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Inflation persistence in the UK 1993-2019: from months to years[*].

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Abstract.

In this paper we model monthly UK inflation and find that there is some small but significant autocorrelation, particularly at 12 months. We find that this autocorrelation in monthly inflation leads to significant persistence in the headline annual inflation figure. A one-off shock to monthly inflation will have an effect on the headline figure equal to 10% of the original shock after 24 months. We find that this 12-month effect is also present in most of the different types of expenditure. We also find that the 12-month effect is present when we introduce a variety of other demand and cost variables. We also look at core inflation (excluding food and energy) across 9 large market economies (including the USA, Germany, Japan and UK) and find that the 12-month effect is significant in all of them.

Keywords: inflation, persistence, UK, CPI

JEL: E17, E31, E71

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1.Introduction

Like most central banks, the Bank of England has an annual inflation target, where annual inflation for any month covers the previous 12 months up to and including the current month. The inflation figures published in newspapers and other media (headline inflation) are also the annual figure. In thus paper we focus on the relationship between month-on-month (mom) inflation and annual inflation. The two are linked by an accounting identity, in which the annual inflation is the sum of the twelve mom figures plus an additional effect due to compounding. What we do is model mom inflation and then use the accounting identity to see what implications this has for the annual inflation figure.

Our approach most closely relates to an earlier UK study by Osborn and Sensier (2009) which also focussed on mom inflation over the period 1983-2003 and also studies using quarterly data such as Pivetta and Reis (2007).[1] However, neither of these papers made the link to the headline annual inflation figure. The focus on mom inflation is also shared by the forecasting approach of Hall et al (2023), but differs from the forecasting framework of Stock and Watson (2007, 2014) and Watson (2014) which use quarterly data and focus on the Phillips curve relationship. Another feature which distinguishes our approach is that we break down CPI inflation into its detailed sub-components and also conduct the analysis at this level.[2]

The mom inflation figures are noisy with strong seasonal effects and are well approximated as white noise with seasonality. Since annual inflation is the (compounded) sum of monthly inflation over twelve months there is a well-known automatic 12-month persistence of monthly inflation shocks. Inflation in a particular month remains in the annual figure for 12 months before it drops out. However, the main finding of this paper is that there is a twelve-month autocorrelation of mom inflation in the UK data. This means that the monthly shock does not die out entirely after 12 months: it persists into year two and beyond. With the estimated coefficients, we find that in the second year 34% of the initial shock persists and in year three about 10%. In essence a little autocorrelation in mom inflation gives rise to considerable persistence in the annual inflation figure. The period we look at is 1993-2019, from the Great Moderation up to the Pandemic, which includes the Great Financial Crisis of 2008-2010. This was a period when inflation was in general low, varying from 0-5% in the period 2007-2019 and in the range 1-3% in the period 1993-2006. We believe that the mechanism we have found in the data provides an alternative explanation to inflation persistence to that of expectations (see for example Carlstrom et al 2009, Cogley et al 2010 and Fuhrer 2017). In the period we are focussing on, inflation was stable around a 2% mean and expectations were stable.

[1] Fuhrer (2010) provides a general survey of the topic of inflation persistence.

[2] This contrasts with studies that break down CPI into its components to see which are the best to forecast inflation or identify “core” inflation, such as Stock and Watson (2016) and Joseph et al (2023).

We look at primarily at the UK CPI data published by the Office for National Statistics (ONS). We find that this 12-month effect in mom is quite robust. First, we look first at the headline CPI data and model mom inflation as an AR(12) process, plus a series of dummies (monthly dummies to capture seasonality, VAT changes etc.). We then drill down into the components of the CPI data, namely the 12 two-digit COICOP expenditure divisions in section 5, and to four-digit COICOP classes in section 7. We model inflation in each COICOP sector in a systematic to see if we can find common patterns despite the great sectoral heterogeneity.

We adopt a general-to specific method to arrive at a simple parsimonious form for the regressions which are more easily interpreted. Specifically, we use the Akaike Information Criterion (AIC) to remove variables, until we arrive at the minimum AIC. Then we remove insignificant variables until we have regressions containing only significant variables. This second step does increase the AIC, but since we apply it from the minimum the effect is only slight and enables us to restrict attention to coefficients which are significant in the classic sense.

We find that the 12-month effect in the aggregate data is reflected in most, but not all, of the 12 COICOP inflation data. Most importantly, we find the 12-month effect applies to sectoral inflation itself: sectors respond to their own 12-month lagged inflation and not the general CPI 12-month lagged inflation. This is an important finding: it shows that the mechanism is not top down, where the components of CPI reflect the aggregate, but rather a bottom-up process where the 12-month effect in (most of) the components of CPI create the 12 month effect at the aggregate level. Restricting the analysis to CPI inflation and its components raises the question of whether the 12-month effect might reflect some omitted variables.

Whilst still focussing on mom inflation, we therefore extend the range of explanatory variables to include consumer demand, unemployment, wages and producer prices. These are variables that cover some of the main supply and demand factors. We find that the 12- month effect is still present: whilst the estimated coefficients are slightly different, the implied effects for annual inflation are largely the same. Again, we look at inflation at the aggregate CPI level and also finer sub-divisions according to COICOP. One of the innovations of the paper is to use a direct measure of consumer demand, being the consumer expenditure matched to the COICOP category. Previous studies have tended to use less closely connected demand variables (for example industrial production Dixon et al (2020) or GDP (Vavra 2013) etc.) at the aggregate level, whereas our output variables are directly matched to the COICOP classification. At the level of aggregate consumption and the two-digit COICOP, this covers the entire dataset (1993-2019), whilst at lower levels it goes back to 1997. Our approach also contrasts with Shapiro (2022a, 2022b), in that we explicitly look at possible determinants of inflation rather than using forecast errors to determine whether inflation is demand or supply driven.

The main finding of the paper is that there is strong and robust evidence of mom inflation having a significant 12-month lagged effect. This gives rise to significant persistence in the headline inflation figure with a monthly shock still leaving an effect after a few years. As an example, consider the simple case where we have mom inflation following the process:

$$\pi_t = 0.25\pi_{t-12} + \varepsilon_t$$

Where π_{t-i} is mom inflation in month *t-i*, and ε_t is the inflation shock at time *t*. This has a zero mean, but we could add a constant to make the average equal to the UK average[1]. In this case, the annual inflation rate is approximately:

$$\Pi_t \simeq \sum_{i=0}^{11} \pi_{t-i} = 0.25 \sum_{i=0}^{11} \pi_{t-i-12} + \sum_{i=0}^{11} \varepsilon_{t-i}$$

By recursive substitution we can express annual inflation as a function of past shocks:

$$\Pi_t \simeq \sum_{i=0}^{11} \varepsilon_{t-i} + \left(\frac{1}{4}\right) \sum_{i=0}^{11} \varepsilon_{t-i-12} + \left(\frac{1}{16}\right) \sum_{i=0}^{11} \varepsilon_{t-i-24} \dots$$

$$\simeq \sum_{j=0}^{\infty} \left(\frac{1}{4}\right)^j \sum_{i=0}^{11} \varepsilon_{t-i-12j}$$

Thus, we can see the "stepwise" persistence of an inflation shock: for the first twelve months it has the usual 100% effect, for months 13-24 it has a 25% effect and months 24-36 a 6.25% and so on. The actual persistence will be more complicated if there are also effects at lags of less than 12 months. The impulse response function for headline annual inflation using this simple arithmetic approach displays considerable persistence even though the mom inflation does not.

There are several possible reasons behind the 12-month effect. The most important explanation is that when price-setters review their prices, deciding whether to change and if so by how much, the natural framework to inform the decision is what has happened over the last 12 months and how much they altered their prices the last time they changed price. The older price change can become a starting point to "frame" the current decision. The UK data has a cross-sectional mean duration for the period 1997-2007 of 10.9 months (Dixon and Tian 2017), which indicates that prices on average are set for almost 1 year. There are of course other possible factors. Some prices (some bus and train tickets) are regulated and the regulated price looks back at inflation over the year and are adjusted annually. However, in our analysis we do not find that this sort of "indexation" to be present except in Transport: within each type of expenditure it is its own lagged inflation that matters rather than general lagged CPI. Lastly, there can be some seasonality in the effect. Whilst we have monthly dummies, these assume a constant seasonal effect. The monthly "seasonal" effect may vary from year to year in a systematic manner[2], for example due to the April budget

[1] The average over the period since 1993 is 2%, so that mom average is 0.17%.

[2] In Hall et al (2023) they note this 12-month effect in CPI, and note that "In the forecasting exercises below we will add a 12th lagged dependent variable to capture the possibility of stochastic seasonality that appears to be present".

where many indirect taxes can vary. [1] However, in terms of the estimated coefficients on lagged inflation these apply to all months and not to particular months. Whilst seasonality may well play a role, we also believe that the behaviour of rice-setters is also important.

In section 8 we widen the analysis to make an international comparison using core inflation (CPI excluding food and energy). Having found that energy and food do not have the 12-month effect, we would expect it to be stronger when we focus on core inflation. We also want to see if this is British peculiarity. We examine core inflation using a consistent OECD dataset of core inflation across 9 countries, including the UK US, Germany and Japan. We find that there is indeed a strong 12-month effect across all countries, and implies a substantial degree of persistence in annual core inflation.

The outline of the paper is that in section 2 we describe the data and its properties. In section 3 we describe our empirical method for estimation. In section 4 we model aggregate mom CPI as an autoregressive process and show how the estimated coefficients for mom inflation feed through into the annual inflation figures, and how a little autocorrelation in mom inflation gives rise to a lot of persistence in the headline figure. In section 5 we look at the twelve different sectors and find that the twelve-month effect is present in most, but not all, sectors. In section 6 we introduce a range of other output and cost variables to check for robustness of the results where only inflation variables were used. We find that the results are robust.

2: The Data.

We will be using the monthly inflation data for CPI, which has been calculated on a monthly basis going back to January 1988. However, there was an inflationary episode in the early 1990s and we are going to focus on the Great Moderation period in the UK which can be identified as starting after this episode. Hence we delay the start of our analysis to January 1993 to the end of 2019 (to leave out the pandemic). This is a period in which inflation has been stable by historical standards despite a range of economic shocks, wars, and terrorism. The main change is the shift in monetary policy from active inflation targeting using the interest rate before the Great Recession of 2008-2009 to the maintenance of an almost constant interest rate close to zero and a shift in focus to maintaining output through QE and “unconventional” monetary policy, with little weight put on inflation in the decisions and deliberations of the MPC.

[1] Osborn and Sensier (2009) consider the effect of the April budgets on inflation, when indirect taxes are changed. This effect can be large: for example in April 1991 the VAT rate was increased from 15% to 17.5% which contributed to mom inflation of 3.4%, the largest since the 1970s. However, our period starts from 1993 when the “great moderation” is established to exclude the turbulent period of the early 90s.

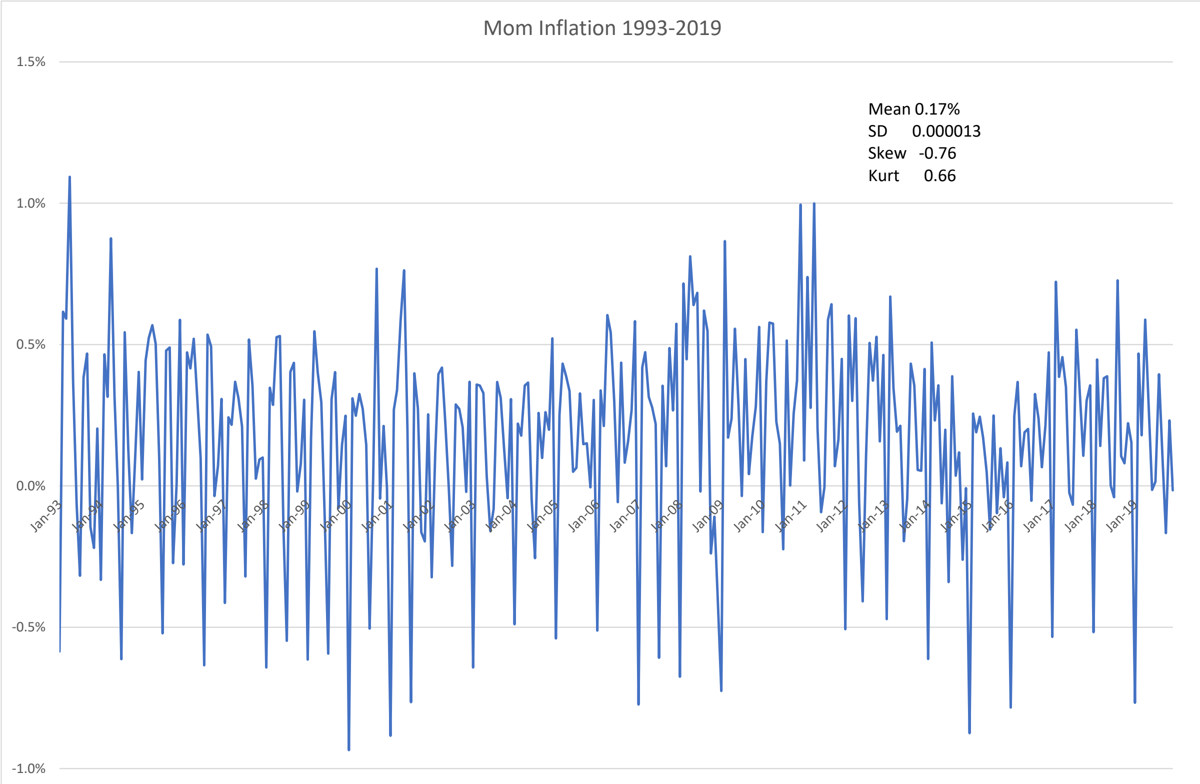

Fig 1: Monthly Inflation 1993-2019

If we look at monthly inflation (month-on-month or mom for short) measured by CPI it is a noisy and highly seasonal series. We can look at the raw data in a couple of other ways. First, the summary statistics for the raw inflation data are in Table 1.

	mean	median	st. dev.	skewness	ex. kurt.
1993-2019	0.17%	0.22%	0.0036	-0.72	0.62
1993-2007	0.15%	0.25%	0.0035	-1.02	0.71
2009-2019	0.17%	0.20%	0.0034	-0.59	1.06

Table 1: Month on Month inflation statistics CPI

Over the whole period and the two sub-periods, the mean is exactly what we would expect when annual inflation averages 2%. There is a small degree of negative skewness, and the excess Kurtosis is slightly positive. These are far enough away from 0 to make the distribution fail standard normality tests, but not that different. If we compare the pre-crisis period, average CPI inflation is a little lower before the GFC than after. There is less (negative) skewness and a more excess Kurtosis as we compare the period after the GFC with the one preceding it.

