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INFLATION EXPECTATIONS AND NONLINEARITIES IN THE PHILLIPS CURVE

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Abstract

This paper examines the role of inflation expectations and nonlinearities in the Phillips curve. We find that nonlinearities *per se* can address the missing disinflation. The estimated model favors two regions, with a flatter slope of the Phillips curve when unemployment is already high. This can explain why during the Great Recession inflation did not decrease as much as predicted by linear models. We also find that consumer expectations can explain the missing disinflation and prove to be a more robust feature of the Phillips curve. Namely, consumer expectations are also key in addressing the Great Inflation in the 1970s and the Volcker disinflation in the 1980s, periods in which nonlinearities have difficulty fitting the data. Our results suggest that both nonlinearities and consumer expectations should be examined jointly and that the latter is a more prevalent feature of the Phillips curve.

Keywords: Inflation expectations, Nonlinearities, Phillips curve
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1 Introduction

Inflation dynamics have long been a subject of prolific economic research. In the 1970s and 1980s, much research in this area was dedicated to understanding the causes and costs of high inflation and how to disinflate effectively. More recently, the focus has shifted to understanding the determinants of inflation and the role of expectations formation in a context of moderate-to-low inflation. Despite the central role of the Phillips curve in economic research, this relationship and its exact functional form remain heavily debated (e.g., Mavroeidis, Plagborg-Møller, and Stock 2014).

In the early 2010s, the Phillips curve again came under attack. As the unemployment rate reached double digits, inflation did not decline nearly as much as a linear Phillips curve predicted. Indeed, similar financial crises such as the Great Depression of the 1930s or the Japanese liquidity trap of the 1990s were followed by deflation, a phenomenon that did not occur in the 2010s. This *missing disinflation* calls for a search of possible explanations. Coibion and Gorodnichenko (2015) argue that the main cause of the missing disinflation is the stability of households' inflation expectations. They find both that the rising oil prices led to a disconnect between inflation expectations of consumers and professional forecasters, and that measuring inflation expectations from the Michigan Survey of Consumers (MSC) brings the Phillips curve closer to the data.

In this paper, we explore a mechanism that can reconcile the Phillips curve with the missing disinflation of the 2010s and with historical evidence. The missing disinflation could be easily explained by nonlinearities in the Phillips curve, in which the high levels of unemployment experienced in the aftermath of the crisis would not lead to a sharp decrease in inflation. In fact, the empirical relationship between wage inflation and unemployment originally documented by Phillips (1958) is represented by a convex curve, not a linear relationship. That means that when unemployment is already high, a further increase in unemployment leads to a smaller disinflation than when unemployment is at its historical average.

We estimate the model using a threshold regression method (Hansen 2000, 2017). This method allows for an endogenous and data-determined number of thresholds and therefore has the advantage that it can be used to approximate an arbitrary form of nonlinearity. The data reject the linear model in favor of the model with one threshold. The curve is flatter in the region with more slack (i.e., high unemployment region). Notably, the model can account for the missing disinflation period. One-step-ahead forecasts obtained from this model predict a 1–2 p.p. higher inflation after the Great Recession than in the linear model.

The presence of nonlinearities in the Phillips curve is robust across several empirical specifications. We consider a backward-looking specification, another with expectations from the Survey of Professional Forecasters (SPF), and a combination of the two. We also consider several inflation measures as well as several measures of economic activity and financial controls.

Despite the robustness of the nonlinearities found in the Phillips curve, an important issue remains. The missing disinflation can be largely explained by the MSC expectations because they were stable during this period. But once we allow for nonlinearities in the Phillips curve, do these expectations remain an important driver of inflation dynamics? Alternatively, could the inclusion of consumer expectations lead to a less prominent role for nonlinearities in the Phillips curve? To answer these questions, we augment the expected inflation term in the nonlinear model with inflation expectations from the MSC; that is, we allow for the mixture of backward-looking expectations, professional forecasters' expectations, and households' expectations. This is an important point of our paper. Papers excluding either nonlinearities or consumer expectations could have misleading results, attributing too much importance to one feature and not enough to the other.

We find that households' expectations remain significant even when incorporating nonlinearities in the Phillips curve. The MSC consumer expectations are usually a dominant component of inflation expectations, but the nonlinear specification makes this point somewhat less prominent. In our preferred specification based on the unemployment gap and headline CPI inflation, households' expectations dominate both professional forecasters' expectations and the lags of actual inflation, with a relative weight of 0.72. This is also true for the headline PCE specification, albeit with a smaller weight of 0.55. However, for other measures such as core CPI, core PCE, and GDP deflator, households' expectations are dominated by the backward-looking component, and sometimes even by the SPF expectations.

When households' inflation expectations are included, nonlinearities can improve the forecasting ability of the Phillips curve. However, the presence of nonlinearities is weakened when including the MSC measure. The threshold plays a role in improving the model's fit, but its significance varies by specification: it is significant at least at a 5 percent level for PCE and GDP deflator specifications, but not for CPI (core and headline) specifications. Overall, we find significant consumer expectations even when using a nonlinear Phillips curve and a range of inflation measures. In addition, controlling for popular measures of financial frictions—such as the corporate bond spread, credit spread, or excess bond premium—does not alter our conclusions.

While the role of consumer expectations of inflation has been studied mostly in the context of the recent post-crisis episode, less is known about the role of expectations during the 1970s' inflation runup and the subsequent Volcker disinflation in the early 1980s. As the Phillips curve is flatter when unemployment is high, the rapid disinflation of the 1980s would be harder to achieve under the threshold model than the linear model. It is an empirical question whether this helps match the large sacrifice ratios during this period or whether it makes the disinflation too slow. We find that unlike in the recent crisis, nonlinearities did not play an important role in the 1970s and 1980s. At the same time, consumer expectations of inflation are key in explaining these episodes. The innovation component of households' inflation expectations (i.e., the variation that cannot be forecast by the lags of expectations, the lags of actual inflation, and other observed data) drive the Phillips curve forecasts of inflation closer to the data.

This paper contributes to several strands of literature. First, we contribute to the emerging literature on nonlinearities of the Phillips curve. Papers that study nonlinearities in U.S. data include Barnes and Olivei (2003) and Kumar and Orrenius (2016), among many others. We differ from many of these papers by not assuming a specific functional form and by combining forward-looking expectations with consumers' expectations. We also look at the crisis and post-crisis data that include many observations of high unemployment, thereby allowing us to estimate the slope for this regime more precisely. Second, our work is related to the literature emphasizing the importance of inflation expectations (e.g., Adam and Padula 2011, Coibion and Gorodnichenko 2015, Coibion, Gorodnichenko, and Kamdar 2017). Third, we contribute to the literature on inflation persistence and the rationality of inflation expectations (Fuhrer and Moore 1995, Erceg and Levin 2003, Fuhrer 2010, Nunes 2010). Fourth, our paper is related to the literature on inflation dynamics in the 1970s and during the Volcker disinflation.[1] There is also some important theoretical literature: Models with a Phillips curve explaining the Volcker period were proposed by Erceg and Levin (2003), Goodfriend and King (2005), Bordo et al. (2007), Nunes (2009); models not specifically applied to the Volcker period include Schaling (2004) and Daly and Hobijn (2014).

The paper proceeds as follows. Section 2 describes our empirical strategy and then presents evidence on the ability of nonlinearities to explain the missing disinflation. Section 3 compares and contrasts the role of nonlinearities and of consumer expectations during this episode. Section 4 analyzes the Great Inflation and Volcker disinflation episodes. Section 5 examines the sensitivity of the results to the choice of the inflation measure as well as the role of financial frictions. Section 6 concludes.

2 Nonlinearities and the Missing Disinflation

2.1 Inflation Expectations and a Linear Phillips Curve

We begin with a linear version of the expectations-augmented Phillips curve:

$$\pi_t = \mu + \mathbb{E}_t\, \pi_{t+1} + \kappa\, u_t + \boldsymbol{\phi}\, \boldsymbol{z}_t + \varepsilon_t, \tag{1}$$

where π_t is the rate of inflation, $\mathbb{E}_t\, \pi_{t+1}$ is one-quarter-ahead expected inflation, u_t is a measure of real economic activity (e.g., unemployment gap), $\boldsymbol{z}_t$ is a vector of controls observed in period t, ε_t is the error term, and μ, κ, and $\boldsymbol{\phi}$ are estimated parameters. The coefficient κ measures the slope of the linear Phillips curve. When κ is large in absolute value, inflation is sensitive to changes in economic activity. Before we proceed to deal with nonlinearities, we discuss a few modeling choices in the context of the linear model. One is the choice of the slack variable u_t, another is the treatment of expectations $\mathbb{E}_t\, \pi_{t+1}$, and still another is the set of control variables $\boldsymbol{z}_t$.

As a measure of slack in the economy, researchers historically used the unemployment rate or—to account for the cyclical component of the inflation–unemployment relationship—the unemployment gap. In the New Keynesian tradition, one can use a microfounded model (e.g., Rotemberg and Woodford 1997) to derive a relationship between inflation and marginal cost. Therefore, an empirical analog of this model calls for a direct measure of marginal cost such as the labor share of income (Galí and

[1] Leduc, Sill, and Stark (2007) find that shocks to inflation expectations in the Livingston Survey can explain high inflation of the 1970s but have little explanatory power in the 1980s. Mankiw, Reis, and Wolfers (2004) find that disagreement in inflation forecasts increased during the Volcker era. Barsky and Kilian (2002) and Blinder and Rudd (2013) focus instead on the supply-side shifters of the Phillips curve. Ball (1997) examines international evidence and the role of the NAIRU. Blanchard (1984) does not find evidence for a regime change during that period. Debelle and Laxton (1997) allow for nonlinearities in the model; however, in their paper nonlinearities come specifically from a time-varying natural rate of unemployment, while we allow for a more flexible form of nonlinearities.

Gertler 1999). However, the downward trend in the labor share observed since at least the early 2000s makes using this measure problematic. For this reason, we use the unemployment gap as a benchmark measure, but we also report estimates of the model using the unemployment rate, the labor share, and an adjusted labor share that accounts partly for the downward trend in the raw labor share (Armenter 2015).[2]

Next, we follow the literature and model inflation expectations as a combination of backward-looking and forward-looking terms (e.g., Galí and Gertler 1999, Fuhrer 2010, Nunes 2010). We employ the SPF, which collects forecasts from expert forecasters for various inflation variables and are available at a one-quarter-ahead horizon. Later, we will also use the MSC, which asks consumers about their expectation of inflation over the following year. The SPF may best capture how large firms set prices, while the MSC reflects consumers' expectation (rather than firms' expectations) and may best capture expectations of small businesses. A large body of literature also emphasizes inflation persistence (e.g., Fuhrer and Moore 1995, Fuhrer 1997, 2006). In the absence of persistent shocks, inflation persistence can be reconciled with the backward-looking expectations models wherein firms' forecast of future inflation is a weighted average of past inflation.

