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Will US inflation awake from the dead? The role of slack and non-linearities in the Phillips curve

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Will US inflation
awake from the dead?
The role of slack and non-linearities
in the Phillips curve

Task force on low inflation (LIFT)

No 2001 / January 2017

Disclaimer: This paper should not be reported as representing the views of the European Central Bank (ECB). The views expressed are those of the authors and do not necessarily reflect those of the ECB.

Task force on low inflation (LIFT)

This paper presents research conducted within the Task Force on Low Inflation (LIFT). The task force is composed of economists from the European System of Central Banks (ESCB) - i.e. the 29 national central banks of the European Union (EU) and the European Central Bank. The objective of the expert team is to study issues raised by persistently low inflation from both empirical and theoretical modelling perspectives.

The research is carried out in three workstreams:

- 1) Drivers of Low Inflation;
- 2) Inflation Expectations;
- 3) Macroeconomic Effects of Low Inflation.

LIFT is chaired by Matteo Ciccarelli and Chiara Osbat (ECB). Workstream 1 is headed by Elena Bobeica and Marek Jarocinski (ECB) ; workstream 2 by Catherine Jaret (Banque de France) and Arnoud Stevens (National Bank of Belgium); workstream 3 by Caterina Mendicino (ECB), Sergio Santoro (Banca d'Italia) and Alessandro Notarpietro (Banca d'Italia).

The selection and refereeing process for this paper was carried out by the Chairs of the Task Force. Papers were selected based on their quality and on the relevance of the research subject to the aim of the Task Force. The authors of the selected papers were invited to revise their paper to take into consideration feedback received during the preparatory work and the referee's and Editors' comments.

The paper is released to make the research of LIFT generally available, in preliminary form, to encourage comments and suggestions prior to final publication. The views expressed in the paper are the ones of the author(s) and do not necessarily reflect those of the ECB, the ESCB, or any of the ESCB National Central Banks.

Abstract

The response of US inflation to the high levels of spare capacity during the Great Recession of 2007-09 was rather muted. At the same time, it has been argued that the short-term unemployment gap has a more prominent role in determining inflation, and either the closing of this gap or non-linearities in the Phillips curve could lead to a sudden pick-up in inflation. We revisit these issues by estimating Phillips curves over 1992Q1 to 2015Q1. Our main findings suggest that a Phillips curve model that takes into account inflation persistence, inflation expectations, supply shocks and labour market slack as determinants explains rather well the behaviour of inflation after the Great Recession, with little evidence of a “missing deflation puzzle”. More important than the choice of the slack measure is the consideration of time-variation in the slope. In fact, we find that Phillips curve models with time-varying slope coefficients are able to outperform significantly the constant-slope model as well as other non-linear models over 2008Q1-2015Q1.

Keywords: Phillips curve, Labour market slack, Inflation dynamics.

JEL Classification: E31, E37, E58

Non-technical summary

The Great Recession of 2007-09 brought about a puzzle in the United States with respect to the relationship between inflation and slack in the economy. According to the historical relationship between these two variables, the observed response of inflation to the high levels of spare capacity in the United States was rather muted.

The literature has provided some reasons for the apparent breakdown in the Phillips curve – the “missing deflation puzzle”: (i) inflation expectations have become more anchored, reflecting an increase in central bank credibility (Ball and Mazumder 2011, Watson 2014, Hatzius and Stehn 2014); (ii) the importance of (external) supply shocks has increased over time, implying that inflation has become less sensitive to domestic developments (Gordon 2013, Watson 2014); (iii) difficulties in the measurement of labour market slack, especially in the light of the large decline in participation rate (Gordon 2013, Krueger et al. 2014, Rudebusch and Williams 2014, Watson 2014); and, finally, (iv) the existence of non-linearities in the relationship between inflation and labour market slack (Debelle and Laxton 1997, Ball and Mazumder 2011, Peach et al. 2011, Hatzius and Stehn 2014).

Against this background, we revisit the Phillips curve relationship in the United States in the following ways. First, we employ several alternative slack measures in hybrid Phillips curves to find out which measure of slack is most relevant in determining inflation dynamics. Particular relevance is given to the slack derived from a new labour market tracking indicator (LMTI) that we build, which captures broader labour market conditions. Second, we shed some light on the question of whether the Phillips curve slope varies over time and explore the relevance of different theories of non-linearities in the Phillips curve. Finally, we assess the forecasting accuracy of a suite of linear and non-linear Phillips curve models.

Our main findings suggest that a Phillips curve model augmented with supply shocks and inflation expectations, estimated between 1992Q1 and 2007Q4, can explain rather well the behaviour of inflation after the Great Recession, with little apparent evidence of a missing deflation puzzle. We find that the Phillips curve specification with slack measured by the LMTI is consistently among the best performing specifications, together with the headline, medium-term and long-term unemployment gaps. More important than the choice of the slack measure, however, is the consideration of a time-variation in the Phillips curve slope. Regressions on a rolling window as well as time-varying estimates using the Kalman filter confirm that the slope does vary over time.

In an out-of-sample forecasting exercise, our models that take into account the time-varying nature of the slope coefficient exhibit the highest forecasting accuracy over 2008Q1 to 2015Q1. In addition, we find that the other (constant-slope) non-linear specifications explored in this paper do not seem to improve on the forecasting accuracy of the linear models.

1 Introduction

Following the Great Recession of 2007-09, a widely-held view is that the response of inflation to the high levels of spare capacity in the United States was rather muted. For example, using Phillips curves estimated over long data samples, Ball and Mazumder (2011) find that inflation should have fallen by more than it did over the period 2008-10. This “missing deflation puzzle” has also surprised policymakers (Williams 2010).¹ This puzzle has led to an intense debate over whether the Phillips curve is still “alive”, as argued by Gordon (2013) and Coibion and Gorodnichenko (2015).

The literature has provided some reasons for the apparent breakdown in the Phillips curve. First, inflation expectations have become more anchored, reflecting an increase in central bank credibility (Ball and Mazumder 2011, Watson 2014, Hatzius and Stehn 2014). Second, the role of (external) supply shocks has increased over time, resulting in inflation becoming less sensitive to domestic developments (Gordon 2013, Watson 2014). Third, difficulties in the measurement of labour market slack, especially in the light of the large decline in participation rate (Gordon 2013, Krueger et al. 2014, Rudebusch and Williams 2014, Watson 2014). Fourth, the existence of non-linearities in the relationship between inflation and labour market slack due, for instance, to the presence of downward nominal wage rigidities that have dampened the fall in inflation (Debelle and Laxton 1997, Ball and Mazumder 2011, Peach et al. 2011, Hatzius and Stehn 2014). Finally, fiscal policy may also help explain the absence of deflation during the Great Recession, in that the combination of policy uncertainty surrounding policy makers’s future behaviour at the zero lower bound and the inflationary pressure stemming from an existing large stock of debt may have prevented the economy from entering a deflationary state (Bianchi and Melosi 2014).

Another potential reason for a breakdown in the Phillips curve is the possibility of mis-measurement in labour market slack. This has become particularly relevant in the recent business cycle. This raises the question of how to best measure economic slack and what concept of slack is most appropriate in determining movements in inflation, as Yellen (2014) noted, “*The assessment of labor market slack is rarely simple and has been especially challenging recently*”. On the one hand, some economists and policymakers have pointed out that during the economic recovery that followed the Great Recession, slack in the labour market may have been more substantial than suggested by the unemployment gap. In particular, Yellen (2014) indicates that the decline in the unemployment rate since the Great Recession may have overstated the improvement in overall labour market conditions, as shown by a labour market conditions index developed by Federal Reserve Board staff. In this view, the existence of more slack in the labour market than measured by the unemployment gap could have led to a temporary breakdown in the Phillips curve.

On the other hand, other researchers have concluded that in recent years, narrower measures of slack may be more relevant in determining inflation, with prices appearing to respond more to short-term unemployment (defined as the unemployed for less than 26 weeks) rather than

¹ “*The surprise is that it [inflation]’s fallen so little, given the depth and duration of the recent downturn. Based on the experience of past severe recessions, I would have expected inflation to fall by twice as much as it has.*”

to headline unemployment (Gordon 2013, Krueger et al. 2014, Rudebusch and Williams 2014, Watson 2014). This finding has not remained uncontested, however, as shown for example by Kiley (2014).

Against this background, our main contribution to this strand of literature consists of the following. First, we employ various alternative slack measures in hybrid Phillips curves augmented with import prices and inflation expectations in order to investigate what measure of slack is most relevant in determining inflation dynamics. Among the slack measures we use, particular relevance is given to the slack derived from a new labour market tracking indicator (LMTI) that we develop, which aims at capturing broader labour market conditions. Second, we revisit the question of whether the Phillips curve slope varies over time and explore the relevance of different theories of non-linearities in the Phillips curve. Third, we assess the forecasting accuracy of a suite of linear and non-linear Phillips curve models by comparing their root mean squared forecast errors.

