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Inflation Forecasting

James H. Stock and Mark W. Watson*

Forecasting inflation is one of the core responsibilities of economists at central banks and in the private sector, and models of inflation dynamics play a central role in determining monetary policy. In this light, it is not surprising that there is a long and rich literature on inflation dynamics and inflation forecasting.

A recurring theme in this literature is the usefulness—or not—of the Phillips curve as a tool for forecasting inflation. Phillips¹ originally documented an inverse relation between the rates of wage inflation and unemployment in the United Kingdom. Samuelson and Solow² extended “Phillips’ curve” to U.S. data and to price inflation. The Phillips curve remains at the core of modern specifications, which additionally include expectations of inflation, often use activity variables other than the unemployment rate, and incorporate sluggish inflation dynamics. Indeed, the central price determination equation in modern dynamic stochastic general equilibrium models, the New Keynesian Phillips Curve, is a direct descendant of the original Phillips curve, augmented to incorporate forward-looking inflation expectations and with a real activity measure serving as a proxy for real marginal cost.

This research summary reviews our work of the past fifteen years on inflation forecasting using small, stand-alone

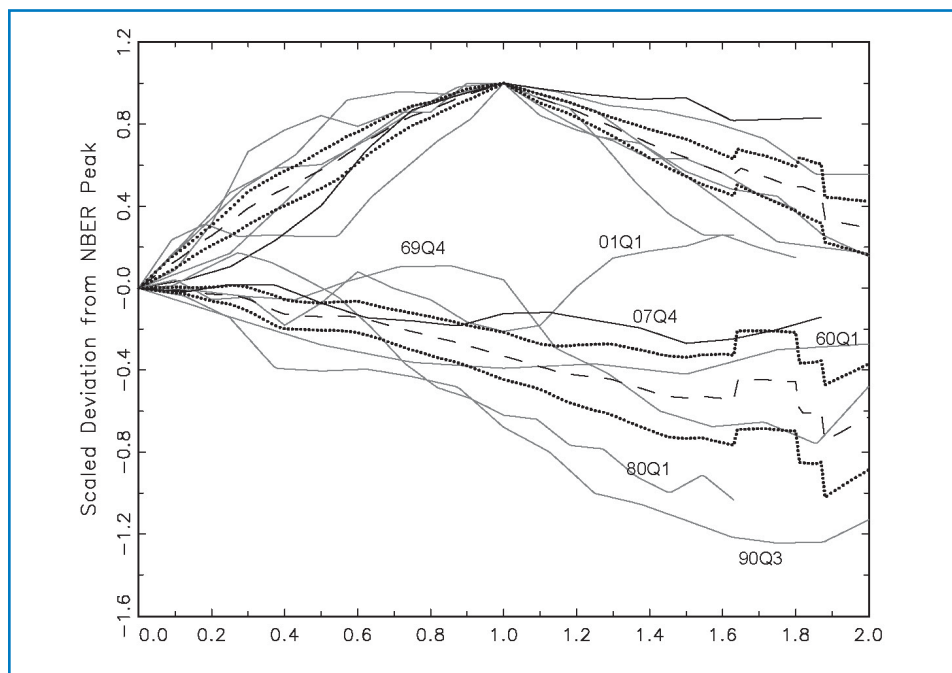


Figure 1—The rate of unemployment (upper lines) and the four-quarter rate of core PCE inflation (lower lines) over six U.S. slumps since 1960, with means (dashed lines) and \pm one standard deviation bands (dotted lines). The rates are expressed as deviations from their values at the NBER-dated peak. The horizontal axis is scaled so that the NBER-dated peak occurs at date 0 and the unemployment rate peaks at date 1. In the postwar U.S., recessions and their aftermath experience disinflation.

models. Most of this work revolves around the use of real economic activity to forecast inflation, to which we refer broadly as Phillips curve models, although other forecasting frameworks (such as incorporating monetary aggregates) are also considered.

