2%

		Total	
		Count	%
Q7. How accurate do you think the annual estimate of GDP growth of 1.5% is likely to be?	Total	136	100.0%
	Very accurate	12	8.8%
	Fairly accurate	105	77.2%
	Not very accurate	17	12.5%
	Very inaccurate	2	1.5%

		Total	
		Count	%
Q8. I would not be surprised if actual GDP growth during the last year was as high as: _ provide #	Total	136	100%
	Selected	116	85%
	Don't know	20	15%

		Total	
		Count	%
Q9. I would not be surprised if actual GDP growth during the last year was as low as: _ provide #	Total	136	100%
	Selected	117	86%
	Don't know	19	14%

		Total	
		Count	%
Q10. How surprised would you be if ONS issued a statement 3 months later which revised the estimate for annual GDP growth to 2%?	Total	127	100%
	Very surprised	17	13.4%
	Fairly surprised	39	30.7%
	Not that surprised	59	46.5%
	Not at all surprised	12	9.5%

		Total	
		Count	%
Q11. What do you think is the chance that GDP grew by exactly 1.5%?	Total	125	100.0%
	Virtually certain – about a 99 in 100 chance (99%)	2	1.6%
	Very likely – about a 9 in 10 chance (90%)	2	1.6%
	Quite likely – about a 6 in 10 chance (60%)	23	18.4%
	Fifty-fifty – about a 1 in 2 chance (50%)	24	19.2%
	Quite unlikely – about a 3 in 10 chance (30%)	27	21.6%
	Very unlikely – about a 1 in 10 chance (10%)	33	26.4%
	Exceptionally unlikely – about a 1 in 100 chance (1%)	14	11.2%

		Total	
		Count	%
Q12. What do you think is the chance that GDP grew by between 1.2% and 1.8%?	Total	125	100
	Virtually certain – about a 99 in 100 chance (99%)	8	6.4%
	Very likely – about a 9 in 10 chance (90%)	43	34.4%
	Quite likely – about a 6 in 10 chance (60%)	48	38.4%
	Fifty-fifty – about a 1 in 2 chance (50%)	13	10.4%
	Quite unlikely – about a 3 in 10 chance (30%)	10	8%
	Very unlikely – about a 1 in 10 chance (10%)	2	1.6%
	Exceptionally unlikely – about a 1 in 100 chance (1%)	1	0.8%

		Count	%	Aggregated Histogram (across the 90% of experts who replied)
Q13. Please indicate the percentage probabilities you would attach to various outcomes for GDP growth. The probabilities should sum to 100%	Total	125	100%	
	Not answered	12	10.0%	
	Less than 0%			2%
	0 to 0.5%			6%
	0.5% to 1.0%			12%
	1.0% to 1.5%			34%
	1.5% to 2.0%			32%
	2.0% to 2.5%			9%
	2.5 to 3.0%			3%
	More than 3%			2%

		Total	
		Count	%
Q14 Suppose you are regularly asked for your advice on UK monetary policy. Imagine that your latest advice is conditioned on this 1.5% GDP growth rate for the year to 2018Q3. Now imagine that the ONS does revise this 1.5% estimate	Total	116	100
	+0.1pp	2	1.7%
	+0.2pp	9	7.8%
	+0.3pp	22	19.0%
	+0.5pp	33	28.5%
	+0.8pp	13	11.2%
	+1.0pp	7	6.0%
	+1.5pp	1	0.9%
	Don't know / not sure	20	17.2%

upwards in the future. How big would the revision need to be for you to reconsider your advice?	Other (please explain)	9	7.8%

		Total	
		Count	%
Q15. ONS regularly publishes revisions to their GDP estimates. Why do you think they do this? (Select all that apply)	Total	113	100%
	Mistakes at the ONS	41	36.3%
	More information becomes available	112	99.1%
	The ONS has vested interests in results / manipulates production or collection	2	1.8%
	The Government has vested interests in the results / interferes in production or collection	5	4.4%
	Limitations to the way GDP is measured	77	68.1%
	Don’t know / not sure	2	1.8%
	Other (please write any other reason)	11	9.7%