To incorporate backward-looking expectations and to account for inflation persistence, we also include five lags of actual inflation. The lags cover a year of observations and minimize the Akaike Information Criterion (AIC) for both the labor share and unemployment gap specifications. Hence, expectations are given by the process

$$\mathbb{E}_t\, \pi_{t+1} = \sum_{i=1}^{5} \delta_i\, \pi_{t-i} + \alpha_1\, \mathbb{E}_t^{\text{SPF}}\, \pi_{t+1}, \tag{2}$$

where $\mathbb{E}_t^{\text{SPF}}\, \pi_{t+1}$ is the median one-quarter-ahead expected inflation in the SPF, and δ_i and α_1 are estimated parameters. Denote $\alpha_0 = \sum_{i=1}^{5} \delta_i$. We constrain the coefficients on the expectation terms to sum to 1 (i.e., $\alpha_0 + \alpha_1 = 1$); thus, $\hat{\alpha}_0$ and $\hat{\alpha}_1$ are estimates of the relative weights of the backward-looking and forward-looking components, respectively, in the expectations-formation process.[3]

Finally, our set of controls $\boldsymbol{z}_t$ includes a comprehensive list of variables used in the literature to account for cost-push shocks (e.g., Barnes and Olivei 2003). In our baseline specification, we use two lags of the growth of the relative price of food and energy, two lags of the change in the nominal exchange rate, and the Gordon (1982) price and wage control variable.

2.2 Nonlinearities and the Threshold Regression

We use the Hansen (2000) threshold regressions to estimate nonlinearities in the Phillips curve. This method is based on approximating the curvature of a nonlinear function by a piecewise-linear function in which the number of kinks (thresholds) is determined endogenously. Relative to other methods of nonlinear estimation, the threshold regression has a number of advantages. Each linear segment can be estimated by ordinary least squares (OLS), and therefore estimation and inference are straightforward.

[2] Armenter (2015) argues that the labor share trends downward because of the changing fraction of proprietors' income allocated to labor. To offset this channel, the adjusted measure sets the fraction to its historical average.

[3] In a standard New Keynesian model, $\alpha_0 + \alpha_1 = \beta$, the discount factor. At a quarterly frequency, $\beta \approx 1$. The unconstrained regressions support this restriction in the vast majority of cases.

There is no need to assume a particular form of nonlinearity: the data decide how much nonlinearity (i.e., how many thresholds) there is. Further, this method has been used before and therefore allows for comparison with previous studies (e.g., Barnes and Olivei 2003). Its major shortcoming is the tendency to produce wide confidence intervals for thresholds. That is, even though we can improve the fit of the model and test explicitly for nonlinearities, we may not be able to determine the thresholds' location with certainty.

We estimate the model with a continuity constraint. Without it, even in the absence of shocks, infinitesimal changes in unemployment would lead to jumps in the inflation rate. Discontinuity could also result in a lack of equilibrium, which would be difficult to reconcile with the U.S. time series and most standard economic models. Hansen (2017) describes in detail the econometric apparatus for the linear constraint case that we analyze here.

A piecewise-linear Phillips curve with a vector $\boldsymbol{\gamma} = (\gamma_1 \dots \gamma_m)$ containing m thresholds can be written as follows:

$$\pi_t = \underline{\mu}(\boldsymbol{\gamma}) + \mathbb{E}_t \pi_{t+1} + \underline{\kappa}(\boldsymbol{\gamma}) u_t + \boldsymbol{\phi} \boldsymbol{z}_t + \varepsilon_t, \tag{3}$$

$$\underline{\mu}(\boldsymbol{\gamma}) = \sum_{j=1}^{m+1} \mu_j \mathbb{I}_{(\gamma_{j-1} \leq u_t < \gamma_j)}, \tag{4}$$

$$\underline{\kappa}(\boldsymbol{\gamma}) = \sum_{j=1}^{m+1} \kappa_j \mathbb{I}_{(\gamma_{j-1} \leq u_t < \gamma_j)}, \tag{5}$$

where $\mathbb{I}_{(\gamma_{j-1} \leq u_t < \gamma_j)}$ is an indicator function of a condition $\gamma_{j-1} \leq u_t < \gamma_j$, assuming $\gamma_0 = -\infty$ and $\gamma_{m+1} = +\infty$. In a single-threshold case, this definition results in two regimes: $u_t < \gamma$ (regime "L") and $u_t \geq \gamma$ (regime "H"). This threshold allows for shifts in the Phillips curve over the range of u_t. To compute the optimal thresholds $\boldsymbol{\gamma}^*$, an OLS regression is run sequentially for all possible values of $\boldsymbol{\gamma}$. We then choose $\boldsymbol{\gamma}^*$ that minimizes the residual sum of squares (Hansen 1996).[4]

To test the null hypothesis of the linear model against the alternative of a one-threshold model, we rely on the Hansen (2000) test. Let S_0 and S_1 be the residual sum of squares under the null hypothesis and under the alternative, respectively. For a sample of n observations, an F-statistic of this test is of the form:

$$F = n \frac{S_0 - S_1}{S_1}, \tag{6}$$

with a distribution that can be approximated through a bootstrap procedure documented in Hansen (2017).[5] Since the critical values of this test depend on parameters of the model, it is more useful to report its p-values.

This test can be extended for the null of an arbitrary number of thresholds $\ell \geq 0$ against the alternative of $\ell + k$ thresholds, $k \geq 1$. The optimal number of thresholds can be determined by running the test sequentially, starting from $\ell = 0$ and $k = 1$ and then increasing ℓ by 1 if the null is rejected. The

[4] To maintain statistical power of the test, we constrain the grid for γ to ensure that each regime contains no less than 10 percent of the sample size.

[5] Confidence intervals for the threshold are computed using a similar bootstrap procedure (see the paper for details).

optimal number of thresholds ℓ^* is the lowest ℓ for which the null is not rejected.

2.3 Nonlinearities and the Missing Disinflation of the Early 2010s

Figure 1 presents graphical evidence and provides intuition about the role of nonlinearities in the missing disinflation. The red and black dots represent historical quarterly inflation rates (CPI-U seasonally adjusted annualized rates) from 1968q4 to 2016q3, while the labeled blue dots focus on the missing disinflation after the Great Recession.

Let us start from the linear case. The green straight line represents the linear fit from an OLS regression of "unexpected" inflation ($\pi_t - \mathbb{E}_t \pi_{t+1}$) on the unemployment gap. In this simple case, the expectations are backward-looking with equally weighted four quarterly lags (Ball and Mazumder 2011). For the missing disinflation episode, a disproportionately high number of blue dots lie above the green line (14 to 6); that is, the backward-looking Phillips curve predicts consistently lower inflation than the one observed in the data.

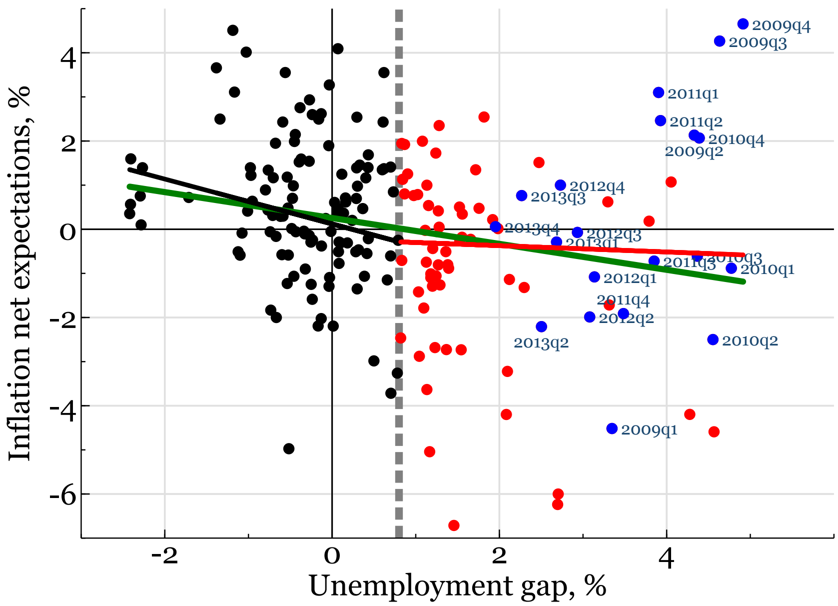
Now consider the Phillips curve estimated using a piecewise-linear specification with one threshold. The black dots represent the regime of a low unemployment gap, and the red and blue dots a high unemployment gap regime. The threshold is represented by the dotted gray line, and a piecewise-linear fit by the black and red lines (a kinked fit). In this case, the number of blue dots above the red line (missing disinflation) equals approximately the number of blue dots below it: the ratio is 11 to 9. Hence, even a very simplistic version of the Phillips curve with nonlinearities (completely backward-looking expectations, no additional controls for cost-push shocks) provides a balanced description of the data and does not predict lower inflation systematically. This result also holds for other measures of inflation (PCE, GDP deflator, core measures) and, when we allow for a more comprehensive functional form (add SPF forecasts and/or additional controls), does not require MSC inflation forecasts.[6]

Another piece of evidence that supports this point comes from one-step-ahead forecasts of inflation. Figure 2 compares realizations of actual inflation (black thick line) with one-step-ahead forecasts obtained from the following three models: the linear model with backward-looking expectations (red dashed line), the linear model with backward-looking and SPF expectations (orange dash-dot line), and the model with SPF forecasts and one threshold (blue thin line). During the period of the missing disinflation, the threshold model's forecast is about 1 p.p. above the linear model's forecast and is consistently closer to actual inflation. Even more strikingly, for 2009q3 the linear models predict a negative inflation rate of –2 percent, while the threshold model predicts close to zero inflation. In fact, actual inflation was above zero, which can be explained by a surge in oil prices. For 2010, the threshold model produces the average of quarterly forecasts that is very close to the actual average, while the linear models are about 1 p.p. below it. Starting in 2013, the three forecasts tend to converge with one another, and the deviation of the models from the actual data diminishes.