Our research on inflation forecasting and inflation dynamics leads us to two broad conclusions. First, there are important regularities in the inflation-output relation. In particular, in the postwar United States, recessions are times of disinflation. This regularity was behind the deflation scares of 2002–3 and 2009–10. Figure 1 plots the rate of unemployment and the four-quarter rate of core PCE inflation for six U.S. slumps from 1960 to the present, labeled by the NBER-dated cyclical peak. The plotted rates are

deviated from their values at the respective NBER-dated peak; the vertical axis is scaled so that all recessions have the same increase in the unemployment rate; and the horizontal axis is scaled so that the total time span is twice the time between the start of the recession and the peak of the unemployment rate. The mean paths of the unemployment rates and inflation are shown as dashed lines, and the dotted lines are \pm one standard deviation bands³. Over these six recessions and recoveries, by the time the unemployment rate peaks, inflation has fallen on average by 0.37 percentage points for each percentage point increase in the rate of unemployment.

Second, we conclude that despite this evident regularity, inflation dynamics and inflation forecasting models exhibit considerable instability. Such

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instability is unsurprising, given the substantial changes in monetary policy, unionization, globalization, and other aspects of the U.S. economy that are relevant to price-setting. Indeed, Figure 1 suggests one important aspect of this instability: the rate of inflation fell by less following the NBER-dated peaks of 2001Q1 and 2007Q2 than it did on average during earlier the previous five recessions. A leading explanation for the more muted response of inflation over the two recent recessions is that monetary policy has succeeded in anchoring inflationary expectations. However, because both disinflationary episodes started at low levels, another candidate explanation is resistance to nominal wage declines.

Time Variation in Inflation Forecasting Models

The first step towards handling instability is admitting that you have a problem. Providing formal statistical evidence of instability entails the use of a variety of methods, including tests for in-sample breaks, tests for breaks at the end of the sample, and pseudo out-of-sample forecast comparisons. We have undertaken such analyses in a number of studies over the past fifteen years; while forecasting models for other macroeconomic variables also exhibit structural instability⁴, relations involving inflation are particularly problematic. This instability extends beyond Phillips Curve models, indeed models using asset prices⁵ or monetary aggregates⁶ appear even more unstable than ones based on aggregate activity.

In a 2008 paper, we showed that there are some meaningful patterns in the instability of the output-inflation relation⁷. In particular, the performance of Phillips curve forecasts is episodic: as Atkeson and Ohanian forcefully demonstrated⁸, it was quite difficult to best naïve univariate forecasting models during much of the Great Moderation period. But, as suggested by Figure 1, Phillips curve forecasts add value during recessions and their aftermath.

The Time-Varying NAIRU

In earlier work, we focused on time variation that entered through movements in the NAIRU (the non-accelerating inflation rate of unemployment).⁹ The NAIRU is the rate of unemployment at which there is no tendency for the inflation rate to increase or to decrease, and the unemployment gap is the deviation of the unemployment rate from the NAIRU. The NAIRU plausibly changes over time because of changes in demographics, in methods of job search, and in other features of the U.S. economy. A time-varying NAIRU can be estimated by introducing time variation into the intercept of a Phillips curve. In a series of papers, we developed methods for estimating a time-varying NAIRU^{10,11} and its standard error, and these methods were used and further developed by Robert J. Gordon¹² and others. One flexible method is to model the NAIRU as an unobserved, or latent, process that follows a random walk. In related methodological work, we developed methods for estimating the variance parameter governing the magnitude of the innovations for this random walk¹³.

Empirically, we found that there has been considerable variation in the NAIRU in the United States over the past fifty years. Confidence intervals for the NAIRU are quite wide, typically exceeding plus or minus one percentage point of unemployment. These intervals are widest towards the end of the sample because we do not have the data on future inflation needed to pin down today's NAIRU.

The unemployment rate is only one measure of economic activity. This observation raises the question of which of the many candidate measures of economic activity one should use for inflation forecasting. One approach is to use very many such predictors, but with statistical discipline that avoids over-fitting. To this end, we developed a dynamic factor model (a method for handling high-dimensional datasets particularly well suited to macro-

economic data) to construct an activity index for forecasting inflation¹⁴. The Chicago Fed currently produces and publishes this monthly index of 85 activity variables as the Chicago Fed National Activity Index (CFNAI)¹⁵.

Time-varying Expectations Anchoring

In addition to time variation arising from an evolving NAIRU, the persistence of U.S. inflation varies over time. This is consistent with the notion suggested by Figure 1 that inflation expectations have been better anchored over the past decade than earlier. We found that this changing persistence can be captured in a simple parsimonious univariate time-series model that performs well across different inflation regimes¹⁶. According to the model, unexpected changes in the rate of inflation during the 1970s and early 1980s were quickly incorporated into inflationary expectations. In contrast, during the past 15 years inflation expectations, and thus inflation itself, have responded far more sluggishly to an inflation surprise.