Our main findings suggest that a Phillips curve model with import prices, inflation expectations and a measure of slack in the economy, estimated between 1992Q1 and 2007Q4, can explain rather well the behaviour of inflation after the Great Recession, with little apparent evidence of a missing deflation puzzle. We find that the Phillips curve specification with slack measured by the LMTI is consistently among the best performing specifications, together with the headline, medium-term and long-term unemployment gaps. More important than the choice of slack measure, however, appears to be the consideration of a time-variation in the Phillips curve slope. Regressions for a rolling window as well as time-varying estimates of the slope coefficient using the Kalman filter suggest that the slope does vary over time; we find tentative evidence that the slope may have increased slightly since 2013. In terms of forecasting, our out-of-sample exercise indicates that models that take into account the time-varying nature of the slope coefficient had the highest forecasting accuracy over 2008Q1 to 2015Q1. Another result worth highlighting relates to the fact that the constant-slope non-linear specifications explored in this paper do not seem to improve on the forecasting accuracy of the linear models.

The remainder of the paper is organised as follows. In the next section, we discuss the measurement of labour market slack in more detail and introduce our own measure of slack based on a labour market tracking indicator. In Section 3, we present Phillips curve models using these measures of slack in the economy. Section 4 investigates whether the slope coefficient of the Phillips curve is time-varying. In addition, we examine whether the dynamics of US inflation are better characterised by certain specific non-linear rather than linear relationships between labour market slack and inflation. Section 5 compares the forecasting accuracy of a suite of linear and non-linear Phillips curve models. Section 6 concludes.

2 Measuring labour market slack

2.1 Existing alternative measures of slack

Available estimates of spare capacity in the US economy are highly uncertain and have diverged considerably over the business cycle that started with the Great Recession. For this reason,

we employ a number of alternative measures of slack, defined as follows – see Table A.1 in the Appendix for descriptive statistics (data from the Bureau of Labor Statistics, BLS):

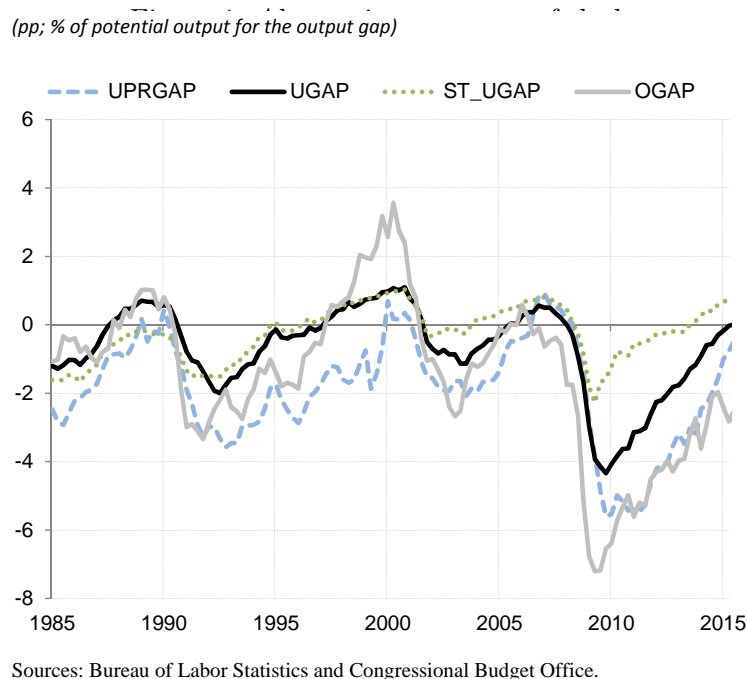
- **Unemployment gap (UGAP):** difference between the estimated non-accelerating inflation rate of unemployment (NAIRU), published by the Congressional Budget Office (CBO), and the unemployment rate.
- **Short-term unemployment gap (STUGAP):** difference between the long-term average of the unemployment rate with a duration up to 26 weeks and the actual data of this series.
- **Medium-term unemployment gap (MTUGAP):** difference between the long-term average of the unemployment rate with a duration between 27 and 51 weeks and the actual data of this series.
- **Long-term unemployment gap (LTUGAP):** difference between the long-term average of the unemployment rate with a duration of 27 weeks and over and the actual data of this series.
- **Combined unemployment and participation gap (UPRGAP):** sum of unemployment and participation gaps, with the latter defined as the gap between the structural and cyclical labour force participation rates, as estimated by the CBO.
- **Output gap (OGAP):** output gap estimate published by the CBO.

The most prominent and commonly used measure of slack in the labour market is defined as the percentage-point difference in the longer-run normal level of the unemployment rate from the actual rate (UGAP above). Using the CBO's NAIRU as the time-varying estimate of the normal unemployment rate indicates that slack in the labour market peaked at over -4pp in late 2009 and gradually diminished in subsequent years to roughly zero by early 2015 (Figure 1). In line with this, the medium-term unemployment gap is also suggestive of little slack by early 2015, while the short-term unemployment gap would indicate that labour market slack was already eliminated by the end of 2013.

By contrast, the indications from other labour market variables continued to suggest the presence of significant slack in early 2015, in line with the spare capacity shown by the output gap. One such indication is that long-term unemployment remains much above its long-term average, reflecting the severity of the last recession. Another sign is that much of the decline in the unemployment rate has been the result of a drop in the labour force participation rate rather than from job creation, explaining around 3/4 of the change in the unemployment rate from its peak in October 2009 (from 10% to 5.3% in June 2015). While Erceg and Levin (2014) argue that the bulk of the decline is attributable to cyclical factors, most of the recent literature finds that a combination of structural and cyclical reasons account for the decline in the participation rate (Cline and Nolan 2014, Aaronson et al. 2012, Hall 2014, CBO 2014). Demographic shifts and a growing reliance on disability programmes have been found to be the most important structural factors, while extended student enrolment times in a weak economic environment as well as discouragement of workers due to poor economic prospects are the most prominent

cyclical factors. This could lead to hysteresis effects, i.e. cyclical factor turning structural. Nevertheless, there is a significant amount of uncertainty regarding the extent to which discouraged workers may permanently leave the labour force due to skills losses.

Since the cyclical part of the decline in the participation rate is likely to be reversed as the recovery gains momentum, reflecting a gradual re-absorption of those who left the labour market temporarily, the cyclical gap between the actual participation rate and an estimated potential participation rate can be interpreted as additional labour market slack or “reserve labour supply”, that can be combined with the unemployment gap. Such a combined estimate of the unemployment and participation gap would suggest more slack in the labour market than the slack based on the unemployment gap alone (Figure 1). While in the early stage of the recent economic recovery, the unemployment gap was the main contributor of the combined gap, the participation gap subsequently assumed a bigger role in driving total labour market slack.



2.2 Slack measured by a labour market tracking indicator

Further evidence that slack has been larger since the Great Recession than measured by the unemployment gap is given by the wide divergence in the signals of different labour market variables. In fact, some indicators do suggest much less of an improvement than implied by the unemployment rate. A weaker picture is painted in particular by the employment-to-population ratio, wage indicators and by broader unemployment measures, such as the U-6 measure of unemployment (all marginally attached workers and total employed part-time for economic reasons are added to the total number of the unemployed). This divergence has led to a number of avenues for summarising the overall labour market information. One such effort has been made by the Federal Reserve Bank of New York, where a labour market dashboard has been created to present “Eight different faces of the labor market”.²

²<http://www.newyorkfed.org/labor-conditions/>.

Other researchers have used a more formal approach to summarise the information contained in different indicators. Chung et al. (2014) have developed a labour market conditions index using a dynamic factor model of 19 labour market indicators. This index assesses the average monthly *change* in labour market conditions over time. Barnes et al. (2007) also construct a summary measure of the *level* of labour market pressure that captures the common movement among twelve of labour market series, obtained as the first principal component. Meanwhile, Hakkio and Willis (2013) build two measures of labour market conditions that gauge both the *level* of and the *change* in labour market activity.

Similar to these approaches in the literature, our aim is to build a measure of labour market slack based on a variety of indicators. The idea is to capture as many dimensions of the labour market as possible, given their recent divergence.³ We construct a single labour market tracking indicator (LMTI) by means of principal component analysis on the basis of eight widely-used labour market variables listed in Table 1, over 1985Q1 to 2015Q2.⁴ We focus on this narrow set of variables as it has the advantage of not only capturing the different characteristics of the labour market, but also of being published on a timely basis.⁵

Table 1: Set of indicators used to construct the LMTI

Indicator	Unit	Weight in LMTI	Correlation with LMTI
Employment/Population ratio	%	15.9	97.2
Part-time workers for economic reasons	Thousands	15.4	-94.4
Unemployed for 27 weeks and over	% of total unemployment	15.0	-91.7
Unemployment rate	% of labour force	14.5	-88.6
Participation Rate	% population (16 yr +)	14.0	85.8
Average hourly earnings	y-o-y % change	12.3	75.3
Average weekly hours	Hours	10.0	61.0
Total non-farm payrolls	m-o-m % change	2.8	17.3

Source: Bureau of Labor Statistics and authors' calculations.