Table 1 presents estimates of the Phillips curve with and without nonlinearities. In column (1), the unemployment gap is used as a benchmark measure. The threshold value of the gap is 1.95 percent, which corresponds to about a 7 percent unemployment rate. The 95 percent confidence interval is rather

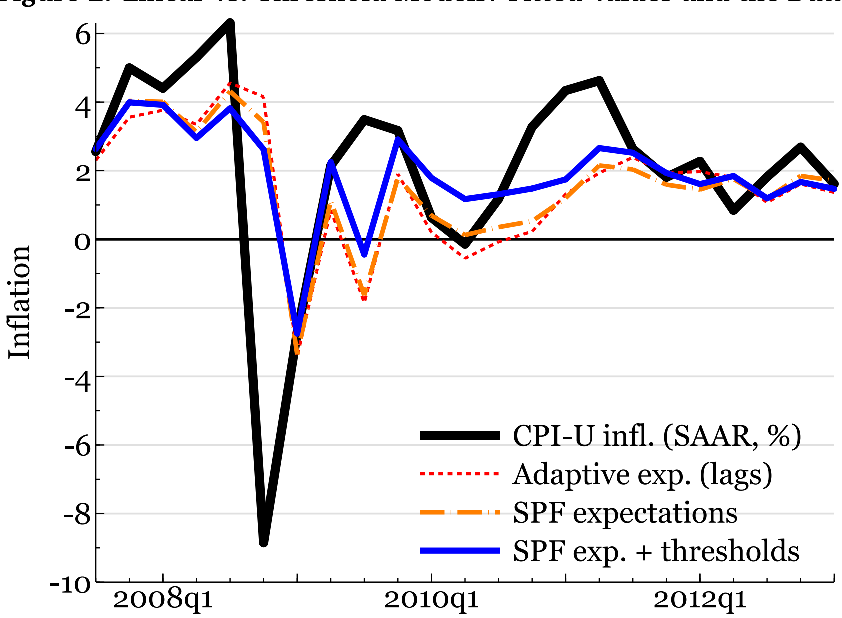
[6]Figure A1 in Appendix A shows that this result stands if we do not consider a continuity constraint.

Figure 1. Can the Nonlinear Phillips Curve Explain the Missing Disinflation?



Notes: This figure shows a scatterplot of the deviation of CPI inflation from the average of the previous four quarters' inflation rates (Ball and Mazumder 2011) and the unemployment gap. The sample period is 1968q4–2016q3. To enhance visibility, the large negative value corresponding to 2008q4 is excluded from this figure. The green line represents the linear fit for the entire sample. The sample is split based on the estimated threshold model. See Table 1 for estimation details. The gray dashed line is for the threshold; the black dots depict values for which the unemployment gap was below the threshold, while the red dots depict the opposite. The blue dots correspond to the period of the missing disinflation 2009–2013. The black and red lines depict the Phillips curve over the respective regimes. The ratio of the blue dots above and below the linear fit (green line) is 14:6 (i.e., the linear model predicts disinflation that did not occur). The corresponding ratio relative to the piecewise-linear fit (red line) is 11:9 (i.e., no missing disinflation according to the threshold model).

Figure 2. Linear vs. Threshold Models: Fitted Values and the Data



Notes: The figure shows predicted values obtained for the linear model with inflation lags only (red dashed line), with lags and SPF inflation expectations (orange dash-dot line), and for the threshold model (blue thin line). The black thick line represents inflation in the data. The threshold variable is the unemployment gap. The sample period is 1968q4–2016q3. All specifications control for two lags of the relative price of food and energy growth, two lags of the change in the nominal exchange rate, and the Gordon (1982) price and wage control variable.

Table 1. Do Nonlinearities Matter? Piecewise-Linear Phillips Curve without Consumer Expectations

	Unemployment		Labor Share	
	Gap	Rate	——	Armenter (2015)
	(1)	(2)	(3)	(4)
Panel A: Linear Model				
Slope, $\hat{\beta}$	-0.34^{***}	-0.24^{***}	0.12^{***}	0.25^{***}
	(0.11)	(0.08)	(0.03)	(0.06)
Panel B: Threshold Model				
Slopes				
left, $\hat{\beta}_L$	-0.70^{***}	-0.40^{*}	-0.00	0.09
	(0.19)	(0.22)	(0.05)	(0.09)
right, $\hat{\beta}_R$	0.32	-0.04	0.35^{***}	0.49^{***}
	(0.28)	(0.23)	(0.12)	(0.15)
Expected inflation				
SPF, $\hat{\alpha}_1$	0.76^{***}	0.73^{***}	0.99^{***}	1.01^{***}
	(0.17)	(0.17)	(0.19)	(0.17)
Sum of lags, $\sum_{i=1}^{5} \hat{\delta}_i$	0.24	0.27	0.01	-0.01
	(0.17)	(0.17)	(0.19)	(0.17)
Threshold				
point est., $\hat{\gamma}$	1.95	6.87	-0.64	-0.65
95 percent CI	$[-0.5, 2.9]$	$[4.5, 8.5]$	$[-7.0, 3.2]$	$[-4.3, 2.5]$
N of thresholds, p-val.				
0 vs. 1, H_0: 0	0.02	0.60	0.07	0.10
1 vs. 2, H_0: 1	0.95	0.61	0.04	0.59
R^2	0.74	0.72	0.72	0.73
N	192	192	192	192

Notes: Estimation sample is 1968q4–2016q3. Dependent variable is CPI-U inflation, seasonally adjusted annualized rate. Alternate threshold variables in columns (1)–(4). Inflation expectations: SPF forecasts of the one-quarter-ahead GDP deflator inflation and five lags of the dependent variable. The SPF forecasts of CPI inflation for the early sample are not available. Additional controls (estimates not reported): two lags of the growth rate of the relative price of food and energy, two lags of the change in the nominal exchange rate, and the Gordon (1982) price and wage control measure. The Armenter (2015) measure that adjusts the labor share to account for the downward trend (column 4) is obtained by setting the fraction of proprietors' income allocated to labor to its historical average. The original variable is extended through 2016q3. The threshold point is estimated using the regression kink method (Hansen 2000, 2017). Newey–West standard errors allowing for autocorrelation of up to five lags are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

wide and corresponds roughly to unemployment rates between 4.5 and 8 percent. The one-threshold model is significant at a 5 percent level in a test using the linear specification as a null hypothesis. The slope is negative and statistically significant below the threshold, and insignificant above it. When we use the unemployment rate as a threshold variable (column 2), the linear model cannot be rejected.[7] Even so, the slopes in the one-threshold model with the unemployment rate support a flat Phillips curve when unemployment is high. Numerical estimates of the threshold are consistent with the gap specification.

Using measures of the labor share produces similar results. In column (3), we use the raw measure as it relates directly to the unobserved output gap (Galí and Gertler 1999). The threshold is again statistically significant at a 10 percent level, and the curve is flat in the high-slack region.[8] Finally, in column (4) we follow Armenter (2015) and use the adjusted measure based on the historical average of proprietors' income allocated to labor. Although the threshold is only marginally significant in this case, the estimates are in line with the other specifications quantitatively. In most cases, a two-threshold

[7] This is hardly surprising given that it is widely known that gap variables are the relevant determinants of inflation.

[8] Note that the high-slack region corresponds to low values of the labor share.

model is rejected in favor of the one-threshold model.[9]

Finally, forward-looking expectations appear to have a larger weight than inflation lags. For unemployment specifications, the weight of SPF forecasts is about three-quarters; for the labor share specifications, it is near one.

The bottom line of these results is two-fold. A simple linear Phillips curve with backward-looking expectations or professional forecasters' expectations can represent the inflation–unemployment relationship reasonably well over a long period of time. In this sense, the (linear) Phillips curve is alive and well. However, the model may perform poorly when economic activity differs drastically from its historical average (e.g., in 2010, when the unemployment gap was at its high). The nonlinear Phillips curve suggests that inflation becomes much less responsive to changes in unemployment when there is slack in the economy. A model that accounts for this effect predicts a much smaller decrease in inflation during the aftermath of the Great Recession than a linear model does. Importantly, our model puts thresholds in different time periods and therefore provides a mechanism different from a structural break resulting in a flattening of the Phillips curve (e.g., Roberts 2006, Simon, Matheson, and Sandri 2013).

3 Phillips Curve Nonlinearities and Consumer Expectations

If consumer inflation expectations and nonlinearities can explain the missing disinflation, then any analysis that does not consider both explanations could produce erroneous results. Consider the following example. If the data-generating Phillips curve is nonlinear, an estimated linear model may suggest that a variable correlated with the probability of being in different regimes has explanatory power, even if such a variable is completely irrelevant in the "correct," nonlinear specification. On the other hand, if consumer expectations are independent of the level of economic activity, nonlinearities may appear significant only because the model without consumer expectations is misspecified. Once one controls for consumer expectations, nonlinearities would disappear.

To examine these possibilities, we augment Equation (2) with the mean tendency of inflation expectations from the MSC while preserving potential nonlinearities. The expectations term can be written as follows:

$$\mathbb{E}_t\,\pi_{t+1} = \sum_{i=1}^{5} \delta_i\,\pi_{t-i} + \alpha_1\,\mathbb{E}_t^{\text{SPF}}\,\pi_{t+1} + \alpha_2\,\mathbb{E}_t^{\text{MSC}}\,\pi_{t+1}. \tag{7}$$

As before, we set the constraint $\alpha_0 + \alpha_1 + \alpha_2 = 1$, where $\alpha_0 = \sum_{i=1}^{5} \delta_i$.

Table 2 presents the results for the sample period 1968q4 to 2016q3. For the unemployment gap specification (column 1), the curve is relatively steep left of the thresholds and essentially flat right of the threshold. This result, as well as the threshold location, is similar to Table 1. However, unlike in the previous case, we cannot reject the linear model in favor of the threshold model, suggesting that accounting for the Michigan survey expectations casts some doubts on the importance of nonlinearities.

[9]The estimates of two thresholds are typically very close to each other, giving rise to a regime with relatively few observations and a rather erratic slope. Therefore, we prefer the model with one threshold even when the two-threshold model is marginally significant (labor share specification).

Table 2. Nonlinearities vs. Consumer Expectations

	Unemployment		Labor Share	
	Gap	Rate	——	Armenter (2015)
	(1)	(2)	(3)	(4)
Panel A: Linear Model				
Slope, $\hat{\beta}$	-0.33^{***}	-0.17^{**}	0.24^{***}	0.33^{***}
	(0.09)	(0.08)	(0.04)	(0.05)
Panel B: Threshold Model				
Slopes				
left, $\hat{\beta}_L$	-0.55^{***}	-0.76	0.16^{**}	0.63^{***}
	(0.19)	(0.46)	(0.07)	(0.18)
right, $\hat{\beta}_R$	0.09	-0.14^{*}	0.33^{***}	0.27^{***}
	(0.19)	(0.08)	(0.10)	(0.07)
Expected inflation				
Michigan Survey of Consumers, $\hat{\alpha}_2$	0.72^{***}	0.75^{***}	1.12^{***}	0.99^{***}
	(0.15)	(0.17)	(0.20)	(0.16)
SPF, $\hat{\alpha}_1$	-0.03	-0.08	-0.15	-0.08
	(0.28)	(0.30)	(0.24)	(0.24)
Sum of lags, $\hat{\alpha}_0$	0.31^{*}	0.33^{*}	0.02	0.08
	(0.18)	(0.18)	(0.19)	(0.17)
Threshold				
point est., $\hat{\gamma}$	1.95	4.50	-1.95	-3.27
95 percent CI	$[-0.8, 2.9]$	$[4.5, 8.5]$	$[-7.0, 3.2]$	$[-4.3, 2.5]$
N of thresholds, p-val.				
0 vs. 1, H_0: 0	0.12	0.85	0.49	0.44
1 vs. 2, H_0: 1	0.94	0.64	0.37	0.42
R^2	0.77	0.75	0.80	0.79
N	192	192	192	192

