Banc Ceannais na hÉireann
Central Bank of Ireland
Eurosystem

Research Technical Paper

Expectations, Unemployment and Inflation: an Empirical Investigation

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Vol. 2021, No. 05

Expectations, Unemployment and Inflation: an Empirical Investigation*

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Abstract

This paper analyses the empirical relation between inflation and unemployment over the past 25 years by using a panel state-space model. After controlling for the global factor, I find that the domestic rate of unemployment explains 11 percent in the variation of headline inflation, suggesting a significant power that domestic slack has in influencing medium-term core inflation. The global factor, in turn, is well explained by global oil and food prices as well as global trade integration. The contribution of the global slack in explaining the global component of inflation is negligible. Additionally, using a set of threshold regressions, I identify break points that split inflation dynamics into various regimes. In particular, I find a higher sensitivity of inflation to unemployment in high-inflation and/or low unemployment regimes. This finding is consistent with less frequent price adjustments of firms in low-inflation and high-unemployment environments.

JEL classification: E31, E32, E50

Keywords: Phillips Curve, State-Space Model, Non-Linearities

*I thank David Doran, Lorenz Emter, Philip Lane, Živilė Žėkaitė and the participants of the Central Bank of Ireland seminar series for helpful comments and suggestions. Luke Doyle provided excellent research assistance. The views expressed in this paper are personal and do not represent the views of the Central Bank of Ireland.

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Non-Technical Summary

The Phillips curve is widely used in policy circles for economic analysis and policy formulation. It relates headline inflation to a measure of economic slack, captured by the output or unemployment gap, as well as expectations and cost-push shocks. Conceptually, this implies that after the Global Financial Crisis (GFC) the decline in unemployment should have been associated with a pick-up of inflation. However, despite substantial gains in employment in advanced economies, inflation still remains subdued. Quoting Blanchard et al. (2015), "...the lack of a reliable relation between inflation and activity ... would require a major rethinking of the inflation targeting architecture."

Building on the existing literature, in this paper I revisit the empirical relation between inflation and unemployment. The main frame of differentiation from previous applied work that addresses a similar question is the application of a panel state-space model followed by threshold regressions for the understanding of the inflation process over the past 25 years.

In terms of results, I find role for both domestic factors and global factors in shaping inflation dynamics. In particular, the domestic rate of unemployment accounts for around 11 percent of variation in headline inflation, after controlling for the global factor. This global factor, on the other hand, is the largest contributor to the variation in headline inflation. This unsurprising, given that the latter is well explained by highly volatile commodity prices. In addition, global trade integration shows a negative and statistically significant association with the global inflation process. This finding is important as it suggest that higher level of protectionism will tend to raise inflation in the medium run. Additionally, I find no evidence that the global slack has a statistically significant effect on inflation.

I also find that the elasticity of inflation is state dependent, with evidence pointing to a higher sensitivity of inflation to unemployment in high-inflation and/or low unemployment regimes. This finding is consistent with less frequent price adjustments of firms in low-inflation and high-unemployment environments. From the policy perspective, my findings suggests that as inflation and inflationary expectations pick up, the effect that domestic slack has on domestic inflation will strengthen.

1 Introduction

The Phillips curve is widely used in policy circles for economic analysis and policy formulation.[1] It relates headline inflation to a measure of economic slack, captured by the output or unemployment gap, as well as expectations and cost-push shocks. Conceptually, this implies that after the Global Financial Crisis (GFC) the decline in unemployment should have been associated with a pick-up of inflation (Figure 1). However, despite substantial gains in employment in advanced economies, inflation still remains subdued. Quoting Blanchard et al. (2015), "...the lack of a reliable relation between inflation and activity ... would require a major rethinking of the inflation targeting architecture."

There is significant amount of empirical work dedicated to the understanding of the relation between inflation and economic activity. The unobserved nature of inflationary expectations and the global factor, however, can be a complicating factor in the treatment of these variables in empirical work. Accordingly, the main frame of reference of this paper is the application of a panel state-space model for the understanding of the inflation process in advanced economies over the past 25 years. Given the lack of consistent and reliable cross-country measures of inflationary expectations, this approach has its advantages as it simultaneously accounts for unobserved global factors and local inflationary expectations.

In particular, I apply the state-space framework to a panel of advanced economies and estimate the relation between inflation and the unemployment rate after controlling for unobserved inflationary expectations. Additionally, I control for the global factor by conditioning on unobserved common time effects in the same state-space specification. Instead of maximum likelihood, I rely on Bayesian methods as the latter tend to have better convergence properties. To understand the nature of global variables in driving the inflation process, I relate the filtered common series from the state-space model to a range of global variables. Finally, I run panel threshold regressions for the Phillips curve and estimate regime-dependent coefficients in order to identify possible break points that results in a "flatter" Phillips curve.

[1] For a discussion see Eser et al. (2020).