Notes: The weights in the third column refer to the share of individual series as a % of total loadings of the first principal component.

The principal component approach models the variance structure of a set of variables using linear combinations of the variables. The first principal component can be interpreted as a summary statistic that captures the common movement among the eight variables, i.e. it gives us the estimate of a signal about the labour market which is common to all the series. In our sample, the first principal component explains 65% of the overall variance of the variables considered (the first and second components together explain 84% of the variance). The employment-to-population ratio and the number of part-time workers for economic reasons have the largest weights in the LMTI, followed by the long-term and standard unemployment rate. The signs

³Another option would have been to construct a broader measure of slack, also based on real economic variables. We have not chosen to go down that route as our aim was to get a comprehensive assessment of labour market slack.

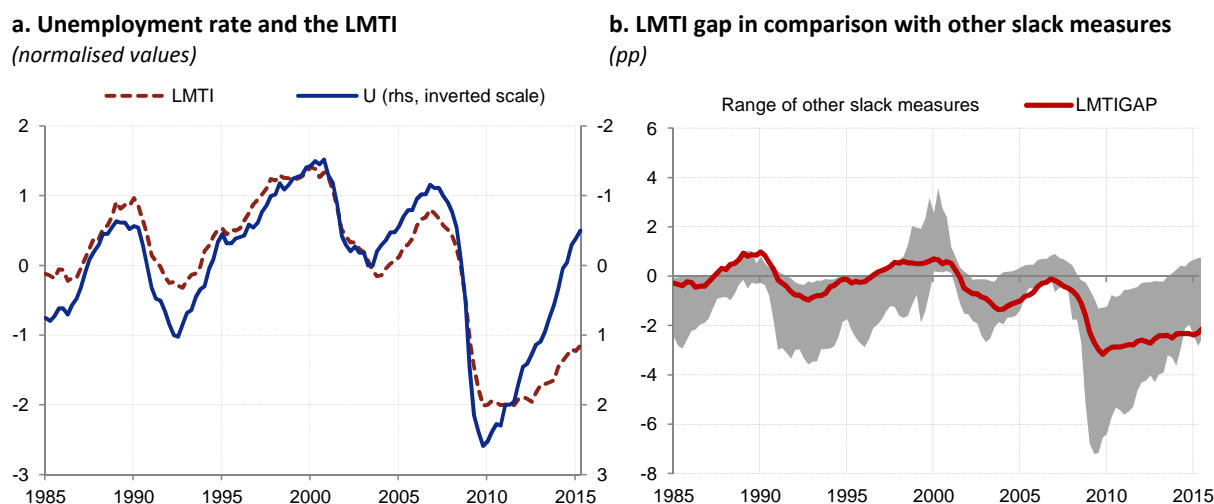
⁴The choice of principal component analysis over factor analysis is motivated by the fact that the principal component is a variable reduction technique that explains as much of the total variance in the data as possible, retaining more of the original variance compared with the factor analysis. Moreover, it is not model dependent as opposed to factor analysis, where the outcome depends to some extent on the initial model formulation and the optimisation routine.

⁵The data are published on the first Friday following the reference month. We transform average hourly earnings and total non-farm payrolls into year-on-year and month-on-month changes, respectively, as they show a clear non-stationary pattern.

of the correlations of each indicator with the LMTI confirm our priors, with, for instance, an increase in the unemployment rate being associated with a worsening in the LMTI, whereas an increase in the employment-to-population ratio being associated with an improvement in the indicator.⁶

The LMTI estimates reveal that the labour market was much weaker than suggested by the unemployment rate for most of the period since the end of the Great Recession and remained from fully recovering to pre-crisis levels by 2015Q2 (Figure 2a). Overall, the LMTI was tracking the unemployment rate quite closely until around the end of 2011, but thereafter the two series started to diverge markedly. In 2015Q2, the LMTI stood at around 1.1 standard deviations below the historical mean, and below the pre-crisis peak. The weakness of the labour market situation in the current business cycle (the recovery started in 2009Q2) can also be seen by the fact that in mid-2015, the indicator stood at close to 1.5 standard deviations below the average of the previous expansion (from November 2001 to December 2007, as defined by the National Bureau of Economic Analysis, NBER). Similarly, the slack derived from the LMTI (measured in comparable units to the unemployment rate) stood at -2.3pp in 2015Q2, larger than that based on the combined unemployment and participation gap, but close to the CBO's measure of the output gap in the same quarter (Figure 2b).⁷

Figure 2: The Labour Market Tracking Indicator



Sources: Bureau of Labor Statistics, Congressional Budget Office and authors' calculations.

Note: The LMTI and the unemployment rate on the left-hand chart have been normalised (zero mean and unit standard deviation). The range of other slack measures on the right-hand chart includes the unemployment gap, the short-term, medium-term and long-term unemployment gaps, the output gap, as well as the combined unemployment and participation gaps.

⁶As robustness checks, we expanded the LMTI with more labour market series, namely by taking into account survey data (National Federation of Independent Business (NFIB)'s percentage of firms with positions not able to fill, percentage of firms planning to increase employment, the ISM manufacturing employment index), jobless claims, hires rate and quits rate. While the results were quantitatively and qualitatively broadly unchanged, higher publication lags of some of those series prevents us from having a timely indicator going forward. The hires and quits rate pose additional challenges as they only go back to December 2000. Moreover, the LMTI also remained robust to alternative sample periods by, for instance, deleting 5 years of data at a time.

⁷The slack implied by the LMTI is calculated as the difference between the NAIRU (estimated by the CBO) and the fitted values from regressing the unemployment rate on the LMTI plus a constant. An alternative option would have been to define LMTI slack as the LMTI relative to its own long-term average. We chose the former approach as it takes into account the possible time-varying nature of the NAIRU.

3 Phillips curves

3.1 Baseline specification

We now analyse what the different measures of slack imply for inflation, by employing a Phillips curve framework. We estimate hybrid Phillips curves (Gali and Gertler 1999), where it is assumed that some firms are forward-looking and set prices optimally to maximise profits, while the rest are backward-looking and set current prices according to past values. The resulting Phillips curve specification relates current inflation to both future inflation expected at time t and lagged inflation, thus allowing for inflation persistence:

$$\pi_t = \theta_0 + \alpha E_t \pi_{t+1} + \beta \pi_{t-1} + \delta \hat{y}_t \quad (1)$$

where θ_0 is a constant term, π_t refers to the current inflation rate, measured as the annual change in the headline personal consumption expenditure (PCE) deflator, $E_t \pi_{t+1}$ is the expectation of the future inflation rate, and \hat{y}_t is a measure of slack in the economy.

Following Gordon (2007)’s “triangle” model of inflation, where the inflation rate depends on a tripartite set of basic determinants – inertia, demand, and supply – we augment the hybrid Phillips curve with supply factors, more specifically with the annual percentage change in import prices (taken from the BLS). These capture both fluctuations in internationally traded goods including commodity prices, as well as globalisation factors.⁸ In addition, although the original model assumes rational expectations for inflation, we use directly observable survey data for inflation expectations instead, derived from the Survey of Professional Forecasters (SPF). More concretely, we employ the SPF’s PCE inflation expectations ten-years ahead. (As robustness, we also provide the results with the SPF’s 1-year ahead CPI inflation expectations, although the comparison is complicated by the need to use a different reference price index from the PCE, since short-term PCE SPF expectations are not available). Moreover, we substitute the real marginal cost term as excess demand variable, as derived in the hybrid Phillips curve model by Gali and Gertler (1999), by the set of slack indicators introduced in Section 2. This results in the following equation that will be used in the estimation:

$$\pi_t = \theta_0 + \alpha \pi_{t+1}^* + \sum_{i=1}^n \beta_i \pi_{t-i} + \sum_{j=0}^k \gamma_j pm_{t-j} + \delta \hat{y}_t + \epsilon_t \quad (2)$$

where π_{t+1}^* are the SPF’s ten-year ahead inflation expectations and pm_t is the annual percentage change in import prices.

In the next section, we estimate equation (2) for 1992Q1-2015Q1. The starting point is dictated by data availability on long-term inflation expectations, and an attempt at avoiding distortions by the inflation regime shift in the 1980s, when inflation expectations dropped significantly, having become more anchored. The preferred specification contains two lags on the dependent variable and on import prices, which was found to be sufficient to ensure white noise residuals.

⁸This specification was found to be superior to others with alternative supply variables, including productivity growth, oil and non-oil import prices and international commodity prices.

3.2 Regression results

The Phillips curve estimates from Table 2 suggest that PCE inflation is very persistent, as indicated by a highly statistically significant coefficient on the lagged dependent variable of roughly 0.8 – it shows how strongly dependent current inflation is on past inflation. Similarly, inflation expectations are generally (borderline) significant. Import prices and labour market gaps also play a role in explaining movements in inflation.