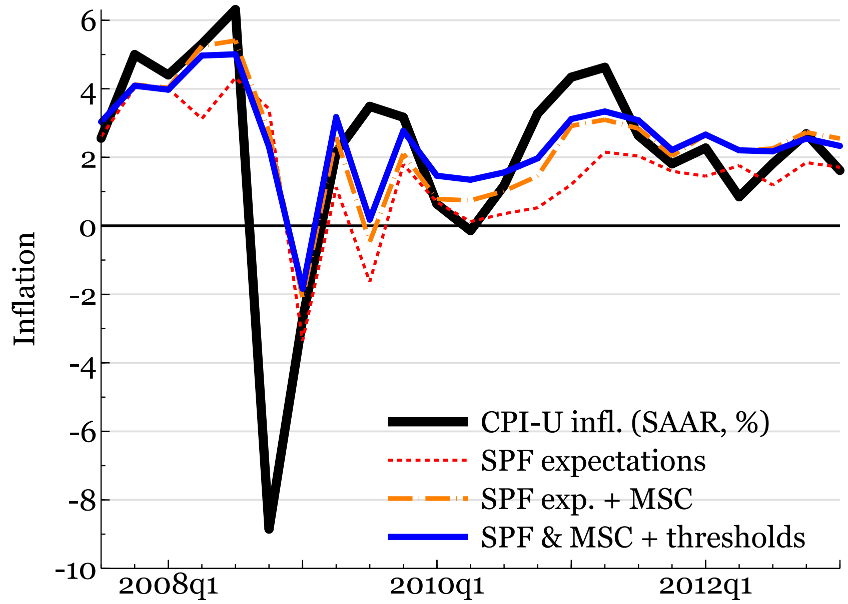
Notes: See notes to Table 1. This table augments expected inflation with consumer expectations measured from the MSC.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results are qualitatively similar for the unemployment rate specification, the main difference being the significance level of the left slope and the threshold location (column 2). The threshold is also statistically insignificant when we use labor's share as a measure of economic activity (columns 3–4). Whether we use the raw measure or the adjusted measure, the slopes from either side of the threshold are positive and significant, as well as reasonably close to the linear estimates.

In all specifications, the Michigan survey measure has the highest weight in the inflation expectations process. For the unemployment rate and gap, the MSC weight is about 0.7, while the weight of inflation lags is 0.3. The SPF carries a weight of virtually 0. The consumer inflation expectations are even more important in the labor share specifications, with a corresponding weight close to 1. While we observe that using data from the full sample results in the dominance of Michigan survey expectations over thresholds, it is still possible that nonlinearities possess some explanatory power for inflation during important subsamples.

We start by examining what happens to the fitted values of inflation when we control for consumers' inflation expectations. First of all, the linear model's fit improves during the missing disinflation episode (Figure 3). For example, in 2009q3 the SPF linear model predicts a deflation of 2 percent. Adding the MSC inflation expectations to the linear model pushes the inflation forecast to −0.5 percent. Considering nonlinearities as well improves the forecast further to 0; the actual inflation was almost 4 percent. The

Figure 3. Consumer Inflation Expectations in the Linear and Threshold Models: Fitted Values



Notes: See notes to Figure 2. The black thick line represents the data. The red dashed line represents the linear model without consumer expectations; the orange dashed-dot line represents the linear model with consumer expectations. The blue thin line represents the threshold model with the full set of expectations.

difference between the models with and without thresholds is more pronounced in 2010: about 1 p.p. More recently, the difference between the two has been negligible. Hence, even though the threshold estimated over the full sample is not statistically significant in most cases, allowing for some curvature in the inflation–unemployment relationship has a nontrivial effect on the Phillips curve's fit during the missing disinflation period.

We then investigate the role played by consumer expectations in this specific episode. To do this, we first isolate the innovation component in the Michigan survey inflation expectations (i.e., the inflation expectations of consumers that cannot be forecast by data available in the previous quarter). To isolate the innovation component, we need to establish a reasonable model for the MSC. Fuhrer (2017b) shows that, at a micro level, MSC participants tend to revise their inflation forecasts in response to the lagged central tendency of survey inflation expectations. Such a mechanism should render persistence in this measure.[10] We also allow the Michigan survey expectations to depend on the lags of real-time inflation,[11] the federal funds rate, and the SPF forecast, as well as the change in oil prices. That is, we estimate the following specification:

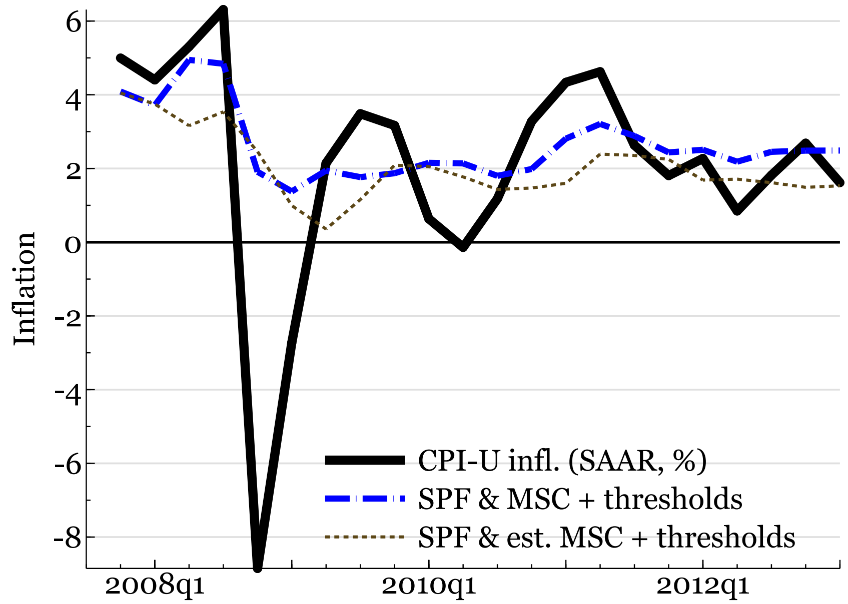
$$\mathbb{E}_t^{\text{MSC}}\,\pi_{t+1} = a + \sum_{i=1}^{4} \rho_i\,\mathbb{E}_{t-i}^{\text{MSC}}\,\pi_{t-i+1} + \sum_{i=1}^{4} b_i\,\pi_{t-i|t} + c\,r_{t-1} + d\,\mathbb{E}_{t-1}^{\text{SPF}}\,\pi_t + f\,\frac{\Delta P_t^{\text{oil}}}{P_{t-1}^{\text{oil}}} + \varepsilon_t^{\text{MSC}}, \qquad (8)$$

where $\pi_{t-1|t}$ is real-time inflation in period $t-1$ as observed in period t, r_t is the nominal federal funds rate, and P_t^{oil} is the oil price. We observe real-time inflation at a monthly frequency and convert it to

[10] Binder (2017) finds that many respondents tend to round their forecasts to the nearest 0 or 5. If inflationary shocks are small, this mechanism can also generate persistence in the measured expectations.

[11] The real-time data go back to 1994q3. We use revised data for the period when real-time data are not available.

Figure 4. Innovations in the Consumer Expectations Process: Dynamic Forecasts of Inflation



Notes: The estimation period is 1968q4–2016q3. The figure shows dynamic forecasts (with respect to the dependent variable) of inflation starting from 2007q4. That is, for the lags of inflation we use in-sample dynamic forecasts, while for other variables we use actual realizations. The unemployment gap is a forcing variable. The list of controls is in the notes to Table 1. The estimated MSC specifications use the in-sample fitted values from Equation (8). The black line represents the data. The blue dash-dot line and the brown dotted line represent the threshold models with actual and fitted values of consumer expectations, respectively.

Table 3. The In-Sample Fit during the Missing Disinflation: RMSE

	Estimated MSC (1)	Actual MSC (2)
Linear model	1.89	1.67
Threshold model	1.63	1.54

Notes: The model is estimated for the sample 1968q4–2016q3. The in-sample forecast RMSEs are computed for the period 2009q1–2013q4. Inflation is measured with the headline CPI.

a quarterly frequency by averaging over the months. That is, $\pi_{t-i|t} = (\pi_{t-i|m1} + \pi_{t-i|m2} + \pi_{t-i|m3})/3$, where $\pi_{t-1|m1}$ is real-time inflation in quarter $t-i$ observed in the first month of quarter t. Averaging over the months as opposed to using $\pi_{t-i|m2}$ brings the aggregation of real-time data closer to the MSC quarterly measure, which is based on interviews in each month of the quarter. With this inflation expectations process in mind, we estimate the model that combines Equation (7) with Equation (1) or (3), where we use either the actual MSC variable $\mathbb{E}_t^{\text{MSC}}\pi_{t+1}$ or its fitted value $\widehat{\mathbb{E}_t^{\text{MSC}}\pi_{t+1}}$.

Figure 4 shows in-sample dynamic forecasts obtained in 2007q4. In each subsequent quarter, we use inflation forecasts obtained in 2007q4, while we use actual realizations of all other variables. The blue dash-dot line incorporates innovations in the Michigan expectations process, while the brown dotted line does not. The fact that the blue dash-dot line lies above the brown dotted line, predicting less disinflation, indicates that the innovation in the Michigan process ($\varepsilon_t^{\text{MSC}}$) plays a role in the piecewise-linear models as well.[12]

We then use the root mean squared error (RMSE) to compare the models' fit in a subsample (Ta-

[12] We find a similar result for the linear case.

ble 3). During the missing disinflation of the 2010s, the RMSE of the linear model with actual MSC is 11.6 percent smaller than the RMSE of the linear model with estimated MSC. For the threshold case, including the innovation component reduces the RMSE by approximately 5.5 percent. When we control for actual MSC, the RMSE of the linear model is 8.4 percent larger than the RMSE of the threshold model.

Although in Table 2 we cannot reject the linear model in favor of the threshold model for the entire sample, the result that the threshold model has a better fit during the missing disinflation suggests that thresholds may add value during episodes of extreme turbulence. To show this point more formally, we conduct a test whether the threshold model should be preferred to the linear model during the missing disinflation. To do this, we compute F-statistics and their distributions from subsample residuals via our bootstrap routine. We reject at a 5 percent level the null hypothesis of a linear model in favor of the alternative hypothesis of a one-threshold model.[13]

Overall, we find that in the inflation–unemployment relationship, consumer expectations and nonlinearities offer separate explanations for the missing disinflation episode. However, the statistical evidence presented in this section favors the explanation of consumer expectations over nonlinearities, since the linear model cannot be rejected. Yet, nonlinearities improve the model's fit in a material way, and the nonlinear model can dominate the linear counterpart in subsamples. In the rest of the paper, we show that analyses of the relative importance of consumer expectations and nonlinearities are more nuanced and differ crucially across historical periods or inflation measures.