The theoretical literature on inflation is vast. Most often it is modelled in a New-Keynesian setup that yields a forward-looking equation linking current inflation to future inflationary expectations and a measure of slack in the economy (Woodford, 2003; Galí, 2015).[2] Galí and Monacelli (2005) extend the standard framework to a small open economy setting. They derive the dynamics of domestic inflation in terms of inflationary expectations and the real marginal cost, which can be written in terms of domestic output and productivity, as well as world output. A canonical representation of the model yields a Phillips curve that is a function of inflationary expectations and domestic output gap, i.e. the deviation of domestic output from its natural level. The latter is defined as the equilibrium level of output in the absence of nominal rigidities and is also conditional on world output.

At an empirical level, Blanchard et al. (2015) relate inflation to the unemployment gap and apply a non-linear Kalman filter with time-varying parameters to quarterly series for a range of countries.[3] They provide evidence for a negative link between inflation and the rate of unemployment, and highlight the reduced sensitivity of inflation to shifts in unemployment compared to the pre-1990 period.[4] Borio and Filardo (2007) add proxies for global economic slack to the standard Phillips curve and find that the global variable adds considerable explanatory power to the traditional equation, both in a pooled setting and country-level regressions. While the regressions do not control for inflationary expectations, addition of the global variable, nevertheless, tends to annihilate the statistical significance of the domestic slack. Forbes (2019) studies the role of globalisation in explaining inflation over the past 25 years. She shows that global

[2] The setup is based on a time-dependent price setting of Calvo (1983). In contrast, in a state-dependent setting price adjustment occurs only for firms further away from the optimal price, with more firms adjusting prices in a higher inflationary environment (Gertler and Leahy, 2008). Accordingly, the behaviour of prices in this framework is more flexible compared to the time-dependent pricing models. Among other approaches, the Rotemberg (1982) framework is based on the quadratic cost of price changes that gives rise to a relation between the current inflation, expected inflation and economic activity. Mankiw and Reis (2002), assuming that some firm-level decisions are based on outdated information, derive a Phillips curve that is characterised with expectations of current variables that are based on the past information set. For a detailed textbook treatment of the New-Keynesian approach see Woodford (2003) and Galí (2015).

[3] Often the quarterly rate of inflation is measured as the price change relative to the same quarter of the previous period, while the theoretical literature on the Phillips curve refers to inflation measured as the price change relative to the previous period.

[4] See also IMF (2013) and Matheson and Stavrev (2013).

factors are significant drivers of headline inflation. These factors, however, have little explanatory power over core inflation.

Similar to the empirical literature above, I study the determinants of inflation for a set of advanced countries over the past 25 years. The main frame of reference and differentiation from the above cited literature is the application of a panel state-space model to the understanding of the inflation process. This framework also accounts for unobserved global factors and local inflationary expectations. This is advantageous given the lack of consistent and reliable cross-country measures of inflationary expectations. Additionally, instead of potentially noisy quarterly data I use annual data that allows to better capture medium-term developments. The short time span of annual observations further reinforces the advantage of the panel framework. Finally, instead of running a varying-coefficient Kalman filter, with its nuances of separating the effects of estimated time-varying coefficients from the filtered series, I estimate panel threshold regressions for the Phillips curve.[5] This approach allows for the estimation of both regime-switching coefficients and identification of potential break points that result in a flatter Phillips curve.

Consistent with the empirical literature above, I find a negative link between inflation and unemployment. This holds true even after controlling for unobserved global factors and inflationary expectations. In this context, I find that the rate of domestic unemployment accounts for around 11 percent of the variation in headline inflation. A significantly larger fraction (58 percent) of variation in headline inflation is attributable to the global factor. This is unsurprising, however, give that the latter is well explained by highly volatile global food and oil prices. Additionally, global trade integration appears to be a significant determinant of the global factor, whereby higher global trade integration is associated with lower domestic inflation. I also find little evidence for the importance of the global slack in shaping inflation dynamics. In terms of regime-switching regressions, the evidence points to a higher sensitivity of inflation to unemployment in high-inflation and/or low-unemployment regimes, a finding that is consistent with less frequent price adjustments of firms in low-inflation and high-unemployment environments.

[5] For a discussion of panel threshold regression see Hansen (1999).

The rest of the paper is structured as follows. Section 2 presents the data and provides an empirical motivation for expectation formations used in the empirical specification. In Section 3 I describe the estimation methodology, while in Section 4 I discuss the findings. Finally, Section 5 concludes.

2 Data

All primary data are taken from the World Bank's World Development Indicators database. These are annual observations for a range of countries and cover the period from 1995 to 2019. The sample is composed of 20 advanced economies. Appendix A lists all countries used in this paper.

I measure inflation by a change in the consumer price index over the previous period. Import price inflation is captured by the change in import unit values over the previous period. The latter are constructed by taking the ratio of goods and services imports in current local currency prices to goods and services imports in constant local currency prices. The unemployment rate is measured by the total number of unemployed as a share of total labour force.