Table 2: Phillips curve estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta_4\text{SPF}_{10Y} \text{ PCE}$	0.168 (0.098)*	0.211 (0.110)*	0.146 (0.091)	0.137 (0.088)	0.178 (0.100)*	0.118 (0.087)	0.156 (0.087)*
$\Delta_4\text{PCE deflator}_{t-1}$	0.793 (0.124)***	0.795 (0.119)***	0.795 (0.123)***	0.807 (0.125)***	0.817 (0.127)***	0.803 (0.118)***	0.794 (0.118)***
$\Delta_4\text{PCE deflator}_{t-2}$	-0.069 (0.112)	-0.053 (0.106)	-0.071 (0.113)	-0.077 (0.116)	-0.087 (0.113)	-0.069 (0.113)	-0.064 (0.112)
$\Delta_4\text{Import prices}_t$	0.162 (0.008)***	0.161 (0.008)***	0.162 (0.008)***	0.162 (0.008)***	0.161 (0.008)***	0.162 (0.008)***	0.161 (0.008)***
$\Delta_4\text{Import prices}_{t-1}$	-0.147 (0.017)***	-0.148 (0.017)***	-0.147 (0.017)***	-0.147 (0.017)***	-0.149 (0.017)***	-0.148 (0.016)***	-0.147 (0.016)***
$\Delta_4\text{Import prices}_{t-2}$	0.044 (0.015)***	0.043 (0.015)***	0.043 (0.015)***	0.044 (0.015)***	0.045 (0.015)***	0.045 (0.015)***	0.044 (0.015)***
UGAP	0.043 (0.014)***						
STUGAP		0.085 (0.030)***					
MTUGAP			0.170 (0.051)***				
LTUGAP				0.046 (0.017)***			
UPRGAP					0.025 (0.014)*		
LMTIGAP						0.049 (0.016)***	
OGAP							0.025 (0.007)***
Constant	0.078 (0.132)	-0.086 (0.159)	0.132 (0.128)	0.139 (0.126)	0.067 (0.129)	0.192 (0.134)	0.104 (0.127)
Observations:	93	93	93	93	93	93	93
Adj. R-squared:	0.948	0.948	0.948	0.947	0.945	0.947	0.948

Notes: OLS regressions with Newey-West corrected standard errors (in parentheses). The dependent variable is the year-on-year change in the PCE deflator over 1992Q1-2015Q1. Δ_4 denotes year-on-year percentage-point changes. Asterisks, *, **, ***, denote, respectively, statistical significance at the 10, 5 and 1% levels.

In our hybrid Phillips curve estimates, the measures of slack in the economy are strongly statistically significant at conventional levels, irrespective of the slack measure considered.⁹ For instance, a one-percentage-point increase in the unemployment gap (implying less slack in the economy) would lead to an increase of PCE inflation of about 0.04 percentage points (column 1). This value is somewhat below those available in the literature – 0.14 in Hatzius and Stehn (2014), 0.2-0.25 in Ball and Mazumder (2011), 0.3 in Fitzgerald and Nicolini (2014), and 0.5 in Gordon (2013). According to the dynamics in our model, the long-term impact of the unemployment gap on inflation is of around 0.16.¹⁰

⁹Table A.2 in the Appendix shows that it is harder to uncover the statistical significance for some of the slack measures when short-term inflation expectations are used instead. This may be related to the higher volatility of the series and also to the fact that the reference price indicator, due to data unavailability, is not the same as the dependent variable.

¹⁰The long-term effect of a variable is its short-run coefficient divided by 1 minus the lagged coefficients on

The fact that our coefficient on the unemployment gap is smaller compared to others might be related to: (i) a different dependent variable, as core CPI is used in Hatzius and Stehn (2014), CPI in Ball and Mazumder (2011) and Fitzgerald and Nicolini (2014); (ii) different time samples, with, for instance, the paper by Gordon (2013) going back to the 60s, which might explain the high coefficient of about 0.5; and (iii) differences in the specifications, namely the number of lags. As a robustness check, we get qualitatively the same results when we use annual inflation based on the Consumer Price Index (CPI) as the dependent variable (Table A.3 in the Appendix). One of the differences is that the coefficients on the slack measures are generally twice as large, making them more comparable with those available in the literature. Moreover, our main regression results are also robust to the use of core PCE inflation (excluding food and energy) as the dependent variable (Table A.4 in the Appendix).¹¹

Our estimates presented above assume that inflation expectations (whether short- or long-term ones) and the alternative measures of slack in the economy are exogenous in the Phillips curve framework. While it is rather standard in the literature to make such assumptions, it might instead be the case that the causality runs the other way around, or that the aforementioned variables are jointly determined. To account for a potential endogeneity bias in our specification, we resort to the Instrumental Variables (IV) estimator. Long-term inflation expectations and our measures of slack are instrumented with 2 lags of their own variables (commonly used as instruments). We find that our baseline results remain robust to the potential endogeneity bias (Table A.5 in the Appendix).

The Phillips curve specifications can shed some light on the “missing deflation puzzle”. The following explanations have been put forward to resolve this puzzle: (i) inflation expectations have become more anchored, reflecting an increase in central bank credibility, thus generating a flatter Phillips curve, as shown in Figure A.1 in the Appendix (Ball and Mazumder 2011, Watson 2014, Hatzius and Stehn 2014) – this phenomenon is unrelated to a structural break due to the financial crisis, as it has instead been ongoing at least since the 1980s; (ii) the role of (external) supply shocks has increased over time, resulting in inflation becoming less sensitive to domestic developments (Gordon 2013, Watson 2014); (iii) difficulties in the measurement of labour market slack, especially in the light of the large decline in participation rate (Gordon 2013, Krueger et al. 2014, Rudebusch and Williams 2014, Watson 2014); and, finally, (iv) the existence of non-linearities in the relationship between inflation and labour market slack due, for instance, to the presence of downward nominal wage rigidities that have dampened the fall in inflation (Debelle and Laxton 1997, Ball and Mazumder 2011, Peach et al. 2011, Hatzius and Stehn 2014), or due to the presence of financial frictions, where liquidity-constrained firms and with weak balance sheets tend to raise prices in response to negative demand or financial shocks (Gilchrist et al. 2015).

Using an estimation window that ends in 2007Q4, and resorting to Equation 2, we produce dynamic out-of-sample forecasts of PCE inflation for the period 2008Q1 to 2015Q1, conditional on the actual paths for inflation expectations, the slack variables and import prices. By stopping our estimation sample at the end of 2007, we observe how our model behaves during and after

the dependent variable: $0.16=0.043/(1-0.793+0.069)$.

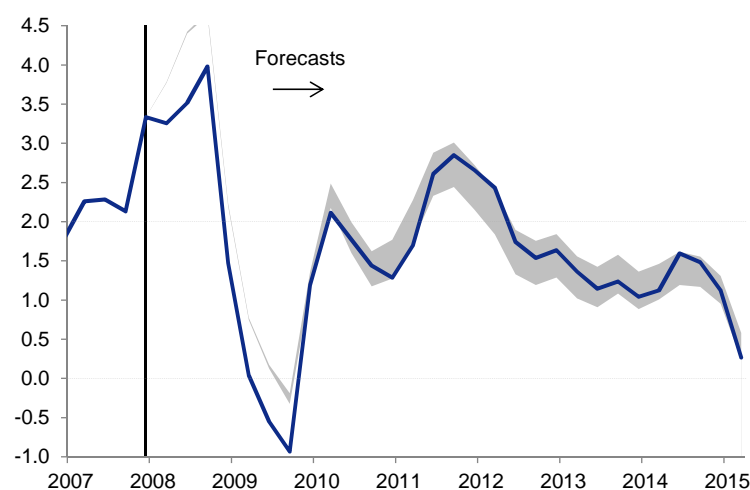
¹¹The only difference from the specification with the headline PCE deflator is that we replace total import prices with non-petroleum goods import prices.

the Great Recession, a period characterised by significant financial turbulence.

According to our results, there is little evidence of a missing deflation puzzle, as our dynamic model forecasts capture rather well the dynamics of actual inflation (Figure 3). We also find that the first two reasons above put forward by the literature to solve this puzzle could be most relevant. More anchored inflation expectations may have played a role in stabilising inflation during the 2007-09 recession (point (i) above), and including supply shocks in the Phillips curve framework also appears to be important, as the same linear model without import prices (not shown here) predicts deflation during the early period of the Great Recession (point (ii)).

In contrast, we do not find evidence that corroborates point (iii) above on the potential mis-measurement of the existing slack in the economy. According to Figure 3, all of our out-of-sample forecasts with the Phillips curve models are close to actual inflation outturns during and after the last recession, irrespective of the slack measure used, where the range of Phillips curve forecasts of PCE inflation shown in the chart is taken from the four models with the lowest root mean square error (RMSE) – the models with the standard unemployment gap, the medium-term unemployment gap, the long-term unemployment gap, and the LMTI gap. The inflation forecasts were slightly above actual inflation in the early period of the US downturn – the last recession started in 2007Q4 and ended in 2009Q2, according to the NBER – this was mainly due to rising import and oil prices until summer 2008, which pushed up the PCE inflation forecast. From 2009 onwards, however, inflation evolved broadly in line with the model forecast. On (iv) above, we explore the role of non-linearities in the next section.

