

# Are lay expectations of inflation based on recall of specific prices? If so, how and under what conditions?

Xiaoxiao Niu, Nigel Harvey <sup>\*</sup>

University College London, UK

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## ABSTRACT

In 2019 when inflation was low and stable, we compared people's direct estimates of inflation with indirect estimates obtained by averaging their estimates of price changes in all 12 product categories on which the consumer price index is based. Indirect estimates were much higher than direct ones and the two types of estimate were uncorrelated. This is consistent with a price-free model in which direct estimates are not based on recall of prices but are determined by other information such as media reports. In May 2022 when inflation was high, expected to rise in the short-term, but highly unpredictable in the longer term, we found that direct and indirect estimates were very similar and highly correlated. This is consistent with a price-recall model in which a representative set of prices is used to estimate overall inflation. Finally, in September 2022 when inflation was fairly stable except for certain product categories (food) where prices were rising rapidly, we found that results were consistent with a third approach, the price-salience model; overall estimates of inflation are selectively influenced by price rises in those product categories where they are particularly high. People's strategy for estimating inflation appears adapted to the prevailing inflation environment.

## 1. Introduction

Lay expectations of inflation are recorded in surveys such as the Michigan Survey of Consumers (MSC), the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE), and the Bank of England's Inflation Attitudes Survey (IAS). Central banks need to know about these expectations because they are assumed to determine future levels of inflation.<sup>1</sup> In other words, they feed into the inflation forecasts made by the banks and therefore influence policy (Ranyard et al., 2017). There are various ways in which lay expectations of inflation could influence actual levels of inflation. Two examples will suffice. First, the more that consumers expect inflation to increase, the more likely it is that they will decide to bring forward their purchases of durable goods; the resulting increase in demand will push up prices for those goods. Second, the more that wage earners expect their cost of living to increase, the more effort they will put into securing increases in their wages; in some cases, these efforts will be successful and result in higher costs for producers, who consequently then need to increase the price of their products.<sup>2</sup>

<sup>\*</sup> Corresponding author at: Department of Experimental Psychology, University College London, Gower Street, London WC1E 6BT, UK.

E-mail address: [n.harvey@ucl.ac.uk](mailto:n.harvey@ucl.ac.uk) (N. Harvey).

<sup>1</sup> King (2022, p3), a former Governor of the Bank of England, has criticised central banks' over-reliance on "a family of theoretical models which rely on the assumption that expectations drive inflation, and central banks drive expectations" (Woodford, 2003), so that "inflation in the long run is determined by the official inflation target".

<sup>2</sup> For additional references to relations between inflation expectations and behaviour, see Supplementary Materials.

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According to rational expectations theory (Muth, 1961), rational economic agents form their expectations in line with what macroeconomic theorists specify as rational. Hence the inflation expectations of experts and lay people should be the same. However, they are not. Sometimes median inflation expectations obtained from lay surveys have turned out to be more accurate than those obtained from professional surveys (e.g., Ang et al., 2007). More often, lay expectations are less accurate and much more heterogeneous than those of experts (e.g., Mankiw et al., 2003; Palardy and Ovaska, 2015). Research into possible causes of the differences in accuracy has been reviewed by Niu and Harvey (2022a).

Unlike experts, lay people may draw on their own personal experience of price changes when forming their expectations for future levels of inflation. This means that differences in personal experience are likely to contribute to the high degree of heterogeneity observed in lay expectations of inflation (e.g., Malmendier and Nagel, 2016). People who judge price rises for specific products to be high would expect inflation to be high, thus leading to a correlation between judgments of specific price rises and judgments of inflation.

We report three experiments designed to test these predictions. In each one, participants completed two judgment tasks. In the direct inflation estimation task, they estimated the average price change for the upcoming year (expected inflation).<sup>3</sup> In the specific price assessment task, they answered a separate set of questions for each of the 12 consumer product divisions on which the Consumer Price Index (CPI) is based. In each set, they were asked to assess either the average cost of a single payment in the category in the current, previous and following years or the price change over the last 12 months and over the next 12 months. Answers to these questions were used to calculate the average expected inflation rate across all 12 categories. This indirect derivation of expected inflation rate was then compared with the rate obtained from the direct estimation task.

Our first experiment, carried out in the summer of 2019 produced results that were not compatible with those previously reported by Bruine de Bruin et al. (2011) and which we discuss in detail in Section 1.2 below. The most obvious difference between our experiment and theirs was that ours was carried out when inflation across all 12 product categories contributing to the CPI was uniformly low whereas theirs was carried out when inflation in some of those categories was very high. An opportunity to determine how important this difference in the inflation environment was in producing the difference in results arose in the summer of 2022 by which time inflation had risen markedly. We repeated our experiment twice and found that, on both occasions, results were indeed different from those that we obtained in 2019. Together, findings from our experiments and those of Bruine de Bruin et al. (2011) indicate that the way that lay people form their estimates of inflation depends on the prevailing inflation environment. In the next section, we discuss three ways in which these estimates can be made.

### 1.1. Three models of the development of expectations of inflation

Do people use their memory of information about past and current prices of different categories of product to estimate future inflation? Broadly speaking, there are three possibilities. First, they do not. Instead they use information that they have gained from the media and other secondary sources (Dräger, 2015; Lamla and Lein, 2014). This is a price-free model of the basis of expectations about inflation. Second, they do use information drawn from memory about past and current prices to estimate price rises across all different categories of product or across a representative sample of those categories. This is a price-recall model of the formation of expectations about inflation. Third, they identify highly salient (typically the largest) price rises that they have recently noticed and use this information to develop their expectations of future inflation. This is a price-salience model of inflation expectations: specific price information is used but it is restricted to selected non-representative categories of consumer product. In what follows, all three experiments test predictions of the first two models and the second two experiments test predictions from all three models.

### 1.2. Review of previous work

Bruine de Bruin et al.'s (2011) study contained three conditions and involved a priming manipulation. In the first condition, the initial priming task required participants to think of *any* price change that they had noticed over the past 12 months, to specify the service or good that they had thought of, and then to estimate the percentage change in the price of that service or good. In the second condition, participants were asked to think of the *largest* price change that they had noticed over the past 12 months, to specify the service or good that they had thought of, and then to estimate the percentage change in the price of that service or good. In the third condition, participants were asked to think of the *average* change in prices that they had noticed over the last 12 months and to estimate the percentage change in that average price (without specifying what goods and services they had included in the average).

After the priming task, all participants expressed their inflation expectations for the next 12 months using the “prices in general” question employed in the Michigan Survey. Specifically, they were first asked “during the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now”. Then, if they had said they expected prices would go up or go down, they were further asked “by what percent do you expect prices to go [up/down] on the average, during the next 12 months”. Bruine de Bruin et al. (2011) measured the extremeness of inflation expectations as the median absolute deviation of inflation expectations from 2%, the Federal Reserve’s implicit inflation target and the European Central Bank’s explicit targeted inflation ceiling. This was 3.50% in the first condition (primed with thinking about any price rise), 5.50% in the second condition (primed with thinking about the largest price rise), and 2.00% in the third condition (primed with thinking about the average price rise): estimates in the first two conditions did not

<sup>3</sup> In some experiments, they also estimated current inflation.

differ significantly from one another but they were both significantly higher than estimates in the third condition. Thus, recall of a *single* price rise (i.e., any one price rise or the largest price rise) produced a priming effect. Also, those who recalled larger price changes in the priming task tended to produce inflation expectations that were further from 2%. This effect explained differences in inflation expectations between the first two conditions and the third one.

Bruine de Bruin et al. (2011) acknowledge that their research leaves some questions unanswered.<sup>4</sup> It is notable that, in a second study in which no priming task was performed, they found that the extremeness of inflation expectations averaged across all 92 participants (i.e., 2%) was identical to the extremeness of inflation expectations in the first study when the priming task was to think about think about the average price rise (i.e., 2%). One way of interpreting this is to conclude that being required to think about the average price rise brought to mind no specific price rises but was based on media reports (the price-free model). Another possibility is that it led people to sample price rises in a representative set of consumer product categories (the price-recall model). In either case, we would expect no priming effect after judging the average price rise.

