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Anchored or Not: How Much Information Does 21st Century Data Contain on Inflation Dynamics?

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Abstract

Inflation was low and stable in the United States during the first two decades of the 21st century and broke out of its stable range in 2021. Experience in the early 21st century differed from that of the second half of the 20th century, when inflation showed persistent movements including the "Great Inflation" of the 1970s. This analysis examines the extent to which the experience from 2000-2019 should lead a Bayesian decisionmaker to update their assessment of inflation dynamics. Given a prior for inflation dynamics consistent with 1960-1999 data, a Bayesian decisionmaker would not update their view of inflation persistence in light of 2000-2019 data unless they placed very low weight on their prior information. In other words, 21st century data contains very little information to dissuade a Bayesian decisionmaker of the view that inflation fluctuations are persistent, or "unanchored". The intuition for, and implications of, this finding are discussed.

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1. Introduction

Consumer price inflation in the United States, as measured by the Consumer Price Index, jumped to just above 7 percent in the twelve months ending in December 2021. Inflation in 2021 reached the highest level seen since the early 1980s. The jump in inflation outside of the range experienced over several decades has raised questions regarding the speed with which, or the degree to which, inflation may return to the 2-percent range consistent with the Federal Reserve's inflation objective. The answers to these questions hinge on the nature of the inflation process, including its persistence and the impact of economic slack on the inflation outlook.

A critical consideration in any work pursuing these questions is how to weigh data from different time periods. For example, one approach would involve specifying a (set of) model(s) and examining the stability of the inflation process across time periods as indicated by statistical tests. An alternative approach would involve a (set of) model(s) in which the parameters of the inflation process evolve over time (a time-varying parameter model) and would combine the model and data to estimate the evolution of parameters and resulting implications for the inflation outlook. Substantial bodies of research have considered both approaches.

This research pursues a different tack. The approach herein is the one a Bayesian decisionmaker would follow. The decisionmaker is endowed with a prior regarding the inflation process consistent with observed U.S. inflation data over the second half of the 20th century. The analysis examines how the Bayesian decisionmaker would use data since 2000 to update his prior view. The approach of the Bayesian decisionmaker has several advantages relative to other approaches. The first advantage is that the approach has not been used to inform an assessment of inflation dynamics and hence provides a new (and different) perspective. The second advantage is that the approach is a natural way to combine prior information/experience with recent data, in two senses: the approach flows directly from the

standard approach to combining prior information with subsequent data laid out by Thomas Bayes 250 years ago (Bayes and Price, 1763); and the approach allows for flexibility in the strength assigned to the 20th century experience in the assessment of the 21st century Phillips Curve. Heuristically, this strength could be termed the degree of conviction in the prior information. In the limiting case of essentially zero conviction in such prior experience, the Bayesian approach is equivalent to the approach in which a break is assumed in the Phillips Curve in the 21st century and only post-1999 data is used to estimate the inflation process (i.e., the first approach above). Finally, the approach yields insights regarding the information in macroeconomic data that are likely broadly relevant in macroeconomics—and therefore can inform future research on other questions. For example, the findings highlight the importance of assessing the strength of information in the data for assessing the evolution of other macroeconomic concepts, building on similar results in Kiley (2020a,b).

The results that emerge from the analysis are very clear. Data over the period 2000-2019 provide very little information with which to update prior views on the inflation process, at least with respect to inflation persistence or the "anchoring" of inflation. As a result, a Bayesian decisionmaker aware of the inflation process from 1960-1999—that is, endowed with a prior consistent with that process—would view the current inflation process as similar to that from 1960-1999 unless they place very little weight on the prior information. A direct implication of this result is that the inflation process may signal substantial persistence, suggesting the high inflation of 2021 may continue in 2022. The intuition for this finding is straightforward. Inflation was very stable from 2000-2019, which means the data witnessed few substantive deviations from its average or lagged values. Because the data contain few sizable deviations of inflation from its average or lagged values, the data provide little information regarding what would happen if inflation were to deviate sizably from its average or lagged values—an intuitive insight that also follows directly from the mathematics of a Bayesian least-squares regression. The lack of information in the data from 2000-2019 contrast sharply with the precision of the prior view

of the role of lagged inflation in the inflation process that is consistent with experience from 1960-1999, when inflation saw sizable swings away from its average value and experience suggests a sizable role for lagged inflation in the Phillips curve. This combination—low information in 2000-2019 data and an informative prior consistent with 1960-1999 experience—implies that the empirical analysis results in substantial inflation persistence unless the prior experience receives very little weight in the Bayesian decisionmaker's calculus. These findings highlight how researchers may find it valuable to assess the information in their recent data using Bayesian methods in cases where there is prior information, as an approach to complement approaches such as time-varying parameter models or structural-break analyses.

Previous literature: The analysis is related to the empirical literature examining the factors that determine the inflation process and how the importance of such factors may have shifted over time to explain high and variable inflation in the 1970s and low and stable inflation in the 21st century.[1] These include the degree to which the inflation process is "anchored" (i.e., the degree to which lagged inflation influences current inflation), the effect of unemployment on inflation (i.e., the slope of the Phillips curve), and the path of "supply shocks" or other supply factors that shift the relationship between inflation and economic slack. While alternative approaches are possible, a common—and simple— approach is to use a reduced-form Phillips curve relating inflation to its lags and the unemployment rate (e.g., Ball and Mazumder, 2011 & 2019; Gordon, 2013; Kiley, 2015; or Blanchard, 2016).