When this univariate model of time-varying expectations anchoring is merged with measures of economic activity, the result is a Phillips curve in which the dynamic effect on inflation of an exogenous change in activity depends on the degree of expectations anchoring. Figure 2 (which extends Figure 14 in Stock and Watson, 2010) shows a dynamic simulation of a Phillips curve model (dashed line) using a "recession unemployment gap" and a single standard error confidence band (dotted lines). The model parameters used to compute the predicted path and standard error bands date from August 2010, while the actual data are through 2011Q4 for unemployment and 2011Q3 for core PCE inflation, so the final five quarters of the plot in Figure 2 provide a true out-of-sample test of the model. In the published model, strong expectations anchoring leads to muted disinflation

during slumps. As can be seen in Figure 2, this model captures the modest disinflation we experienced subsequent to the 2007Q4 recession.

Ongoing Research Questions

Many important questions remain. One is how to develop a single Phillips curve forecasting model with explicit time variation, with the goal of outperforming univariate models during recessionary episodes and performing at least as well otherwise. In current work, Stella and Stock make some positive steps towards this goal¹⁷.

An important remaining question is whether we can ascertain why the disinflations following the 2001Q1 and 2007Q4 recessions were so muted. The easy answer is anchored expectations and greater confidence in the conduct of monetary policy. It is, however, incumbent on researchers to question the easy answers and to rule out other proximate, coincidental causes, such as exchange rate movements (as occurred in 2003–4) and energy price increases (as occurred in 2010–11). Our work on these and related issues of inflation forecasting and inflation dynamics is ongoing.

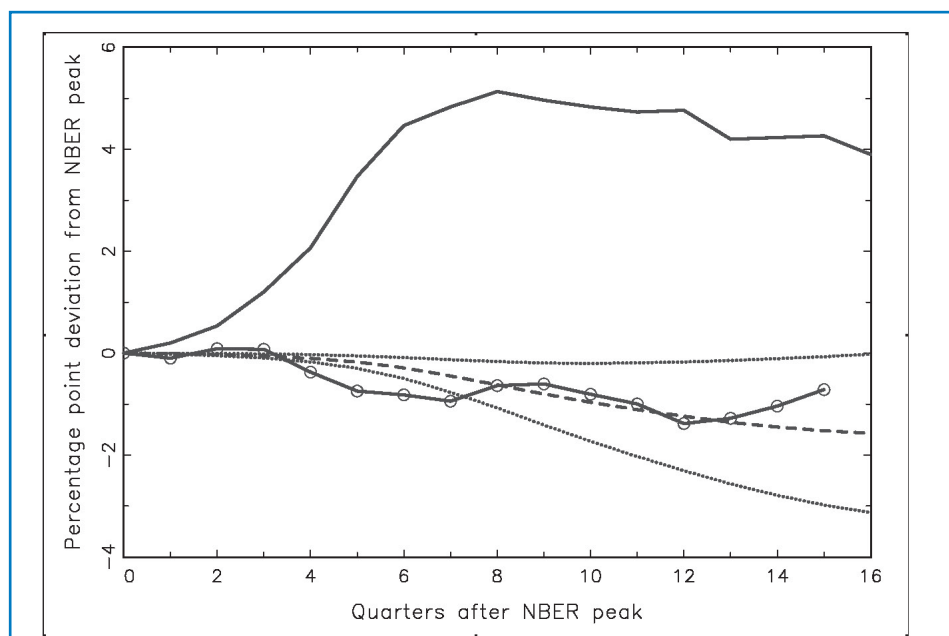


Figure 2—The rate of unemployment (upper line) and four-quarter rate of core PCE inflation (lower line) for 16 quarters following the 2007Q4 NBER-dated peak, deviated from their 2007Q4 value. The solid and dashed lines are the mean from a dynamic simulation of the model in Stock and Watson (2010) and a \pm one standard error band.