Bruine de Bruin et al. (2011, p839) pointed out that their results suggest that “memories for the past year’s changes in prices are biased towards those goods and services that have shown the largest price changes, affecting the extremeness and dispersion of subsequently reported inflation expectations”. In other words, they were consistent with the price-salience model.

## 2. Experiment 1

This experiment was designed primarily to test hypotheses arising from the price-free and price-recall models but certain patterns of results could have implications for the price-salience model. Participants in one condition produced inflation expectations with no prior priming task. Those in a second condition produced those expectations only after completing a priming task in which they answered questions about the previous, current and future cost of items in all 12 consumer product divisions on which the CPI is based.

Neither the price-free model nor the price-recall model predicts a priming effect. Inflation expectations should be similar in the two conditions. According to the price-free model, we would not expect a difference between them because estimating inflation is not based on recall of specific prices and so not influenced by them. According to the price-recall model, we would not expect a difference between the two conditions because estimates of overall inflation depend on recall of all specific price rises anyway; priming people by asking them to recall those price rises would merely be asking them to carry out the processing that they would carry out anyway to estimate inflation.

If a priming effect is obtained such that overall inflation is expected to be higher after answering questions about prices in all 12 consumer product categories, it could be explained by the price-salience model. We would need to assume that going through all 12 categories highlights the one with the largest price change as particularly salient and that price changes in this single category are used to estimate overall inflation.

According to the price-recall model, people normally use an average of all price rises (or a representative sample of them) to generate their inflation expectations. This suggests that we should expect there to be no difference between people’s inflation expectations and the average of all price rises that they had produced in the priming task. There should also be a correlation between these two measures: people whose price rise judgments are, on average, high should also have high expectations of inflation. This is because they use the former to produce the latter.

In contrast, if the price-free model holds and inflation expectations are not normally based on recalled price rises for specific categories of product, there is no reason to expect that overall inflation expectations will be the same as the judged price rises for the following 12 months averaged across all 12 consumer product divisions. Any difference between these two measures would be consistent with the price-free model but not be expected with the price-recall model. Furthermore, finding no correlation between these two measures would also be consistent with the price-free model (though this model could also accommodate such a correlation).

In summary, consistent with the price-free model but not with the price-recall model, we hypothesise that there will be a significant difference between the mean of inflation expectations and the mean of price rise judgments across all 12 consumer product divisions on which the CPI is based ( $H_1$ ). Consistent with the price-recall model, we hypothesise that there will be a significant correlation across individual participants between the mean of inflation expectations and the mean of price rise judgments across all 12 consumer product divisions on which the CPI is based ( $H_2$ ). Finally, consistent with the price-salience model but not with either the price-free model or the price-recall model, we hypothesise that judgments in the inflation estimation task will be affected when people first perform the specific price assessment task ( $H_3$ ).

### 2.1. Method

The experiment used a mixed design with a within-participant and a between-participant variable. Task type was varied within-participants: the tasks were a) estimating overall inflation for the current and following year, and b) making five judgments, including assessments of price changes, about each of the 12 consumer product divisions on which the CPI is based. We term these tasks inflation estimation and specific price assessment. The between-participant variable was task order: half the participants performed the inflation estimation task followed by the specific price assessment task and the rest performed them in the opposite order.

<sup>4</sup> For example, they point out that: “Another limitation of Study 1 is that it provides no insights into whether or not participants who were instructed to recall the average change in prices tried to remember specific changes in prices” (Bruine de Bruin et al., 2011, p840).

### 2.1.1. Participants

Mean age of the 123 participants (76 female, 47 male) was 25 years ( $SD = 8$  years). Twenty-one people were recruited from the participant pool at University College London and given 0.25 credits for taking part; 50 were recruited from China via [Qualtrics.com](https://www.qualtrics.com) and paid 3 RMB; 52 were recruited via [Prolific.com](https://www.prolific.com) and paid £1.25. Thirty-four participants came from countries other than the UK and China: Australia (1), Austria (1), Bulgaria (1), Canada (4), Germany (1), Greece (1), Italy (3), Mexico (7), Portugal (8), USA (7).<sup>5</sup> Participants were randomly assigned to the two conditions. This resulted in 62 of them being in the condition in which specific price assessment followed inflation estimation and 61 of them being in the condition in which inflation estimation followed specific price assessment. Data were collected between 1st June 2019 and 31 August 2019.

### 2.1.2. Stimulus materials

In the inflation estimation task, participants were initially provided with a simple definition of inflation and price change. They then completed two inflation estimation tasks. One asked them to provide their inflation expectations: "What is your prediction of the average price change (as a %) from the year June 2018-June 2019 to the year June 2019-June 2020." The other asked them to provide their estimate of current inflation: "What is your estimate of the average price change (as a %) from the year June 2017-June 2018 to the year June 2018-June 2019."

In the specific price assessment task, participants answered 60 questions. These comprised five questions in each of the 12 consumer product divisions on which the CPI is based. These divisions were extracted from the Consumer Price Indices Technical Manual published by the UK Office for National Statistics. Each screen in this task was headed by a label corresponding to one of the CPI consumer product divisions. Underneath each heading, there was a specification of the items that the category included. Participants answered the following five questions for each product division: 1) How many times do you buy this category per month, 2) What is the average cost of a single payment this year (June 2018-June 2019)? 3) What was the average cost of a single payment last year (June 2017-June 2018)? 4) What will be the average cost of a single payment next year (June 2019-June 2020)? 5) What percentage of your knowledge of prices in this category comes from your personal experience of them rather than hearing about the prices from other people or the media? Respond using the sliding scale below where 0% is all knowledge is from other people or the media and 100% is all knowledge is from my personal experience.

The experiment was programmed in two versions: English and Chinese. To ensure that these were comparable, an initial translation was followed by an independent back-translation which was then matched to the original version. This process was iterated until a good match was obtained.

### 2.1.3. Design

Participants were randomly assigned to one of the two conditions with the constraint that there was an equal number of people in each one. The order of the two questions in the inflation estimation task was randomised separately for each participant. The order of the 12 consumer product divisions in the specific price assessment task was also randomised separately for each participant.

### 2.1.4. Procedure

Participants accessed the experiment via the Prolific website. Each one was first asked whether they had lived in the same country for the last two years (i.e., from June 2017 to the date of the participant's response). Those who had not done so were excluded from the study. Remaining participants then saw an information screen that described the experiment in broad terms and a consent screen that gave them details of the ethical permission for the study and elicited their consent for taking part in it. They completed the two tasks, filled in demographic details, and were debriefed.

### 2.1.5. Data processing

Participants' judgments in the direct inflation estimation task were entered into our analyses without modification. To obtain inflation estimates from price judgments in the specific price assessment task, two steps were required. To produce an estimate of expected inflation for each of the 12 consumer product divisions, the first step was to subtract the assessed price for the current year in a particular category from the assessed price for the next year in that category and then divide this difference by the assessed price for the current year in that category. To obtain a percentage estimate for expected inflation in that category, the result of this calculation was multiplied by 100.<sup>6</sup>

A second step was needed to produce an overall estimate of inflation from the individual estimates of inflation for each category. To do this, we calculated the average of the separate estimates from the 12 categories, each weighted by the individuals' estimates of their frequency of purchasing items in that category. The frequency-weighted average is a more appropriate measure than other alternatives such as using equal weights or weights based on expenditure share. This is because it is derived from people's experience of recent price rises contingent on their actual purchasing behaviour and because [D'Acunzio et al. \(2021, p1615\)](#) have shown that the "weights consumers assign to price changes depend on the frequency of purchase, rather than expenditure share".<sup>7</sup>

Some estimates of inflation were extremely high. For example, one participant made price assessments that resulted in estimates of

<sup>5</sup> Inflation estimates in Western and Eastern (Chinese) subsamples were not significantly different. See Supplementary Materials.

<sup>6</sup> An analogous procedure was used to extract an estimate of current inflation for each of the 12 consumer product divisions.

