Can The Inclusion of International Factors Enhance UK Inflation Forecasting Accuracy?
A Phillips Curve approach for the UK as a Small Open Economy

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Abstract:

This paper applies international factors, from the Euro Area and the US, into parsimonious domestic Phillips curve models to assess whether UK inflation forecasting accuracy can be improved. Year-on-year growth of CPI and CPIH inflation data, from January 2000 until December 2022, is utilised to evaluate the out of sample accuracy of a domestic Workhorse Phillips curve model and subsequent Open Economy Phillips curve model—composed of international slack. This study's initial results are in favour of the related literature; additional domestic indicators within the Phillips curve are not useful in forecasting inflation. However, this study finds that utilising the unemployment rate within the Workhorse Phillips curve leads in forecasting accuracy—highlighting a presence of the traditional Phillips curve relationship. Importantly for monetary policy makers, including international factors greatly improves the forecasting accuracy of the Workhorse model—when combined with domestic slack measures beyond the unemployment rate.

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1. Introduction

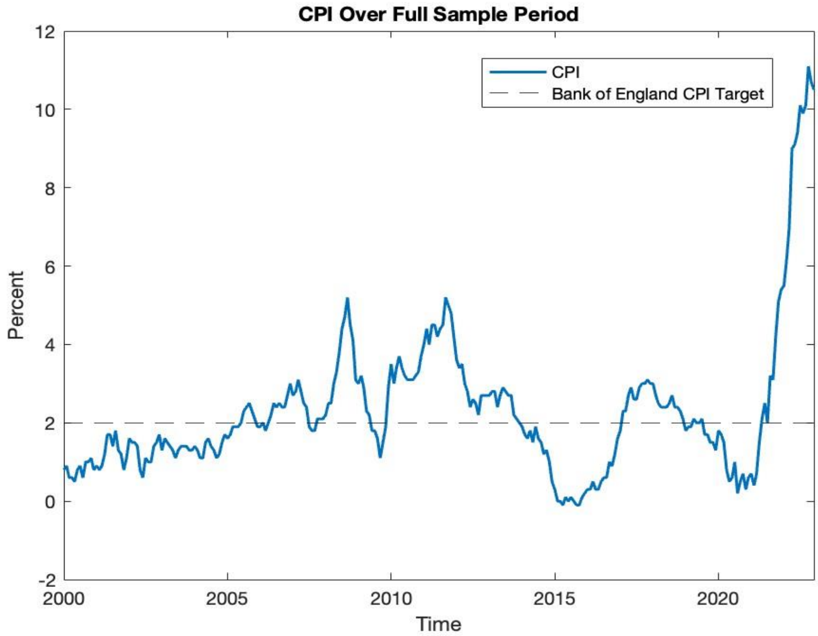
Inflation is the backbone of the global macroeconomy. Therefore, central banks must emphasise accurately forecasting inflation dynamics to achieve price stability. While globally this goal remains shared, across localised regions the targeted inflation interval tends to vary.

The UK began targeting inflation in October 1992, after exiting the Exchange Rate Mechanism. In 1997, the Bank of England was granted full operational independence over the country's inflation target. Since 2004, the Bank has targeted the Consumer Price Index (CPI), as the UK's main measure of inflation, to be at 2%[1]. However, the UK has frequently deviated from this target, particularly when global structural shifts drive domestic inflation, as illustrated in Figure 1.1.

Figure 1.1 displays the CPI series from January 2000 until December 2022, covering this study's full sample period. This sample period covers multiple UK inflation regimes during major economic shocks, including the Global Financial Crisis (2008-2010), Brexit referendum (2016-2017) and the COVID-19 pandemic (2020-2022). During these periods of global economic uncertainty, accurately forecasting inflation becomes critical as monetary policymakers require a reliable estimate of domestic inflation to guide the implementation of recovery monetary policy. However, the Bank of England has demonstrated inconsistency in delivering accurate inflation forecasts, especially in periods of global uncertainty.

[1] See Benati (2005) historical overview of the UK's inflation target

Figure 1.1: CPI inflation from January 2000 until December 2022



CPI has been plotted in year-on-year growth rates, within Figure 1.1, between January 2000 until December 2022 as this study's full sample period. Source: Office for National Statistics (ONS)

This inconsistency was exemplified by the Bank of England's significant misforecast of the impact COVID-19 had on CPI inflation. The Bank anticipated the initial shock of the pandemic as purely transitory, based on forecasts from the Bank's main forecasting model—COMPASS[2]. This resulted in necessary timely monetary policy, such as cutting interest rates, being significantly delayed, as the Bank's forecasts were consistent that inflation would quickly return to its 2% target.