Secondly, we can depict the inflation as a histogram, looking at the frequency of the different levels of mom inflation. The shape reflects the negative skewness with a longer left hand tail, whilst the excess Kurtosis also reflects the fat left hand tail.

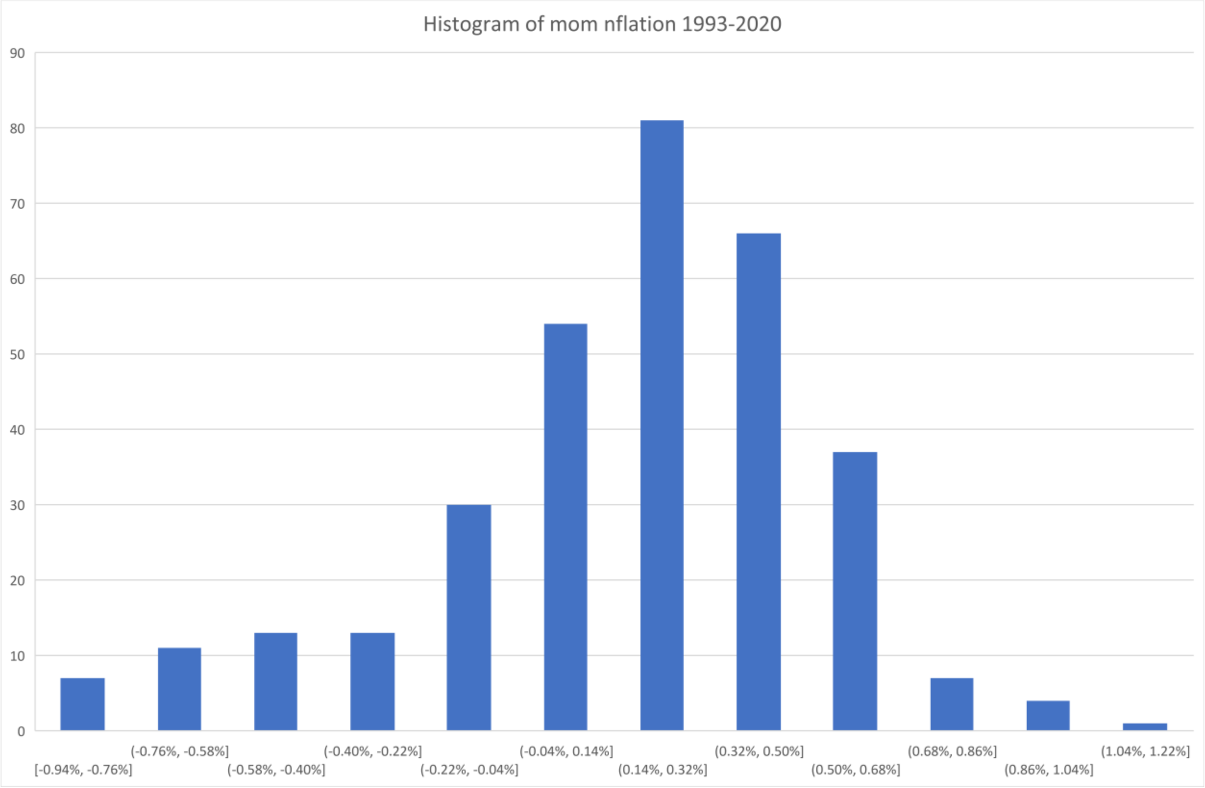

Figure 2: Histogram of monthly inflation 1993-2020

Whilst the raw data we will be using is the mom inflation rate, we are seeking to see what the implications are for the headline inflation figures so widely reported, which are an annual inflation figure giving the total inflation over the last 12 months.

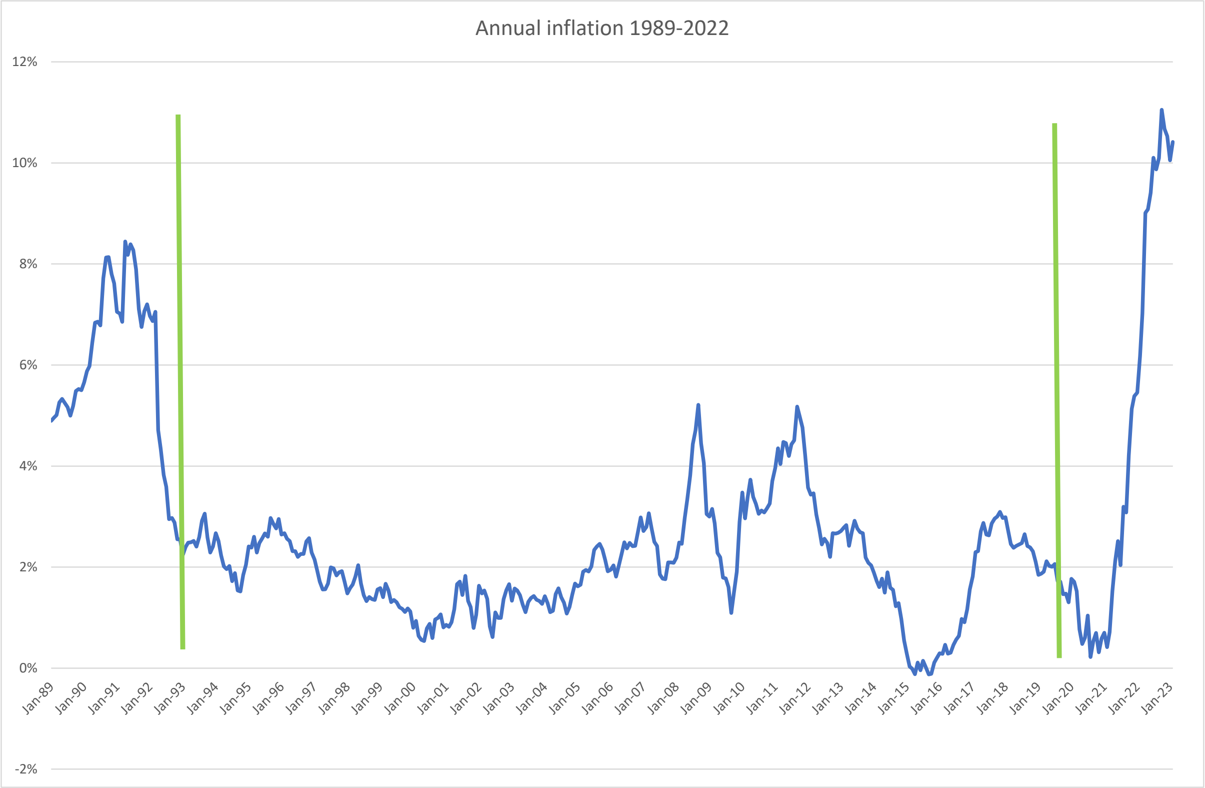

Figure 3: Annual inflation 1989-2023

If we look at the headline annual inflation published each month, we can see it is a smooth and highly correlated series. The period covered in our data is between the green lines and excludes the higher inflation periods prior to 1993 and 2020-23. This is just to remind us that “trend” inflation itself can move around. Whilst it has remained stable for the period we are looking at post-1993, it can drift off to higher levels as it did in the 70s and 80s. Indeed, in the more recent period since 2021 we have seen just such an increase again. In the period 1994 to March 2008, CPI inflation remained in the range 1-3% except for 5 months over the period September 1995-November 1996. In the crisis period and its aftermath, interest rates remained close to zero and no active attempt was made to stabilize inflation. Inflation became more variable and went above 3% for two periods (April 2008 to February 2009 and December 2010 to March 2012), and went below 1% for a period of over 18 months from December 2014 to August 2016. We can of course tell a story about what was happening to headline inflation: it would include devaluations, the Brexit referendum, the “forward guidance “ of the Governor of the Bank of England and other elements. The inflation is, or at least appears to be stationary around a mean of 2%, but the deviations of inflation appear to be quite persistent and can remain away from the mean for prolonged periods.

When we talk about inflation persistence, we can examine it from different perspectives. Firstly, there is whether or not theoretical models are able to generate the empirical persistence of inflation found in the data. There has been a long running discussion about whether the DGSE models of various sorts can generate impulse response functions that resemble estimated VARs. For example, if there is a monetary shock, what does the response of inflation look like: does the model “fit” the data? Some of the papers in the last 20 years that have explored this issue include Smets and Wouters (2003, 2007), Eichenbaum et al (2004), and Dixon and Kara (2011) and Dixon and Le Bihan (2012). Secondly, there is the focus of this paper, namely what is the link between shocks to mom inflation and the resultant behaviour of headline inflation. Our approach is primarily empirical and is based on the time-series modelling of mom inflation and what that implies for the headline annual inflation figures.

3: Our methodology for modelling Mom Inflation.

Our starting point is the raw data in terms of mom inflation. In a low inflation environment, such as the UK in the period 1993-2019, the annual or headline inflation is approximated very well by the sum of the twelve mom inflation rates. We will model mom inflation and then see what this implies for the behaviour of headline inflation. Our baseline model is to represent mom inflation as a single equation AR(12) process with seasonality and various dummies to reflect factors such as VAT changes. We use the UK CPI data from January 1993 to December 2019. The endpoint is natural, so that we exclude the Covid Pandemic which raises many other issues. The starting point is perhaps less obvious. However, in the UK there was a spike in inflation in the early 1990s and various special budgetary measures were employed which had direct effects on inflation (for example, changes in indirect taxation). These were studied by Osborn and Sensier (2009) who adopted an approach similar to the one we use for the period 1983-2003. Although we include the Great Recession 2008-9, 1993-2019 is a period when inflation was below 5% and most of the time in the range 1-3%. We consider CPI rather than CPIH or RPIX, because RPIX is obsolete and much the same results hold for CPIH as for CPI.

Our analysis of the data will also be at the level of the 12 COICOP two-digit divisions of expenditure and indeed also to a lesser extent at the three and four digit levels. The source of our CPI data at this level of disaggregation are the consumer price inflation tables published by the ONS every month with the release of the new inflation figures. Our approach proceeds in four stages:

Stage 1: we explain current inflation by past inflation. For headline CPI inflation, this means treating CPI inflation as an AR(12) process with seasonal and VAT dummies.

Stage 2: We look at the 12 COICOP Divisions, we will also look at the role of lagged inflation within the sector and the effect of lagged CPI. We simplify the regressions to obtain a parsimonious specification (we use the AIC criterion and then adjust so that we are left with only significant coefficients).

Stage 3: we introduce a number of other variables into the mix as possible explanatory variables. These are

(a) Output growth, measured by consumption measured at the aggregate level for CPI and also for each of the 12 COICOP divisions[1]. This is a good output variable for consumer prices and captures more accurately the demand by households for the items included in the CPI measure. GDP is a much broader measure of output and demand, whilst industrial production is a narrow measure and less directly related to final household consumption.
(b) Unemployment. This has been shown to be an important variable in recent work on pricing behaviour in relation to sales (Kryvtsov and Vincent 2021). It captures uncertainty and conditions in the labour market.
(c) PPI inflation. PPI measures the behaviour of producer prices and this may well represent a pipeline effect: the prices included in PPI might be intermediates going into future consumption goods, or final consumer goods as they make their way to retailers.