Figure 3: Out-of-sample forecasts for PCE inflation (% yoy)



Source: Bureau of Economic Analysis and authors' calculations.

Note: Dynamic out-of-sample forecasts for 2008Q1-2015Q1, with the forecast range derived from the four best performing slack measures in the hybrid Phillips curve: the unemployment gap, the medium-term gap, the long-term gap, and the LMTI gap.

4 The role of non-linearities

The linear Phillips curve model with a constant slope coefficient shown above appears to explain inflation developments after the Great Recession rather well. Nevertheless, these estimates of the Phillips curve slope refer to the average relationship between slack and inflation over

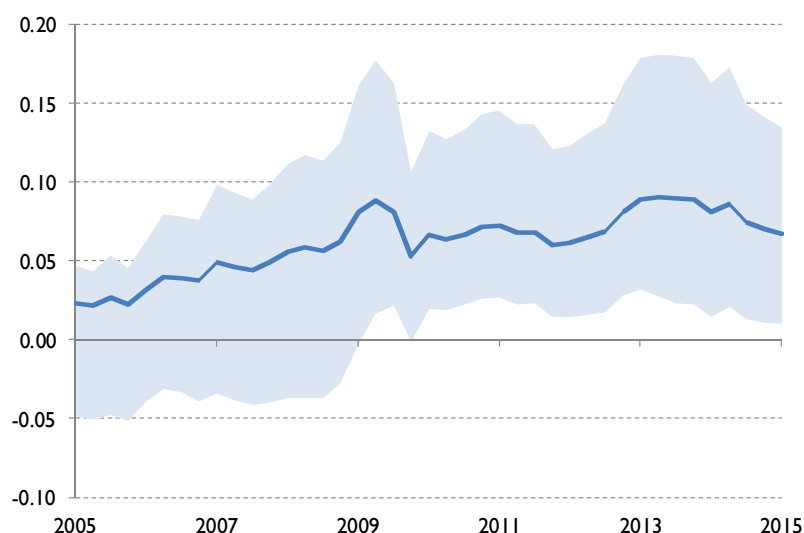
the estimation period, ignoring any possible changes in the slope over time. Meanwhile, the Phillips curve relationship has been much discussed recently, with the debate turning to the question of whether inflation could rise in a non-linear fashion once labour market slack has been eliminated. We add to this debate by exploring the question of whether the Phillips curve slope is time-varying in our sample, while also exploring in more detail the role of some specific non-linearities.

4.1 Time-varying Phillips curve slope

Table 2 showed that our estimates of the Phillips curve slope vary between 0.025 and 0.17, depending on the measure of slack used. But these are average coefficients over a (relatively) long sample. We investigate whether the relationship between slack and inflation may change over time with the following two approaches.

The first one involves rolling regressions, using the hybrid Phillips curve model with the unemployment gap. We initially estimate this model from 1992Q1 to 2004Q4 (13 years), which we consider a sufficiently long time sample in order to draw some inference on the robustness of the coefficient on the unemployment gap.¹² The estimation window is then rolled forward one quarter at a time, ensuring that the number of observations remains constant across specifications. The results shown in Figure 4 indicate that over the last 10 years, the coefficient on the unemployment gap has been steadily increasing from as low as 0.02 to close to 0.07 more recently.

Figure 4: Coefficient on the unemployment gap from rolling regressions



Note: Rolling regressions with a constant number of observations, using 1992Q1-2004Q4 as the starting estimation window, and then rolling the window one quarter at the time until the last observation (2015Q1) is reached. The solid line refers to the point estimates on the unemployment gap, while the shaded area represents the associated ± 2 standard error confidence bands.

In the second approach, we also allow the slope of the Phillips curve, as well as the coefficients on inflation expectations, lagged inflation, and import price inflation, to be time-varying, by

¹²The analysis is robust to employing alternative rolling samples and alternative measures of slack.

using the Kalman filter in a state space form of the model, with the signal equation (3) and state equations (4), (5), (6) and (7), respectively, defined in the following manner:

$$\pi_t = \theta_0 + \alpha_t \pi_{t+1}^* + \kappa_t \sum_{i=1}^n \beta_i \pi_{t-i} + \mu_t \sum_{j=0}^k \gamma_j p m_{t-j} + \delta_t \hat{y}_t + \epsilon_t \quad (3)$$

where δ_t , α_t , κ_t and μ_t are the state variables. The error term ϵ_t is normally distributed with mean zero and variance σ_ϵ^2 . The state variables are modelled as follows:

$$\delta_t = \delta_{t-1} + v_t \quad (4)$$

$$\alpha_t = \alpha_{t-1} + w_t \quad (5)$$

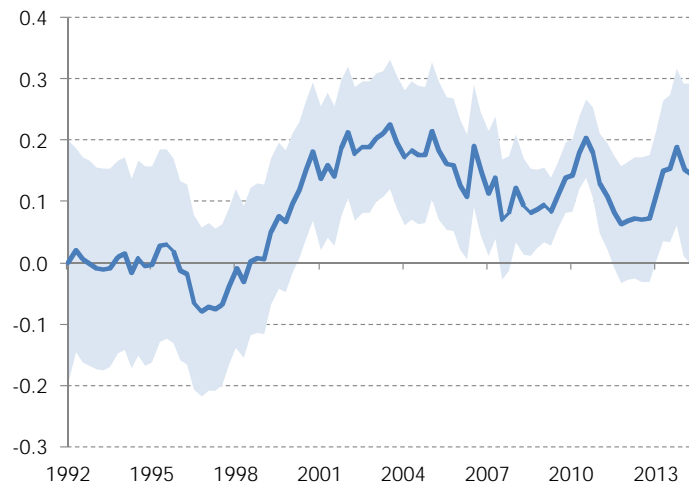
$$\kappa_t = \kappa_{t-1} + z_t \quad (6)$$

$$\mu_t = \mu_{t-1} + q_t \quad (7)$$

where v_t , w_t , z_t and q_t are normally distributed with mean zero and variances σ_v^2 , σ_w^2 , σ_z^2 and σ_q^2 , respectively. The model is estimated via Maximum Likelihood.¹³

Figure 5 shows the Kalman smoothed estimates of the time-varying Phillips curve slope coefficient, δ_t , taking the standard unemployment gap as the slack measure, together with a 1-standard error (84%/16%) confidence interval (all time-varying coefficients are shown in Figure A.2 in the Appendix).¹⁴

Figure 5: Kalman-smoothed time-varying unemployment gap coefficient



Note: Kalman-smoothed time-varying unemployment gap coefficients. The solid line refers to the point estimates on the unemployment gap, while the shaded area represents the associated +/- 1 standard error confidence bands.

¹³The variance σ_ϵ^2 is estimated, while the other variances are assumed to be fixed.

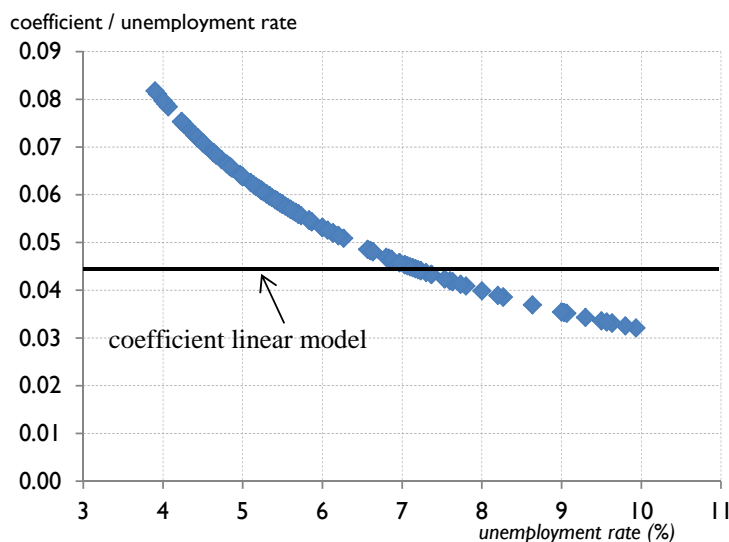
¹⁴Our estimates of the other time-varying coefficients suggest that US inflation has become less persistent over time, in line with the findings of other researchers, see for example the discussion in Williams (2006). In addition, inflation appears to have become more anchored to long-term inflation expectations (as shown by the increase in the coefficient on inflation expectations), while the influence of import price inflation has also risen over time.

The results broadly confirm the earlier result that the slope of the Phillips curve varies over time. There is also some tentative evidence that the slope may have steepened somewhat since mid-2013: the average slope coefficient since then is 0.15, although not statistically significant over the entire period. Overall, the findings from the Kalman filter estimates support the view that the trade-off between slack and inflation could be modelled as a non-linear relationship.