This severe misforecast sparked Bernanke's (2024) extensive review of the Bank of England's forecasting approach, which largely attributed the Bank's unreliable forecasts as a product of its out-of-date forecasting techniques and modelling. Specifically, Bernanke heavily criticised the Bank's COMPASS model—describing it as a "*complicated and unwieldy system*" (Bernanke, 2024, p.6). Bernanke's review concluded with a list of detailed recommendations

[2] The Central Organising Model for Projection Analysis and Scenario Simulation (COMPASS) is a New Keynesian stochastic general equilibrium model. This model has served as the Bank's primary inflation forecasting model since 2011(Source: Bank of England, 2013)

for the Bank of England to enhance its inflation forecasting framework. One of which emphasised that the Bank must replace or reconstruct the COMPASS model over the long term. Bernanke also advised the Bank to place a greater focus on supply-side drivers to UK inflation, such as labour market dynamics, productivity changes and trade disruptions.

Bernanke's (2024) recommendations provide a strong justification for researchers to explore alternative UK inflation forecasting specifications. In contribution, this study employs the Phillips Curve model to forecast UK inflation, which encompasses a negative relationship between economic slack and inflationary trends.

The stability of the Phillips curve framework has remained the subject of a large body of literature, where the joint consensus is that the relationship between economic slack and inflation has flattened over time[3]. Uncertainty around this relationship was sparked by the global missing disinflation period, during the midst of the financial crisis[4]. Within this period, unemployment rose significantly whilst inflation remained on trend, revealing the breakdown of the expected inverse relationship between inflation and economic slack. Therefore, by applying the Phillips curve within this study, inference can be drawn on whether this longstanding macroeconomic relationship remains 'flattened' for the UK's small open economy. Furthermore, the UK's inflation levels remain shaped by global interdependencies. The global disinflation period demonstrates the co-movement of inflation trends across both large and small open economies. Therefore, as the wider macroeconomy becomes increasingly globalised, the global co-movement across inflation levels is ever more apparent.

[3] See Blanchard et al. (2015)
[4] See Coibion and Gorodnichenko (2015)

Auer et al. (2017) highlight how global inflationary forces have gained prominence, particularly through the rise of integrated global value chains and the internationalisation of labour markets. This observed global influence is further magnified within small open economies, where ongoing international trade plays a crucial role in maintaining economic stability. Therefore, it remains imperative to assess the role of international linkages between large and small open economies on domestic inflation levels. An area of study which has been thoroughly investigated for large open economies, yet remains scarcely researched for small open economies—such as the UK. In response, this paper further contributes to the literature by examining whether international macroeconomic factors can improve UK inflation forecasting accuracy.

This study utilises monthly data from January 2000 until December 2022, to estimate expanding window out-of-sample forecasts on the year-on-year growth of the Consumer Price Index (CPI) and Consumer Price Index with Housing Costs (CPIH) series. In doing so, the forecast evaluation period will be between January 2010 to December 2022. Furthermore, by adopting a 1,3,6 and 12-month ahead forecast horizon, this study's Phillips curve forecasts capture the short to medium-long term evolution of UK inflation dynamics. A timeframe of interest to monetary policy makers and the Bank of England in supporting the implementation of appropriately anticipated short to medium-long term monetary policy.

This study also maintains a parsimonious approach across modelling, by incorporating simple Phillips curve specifications as well as employing a small number of total variables. Inflation forecasts are initially estimated from a domestic Workhorse model, utilising solely measures of domestic economic slack to simulate the domestic economy. This model is later interacted with international slack, from both the US and Euro Area. Similar to Renberg and Westman (2023), this latter combination will be referred to as the Open Economy (Phillips Curve) model.

All Phillips curve forecasts will be evaluated relative to the forecasting performance of the Naïve random walk, as the main benchmark, as well as the autoregressive model of order one, AR(1), against the random walk as the competing model. Furthermore, the performance of the Open Economy model's inflation forecasts will be directly compared to the forecasting accuracy of the best-performing domestic Workhorse specifications. The result of this comparison will determine if international spillover effects contribute significantly to the UK's small open economy.