In this taxonomy, an "anchored" inflation process shows little effect of current inflation on subsequent inflation. The empirical work herein links anchoring to the persistence in inflation, which could reflect a variety of structural factors. For example, a sizable body of research has suggested that inflation persistence may have fallen in the 21st century. (e.g., Williams, 2006a,b; Kiley, 2008b; Ball and

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[1] Theoretical modeling has also considered possible factors, e.g., Kiley (2007).

Mazumder, 2011, 2019; Stock, 2011; Watson, 2014; Coibion and Gorodnichenko, 2015; Kiley, 2015b; Blanchard, 2016; Jorgenson and Lansing, 2019; and Carvalho et al, 2021). A prominent line of thought in this research is that inflation expectations (in the Phillips Curve) followed an accelerationist structure in the decades before 2000—responding strongly to recent inflation experience—and that inflation expectations were anchored in the years after 2000—responding little to lagged inflation. But much of this work is similar to the approach herein, focusing on inflation persistence with little direct attention to expectations. Future work can consider the implications of the approach herein for expectations *per se*. Some research also has questioned the decline in inflation persistence (e.g., Pivetta and Reis, 2007— although this study predates the low and stable inflation of the first two decades of the 21st century).

Research has also suggested a weaker relationship between unemployment and inflation in recent decades—that the Phillips curve has flattened in the 21st century or earlier (Atkeson and Ohanian, 2001). Ball and Mazumder (2011) suggest that "menu cost" models of nominal price and wage rigidity imply that such rigidities increase as the average rate of inflation falls, implying that more of the adjustment in nominal aggregate demand falls on output and less on inflation when inflation is low; this is exactly the finding emphasized in Kiley (2000), which analyzed support for this prediction across a large sample of countries. Research exploring the effects of downward nominal-wage rigidity points to a reduced effect of labor-market weakness on inflation in a low-inflation environment (Daly and Hobijn, 2014). Kiley (2008b) and Boivin, Kiley, and Mishkin (2010) present evidence that a clear commitment to price stability in recent decades, in the form of a monetary policy rule with a more sizable response to inflation, acts to substantially stabilize inflation expectations and mitigate fluctuations in inflation. Such a shift in monetary policy behavior is consistent with an observed flattening in the Phillips curve in the 21st century. Del Negro et al (2020) find a similar role for monetary policy but find a large role of for structural factors related to aggregate supply in the flattening of the Phillips Curve.

The literature pursues different empirical approaches, within or outside a Phillips curve approach. Much of the literature considers reduced-form Phillips curves estimated across subsamples of the data—i.e., considers breaks in estimated equations. Examples include Williams (2006), Kiley (2008b and 2015), Blanchard (2016), and Ball and Mazumder (2019). Other work explicitly models time variation in parameters, for example in vector autoregressions as in Cogley and Sargent (2005) and Primiceri (2005). A particularly influential class of time-varying parameter models are time-varying parameter unobserved component models (Stock and Watson, 2007; and Kiley, 2008a). In this approach, it is common for results to suggest that the variance of the permanent drift components was lower in the 2000-2019 period than earlier—i.e., that inflation was anchored in the 21st century.

The approach herein uses the textbook approach to Bayesian regression (e.g., Kim and Nelson 1999, Chapter 7) to examine the information content of the data for parameters of a Phillips Curve relative to the information in a reasonable prior. This approach has not been used in discussions of inflation dynamics. Bayesian approaches are often used in estimation of time-varying parameter models, as in Primiceri (2005)—but these analyses do not focus on the information content in the data relative to that in the prior; rather, they emphasize the value of Bayesian methods given the complexity of estimating such models. Kiley (2020a, 2020b) highlights how macroeconomic relationships may be poorly informed by aggregate time-series data and how the available data may not lead posterior assessments to differ from prior views in an examination of the equilibrium real interest rate.[2]

The analysis also raises questions regarding why inflation was more stable from 2000 onward. The Bayesian approach indicates that the data do not contain information to suggest a very large change in inflation persistence relative to pre-2000 experience. Under this view, the post-2000 inflation

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[2] Given limited information in aggregate time-series data, Fitzgerald and Nicolini (2014) and Kiley (2015a) analyze Phillips curves using city-level and state-level data, respectively. Hooper et al (2019) and Hazell et al (2020) build on this approach.

experience would be ascribed to "luck" that resulted in smaller shocks to inflation. Previous research has noted the challenges associated with distinguishing "luck" from structural changes (e.g., Ahmed, Levin, and Wilson, 2004).

Structure of the remaining sections: Section 2 discusses data and the framework a Bayesian decisionmaker endowed with a prior for the inflation process in the United States consistent with data over the second half of the 20th century would use to incorporate the information from the data over the 2000-2019 period in their view on the inflation process. Section 3 presents results, intuition, and implications. Section 4 concludes.