4.2 Threshold and other non-linear Phillips curve models

The results of Section 4.1 may suggest that a non-linear model may fit better the Phillips curve relationship. Non-linearities could be caused by a number of factors. Peach et al. (2011) have investigated the role of threshold effects, where slack needs to fall below or rise above a certain critical value before noticeably driving movements in inflation.

Meanwhile, Akerlof et al. (1996) highlight the importance of downward nominal wage rigidities, which imply that wages might respond asymmetrically in periods of low versus high labour market slack. While wages are bid up when the labour market is tight, they might be less responsive once high levels of slack would require a decline in wages as downward rigidities prevent firms from lowering wages during downturns.¹⁵ The authors argue that such downward wage constraints act like a real cost shock, which constrained firms pass on to consumers in terms of higher prices, similar in spirit to Gilchrist et al. (2015). Thereby, wage rigidities can also influence inflation dynamics. Their model would imply that the Phillips curve may be flatter in times when the unemployment rate is high and turn steeper as slack is eliminated. An illustration of this is shown in Figure 6.



While in the linear model the coefficient on UGAP is constant, in the non-linear model, the coefficient on slack is larger (smaller) when the unemployment rate is low (high). At some point, firms may raise wages at a significantly more rapid pace once “pent-up wage deflation” has been absorbed (Yellen 2014).¹⁶ According to Debelle and Laxton (1997), under this type

¹⁵See also International Monetary Fund (2013) and Stock and Watson (2010).

¹⁶Using data across industries, Daly and Hobijn (2015) investigate the role of pent-up wage deflation and find

of non-linearity, the economy has to operate longer in the region of slack (compared with no slack) to prevent inflation from drifting upward over time, which has been the case for the United States at least since 1985. In a similar vein, Kumar and Orrenius (2014) find evidence that their wage-price Phillips curve is non-linear and convex in that declines in the unemployment rate below its historical average exert a stronger pressure on wages than declines at above-average unemployment rates.

Another type of non-linearity may arise as in a low-inflation environment it is less costly for firms to leave prices unchanged (as menu costs are lower), so that firms may adjust prices less frequently. Consequently, inflation may react less strongly to changes in demand in times of low inflation (Dotsey et al. 1999, Ball et al. 1988).

Overall, the presence of such non-linearities may lead to a sudden rise in inflationary pressures – more strongly than suggested by a linear Phillips curve – as inflation may become more sensitive to slack at some point in the course of the expansion.

We revisit the issue by focusing on three specific forms of non-linearities. First, we use simple thresholds for the unemployment gap, corresponding to the 75th and 25th percentiles in our sample. Second, we test the extent to which the slope of the Phillips curve depends on the labour market tightness, by allowing the unemployment gap to have a larger impact on inflation when unemployment is low. This is done by dividing UGAP by the level of the unemployment rate, following the approach by Debelle and Laxton (1997). The third approach explores the role of state-dependent pricing, building on De Veirman (2007)’s work on Japan, whereby the slope of the Phillips curve depends on the level of trend inflation, as shown in Equation 8:

$$\pi_t = \theta_0 + \alpha\pi_{t+1}^* + \sum_{i=1}^n \beta_i \pi_{t-i} + \sum_{j=0}^k \gamma_j p m_{t-j} + (\delta_1 + \delta_2 \bar{\pi}_t) \hat{y}_t + \epsilon_t \quad (8)$$

where $\bar{\pi}_t$ is trend inflation. We define trend inflation as the average annual inflation rate over the previous ten years (it excludes the current inflation rate so as to avoid potential endogeneity issues).

Our results provide tentative evidence that threshold effects and downward wage rigidities may indeed play a role. Using the aforementioned thresholds for the unemployment gap,¹⁷ we find that the unemployment gap only affects inflation in a statistically significant way when it lies outside of those threshold values (Table 3, column 2).¹⁸ As regards the Debelle-Laxton non-linear model, the coefficient on the unemployment gap divided by the level of the unemployment rate is highly statistically significant, providing some support to the view that the slope of the Phillips curve depends on the degree of the labour market tightness (column 3).

By contrast, we do not find any statistical evidence of the slope varying with the level of trend inflation (column 4). Although δ_2 – the coefficient on the slack measure interacted with trend

some evidence that the reluctance of firms to cut wages during the downturn has restrained wage growth during the recovery following the Great Recession.

¹⁷Upper threshold of 0.18 and a lower threshold of -0.92. Our findings are robust to employing alternative thresholds (e.g. 70th/30th or 80th/20th percentiles).

¹⁸Our findings are consistent with a recent study by Peach et al. (2011), who estimate the thresholds based on a grid search approach. For a sample starting in the 1950s, they find optimal threshold values (set to be symmetric) of +/-1.56.

Table 3: Threshold and other non-linear Phillips curve estimates

	(1) Linear	(2) Threshold	(3) Non-linear (D-L)	(4) Trend inflation
UGAP	0.043 (0.014)***			0.174 (0.150)
UGAP*INTHRES		0.044 (0.081)		
UGAP*EXTHRES		0.045 (0.014)***		
EXTHRES		0.030 (0.080)		
UGAP/UR			0.319 (0.098)***	
TRENDINF*UGAP				-0.057 (0.066)
Observations:	93	93	93	93
Adj. R-squared:	0.948	0.947	0.948	0.948

Notes: OLS regressions with Newey-West corrected standard errors (in parentheses). The dependent variable is the year-on-year change in the PCE deflator over 1992Q1-2015Q1. INTHRES is a dummy that takes the value of 1 when UGAP falls within the thresholds and 0 otherwise. EXTHRES is a dummy that takes the value of 1 when UGAP falls outside of these thresholds. The constant term and the coefficients on lagged inflation, inflation expectations and import prices are not shown.

inflation – is negative, suggesting that the Phillips curve slope was flatter when trend inflation was lower, the coefficient is not statistically significant. Our finding may be related to the fact that trend inflation was relatively stable during most of our sample period (ranging between 3.8% at the beginning of 1992 to 1.8% during 2003-05). In fact, a much sharper decline in trend inflation occurred between the mid-1980s and the early 1990s, a period during which the impact of state-dependent pricing may have been more important.

5 The forecasting performance of different specifications

In this section we compare the forecasting accuracy of the linear hybrid Phillips curve model, introduced in Section 3, with the alternative specifications that were introduced in the previous sections. We also investigate the extent to which the forecasting accuracy of the linear hybrid model changes when we employ alternative measures of long-term inflation expectations. As in Section 3.2, we use an estimation window that spans the period from 1992Q1 to 2007Q4, and then we produce dynamic out-of-sample forecasts of PCE inflation for 2008Q1 to 2015Q1, conditional on the actual data for inflation expectations, import prices and the different measures of slack in the economy. The forecasting performance across models is compared with the RMSE.

First, we investigate which is the most relevant measure of slack to forecast inflation. Our findings do not provide evidence that the short-term unemployment gap is more powerful than the headline or the long-term unemployment rate in influencing inflation developments (Table 4). Hence, in contrast to the evidence by some recent studies, we do not find support for the hypothesis that those out of work for less than 26 weeks have been more influential in determining inflation developments between 2008 and 2015. At the extreme, Krueger et al. (2014) have argued that the long-term unemployed do not exert any influence on inflation, since they are detached from the labour market. Our results do not corroborate this finding.

Across all specifications, we find that the broader measure of the labour market, the LMTI, is consistently among the best performing specifications, followed by the headline, medium-term and long-term unemployment gaps. Overall, however, the differences in the forecasting accuracy across Phillips curves with alternative slack measures are not large.

Table 4: RMSE of out-of-sample PCE inflation forecasts for 2008Q1-2015Q1

	Linear	Rolling	Kalman	Michigan	5y5y	Backward	Non-lin (D-L)
UGAP	0.42	0.18	0.36	0.46	0.32	0.76	0.47
STUGAP	0.56	0.18	0.30	0.53	0.42	0.82	0.54
MTUGAP	0.37	0.18	0.26	0.43	0.30	0.67	0.50
LTUGAP	0.43	0.20	0.29	0.37	0.64	0.68	0.46
UPRGAP	0.68	0.20	0.29	0.57	0.40	0.95	0.63
LMTIGAP	0.40	0.19	0.28	0.43	0.35	0.50	0.46
OGAP	0.47	0.17	0.29	0.50	0.47	0.74	-
Combination of best 4	0.37	0.18	0.26	0.41	0.32	0.64	0.46

Notes: Most of the specifications were estimated from 1992Q1 to 2007Q4, with the exception of the 5y5y, where data availability issues implied that it is estimated only from 1999Q1. Column 3 refers to rolling forecasts taking 1992-2007 as the estimation window, whereas column 4 uses a Kalman filter with time-varying parameters on all variables.