This study finds that incorporating measures of international economic slack, improves inflation forecasting accuracy over competitive univariate benchmarks and most specifications of the best performing Workhorse models. This is highlighted by the lower Mean Squared Forecast Errors (MSFE) and Mean Absolute Forecast Errors (MAFE) from the Open Economy forecasts, compared to the larger forecasting losses associated with the univariate benchmarks and the Workhorse model.

Departing from the related literature, this study also finds that incorporating domestic unemployment within the Workhorse model, reflecting a traditional Phillips curve relationship, enables the Workhorse forecasts to consistently outperform univariate models. Furthermore, incorporating international factors within the traditional Phillips curve model, does improve the model's forecasting accuracy. However, this improvement is shown to be minimal in comparison to the stand-alone forecasting performance of the traditional Phillips curve model.

This result indicates that there is evidence to suggest the Phillips curve relationship remained present within the UK from January 2010 to December 2022. Offering valuable insight to the Bank of England that a parsimonious forecasting approach can serve as a reliable alternative to COMPASS, for forecasting UK inflation.

2. Literature Review

This paper will add to the wide body of literature surrounding inflation forecasting. Across the literature, a recurring theme has been the variety and evolution of empirical modelling. This has included dynamic factor models (Stock and Watson, 1999; Eickmeier and Ziegler, 2008), VARs (Dées and Güntner, 2017; Clements and Galvao, 2013), Bayesian techniques (Cogley et al., 2005; Domit et al., 2019), Phillips curve models (Atkeson and Ohanian, 2001; Kapur, 2013) and machine learning models (Szafranek, 2019; Vargas, 2020).

This literature review will provide an overview of relevant literature in relation to this paper's adopted Phillips curve approach. Firstly, exploring the historical nature, persistence and adaptability of utilising the Phillips Curve to forecast inflation. Secondly, reviewing the limitations of overly specified Phillips curve models and the achievements of simple modelling when forecasting inflation. Finally, examining the incorporation of international slack in improving inflation forecasting accuracy. This paper will utilise both the widely applied domestic 'Workhorse' and Open Economy Phillips curve models to provide out of sample forecasts of UK inflation.

This approach was made possible by the seminal work of Phillips (1958), laying the groundwork for extended empirical studies. By examining 96 years of UK labour market and inflation time series data, Phillips uncovered a negative relationship between unemployment and wage growth—now known as the Phillips curve relationship. The present Phillips curve is acknowledged as an inverse relationship between economic slack and inflation. This relationship has remained widely applied throughout time, with macroeconomists and global policy makers utilising the Phillips curve to set inflation expectations, guide monetary policy and ultimately help forecast inflation. A primary driver of this continued utilisation stems from the ease of adaptability within the Phillips curve framework.

For instance, Bańbura and Bobeica (2023) recently undertook a systematic comparison of several adapted Phillips curve models, to determine which Phillips curve specification aids in forecasting Euro Area inflation. The authors explored Phillips curve specifications which included time-varying inflation trends and alternative economic slack measures beyond the standard unemployment rate. The authors also employ a set of 'new generation' Phillips curve models—incorporating time-varying parameters, stochastic volatility and model-determined measures of economic slack.

Bańbura and Bobeica (2023) find that the flexible formulations of the Phillips curve, particularly the 'new generation' Phillips curve models, can outperform univariate models—including random walk benchmarks such as Atkeson and Ohanian (2001) widely used 'AO' model. Where the inflation rate at $\pi t{+}h$ is forecasted using solely the average inflation rate observed over the previous 4 quarters.

Similarly, Barnichon and Shapiro (2022) recently adapted the Workhorse Phillips curve to incorporate a broad range of domestic slack indicators. These indicators included the traditional unemployment rate, output gap as well as a varied set of labour market indicators. The authors find labour market tightness, particularly the vacancy to unemployment ratio, outperforms conventional slack measures within a Phillips curve model in forecasting US inflation. The authors recommend prioritising such indicators over the traditional unemployment rate to better capture US inflation dynamics. Supporting these findings, Crust et al. (2023) demonstrate that incorporating the vacancy to unemployment ratio, within Phillips curve forecasts can help explain the rising trend of the 12-month core PCE inflation (post 2021).