<sup>7</sup> We also analysed the simple averages of the separate estimates from the 12 categories. Results of those analyses were not substantially different from those that we report here.

current and future values of inflation of 1022% and 1586%, respectively. Another made direct estimates of current and future inflation of 105% and 100%, respectively. [Bruine de Bruin et al. \(2011\)](#) also report some unrealistically high estimates of inflation. We excluded participants who produced inflation estimates and purchasing frequencies beyond 3.0 standard deviations from the mean value. After exclusion according to these criteria, our sample comprised 92 participants (53 female, 39 male) with a mean age of 26 years ( $SD = 9$  years). Forty-four were in the condition in which people performed the specific price assessment task before the inflation estimation task and 48 were in the condition in which tasks were performed in the opposite order. However, the effects that were significant when outliers were excluded were identical to those that were significant when they were not excluded.

To examine how their experimental manipulations affected the quality of participants' current inflation estimates, [Bruine de Bruin et al. \(2011\)](#) extracted the absolute deviation of those estimates from 0%. This measure showed a high correlation with the absolute deviation of the estimates from the actual CPI (1.1%) in the 12 months preceding their survey. To obtain corresponding measures of the quality of participants' inflation expectations, they calculated the absolute deviation of the participant's estimates from 2%. (This was both the Federal Reserve's implicit inflation target and the European Central Bank's explicit targeted inflation ceiling.) We were in a different position.

When we performed our analyses, official inflation rates for all countries from which our participants were drawn had been published and were obtained from the website [inflation.eu](http://inflation.eu), the Office for National Statistics (UK), and the Australian Bureau of Statistics (Australia). We averaged the 12-month inflation rates published each month over the 13-month period (e.g., June 2018 - June 2019) for which participants were asked to estimate inflation to obtain criteria against which participants' judgments were assessed. (We averaged over 13-month rather than a 12-month period because our instructions did not specify a date within the month of June. In practice, there is minimal difference between criteria based on 12-month and 13-month periods.)<sup>8</sup>

We extracted two error measures for each participant. The constant error or bias was the arithmetic difference obtained by subtracting the official inflation rate (CPI) from the participant's estimate. The absolute error was calculated as the absolute deviation of the participant's estimate from the CPI.

## 2.2. Results

Here we report analyses needed to test our hypotheses. For data tables and additional analyses of this and later experiments, see [Supplementary Materials](#).

We compared direct inflation estimates with those obtained by taking the frequency-weighted average of inflation estimates derived from specific price assessments in the 12 product categories. We carried out three three-way mixed model analyses of variance (ANOVAs) on judgments, constant errors and absolute errors, each of which used Task Order (inflation estimation first versus specific price assessment first) as a between-participants factor and Task Type (inflation estimation versus specific price assessment) and Judgment Type (current inflation estimate versus expected inflation) as within-participant factors. There was only a main effect of Task Type in the analyses of Judgment ( $F(1, 90) = 20.77; p < 0.001, ges = 0.0595$ ) and Constant Error ( $F(1, 90) = 20.77; p < 0.001, ges = 0.0594$ ).<sup>9</sup> There was a main effect of Task Type on Absolute Error ( $F(1, 90) = 41.47; p < 0.001, ges = 0.1108$ ) and an interaction effect of Task Type and Task Order ( $F(1, 90) = 3.96; p = 0.05, ges = 0.0118$ ). However, simple effect analyses showed an effect of Task Type both when inflation estimation occurred first ( $F(1, 47) = 31.41, p < 0.001, ges = 0.2325$ ) and when specific price assessment occurred first ( $F(1, 43) = 11.86, p = 0.001, ges = 0.0992$ ). The simple effect of Task Order was not found for either Task Type. Effects of Task Type on Mean Constant Error and Mean Absolute error are shown in [Fig. 1](#).

Separately for judgments of current and future inflation, we then calculated correlations across all 92 participants (i.e., ignoring task order) between absolute error of direct inflation estimates and absolute error of inflation estimates derived indirectly from specific price assessments. Neither of these correlations was significant. We repeated this procedure but using measures of constant error. Again, neither correlation was significant.

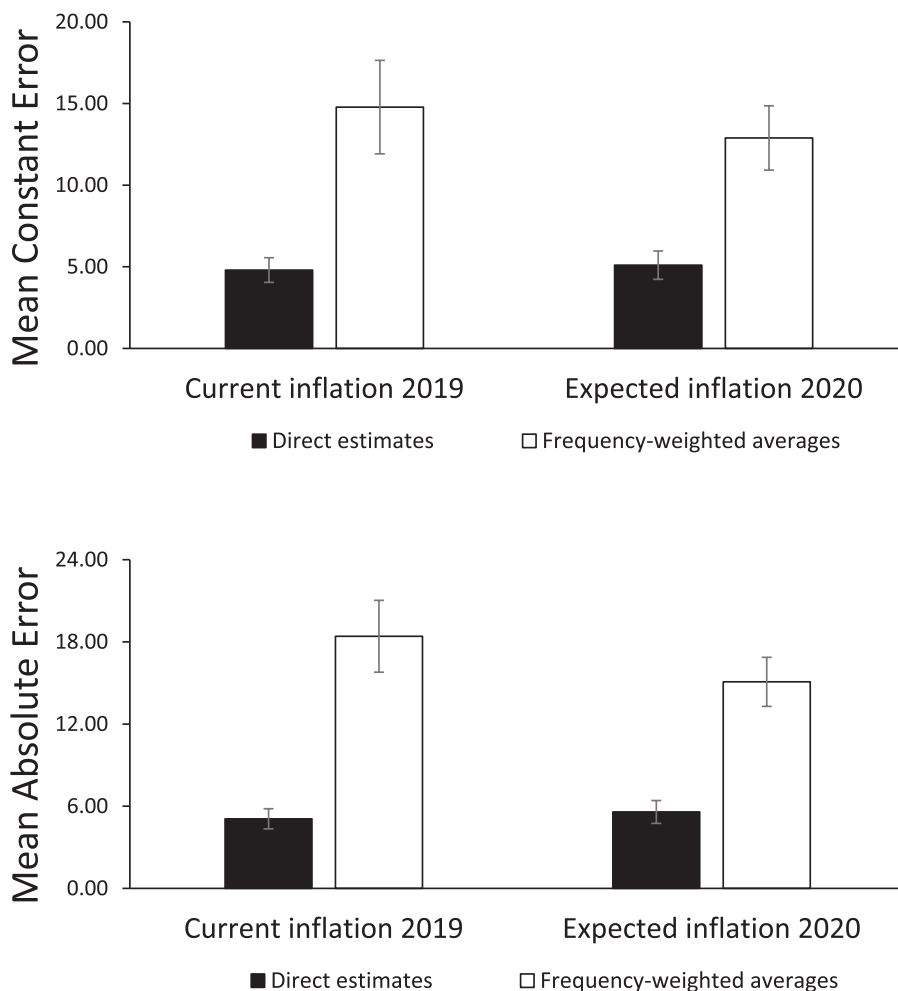
## 2.3. Discussion

[Fig. 1](#) shows a clear difference in the inflation rate that people directly estimated and the one that was derived from their estimates of prices in all product categories, a finding that is consistent with  $H_1$ . Also, errors were much greater in the second case. There were no significant correlations between inflation rates or errors in those rates across the two tasks for judgments of current inflation and future inflation ( $H_2$ ). Also, there was no evidence that first assessing the levels of prices in different years for each category of goods or services that contribute to the CPI influenced later direct estimates of inflation ( $H_3$ ). This pattern of results is consistent only with the price-free model of inflation estimation.

Direct estimates of overall inflation were somewhat too high. Why was this? Even if media reports and memory for prices are reasonably accurate and people have some ability to extrapolate from the past into the future, the price-free and price-recall approaches can still produce expectations of inflation that are too high. This is because people expect inflation rate (as distinct from prices) to go up even when it does not do so. [Niu and Harvey \(2022a\)](#) found that when separate groups of people estimated current and future inflation rates, the rates they gave were not significantly different. However, when the same group of people estimated both

<sup>8</sup> Australia, where one of our participants lived, publishes annual inflation rates quarterly but not monthly. Criteria for this participant were obtained by averaging over four quarters, July – September, October – December, January – March, and April – June.