Stage 4: simplify the regressions obtained in Stage 3 to obtain a final parsimonious form.

[1] Data on household consumption at the level of the 12 COICOP divisions is to be found in Economic Trends.

Output and unemployment can be thought of as classic "Phillips curve" type variables, and we would expect output growth to increase inflation and unemployment to reduce it. PPI can be thought of as a cost-push variable and we would expect PPI inflation to lead to more CPI inflation.

4. CPI inflation as an autoregressive process.

In this section, we will first present a theoretical analysis of modelling annual inflation as the sum of month-on-month inflation. Our first task is to show how to link together the autoregressive process for mom with annual inflation, obtaining a reduced form expression for current annual inflation as an infinite sum of current and past inflation shocks. We then estimate the mom process, which we reduce down into a parsimonious form.

4.1 Modelling annual inflation from mom inflation.

We will estimate an AR(12) process for mom inflation, which takes the general form:

$$\pi_t = \sum_{i=1}^{12} a_i \pi_{t-i} + \varepsilon_t \tag{1}$$

We can then write (1) using the lag operator *L*, so that

$$\pi_t = \Phi(L)\varepsilon_t \tag{2}$$

Annual inflation is then approximated[1] by

$$\Pi_t = \sum_{i=0}^{11} \pi_{t-i} = \Phi(L)\sum_{i=0}^{11}(\varepsilon_{t-i} - \varepsilon_{t-i-1}) \tag{3}$$

However, if we note that

$$\sum_{i=0}^{11}(\varepsilon_{t-i} - \varepsilon_{t-i-1}) = \varepsilon_t - \varepsilon_{t-12}$$

Then we can rewrite (3) as

$$\Pi_t = \Phi(L)(\varepsilon_t - \varepsilon_{t-12}) \tag{4}$$

[1] The approximation uses $\ln(1+\pi) = \pi$. Given that mom inflation is almost always less than 0.01 and averages 0.0017, this is an excellent approximation in this setting, as the higher powers π^r are close to zero for r>1. In Appendix A1 we examine how this approximation worked given the actual UK inflation data.

Equation (4) represents the current annual inflation as a function of current and past inflation shocks e_{t-i} for $i = 0...\infty$.

The exact general form for the individual coefficients on each ε_{t-i} are very complicated. However, to evaluate the effect of shocks we can use the general Taylor expansion for Φ as:

$$\Phi(L) = 1 + \sum_{j=1}^{\infty} \left(\sum_{i=1}^{12} a_i L^i \right)^j \tag{5}$$

In practice, to evaluate (5) we will need to approximate it by a truncated Taylor approximation, for example with $j = 2$. However, since most estimated coefficients are not significantly different from 0, combined with the fact that they are small (less than 0.27), the terms rapidly tend to zero for small *j*. In section 4.3 below, we illustrate how to evaluate (5) with the actual estimated coefficients.

The simple example given in the introduction was the special case when only a_{12} was non-zero. More generally, when it comes to following the impact of a shock going forward in time, it is relatively simply to construct the impulse-response implied by the estimated coefficients, since we assume that all previous shocks were zero and simply trace forward the cumulative effect through time.

4.2 The estimated AR(12) for mom inflation

The first stage of our analysis is to look at the aggregate level. We first run the AR(12) for mom CPI with dummies for VAT changes, the crisis and calendar months, we can see from the first column in Table 2 that the only significant variables (other than constant and dummies for months and the three VAT changes), are the first and twelfth lags of inflation. The coefficients on lagged inflation are not large: 0.12 on the first lag and 0.24 on the twelfth. This implies very little autocorrelation and persistence in mom inflation. For example, the half-life of a shock is just one month. If we are looking at inflation in January 2019, there is an effect from the previous month of December 2018 and also the previous January 2018. If we simplify the equation into a parsimonious form, we get much the same result with coefficients on the first lag of 0.11 and 0.27 respectively.

Table 2 Regressions for CPI on itself.

	Dependent variable:	
	CPI	CPI (Stepwise)
lag1	0.12*	0.11*
lag2	-0.04	
lag3	0.05	
lag4	0.04	
lag5	0.01	
lag6	-0.01	
lag7	0.02	
lag8	0.01	
lag9	0.06	
lag10	-0.01	
lag11	0.07	
lag12	0.24**	0.27**
Observations	324	324
R^2	0.74	0.73
Adjusted R^2	0.71	0.72
Residual Std. Error	0.19	0.19
F Statistic	29.66**	46.46**

Note: * p<0.05; ** p<0.01;

Both regressions include dummies for the month VAT changes and the GFC.

Is the significant coefficient on the 12-month lag just a "seasonal" effect? Not in the sense that we have controlled for each calendar month, and that the 12-month lag effect is a common effect that is the same for each month in the regression. Seasonal dummies are a very basic way of correcting for seasonality: implicitly it assumes that the seasonal effect is the same in every year in the sample. However, a 12-month lag is certainly seasonal in the sense that it links inflation in a particular month with inflation in the same month a year earlier. There are also faint echoes of the longer past: there is a small effect of 0.06 from two years ago (0.24^2). We will discuss the possible causes of this 12-month effect in later sections.

4.3 Simulating the effect of an inflation shock on headline annual inflation.

What are the implications of this structure of lags for the persistence of headline inflation? CPI inflation is approximated as the 12-month sum of inflation from the current month to the 11th lag. Suppose there is an inflation shock of 100. We will look at 4 scenarios.

Scenario 1: there is no autocorrelation in mom inflation, $a_i = 0,\ i = 1...12.$

Scenario 2: there is only autocorrelation at 1 month $a_1 > 0, a_i = 0,\ i > 1.$

Scenario 3: there is only autocorrelation at 12 months, $a_{12} > 0, a_i = 0,\ i < 12.$

Scenario 4: there is autocorrelation at 1 and 12 months.
$a_{12} > 0,\ a_1 > 0,\ a_i = 0,\ 1 < i < 12.$

To follow each scenario, we depict each scenario in terms of mom and annual inflation (π and Π respectively) in Table 3 over 24 months after the shock. Prior to the shock, annual and mom inflation are assumed to be at zero (the steady-state) as are prior shocks.

Month	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
	Π	π	Π	π	Π	π	Π	π
1	100	100	100	100	100	100	100	100
2	100	0	111.00	11	100	0	111	11
3	100	0	112.21	1.21	100	0	112.21	1.21
4	100	0	112.34	0.13	100	0	112.34	0.13
5	100	0	112.36	0.01	100	0	112.36	0.01
6	100	0	112.36	0	100	0	112.36	0
7	100	0	112.36	0	100	0	112.36	0
8	100	0	112.36	0	100	0	112.36	0
9	100	0	112.36	0	100	0	112.36	0
10	100	0	112.36	0	100	0	112.36	0
11	100	0	112.36	0	100	0	112.36	0
12	100	0	112.36	0	100	0	112.36	0
13	0	0	12.36	0	25	25	37.36	25.00
14	0	0	1.36	0	25	0	31.86	5.50
14	0	0	0.02	0	25	0	31.56	0.13
16	0	0	0	0	25	0	31.56	0.02
17	0	0	0	0	25	0	31.56	0
18	0	0	0	0	25	0	31.56	0
18	0	0	0	0	25	0	31.56	0
20	0	0	0	0	25	0	31.56	0
21	0	0	0	0	25	0	31.56	0
22	0	0	0	0	25	0	31.56	0
23	0	0	0	0	25	0	31.56	0
24	0	0	0	0	6.25	6.25	12.81	6.25
25	0	0	0	0	6.25	0	9.37	2.06

Table 3: The effect of an inflation shock over 25 months

Scenario 1. Let us suppose that there was no significant autocorrelation in mom inflation and that all the lagged coefficients were zero. In this case, since annual inflation is the sum of the twelve mom inflation rates, we get the familiar 12-month persistence of a monthly shock: the shock remains in the inflation figure for 12 months before it “drops out”. This mechanical relation is depicted in Figure 4, where we set the initial shock as 100 so that the vertical axis can be read as the % proportion of the shock persisting after x-months (horizontal axis).

Scenario 2. In this case we allow for first order autocorrelation of 0.11 in mom inflation. This gives rise to positive month on month inflation after month 1, but which dies away very quickly, with 11 in month 2, 1.21 in month 2 and so on. In subsequent months it gets closer to zero and is recorded as 0 to two d.p. Turning to annual inflation, we see a “hump shape”, as the additional in months 2-4 causes the headline figure to increase and then remains more or less constant from month 5 until the inflation from months 1-4 drops out and is back to zero by month 16.

Scenario 3, with only the twelve-month autocorrelation set at 0.25 (slightly below the estimated value). Here we see a step function. For the first 12 months headline inflation is at 100, then after the initial shock leaves the figures the new shock from autocorrelation kicks in at 25 leaving inflation at 25 for year 2 (months 13-24), and likewise there is a step fall from 25 to 6.5 in month 25. This is exactly the scenario we gave in the introduction.

In scenario 4, we combine both autocorrelation at 1 month and 12 months. In this case, we see the hump from scenario 2, and the persistence in years 2 and three which is greater than in the scenario 3, with 32 in year 2 and 9 in year 3. The first and twelfth order correlation reinforce each other. This corresponds most closely to the estimated effect from the simplified regression in Table 2.

We depict the four scenarios over 38 months in Figure 4, with the *estimated* scenario 4 in burgundy with the thickest line (using the second column “Stepwise CPI”), scenarios 2 and 3 in the less thick grey and brown lines, and lastly the dotted black line for scenario 1.

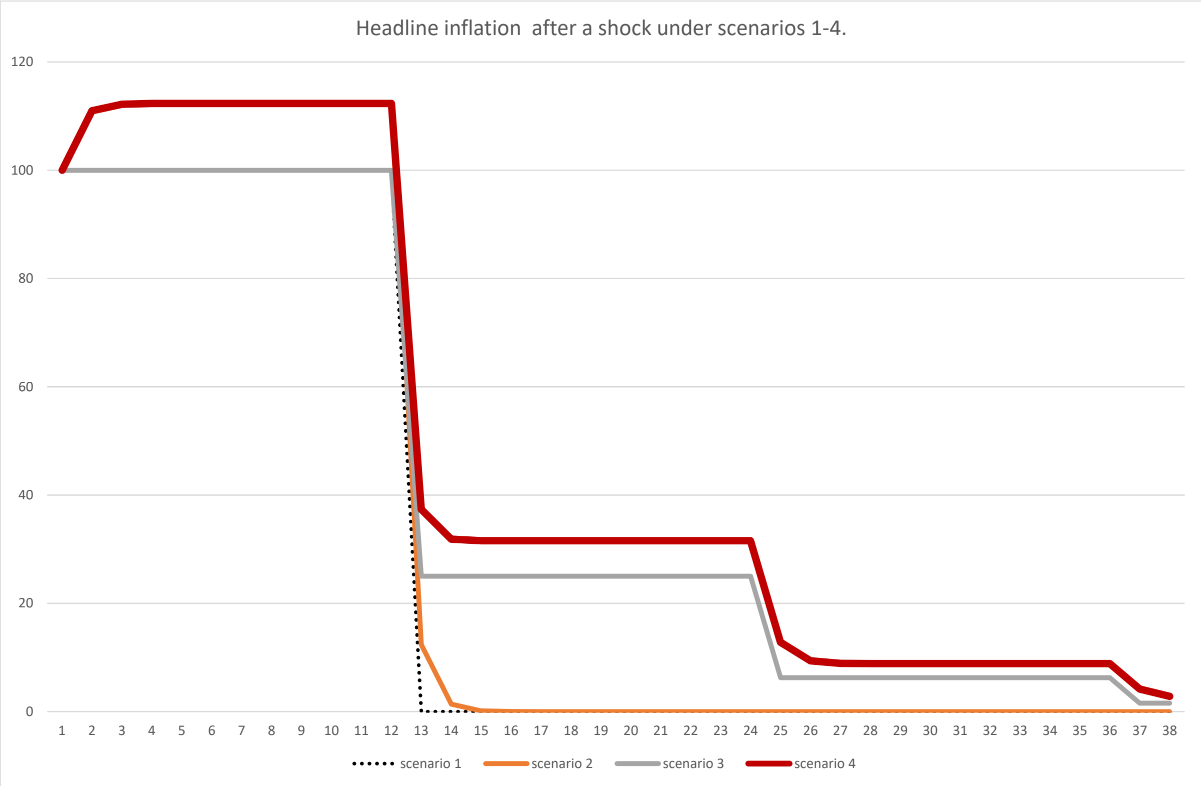

Figure 4: Responses of annual inflation to a shock in mom inflation under scenarios 1-4.