I also consider the impact of the global factors on the inflation process. For this reason, I take the rate of global unemployment from the World Bank's *World Development Indicators* as a measure of the global slack. From the same data source I also take the ratio of global trade to global GDP to proxy for increased interdependence, whereby trade is measured as the sum of exports and imports of goods and services. A range of global commodity prices are taken from the *World Economic Output* of the IMF. In particular, I compute inflation for global brent in USD, inflation for food and beverages, inflation for agricultural raw materials, and inflation for commodity metals.[6]

Finally, to shed light on the empirical specification, I regress a measure of inflationary expectations on the lagged level of headline inflation. The data for expectation comes from the IMF's *World Economic Outlook*, and represents one year ahead forecast of headline inflation. These observations are taken from the dataset made available by Forbes (2019).

[6] Agricultural raw materials include prices for timber, cotton, wool and rubber. Commodity metals include copper, aluminum, iron ore, tin, nickel, zinc, lead, and uranium.

The outcome of the regression is presented in Table 1. The first lag of headline inflation appears to be statistically significant in explaining one year ahead inflationary expectations. Furthermore, lagged inflation explains more than half of the variability of expectations when using IMF fall forecasts, as is captured by the R-squared. Regressing inflation projections on the second lag yields qualitatively similar results with, unsurprisingly, lower R-squared. While the regression is minimalistic, it suggests a significant backward looking component in inflationary expectations. Furthermore, there is no reason to take the IMF's inflationary projections as representing those of domestic economic agents. For these reasons, it is pragmatic to adopt an empirical framework with adaptive expectations, where the expectations are simultaneously estimated together with model parameters. The specification is explained in the next section.

3 Empirical Methodology

3 Panel state-space model

Inflation is modelled as a linear function of unobserved inflationary expectations ($\pi^e_{i,t}$), a deviation of domestic unemployment rate ($u_{i,t}$) from its medium-term equilibrium value ($\bar{u}_{i,t}$), and import price inflation ($\pi^m_{i,t}$):

$$\pi_{i,t} = \alpha_{\pi,i} + \eta_t + \theta_e \pi^e_{i,t} + \theta_u \left(u_{i,t} - \bar{u}_{i,t}\right) + \theta_m \pi^m_{i,t} + \upsilon_\pi \varepsilon^\pi_{i,t} \tag{1}$$

where $\alpha_{\pi,i}$ is a country fixed effect. The specification also conditions on an unobserved variable (η_t) that is common to all countries in the sample. This common variable is in essence a time effect and is intended to capture the impact of global factors. The rest of variation in inflation is attributed to shocks ($\varepsilon^\pi_{i,t}$) not captured by the listed factors.

It is common to assume that the natural rate of unemployment follows a random walk. While this is a simplifying assumption that is intended to approximate the behaviour of series in finite samples, random-walk series are characterised by variance that is proportional to time. Since the rate of unemployment is by construction less than 1, its variance is also constrained regardless of the length of the series.[7] For this reason, I assume that the medium-run equilibrium rate of unemployment is relatively stable, with $\bar{u}_{i,t} = \bar{u}_i$. Thus, equation (1) can be rewritten as follows:

$$\pi_{i,t} = \mu_{\pi,i} + \eta_t + \theta_e \pi^e_{i,t} + \theta_u u_{i,t} + \theta_m \pi^m_{i,t} + \upsilon_\pi \varepsilon^\pi_{i,t} \tag{2}$$

where $\bar{u}_i$ has been absorbed into $\mu_{\pi,i}$.

As explained above, I choose to model inflationary expectations ($\pi^e_{i,t}$) in an additive fashion:

$$\pi^e_{i,t} - \pi^e_{i,t-1} = \lambda(\pi_{i,t-1} - \pi^e_{i,t-1}) + \upsilon_e \varepsilon^e_{i,t} \tag{3}$$

whereby expectations are revised upwards when past inflation overshoots past expectations. The residual variation of the expectations is captured by shifts in expectations ($\varepsilon^e_{i,t}$) that are not related to past inflation. The rest of the variables are assumed to follow a first order autoregressive process:

$$u_{i,t} = \mu_{u,i} + \rho_u u_{i,t-1} + \upsilon_u \varepsilon^u_{i,t} \tag{4}$$

$$\pi^m_{i,t} = \mu_{m,i} + \rho_m \pi^m_{i,t-1} + \upsilon_m \varepsilon^m_{i,t} \tag{5}$$

Instead of running country-level estimations, I rely on a panel structure to fully utilise the information content of the data. To estimate the above model by state-space methods uninformative priors are imposed. In particular, I assume that the global unobserved variable follows $\eta_t = \upsilon_\eta \varepsilon^\eta_t$ process, where ε^η_t is a draw from the standard normal distribution, while υ_η follows an inverse gamma distribution with 0.05 mean and infinite variance.[8] Similarly, to estimate variance of errors, I assume that υ_j are drawn from an inverse gamma distribution with 0.05 mean and infinite variance, while $\varepsilon^j_{i,t}$ are assumed to be independently normally distributed with $N(0, 1)$ for $j \in (\pi, e, u, m)$. This assumption constrains the variance of shocks to be homogeneous across all countries. The prior for the rest of model parameters is that of normal distribution with zero mean

[7] Alternatively, it is possible to model the unemployment rate as a regime-switching process, with close to a random-walk behaviour in one regime, but strong mean reversion in another regime.