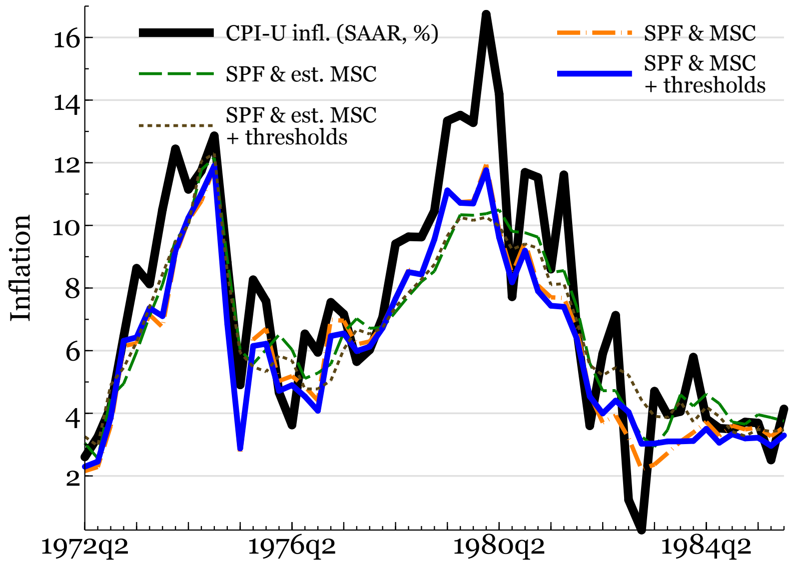
4 The Great Inflation of the 1970s and the Volcker Disinflation

Recent literature on the in-sample fit of the Phillips curve (e.g., Ball and Mazumder 2011, Fuhrer 2017a) focuses on the ability of the model to explain inflation dynamics following the 2008–09 Great Recession. As the Great Recession was a rare episode of the unemployment rate reaching double digits, this literature examines the ability of theoretical models to explain the data when macroeconomic fundamentals are far from their historical averages. We followed this route in the previous section and in this section, we also bring evidence from two other key episodes when inflation, rather than unemployment, reached and then pulled back from double digits: the Great Inflation of the 1970s and the subsequent Volcker disinflation.

The October 1973 oil embargo sharply increased oil prices. By the end of the embargo in March 1974, crude oil prices had quadrupled. After this first oil price shock, a second shock followed with the 1979 Iranian revolution. Iran drastically decreased oil production, and exports were suspended. Although other OPEC members increased their oil output, the worldwide production of oil was down by about 4 percent. The price of crude oil more than doubled over the course of the year and did not return to its pre-crisis level until the mid-1980s. The energy crisis, among other factors such as passive monetary policy, contributed to a sharp rise in inflation (see the black line in Figure 5), peaking at 16.7 percent in 1980q1.

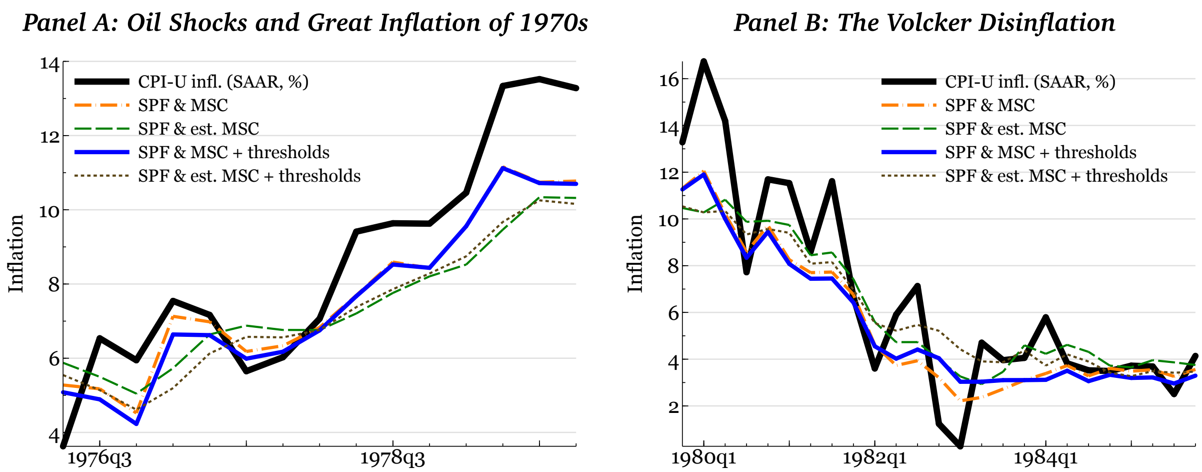
[13] Details are presented in Appendix B.

Figure 5. Phillips Curves and the Dynamic Forecasts of Inflation in the 1970s and 1980s



Notes: Dynamic forecasts start in 1972q2. The estimation period is 1968q4–2016q3. See Figure 4 notes for specification and estimation details.

Figure 6. Consumer Expectations and Nonlinearities



Notes: Panel A: Dynamic forecasts start in 1976q2. Panel B: Dynamic forecasts start in 1979q4. The estimation period is 1968q4–2016q3. See Figure 4 notes for specification and estimation details.

Table 4. Inflation Dynamics and the Models' Fit: Early Sample Period

Inflation	Great Inflation		Volcker Disinflation	
	Peak-to-Trough	RMSE	Peak-to-Trough	RMSE
	(1)	(2)	(3)	(4)
Change in CPI	13.1	–	−16.5	–
Linear model				
estimated MSC	4.5	2.52	−7.0	2.80
actual MSC	6.7	1.86	−9.8	2.67
Threshold model				
estimated MSC	4.7	2.54	−5.9	3.05
actual MSC	6.7	1.93	−8.9	2.83

Notes: The Great Inflation episode is defined as the period between 1976q2 and 1980q1, based on the lowest and highest CPI inflation values around the crisis. The Volcker disinflation episode is 1980q1–1983q1.

In August 1979, Paul Volcker became chair of the Federal Reserve, arriving with a commitment to fight rising inflation. To achieve this goal, the Federal Open Market Committee (FOMC) drastically raised the federal funds target rate. The federal funds rate averaged around 11 percent in 1979 and reached a peak of 20 percent by mid-1981. A combination of the oil shock and high rates contributed to the 1980–82 recession. Remarkably, inflation fell below 3 percent by 1983.

Did the Phillips curve accurately describe these two remarkable inflation swings? Do nonlinearities improve the fit of the Phillips curve in these episodes? Figure 5 presents dynamic forecasts of the Phillips curve that allow for a mix of backward-looking, professional forecasters', and consumers' inflation expectations. The forecasts are made in 1972q2, before the first oil shock.[14] The orange dash-dot line represents the linear model and the blue solid line represents the threshold model. It appears that nonlinearities did not play an important role in the 1970s and early 1980s. The two lines are virtually on top of each other, with a few minor deviations in 1975–76 and 1983.

Instead, MSC expectations played a more important role. The green dotted and brown dotted lines show the dynamic forecasts of the linear and threshold models, respectively, when we use the predicted values measured as in Equation (8) instead of the actual values of the MSC expectations. The difference between these lines and their counterparts based on actual MSC expectations gauges the contribution of innovations in expectations. This contribution is often close to 1 p.p. Unlike nonlinearities, accounting for MSC inflation expectations leads to more noticeable effects, especially during the 1979 oil shock and the Volcker disinflation.

Making forecasts in 1972 prevents the model from incorporating readings of actual inflation right before the second oil shock. We therefore focus on each episode separately in Figure 6. Panel A shows dynamic forecasts starting in 1976q2. During the Great Inflation, the forecasts of the linear and threshold models are virtually indistinguishable from each other and are below actual inflation by about 3 p.p. Unlike nonlinearities, MSC expectations are important to bring the Phillips curve closer to the data during the Great Inflation. The two models with the actual inflation expectations produce forecasts about 2 p.p. above those of the models without them, which improves the fit of the model.

Panel B of Figure 6 focuses on the Volcker disinflation episode. The difference between the linear and threshold models is visible in 1983, at the end of the disinflation episode and when the unemployment rate reached a 10 percent mark. In fact, nonlinearities deteriorate the fit of the Phillips curve in this period. While the nonlinearity helped the model to fit the missing disinflation during the Great Recession, the same reasoning impedes model performance during the Volcker disinflation.

While nonlinearities are counterproductive in matching the Volcker disinflation, MSC expectations of inflation provide a mechanism for the Phillips curve to catch up with the data. In particular, the model with consumer expectations predicts a disinflation 1 p.p. faster than the model without them.

Table 4 summarizes the performance of the models during the Great Inflation and the Volcker disinflation according to two criteria. The first criterion is the change in inflation from the beginning to the end of the period; the runup in inflation during the Great Inflation was about 13.1 p.p. and the Volcker period implies a disinflation of about 16.5 p.p. The second criterion is the RMSE during the two periods.

[14]This method employs model-generated inflation forecasts, rather than actual values, as inflation lags over the forecast horizon. Other variables are used at their actual values (i.e., the forecast is dynamic only with respect to inflation).

The table shows that during the Great Inflation, nonlinearities played at best a minor role in explaining the inflation runup observed in the data, while the models with actual MSC expectations perform better than the models without actual consumer expectations (column 1). This conclusion also holds when model performance is evaluated based on the RMSE (column 2) or during the Volcker disinflation episode (columns 3 and 4).

Overall, allowing for a high-unemployment regime helps the Phillips curve match the data during the missing disinflation in the 2010s but does not help in matching the data in other key periods, namely the Great Inflation of the 1970s and the subsequent disinflation period. We also confirm this evidence by formally testing nonlinearities in each of the three episodes. The F-test rejects the linear model for the missing disinflation period, but prefers the linear model for the other two episodes (see Appendix B for details). Yet, consumer inflation expectations play a crucial role in all the episodes examined here. For this reason, when allowing for a Phillips curve with both consumer inflation expectations and nonlinearities, the former are highly significant in the entire sample, whereas the latter are not (see Table 2).

5 Sensitivity of Baseline Estimates to Specification Choices

5.1 Alternative Measures of Inflation

In this section, we examine results sensitivity to using different measures of inflation. Following the literature on the missing disinflation, our baseline specification employs the headline CPI. The literature has used CPI inflation partly because MSC respondents are asked about this measure.

However, there are some disadvantages. The MSC asks respondents about inflation expectations the following year, not the following quarter as mandated by the specification of the Phillips curve. The time series of SPF forecasts of CPI inflation is short, whereas the SPF forecasts of deflator-GDP inflation extend back to the late 1960s. Unlike the MSC CPI expectations, the SPF GDP deflator expectations refer to the following quarter. Further, the Fed's preferred measure of inflation and its inflation target at 2 percent are based on the PCE index; hence, significant media coverage relates to this measure. We therefore consider measuring inflation with indices other than the CPI.