2. Data and approach

2.1 Data

The study analyses inflation in the United States. The analysis focuses on the Consumer Price Index (CPI), produced monthly by the U.S. Bureau of Labor Statistics. The focus of the investigation is the evolution of the persistence of inflation and, to a lesser extent, the slope of the Phillips Curve. To abstract from the volatility induced by fluctuations in food and energy prices, the empirical work uses the CPI excluding food and energy (core CPI), which is available from January 1957 to December 2021. The results are generally similar for the overall CPI, reflecting the correlation between overall and core CPI (e.g., Kiley, 2008a). The results are also similar when the price index considered is the chain-weighted price index for personal consumption expenditures (PCE prices). Note that the Federal Open Market Committee (FOMC) of the Federal Reserve System has defined its inflation objective of 2 percent in terms of PCE prices since 2012 and inflation as measured by the CPI index has averaged a few tenths above inflation as measured by PCE prices in recent decades; for this reason, we will refer to the inflation objective in the United States, as measured by the CPI, as in the range of 2 percent.

The Phillips Curve framework relates inflation to a measure of economic slack. The analysis uses the unemployment rate of the civilian noninstitutional population aged 16 and over (the unemployment rate), produced monthly by the U.S. Bureau of Labor Statistics.

Figure 1 presents the data on inflation and the unemployment rate. The inflation measure presented is the 12-month change in the natural logarithm of the core CPI (upper panel). Inflation was low and stable in the late 1950s and early 1960s. Inflation rose over the late 1960s and was both higher and more volatile over the 1970s. After the tightening in monetary policy associated with the Volcker disinflation that began in late 1979, inflation drifted lower over the course of the 1980s and early 1990s. Over this period from the late 1950s through the mid-1990s, inflation appeared to be persistent—that is, years in which inflation exceeded the average over this period tended to be followed by years in which inflation was above its average. From 2000 until 2019, inflation was generally low—near 2 percent—and stable. Inflation jumped out of its 2000-2019 range in 2021, reaching about 5½ percent in a twelve-month basis in December 2021. The unemployment rate (the bottom panel) rises sharply during recessions and declines during expansions, highlighting how it is a good measure of the state of the U.S. business cycle.

Table 1 presents some summary statistics on inflation and the unemployment rate. Statistics are presented for monthly data and for data on an annual average basis, as the Phillips Curve analysis will consider data at both the monthly and annual frequency as one robustness check. Statistics are shown for three sample periods: late 1950s-2019, late 1950s-1999, and 2000-2019. These three sample periods will be referred to as the full sample, the pre-2000 sample, and the post-1999 sample. The years 2020 and 2021 are excluded from the table and the estimation sample, reflecting the unprecedented (and unusual) effects of the COVID-19 pandemic; econometric work will almost surely

explore various ways to treat these unusual years in emerging research.[3] Two aspects of the summary statistics will prove important in understanding the results. First, inflation was much more volatile in the pre-2000 period than in the post-1999 period, as can be seen in the standard deviations of the series during the periods. Second, inflation was much more persistent in the pre-2000 period than in the post-1999 period, as can be seen in the autocorrelation of the series.

2.2 Empirical Approach

The analysis considers estimates of a Phillips Curve in which inflation ($\Delta p(t)$) depends on its own lags and the (lagged) unemployment rate ($u(t)$) as in equation (1) (in which a constant term is suppressed):

(1)	$$\Delta p(t) = \sum_{j=1}^{N-1} b(j) \cdot \Delta p(t-j) + a \cdot u(t-1) + e(t).$$

b(j) are the coefficients governing persistence, a is the slope of the Phillips curve, and e(t) is the residual reflecting "supply" shocks and other unmodeled factors which follows a Normal distribution ($e(t) \sim \mathrm{N}(0, \sigma^2)$). An anchored Phillips Curve would tend to have small b(j), whereas an unanchored Phillips Curve will tend to have large b(j). The sum of these coefficients, $\sum_{j=1}^{N} b(j)$, will be the statistic of focus, with a sum near 1 representing an unanchored accelerationist Phillips Curve.

The vector of coefficients in equation (1) is denoted by Γ. The matrix containing the dependent variable (inflation) will be denoted Y (Tx1, where T is the number of observations), the matrix of right-hand side variables will be denoted X (TxN), and the matrix of error terms will be denoted E (Tx1), yielding

(2)	$$Y = X\Gamma + E.$$

The classical approach to inference would estimate Γ by least squares as $\Gamma^{LS} = (X'X)^{-1}X'Y$.

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[3] Lenza and Primiceri (2020) and Schorfheide and Song (2021) highlight the potential sensitivity of macroeconometric estimates to the COVID-19 pandemic period, with the former suggesting some approaches to handling these issues.

The decisionmaker herein follows a Bayesian approach. The decisionmaker is endowed with a prior for Γ that is given by the Normal distribution with mean $\tilde{\Gamma}$ and variance-covariance matrix V—i.e., a prior distribution $\Gamma \sim N(\tilde{\Gamma}, V)$. The analysis proceeds under the assumption that the decisionmaker knows the variance of e(t) (σ^2), so the Bayesian estimation is conditional on σ^2 and the assumed prior is the natural conjugate prior for Γ conditional on σ^2. An alternative approach would also specify a prior view on σ^2 and jointly estimate the posterior distributions of Γ and σ^2. This alternative approach yields essentially identical results for reasonable priors on σ^2, but yields more complicated algebraic expressions that slightly impede intuition for those less familiar with Bayesian least squares. As a result, the simpler approach is adopted herein.