[8] In an alternative specification I have also modelled the global variable as following an AR(1) process. The estimated autoregressive term was not statistically different from zero.

and standard deviation of 100. Finally, observe that all equations, with exception of equations (3), contain country specific constants.[9]

For a panel of 20 countries, 71 parameters need to be identified: 60 are country-specific fixed effects ($\mu_{\pi,i}$, $\mu_{u,i}$, $\mu_{m,i}$), 10 are parameters and variances constrained to be homogeneous across countries, and 1 refers to the variance of the global shock. The estimation also yields 20 filtered country-specific time series of inflationary expectations. The estimation is conducted by first finding the mode of the posterior distribution, followed by the Metropolis-Hastings algorithm. A sample of 10 million draws per chain is created for 5 chains. The rejection rate per chain is 75.6 percent. The estimation is done with DYNARE.

3 Threshold regression

Blanchard et al. (2015) report a decline in the slope of the Phillips curve, with most of the decline taking place from mid-1970 to the early 1990s. Hence, it is possible that dynamics of inflation are not linear but are regime dependent. In particular, it is reasonable to expect that during periods of high inflation or low unemployment, the sensitivity of wage inflation to shifts in employment will be higher than in regimes with low inflation or high unemployment. Conditional on wage-inflation pass-through, the high-inflation or low unemployment regime, in turn, will tend to be characterised with higher sensitivity of inflation to unemployment than the regime with lower inflation or higher unemployment.

In this context, threshold models can help shed light on turning points as well as provide estimates of regime-dependent sensitivities. Accordingly, I estimate the following panel threshold regression *a la* Hansen (1999):

$$\pi_{i,t} = \epsilon_{it} + \mu_{\pi,i} + \begin{cases} \theta_e^1 \hat{\pi}_{i,t}^e + \theta_u^1 u_{i,t} + \theta_m^1 \pi_{i,t}^m + \theta_\eta^1 \hat{\eta}_t \text{ if } \tau_{i,t-1} < \tau \\ \theta_e^2 \hat{\pi}_{i,t}^e + \theta_u^2 u_{i,t} + \theta_m^2 \pi_{i,t}^m + \theta_\eta^2 \hat{\eta}_t \text{ if } \tau_{i,t-1} \geq \tau \end{cases} \tag{6}$$

[9] There is no scope for an intercept in equation (3).

where 1 and 2 indicate the underlying regime, $\tau_{i,t-1} \in (\pi_{t-1}, u_{t-1})$ is the threshold variable, and τ is the threshold.[10] The specification also allows for a regime-dependent sensitivity to inflationary expectations ($\hat{\pi}^e_{i,t}$) and the global factor ($\hat{\eta}_i$), with these series extracted from the state-space model described in the previous subsection.

Alternatively, equation (6) can be rewritten as follows:

$$\pi_{i,t} = \mu_{\pi,i} + \mathbf{X}_{i,t}\mathbf{\Theta}_1 I\left[\tau_{i,t-1} < \tau\right] + \mathbf{X}_{i,t}\mathbf{\Theta}_2 I\left[\tau_{i,t-1} \geq \tau\right] + \epsilon_{it} \tag{7}$$

where $\mathbf{X}_{i,t} = \left[\hat{\pi}^e_{i,t}, u_{i,t}, \pi^m_{i,t}, \hat{\eta}_t\right]$, $\mathbf{\Theta}'_j = \left[\theta^j_e, \theta^j_u, \theta^j_m, \theta^j_\eta\right]$ and $I\left[\cdot\right]$ is an indicator function that takes a value of 1 when the condition within the function is satisfied and zero otherwise. Conditional on the threshold τ, the model is linear in parameters, hence it can be estimated by OLS, while the threshold is estimated by minimising the residual variance $\hat{\tau} = \arg\min_\tau \left(\hat{\sigma}^2_\epsilon\right)$.

4 Econometric Evidence

4 Panel state-space model

Table 2 presents the results of Bayesian estimation. The estimated coefficient on inflationary expectations (π^e) is approximately equal to 0.42, with the 90 percent confidence band of (0.36; 0.48). In comparative terms, the estimated coefficient is smaller than the coefficients estimated by Blanchard et al. (2015) and Forbes (2019). While in the latter case IMF WEO projections are used in a panel setting, a different model at a country level is used by the former authors. In contrast, this paper estimates a panel state-space model, where inflationary expectations are unobserved and are modelled in an additive fashion.