Our second exercise focuses on the predictive information content from constant-slope non-linear models and time-varying coefficient models. We employ here three models which were presented in the previous section: the Kalman-filter based model with time-varying coefficients, the rolling regressions, and the non-linear (D-L) model from Table 3. Overall, the two time-varying models have a considerably higher forecasting power than the linear model with the constant slope. In particular, the increase in accuracy from the rolling regressions model is not surprising (“Rolling”), as it is in line with the findings from Giacomini and White (2006), in that a rolling-window forecasting scheme is suitable to deal with data heterogeneity and structural shifts in the data. In addition, the time-varying coefficient model (“Kalman”) also yields a lower RMSE than the constant slope models shown in column (1). In contrast, the RMSE of the non-linear (D-L) model where the slope varies with the unemployment rate does not improve over the linear model.

Finally, we also investigate the robustness of the model to two alternative measures of long-term inflation expectations: the University of Michigan’s 5 to 10-year ahead inflation forecast, and the 5-year 5-year ahead market-based forward inflation compensation. The results from Table 4 indicate that the benchmark specification with the SPF’s 10-year ahead PCE inflation (“Linear”) is able to outperform the one with the University of Michigan’s inflation expectations (“Michigan”). Although the model with the market-based inflation expectations (“5y5y”) has a slightly lower RMSE, this is because we employ a different and shorter sample period (the market-based inflation data only start in 1999). In effect, over the same sample period, the model with SPF inflation expectations also outperforms the specification with market-based inflation expectations.¹⁹ For completeness, we also show the forecasting accuracy of a backward-looking Phillips curve model (“Backward”), where the inflation process evolves according to its past values and are not influenced by future inflation expectations. This model yields a much higher RMSE compared with Phillips curve with inflation expectations, giving further evidence of the

¹⁹Results available upon request.

importance of the expectations in anchoring inflation.

6 Concluding remarks

Our paper shows that the Phillips curve relationship between inflation and slack remains valid in the United States, by underscoring the importance of taking into account inflation persistence, expectations of future inflation, as well as import prices in addition to the amount of slack in the economy. A model with these determinants is able to explain rather well the behaviour of inflation after the Great Recession, with little apparent evidence of a missing deflation puzzle.

In terms of the forecasting properties of the different slack measures, our out-of-sample exercise finds that slack measured by the LMTI, together with the headline, medium-term and long-term unemployment gaps lead to the best performing specifications. More important than the choice of slack measure, however, is the consideration of a time-variation in the Phillips curve slope; we find tentative evidence that the slope has increased slightly since 2013. Phillips curve models that take into account this change in the slope over time are able to outperform the constant-slope and non-linear models over 2008Q1 to 2015Q1, as shown by a higher forecasting accuracy. Models examined in this paper with specific forms of non-linearities but a constant slope are not able to outperform the linear models, however, as indicated by higher RMSE.

Appendix

Table A.1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Δ_4 PCE deflator	93	1.9	0.8	-0.9	4.0
Δ_4 SPF_10Y PCE	94	2.4	0.4	2.0	3.7
Δ_4 Michigan_5-10Y Infl	93	3.0	0.2	2.5	3.8
Δ_4 5y5y	66	2.6	0.3	1.9	3.1
Δ_4 Import prices	93	1.2	5.2	-14.5	16.2
UGAP	94	-0.8	1.3	-4.3	1.1
STUGAP	94	0.0	0.7	-2.3	1.0
MTUGAP	94	-0.2	0.3	-1.3	0.2
LTUGAP	94	-0.6	1.1	-3.4	0.5
UPRGAP	94	-2.1	1.6	-5.6	0.9
LMTIGAP	94	-1.0	1.2	-3.2	0.7
OGAP	94	-1.7	2.4	-7.2	3.6

Source: Bureau of Labor Statistics, CBO, Federal Reserve Board, Federal Reserve Bank of Philadelphia, University of Michigan, and authors' calculations.

Table A.2: Phillips curve with short-term inflation expectations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ_4 SPF_1Y CPI	0.145 (0.096)	0.160 (0.093)*	0.137 (0.097)	0.145 (0.098)	0.166 (0.094)*	0.125 (0.101)	0.139 (0.092)
Δ_4 PCE deflator $_{t-1}$	0.792 (0.122)***	0.795 (0.119)***	0.790 (0.122)***	0.794 (0.123)***	0.800 (0.123)***	0.795 (0.119)***	0.789 (0.118)***
Δ_4 PCE deflator $_{t-2}$	-0.066 (0.112)	-0.059 (0.111)	-0.069 (0.112)	-0.077 (0.112)	-0.080 (0.109)	-0.069 (0.111)	-0.063 (0.112)
Δ_4 Import prices $_t$	0.159 (0.008)***	0.158 (0.008)***	0.16 (0.008)***	0.159 (0.008)***	0.159 (0.008)***	0.160 (0.008)***	0.158 (0.008)***
Δ_4 Import prices $_{t-1}$	-0.146 (0.017)***	-0.146 (0.017)***	-0.146 (0.017)***	-0.145 (0.017)***	-0.146 (0.017)***	-0.146 (0.017)***	-0.145 (0.017)***
Δ_4 Import prices $_{t-2}$	0.044 (0.015)***	0.043 (0.015)***	0.043 (0.015)***	0.045 (0.015)***	0.045 (0.014)***	0.044 (0.015)***	0.044 (0.015)***
UGAP	0.022 (0.014)						
STUGAP		0.037 (0.025)					
MTUGAP			0.100 (0.055)*				
LTUGAP				0.026 (0.018)			
UPRGAP					0.008 (0.012)		
LMTIGAP						0.031 (0.018)*	
OGAP							0.016 (0.007)**
Constant	0.113 (0.128)	0.044 (0.110)	0.143 (0.135)	0.130 (0.132)	0.073 (0.125)	0.174 (0.153)	0.136 (0.129)
Observations:	93	93	93	93	93	93	93
Adj. R-squared:	0.948	0.947	0.948	0.947	0.947	0.948	0.948

Notes: OLS regressions with Newey-West corrected standard errors (in parentheses). The dependent variable is the year-on-year change in the PCE deflator over 1992Q1-2015Q1. The measure of inflation expectations is the SPF's 1-year ahead CPI. Δ_4 denotes year-on-year percentage-point changes. Asterisks, *, **, ***, denote, respectively, statistical significance at the 10, 5 and 1% levels.

Table A.3: Phillips curve estimates for CPI

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta_4\text{SPF_10Y CPI}$	0.227 (0.128)*	0.328 (0.151)**	0.183 (0.117)	0.134 (0.109)	0.140 (0.110)	0.135 (0.113)	0.212 (0.113)*
$\Delta_4\text{CPI}_{t-1}$	0.766 (0.137)***	0.770 (0.127)***	0.762 (0.137)***	0.803 (0.132)***	0.839 (0.125)***	0.763 (0.125)***	0.772 (0.130)***
$\Delta_4\text{CPI}_{t-2}$	-0.050 (0.125)	-0.032 (0.117)	-0.053 (0.126)	-0.041 (0.133)	-0.020 (0.135)	-0.060 (0.126)	-0.054 (0.124)
$\Delta_4\text{Import prices}_t$	0.223 (0.014)***	0.222 (0.014)***	0.224 (0.014)***	0.225 (0.015)***	0.226 (0.016)***	0.223 (0.014)***	0.221 (0.014)***
$\Delta_4\text{Import prices}_{t-1}$	-0.210 (0.027)***	-0.214 (0.026)***	-0.209 (0.027)***	-0.214 (0.027)***	-0.221 (0.026)***	-0.209 (0.024)***	-0.210 (0.025)***
$\Delta_4\text{Import prices}_{t-2}$	0.066 (0.021)***	0.066 (0.019)***	0.063 (0.022)***	0.062 (0.022)***	0.058 (0.022)***	0.069 (0.021)***	0.068 (0.021)***
UGAP	0.089 (0.028)***						
STUGAP		0.181 (0.053)***					
MTUGAP			0.367 (0.104)***				
LTUGAP				0.080 (0.034)**			
UPRGAP					0.022 (0.023)		
LMTIGAP						0.120 (0.031)***	
OGAP							0.052 (0.015)***
Constant	0.038 (0.210)	-0.341 (0.257)	0.167 (0.210)	0.156 (0.220)	0.011 (0.216)	0.35 (0.217)	0.088 (0.199)
Observations:	93	93	93	93	93	93	93
Adj. R-squared:	0.924	0.925	0.924	0.92	0.916	0.925	0.925

Notes: OLS regressions with Newey-West corrected standard errors (in parentheses). The dependent variable is the year-on-year change in CPI over 1992Q1-2015Q1. Δ_4 denotes year-on-year percentage-point changes. Asterisks, *, **, ***, denote, respectively, statistical significance at the 10, 5 and 1% levels.