Given the prior information, the decisionmaker estimates Γ by combining their prior information and the data—i.e., the prior distribution and the likelihood function of the data—to form the posterior distribution for Γ and estimates Γ to maximize this posterior distribution. This is a textbook example of Bayesian regression (Kim and Nelson 1999, Chapter 7), with the resulting estimate $\hat{\Gamma}$ given by

(3)	$$\hat{\Gamma} = (V^{-1} + \sigma^{-2}X'X)^{-1}(V^{-1}\tilde{\Gamma} + \sigma^{-2}X'X\Gamma^{LS}).$$

Notice in equation (3) that the Bayesian decisionmaker estimates the parameters as the matrix-weighted average of their prior information and the least-squares estimate, with weights given by the precision of the information in the prior and the data (e.g., by the inverses of the variance-covariance matrices of $\tilde{\Gamma}$ and Γ^{LS}, V and $\sigma^2(X'X)^{-1}$).

Equation (3) suggests a natural approach to considering different degrees of conviction regarding the prior information. The Bayesian decisionmaker can further "weight" their prior by a factor w, as in

(4)	$$\hat{\Gamma} = (wV^{-1} + (1-w)\sigma^{-2}X'X)^{-1}(wV^{-1}\tilde{\Gamma} + (1-w)\sigma^{-2}X'X\Gamma^{LS}).$$

Intuitively, essentially zero weight on the prior information returns the least-squares estimate. This "weighting" terminology is convenient. Mathematically, it is equivalent to considering a less informative prior. Specifically, estimates with a weight of w on the prior information are equivalent to estimates with a prior for Γ with the same mean and a variance-covariance matrix equal to $\frac{1-w}{w}V$. For example, a weight on the prior equal to 20 percent (w=0.2) is equivalent to a prior with a four-times looser variance-covariance matrix $4V$.

With this background, the approach involves choosing the lag specification in the Phillips Curve, a choice of the prior distribution and consideration of alternative weights on this prior distribution.

- **Lag specification in the Phillips Curve**: In the estimates using monthly data, the lag length equals 12 (N=13) and the coefficients on the 1st through 12th lag are equal—i.e., $\sum_{j=1}^{N-1} b(j) \cdot \Delta p(t-j) = b(1) \sum_{j=1}^{12} \Delta p(t-j)/12;$ alternative choices for the lag structure yielded similar results (see section 3.3), and this specification is simplest. For the estimates using annual data, the lag length equals 1 (N=2).

- **Choice for prior $\Gamma \sim N(\tilde{\Gamma}, V)$**: The prior distribution used to inform estimates of the 21st century Phillips curve is given by the values consistent with the pre-2000 sample. $\tilde{\Gamma}$ is given by the least-squares estimate for this sample and V is the associated variance-covariance matrix. This is akin to an empirical Bayesian approach. The thought experiment is one in which the decisionmaker was endowed with information on the Phillips Curve in the latter half of the 20th century and chooses to update their view following the realization of data from 2000-2019.

- **Choice of weights w**: To consider decreasing levels of conviction in the relevance of the 20th century prior (i.e., looser priors), four values for weights on the prior are considered, with the

factor w taking values of 0.5, 0.2, 0.05, or (approximately) 0—corresponding to variance covariance matrices for the prior equal to $V, 4V, 19V$, and an uninformative prior.

Figure 2 presents the prior distributions for the coefficient on the lags of inflation and the slope of the Phillips Curve for these alternative weights. The priors show high values of persistence (a central tendency for the sum on inflation lags near 1) and a notable slope to the Phillips Curve (i.e., a negative slope with a degree of precision in the prior distribution).[4]

3. Results

3.1 Estimates

The results for posterior estimates of the Phillips Curve parameters conditional on data from 2000-2019 by the Bayesian decisionmaker are shown in figure 3 and table 2. Two results emerge clearly.

First, the degree of persistence in the posterior estimates is high in all cases except those with very little weight on the 20th century prior. In the monthly estimates, the coefficient on lagged inflation exceeds 0.9 with equal weights on prior and data, exceeds 0.85 when the weight on the prior is 0.20, and is near 0.7 when the weight on the prior is 0.05; in the limiting case of essentially no weight on the prior, the coefficient on the lags is small at about 0.2 (in line with simple least squares for the 2000-2019 period). For the annual data, the coefficient on lagged inflation in the posterior is about 7/8, ¾, and ½ for weights on the prior of 0.5, 0.2, and 0.05—whereas the coefficient is 0 for the uninformative prior.

Second, the slope of the Phillips Curve is consistently smaller in absolute value in the posterior estimates of the parameters—irrespective of the weight on the prior. For example, the slope of the Phillips Curve

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[4] The estimates use inflation data expressed at annual rates. This convention makes the slope coefficients somewhat more comparable (albeit still not strictly comparable, reflecting how time-averaging would affect impact estimates at different frequencies).

is less than ½ the prior value (the pre-2000 data value from least squares) in the posterior estimates for all weights on the prior.