The estimated coefficient on the unemployment rate stands at -0.12, with an estimated range of (-0.14; -0.09). Thus, consistent with other reduced form estimates found in literature, the results provide support for the Phillips curve, whereby higher unemployment rate is associated with lower rate of inflation. The estimated sensitivity,

[10] One can think of the estimated parameters from the previous section as being weighted averages from a threshold model. Thus, while data on inflationary expectations were extracted from a linear model, equation (6) can still be used to split the coefficients by regimes.

however, is substantially lower and falls outside the range of coefficients attained by Blanchard et al. (2015). Differences in the empirical specifications drive these results. In particular, Blanchard et al. (2015) estimate the sensitivity of inflation to the unemployment gap, where the natural rate is modelled as a random-walk process. In contrast, the empirical specification in the current paper conditions on the actual rate of unemployment. On the other hand, the mean estimate attained from a panel state-space model is similar in magnitude to the estimated coefficient on domestic slack of Forbes (2019).

The impact of import price inflation on headline inflation, while statistically significant, is substantially smaller. The estimates imply that a one percentage point higher import price inflation is associated with higher headline inflation of around 5 basis points. In comparison, Forbes (2019) finds a statistically insignificant coefficient on import price inflation, with a point estimate of 0.09. Interestingly, she finds coefficients with similar order of magnitude on world oil prices and world commodity prices. While these are partly reflected in import prices, these variables are common to all countries, and accordingly their impact in the current model will be captured by the common unobserved factor (η_t).

Finally, the revision of inflationary expectations, captured by λ coefficient, is estimated at 1.33, with a range of (1.15; 1.50). The estimated range for λ clearly points to a coefficient that is statistically larger than one, suggesting a very strong effect that past historical inflation has on expectations formation. Thus, when past inflation overshoots past expectations by one percentage point, inflationary expectations tend to be revised upwards by around 133 basis points. Such high sensitivity could explain the significant decline in inflationary expectations given the recent history of inflation. On the other hand, the estimates imply that a sustained pick up in headline inflation will be reflected in a larger pick up of inflationary expectations.

Turning to the global factor, Forbes (2019) finds a statistically significant response of headline inflation to shifts in global variables such as world oil prices, world commodity prices and world slack. Similarly, Borio and Filardo (2007) provide some evidence that their measure of global economic slack has considerable explanatory power in explaining the dynamics of inflation. In contrast, the state-space model of this subsection does not specify which global factors affect inflation, and estimates this unobserved common factor together with the model parameters. The approach also provides a way to assess contributions of all variables to the variance of inflation via posterior mean-variance decomposition. This is done in Table 3. The first row of the table shows the decomposition for the headline inflation, while the second row shows the decomposition for inflationary expectations. Since the variance is constrained to be the same across all countries for each of the shocks, the resulting mean-variance decomposition is also the same across countries.

Starting with inflationary expectations, only 21 percent of variance is explained by shocks to expectations. Since the expectations are a function of past inflation, past expectations and shocks, it is reasonable to conclude that a good fraction of variance for inflationary expectations is explained by past inflation. While this, in a way, is the structure of the empirical model, the prior for λ is normal distribution with zero mean and 100 standard deviation. Were there no dependence of expectations on past inflation in the data, the estimate of λ should have been zero.

Finally, the largest contributor to the variance of headline inflation is the global factor, with share of variance standing at around 58 percent. The next 23 percent of variance is explained by shocks to the inflation equation (i.e. cost-push shocks). Shocks to the unemployment equation explains around 11 percent of the variance. As I show in the next section, food and oil prices are a major determinant of the global factor, suggesting that domestic slack has sufficient explanatory power to shape the medium-term dynamics of core inflation. The rest of the variance is explained by shifts in expectations unrelated to the history of inflation and import prices.

4 Explaining the global factor

The implicit nature of time effects is general enough to allow for simultaneous control of various global co-variates. It is, however, tempting to understand the nature of this factor that has such a large impact on the inflation process. For this reason, I regress the filtered time effects on a range of global variables that have been found important in the literature (Borio and Filardo, 2007; Forbes, 2019). Table 4 displays the outcome of these regressions.

The second column tabulates the results from a simple OLS regression with robust standard errors. The rate of global unemployment is negative, but statistically insignificant. Consistent with Forbes (2019), shifts in oil prices have a statistically significant and positive effect on the inflation process. Unsurprisingly, global food prices are also an important determinant of the global factor: the estimated coefficient is positive and statistically significant. The global price of agricultural commodities is not statistically significant in the regression. Price of metals, on the other hand, shows negative correlation with the shifts in the global component of inflation. Additionally, higher global trade shows a negative and statistically significant association with the global inflation process. This finding is important as it suggest that higher level of protectionism will tend to raise inflation in the medium run. Finally, in contrast to Borio and Filardo (2007) and Forbes (2019), I find no evidence that the global slack has a statistically significant effect on inflation.

Due to mild serial correlation in regression residuals, I also run a Prais-Winsten regression with the same data. While there is no significant change in the magnitude of the estimated coefficients, the improved efficiency is reflected in smaller standard errors. Turning to the relative importance of individual variables, the most important global factor seems to the global trade, with a marginal R-squared of 0.4. This is followed by the global inflation in food and beverages with a marginal R-squared of 0.3. The global price of oil comes in the third place with a marginal R-squared of 0.24, followed by inflation in prices of metals and the rate of global unemployment. It is important to mention that combined impact of all commodities is at least as large as that of global trade. Finally, the R-squared of the regression stands at 0.7, suggesting that a third of variation in the global factor remains to be explained by addition of other global variables or utilisation of better proxies.[11]

4 Threshold regression

In this sub-section, I relax the assumption of a single regime and turn to a regime-switching model as represented by equation (7).[12] The results for the threshold panel regression are displayed in Table 5, where the regime variable is the lagged level of headline inflation. The threshold is estimated together with regime-switching

[11] For instance, while the global trade is statistically and economically significant, it can be a poor proxy of increasing global competition and global value chains.