		Total	
		Count	%
Q16. How well do you think the average British person understands that there is uncertainty around economic estimates such as GDP?	Total	113	100.0%
	Very well	1	0.9%
	Well	2	1.8%
	Fair	15	13.3%
	Poorly	48	42.5%
	Very poorly	44	38.9%
	Don't know / not sure	3	2.7%

		Total	
		Count	%
Q17. How satisfied are you with how uncertainty around economic estimates such as GDP is communicated to the public by journalists/media?	Total	113	100.0%
	Very satisfied	5	4.4%
	Quite satisfied	4	3.5%
	Neither satisfied, nor dissatisfied	29	25.7%
	Quite dissatisfied	45	39.8%
	Very dissatisfied	27	23.9%
	Don't know / not sure	3	2.7%

		Total	
		Count	%
Q18. Please briefly describe what journalists/media do well. (optional)	Total	113	100%
	Answered	44	39%

		Total	
		Count	%
Q19. Please briefly describe what journalists/media could improve. (optional)	Total	113	100%
	Answered	55	49%

		Total	
		Count	%
Q20. Do you feel confident in interpreting the uncertainty around economic estimates such as GDP?	Total	112	100%
	Very confident	17	15.2%
	Quite confident	68	60.7%
	Not that confident	21	18.8%
	Not at all confident	4	3.6%
	Don't know / not sure	2	1.8%

		Total	
		Count	%
Q21. How confident do you think the average user of ONS economic statistics (e.g. economists, policymakers, civil servants etc.) is in interpreting the uncertainty around economic estimates such as GDP?	Total	112	100%
	Very confident	5	4.5%
	Quite confident	39	34.8%
	Not that confident	40	35.7%
	Not at all confident	14	12.5%
	Don't know / not sure	14	12.5%

		Total	
		Count	%
Q22A. How satisfied are you with how uncertainty around economic estimates is communicated to you as a user of economic statistics by the following groups? [The ONS]	Total	112	100%
	Very satisfied	13	11.6%
	Quite satisfied	47	42.0%
	Neither satisfied, nor dissatisfied	25	22.3%
	Dissatisfied	17	15.2%
	Very dissatisfied	2	1.8%
	Don't know / not sure	8	7.1%

		Total	
		Count	%
Q22B. How satisfied are you with how uncertainty around economic estimates is communicated to you as a user of economic statistics by the following groups? [The Bank of England]	Total	112	100%
	Very satisfied	13	11.6%
	Quite satisfied	47	42.0%
	Neither satisfied, nor dissatisfied	27	24.1%
	Dissatisfied	7	6.3%
	Very dissatisfied	1	0.9%
	Don’t know / not sure	17	15.2%

		Total	
		Count	%
Q22C. How satisfied are you with how uncertainty around economic estimates is communicated to you as a user of economic statistics by the following groups? [Journalists]	Total	112	100%
	Very satisfied	2	1.8%
	Quite satisfied	5	4.5%
	Neither satisfied, nor dissatisfied	30	26.8%
	Dissatisfied	40	35.7%
	Very dissatisfied	29	25.9%
	Don’t know / not sure	6	5.4%

		Total	
		Count	%
Q22D. How satisfied are you with how uncertainty around economic estimates is communicated to you as a user of economic statistics by the following groups? [Government]	Total	112	100%
	Very satisfied	1	0.9%
	Quite satisfied	13	11.6%
	Neither satisfied, nor dissatisfied	23	20.5%
	Dissatisfied	43	38.4%
	Very dissatisfied	23	20.5%
	Don’t know / not sure	9	8.0%

		Total	
		Count	%
Q22D. How satisfied are you with how uncertainty around economic estimates is communicated to you as a user of economic statistics by the following groups? [Economists and researchers]	Total	112	100%
	Very satisfied	11	9.8%
	Quite satisfied	40	35.7%
	Neither satisfied, nor dissatisfied	33	29.5%
	Dissatisfied	13	11.6%
	Very dissatisfied	8	7.1%
	Don’t know / not sure	7	6.3%

		Total	
		Count	%
Q23. Please briefly describe what these groups do well.	Total	112	100%
	Answered	41	37%

		Total	
		Count	%
Q24. Please briefly describe what these groups could improve.	Total	112	100%
	Answered	42	38%