These results suggest that the approach of a Bayesian decisionmaker confirms the finding in the literature that the Phillips Curve is "flatter". In contrast, the approach of a Bayesian decisionmaker does not find the degree of "anchored" inflation as would be implied by an estimate using only recent data, in the sense that the coefficient on lagged inflation is substantial when prior information is incorporated. Nonetheless, the coefficient on the lags of inflation is less than one—so the process is not of the "accelerationist" type and would generally imply that deviations of inflation from its average may be long-lived but are ultimately transitory.

3.2 Intuition

The results are clear—but they are also very intuitive. Recall from equation (4) that the posterior estimates are the matrix-weighted average of the prior mean and least-squares estimate for the post-1999 period, with weights given by the inverse of the variance-covariance matrices.

For the slope of the Phillips Curve, the variance-covariance matrix of the post-1999 least-squares estimate implies a fair degree of precision. Recall that this matrix is $\sigma^2(X'X)^{-1}$ and its inverse is $\sigma^{-2}X'X$. The component of this matrix that "weights" the least-squares estimate is dominated by the sum of squared deviations of the unemployment rate from its mean (assuming a modest covariance between inflation and unemployment). The summary statistics in table 1 show that this sum of squares remains sizable relative to its pre-2000 value, as indicated by the standard deviation of the unemployment rate. As a result, the least-squares estimate receives considerable weight in the Bayesian decisionmaker's calculus.

In contrast, inflation is quite stable in the post-1999 period. Its sum of squared deviations from the mean are modest relative to the pre-2000 experience, as indicated by the standard deviation. This

implies the data for 2000-2019 receive relatively little weight in a Bayesian decisionmaker's calculus when assessing the persistence of inflation. In words, inflation did not deviate from its average value much over 2000-2019, and hence a Bayesian decisionmaker does not weigh experience over that period highly when evaluating how persistent a deviation of inflation from its mean is likely to be. This is intuitive—the data do not provide examples of what would happen should inflation deviate from its mean, and hence the data are not informative about what would happen following such a deviation.

A look at measures of fit provides some intuition for why models with such different dynamic properties—the estimates with different weights on the prior—emerge. Figure 4 presents a dynamic simulation of the estimates from 2000-2019 in the top panel and the residuals implied by each estimate in the bottom panel, in both cases for the monthly-data specification. All the estimates lead to a dynamic simulation of relatively low and stable inflation—although the case with a weight of 0.5 on the prior information shows more variability and a worse "fit" than the others. Looking at one-period misses, the residuals are all very highly correlated. The residuals are highly correlated across specifications with a large coefficient on the lag and a small coefficient on the lag because inflation has been stable and the contribution of the lag is small, irrespective of the coefficient. This intuition is the same as that above—inflation has been stable and hence the data do not differentiate much between a specification with a large or small coefficient on lagged inflation.

This intuition also provides insight into the comparison of the full sample results from least squares (reported in table 2) with the results from a Bayesian approach. The full sample results are similar to those of a Bayesian decisionmaker that places weight on the pre-2000 experience—inflation is persistent, and the Phillips Cure is flatter than in the pre-2000 period. The pre-2000 experience dominates the variation in the data and hence drive the full sample estimates of persistence. This comparison also highlights a potential weakness of the approach of a Bayesian decisionmaker for a researcher that views a structural break as likely. The Bayesian decisionmaker views the parameters as

drawn from a stable distribution and allows the data to move them away from their prior view. This

approach is consistent with the notion that the future may look different than embedded in prior

information, but not consistent with a structural break—which would imply prior information has no

value. The findings herein suggest that a researcher may wish to entertain the possibility that

experience from 2000-2019 is consistent with a sizable degree of persistence in inflation, but also may

wish to consider alternative approaches that allow for structural breaks or time-varying parameters.

3.3 Robustness and Implications

As noted above, the basic results do not depend upon the specific lag structure assumed for inflation in

the results reported in table 2. To illustrate the robustness of the results to alternative specifications,

table 3 considers a slightly more flexible lag structure, as in

$$\Delta p(t) = b(1) \sum_{j=1}^{3} \frac{\Delta p(t-j)}{3} + b(2) \sum_{j=4}^{12} \frac{\Delta p(t-j)}{9} + a \cdot u(t-1) + e(t).$$

In this alternative, the sum of the coefficients on the lags of inflation ($b(1) + b(2)$) gives a rough gauge

of the persistence of inflation. The results are substantially similar to those for the simpler specification

in table 2, with $b(1) + b(2)$ estimated at essentially the same values as those for $b(1)$ in table 2.

The implications of the results for inflation forecasts are direct. A Phillips Curve based on post-1999

data alone would imply a sharp deceleration of inflation in 2022, as there is very little persistence

estimated in that case. In contrast, the Bayesian estimates imply that inflation will remain quite high in

2022 in the absence of unexpected shocks. Generally speaking, the results herein suggest a higher

degree of persistence is plausible, pointing to potentially higher inflation in 2022.

4. Conclusions

This analysis examined the extent to which the experience from 2000-2019 should lead a Bayesian

decisionmaker to update their assessment of inflation dynamics. Given a prior for inflation dynamics

consistent with 1960-1999 data, a Bayesian decisionmaker would not update their view of inflation persistence in light of 2000-2019 data unless they placed very low weight on their prior information. In other words, 21st century data contains very little information to dissuade a Bayesian decisionmaker of the view that inflation fluctuations are persistent, or "unanchored".