[12] These estimations are done in STATA using *xthreg* command written by Wang (2015).

coefficients. F-stat on the fifth row provides a test for threshold effects, with p-values constructed from 10000 bootstrap samples as described by Hansen (1999). The table reports the presence of statistically significant threshold effects, as captured by the high value of the F-stat for $\bar{\pi}$. To judge the precision of the estimated threshold, however, an alternative test statistic is necessary (Hansen, 1999).

This test statistic is the inverse log-likelihood ratio and is plotted in the left panel of Figure 1. A ratio below the dashed red line indicates statistical significance of the threshold at 1 percent, while a ratio below the dotted line indicates statistical significance at 5 percent. The estimated threshold for the lagged level of headline inflation is around 1.5 percent. This suggests that the sensitivity of inflation to the specified factors varies with rates of past inflation below and above 1.5 percent. The point estimate of the threshold, however, is not precise as the confidence bands are quite wide and range from around 1.2 percent to 2.5 percent.

Turning to benchmark estimates in Table 5, the first column displays the results for the regime with low inflation, while the second column displays the results for the high inflation regime. Column 3 provides the F-statistic for testing the null hypothesis that the regime-dependent coefficient is the same across both regimes, while the last column provides the corresponding P-value. All estimated coefficients are statistically significant across both regimes with expected signs.

Starting with domestic slack, inflation is almost twice more sensitivity to the domestic unemployment rate in the high-inflation regime than in the low-inflation regime. It is reasonable to expect that during periods of high inflation the sensitivity of wage inflation to shifts in employment tends to be higher than in regimes with low inflation. Conditional on wage-inflation pass-through, the high-inflation regime is thus characterised with higher sensitivity of inflation to unemployment.

Inflation also shows visibly higher sensitivity to the global factor in the low-inflation regime, though the difference of sensitivities between the regimes is insignificant. While the rest of the coefficients have the expected sign, they are not significantly different across the regimes either. Overall, the combined results are consistent with less frequent price adjustments of firms in a low inflation environment.

While the results are in line with theoretical priors, it might be the case that inflation is not the best variable for regime identification. For this reason, I re-estimate equation

(7) with the lagged level of the unemployment rate as the regime variable. The results of this specification are displayed in Table 6. There is statistically significant evidence of threshold effects, as captured by the high value of the F-stat for $\bar{u}$. While the estimated threshold for the unemployment rate stands at 6.1 percent, the confidence bands are quite wide (see panel (b) of Figure 1).

In general, all point estimates are statistically significant and are in line with the theoretical priors. In contrast to the previous specification, the coefficient on the expectations term is now significantly different across the regimes, with inflation being more sensitive to expectations in the low-unemployment regime. Complementing the previous results, inflation shows more sensitivity to domestic unemployment in the low-unemployment regime (with an estimated coefficient of -0.12) than in the high unemployment regime (with an estimated coefficient of -0.09). The difference between the two is also statistically significant. Meanwhile, the sensitivity to the global factor in the high-unemployment regime is significantly higher than in the low-unemployment regime and stands at 1.27 and 0.96 respectively. Finally, as before, there is no differential impact of import prices on the headline inflation across the two regimes.

Overall, the results imply that during periods of high inflation and low unemployment, the sensitivity of wage inflation to shifts in employment tends to be higher than in regimes with low inflation and high unemployment rate. Conditional on the wage-inflation pass-through, high-inflation and low-unemployment regimes are thus characterised with higher sensitivity of inflation to unemployment. Thus, the combined results are consistent with less frequent price adjustments of firms in a low-inflation and high unemployment environment.

5 Conclusions

Building on the existing literature, in this paper I revisit the empirical relation between inflation and unemployment. The main frame of differentiation from previous applied work that addresses a similar question is the application of a panel state-space model followed by threshold regressions for the understanding of the inflation process over the past 25 years.

I find role for both domestic factors and global factors in shaping inflation dynamics. In particular, I find that the largest contributor to the variation in headline inflation is the global factor. This unsurprising, given that the latter is well explained by highly volatile commodity prices. In addition, global trade integration shows a negative and statistically significant association with the global inflation process. This finding is important as it suggest that higher level of protectionism will tend to raise inflation in the medium run. Additionally, I find no evidence that the global slack has a statistically significant effect on inflation. Finally, the domestic rate of unemployment accounts for around 11 percent of variation in headline inflation. All these findings combined suggest a significant power that domestic slack has in influencing medium-term core inflation.