		Total	
		Count	%
Q25. Here are three different ways of communicating economic uncertainty around ONS's GDP estimate to users of economic statistics. Please rank these according to how effective you think they would be. (1 = most effective, 3 = least effective). Please rank these according to how effective you think they would be in communicating uncertainty to users of economic statistics. (1 = most effective, 3 = least effective).	Total	109	100%
	A – B – C	14	12.8%
	A – C – B	13	11.9%
	B – A – C	10	9.2%
	B – C – A	20	18.3%
	C – A – B	6	5.5%
	C – B – A	46	42.2%

		Total	
		Count	%
Q26. Please provide feedback on any of the proposed ways of presenting economic uncertainty, and any suggestions or ideas you may have on how to present economic uncertainty.	Total	109	100%
	Answered	46	42%

Online Appendix B: Experts' qualitative views on the communication of data uncertainty

This appendix summarises the qualitative responses to the more open ended questions in the expert survey. Additional summary statistics from the expert survey, referred to in the main paper, are also presented.

B.1 Ranking alternative communication methods

As well as being asked to rank, according to their perceived effectiveness, the three quantitative representations of uncertainty, as presented separately to Groups 4 to 6 in the public survey, experts were invited to provide qualitative feedback. They were also asked for any suggestions or ideas that they may have on how to present data uncertainty. 46 experts replied to this (optional) question. Here we summarise qualitatively these experts' views.

Option A (simple confidence interval) was both praised and criticised for its simplicity. Some respondents said it implied a uniform distribution and that option B (density strip) and C (fan chart) demonstrated better how the relative likelihood of the true value was nearer the central estimate. In contrast, other respondents noted that this simple confidence interval could be better for some users and people not working within the economic field, notably the public and in newspapers:

'It depends on the user. For the general public a range as provided in Option A might be easier to understand and do the job.' – *Academic*

Option B (density strip) received mixed responses. Some respondents praised it for being more visually and aesthetically appealing than Option C (fan chart), and possibly more intuitive and easier to understand for most audiences, though it doesn't give as much information. One respondent suggested to add likelihood labels with percentages like in Option C to mitigate this.

Option C (fan chart) was praised for its level of detail, but its key message may be too complicated for many users. Many respondents noted that Option C would likely be the most effective in conveying uncertainty to statisticians and other expert users, with familiarity of probability distribution functions. However, concern was expressed that there was too much information, particularly for more general audiences:

'While I find Option C the clearest, I suspect many journalists would not understand it and certainly would not pass it on to the public.' – *Private consultant*

Some respondents suggested ways of improving the probability distribution function. One respondent suggested that cumulative distributions might be better than densities. There was also some discussion about how useful the vertical axis was, with mixed views about whether it added value to see the height. One respondent expressed concern that some people would default to thinking of the vertical axis as representing growth. Other respondents suggested making the supporting text more easily accessible, for instance by presenting key messages in bullet points. It is clear from this that many experts saw value in each of these three specific ways of conveying uncertainty. It was a common argument that their relative value depended on the specific audience:

'Different approaches might suit different user groups. Therefore, multiple ways of communicating the same information has its benefits.' – Private business employee

'I think the effectiveness of communication strongly depends on the audience. I would feel best with option C, but persons less adapt to seeing and working with data and statistics may be better off with option A.' – Public organisation employee

A few respondents also remarked that sometimes you need to be able to convey uncertainty in words rather than through illustrations because many people struggle with graphs. Journalists may be unable to reprint graphs in articles; and radio programmes need to convey the information orally. This was, of course, tested in the public survey (Groups 2 and 3), but not considered in the expert survey. Without having seen these questions, some experts suggested using the word "probably" or presenting the estimate followed by a likely range. In cases where graphs were applicable, a communications employee in a regional government suggested that info graphics may be helpful.

Some respondents offered other suggestions on how to present uncertainty. Ideas included providing specific examples of why past revisions took place, using more accessible language and shortening the text.

A number of respondents said the reporting of uncertainty should not be a priority. Some argued that the reporting of uncertainty would come at the cost of public engagement and comprehension and that most people do not care about uncertainty and just want the most accurate estimate available. As such, some respondents argued that information about uncertainty belongs in the appendix (of any press release) for very engaged users rather than on the front page.