This is really quite remarkable. A simple one-month shock to mom inflation has a very persistent effect on the headline CPI inflation. There is the mechanical "drop-in drop-out" effect coming from the annual nature of CPI inflation. However, the small degree of autocorrelation leads to a dramatic increase in persistence. The first-order autocorrelation gives rise to the hump shaped response, but the persistence is mainly driven by the twelfth lag, with the two reinforcing each other after month 12.

This is an important lesson. Even a little correlation in mom inflation can lead to a lot of persistence in the annual inflation figure. Looking back at our statistical model in equations (2)-(5), for the estimated model in scenario 4 we have the

$$\pi_t = a_1 \pi_{t-1} + a_{12} \pi_{t-12} + \varepsilon_t$$

Using the lag operator *L*, we have the explicit form for $\Phi(L)$

$$\pi_t = (1 - a_1 L - a_{12} L^{12})^{-1} \varepsilon_t \tag{6}$$

Which gives us the equation for annual inflation and the change in annual inflation[1]:

$$\Pi_t = (1 - a_1 L - a_{12} L^{12})^{-1} (\sum_{i=0}^{11} \varepsilon_{t-i}) \tag{7}$$

$$\Delta \Pi_t = \Pi_t - \Pi_{t-1} = (1 - a_1 L - a_{12} L^{12})^{-1} (\varepsilon_t - \varepsilon_{t-12}) \tag{8}$$

[1] I would like to thank Ron Smith for pointing out this form of representing the dynamics of inflation.

If we expand the inverse of the lag polynomial in (6)-(8), we have:

$$(1-a_1L-a_{12}L^{12})^{-1}=\sum_{j=0}^{\infty}\left[a_1L+a_{12}L^{12}\right]^j \tag{9}$$

This is a binomial expression, in which each square bracket can be written as:

$$(a_1L+a_{12}L^{12})^j=\sum_{k=0}^{j}C_j^k\left(a_1L\right)^{j-k}\left(a_{12}L^{12}\right)^k \tag{10}$$

Where C_k^j is the combinatorial function:

$$C_k^j=\frac{j!}{k!(j-k)!}$$

Hence we can write annual inflation (7) explicitly in terms of current and past shocks as

$$\Pi_t=\sum_{j=0}^{\infty}\sum_{k=0}^{j}C_k^j\left(a_1L\right)^{j-k}\left(a_{12}L^{12}\right)^k\left(\sum_{i=0}^{11}\varepsilon_{t-i}\right) \tag{11}$$

Likewise for mom inflation and changes in annual inflation:

$$\Delta\Pi_t=\sum_{j=0}^{\infty}\sum_{k=0}^{j}C_k^j\left(a_1L\right)^{j-k}\left(a_{12}L^{12}\right)^k\left(\varepsilon_t-\varepsilon_{t-12}\right)$$

$$\pi_t=\sum_{j=0}^{\infty}\sum_{k=0}^{j}C_k^j\left(a_1L\right)^{j-k}\left(a_{12}L^{12}\right)^k\left(\varepsilon_t\right)$$

Whilst these infinite expansions are exact, with the estimated values $a_1=0.11$ and $a_{12}=0.25$ only the first few terms will have quantitatively significant values. The terms in the combinatorial expansions will be sequences of length *j*, resulting in with a_{12} to the power *k* and a_1 to the power *j-k*. An Upper bound to each term $a_i^{(j-k)}a_{12}{}^k$ is thus 0.25^j and hence for *j>6*, the coefficients are less than 0.0001. Hence if we take *j=6* as the cut off, we can see that current mom inflation depends on the shocks *t-i* for *i=0,1,2..17.* Annual inflation will depend primarily on shocks from those same periods and further back to up to *i=28*.

In the absence of autocorrelation, we have $a_1=a_{12}=0$. From (7) this yields scenario 1 and we have the simple drop-in drop-out model: inflation in period *t* is simply equal to its previous value plus the difference between the new shock ε_t dropping in and the old shock ε_{t-12} which drops out. However, in the case where all of the estimated coefficients are significant, the form of (11) will be complicated. In Appendix A2, we provide a more detailed analysis of the relationship between the estimated coefficients of the autoregressive mom inflation process and the implied weights put on past inflation via the arithmetical relationship of annual to monthly inflation.

5. Inflation for different expenditure types.

In this section we move on to stage 2 and focus on the 12 different types of expenditure (the two-digit COICOP divisions). The headline CPI is a weighted average of the 12 COICOP divisions. We model mom inflation for each division using the same dummies and lag structure. However, there is an important difference: we also include the aggregate CPI inflation with up to 12 lags. This enables us to see if the 12-month lag we found in the previous section is primarily the prices in each division reacting to the aggregate CPI figure or to prices in their own division. We can state this as two alternative hypotheses:

H1: The 12-month effect found in the aggregate CPI is due to the CPI from 12 months ago affecting the two-digit COICOP divisions.

H2: The 12 month effect in aggregate CPI is due to a 12 month effect within each two-digit COICOP division.

These two hypotheses are not exhaustive, but the data clearly rejects H1 and shows that H2 is most likely. There is almost no evidence for a 12-month effect of aggregate CPI on inflation in the 12 divisions. We give the 12 divisions simple acronyms: the first two digits are their number and the second are two letters contained in their full names.[1]

Since we now have 12 equations and more variables in each equation, we employ a systematic method to simplify equations. First, we searched for the optimal specification in terms of minimizing the Akaike Information Criterion (AIC). As is well known, the specification which minimises the AIC might contain insignificant variables. This was the case for 7 out of the 12 equations. We therefore adopted a second step where we took a cut-off p value of 0.1 and performed a joint test that all the coefficients with p values greater than 0.1 could be set to 0 (using a standard F-test). This restriction was accepted for most equations: where there were still insignificant estimates, we repeated until we were left with only significant variables. The details of the process are included in Appendix B, where we also report the specifications that minimised the AIC criteria along with the general unrestricted equations.

The benefit of this procedure is that we first move to the optimum according to AIC. At the optimum, the AIC is “flat”, and when we make small adjustments to ensure a set of significant coefficients there is only a very small increase in the AIC. Furthermore, for most equations the overall F-statistic improves as does the Bayesian Information Criterion (BIC). This reflects the fact that the different criteria put different weights on the “saving” made by removing coefficients. The end result is shown in Table 4, where

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[1] Thus we have Food and Non-Alcoholic Beverages is 01FN, Alcohol and Tobacco is 02AT, Clothing and Footwear is 03CF, Housing, Water and Energy is 04HW, Furniture and Household Equipment 05FH, Health 06HL, Transport 07TR, Communication 08CM, Recreation and Culture 09RC, Education 10ED, Restaurants and Hotels 11RH, Miscellaneous Goods and Services 12MS.

for ease of exposition we just state the significance level of coefficients for the lagged dependent variables (LDV) and lagged CPI.

The results show that for all but two sectors the 12-month lag on sectoral inflation (LDV 12) is significant and positive. Whilst there are some significant lagged coefficients for CPI,[1] the 12-month lag is not positive for any COICOP type. In fact there are very few significant lagged CPIs beyond 6 months with the longest being marginally significant at 11 months. This indicates that when we interpret the 12-month coefficient in the single equation, the causation does not go from CPI to the sectoral equations. Rather the current inflation in most sections is correlated with its own 12-month lag and it is this which is reflected in the aggregate regressions. This therefore provides solid and consistent evidence against H1 (since the 12 lags of CPI is insignificant in all equations) and strong evidence for H2 (since the 12 LDV is significant in 10 out of 12 divisions).

One surprising result is that there is a clear preponderance of a negative coefficients on the first LDV for most sections which stands in contrast to the positive coefficient at the aggregate level. Also, whilst nothing is significant at the aggregate level for LDV coefficients for months 2-11, we can see a variety of patterns within each sector. Whilst some sectors have several significant LDV coefficients (04CF and 06HW for example), others have just one or two (08CM and 10ED for example). Whilst the 12-month LDV is always positive when significant, we can see a variety of signs for coefficients: out of 132 possible coefficients for lags 1-11, we see 17 are significantly positive and 25 are significantly negative. Given this heterogeneity at the Divisional level for lags other than 12-month, it is perhaps unsurprising that the lags are not significant at the aggregate level.

[1] Out of 120 possible coefficients, only 20 are significant for lagged CPI.

	01FB	02AT	03CF	04HW	05FH	06HL	07TR	08CM	09RC	10ED	11RH	12MS
LDV1	0.14**	−0.17***	−0.21***	0.22***	−0.28***	−0.38***			−0.18***		−0.11**	−0.12**
LDV2		−0.09*	−0.13***		−0.21***	−0.39***						
LDV3			−0.14**			0.13**						0.13**
LDV4	−0.12*		−0.12**			−0.24***		−0.11**	0.13**			
LDV5			0.10**			−0.19***			0.14***			
LDV6			0.32***		0.23***	−0.22***			0.19***			
LDV7			0.10*	0.10*	0.09*							
LDV8				−0.10*								−0.09*
LDV9			0.09*				−0.13**	0.11*			−0.11*	
LDV10		0.09*			−0.16***							
LDV11					−0.11**	−0.15***						
LDV12	0.12**	0.28***	0.30***	0.14**	0.35***		0.22***		0.21***	0.47***	0.19***	0.11**
CPI_1							0.58***					0.16*
CPI_3		0.37**	0.68***	0.34**			−0.56***	0.46***		0.64**		
CPI_4	0.49***			0.27*							0.09*	
CPI_6		0.65***		−0.32**			−0.38*		−0.18**			
CPI_7		−0.51***			0.51***							
CPI_8	0.32**											
CPI_9							0.44*					
CPI_11									0.15*			
Num.Obs.	324	324	324	324	324	324	324	324	324	324	324	324
R2	0.284	0.632	0.935	0.332	0.923	0.434	0.56	0.191	0.365	0.593	0.459	0.197
R2 Adj.	0.235	0.604	0.929	0.28	0.917	0.39	0.528	0.14	0.317	0.569	0.423	0.141
AIC	568.1	573	692.8	573.3	413.3	704.4	739.6	656.6	140.6	1028.7	−206.6	152.4
BIC	655.1	667.5	798.6	667.8	511.6	798.9	830.4	736	235.1	1104.4	−123.4	239.4
F	5.712	22.379	164.601	6.472	149.196	9.989	17.443	3.768	7.509	24.656	12.845	3.531
RMSE	0.54	0.54	0.65	0.54	0.42	0.66	0.7	0.62	0.28	1.11	0.16	0.29

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Estimates for the 12 COICOP expenditure classes after simplification

These results indicates that the 12-month effect we find in the aggregate level is a result of this effect coming from most of the COICOP divisions. We can now perhaps address the issue of seasonality for some types of expenditure. Alcohol and Tobacco (02AT) is seasonal as changes to taxes on items in this category are made at the time of budgets, which in the period covered in the data happened in April and since 2017 there has been an additional Autumn Budget in October/November. Whilst there are monthly dummies, the dummy assumes the effect is the same for each year. However, the budget changes in particular years will vary. However, the 12-month effect would only be generated if the changes in indirect taxes were correlated across years. Whilst there is a strong April Budget effect, the pricing of alcohol reflects other seasonal effects. The other expenditure that is highly seasonal is Education, which is unchanged for 10 months of the year and changes only in September and October. For Education (10ED), the monthly dummies for September and October are the only significant ones. The 12-month lag coefficient of 0.46 for 10ED is the highest across the 12 COICOP divisions. This is not the result of changes in indirect taxes. What this probably shows is the fact that the pricing decision adopted in this sector is one of revising the previous year's increase. In this case the annual correlation probably reflects a framing effect, the starting point to this year's decision is the decision of the previous year. These two sectors, 02AT and 10ED probably have the biggest seasonal element in that the changes in price tend to be concentrated in particular months. In other sectors, whilst there are seasonal effects with different patterns of dummies in terms of sign and significance.

6. Do other variables help us to explain inflation?

In this section we move onto stage 3 and we consider how variables other than inflation might be used to explain inflation. This can be considered to be testing the robustness of the results found in stages 1 and 2. Will the 12-month lag coefficients still be significant when we introduce additional variables? To do this, we introduce the following variables:

1. Output growth. For output we use Consumption expenditure from Consumer Trends published by the ONS. Whilst this is quarterly, we transform this into monthly data.
2. The level of unemployment.
3. Producer Price Index.
4. Average hourly wages.

The first two variables can be thought of as "Phillips curve" or demand related variables, linking output and unemployment to price inflation. The last two variables can be thought of as cost variables, linking the growth of costs of intermediate inputs and wages to inflation. Using consumer expenditure growth as our demand variable is different to other studies. For example, Dixon, Luintel and Tian (2020) use industrial production. However, the consumer expenditure data is available at the 12 2-digit COICOP division level and is more directly related to consumer prices than measures such as industrial output or GDP.

The purpose of this exercise is mostly one of testing the robustness of our exercise without the additional variables. Is the importance of the twelfth month effect an illusion due to omitted variables? We can be more confident that we are capturing a real mechanism if it is present even in the model inflation with additional variables.