Notably, Stock and Watson (1999) demonstrate the persistent adaptability of Phillips curve modelling when forecasting inflation. The authors adapted the Workhorse Phillips curve model to accompany 168 domestic US macroeconomic indicators, concluding that the adapted Workhorse model consistently outperformed the traditional Phillips curve-based solely on unemployment. Stock and Watson (1999) results are considered largely robust, as the authors applied sophisticated dynamic factor modelling to mitigate overfitting when forecasting with a large set of predictors. This empirical approach expands upon their earlier work, in Stock and Watson (1998), however their 1999 study was among the first to apply dynamic factor modelling to the Phillips curve.

In this implementation, Stock and Watson (1999) extracted only the latent factors from the total set of 168 macroeconomic indicators. These factors summarise the shared variation across all predictors, negating the inclusion of each slack indicator within each forecast. This modelling approach to forecast inflation has since remained applied within the related literature, see; Eickmeier and Ziegler (2008) and Liu and Jansen (2011).

This paper will take inspiration from the related literature by adopting the adaptable Workhorse Phillips curve model to provide a short to medium-long term out of sample forecast of CPI and CPIH year-on-year growth series. Within these forecasts, domestic economic slack proxies will include the Unemployment rate, Industrial production index, Real effective exchange rate and Interest rate. This study also considers gap-based measures of economic slack, by applying the Unemployment and Industrial production gap within the Workhorse Phillips curve model. These indicators will be largely identical for the Euro Area and the US, within the Open Economy model. Therefore, this study will only utilise a small total array of economic slack indicators for all its Phillips curve inflation forecasts, differing from a large proportion of the related literature—especially Stock and Watson (1999). By doing so, this study will be able to evaluate the contribution of each slack indicator in forecasting UK inflation, rather than just the shared latent factors across all applied predictors. Allowing for more detailed economic interpretation of the stability of the Phillips curve when forecasting UK inflation, whilst maintaining a simpler, parsimonious approach throughout modelling.

The motivation for this study's employed parsimonious methodology is highlighted in the second set of literature below, which investigates the shortcomings surrounding complicated and sophisticated modelling when forecasting inflation.

A strong benchmark within inflation forecasting has often been a simple one, such as the random walk or the AR(1), where the inflation rate at πt+h is forecasted solely by the inflation rate in the previous period (πt). These simple benchmarks have been shown to frequently outperform much more sophisticated models, including empirically complicated Phillips curve models. For instance, Stock and Watson (2007) utilised a simple, parsimonious model to forecast US inflation, which remained linear in estimation whilst including a select few variables. When focusing on forecasting accuracy, their simple model remained consistent in outperforming alternative sophisticated models, importantly, including a set of well-specified Phillips curve models. However, as the authors highlighted, this result suffers criticism as their simple model lacked robustness over the examined forecast horizons compared to conventional benchmarks.

Building on this, Stock and Watson (2008) investigate the forecasting performance of 192 sophisticated forecasting models, including various Phillips curve specifications, against an array of simple univariate benchmarks. The authors conclude that while certain multivariate

Phillips curve models perform well in sub-periods, particularly during high inflation regimes, both the simple random walk of Atkeson and Ohanian (2001) and various AR(1) univariate models remain difficult to outperform. The consensus from this empirical evidence reinforces the premise that sophisticated Phillips curve frameworks struggle to outperform simple benchmarks when forecasting inflation.

Furthermore, Faust and Wright (2013) presented a simple AR(1) model to forecast US inflation. Their model surpassed the forecasting accuracy of the random walk and a set of sophisticated autoregressive models, composed of multiple lags. The authors considered multiple unique measures to evaluate their forecasts across a multitude of short- and long-term forecast horizons. Thus, the author's findings are widely interpreted as a systematic trend of improving forecasting performance from their simple model, rather than forecasting gains derived from capturing short-term inflation persistence or random noise.

In addition to the parsimonious approach adopted by this study, the Phillips curve specification of interest will be an Open Economy model, composed of international slack alongside the best-performing initial set of domestic slack measures. The final set of literature demonstrates the effectiveness of Open Economy models, which build upon the densely studied interconnectedness between the domestic macroeconomy and inflation dynamics.