The idea that data over short sample periods may provide limited information regarding macroeconomic relationships may be relevant for other areas in macroeconomics. For example, Kiley (2020a,b) finds modest information in the data for estimates of the equilibrium real interest rate. These findings suggest macroeconomists may find useful a Bayesian approach that examines the information in the data more thoroughly than is common in empirical macroeconomics.

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Table 1: Data Summary Statistics

	Observations	Mean (annual rate)	Std. Deviation	Auto-Correlation
Monthly data				
Full sample				
CPI inflation (percent)	744	3.6	0.25	0.66
Unemployment rate (percent)	-	6.0	1.6	0.99
Pre-2000 sample				
CPI inflation (percent)	504	4.3	0.27	0.62
Unemployment rate (percent)	-	6.0	1.5	0.99
Post-1999 sample				
CPI inflation (percent)	240	2.0	0.08	0.21
Unemployment rate (percent)	-	5.9	1.8	0.99
Annual data				
Full sample				
CPI inflation (percent)	61	3.6	2.4	0.88
Unemployment rate (percent)	-	6.0	1.6	0.80
Pre-2000 sample				
CPI inflation (percent)	41	4.4	2.6	0.83
Unemployment rate (percent)	-	6.0	1.5	0.78
Post-1999 sample				
CPI inflation (percent)	20	2.0	0.4	0.42
Unemployment rate (percent)	-	5.9	1.8	0.77

Source: Bureau of Labor Statistics and author's calculations. Full sample: Jan. 1958-Dec. 2019 (monthly) and 1959-2019 (annual); Pre-2000 sample: Jan. 1958-Dec. 1999 (monthly) and 1959-1999 (annual); Post-1999 sample: Jan. 2000-Dec. 2019 (monthly) and 2000-2019 (annual).

Table 2: Estimation of posterior of parameters

$$\Delta p(t) = b(1) \sum_{j=1}^{N} \Delta p(t-j)/N + a \cdot u(t-1) + e(t).$$

Monthly data (lag length N = 12)

	Estimates of a Bayesian decisionmaker				*Classical least-squares estimates*		
	Weight on prior=0.5	Weight on prior=0.2	Weight on prior=0.05	Uninformative prior	Full sample	Pre-2000 sample	Post-2000 sample
b(1)	0.92	0.86	0.66	0.17	0.95	0.97	0.17
s.e.	0.03	0.05	0.10	0.16	0.03	0.04	0.16
a	-0.07	-0.04	-0.06	-0.13	-0.19	-0.32	-0.13
s.e.	0.03	0.03	0.03	0.04	0.05	0.07	0.04

Annual data (lag length N = 1)

b(1)	0.86	0.74	0.43	-0.05	0.92	0.94	-0.05
s.e.	0.05	0.10	0.17	0.24	0.06	0.08	0.24
a	-0.05	-0.05	-0.09	-0.16	-0.23	-0.41	-0.16
s.e.	0.04	0.04	0.05	0.05	0.09	0.15	0.05

Source: Bureau of Labor Statistics and author's calculations.

Note: Full sample: Jan. 1958-Dec. 2019 (monthly) and 1959-2019 (annual); Pre-2000 sample: Jan. 1958-Dec. 1999 (monthly) and 1959-1999 (annual); Post-1999 sample: Jan. 2000-Dec. 2019 (monthly) and 2000-2019 (annual).

Table 3: Estimation of posterior of parameters—alternative lag specification

$$\Delta p(t) = b(1) \sum_{j=1}^{3} \frac{\Delta p(t-j)}{3} + b(2) \sum_{j=4}^{12} \frac{\Delta p(t-j)}{9} + a \cdot u(t-1) + e(t).$$

Monthly data

	Estimates of a Bayesian decisionmaker				Classical least-squares estimates		
	Weight on prior=0.5	Weight on prior=0.2	Weight on prior=0.05	Uninformative prior	Full sample	Pre-2000 sample	Post-2000 sample
b(1)	0.52	0.47	0.39	0.24	0.53	0.52	0.24
s.e.	0.05	0.07	0.09	0.10	0.05	0.06	0.10
b(2)	0.40	0.39	0.28	-0.05	0.41	0.44	-0.05
s.e.	0.05	0.08	0.11	0.15	0.06	0.07	0.15
a	-0.05	-0.03	-0.06	-0.13	-0.12	-0.21	-0.13
s.e.	0.03	0.03	0.03	0.04	0.05	0.08	0.04

Source: Bureau of Labor Statistics and author's calculations.