I also find that the elasticity of inflation is state dependent, with evidence pointing to a higher sensitivity of inflation to unemployment in high-inflation and/or low unemployment regimes. This finding is consistent with less frequent price adjustments of firms in low-inflation and high-unemployment environments. From the policy perspective, my findings suggests that as inflation and inflationary expectations pick up, the effect that domestic slack has on domestic inflation will strengthen.

As to the measurement of inflationary expectations and practical implementation, the results suggest that conditioning on the lag of inflation could be sufficient, given the dependence of expectations on the history of inflation.

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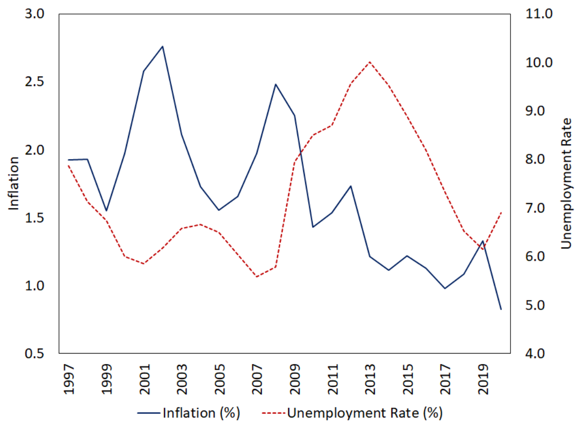
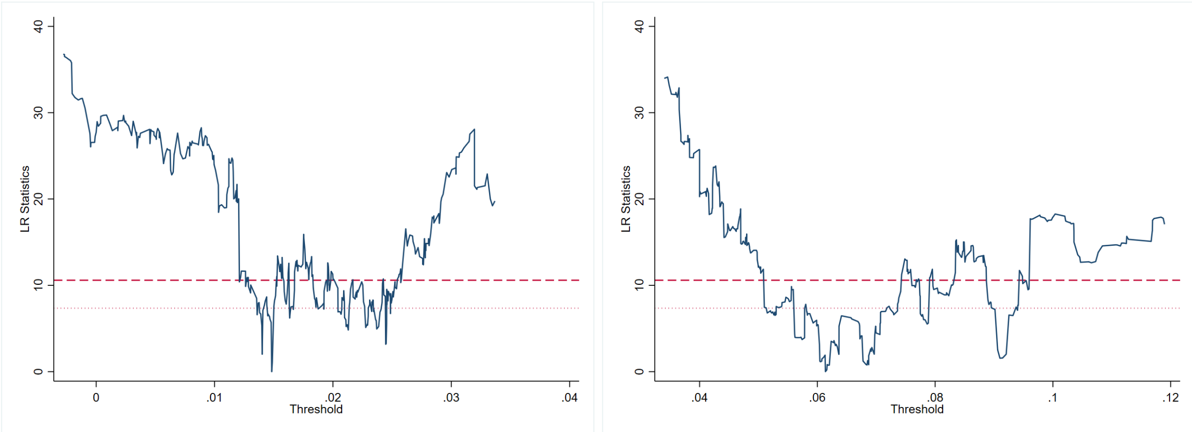
Figure 1. Average Core Inflation and Unemployment



Note: The figure shows the average rate of core inflation and the average rate of unemployment for 20 advanced economies.

Figure 2. Inverse Log-Likelihood Ratio



(a) Threshold variable: π_{t-1} (b) Threshold variable: u_{t-1}

Note: The figure plots the inverse log-likelihood ratio for the estimated threshold parameter. A ratio below the dashed red line indicates statistical significance of the threshold at 1% level, while a ratio below the dotted line indicates statistical significance at 5% percent level.

Table 1. Inflation and Expectations

	(1)	(2)	(3)	(4)
	Fall		Spring	
π_t	0.499		0.451	
	(0.021)***		(0.021)***	
π_{t-1}		0.359		0.356
		(0.023)***		(0.021)***
Observations	480	480	480	480
R-squared	0.554	0.351	0.496	0.377
Countries	20	20	20	20

Notes: The dependent variable is one year ahead IMF WEO inflation forecast, $\pi_{t+1}^{forecast}$, while π stands for headline inflation. The sample period ranges from 1980 to 2018. The projected series are taken from the dataset made available by Forbes (2019). Within R-squared values are reported. All specifications include country fixed effects. Asterisks ***,**,* indicate significance at 1%, 5% and 10% levels respectively.

Table 2. Prior and Posterior Distribution of Parameters

	Prior Distribution Distr.	Mean	St. Dev.	Mean	5 percent	95 percent
θ^e	Normal	0	100	0.4194	0.356	0.482
θ^u	Normal	0	100	-0.1189	-0.144	-0.094
θ^m	Normal	0	100	0.0512	0.032	0.070
λ	Normal	0	100	1.3257	1.151	1.499
ρ_u	Normal	0	100	0.8954	0.870	0.921
ρ_m	Normal	0	100	0.0172	-0.058	0.093
v_e	Inverse Gamma	0.05	Inf	0.0086	0.007	0.010
v_u	Inverse Gamma	0.05	Inf	0.0111	0.011	0.012
v_w	Inverse Gamma	0.05	Inf	0.0103	0.008	0.013
v_m	Inverse Gamma	0.05	Inf	0.0392	0.037	0.041
v_π	Inverse Gamma	0.05	Inf	0.0064	0.006	0.007

Note: The posterior distribution is obtained using Metropolis-Hastings algorithm. The estimations are done for a panel of 20 countries in DYNARE with 5 chains, 10,000,000 draws per chain and 8,000,000 burn out. The rejection rate for all chains is 75.6 percent. The model accounts for country-level as well as common time effects.