The initial domestic side focus when forecasting inflation can be traced back to the foundational findings of Phillips (1958), which established a significant emphasis on the domestic economy in shaping inflationary movements. Therefore, subsequent studies which utilised the Phillips curve framework to forecast inflation primarily focused upon domestic measures of economic slack. This included Stock and Watson (1999), whose findings played a crucial role in extending this narrowed approach. The authors failed to significantly capture potential key drivers of US inflation within a globalised context, by mainly focusing upon a domestically centred US Phillips curve[5]. Resulting in much of the extended literature progressing with this trend and largely omitting the potential interconnectedness of the global macroeconomy and domestic inflation dynamics[6].

However, global macroeconomic factors have been shown to be crucial in helping to capture domestic inflation volatility. This has been evidenced by Mumtaz et al. (2011), Ciccarelli and Mojon (2010) and Forbes (2019), who have all researched this area across differing methodologies, yet result in a largely shared conclusion.

Mumtaz et al. (2011) utilised dynamic factor modelling to analyse how global inflation shapes domestic inflation across 36 countries. The author's decomposed inflation rates by global factors, country-specific factors and domestic influences to understand the relative global and domestic contributions to country-specific inflation between 1806 to 2006. The authors found that global factors have played an increasingly significant role in shaping inflation dynamics across all 36 examined countries after 1985. During this period, the global economy experienced a rise in globalisation across supply chains, driven by continued economic integration with the US, EU and Asia.

Ciccarelli and Mojon (2010) highlight the similarities in global inflation patterns shaping national inflation. By focusing on 22 OECD countries, the authors applied both static and dynamic factor models alongside a simple cross country inflation average. The authors find a common global inflation factor across the selected OECD countries, accounting for 70% of the

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[5] Stock and Watson (1999) only consider 5 European exchange rates relative to the US. The remaining 163 measures of economic slack remain entirely domestic
[6] See, for example, Atkeson and Ohanian(2001), Fisher et al (2002) and Dotsey et al. (2018)

total variation in their domestic inflation rates. The authors also explore the forecasting performance of including a global inflation indicator within simple forecasting models. When applied, forecasts resulted in lower Root Mean Squared Errors (RMSE) in comparison to traditional univariate autoregressive models and the domestic Phillips curve. This finding further validates the importance of global factors in helping to explain regional inflation dynamics, particularly within OECD countries.

Supporting this, Forbes (2019) finds that global factors have greatly contributed to shaping CPI inflation. Forbes depicts that whilst domestic slack remains significant in influencing CPI inflation levels, international factors "*have had a stronger relationship with CPI inflation over the last decade*" (Forbes, 2019, p.36). From this finding, Forbes emphasises the increasing importance of including international factors, such as exchange rates and import prices, within inflation forecasts.

This shared conclusion from the related literature validates the continued use of the Open Economy Phillips curve model, which utilises both international and domestic slack measures to forecast inflation. When applied, studies have displayed the strong forecasting performance associated with Open Economy models in comparison to the domestic-centric Workhorse Phillips curve forecasts[7]. However, most of the related literature has placed a focus on applying international factors to help forecast inflation of large open economies. Therefore, examining whether global factors can enhance inflation forecasting of small open economies remains scarcely explored.

[7] See, Kabukçuoğlu and Martínez-García (2018)

Renberg and Westman (2023) contribute to this gap within the literature by focusing upon the application of US, UK, Denmark and Norway economic slack measures to help forecast Sweden's year-on-year core and headline inflation. By utilising parsimonious modelling, the authors find that their Open Economy Phillips curve generated stronger forecasts than those of a random walk. However, this result lacks robustness as the authors fail to include both international interest and exchange rates, within their Open Economy forecasts, as staple global macroeconomic factors influencing Sweden's inflation volatility. This influence remains even more pronounced within small open economies, such as Sweden, where globalisation remains dependent upon to maintain a stable domestic economy. Therefore, the economic state of global markets, which is reflected in the strength of exchange rates and the nominal level of interest rates, plays a crucial role in shaping Swedish inflation.

For the UK, the influence of international factors has hardly been researched when forecasting inflation. However, the Governor of the Bank of England, Andrew Bailey, has recently stated the importance of understanding "*What are the global factors driving UK inflation and economic activity*" as one of the Bank's priority research topics for 2025 (Bank of England, 2024). Therefore, this paper contributes to the literature by employing a small set of international factors, across the US and Euro Area, within a parsimonious Open Economy Phillips curve model to forecast UK inflation. Thereby, assessing whether the inclusion of international factors enhances UK inflation forecasting accuracy.