<sup>9</sup> We used generalised eta squared ( $ges$ ) to measure effect size ([Olejnik and Algina, 2003](#)).



**Fig. 1.** Experiment 1: Effects of Task Type on constant errors and absolute errors in judgments of current and expected inflation. The figure shows the errors in frequency-weighted averages of inflation estimates derived from assessments of specific prices and in direct estimates of inflation.

current and future inflation rate, their mean estimate for the future inflation rate was significantly higher than that for the current rate. [Niu and Harvey \(2022b\)](#) suggest that people's use of the availability heuristic leads them to expect inflation to rise: media coverage of potential and actual rises in inflation is much more extensive than corresponding coverage of falls in inflation. This is an example of media-based risk-amplification.

[Dietrich et al. \(2022\)](#) reported results of a survey carried out between July 2020 and September 2021. They found that direct estimates of expected inflation were higher than indirect estimates obtained by aggregating expectations across product categories. They argue that this difference shows that aggregate (i.e., direct) estimates of inflation are not derived from a weighted average of beliefs about inflation in each category. Specifically, "the heuristics involved in expressing aggregate expectations may differ from the processes underlying aggregated inflation expectations" (p25). Thus, [Dietrich et al. \(2022\)](#) argue that both direct and indirect (aggregated) inflation expectations are derived from respondents' personal experience with prices but via different cognitive processes. But, in their study, direct estimates of inflation were higher than inflation expectations in any one product category. What sort of heuristic based on experienced price information could have produced such a result? [Dietrich et al. \(2022, p25\)](#) simply say that it must be nonlinear. We would argue that, like us, they have produced evidence consistent with the price-free model. Direct estimates of inflation in their study were based on recall of media reports and other secondary sources. During the period of their study, the experts whose views formed the basis of such reports considered that inflation would rise faster than the price experience of lay people indicated.

### 3. Experiments 2a and 2b

[Bruine de Bruin et al. \(2011\)](#) found that first making a judgment about a single specific price change over the previous 12 months

(‘any price change’ or ‘the largest price change’) resulted in higher and significantly less accurate inflation expectations for the next 12 months. However, first asking people to provide the average change in prices over the previous 12 months did not have that effect. We have shown that asking people for many specific price changes also does not have that effect. This implies that the original finding was not due to the price specificity of the priming task but to the fact that just a single price was required. This is consistent with Bruine de Bruin et al.’s (2011, p835) view that their original finding was produced by an anchoring effect and is what is to be expected according to the price-salience model.

Findings from Experiment 1 are consistent with the price-free model but, as we have seen, Bruine de Bruin et al.’s (2011) results were consistent with the price-salience model. What could have caused this difference? There are two possibilities. First our experiment was carried out when inflation rates were low across all product categories: for the UK and China, overall inflation rates were 2.19% and 2.20% respectively. The inflation environment was very different when Bruine de Bruin et al. (2011) carried out their work. In the 12 months before they released their surveys in August 2010, overall inflation was low at 1.1% but, for certain commodities, it was very high. For fuel oil, it was 10.6% and for used cars and trucks, it was 15.5% (Bureau of Labor Statistics, 2010a). Twelve-monthly inflation rates for these and related commodities had been high and changing for some time; for example, corresponding figures in March 2010 for fuel oil and for used cars and trucks were 27.2% and 16.3%, respectively even though overall inflation rate was just 2.3% (Bureau of Labor Statistics, 2010b). In situations such as this, it is likely that consumers would closely monitor prices only in those categories where they showed saliently high increases. Information obtained from this limited price monitoring may have then primed (biased) their overall estimates of inflation via use of an anchor-and-adjust heuristic just as Bruine de Bruin et al. (2011) suggest.

There is a second possibility. In our experiment, respondents were given a definition of inflation in terms of price change and then asked for their expectation of the average price change (as a %) for the next year. In contrast, Bruine de Bruin et al.’s (2011) participants reported their year-ahead inflation expectations using the Michigan Survey’s ‘prices in general’ question. Bruine de Bruin et al. (2012) found that inflation expectations were lower when respondents were asked to estimate inflation than when they were asked to estimate ‘prices in general’ or ‘prices you pay’. In addition, participants reported thinking more about ‘prices of things you usually spend your money on’ and less about ‘the US inflation rate’ when answering questions about ‘prices in general’ or ‘prices you pay’ than when answering questions that specifically included the term ‘inflation’.

Our questions in Experiment 1 did not include the term ‘inflation’; they asked respondents to estimate ‘the average price change’. Of the three question formats that Bruine de Bruin et al. (2012) compared, this appears most similar to the one that asked people to estimate changes in ‘prices in general’. Any difference between asking for the average price change across all products (Experiment 1) and the average change in prices in general (Bruine de Bruin et al., 2011) is subtle indeed. Hence we would not expect that the difference between our results in Experiment 1 and those of Bruine de Bruin et al. (2011) arose from this minor difference in question format. However, given Bruine de Bruin et al.’s (2012) results, it remains possible that use of a question format that specifically includes the term ‘inflation’ would lower direct estimates of inflation, reduce recall of specific prices, and thereby increase evidence in favour of the price-free model.

An opportunity to test the hypothesis that the prevailing inflation environment affects how people estimate inflation arose in summer 2022. At that time, CPI in the UK had risen sharply first to 9.1% in the 12 months to May 2022 (Office for National Statistics, 2022a) and then to 10.1% in the 12 months to September 2022 (Office for National Statistics, 2022b). It is reasonable to expect that when inflation rate is so high, changing rapidly and affecting many product categories, people monitor price changes in either all those categories or in those categories showing particularly large increases. In other words, results should be consistent with the price-recall or the price-salience model.

To examine whether this would be so, we carried out two versions of an experiment and tested the same hypotheses as before. In Experiment 2a, we adapted the second question format used by Bruine de Bruin et al. (2012) in which questions specifically mentioned the term ‘inflation’. In Experiment 2b, we employed the same question format that we used in Experiment 1. Thus differences between Experiment 1 and Experiment 2b can be attributed to the difference in inflation environment and differences between Experiments 2a and 2b are likely to arise from differences in question wording. In both experiments, we test the same hypotheses examined in Experiment 1.

In addition, we tested two further hypotheses. To test the hypothesis (H<sub>4</sub>) that initially assessing prices for all 12 categories of consumer product does not influence the later estimation of inflation whereas assessing the price of a single product category does do so, we varied the priming task in different experimental conditions. We compared the effects of priming with the task of estimating prices in all 12 product categories (as in Experiment 1) with a no-priming control condition and with the effects of priming with a task of estimating prices in a single product category (as in Bruine de Bruin et al., 2011).

To examine the role of memory in identifying the product category with the largest price change, we used two versions of the ‘single product category’ priming task. In the first of these, the 12 product categories were displayed and participants chose (i.e., recognised) the one with the largest price changes before estimating prices in that category. In the second, the categories were not displayed but participants simply entered (i.e., recalled) the name of the product category with the largest price changes before estimating prices in that category. This second ‘recall’ version corresponds closely to the ‘largest price change’ condition examined by Bruine de Bruin et al. (2011). This allowed us to examine whether explicitly providing categories in the ‘recognition’ version of the task facilitates their identification of a category with a higher price change. If it does, this would result in higher inflation estimates in the ‘recognition’ version of the task than in the ‘recall’ version (H<sub>5</sub>).

### 3.1. Method

In both Experiment 2a and 2b, there were four conditions. In the no-priming control condition (Condition 1), people simply carried out the main task of estimating overall inflation rates. In the other three conditions, they carried out a priming task before this main task: a) in the 12-product category priming task (Condition 2), they estimated current and future inflation in each of those categories; b) in the 'recognition' single product category priming task (Condition 3), they were provided with the list of the 12 product categories, chose the one that had shown the largest price rise over the previous 12 months, and then estimated current and future inflation in just that category; c) in the 'recall' single product category priming task (Condition 4), they were asked to identify the product category that had shown the largest price rise over the previous 12 months, and then estimated current and future inflation in just that category.