Firstly, as in section 4 we focus on the aggregate CPI and go from the general to specific across all variables. We include 12 lags of inflation and all four of the additional variables and then simplify using the AIC criteria and then reducing to obtain only significant coefficients. Secondly, as in section 5 we perform the same exercise for each of the twelve COICOP expenditure types. The data in Consumer trends is broken down into each COICOP division. This is another advantage of using consumption data directly rather than aggregate data such as industrial production or monthly GDP which cannot be broken down in this way.

The full details of the regressions are contained in the appendix. However, we report the final form of the regression with CPI as the dependent variable after we have minimised the AIC and then used F-tests to remove the insignificant variables. We found that none of the consumer demand variables survived the selection process, whilst the other Phillips curve variable unemployment did have two significant coefficients for lags 5 and 6, but with opposite signs. Turning to the cost variables, none of the wage lags were significant, but some PPI lags were significant, with a quantitatively large coefficient of 0.16 on the first lag.

	CPI
CPI_11	0.16**
CPI_12	0.17**
PPI_1	0.16***
PPI_9	0.06***
PPI_12	−0.07**
U_5	−0.01*
U_6	0.01**
Num.Obs.	227
R2	0.782
R2 Adj.	0.757
AIC	−139.8
BIC	−54.1
F	31.625
RMSE	0.16

Table 5: The simplified equation with additional explanatory variables.

However, the most important aspect for us is the behaviour of the coefficients on lagged inflation. Lag 1 has ceased to be significant, Lag 12 is significant but smaller in value and we have a coefficient on lag 11 similar to lag 12. The overall diagnostics for the model with the additional variables are slightly better than the simple model in section 4, in terms of the AIC, BIC and adjusted R^2 and the overall F statistic.

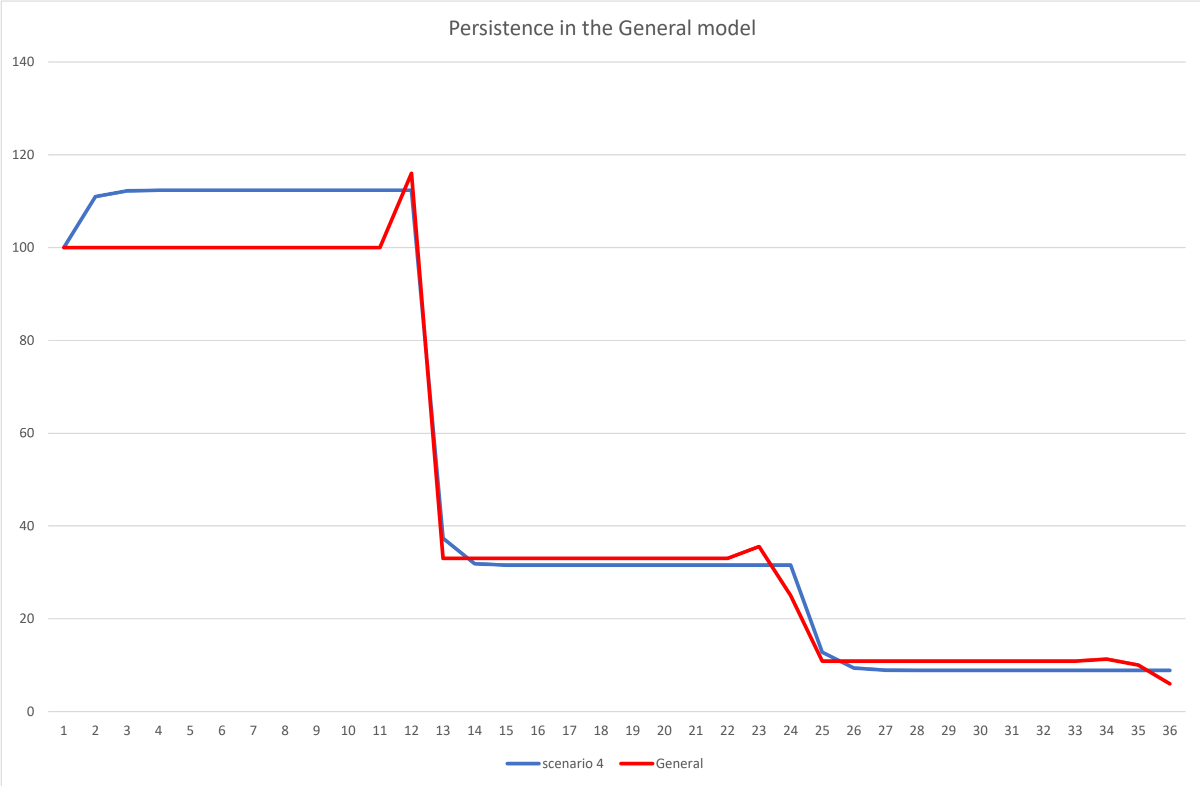


Figure 5: The response of headline inflation to a shock with estimated coefficients with additional variables.

If we compare the inflation persistence with the estimated coefficients from the simplified version of the model with extra variables, we get an inflation response which looks very similar to the one found with the original model: we put them side by in Figure 5, the original in blue with new one labelled "general".[1] The main difference happens in the first twelve months. The new response function lacks the one-month lag coefficient to build up inflation for the first 10 months. Inflation then increases in month 11 to be almost what it was in the original model. In year 2 for both models most of the time inflation remains at 33-34% of the original shock, and in year 3 10-11%. We can conclude that the estimated coefficients in the simplified form of both the original model and the with additional variables are both similar in terms of the inflation dynamics they imply, despite the differences in the precise coefficients in the final equations. In particular, the fact that both the 11 and 12 month lags are significant in the expanded model compensates for a smaller value of the 12 month lag coefficient and absence of the first coefficient. The twelfth month effect is still there and reinforced by an 11th month effect.

If we turn now to the 12 expenditure types, we can perform exactly the same exercise expanding the approach in section 5 with the additional variables. The demand

[1] In both cases we use the estimated values, so that the "original" differs from scenario 4 in that the coefficient on the 12 month lag equals 0.27 and not 0.25.

variable is specific to each type of consumption expenditure. However, the other additional variables are all generic across sectors. We provide the full results in the appendix, but only report the final output. The results are rather large, so we divide the Table into two.

In Table 6A, we report the final coefficients for the LDV and lagged CPI inflation, plus the overall diagnostics. In Table 6B, we report the additional variables. The first thing to note is that we still have a significant and positive “Twelfth month” effect for 7 of the COICOP divisions, although Transport has a negative coefficient. However, with the additional variables we can see that a 12^{th} lag on CPI comes in for Transport with a significant and large positive coefficient. This may reflect the fact that a large proportion of Transport prices are regulated (for example rail and local bus fares), being linked to inflation (either the RPI or CPI measure).

	01FB	02AT	03CF	04HW	05FH	06HL	07TR	08CM	09RC	10ED	11RH	12MS
CPI_1						−0.23**					0.17***	0.20*
CPI_2						0.16*						
CPI_3		0.42**						0.83***				
CPI_4	0.51**	0.55***									0.11**	
CPI_5					0.39**							−0.17*
CPI_6		0.79***		−0.89***	0.38**							
CPI_7		−0.64***	0.61**		0.71***	0.23***			−0.26**	−1.02***		
CPI_8	0.34*		0.59**				−0.47*					
CPI_10										0.66**		−0.21*
CPI_11						−0.23**			0.27**			
CPI_12							0.53**					
LDV1		−0.26***	−0.22***	0.19***	−0.35***	−0.11*	−0.38***		−0.18***		−0.24***	−0.18***
LDV2		−0.16***	−0.13**		−0.24***		−0.12**	0.15***				
LDV3								0.13**		0.31***		
LDV4	−0.20***							−0.21***				
LDV5			0.23***		−0.11*		−0.12**					
LDV6			0.23***		0.20***				0.12*		−0.15**	
LDV7				0.12**		−0.17**						
LDV8							0.17**					
LDV9									0.12*	−0.13**		0.15**
LDV10			−0.12**		−0.17***	−0.16**					0.14**	
LDV11					−0.12**							
LDV12		0.27***	0.22***		0.27***	0.17***	−0.15**			0.34***	0.13**	
Num.Obs.	227	227	227	227	227	227	227	227	227	227	227	227
R2	0.395	0.725	0.931	0.537	0.936	0.596	0.819	0.311	0.465	0.802	0.646	0.302
R2 Adj.	0.32	0.677	0.92	0.455	0.924	0.537	0.792	0.241	0.389	0.771	0.589	0.204
AIC	375.9	400.6	495.9	345.8	289.4	42.4	401.4	406.7	138.5	637.7	−174.5	95.4
BIC	468.4	523.9	608.9	469.1	422.9	148.6	511	485.5	241.3	750.7	−61.5	198.1
F	5.253	14.923	84.856	6.556	75.127	10.023	29.601	4.416	6.136	25.481	11.464	3.063
RMSE	0.49	0.5	0.62	0.44	0.39	0.23	0.51	0.54	0.29	0.85	0.14	0.26

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6A: The coefficients for LDV and lagged CPI with additional variables.

In Table 6B, we report the coefficients for the additional variables contained in the results reported in Table 6A. Some variables seem to be important for some expenditures but not for others. Whilst consumption was not significant at the aggregate level, it does appear to be significant at certain lags for most divisions except for 01FB and 08CM. To a lesser extent the same is true for wages, PPI and unemployment. It is beyond the scope of this paper to provide a detailed analysis of all 12 COICOP divisions. The main take-away is that our additional variables do seem to play an important role at the more disaggregated level. However, the most important difference is for Transport: we find a highly significant twelfth month effect for CPI and a significant but perverse own effect. This indicates that when we introduce additional sector specific variables, there is some evidence of an effect from aggregate CPI to inflation in at least one sector (07TR), but otherwise the general picture is that H2 holds up as opposed to H1.

	01FB	02AT	03CF	04HW	05FH	06HL	07TR	08CM	09RC	10ED	11RH	12MS
Con_1		0.22**		0.34***			0.24***			3.54***		−0.04**
Con_2		−0.19*		−0.31**			−0.14**			−3.17***	0.06***	
Con_3			0.24***	0.23**	0.08*	0.06*			0.09***			
Con_4		0.34***			−0.13**	−0.10**						−0.09***
Con_5		−0.42***			0.10*	0.07**						0.08**
Con_7		0.31***					−0.13**		0.07**			−0.10***
Con_8		−0.17*	−0.18**		0.09**							0.08***
Con_9			0.25***									
Con_10				0.30***	−0.12**					1.30***		
Con_11		0.17**	−0.24***		0.12**					−1.10***		
Con_12		−0.12*	0.14*									
PPI_1	0.20***				0.13**		0.97***					
PPI_3				0.33***				−0.34***		0.38***		
PPI_4									−0.08*			
PPI_6				0.24***	−0.24***				−0.13**		0.04*	
PPI_7	0.18**		−0.40***						0.15***			0.13***
PPI_8				0.16**			−0.24**					
PPI_9												
PPI_10												0.10**
PPI_11				0.19**	0.11*				−0.11**			
PPI_12				−0.19**		0.09**						
U_1											−0.01*	
U_3											−0.01*	
U_4		−0.05*										
U_5				−0.05**							−0.01**	
U_6				0.05**								
U_7						0.02*					−0.01**	
U_8			−0.06**									
U_9	0.04*						0.07***			−0.08*		
U_11					0.04**				0.04***		0.01*	
WAGE_1										−0.23**		
WAGE_2							0.12**			−0.19**	0.04***	
WAGE_3										−0.17*		

	01FB	02AT	03CF	04HW	05FH	06HL	07TR	08CM	09RC	10ED	11RH	12MS
WAGE_4	0.08*				0.08*							
WAGE_5				−0.14***								
WAGE_6				−0.12**								
WAGE_7										−0.23***		
WAGE_9	0.11**	−0.11*		−0.11**								
WAGE_10	0.10**	−0.11*										
WAGE_11				−0.12**							0.03**	
Num.Obs.	227	227	227	227	227	227	227	227	227	227	227	227
R2	0.395	0.725	0.931	0.537	0.936	0.596	0.819	0.311	0.465	0.802	0.646	0.302
R2 Adj.	0.32	0.677	0.92	0.455	0.924	0.537	0.792	0.241	0.389	0.771	0.589	0.204
AIC	375.9	400.6	495.9	345.8	289.4	42.4	401.4	406.7	138.5	637.7	−174.5	95.4
BIC	468.4	523.9	608.9	469.1	422.9	148.6	511	485.5	241.3	750.7	−61.5	198.1
F	5.253	14.923	84.856	6.556	75.127	10.023	29.601	4.416	6.136	25.481	11.464	3.063
RMSE	0.49	0.5	0.62	0.44	0.39	0.23	0.51	0.54	0.29	0.85	0.14	0.26

Table 6B: The coefficients for additional variables for regressions in Table 6A

7: Results at the 3 and 4-digit COICOP level.