Note: Full sample: Jan. 1958-Dec. 2019 (monthly); Pre-2000 sample: Jan. 1958-Dec. 1999 (monthly); Post-1999 sample: Jan. 2000-Dec. 2019 (monthly).
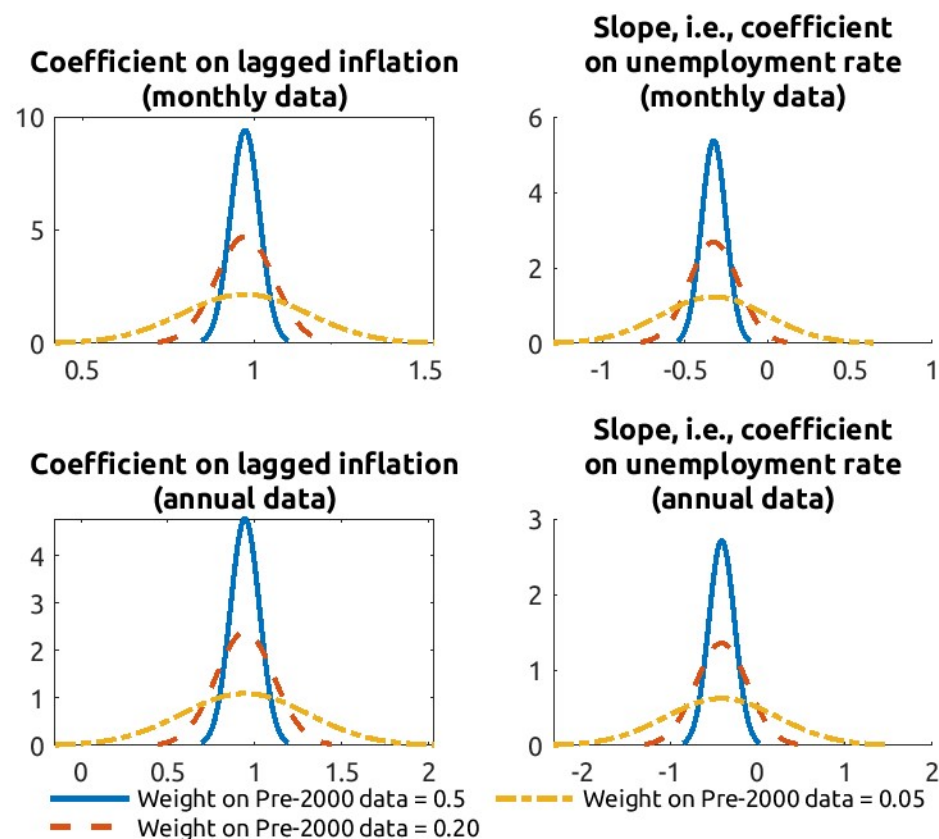
Figure 1: CPI Inflation and the Civilian Unemployment Rate