Another related point was that some respondents noted that the exercise presupposes that the ONS know the real level of uncertainty, and pointed out that in reality there is uncertainty around the level of uncertainty. One respondent said that the intervals around the estimate should be skewed to take into account any revision bias, as some statistics are more likely to be revised upwards.

B.2 Additional analysis of confidence question

Most experts showed a high degree of confidence, those who used GDP statistics more frequently expressed more confidence in interpreting uncertainty. The sample sizes are shown in the graph below to indicate that these results are highly volatile due to the small sample sizes in each group.

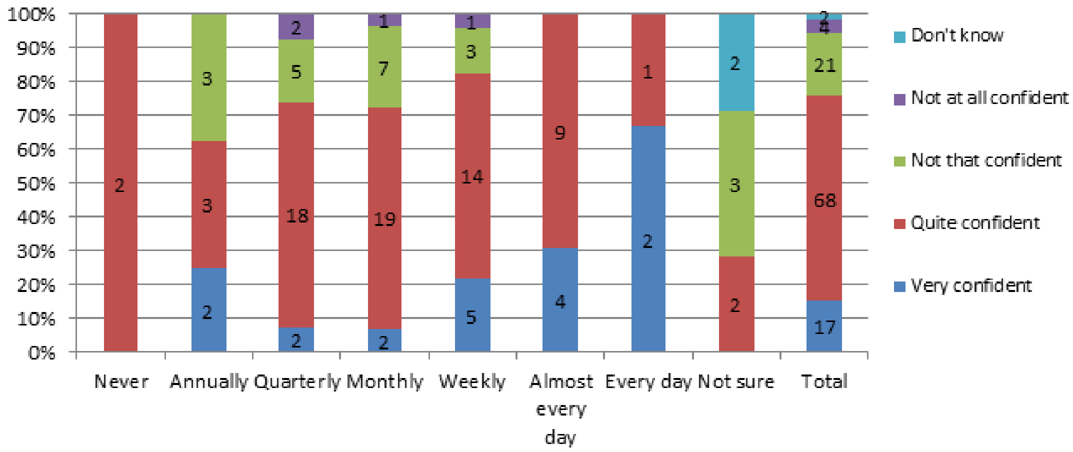


Figure B1. Confidence in interpreting economic uncertainty, by frequency of use of GDP statistics (N=112)

B.3 Appendix B3. Experts' views on how uncertainty is communicated to the public by the media

The experts were asked two open-ended questions about how journalists and the media present economic uncertainty, both what they do well and what they could improve. The questions received 44 and 55 responses, respectively.

There was a mix of responses regarding the media's reporting of uncertainty. Some experts noted that journalists typically use language that indicates uncertainty, such as referring to figures as estimates and by mentioning the possibility of future revisions. However, most experts said that only a few journalists report the uncertainty around economic statistics well. Experts wanted better explanations of how data were collected and its limitations, more emphasis on the fact that they are the best available estimates and are open to revisions. Some suggested the media should focus more on what this actually means, and potentially provide indicators of the extent of this uncertainty. One expert noted that the media and journalists had become much better at flagging the uncertainty around early estimates based on less information, though no one else commented on improvements over time. Some experts said that rather than necessarily reporting the uncertainty, they wanted more discretion as to what changes were reported at all, so small insignificant changes did not make the headlines.

A common observation was that the reporting of uncertainty depended on the experience of the journalist or the nature of the publication, with some mentioning the FT and the Economist as examples of *good* reporting on economic statistics and holding the ONS to account. In contrast, most journalists follow ONS's lead, which led some experts to argue that any changes in the emphasis of the reporting ultimately need to come from the ONS and other similar organisations, partly because some journalists simply did not have the necessary understanding of economics to effectively question the data.

Experts often argued that the media should focus less on small changes and short-term fluctuations that are often within the band of uncertainty, and instead emphasise longer time trends. Sometimes, the focus on small changes went hand-in-hand with, sometimes spuriously, attributing these changes to recent events. Some experts felt that journalists did not acknowledge how early estimates can impact narratives and political debates. The most prominent example cited by some experts was the exaggerated focus and narrative around recessions compared to periods of low growth and particularly the focus on the 'double dip' recession in 2012. Generally, some experts felt that the media focused too much on GDP and used it for purposes it could not sustain, such as a proxy for economic well-being. Another point made by an employee in the financial sector was that journalists should focus less on very volatile monthly growth rates.