#### 3.1.1. Participants

In Experiment 2a, 225 participants were recruited via [Prolific.com](https://www.prolific.com). Four of them were excluded because they provided incorrect answers to three simple attention screening questions (e.g., what colour is the sky with options of orange, blue, green and red). The remaining 221 participants (151 females, 69 males, 1 prefer not to say) were paid £1 for their participation. All of them were from UK. Their mean age was 41 years ( $SD = 15$  years). Data were collected between 9 May 2022 and 13 May 2022.

In Experiment 2b, 260 participants were recruited via [Prolific.com](https://www.prolific.com). Three of them were excluded because they provided incorrect answers to two simple attention screening questions. The remaining 257 participants (153 females, 100 males, 4 prefer not to say) were paid £1 for their participation. All of them were from UK. Their mean age was 29 years ( $SD = 9$  years). Data were collected between 23 September 2022 and 29 September 2022.

#### 3.1.2. Design

In both experiments, participants were randomly allocated to one of four conditions. In Experiment 2a, 56 participants allocated to Condition 1, 55 to Condition 2, 56 to Condition 3, and 54 to Condition 4. In Experiment 2b, 58 participants allocated to Condition 1, 82 to Condition 2, 61 to Condition 3, and 56 to Condition 4. In Condition 2 of both experiments, the order of the 12 categories was randomized separately for each participant.

#### 3.1.3. Stimulus materials

In both experiments, participants carried out the main inflation estimation task that required them to forecast overall inflation. In Experiment 2a, they were asked: "During the next 12 months, do you think that inflation will go up, go down, or stay where it is now?" and, then, those who answered that it would go up or would go down were further asked to state the percentage by which it would change. In Experiment 2b, they were asked: "What is your prediction of the average price change (as a %) from the year September 2021- September 2022 to the year September 2022- September 2023?".

In the 12-product category priming task in Condition 2 of Experiment 2a, participants were presented with the 12 product categories one at a time (in a different random order for each participant) and, for each category, they were asked 1) whether prices they paid over the past 12 months had gone up, gone down or stayed the same and, if they had changed, by what percentage they had changed and 2) whether prices they thought they would pay over the next 12 months would go up, go down or stay the same and, if they thought they would change, by what percentage they expected them to change. After they had answered these questions for each of the 12 categories, they saw a screen on which those categories were listed. They filled in cells adjacent to each category label to report their monthly purchasing frequency for each category in turn. In Condition 2 of Experiment 2b, the wording of the questions was the same as in Experiment 1 but with the dates changed to reflect the fact that the experiment took place in September 2022 rather than June 2019. For example, to elicit assessments of current prices, participants were asked: "What is the average cost of a single payment this year (September 2021-September 2022)?".

In Condition 3, the 12 consumer product categories were displayed to participants and they were asked to click on the category that had the largest price change over the past 12 months. In Condition 4, participants were asked to "think of the largest price change you have noticed over the last 12 months" and to enter to specific good or services category that produced that change. After that, participants in Conditions 3 and 4 responded to the same questions as were put to the participants in the 12 consumer product priming task but they did so only for the single category that they had specified as showing the largest price change.

#### 3.1.4. Procedure

Participants first responded to demographical questions about their age, gender, nationality, country of residence, occupation, education level, income level, ethnicity and marital status. They were then provided with a simple definition of inflation before completing their experimental tasks.

### 3.2. Results of Experiment 2a

Sixteen participants were excluded because their direct inflation forecasts or their estimates of price changes were more than 3.0 standard deviations from the mean value. As a result, the analyses were carried out on 205 participants (139 females, 65 males, 1 prefer not to say) whose mean age was 41 years ( $SD = 15$  years). Of these, 56 were in Condition 1, 44 were in Condition 2, 53 were in Condition 3, and 52 were in Condition 4.

Below, we report analyses of the level of inflation judgments and of both CE and AE levels in those judgments. Inflation outcomes for the 12 months following the date of the experiment were not available when these analyses were performed. Hence, to calculate



errors in inflation expectations, we averaged the quarterly CPI inflation forecasts from the third quarter of 2022 to the second quarter of 2023 published by Monetary Policy Committee (8.9%) (Monetary Policy Committee, 2022a).

To compare the effect of different types of priming on the main task of producing direct estimates of future inflation (forecast, CE, AE) in the four groups, we carried out one-way ANOVAs using Task Type (no prime and the three priming conditions) as a between-participants factor. The analyses of forecasts and CEs<sup>10</sup> (upper panel of Fig. 2) and AEs (lower panel of Fig. 2) showed no significant effect of this factor. In summary, these analyses fail to show any effect of priming on the main task.

To obtain the indirect estimate of expected inflation for the 12 months from May 2022 in Condition 2, we proceeded in the same way as we did in Experiment 1: we took the frequency-weighted average of the changes in the estimated prices in each of the 12 categories of consumer product. We then used two-way mixed ANOVAs with Task Type (i.e., the three different types of priming task) as a between-participant factor and Estimate Type (Direct versus Indirect) as a within-participant factor to examine the relation between the two types of estimate in the three priming conditions. To obtain the indirect estimates of inflation in Conditions 3 and 4, we used the estimates of the price change that participants had specified for the single product category that they had selected as the one showing the largest price change.

The analyses of forecasts and CEs (upper panel of Fig. 2) showed main effects of Task Type ( $F(2, 146) = 13.88, p < 0.001, ges = 0.0950$ ) and Estimate Type ( $F(1, 146) = 60.56, p < 0.001, ges = 0.1568$ ), together with an interaction between these variables ( $F(2, 146) = 14.06, p < 0.001, ges = 0.0795$ ). The simple effect of Estimate Type was significant in Condition 3 ( $F(1, 52) = 46.80, p < 0.001, ges = 0.2907$ ), and Condition 4 ( $F(1, 51) = 22.43, p < 0.001, ges = 0.1670$ ). The simple effect of Task Type was significant only for indirect estimates of inflation derived from differences in assessments of specific prices ( $F(2, 146) = 15.45, p < 0.001, ges = 0.1747$ ). Pairwise comparisons using the BH adjustment method (Benjamini and Hochberg, 1995) showed significant differences between Condition 2 and the other two priming tasks: Condition 3 ( $p < 0.001$ ), and Condition 4 ( $p < 0.001$ ).

The analysis of AEs (lower panel of Fig. 2) showed main effects of Task Type ( $F(2, 146) = 12.73, p < 0.001, ges = 0.0815$ ) and Estimate Type ( $F(1, 146) = 35.48, p < 0.001, ges = 0.1067$ ), together with an interaction between these variables ( $F(2, 146) = 10.26, p < 0.001, ges = 0.0646$ ). The simple effect of Estimate Type was significant in Condition 3 ( $F(1, 52) = 29.22, p < 0.001, ges = 0.2214$ ), and Condition 4 ( $F(1, 51) = 14.63, p < 0.001, ges = 0.1213$ ). The simple effect of Task Type was significant only for indirect estimates of inflation derived from differences in assessments of specific prices ( $F(2, 146) = 12.17, p < 0.001, ges = 0.1429$ ). Pairwise comparisons using the BH adjustment method showed significant differences between Condition 2 and the other two priming conditions: Condition 3 ( $p < 0.001$ ), and Condition 4 ( $p = 0.001$ ).

For Condition 2, there were correlations between direct and indirect estimates of future inflation ( $r = 0.56, t(42) = 4.37, p < 0.001$ ) and between the CE values in those estimates ( $r = 0.56, t(42) = 4.37, p < 0.001$ ), but not between the AE values in them. For Conditions 3 and 4, there were no significant correlations between direct and indirect estimates, between CE values in those estimates, or between AE values in them.

### 3.3. Results of Experiment 2b

Thirty-two participants were excluded because their direct inflation forecasts or their estimates of price changes or purchasing frequency were more than 3.0 standard deviations from the mean value. As a result, the analyses were carried out on 225 participants (134 females, 87 males, 4 prefer not to say) whose mean age was 29 years ( $SD = 9$  years). Of these, 58 were in Condition 1, 59 were in Condition 2, 57 were in Condition 3, and 51 were in Condition 4.