This section provides a more detailed level of COICOP classification at the three and four digit level (38 groups and 71 classes) using the same approach as section 5, with the LDV and lagged CPI. The first step is to look at group levels, and then we move onto class levels where these are available. The main text only reports the parsimonious results for 38 groups, with a summary table for the classes.

The results for the groups are shown in parsimonious form after simplification in Tables From 7A to 7D. The one month lag effect holds for 21 groups out of 38 (although mostly with negative coefficients), whilst 12-month LDV is significant for 23 groups and always has a positive sign. CPI does appear to have some effects on the individual groups when we consider the whole range of results. There are, however, few significant lags (no lag length is found in more than three groups), with the most common lag being six months, with different signs amongst the groups. Overall, there is a total absence of 5, 10, 12 month CPI lags. There is a strong signal here, which suggests that pricing behaviour is more influenced by group concerns than by aggregate factors. This reinforces our findings at the two-digit divisional level in section 5, supporting H2 rather than H1.

When we are looking at class levels (four-digit COCOP), it is possible that groups (divisions) do not have sub-classes in our data set. We replace it with groups if this is the case, or we replace it with divisions if there are no groups. For example, under

Education (10), there are no sub-categories in our dataset, whether divisions or groups, so we use division data instead. This ensures that the whole COICOP range is covered for the CPI, although it does replicate some of the same data in Tables 4 and 7. Using the same dummies and lag structure, we model mom inflation for each class. We merely report a summary table 8 with the full detail in appendix C.

In Table 8, we summarise the proportion of regressions with significant coefficients in with CPI weights (columns 3 and 4) and unweighted (columns 1 and 2). We report results for the 1% and 5% significance levels. Hence in the first row, column 1 we have 48.24% (unweighted) of regressions have a significant one-month LDV significant at the 1% level, with 46.2% significant at 1% when weighted. Turning to the 12-month LDV, we can see that 62.4% are significant at the 5% level (unweighted) and 61.4% (weighted). Again, where as many of the significant coefficients of LDV are negative, almost all on LDV 12 are positive. If we look at the lagged CPI coefficients, the proportion of significant variables is much smaller: the largest is CPI lag 6 at 21.4% (weighted), whilst most are much lower. This contrasts to the LDVs, where most lagged values have a proportion of significant coefficients at 10-20% (the exception being LDV 5). Also, the 12^{th} lag of CPI is only significant in 7% of cases (weighted and unweighted). Again H1 seems to be refuted in favour of H2.

Overall, whilst we can see more diversity revealed as we deal with more disaggregated data, we can see that when we go down to three and four-digit groups and classes, the general story still holds. First, for the majority of cases there is a significant and positive 12-month LDV effect, as found in the aggregate CPI. Second there is also a large proportion of cases where the first LDV is significant, although as in the two-digit case in section 5, many of these are negative. Thirdly, whist there is some evidence of a direct effect of CPI on its constituent groups and classes, this is not uniform and there is little evidence of a 12 month effect from CPI to its constituent sub-categories, with a few exceptions.

Table 7A Stepwise Analysis: Groups 1 (Monthly data)

	Dependent variable:								
	FOOD	NON-ALCOHOLIC BEVERAGES	ALCOHOLIC BEVERAGES	TOBACCO	CLOTHING	FOOTWEAR INCLUDING REPAIRS	ACTUAL RENTALS FOR HOUSING	REGULAR MAINTENANCE AND REPAIR OF THE DWELLING	WATER SUPPLY AND MISC. SERVICES FOR THE DWELLING
lag1	0.15*	-0.30*	-0.44*		-0.22*				
lag2		-0.16*	-0.27*						
lag3			-0.16*						
lag4									
lag5									
lag6					0.34*	0.17*		0.19*	
lag7		0.15*							
lag9								0.14*	
lag11						0.17*			
lag12		0.19*	0.24*	0.27*	0.29*	0.27*	0.73*		0.27*
CPI_1									
CPI_3			0.80*		0.60*				
CPI_4				0.58*					
CPI_5									
CPI_6			1.17*						
CPI_7									
CPI_9							-0.17*		
CPI_12									
Observations	324	324	324	324	324	324	324	324	324
R^2	0.25	0.33	0.72	0.40	0.93	0.84	0.86	0.24	0.57
Adjusted R^2	0.21	0.29	0.70	0.36	0.93	0.83	0.86	0.18	0.54
Residual Std. Error	0.62	0.76	0.82	0.73	0.74	0.74	0.22	0.38	1.04
F Statistic	5.74*	6.88*	35.49*	11.14*	168.42*	78.54*	96.40*	4.47*	23.57*

Note: * p<0.01;

Table 1B Stepwise Analysis: Groups 2 (Monthly data)

	Dependent variable:								
	ELECTRICITY, GAS AND OTHER FUELS	FURNITURE, FURNISHINGS and CARPETS	HOUSEHOLD TEXTILES	HOUSEHOLD APPLIANCES, FITTING AND REPAIRS	GLASSWARE, TABLEWARE and HOUSEHOLD UTENSILS	TOOLS AND EQUIPMENT FOR HOUSE AND GARDEN	GOODS AND SERVICES FOR ROUTINE MAINTENANCE	MEDICAL PRODUCTS, APPLIANCES AND EQUIPMENT	OUT-PATIENT SERVICES
lag1	0.26*	-0.50*	-0.35*	-0.20*	-0.31*		-0.22*	-0.43*	
lag2		-0.37*	-0.16*					-0.35*	
lag3		-0.14*							
lag4							-0.17*	-0.16*	
lag5									
lag6		0.14*							
lag7		0.12*		0.15*					
lag8							-		
lag10		-0.19*							-0.20*
lag11		-0.22*							
lag12		0.26*	0.18*	0.24*	0.14*				
CPI_1									
CPI_2						0.62*			
CPI_3									
CPI_4						0.52*			
CPI_5									
CPI_6			0.66*						
CPI_7							0.84*		0.37*
CPI_8						0.63*			
CPI_9									
CPI_11					0.62*				
CPI_12									
Observations	324	324	324	324	324	324	324	324	230
R^2	0.13	0.91	0.88	0.40	0.68	0.25	0.26	0.39	0.29
Adjusted R^2	0.08	0.90	0.87	0.36	0.65	0.20	0.21	0.34	0.22
Residual Std. Error	1.59	0.90	0.80	0.99	0.85	0.65	0.56	0.76	0.40
F Statistic	2.63*	106.00*	103.43*	10.65*	27.66*	4.76*	5.00*	7.91*	4.44*

Note: * p<0.01;

Table7C Stepwise Analysis: Groups 3 (Monthly data)

	Dependent variable:								
	HOSPITAL SERVICES	PURCHASE OF VEHICLES	OPERATION OF PERSONAL TRANSPORT EQUIPMENT	TRANSPORT SERVICES	POSTAL SERVICES	TELEPHONE AND TELEFAX EQUIPMENT AND SERVICES	AUDIO-VISUAL EQUIPMENT AND RELATED PRODUCTS	OTHER MAJOR DURABLES FOR RECREATION AND CULTURE	OTHER RECREATIONAL ITEMS, GARDENS and PETS
lag1		0.39*	0.31*	-0.49*					-0.42*
lag2				-0.34*					
lag3	-0.25*			-0.40*			0.17*		-0.15*
lag4				-0.27*					
lag5		-		-0.24*					
lag6	-0.21*			-0.31*			0.16*		
lag7				-0.30*					-0.15*
lag8				-0.18*			0.19*		
lag9				-0.39*					
lag10		0.15*		-0.32*					
lag11			0.18*	-0.20*					
lag12	0.47*			0.26*			0.17*		0.26*
CPI_2			-1.00*	1.85*					
CPI_3									
CPI_5									
CPI_7		-0.42*							
CPI_9				1.60*					
Observations	216	324	324	324	324	324	324	228	324
R^2	0.67	0.41	0.33	0.80	0.21	0.17	0.35	0.36	0.38
Adjusted R^2	0.64	0.37	0.29	0.78	0.17	0.12	0.31	0.30	0.33
Residual Std. Error	0.47	0.51	0.95	1.89	1.63	0.70	0.86	0.43	0.75
F Statistic	20.81*	10.02*	7.58*	37.07*	4.63*	3.48*	8.31*	6.53*	8.68*

Note: * p<0.01;

Table 7D Stepwise Analysis: Groups 4 (Monthly data)

	Dependent variable:										
	RECREATIONAL AND CULTURAL SERVICES	BOOKS, NEWSPAPERS AND STATIONERY	PACKAGE HOLIDAY	CATERING SERVICES	ACCOMMODATION SERVICES	PERSONAL CARE	PERSONAL EFFECTS (NEC)	SOCIAL PROTECTION	INSURANCE	FINANCIAL SERVICES (NEC)	OTHER SERVICES (NEC)
lag1	-0.17*	-0.21*	0.43*		-0.21*	-0.21*	-0.16*				
lag2			0.24*								
lag3									0.25*		
lag6					-0.19*		0.18*		0.15*		
lag8											
lag9										0.18*	0.17*
lag12	0.22*	0.26*		0.20*		0.16*	0.18*	0.36*	0.14*		0.21*
CPI_1							0.55*				
CPI_2											
CPI_3											
CPI_4				0.11*							
CPI_6					-0.56*		0.44*				
CPI_7											
CPI_9	0.34*										
CPI_10											
CPI_11											
CPI_12											
Observations	324	324	311	324	281	324	324	228	324	324	324
R^2	0.62	0.34	0.47	0.53	0.34	0.23	0.74	0.61	0.25	0.08	0.28
Adjusted R^2	0.60	0.30	0.43	0.50	0.30	0.18	0.72	0.57	0.20	0.02	0.23
Residual Std. Error	0.45	0.70	0.29	0.12	0.69	0.46	0.53	0.15	1.01	1.74	0.51
F Statistic	23.95*	7.19*	12.66*	16.34*	7.21*	4.67*	41.44*	14.41*	5.06*	1.43	5.87*
Note:											* p<0.01;

Table 8 Summary table (simplified Class level)

	Unweighted		Weighted	
	$p<0.01$	$p<0.05$	$p<0.01$	$p<0.05$
LDV1	48.24%	54.12%	46.02%	52.46%
LDV2	25.88%	35.29%	22.35%	33.88%
LDV3	16.47%	23.53%	14.18%	20.57%
LDV4	5.88%	15.29%	5.73%	13.08%
LDV5	5.88%	9.41%	5.70%	8.51%
LDV6	15.29%	23.53%	17.93%	25.95%
LDV7	8.24%	14.12%	7.43%	11.98%
LDV8	7.06%	12.94%	7.36%	12.67%
LDV9	10.59%	17.65%	9.41%	15.53%
LDV10	7.06%	12.94%	6.38%	10.89%
LDV11	7.06%	15.29%	7.74%	14.44%
LDV12	48.24%	62.35%	45.78%	61.38%
CPI_1	3.53%	11.76%	2.97%	10.71%
CPI_2	4.71%	11.76%	4.46%	14.22%
CPI_3	3.53%	12.94%	3.90%	12.71%
CPI_4	8.24%	10.59%	10.28%	12.55%
CPI_5	1.18%	8.24%	0.99%	8.34%
CPI_6	10.59%	16.47%	12.75%	21.28%
CPI_7	3.53%	10.59%	2.87%	8.63%
CPI_8	1.18%	5.88%	0.74%	5.29%
CPI_9	3.53%	12.94%	3.22%	11.07%
CPI_10	3.53%	8.24%	3.28%	8.08%
CPI_11	1.18%	8.24%	0.74%	10.22%
CPI_12	1.18%	7.06%	0.95%	6.87%

8 An International comparison using core inflation.

In this section we examine whether the 12 -month effect is present in other countries as well as the UK. We will use the OECD measure of core inflation (excluding food and energy) obtained from the FRED database and covering the years 1992-2019. We look at 9 large economies: in addition to the UK, we have the USA, Germany, France, Japan, Canada, Italy, Spain and South Korea. As we noted when looking at the UK CPI components, the 12-month effect was present in most of the core components, but absent in most of the non-core components (where we take core as CPI excluding food and energy). We would thus expect the 12-month effect to be larger in the core inflation in the UK and by analogy across the other countries. This is indeed what we find: in the UK the 12 month effect has a coefficient of 0.40 for core CPI. In Table XX we show the regression results for a simple AR(12) of mom inflation (with monthly dummies included to allow for seasonality).