Column (1) of Table 5 presents our baseline specification estimates when inflation is measured using the PCE index. In this specification, nonlinearities play a far more important role than they do in the CPI specification. The linear model is rejected at a 1 percent level. The relative weight of the MSC expectations decreases from 0.72 to 0.55, while the weight of the SPF expectations increases from near 0 to 0.18.

Column (2) of Table 5 focuses on GDP deflator inflation. This inflation measure has been often preferred in the DSGE literature (e.g., Smets and Wouters 2007). Again, the threshold is significant at a 5 percent level. The MSC weight in this model (0.28) is even lower than for the PCE, while the SPF weight is up to 0.26 and different from zero at a 5 percent level. The higher role of the SPF expectations can be explained by the fact that both actual inflation and predicted inflation are measured for the GDP deflator.

Finally, columns (3) and (4) present our estimates for core measures of inflation. The results are

Table 5. Nonlinearities and Alternative Measures of Inflation

	PCE (1)	GDP Deflator (2)	CPI core (3)	PCE core (4)
		Panel A: Linear Model		
Slope, $\hat{\beta}$	-0.17^{***}	-0.16^{***}	-0.24^{***}	-0.10^{***}
	(0.06)	(0.05)	(0.06)	(0.04)
		Panel B: Threshold Model		
Slopes				
left, $\hat{\beta}_L$	-0.40^{***}	-0.51^{***}	-0.55^{**}	-0.21^{***}
	(0.13)	(0.12)	(0.24)	(0.06)
right, $\hat{\beta}_R$	0.25^{*}	-0.05	-0.21^{***}	0.21^{*}
	(0.14)	(0.06)	(0.06)	(0.11)
Expected inflation				
MSC, $\hat{\alpha}_2$	0.55^{***}	0.28^{***}	0.34^{***}	0.22^{***}
	(0.08)	(0.07)	(0.13)	(0.05)
SPF, $\hat{\alpha}_1$	0.18	0.26^{**}	0.18	0.29^{**}
	(0.17)	(0.13)	(0.23)	(0.12)
Sum of lags, $\hat{\alpha}_0$	0.27^{**}	0.46^{***}	0.47^{***}	0.50^{***}
	(0.13)	(0.08)	(0.13)	(0.09)
Threshold				
point est., $\hat{\gamma}$	1.95	0.24	−0.77	2.47
95 percent CI	[−0.8, 2.9]	[−0.8, 2.3]	[−0.8, 2.9]	[−0.8, 2.9]
N of thresholds, p-val.				
0 vs. 1, H_0: 0	0.01	0.03	0.72	0.03
1 vs. 2, H_0: 1	0.74	0.92	0.42	0.52
R^2	0.83	0.90	0.86	0.91
N	192	192	192	192

Notes: See notes to Tables 1 and 2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

similar to those for the respective headline measures. Appendix Tables A1–A4 present a full set of results that include measures of slack other than the unemployment gap (i.e., unemployment rate and labor share). They are consistent with our main conclusions.[15]

This section establishes two main facts. First, the MSC measure of consumer inflation expectations is important not only for CPI but also for a wide range of inflation measures. Second, nonlinearities are either marginally significant or insignificant in specifications with CPI inflation and MSC expectations. However, they are highly significant with other measures of inflation, such as the PCE or GDP deflator, even when controlling for consumer expectations.

5.2 Financial Frictions

The recent global financial crisis brought to the forefront financial frictions as a factor affecting economic fluctuations. Philippon (2009), Gilchrist and Zakrajšek (2012), and others emphasized the predictive content of corporate bond credit spreads for consumption, output, and inflation. We test whether these measures of the state of financial markets can explain our results on nonlinearities and expectations.

In column (1) of Table 6, we control for the Baa–Aaa corporate bond spread, a popular measure used in the literature.[16] We find that this measure has virtually no effect on the estimates. The coefficient on

[15]Appendix Figures A2–A4 and Table A5 show the models' fit for PCE and GDP deflator inflation.

[16]We report our results for deflator GDP inflation and relegate those for other inflation measures to Appendix Table A6. We focus on this measure because in this case, unlike for CPI inflation, nonlinearities are statistically significant. Therefore, we

Table 6. Nonlinearities and Credit Spreads

	Baa–Aaa spread (1)	Gilchrist and Zakrajšek (2012) Credit Spread (2)	Gilchrist and Zakrajšek (2012) Excess Bond Premium (3)	GZ Sample Period (4)
Panel A: Linear Model				
Slope, $\hat{\beta}$	-0.16^{***}	-0.07^{*}	-0.09^{**}	-0.09^{**}
	(0.06)	(0.04)	(0.04)	(0.04)
Panel B: Threshold Model				
Slopes				
Left, $\hat{\beta}_L$	-0.50^{***}	-1.03^{***}	-1.12^{***}	-0.98^{***}
	(0.12)	(0.29)	(0.30)	(0.34)
Right, $\hat{\beta}_R$	−0.05	0.00	−0.01	−0.02
	(0.06)	(0.04)	(0.04)	(0.05)
Expected Inflation				
Michigan Survey of Consumers, $\hat{\alpha}_2$	0.28^{***}	0.34^{***}	0.29^{***}	0.30^{***}
	(0.08)	(0.08)	(0.08)	(0.08)
SPF, $\hat{\alpha}_1$	0.26^{**}	0.28^{***}	0.34^{***}	0.33^{**}
	(0.13)	(0.13)	(0.12)	(0.13)
Sum of lags, $\hat{\alpha}_0$	0.46^{***}	0.38^{***}	0.38^{***}	0.37^{***}
	(0.09)	(0.07)	(0.06)	(0.07)
Credit spread	−0.03	-0.15^{***}	-0.28^{**}	—
	(0.22)	(0.06)	(0.11)	
Threshold				
point est., $\hat{\gamma}$	0.24	−0.27	−0.27	−0.27
95 percent CI	[−0.8,2.3]	[−0.7,1.6]	[−0.7,1.6]	[−0.7,1.8]
N of thresholds, p-val.				
0 vs. 1, $H_0: 0$	0.03	0.00	0.00	0.02
1 vs. 2, $H_0: 1$	0.90	0.86	0.70	0.88
R^2	0.90	0.93	0.93	0.92
N	192	174	174	174

Notes: Updated Gilchrist and Zakrajšek (2012) data are available at people.bu.edu/sgilchri/Data/data.htm. The forcing variable is the unemployment gap. Inflation is measured with deflator GDP. Estimation sample is 1968q4–2016q3 (baseline) in column (1) and 1973q1–2016q2 in columns (2)–(4). See notes to Tables 1 and 2 for estimation details. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

the corporate bond spread is close to zero and statistically insignificant. Other coefficients, including the slopes, expectation components' weight, and threshold location, are unaffected.

In column (2) of Table 6, we control for the Gilchrist and Zakrajšek (2012, henceforth, GZ) credit spread, an index based on individual corporate bonds traded in the secondary market and shown to be highly informative about economic activity.[17] In addition to the component measuring countercyclical movements in expected defaults—which is similar to the Baa–Aaa corporate bond spread—the GZ credit spread captures the excess bond premium (EBP), measuring changes in the relationship between measured default risk and credit spreads. Estimates from the specification with the excess bond premium are reported in column (3). The negative coefficients on the GZ credit spread and EBP are statistically significant, and the direction of the effect is consistent with findings in Gilchrist and Zakrajšek (2012).

Controlling for GZ credit spread or EBP does not have a material effect on the results. This can be seen by comparing the results in columns (2) and (3) with those in column (4), our baseline results

can test if controlling for financial frictions makes the kink less pronounced. Qualitatively, the results for other measures are similar.

[17]For additional details and the use of this index as a measure of financial markets shocks, see also Gilchrist, Yankov, and Zakrajšek (2009).

when we restrict the sample period to match that of GZ specifications.[18] Controlling for the GZ measures does not affect the threshold location, and the effect on the slopes is small, within statistical error. The nonlinear model dominates the linear case statistically, and the relative weights of inflation expectations' components are affected only marginally. Overall, our results are robust to financial frictions controls based on credit spreads.

6 Concluding Remarks

In this paper, we show that nonlinearities can explain the recent missing disinflation episode. A single kink in the Phillips curve accounts for the missing disinflation as much as households' inflation expectations do. However, extensive tests of the role of nonlinearities relative to consumer expectations suggest that the latter is a more robust feature of the Phillips curve. Nonlinearities played a role in the 2010s but, contrary to consumer expectations, were not important in the 1970s and 1980s. More formal econometric tests confirm these conclusions. In addition and in line with these results, nonlinearities are significant for some measures of inflation but not for others. Consumer expectations meanwhile are robust and remain significant for all measures used.

We also find that including MSC CPI expectations is key, even when the inflation measure does not correspond exactly to that of the MSC. Despite the importance of consumer expectations, we should note that nonlinear dynamics regain significance whenever there is a mismatch between the measures of actual inflation and inflation expectations. Considering linear first-order approximations in such cases appears insufficient.

The recent literature concludes that the Phillips curve is alive and well, and our paper confirms this view from a different angle. We expect more research to explain inflation dynamics through the lens of the Phillips curve in the future.

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[18] The GZ sample period starts in 1973. As a result, relative to the baseline we lose over four years of observations with high inflation. The effect of this shift in the sample composition on our baseline results is, however, modest. Most of the difference is in the left slope and comes from the shift in the threshold location to the left, resulting in fewer observations in the left region.

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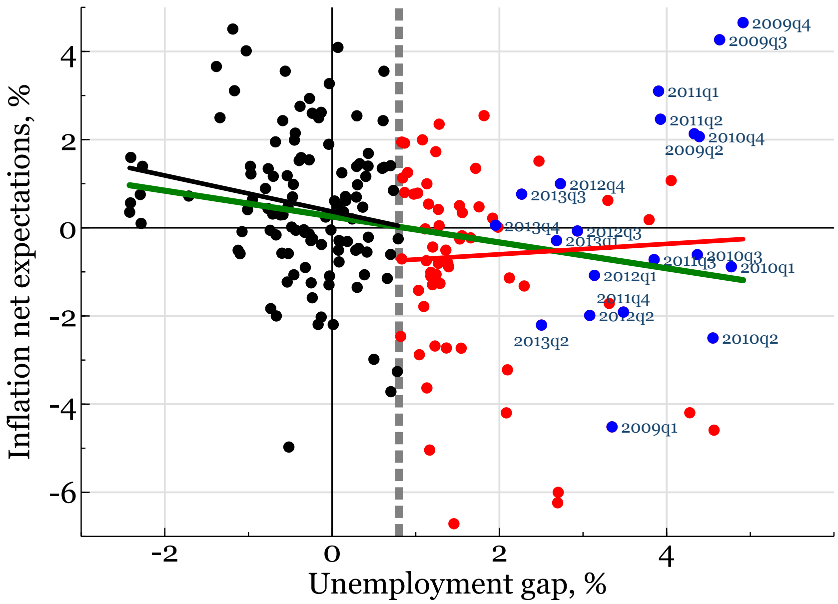
Appendix

A Additional Results

Figure A1. Robustness: Dropping the Continuity Constraint



Notes: See notes to Figure 1. This scatterplot does not impose a continuity constraint.