Below, we report analyses of the level of inflation judgments and of both CE and AE levels in those judgments. Inflation outcomes for the 12 months following the date of the experiment were not available when these analyses were performed. Hence, to calculate errors in inflation expectations, we averaged quarterly inflation rate forecasts from the fourth quarter of 2022 to the third quarter of 2023 published by Monetary Policy Committee (11.5%) (Monetary Policy Committee, 2022b).

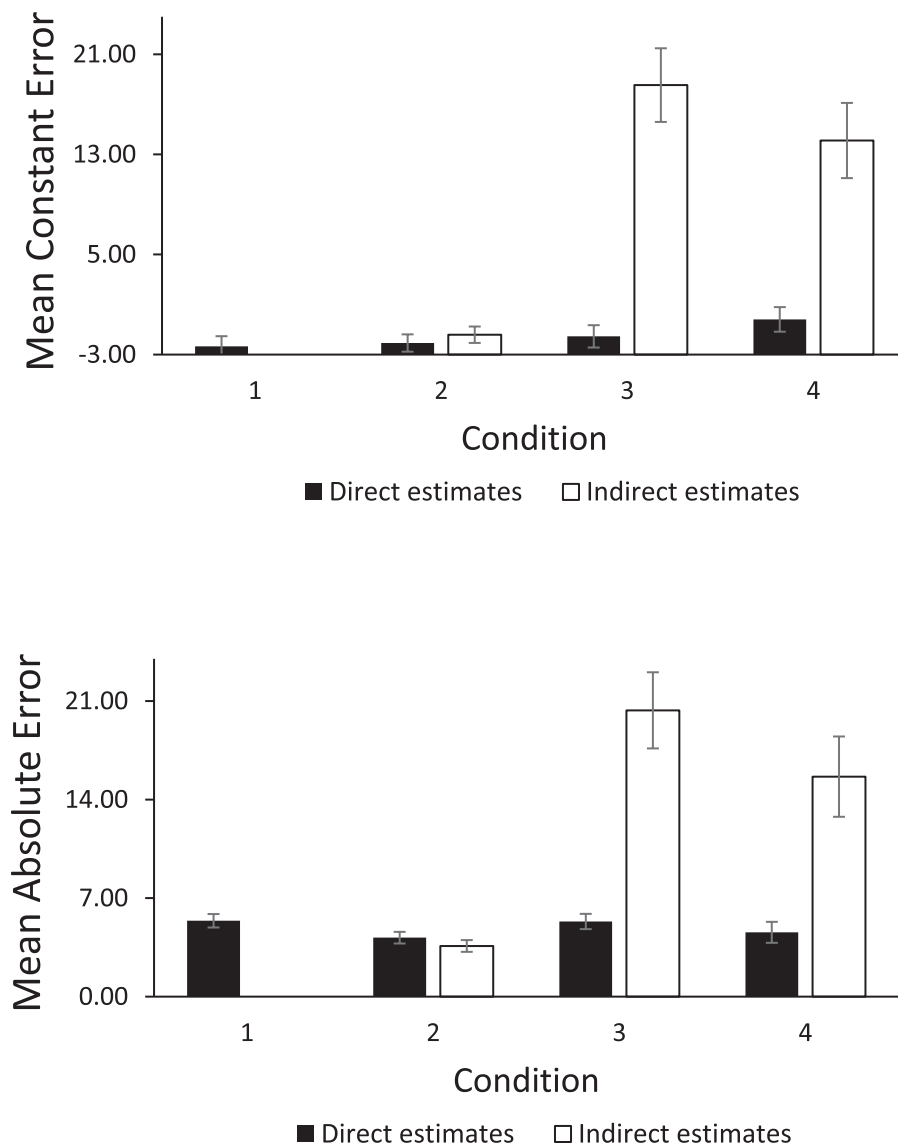
Levene's test showed that the ANOVA assumption of homogeneity of variance was violated. When sample sizes are similar and variances are proportional to means (as here), ANOVA seems fairly robust to violation of this assumption (Field et al., 2012). Below we report results of ANOVAs but, in the Supplementary Materials, we also report results from robust ANOVAs. Conclusions do not differ for the analyses that we report below.

To compare direct estimates of inflation in the four conditions, we used one-way ANOVAs with Task Type (no prime and the three priming conditions) as a between-participants factor. Results for CE (and forecasts) revealed a significant effect of Task Type:  $F(3, 221) = 10.32, p < 0.001, ges = 0.1229$ . Pairwise comparisons using BH adjusted method showed significant difference between Condition 1 and condition 3 ( $p < 0.001$ ), between condition 1 and condition 4 ( $p = 0.01$ ), between condition 2 and condition 3 ( $p < 0.001$ ) and between condition 2 and condition 4 ( $p = 0.02$ ).

Results for AE showed a similar pattern. There was a significant effect of Task Type:  $F(3, 221) = 8.30, p < 0.001, ges = 0.1012$ . Pairwise comparisons using BH adjusted method showed significant difference between Condition 1 and condition 3 ( $p < 0.001$ ), between Condition 1 and condition 4 ( $p = 0.02$ ), between condition 2 and condition 3 ( $p < 0.001$ ) and between condition 2 and condition 4 ( $p = 0.03$ ).

To compare direct and indirect estimates of future inflation, we used two-way mixed ANOVAs. The analysis of CE (and forecasts) revealed a significant effect of Task Type:  $F(2, 164) = 6.63, p = 0.002, ges = 0.0517$ . Pairwise comparisons using BH adjusted method

<sup>10</sup> These analyses produce the same results because CE equals the forecast minus a constant value, the true inflation rate.



**Fig. 2.** Experiment 2a: Effects of Task Type on the constant errors and absolute errors of the direct and indirect inflation forecasts in each of the four conditions.

showed significant difference between condition 2 and condition 3 ( $p < 0.001$ ), and between condition 3 and condition 4 ( $p = 0.009$ ). There was also a significant main effect of Estimation Type:  $F(1, 164) = 6.22, p = 0.01, ges = 0.0122$ .

Analysis of AE showed a significant main effect of Task Type:  $F(2, 164) = 9.62, p < 0.001, ges = 0.0690$ . Pairwise comparisons using BH adjusted method showed significant difference between condition 2 and condition 3 ( $p < 0.001$ ), between condition 2 and condition 4 ( $p = 0.02$ ), and between condition 3 and condition 4 ( $p = 0.02$ ). There was also a significant main effect of Estimation Type:  $F(1, 164) = 8.14, p = 0.005, ges = 0.0179$ .

For participants in all three priming conditions, there were correlations between direct and indirect estimates of future inflation ( $r = 0.38, t(165) = 5.25, p < 0.001$ ), between CE values in those estimates ( $r = 0.38, t(165) = 5.25, p < 0.001$ ), and between the MAE values in those estimates ( $r = 0.32, t(165) = 4.36, p < 0.001$ ).

### 3.4. Discussion

In Experiment 2a, there was no evidence of any priming effects. With respect to Condition 2, this replicates our finding in Experiment 1 (H<sub>3</sub>). With respect to Conditions 3 and 4, it represents a failure to replicate the findings reported by Bruine de Bruin et al.

(2011): overall estimates of inflation in the main task were not elevated when people were first asked to identify the product category with the largest price change in the previous year and to estimate the size of that change ( $H_4$ ). Furthermore, the lack of a priming effect in either of these conditions meant that providing people with a list of candidate product categories from which to select the one with the largest price rise did not lead to a greater priming effect than requiring them to search their memory for the category with the largest price rise ( $H_5$ ).

There were two ways in which the results of Experiment 2a differed from those of Experiment 1. First, whereas indirect estimates of inflation based on the frequency-weighted average of annual changes in judged prices of each of the 12 product categories were much higher (and, hence, less accurate) than direct estimates in Experiment 1 (Fig. 1), there was no significant difference between them in this experiment (Fig. 2, Condition 2). Thus, whereas the previous experiment produced evidence inconsistent with the view that assessments of specific prices (across all product categories) are used to form people’s overall estimates of inflation ( $H_1$ ), no such evidence was obtained in the present experiment. In fact, the close similarity of people’s direct estimates of overall inflation with the indirect estimates based on their earlier assessments of price changes in all 12 categories implies that the former were based on the latter.