Table 9: International comparison for core inflation

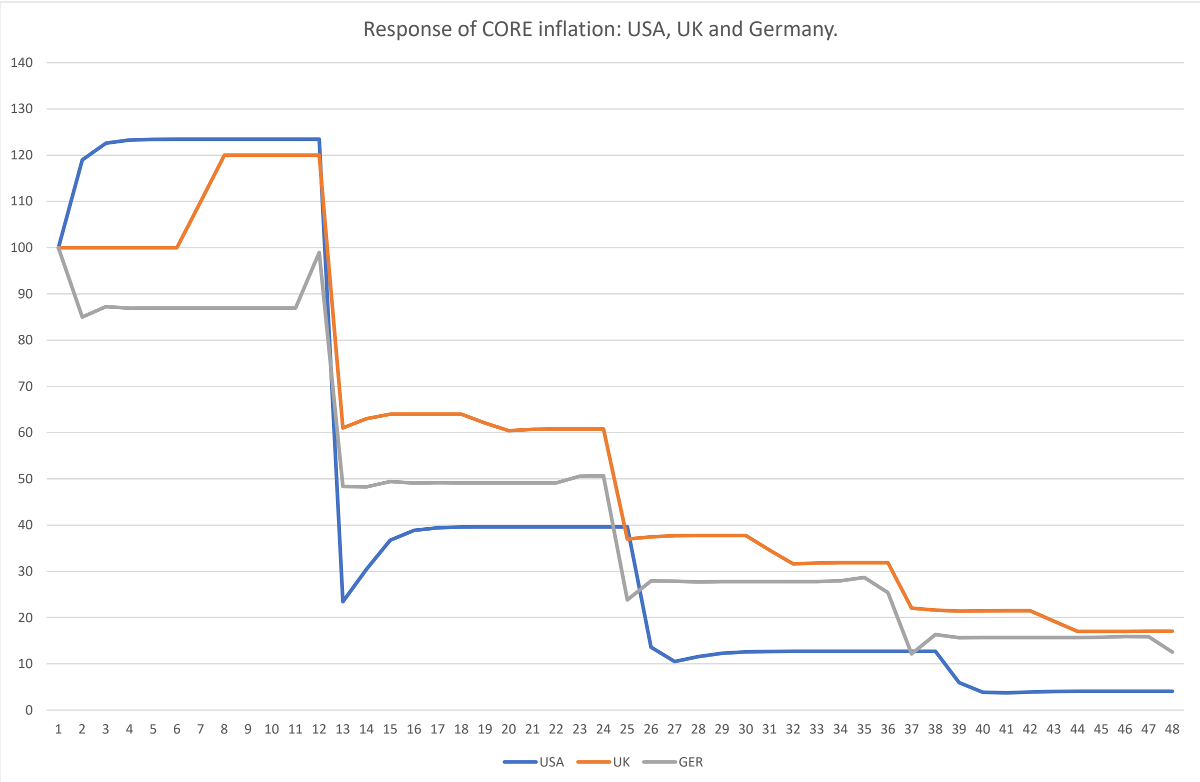
	UK	USA	Germany	France	Japan	Canada	Italy	Spain	Korea
constant	0.13*	0.24*	0.12	0.12*	-0.12*	0.33*	0.06	0.06	0.12*
lag 1		0.19*	-0.15*	-0.12*					0.21*
lag 2								-0.12	
lag 3								-0.11*	0.12
lag 4				0.09			0.13*		
lag 5									
lag 6	0.13*				0.15*			0.26	0.10
lag 7					0.12	-0.12	-0.11*		
lag 8							0.15*	0.10	
lag 9						-0.11			
lag 10									
lag 11			0.12*	-0.08			0.15		
lag 12	0.44*	0.29*	0.55*	0.63*	0.29*	0.30*	0.49*	0.57*	0.27*
n	324	324	324	324	324	324	324	324	324
R^2	0.8178	0.7646	0.6348	0.8246	0.6400	0.3682	0.5969	0.9176	0.4595
$\bar{R}^2$	0.8096	0.7539	0.6170	0.8155	0.6225	0.3375	0.5746	0.9128	0.4313
RSE	0.0255	0.0079	0.0648	0.0196	0.0352	0.0502	0.0233	0.0409	0.0470
F-stat	102.9	74.5	37.1	93.8	37.9	12.4	27.7	196.2	170.0
F (prob)	1.68E-109	8.34E-92	7.08E-61	4.18E-110	7.50E-62	2.63E-24	1.08E-52	8.93E-160	6.77E-34

*All regressions included monthly dummies (February omitted) and were estimated using **OLS**. These are the simplified regressions, using stepwise regression until all the lagged coefficients remaining were significant at the 5% level (p<0.05). Those significant at the 1% level (p<0.01) have an asterisk. Coefficients are reported to two decimal places.*

As we can see, the 12-month effect is highly significant without exception (with a p-value of less than 0.0000). The values are all positive, ranging from a high of 0.59 (France) to 0.26 (USA) with a median value of 0.40 (the UK) and (unweighted) average 0.41. Hence we can see that the UK behaviour of core inflation is not at all unrepresentative, but falls very much in the middle. There are three countries with a low coefficient 0.26-0.29, three with a high coefficient (0.53-0.59) and three "in the middle" (0.3-0.49). In all countries we find a significant and positive 12-month effect for core inflation.

If we look at other lags, there is a mixed story across different countries. The one-month lag is significant (p<0.05) in 5 countries (USA, Germany, France, Spain and South Korea). Lag 4 is significant in 2 countries (France and Italy), lag 11 in three (Germany, France, Italy). Clearly, the exact spread of coefficients will give rise to slightly different patterns of behaviour when we translate this into the annual core inflation measure.

We can illustrate this by looking at the response of annual core inflation to a one month shock (as in Figure 4 above) for 48 months. We select one country with a low coefficient on lag 12 (USA), one with a median value (UK) and one with a high value (Germany). We also allow for the other significant coefficients. The patterns diverge in the first 12 months: Germany has a fall in inflation (with its negative coefficient on lag 1), whilst the US has a mirror image resulting from its positive lag 1 coefficient. The UK has a "jagged" increase in months 6 and 7. However, once we get beyond month 12 things are much more similar as the drop out of inflation from 12 months previously dominates. However, in all years 2-4 we see the ranking of UK with higher inflation, the USA with lower inflation, and Germany in between. The half-life of the US inflation is 13 months, and the UK 25 months, with Germany going below 50% at 13 months and coming up above again briefly in months 23 and 24. In year 4 there is still over 10% of the shock left the UK and Germany, and still a significant amount of 4% in the USA.



To conclude, whilst the exact pattern of the autocorrelation of mom core inflation differs across the 9 countries considered, there is a common positive and large 12-month effect in all of them. This gives rise to a greater persistence of annual inflation than we saw in the UK CPI. For the UK there is over 60% in year 2, 30% in year 3 and over 17% in year 4. In all countries, core inflation is highly persistent. This explains why it is a good predictor of future inflation, since the shocks to core inflation each month live on for a long time in the annual figures.

9.Conclusion.

In this paper we have looked in detail at the relationship between how we model month on month inflation and the implications this has for the headline annual inflation we hear about in the news. Mom inflation itself displays little persistence. There is a little autocorrelation with the first and twelfth-month lags. However, this small autocorrelation is sufficient to give rise to significant persistence in the annual inflation figure. A single one month shock raises annual inflation significantly, with 34% of the shock present in the second year and 10% in the third year.

When we look at the 12 COICOP divisions, we find that the 12-month lag in mom inflation is present for inflation within the division and does not come from the aggregate CPI. This implies that prices in each division are reacting to their own price increases 12 months ago, not to what was happening to CPI. This indicates that one potential explanation of the 12 month coefficient is a "framing effect": current pricing decisions are influenced by the how price changed 12 months ago. In the case where prices are reviewed and/or reset annually this is an obvious link across the 12 months. However, even where prices are reviewed and/or reset more frequently, this effect might also be present.

We find that the effect is robust when we add additional explanatory variables, both at the aggregate and the two-digit COICOP level.

Bibliography

Carlstrom C., Fuerst T, Paustian M. (2009). Inflation Persistence, Monetary Policy, and the Great Moderation, Journal of Money Credit and Banking, (41), 767-786. https://doi.org/10.1111/j.1538-4616.2009.00231.x

Cogley, T., G. E. Primiceri and T. J. Sargent (2010), Inflation-gap Persistence in the U.S., American Economic Journal: Macroeconomics, Vol. 2, pp. 43-69.

Dixon H., Kara E. (2010). Can We Explain Inflation Persistence in a Way that Is Consistent with the Microevidence on Nominal Rigidity? Journal of Money, Credit and Banking, (42) 151-170. https://doi.org/10.1111/j.1538-4616.2009.00282.x

Dixon H., Le Bihan H. (2012). Generalised Taylor and Generalised Calvo price and wage setting: micro-evidence with macro implications. Economic Journal, (122), pp. 532-554. https://doi.org/10.1111/j.1468-0297.2012.02497.x

Dixon H., Luintel K., Tian K. (2020) The impact of the 2008 crisis on UK prices: what we can learn from the CPI microdata. *Oxford Bulletin of Economics and Statistics*, (82), 1322-1341. https://onlinelibrary.wiley.com/doi/full/10.1111/obes.12373

Furhrer, J. (2010), Inflation Persistence. Chapter 9, Handbook of Monetary Economics, (ed. Benjamin M. Friedman, Michael Woodford) (3), 423-486. https://doi.org/10.1016/B978-0-444-53238-1.00009-0

Fuhrer, J. (2017), "Expectations as a Source of Macroeconomic Persistence: Evidence from Survey Expectations in a Dynamic Macro Model", Journal of Monetary Economics, Vol. 86, pp. 22-35.

Hall, S., Tavlas G., Wang Y. (2023) Forecasting inflation: the use of dynamic factor analysis and nonlinear combinations, Journal of Forecasting, (43), 514-529, https://doi.org/10.1002/for.2948

Jain, M., (2019), "Perceived Inflation Persistence", Journal of Business and Economic Statistics, 37:1 pp. 110-120.

Andreas Joseph, Galina Potjagailo, Eleni Kalamara, Chiranjit Chakraborty and George Kapetanios (2023), Forecasting UK inflation bottom up, Bank of England Working Paper 915.

Osborn D., Sensier M. (2009). UK inflation: Persistence, Seasonality and monetary policy, Scottish Journal of Political Economy, (56), 24-44. https://doi.org/10.1111/j.1467-9485.2009.00471.x

Pivetta F., Reis R. (2007). The persistence of inflation in the United States, Journal of Economic Dynamics and Control, (31), 1326-1358. https://doi.org/10.1016/j.jedc.2006.05.001

Shapiro, A.H. (2022a) How Much Do Supply and Demand Drive Inflation. *FRB San Francisco Economic Letter* 2022-15. https://www.frbsf.org/wp-content/uploads/sites/4/el2022-15.pdf

Shapiro, A.H. (2022b) A Simple Framework to Monitor Inflation. *FRB San Francisco Working Paper* 2020-29. https://www.frbsf.org/wp-content/uploads/sites/4/wp2020-29.pdf

Stock J., Watson M., (2007). Why Has U.S. Inflation Become Harder to Forecast? Journal of Money Credit and Banking, (39), 4-32. https://doi.org/10.1111/j.1538-4616.2007.00014.x

Stock J., Watson M., (2016). "Core Inflation and Trend Inflation," The Review of Economics and Statistics, (98), 770-784. https://doi.org/10.1162/REST_a_00608

Stock J., Watson M., (2008). "Phillips curve inflation forecasts," Conference Series; [Proceedings], Federal Reserve Bank of Boston.

Watson, M. (2014). "Inflation Persistence, the NAIRU, and the Great Recession," American Economic Review, American Economic Association, (104), 31-36. https:// doi.org/10.1257/aer.104.5.31

Appendix A: Technical appendix

A1: From months to years: compounding.

In the text, we have used the approximation that the annual inflation rate is equal to the sum of the monthly inflation rates. Now, we know that for mom inflation $|\pi| < 1$ we have the standard binomial expansion for the exact *n*-period gross inflation rate:

$$(1+\pi)^n = 1 + n\pi + \left[\frac{n(n-1)}{2!}\right]\pi^2 + \left[\frac{n(n-1)(n-2)}{3!}\right]\pi^3 .. + \pi^n$$

For *n=12*, we have:

$$(1+\pi)^{12} = 1 + 12\pi + \left[\frac{132}{2}\right]\pi^2 + \left[\frac{1320}{6}\right]\pi^3 .. + \pi^n$$

For 99% of the months, $|\pi| < 0.01$ and the mean is $\bar{\pi} = 0.0017$. Clearly, although the binomial coefficients can be quite large, the higher powers of π fall off much more rapidly. The highest binomial coefficient[17] is 925 for the 6th power of π which will be very small for values of $\pi < 0.01$. We can express the omitted compounding error both in absolute terms (percentage points pp) or proportional (as a proportion of the true value):

π (mom)	True Annual	Approx. Annual	Error (pp)	Error/True
0.0017	2.0592%	2.04%	0.0192%	0.0093
0.002	2.4266%	2.40%	0.0266%	0.0110
0.0025	3.0416%	3.00%	0.0416%	0.0137
0.003	3.6600%	3.60%	0.0600%	0.0164
0.04	4.9070%	4.80%	0.1070%	0.0218
0.05	6.1678%	6.00%	0.1678%	0.0272
0.01	12.6825%	12.00%	0.6825%	0.0538

The first point to note is that for mom inflation less than 0.004, the error is less than 0.1 pp. However, the approximation gets worse fairly rapidly and by 0.01, the error is almost 0.7 pp, which means the approximation is proportionately over 5% below the true value (and almost 0.7 pp). In our simulation results, we can interpret them as fairly accurate in the world where inflation is below 3% per year. In a world where inflation exceeds this but is still within the sample range (0-5%), the results are still a fairly good approximation to within 0.1 pp of the true value.