Table A.4: Phillips curve estimates for core PCE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ_4 SPF_10Y PCE	0.133 (0.058)**	0.152 (0.060)**	0.121 (0.056)**	0.121 (0.056)**	0.167 (0.061)***	0.104 (0.055)*	0.121 (0.054)**
Δ_4 Core PCE deflator $_{t-1}$	0.956 (0.111)***	0.951 (0.109)***	0.967 (0.109)***	0.969 (0.115)***	0.953 (0.117)***	0.975 (0.109)***	0.954 (0.109)***
Δ_4 Core PCE deflator $_{t-2}$	-0.162 (0.125)	-0.143 (0.123)	-0.171 (0.123)	-0.179 (0.126)	-0.184 (0.124)	-0.171 (0.122)	-0.153 (0.124)
Δ_4 Non-petro. IP $_t$	0.078 (0.019)***	0.076 (0.018)***	0.079 (0.020)***	0.078 (0.019)***	0.076 (0.019)***	0.078 (0.019)***	0.077 (0.019)***
Δ_4 Non-petro. IP $_{t-1}$	-0.102 (0.030)***	-0.101 (0.030)***	-0.103 (0.031)***	-0.100 (0.030)***	-0.098 (0.030)***	-0.100 (0.031)***	-0.101 (0.030)***
Δ_4 Non-petro. IP $_{t-2}$	0.047 (0.016)***	0.047 (0.016)***	0.046 (0.016)***	0.045 (0.016)***	0.045 (0.016)***	0.046 (0.016)***	0.048 (0.016)***
UGAP	0.024 (0.012)**						
STUGAP		0.049 (0.024)**					
MTUGAP			0.085 (0.043)*				
LTUGAP				0.027 (0.016)*			
UPRGAP					0.020 (0.011)*		
LMTIGAP						0.023 (0.013)*	
OGAP							0.015 (0.006)**
Constant	0.059 (0.086)	-0.03 (0.100)	0.083 (0.085)	0.094 (0.087)	0.047 (0.086)	0.112 (0.091)	0.080 (0.082)
Observations:	93	93	93	93	93	93	93
Adj. R-squared:	0.911	0.911	0.91	0.91	0.91	0.909	0.912

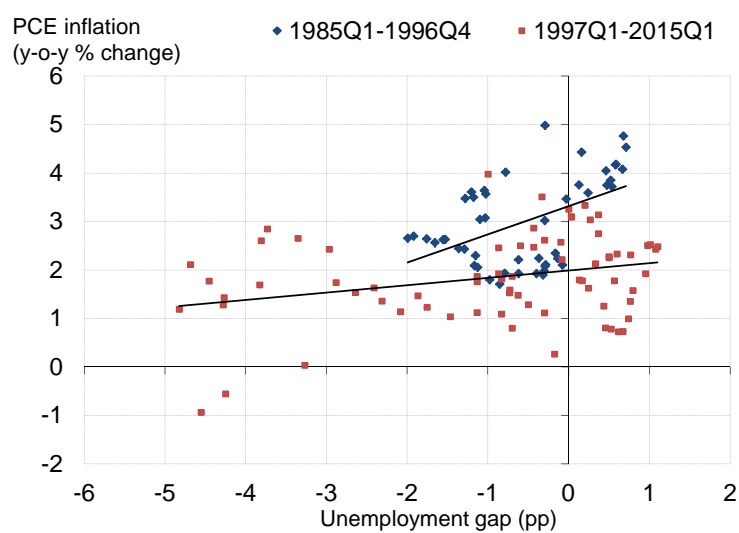
Notes: OLS regressions with Newey-West corrected standard errors (in parentheses). The dependent variable is the year-on-year change in the core PCE deflator over 1992Q1-2015Q1. Δ_4 denotes year-on-year percentage-point changes. Asterisks, *, **, ***, denote, respectively, statistical significance at the 10, 5 and 1% levels.

Table A.5: IV regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ_4 SPF_10Y PCE	0.189 (0.108)*	0.243 (0.122)**	0.162 (0.097)*	0.157 (0.096)	0.203 (0.111)*	0.133 (0.095)	0.176 (0.094)*
Δ_4 PCE deflator $_{t-1}$	0.796 (0.129)***	0.793 (0.125)***	0.809 (0.125)***	0.816 (0.128)***	0.823 (0.132)***	0.810 (0.121)***	0.801 (0.123)***
Δ_4 PCE deflator $_{t-1}$	-0.077 (0.111)	-0.062 (0.105)	-0.078 (0.113)	-0.085 (0.115)	-0.099 (0.112)	-0.075 (0.113)	-0.073 (0.111)
Δ_4 Import prices $_t$	0.163 (0.008)***	0.161 (0.008)***	0.163 (0.008)***	0.163 (0.008)***	0.162 (0.008)***	0.163 (0.008)***	0.161 (0.007)***
Δ_4 Import prices $_{t-1}$	-0.150 (0.018)***	-0.150 (0.018)***	-0.151 (0.018)***	-0.151 (0.018)***	-0.152 (0.018)***	-0.151 (0.017)***	-0.149 (0.017)***
Δ_4 Import prices $_{t-1}$	0.047 (0.016)***	0.046 (0.015)***	0.045 (0.016)***	0.046 (0.015)***	0.048 (0.015)***	0.046 (0.015)***	0.047 (0.015)***
UGAP	0.045 (0.015)***						
STUGAP		0.096 (0.032)***					
MTUGAP			0.143 (0.054)***				
LTUGAP				0.043 (0.017)**			
UPRGAP					0.026 (0.015)*		
LMTIGAP						0.049 (0.016)***	
OGAP							0.024 (0.007)***
Constant	0.043 (0.143)	-0.140 (0.174)	0.075 (0.132)	0.088 (0.134)	0.021 (0.139)	0.158 (0.144)	0.060 (0.134)
Observations:	92	92	92	92	92	92	92
Adj. R-squared:	0.948	0.948	0.948	0.947	0.945	0.947	0.948

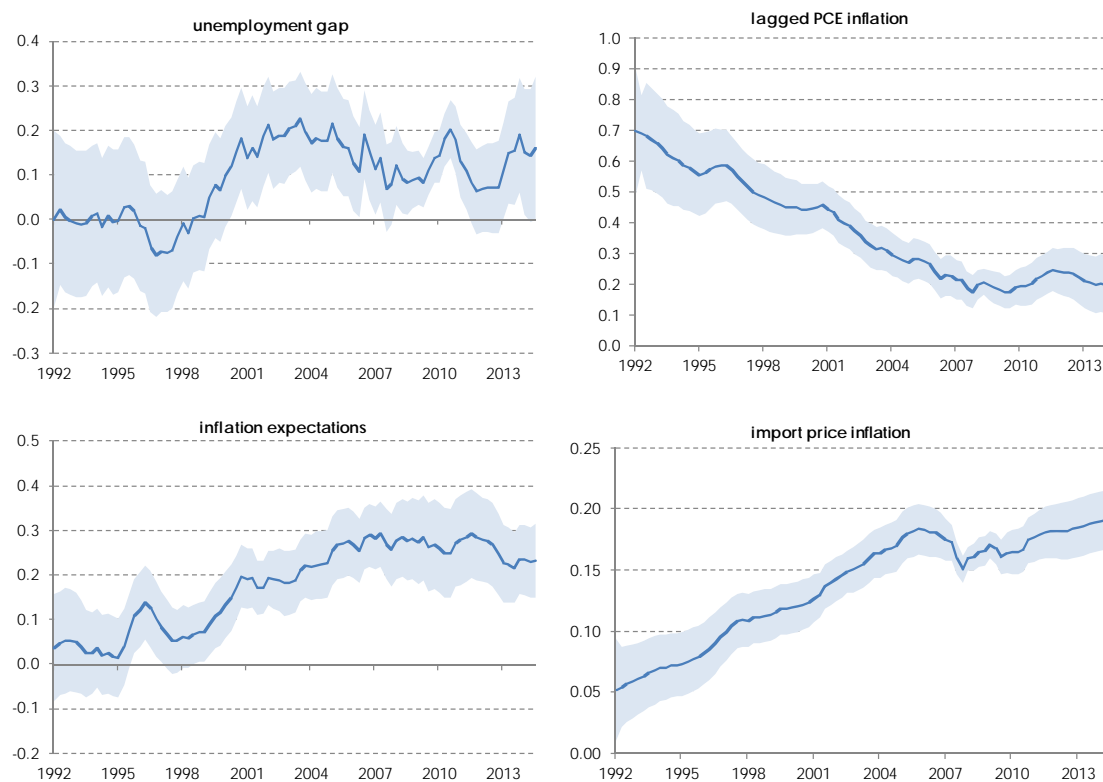
Notes: IV regressions with Newey-West corrected standard errors (in parentheses). The IV estimation instruments SPF_10Y PCE and each of the slack measures with 2 lags of their own variables. The dependent variable is the year-on-year change in the PCE deflator over 1992Q1-2015Q1. Δ_4 denotes year-on-year percentage-point changes. Asterisks, *, **, ***, denote, respectively, statistical significance at the 10, 5 and 1% levels.

Figure A.1: Relationship between PCE inflation and the unemployment gap



Source: Bureau of Labour Statistics.

Figure A.2: Kalman-smoothed time-varying coefficients



Note: Kalman-smoothed time-varying coefficients. The solid line refers to the point estimates, while the shaded area represents the associated ± 1 standard error confidence bands.

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