Second, whereas in the previous experiment, there was no correlation across participants between indirect and direct estimates of inflation ( $H_2$ ), the present experiment did reveal significant correlations between these variables in Condition 2. If the price-recall

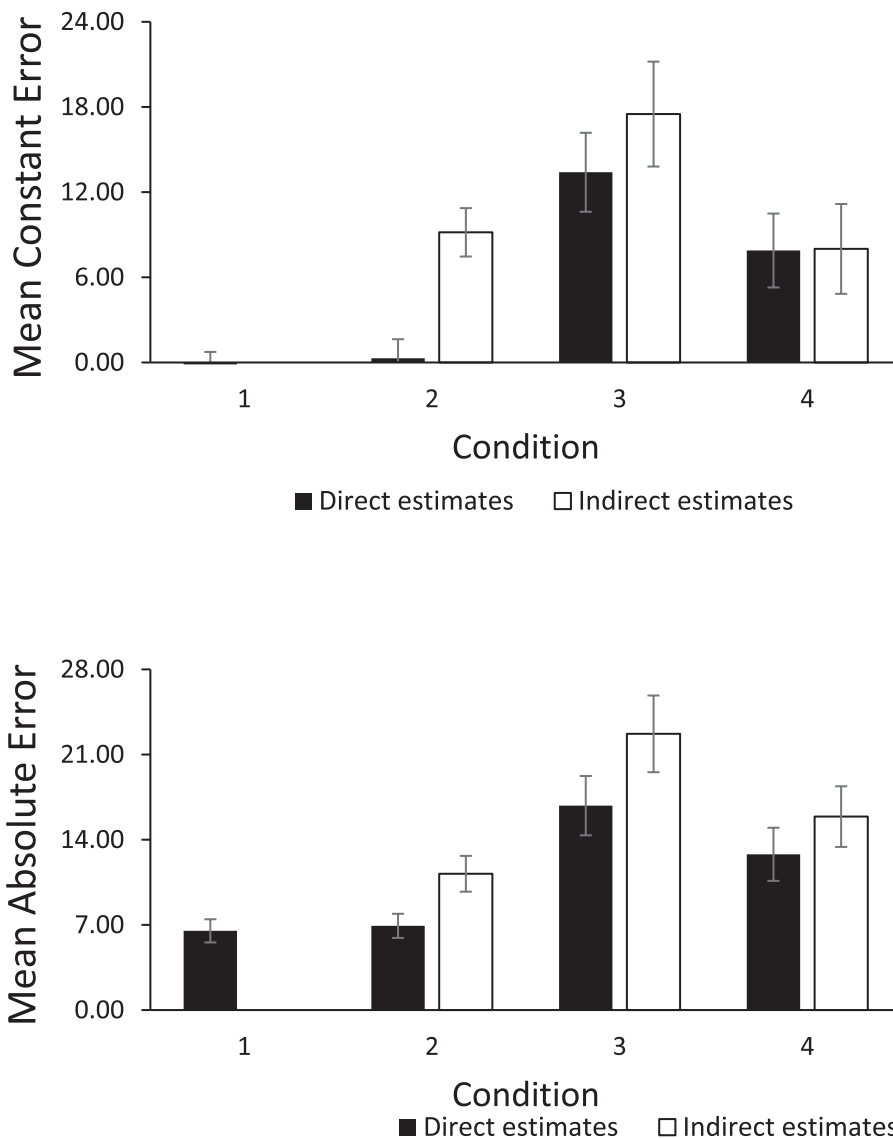


Fig. 3. Experiment 2b: Effects of Task Type on the constant errors and absolute errors of the direct and indirect inflation forecasts in each of the four conditions. Note that constant errors in Conditions 1 and 2 were very close zero and so only the top half of their error bars are visible in the figure.

model is correct, we would expect the correlation to be significant in Condition 2. We would not expect it to be significant in Conditions 3 and 4 if people recognise that the prices that they have recalled for only the single product category with the largest price change should not be used as a guide for their estimate of overall inflation. In summary, whereas the results of Experiment 1 were best explained by the price-free model, results from Experiment 2a are most consistent with the price-recall model.

Findings in Experiment 2b are somewhat different. Priming effects occurred when direct estimates of inflation were primed by recall of price changes in a single product category (Conditions 3 and 4) but not when they were primed by recall of price changes in all product categories (Condition 2). This is consistent with results reported by Bruine de Bruin et al. (2011). Furthermore, despite the lack of a priming effect in Condition 2, indirect estimates of inflation based on a frequency-weighted average of all product categories were significantly higher and less accurate than direct estimates of inflation (Fig. 3). There are two ways of explaining this. First, direct estimates of inflation were not based on recall of price changes in individual product categories but were based on media reports and other secondary sources; in other words, as in Experiment 1, the price-free model holds. Alternatively, when making direct estimates of inflation, people may have recalled prices that they had paid for various types of product but their recall of price changes in all types of product enabled them to allow for the effects of their own relatively high purchase of products that showed particularly high price increases (food, fuel).

Can we select between these two accounts? In contrast to Experiment 1, there were quite strong correlations between direct and indirect estimates of inflation. These would certainly be expected if people based their direct estimates on recall of prices. However, they could also be explained by a price-free model if people who attend more to expert estimates of inflation transmitted via the media are also better at estimating price changes in individual product categories. We cannot exclude this possibility. But only a price-salience model explains the priming effects in Conditions 3 and 4. It also most easily accounts for correlations between direct and indirect estimate of inflation. However, it must be elaborated somewhat to explain the difference between direct and indirect estimates of inflation in Condition 2.

Why were results from Experiment 2b somewhat different from those of Experiment 2a? The 'inflation' wording used in Experiment 2a can explain why estimates were generally lower (and, hence, more accurate) than those in Experiment 2b, where the 'price change' wording was used. Bruine de Bruin et al. (2012) showed that inflation wording produces lower estimates. However, wording effects do not easily account for other differences, such as the appearance of priming and the difference between direct and indirect estimates in Experiment 2b but not in Experiment 2a. These are better interpreted as effects of a switch from a price-recall model (Experiment 2a) to a price-salience model (Experiment 2b). Why would such a switch have occurred between May and September 2022? In that period, inflation in just one or two crucial product categories that are purchased by everyone had increased very rapidly; in particular, inflation for food and non-alcoholic beverages had increased from 8.6% to 14.5% (c.f., D'Acunto et al., 2021). This is the type of phenomenon that was present when Bruine de Bruin et al. (2011) carried out their work that showed priming after recall of price changes for single products.

#### 4. General discussion

In Experiment 1, direct estimates of overall inflation for the following year were different from indirect estimates obtained by averaging the differences in people's estimates of the costs of each of the 12 categories of consumer product for the next year and their estimates of the costs of the same product for current year (Fig. 1). Furthermore, there was no correlation between these different types of estimate. These results fit well with the price-free model. In Experiment 2a, results were different: direct estimates of inflation were very similar to indirect estimates derived from people's estimates of the costs of all categories of item, the two types of estimate were quite highly correlated ( $r = 0.56$ ), and there was no evidence of priming effects. These results are what we would expect from the price-recall model. In Experiment 2b, results were different again. As in Bruine de Bruin (2011), there was strong evidence of a priming effect when people recalled the single product category with the highest price rise over the previous year. Direct and indirect estimates of inflation were again quite highly correlated but the latter were somewhat higher and less accurate than the former. These results are most easily accommodated within the price-salience model.

These differences in the cognitive processing underlying the formation of people's expectations for future inflation appear to be related to the inflation environment prevailing during the period when the judgments were made. Experiment 1 was carried out in the summer of 2019 when levels of inflation were historically very low, when they had not changed substantially for many years, and when they were not expected to change much in the future. Media reports ensured that people had this information available to them. As a result, they had no need to monitor prices of different categories of consumer product. Consequently, their estimates of overall inflation were not based on knowledge of how the costs of different types of product were changing: they used a price-free approach to making those estimates.