Table 3. Posterior Mean-Variance Decomposition

	ε^e	ε^u	ε^m	ε^τ	ε^p
π	5.99	10.46	2.48	57.86	23.21
$\hat{\pi}^e$	21.17	6.67	2.11	50.09	19.97

Note: The table shows the posterior mean-variance decomposition for inflation (π) and filtered inflationary expectations (π^e).

Table 4. Time Effects and Global Factors

	OLS	MR^2_{ols}	PW	MR^2_{pw}
Global Unemployment Rate	-0.634	0.108	-0.336	0.072
	(0.463)		(0.283)	
Oil	0.007	0.129	0.008	0.244
	(0.004)*		(0.003)**	
Food and Beverage	0.031	0.198	0.030	0.290
	(0.015)*		(0.011)**	
Agricultural Raw Materials	0.017	0.067	0.011	0.050
	(0.017)		(0.011)	
Metals	-0.008	0.078	-0.011	0.185
	(0.005)*		(0.005)*	
Trade (% of GDP)	-0.041	0.252	-0.036	0.396
	(0.019)**		(0.011)***	
Constant	0.058		0.038	
	(0.034)		(0.020)*	
Breusch-Godfrey LM				
Chi2	3.644			
Prob	0.056			
Observations	25		25	
R-squared	0.639		0.694	

Note: Column OLS display the results from a simple OLS regression with robust standard errors. Columns PW displays the result of Prais-Winsten regression. MR^2 is computed as $MR^2 = 1 - RSS/RSS0$, where RSS is the residual sum of squares from either column OLS or PW, while RSS0 is the residual sum of squares that restricts the coefficient of the variable in question to zero. The restrictions are done one at a time. Asterisks ***,**,* indicate significance at 1%, 5% and 10% levels respectively.

Table 5. Threshold Panel Regression: Lagged Inflation

	$\pi_{i,t-1} < \bar{\pi}$	$\pi_{i,t-1} \geq \bar{\pi}$	F-stat.	Prob.
$\hat{\pi}^e_{i,t}$	0.641	0.619	0.38	0.540
	(0.032)***	(0.022)***		
$u_{i,t}$	-0.070	-0.114	36.3	0.001
	(0.009)***	(0.009)***		
$\pi^m_{i,t}$	0.042	0.049	0.31	0.576
	(0.009)***	(0.008)***		
$\hat{\tau}_{i,t}$	1.230	1.105	1.68	0.195
	(0.085)***	(0.046)***		
F-stat. for $\bar{\pi}$	55.55***			
$\bar{\pi}$	0.0148			
σ	0.0043			
Observations	480			
R-squared	0.864			
Countries	20			

Note: F-stat. for $\bar{\pi}$ provides a test for threshold effects, with p-values constructed from 10000 bootstrap samples as described by Hansen (1999). F-stat. in column (4) and the corresponding Prob. in column (5) provide the results from testing the null hypothesis that the regime-dependent coefficient is the same across the two regimes. The specification includes regime-invariant panel fixed-effects. Asterisks ***,**,* indicate significance at 1%, 5% and 10% levels respectively.

Table 6. Threshold Panel Regression: Lagged Unemployment Rate

	$u_{i,t-1} < \bar{u}$	$u_{i,t-1} \geq \bar{u}$	F-stat.	Prob.
$\hat{\pi}^e_{i,t}$	0.601	0.508	9.01	0.003
	(0.027)***	(0.018)***		
$u_{i,t}$	-0.122	-0.093	3.15	0.076
	(0.020)***	(0.009)***		
$\pi^m_{i,t}$	0.043	0.046	0.06	0.805
	(0.008)***	(0.009)***		
$\hat{\tau}_t$	0.961	1.266	13.2	0.001
	(0.057)***	(0.060)***		
F-stat. for $\bar{u}$	36.05**			
$\bar{u}$	0.0614			
σ	0.0044			
Observations	480			
R-squared	0.860			
Countries	20			

Note: F-stat. for $\bar{u}$ provides a test for threshold effects, with p-values constructed from 10000 bootstrap samples as described by Hansen (1999). F-stat. in column (4) and the corresponding Prob. in column (5) provide the results from testing the null hypothesis that the regime-dependent coefficient is the same across the two regimes. The specification includes regime-invariant panel fixed-effects. Asterisks ***,**,* indicate significance at 1%, 5% and 10% levels respectively.

Appendix A: List of Countries

Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States.

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