This simple example has assumed that the value of π is constant, whereas we know it varies over time. In this case we have to unpack the binomial coefficients to allow for the different values of π_i. So, for the squared terms we have the 66 pairs:

[17] The sequence of binomial coefficients for *n=12* is {1, 12, 66, 220, 495, 792, 924,792,495, 220, 66, 12, 1}.

$$\frac{1}{2}\sum_{i=1}^{12}\sum_{j\neq i}^{12}\pi_i\pi_j$$

Note that we need to divide by two to avoid double counting. Alternatively, we could have written the same sum as:

$$\sum_{i=1}^{12}\sum_{j>i}^{12}\pi_i\pi_j$$

Note that this has exactly 66 elements with no double counting (66=1+2+3+4+…+10+11). The same principles apply as we look at triples and above, but the summations become much more complex.

What we provide here is a look at real sequences of twelve mom inflation figures, each taken from a specific calendar year from the UK CPI data we use in the paper with additional years up to 2022. This is shown in Figure A1: the stacked columns show the actual (true) inflation in each year given by the LHS axis, subdivided into the approximate value (light blue) and the error (red), whilst the yellow line gives the error as a proportion of the true value (RHS axis). As we can see, in the period 1993-2019, the approximation is excellent, with only a small error less than 1% of the true value[18] in nearly all years except for the 2 years with inflation above period 2010 and 2011 where the error is 1.5% and 1.7% respectively. However, in the more recent period of high inflation, the approximation is worse, which would indicate that it is best to use the true values.

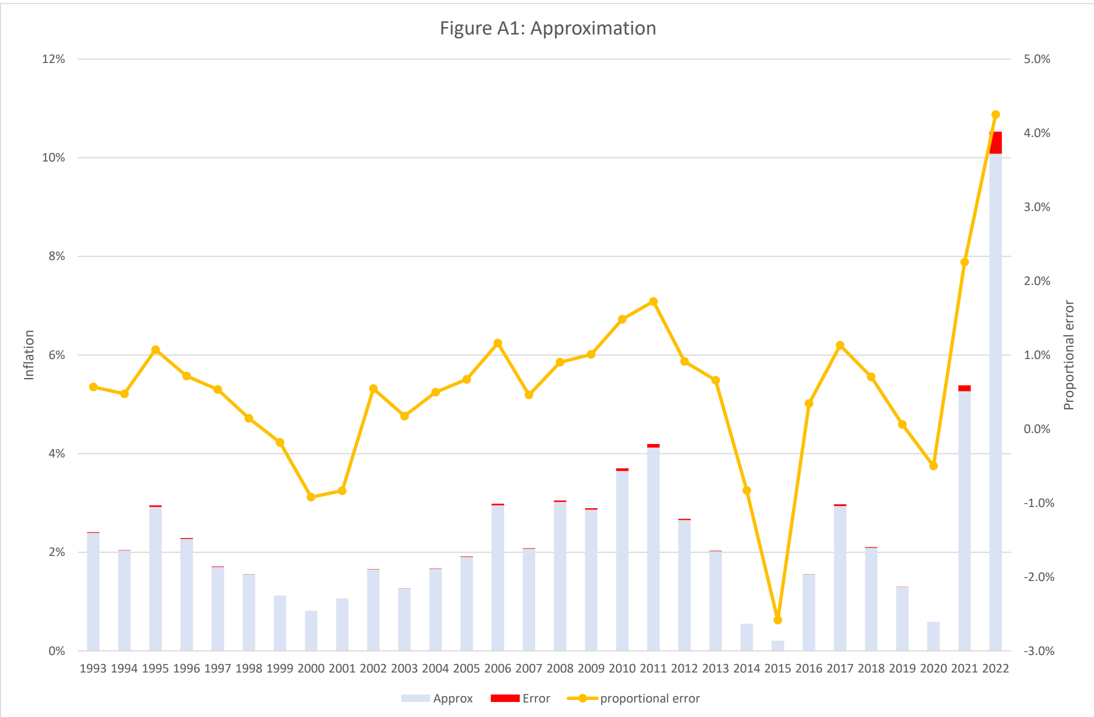


Figure A1: Approximation

[18] This is a proportional error, not percentage points. The error in terms of percentage points is the proportional error times the true inflation rate.

A2: The simple arithmetic of general lag structures.

In this section we will look at the simple arithmetic when we have a general 12 period autoregressive process for mom inflation.

$$\pi_t = \sum_{i=1}^{12} a_i \pi_{t-i} + \varepsilon_t \tag{12}$$

In this case we have the following equation for annual inflation:

$$\Pi_t \simeq \sum_{i=0}^{11} \pi_{t-i} = \sum_{i=0}^{11} \sum_{k=1}^{12} a_k \pi_{t-i-k} + \sum_{i=0}^{11} \varepsilon_{t-i} \tag{13}$$

Clearly, this process could be iterated by successively substituting for lagged inflation using (12) until we have only the error terms left as shown in equation (4). However, for now we will explore in more detail the implied lag structure from (13), which we can illustrate from the actual estimates in the paper.

The double summation can also be written as:

$$\sum_{k=1}^{12} \sum_{i=0}^{11} a_k \pi_{t-i-k} = \sum_{i=1}^{23} b_i \pi_{t-i}$$

Where:

$$b_i = \sum_{j=1}^{i} a_j \text{ when } i \le 12$$

$$b_i = \sum_{j=i-11}^{12} a_j \text{ when } i > 12$$

In our estimated equations we have $a_1, a_{12} > 0$ and $a_i = 0$ for *i=2..11*. Hence we have:

$$b_i = a_1 \text{ when } i < 12$$

$$b_i = a_1 + a_{12} \text{ when } i = 12$$

$$b_i = a_{12} \text{ when } j > 12$$

Perhaps it is easiest to see this in the form of a table when we allow for all a_i to be non-zero. Each row gives the sum of a_i's corresponding to the particular b_i in column 2.

lag	coefficients	estimated	
i	b_i	general	simplified
1	a_1	0.12	0.11
2	a_1+a_2	0.08	0.11
3	$a_1+a_2+a_3$	0.13	0.11
4	$a_1+a_2+a_3+a_4$	0.17	0.11
5	$a_1+a_2+a_3+a_4+a_5$	0.18	0.11
6	$a_1+a_2+a_3+a_4+a_5+a_6$	0.17	0.11
7	$a_1+a_2+a_3+a_4+a_5+a_6+a_7$	0.19	0.11
8	$a_1+a_2+a_3+a_4+a_5+a_6+a_7+a_8$	0.20	0.11
9	$a_1+a_2+a_3+a_4+a_5+a_6+a_7+a_8+a_9$	0.26	0.11
10	$a_1+a_2+a_3+a_4+a_5+a_6+a_7+a_8+a_9+a_{10}$	0.25	0.11
11	$a_1+a_2+a_3+a_4+a_5+a_6+a_7+a_8+a_9+a_{10}+a_{11}$	0.32	0.11
12	$a_1+a_2+a_3+a_4+a_5+a_6+a_7+a_8+a_9+a_{10}+a_{11}+a_{12}$	0.56	0.38
13	$a_2+a_3+a_4+a_5+a_6+a_7+a_8+a_9+a_{10}+a_{11}+a_{12}$	0.44	0.27
14	$a_3+a_4+a_5+a_6+a_7+a_8+a_9+a_{10}+a_{11}+a_{12}$	0.48	0.27
15	$a_4+a_5+a_6+a_7+a_8+a_9+a_{10}+a_{11}+a_{12}$	0.43	0.27
16	$a_5+a_6+a_7+a_8+a_9+a_{10}+a_{11}+a_{12}$	0.39	0.27
17	$a_6+a_7+a_8+a_9+a_{10}+a_{11}+a_{12}$	0.38	0.27
18	$a_7+a_8+a_9+a_{10}+a_{11}+a_{12}$	0.39	0.27
19	$a_8+a_9+a_{10}+a_{11}+a_{12}$	0.37	0.27
20	$a_9+a_{10}+a_{11}+a_{12}$	0.36	0.27
21	$a_{10}+a_{11}+a_{12}$	0.30	0.27
22	$a_{11}+a_{12}$	0.31	0.27
23	a_{12}	0.24	0.27

Table A1: The estimated coefficients on lagged inflation from equation (13).

The structure is "triangular" in that the number of coefficients increases by 1 until it hits 12 and then decreases by 1 until it is down to 1. However, each row is unique and contains at least one coefficient that differs from each of the other rows. For example, if we compare rows 11 and 13, 11 contains a_1 but excludes a_{12}, whilst row 13 includes a_{12} but excludes a_1. In fact all rows 1-11 exclude a_{12} and include a_1 whilst all rows 13-23 include a_{12} but exclude a_1. The only row which includes both a_1 and a_{12} is row 12.

Columns 3 and 4 give the implied values of the b_i's corresponding to the estimates of the a_i's from Table 2. Column 3 uses all of the estimated a_i's (significant and insignificant), whilst column 4 just uses the two left after the stepwise simplification. In Figure A2 we show the weights in column 3 and 4.

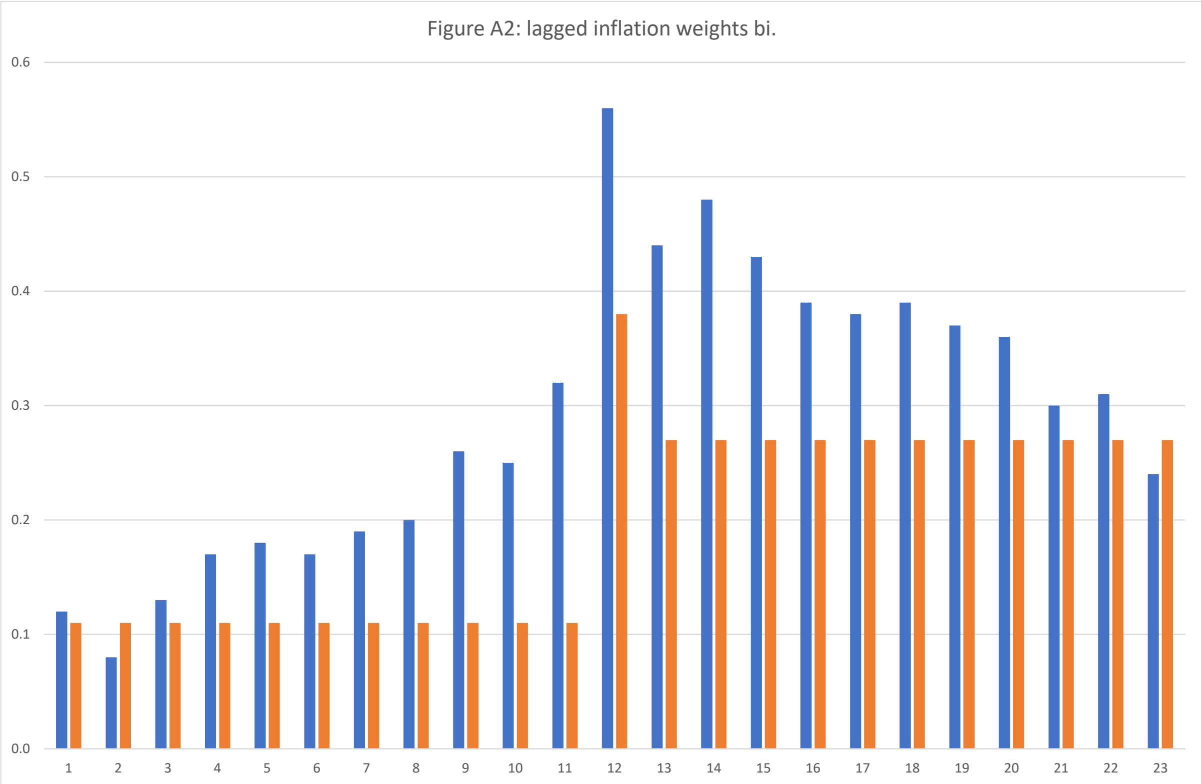


Figure A2: Lagged inflation weights b_i's

We could of course iterate the process to replace each mom inflation going backward until (asymptotically) we just have the inflation shocks ε_{t-i}. In each step the number of terms becomes much larger as the cross-product terms proliferate combinatorically. However, as argued in the main text, given the fact that the estimated coefficients are all small, the terms will rapidly tend to zero.