Experiment 2a was carried out in May 2022. At the time, inflation had risen very rapidly to 9.1% (Office for National Statistics, 2022a), a 40-year high, and was forecast to rise to 10.19% in the fourth quarter of 2022, before dropping back to 3.56% by the end of 2023 (Monetary Policy Committee, 2022a). However, MPC inflation forecasts have been changing rapidly: in May 2021, the forecast for the fourth quarter of 2022 was just 2.02%; now it is in double figures. At the time of writing (May 2023), there is great uncertainty about how long high inflation will last and the notion that it will be as transient as the May 2022 forecasts suggest is increasingly regarded as optimistic. Also, while inflation for certain product categories (fuel, food) was higher than that for others in May 2022, inflation was increasing rapidly in all categories. In such circumstances, people need to carefully monitor price changes themselves to produce sensible decisions about their consumer behaviour. Given this, it is not surprising that the price-recall model provided the best account of the data from Experiment 2a.

Experiment 2b was carried out in September 2022. Results replicated the priming effects that Bruine de Bruin et al. (2011) obtained

in support of a price-salience model. What aspects of the inflation environment were common to the period when they carried out their studies and when we carried out Experiment 2b? In the 12 months before they released their surveys in August 2010, inflation was low at 1.1%. For most products, it had changed little in the recent past. However, for certain commodities, it was very high and changing rapidly. For example, monthly inflation rate for fuel oil, the product category with the highest level of inflation, differed by 16.6% between March and August 2010 (Bureau of Labor Statistics, 2010a, b). When we carried out Experiment 2b in September 2022, inflation rates for different product categories varied widely but, for most of them, it had stabilised. However, there were two exceptions. First, annual inflation rate for Food and Non-alcoholic beverages increased from 5.9% to 14.5% between March and September and that for Housing and Fuel rose from 7.7% to 20.2% in the same period.

In August 2010 and September 2022, there was little need to monitor all product categories as most of them were fairly stable. However, in both cases, inflation rate for one or two important product categories was changing very rapidly. Consumers needed to monitor price changes in these salient categories. Thus, following Bruine de Bruin et al. (2011), we conclude that recall of inflation levels in these categories produces judgment anchors and that, as a result of under-adjustment (Tversky and Kahneman, 1974), direct estimates of overall inflation are biased upwards.

We emphasise that we are not suggesting that high inflation in a product category leads that category becoming salient and, hence, in need of monitoring. Instead, it is changing and highly variable rates of inflation that have that effect. Hence, the categories that participants recognized or recalled in Conditions 3 and 4 of Experiments 2a and 2b as having the largest price change over the last 12 months do not allow us to identify what product categories were being monitored. It is possible for people using a price free strategy to correctly identify product categories with the highest price rises by attending to media reports.

In summary, the model that best explains consumers' use of information about specific prices when estimating overall inflation rates depends on the inflation environment at the time. Rather than thinking of the price-free, price-recall, and price-salience approaches as competing models each of which is aimed at explaining all estimates of inflation, we should think of them as different cognitive strategies, each of which is adapted to a different inflation environment.

This approach assumes that people obtain some broad-brush information about how much prices are changing in different product categories. They may obtain this from the media or from very occasional sampling of prices in different categories. They then use it to decide whether to monitor prices in any or all of the product categories more thoroughly. Comprehensive price monitoring may be effective for estimating overall inflation but it is likely to be resource-demanding. Consumers are unlikely to carry it out unless it is worth their while. More intensive processing of price information will improve their economic decision making but the advantages gained may outweigh the effort that it requires only when inflation rates are high, unstable, difficult to predict, and variable across product categories.

Do we have evidence of an effect of the wording used in the estimation tasks? Bruine de Bruin et al. (2012) found that asking people to estimate inflation produce lower values than asking them to estimate changes in "prices in general" or "prices you pay". We found a similar effect: in Experiment 2a, direct estimates of inflation were unbiased when people were asked to estimate "inflation" as a percentage (Fig. 2) whereas, in Experiments 1 and 2b, they were biased upward when people were asked to estimate the average percentage price change (Figs. 1 and 3). However, wording does not seem to influence other aspects of the data. For example, clear correlations between direct and indirect estimates of inflation appeared both when the "inflation" wording was used (Experiment 2a) and when the "price change" wording was used (Experiment 2b). Features of the data other than the absolute level of estimates are more simply explained in terms of the prevailing inflation environment.

#### 4.1. Limitations

Bruine de Bruin et al. (2011) recognized potential problems with the priming methodology. Asking someone to complete a priming task (e.g., estimating the price rise in the product category with the largest price rise) may influence their later performance on the main task (i.e., estimating overall inflation rate). But that does not mean that when carrying out the main task without the priming task, they would prime themselves by implicitly thinking of the largest price rise. This needs to be borne in mind when interpreting evidence from Experiment 2b that is consistent with the price-salience model.

An alternative approach adopted by Bruine de Bruin et al. (2011) in their second study was to ask people to estimate overall inflation rate without any priming task but afterwards to ask them whether they had thought of specific price rises when making their estimates. When we used this approach in our second experiment, we obtained data consistent with the rest of our results (Fig. SM2 in Supplementary Materials). However, these data were not crucial for testing our hypotheses and, within dual system theories, people's introspections about their thought processes may represent conscious (System 2) post-hoc rationales for the way they used their intuition (System 1) to estimate inflation rate (Evans, 2008).

#### 4.2. Implications

People made overall estimates of inflation that were 3–7% too high when they used a price-free strategy based on media reports and other secondary sources (Experiment 1; Fig. 1). However, when they used a price-recall or price-salience strategy based on their own purchasing experience, this bias either switched to being negative (Fig. 2) or was almost absent (Fig. 3). This supports our view that the bias in the former case largely arises from media-based risk amplification: media reports to which people attend more frequently deal with rises than falls in inflation.

When people use a price-salience strategy, biases in estimates of overall inflation will be much larger. Without priming, Bruine de Bruin et al. (2011, Study 2) found mean overall inflation rate was expected to be 3.66%. However, when respondents first estimated

the largest price change that they had noticed over the previous 12 months, they expected mean overall inflation rate to be 7.11% (Study 1). Similarly, in Experiment 2b, mean overall inflation was expected to be 10.96% without priming but 24.89% and 19.39% when people first estimated price rises in the category that they had recognised or recalled to be the one with the highest price rise (Fig. 3). This suggests that consumer decisions will be particularly impaired during periods in which people use a price-salience strategy. For example, compared with those using a price-recall strategy, the wage rises that they seek will be higher and seen as less reasonable by employers.

This suggests that we need to consider the factors that lead consumers to switch from one strategy to another. The first is the inflation environment. As inflation increases from a previously stable and low level, it is likely to affect one or two product categories (e.g., fuel, food) first: this is likely to trigger a switch from a price-free strategy to a price-salience one. If inflation continues to increase, more product categories will show high price rises and those price rises are likely to be less predictable: this is likely to trigger a switch from a price-salience strategy to a price-recall strategy. The second factor is that monitoring prices places a demand on cognitive resources. If the gain that monitoring produces no longer exceeds to cost that it incurs, people are likely to switch from a price-recall to a price-salience strategy or from a price-salience strategy to a price-free strategy.

#### 4.3. Conclusion

Data reported here, together with earlier findings reported by others, are consistent with the view that the degree to which people recall past and present prices of specific products when forming their expectations for future levels of inflation depends on the inflation environment at the time. If inflation has been low and its level is not expected to change, people do not use their personal experience of specific prices; instead their expectations are based on media reports and other secondary sources. Due to media-based risk amplification, expectations may then be somewhat too high. If inflation is generally stable but rises to higher levels for some product categories, they monitor the prices in those categories. The results of this monitoring are used to produce their estimates of the overall level of future inflation; consequently, these estimates may be much too high. If inflation is generally high, unpredictable, and possibly variable across product categories, people monitor prices in all product categories. Because media reports are not used with this strategy, media-based risk amplification does not occur. As a result, inflation estimates are unbiased (Fig. 2, upper panel).

#### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Data availability

Data are available at <https://osf.io/df962/>.

#### Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.joep.2023.102662>.

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