Core CPI Prices

Unemployment Rate
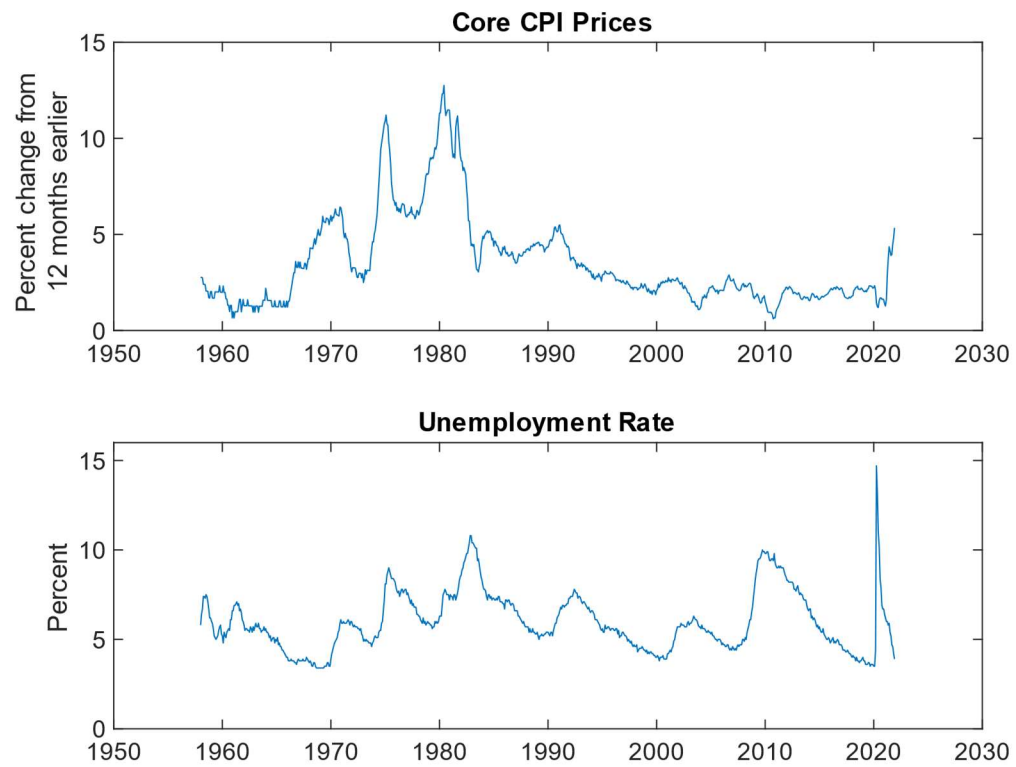
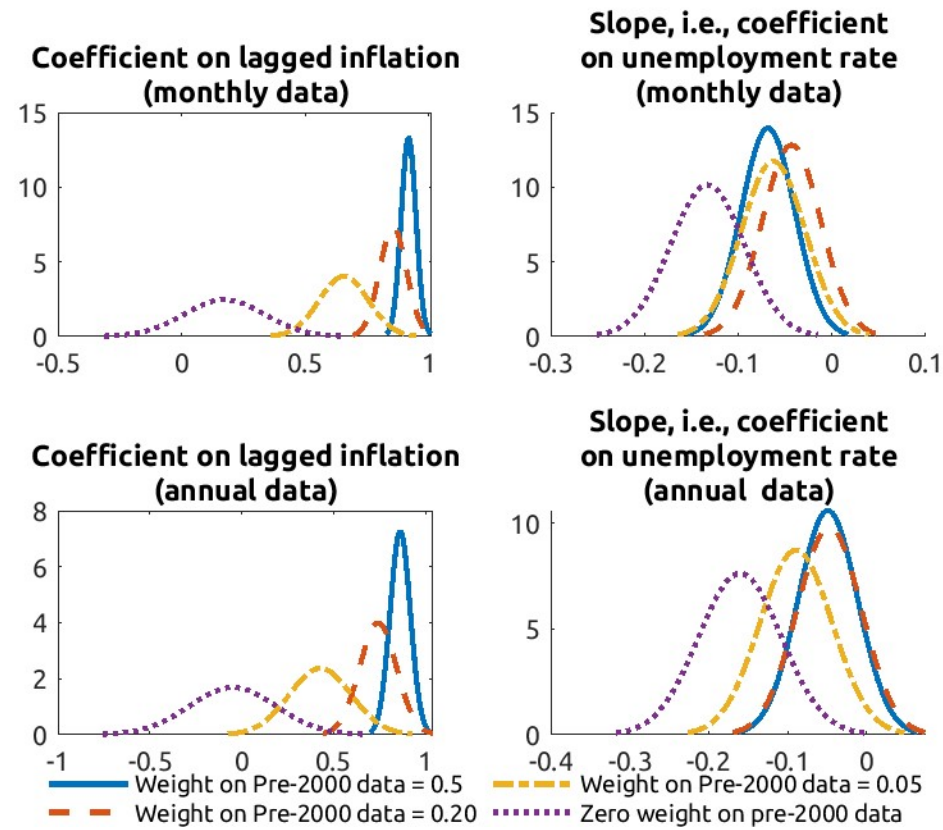Source: Bureau of Labor Statistics and author's calculations.
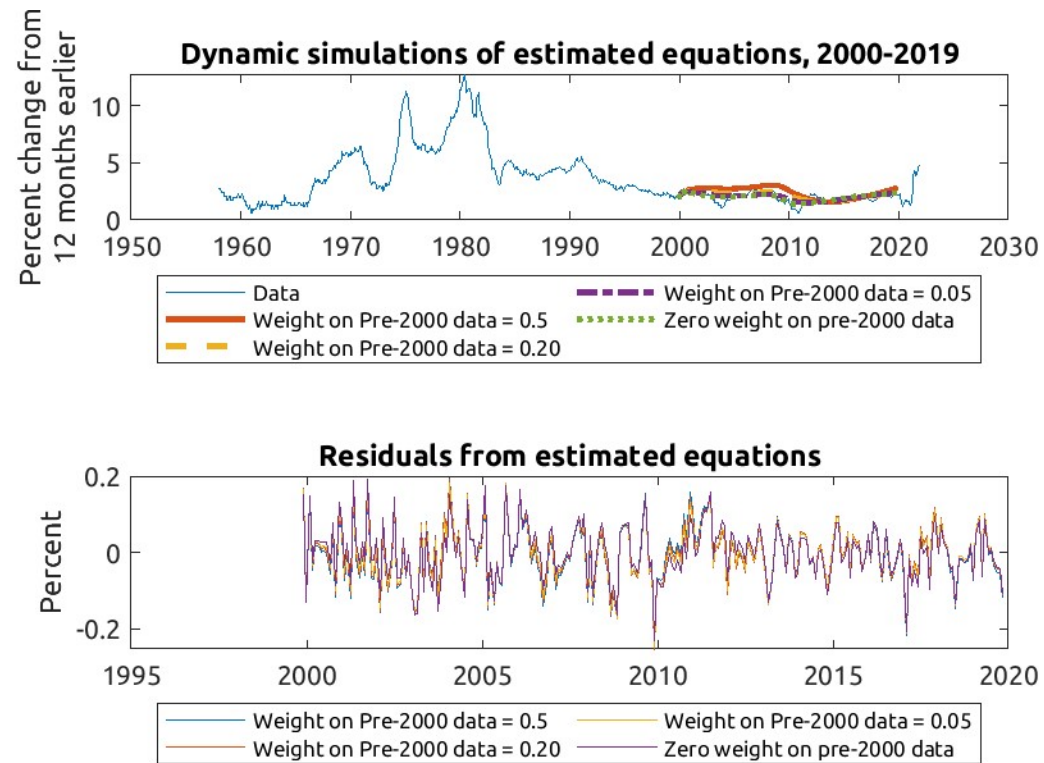
Figure 2: Prior Information

Source: Bureau of Labor Statistics and author's calculations.

Figure 3: Posterior Estimates

Source: Bureau of Labor Statistics and author's calculations.

Figure 4: Visual Assessments of Fit

Source: Bureau of Labor Statistics and author's calculations.