Table A1. Nonlinearities and Alternative Measures of Inflation: PCE

	Unemployment		Labor Share	
	Gap	Rate	——	Armenter (2015)
	(1)	(2)	(3)	(4)
Panel A: Linear Model				
Slope, $\hat{\beta}$	-0.17^{***}	-0.06	0.16^{***}	0.24^{***}
	(0.06)	(0.06)	(0.03)	(0.04)
Panel B: Threshold Model				
Slopes				
left, $\hat{\beta}_L$	-0.40^{***}	-0.23^{*}	0.12^{***}	0.18^{***}
	(0.13)	(0.14)	(0.02)	(0.04)
right, $\hat{\beta}_R$	0.25^{*}	0.15	0.48^{***}	0.46^{***}
	(0.14)	(0.13)	(0.18)	(0.17)
Expected inflation				
Michigan Survey of Consumers, $\hat{\alpha}_2$	0.55^{***}	0.60^{***}	0.81^{***}	0.69^{***}
	(0.08)	(0.09)	(0.10)	(0.09)
SPF, $\hat{\alpha}_1$	0.18	0.10	0.19	0.37^{**}
	(0.17)	(0.17)	(0.16)	(0.16)
Sum of lags, $\hat{\alpha}_0$	0.27^{**}	0.31^{**}	-0.00	-0.06
	(0.13)	(0.13)	(0.16)	(0.13)
Threshold				
point est., $\hat{\gamma}$	1.95	6.87	1.94	0.64
95 percent CI	$[-0.8, 2.9]$	$[4.5, 8.5]$	$[-5.3, 3.2]$	$[-4.3, 2.5]$
N of thresholds, p-val.				
0 vs. 1, H_0: 0	0.01	0.16	0.05	0.22
1 vs. 2, H_0: 1	0.74	0.33	0.24	0.38
R^2	0.83	0.82	0.85	0.85
N	192	192	192	192

Notes: See notes to Table 2. Inflation measure: headline PCE. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2. Nonlinearities and Alternative Measures of Inflation: GDP Deflator

	Unemployment		Labor Share	
	Gap	Rate	——	Armenter (2015)
	(1)	(2)	(3)	(4)
Panel A: Linear Model				
Slope, $\hat{\beta}$	-0.16^{***}	-0.11^{**}	0.09^{***}	0.16^{***}
	(0.05)	(0.04)	(0.02)	(0.03)
Panel B: Threshold Model				
Slopes				
left, $\hat{\beta}_L$	-0.51^{***}	-0.73^{**}	0.05^{**}	0.08^{**}
	(0.12)	(0.30)	(0.02)	(0.03)
right, $\hat{\beta}_R$	-0.05	-0.08^{*}	0.45^{***}	0.54^{***}
	(0.06)	(0.05)	(0.10)	(0.12)
Expected inflation				
Michigan Survey of Consumers, $\hat{\alpha}_2$	0.28^{***}	0.29^{***}	0.41^{***}	0.34^{***}
	(0.07)	(0.07)	(0.07)	(0.07)
SPF, $\hat{\alpha}_1$	0.26^{**}	0.20^{*}	0.19^{*}	0.35^{***}
	(0.13)	(0.12)	(0.11)	(0.11)
Sum of lags, $\hat{\alpha}_0$	0.46^{***}	0.51^{***}	0.40^{***}	0.30^{***}
	(0.08)	(0.08)	(0.06)	(0.07)
Threshold				
point est., $\hat{\gamma}$	0.24	4.50	1.94	0.80
95 percent CI	$[-0.8, 2.3]$	$[4.5, 8.5]$	$[-2.0, 3.2]$	$[-2.0, 2.5]$
N of thresholds, p-val.				
0 vs. 1, H_0: 0	0.03	0.30	0.00	0.00
1 vs. 2, H_0: 1	0.92	0.54	0.08	0.16
R^2	0.90	0.89	0.90	0.91
N	192	192	192	192

Notes: See notes to Table 2. Inflation measure: GDP deflator. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3. Nonlinearities and Alternative Measures of Inflation: CPI Core

	Unemployment		Labor Share	
	Gap	Rate	——	Armenter (2015)
	(1)	(2)	(3)	(4)
Panel A: Linear Model				
Slope, $\hat{\beta}$	-0.24^{***}	-0.15^{**}	0.12^{***}	0.16^{***}
	(0.06)	(0.06)	(0.03)	(0.04)
Panel B: Threshold Model				
Slopes				
left, $\hat{\beta}_L$	-0.55^{**}	-0.01	0.05	0.14^{***}
	(0.24)	(0.11)	(0.05)	(0.04)
right, $\hat{\beta}_R$	-0.21^{***}	-0.44^{***}	0.17^{***}	0.60
	(0.06)	(0.18)	(0.05)	(0.41)
Expected inflation				
Michigan Survey of Consumers, $\hat{\alpha}_2$	0.34^{***}	0.35^{**}	0.52^{***}	0.40^{***}
	(0.13)	(0.14)	(0.14)	(0.14)
SPF, $\hat{\alpha}_1$	0.18	0.13	0.14	0.24
	(0.23)	(0.24)	(0.18)	(0.22)
Sum of lags, $\hat{\alpha}_0$	0.47^{***}	0.52^{***}	0.34^{***}	0.36^{***}
	(0.13)	(0.13)	(0.12)	(0.13)
Threshold				
point est., $\hat{\gamma}$	-0.77	7.40	-3.29	2.54
95 percent CI	$[-0.8, 2.9]$	$[4.5, 8.5]$	$[-7.0, 3.21]$	$[-4.3, 2.5]$
N of thresholds, p-val.				
0 vs. 1, H_0: 0	0.72	0.30	0.61	0.61
1 vs. 2, H_0: 1	0.42	0.14	0.48	0.47
R^2	0.86	0.86	0.87	0.86
N	192	192	192	192

Notes: See notes to Table 2. Inflation measure: CPI core. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

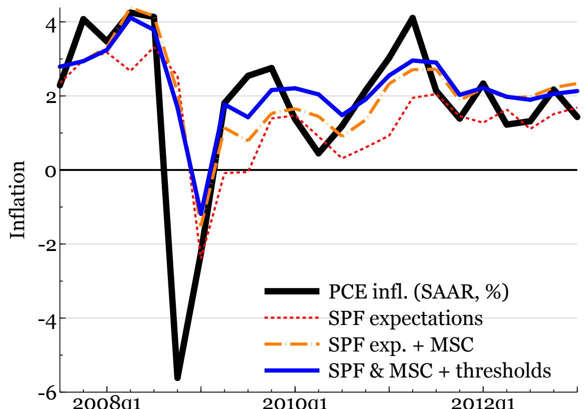
Table A4. Nonlinearities and Alternative Measures of Inflation: PCE Core

	Unemployment		Labor Share	
	Gap	Rate	——	Armenter (2015)
	(1)	(2)	(3)	(4)
Panel A: Linear Model				
Slope, $\hat{\beta}$	-0.10^{***}	-0.05	0.07^{***}	0.11^{***}
	(0.04)	(0.04)	(0.02)	(0.02)
Panel B: Threshold Model				
Slopes				
left, $\hat{\beta}_L$	-0.21^{***}	-0.55^{*}	0.04^{***}	0.05^{**}
	(0.06)	(0.31)	(0.01)	(0.02)
right, $\hat{\beta}_R$	0.21^{*}	-0.02	0.31^{***}	0.45^{***}
	(0.11)	(0.04)	(0.07)	(0.11)
Expected inflation				
Michigan Survey of Consumers, $\hat{\alpha}_2$	0.22^{***}	0.24^{***}	0.32^{***}	0.26^{***}
	(0.05)	(0.05)	(0.05)	(0.05)
SPF, $\hat{\alpha}_1$	0.29^{**}	0.30^{**}	0.32^{***}	0.41^{***}
	(0.12)	(0.14)	(0.10)	(0.10)
Sum of lags, $\hat{\alpha}_0$	0.50^{***}	0.47^{***}	0.37^{***}	0.34^{***}
	(0.09)	(0.12)	(0.08)	(0.09)
Threshold				
point est., $\hat{\gamma}$	2.47	4.50	1.78	1.27
95 percent CI	$[-0.8, 2.9]$	$[4.5, 8.5]$	$[-2.0, 3.2]$	$[-2.3, 2.5]$
N of thresholds, p-val.				
0 vs. 1, H_0: 0	0.03	0.37	0.00	0.00
1 vs. 2, H_0: 1	0.52	0.21	0.84	0.97
R^2	0.91	0.91	0.92	0.92
N	192	192	192	192

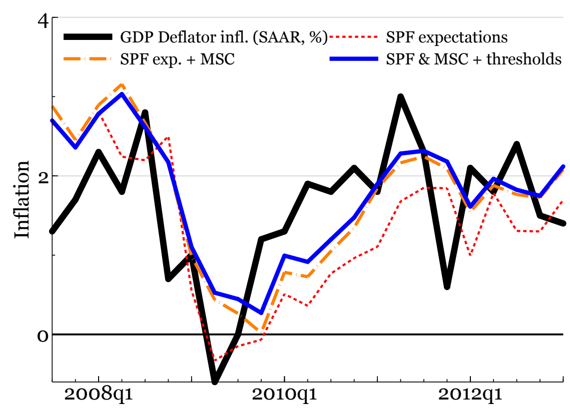
Notes: See notes to Table 2. Inflation measure: PCE core. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A2. Linear vs. Threshold Model: Alternative Measures of Inflation

Panel A: PCE Inflation



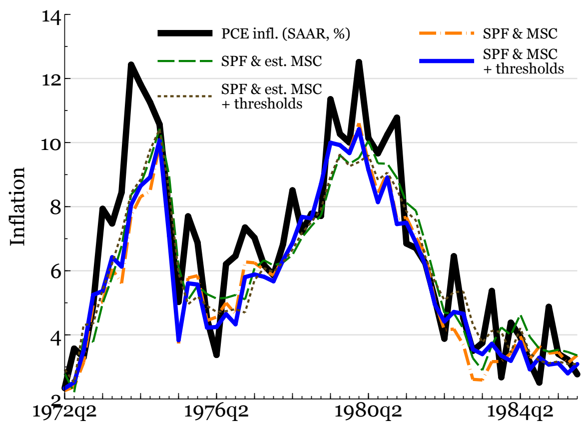
Panel B: GDP Deflator Inflation



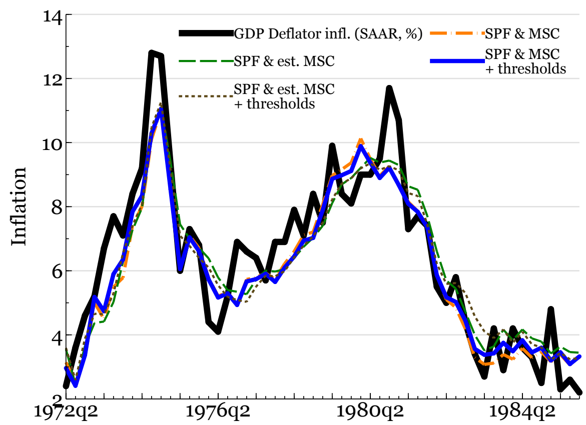
Notes: See notes to Figures 2 and 3.