Instead, experts argued journalists should focus more on long-term trends and structural shifts to avoid reporting uncertain short-term fluctuations. This focus should be accompanied by contextual information and explanations to give the bigger picture. One respondent commented that, in any case, the media should be better at flagging when they reported shorter and longer term changes, and in explaining that short-term figures (even when they are not revised) can be volatile.

A journalist argued that reporting uncertainty should not be a priority since "*it is of little consequence to the media and the general public*" and instead suggested the focus should be on describing the best available estimate at the time. This sentiment was echoed by a private consultant who said that, as long as the uncertainty was not caused by bias, the public would not be interested in whether the economic estimates were a little higher or lower than initially thought. Another respondent working for a data consultancy argued that attempting to communicate uncertainty would significantly reduce public engagement and comprehension.

Others made the opposite argument. A private consultant and an academic argued that the failure to report uncertainty appropriately had led to a false sense of trust in the accuracy of economic statistics among the public and policymakers, eventually leading to a distrust in the statistics themselves.

Some experts showed some scepticism about journalists' ability to grasp and communicate uncertainty around economic measurement, saying that some journalists simply did not have an adequate understanding of statistics and how it is compiled, and debates about methodology are simply not interesting for the media or the public.

Following from that, others commented that more basic issues than reporting uncertainty had to be addressed, such as the understanding, reporting and explanation of basic numbers and concepts. It is important, they said, not to confuse growth rates with levels or confuse quarterly with annualised changes.

Another point raised was that the failed reporting of GDP as a concept overshadowed the problems in reporting the uncertainties associated with the estimate. An academic commented:

'Far too much focus on GDP for purposes that the measure cannot support (e.g. economic well-being of individuals in population). This problem dwarfs problems of communicating measurement uncertainty.' – Academic

Another theme was the independence of the ONS as an official statistics provider. Some experts felt the strength arising from the lack of government interference in statistics measurement was not communicated well in the media.

B.4 Experts' views on how uncertainty information is communicated to them

Many experts said the Bank of England are very good at conveying uncertainty. They highlighted their innovative use of fan charts. The fan charts were praised for demonstrating both past and future uncertainties, and that uncertainty increases the further you go into the forecasting period. A couple of experts argued that while the fan charts were good and praised the Bank of England for at least communicating uncertainty, they noted that much of the subsequent discussion lost sight of this and reverted to focus on the central estimate. The ONS were also mentioned by some experts for explaining measurement complexities and making it clear when they present estimates that they are subject to revision. However, some experts said that this uncertainty information could be advertised better, rather than hidden in footnotes and hyperlinks.

A number of experts discussed more generally what represents effective communication of uncertainty and how it can be improved. Some said it was important to use the right language to make it clear that economic data are not set in stone. This could be achieved by referring to 'estimates' and noting that they are subject to revisions. Some also suggested going further by quantifying this uncertainty, for instance through providing confidence intervals, fan charts and standard errors. Some also suggested providing ranges rather than single estimates. Finally, some experts said it was important to provide good descriptive narratives around the estimates and to be sensible in what conclusions are drawn, rather than providing what a financial sector respondent called '*spuriously-precise, overconfident analyses of economic trends.*'

Similarly to responses about how the media communicate uncertainty to the public, a common theme was to focus more on long-term trends and the bigger picture rather than small short-term changes. One expert highlighted that the US Bureau of Labor Statistics are good at presenting changes and especially whether they are statistically significant or not. A typical comment was:

'Being too obsessed about the latest short-term figures can be very misleading — they should all be clear about the 'so what?' and honest about it, too.' – Private consultant

Some experts reflected on uncertainty as a concept. They argued that there are two sources of revisions: a) changes in methodology, and b) incorporating more information and data. These experts typically argued that researchers and government economists should be better informed about the sources of revisions. Some experts recommended making the process of revisions clearer, for instance by reporting on the pattern of past revisions and any revision bias, making it clearer when data are updated and when the final estimates are likely to be available, as well as describing details about how likely future revisions are.