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¹¹ D. Staiger, J.H. Stock, and M.W. Watson, “Prices, Wages and the U.S. NAIRU in the 1990s,” NBER Working Paper No. 8320, June 2001, and Ch. 1

¹ A.W. Phillips, “The Relation Between Unemployment and the Rate of Change of Money Wage Rates in the United Kingdom, 1861–1957,” *Economica*, 25, 1958, pp. 283–99.

² P.A. Samuelson and R.M. Solow, “Analytical Aspects of Anti-Inflation Policy,” *American Economic Review*, Papers and Proceedings, 50, 1960, pp. 177–94. The history of the Phillips curve is reviewed in R.J. Gordon, “The History of the Phillips Curve: Consensus and Bifurcation,” *Economica* 78, 2011, pp. 10–50.

³ Figure 1 merges the recessions beginning in 1980Q1 and 1981Q3 because of the brevity of the 1980Q1 recession, and omits the 1973Q4 recession, which saw an initial increase in inflation because of the oil price shock. Figure 1 is an updated version of Figure

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¹² R.J. Gordon, “Foundations of the Goldilocks Economy: Supply Shocks and the Time-Varying NAIRU,” *Brookings Papers on Economic Activity* 1998:2, pp. 297–333.

¹³ J.H. Stock and M.W. Watson, “Median Unbiased Estimation of

Coefficient Variance in a Time Varying Parameter Model,” NBER Technical Working Paper No. 201, August 1996, and *Journal of the American Statistical Association*, 93 (1998), pp. 349–58.

¹⁴ J.H. Stock and M.W. Watson, “Forecasting Inflation,” NBER Working Paper No. 7023, March 1999, and *Journal of Monetary Economics* 44, no. 2, (1999), pp. 293–335.

¹⁵ <http://www.chicagofed.org/webpages/>

publications/cfnai/index.cfm.

¹⁶ J.H. Stock and M.W. Watson, “Why Has Inflation Become Harder to Forecast,” NBER Working Paper No. 12324, June 2006, and *Journal of Money, Credit, and Banking*, 39 (2007), pp. 3–34.

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Wealth After Retirement

Steven Venti*

Over the past two decades, the aging of the “Baby Boomers” has focused attention on how members of this generation accumulated assets during their working years. Now that the leading edge of this group has passed into retirement, the focus of researchers — as well as policymakers and the financial services industry — is shifting to the draw-down of financial resources in later life. My recent research, much of which is co-authored with James M. Poterba and David A. Wise, focuses on the factors that shape the age profile of wealth after retirement. The goal of this work is to better understand what households do with their assets after retirement and, in particular, to understand how asset draw-down decisions are affected by health, education, and the structure of public and private annuities.

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Wealth at Retirement

Retired households depend primarily on three sources of financial support in retirement: benefits from the Social Security system; payments from private defined benefit (DB) pension plans; and withdrawals from household savings, including withdrawals from personal retirement accounts (PRAs) such as IRAs, Keoghs, 401(k)s and similar defined contribution plans. Benefits from Social Security and DB pensions are in the form of annuities that provide a stream of payouts until death. Assets held in PRAs or financial assets held outside of retirement accounts are typically not annuitized and are instead spent or saved at the owners’ discretion. In a recent paper, we describe the balance sheets for households headed by someone between the ages of 65 and 69 in the 2008 wave of the Health and Retirement Study (HRS).¹ To facilitate comparison of the various portfolio components, we capitalize Social Security and DB pension payouts. Averaged over all households, the capitalized value of Social Security ben-

efits accounts for about one-third of all household wealth and housing and other real estate account for another one-quarter of wealth. The capitalized value of DB pension benefits, assets held in PRAs, and financial assets held outside PRAs each account for an additional 10 to 15 percent of total wealth.

These averages hide substantial differences in both the level of total wealth and its composition. At the 90th percentile of the wealth distribution, financial assets (including PRAs) and DB pension wealth account for over half of all balance sheet wealth and Social Security is relatively unimportant. At the other extreme, in the lower part of the wealth distribution, many households have few assets outside of Social Security and housing. Half of all households headed by someone between 65 and 69 had total financial assets, including 401(k)s and IRAs, of less than \$52,000 in 2008. Thus, a large fraction of households have few assets, with the possible exception of housing equity, to supplement annuity income — primarily Social Security — in retirement. For example, only 47 percent of these households have sufficient finan-