Figure A3. Phillips Curves and the Dynamic Forecasts of Inflation: Alternative Measures

Panel A: PCE

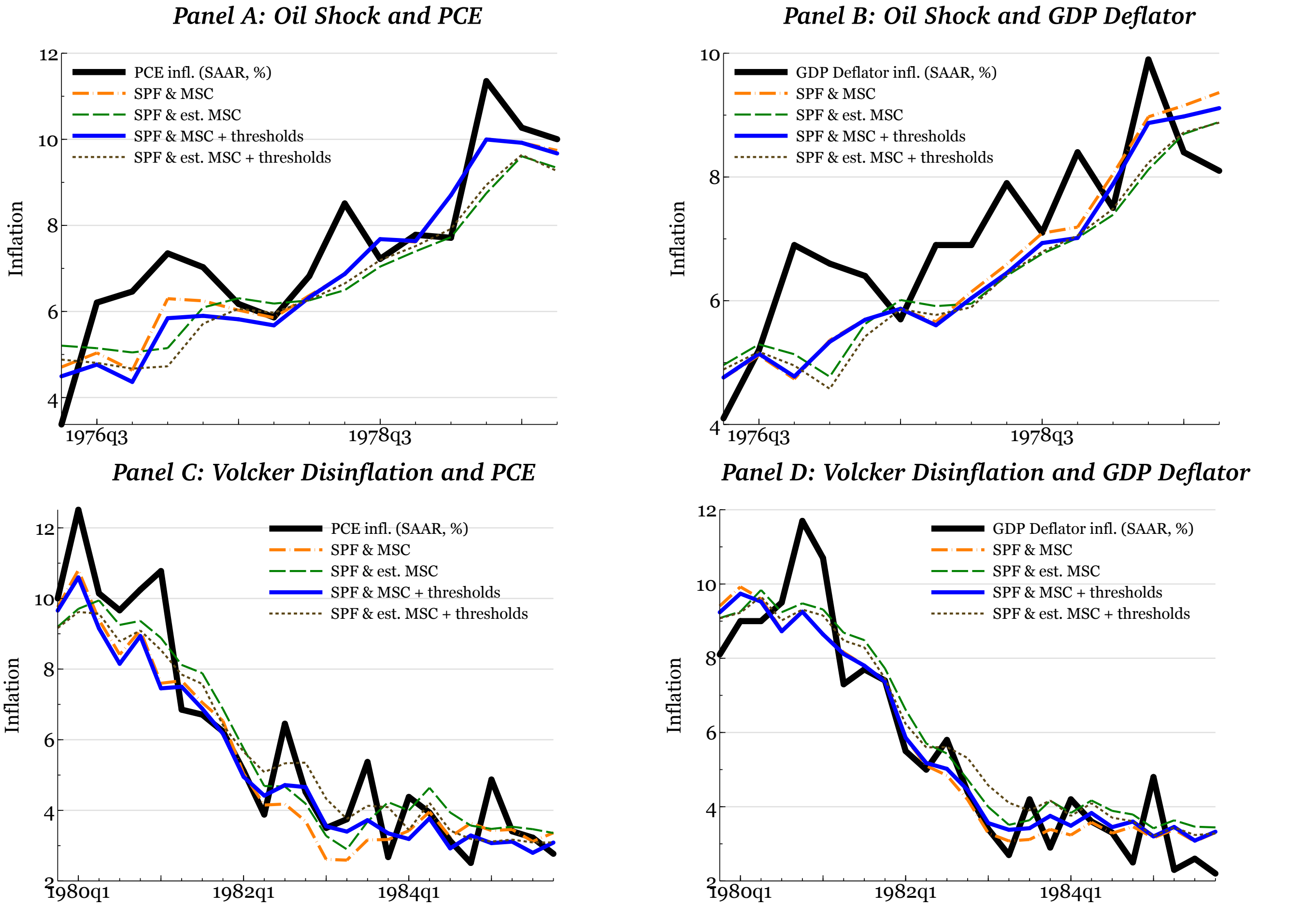


Panel B: GDP Deflator



Notes: Dynamic forecasts start in 1972q2. The estimation period is 1968q4–2016q3. See notes to Figure 4 for specification and estimation details.

Figure A4. Consumer Expectations and Nonlinearities: Alternative Measures



Notes: Panels A, B: Dynamic forecasts start in 1976q2. Panels C, D: Dynamic forecasts start in 1979q4. The estimation period is 1968q4–2016q3. See notes to Figure 4 for specification and estimation details.

Table A5. Inflation Dynamics and the Models' Fit: Alternative Measures

Inflation	Great Inflation		Volcker Disinflation		2010s Missing Disinflation
	Peak-to-Trough	RMSE	Peak-to-Trough	RMSE	RMSE
	(1)	(2)	(3)	(4)	(5)
			Panel A: PCE		
Actual PCE	9.1	–	−9.0	–	–
Linear model					
estimated MSC	4.3	1.45	−6.4	1.25	1.14
actual MSC	5.9	1.06	−8.2	1.36	1.10
Threshold model					
estimated MSC	4.5	1.51	−5.3	1.30	0.89
actual MSC	5.9	1.17	−7.1	1.34	0.96
			Panel B: GDP Deflator		
Actual GDP deflator	4.9	–	−5.6	–	
Linear model					
estimated MSC	4.2	1.06	−5.3	0.99	0.97
actual MSC	5.4	1.03	−6.6	1.03	0.85
Threshold model					
estimated MSC	4.3	1.10	−4.7	1.03	0.85
actual MSC	5.1	1.03	−6.2	1.00	0.77

Notes: The Great Inflation episode is defined as the period between 1976q2 and 1980q1, based on the lowest and highest CPI inflation values around the crisis. The Volcker disinflation episode is 1980q1–1983q1. The missing disinflation episode covers 2009q1–2013q4.

Table A6. Nonlinearities and Credit Spreads: Alternative Inflation Measures

	Baa–Aaa Spread		GZ Spread		GZ EBP	
	CPI	PCE	CPI	PCE	CPI	PCE
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Linear Model						
Slope, $\hat{\beta}$	-0.27^{***}	-0.14	-0.23^{***}	-0.07	-0.31^{***}	-0.12^{*}
	(0.13)	(0.08)	(0.08)	(0.06)	(0.09)	(0.07)
Panel B: Threshold Model						
Slopes						
Left, $\hat{\beta}_L$	-0.49^{***}	-0.37^{***}	-2.73^{***}	-2.22^{***}	-3.87^{***}	-2.85^{***}
	(0.13)	(0.10)	(0.85)	(0.58)	(1.48)	(0.90)
Right, $\hat{\beta}_R$	0.16	0.28	-0.13	0.05	-0.23^{**}	-0.03
	(0.31)	(0.19)	(0.09)	(0.07)	(0.09)	(0.07)
Expected Inflation						
Michigan Survey of Consumers, $\hat{\alpha}_2$	0.66^{***}	0.52^{***}	1.00^{***}	0.74^{***}	0.80^{***}	0.60^{***}
	(0.18)	(0.11)	(0.23)	(0.13)	(0.20)	(0.12)
SPF, $\hat{\alpha}_1$	-0.04	0.16	-0.36	0.03	-0.24	0.10
	(0.29)	(0.18)	(0.33)	(0.24)	(0.38)	(0.26)
Sum of lags, $\hat{\alpha}_0$	0.39^{*}	0.31^{**}	0.36^{**}	0.23	0.44^{**}	0.30^{*}
	(0.20)	(0.16)	(0.17)	(0.17)	(0.21)	(0.18)
Credit spread	-0.49	-0.24	-0.77^{***}	-0.53^{***}	-0.71	-0.55
	(1.00)	(0.68)	(0.23)	(0.16)	(0.56)	(0.38)
Threshold						
point est., $\hat{\gamma}$	1.95	1.95	-0.52	-0.39	-0.67	-0.52
95 percent CI	[−0.8,2.9]	[−0.8,2.9]	[−0.7,1.9]	[−0.7,1.4]	[−0.7,3.3]	[−0.7,1.9]
N of thresholds, p-val.						
0 vs. 1, $H_0 : 0$	0.13	0.01	0.11	0.00	0.14	0.01
1 vs. 2, $H_0 : 1$	0.94	0.80	0.34	0.18	0.55	0.40
R^2	0.77	0.83	0.81	0.86	0.78	0.85
N	192	192	174	174	174	174

Notes: The forcing variable is the unemployment gap. Estimation sample is 1968q4–2016q3 (baseline) in columns (1)–(2) and 1973q1–2016q2 in columns (3)–(6). See notes to Tables 1 and 2 for estimation details. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B Testing the Threshold in Subsamples: Wild Bootstrap

To test the significance of nonlinearities against the null of a linear model, we use the method outlined in Hansen (2017). Here we describe how we use this algorithm to also test the null hypothesis of a linear model against a one-threshold model on important historical subsamples. We slightly alter the procedure described earlier. As before, we fit both the linear and one-threshold models in the entire sample, and we generate F-statistics for each subsample i of the form:

$$F_i = n_i \frac{S_{0i} - S_{1i}}{S_{1i}},$$

where n_i is the number of observations in the subsample, and S_{0i} and S_{1i} are the residual sum of squares in the subsample for the linear model and one-threshold model, respectively. We generate a distribution for each subsample F_i using the exact same bootstrap procedure we used for the full sample F-statistic from Hansen (2017), drawing residuals with replacement from the entire sample and refitting both models on each iteration. We can then use each F_i distribution to generate a critical value and assign p-values for the given subsample.

The test results are presented in Table B1. During the early sample period (the Great Inflation and Volcker disinflation), we cannot reject the null of a linear model at conventional significance levels. Hence, the linear model is preferred during these periods. For the missing disinflation, however, we reject the null at a 5 percent significance level, implying that the one threshold model should be preferred.

Table B1. Linear vs. Threshold Model in Subsamples

	p-val.
Great Inflation	0.948
Volcker disinflation	0.956
Missing disinflation of the 2010s	0.022

Notes: The null hypothesis is no thresholds (linear model). The alternative is a one-threshold model. The forcing variable is the unemployment gap. Estimation sample is 1968q4–2016q3. The Great Inflation episode is defined as the period between 1976q2 and 1980q1, based on the lowest and highest CPI inflation values around the crisis. The Volcker disinflation episode is 1980q1–1983q1. The missing disinflation period covers 2009q1–2013q4.