3. Methodology

To outline the methodology applied within this study, this section first explains the data selection process, followed by describing the out-of-sample forecasting methods utilised. The discussion moves on to outlining the chosen single and multi-period forecast horizons as well as the applied forecasting models. This section concludes by describing the model selection process and the selected loss functions for evaluating forecasting accuracy.

3.1 Data:

Forecasts will be centred around CPI inflation, which the Bank of England aims to maintain at 2%. To achieve this objective, the Bank must also consider broader price measures such as CPIH inflation, which accounts for nationwide occupiers housing costs and may provide additional insights into the persistence of CPI inflation dynamics. Therefore, this study forecasts both CPI and CPIH series, which have been sourced in year-on-year growth rates, to provide useful results for monetary policymakers. However all applied domestic and international variables have been sourced in a monthly frequency in percentage levels.

3.1.1 Variable selection process

To estimate forecasts consistent with a traditional Phillips curve, this study initially employs the domestic unemployment rate together with a variety of alternative domestic slack proxies. Subsequently, international slack indicators are utilised alongside the best-performing domestic slack measures, within an Open Economy Phillips Curve.

3.1.2 Domestic Variables

Domestic slack in the Workhorse model is proxied using indicators from the domestic financial market, labour market, and product market. Domestic financial market indicators include the Interest Rate (IR) and the Real Broad Effective Exchange Rate (RBER). The RBER is a weighted average of the strength of the Pound Sterling against a basket of global major currencies—serving as a close proxy for the UK's domestic currency strength. Unemployment (UE) and the Unemployment Gap (UE-Gap) have been utilised as primary measures of domestic labour market slack, to capture the relationship between the UK's labour market and domestic inflation volatility.

Lastly, Industrial Production (IP) and the Industrial Production Gap (IP-GAP) have been employed as measures of domestic product market slack. Industrial production here serves as an alternative to Real GDP, as both indicators capture a country's total volume of economic output. Hence, the IP-GAP will be interpreted as a proxy for the domestic output gap—the difference between raw industrial production levels and potential industrial production, to highlight whether the UK economy is above or below full production capacity.

3.1.3 Variable Transformations

Given limited data availability for UK economic gap measures, the Hodrick and Prescott (HP) -filter (Hodrick and Prescott, 1997) was applied to the domestic industrial production and unemployment series. By doing so, an estimation of both the domestic IP-Gap and UE-Gap was calculated and applied for study. To maintain consistency in estimation, HP Filtering was identically applied to the US and Euro Area industrial production and unemployment series, to produce the international UE-Gap and IP-Gap measures. The HP Filter was implemented with a smoothing parameter of $\lambda = 14400$, the conventional for monthly data, to derive the trend component for all utilised unemployment and industrial production series. By taking away this trend component from the actual data, the resulting UE-Gap and IP-Gap capture the cyclical deviations from their long-term trend.

Table 3.1: Domestic Predictors – Data Sources and Types

Indicator	Description	Frequency	Variable Type	Source
CPI	Consumer Price Index for the UK	Monthly	Year-on-year growth rates	Office for National Statistics (ONS)
CPIH	Consumer Price Index (with Occupier Housing Costs) for the UK	Monthly	Year-on-year growth rates	ONS
Unemployment Rate	Unemployment rate (% of the total UK labour force, age 16+).	Monthly	%level, Seasonally Adjusted	ONS
Unemployment Gap	Estimated by taking the HP filter potential UE trend (with λ = 14400) from the actual UK UE data	Monthly	%level	ONS (Raw Data) & HP Filter Estimation
Industrial production	The total output of production industries across major UK sectors. Index Base Year=100	Monthly	%level, Seasonally Adjusted	ONS
Industrial production Gap	Estimated by taking the HP filter potential IP trend (with λ = 14400) from the actual IP data	Monthly	%level	ONS (Raw Data) & HP Filter Estimation
Interest Rate	Interest Rate: Long term Government Bond Yields (10 Year Main)	Monthly	%level	St Louis Fed
Real Broad Effective Exchange Rate	Weighted average of bilateral exchange rates adjusted by relative consumer prices. Index 2020=100	Monthly	Nominal %level	St Louis Fed

Note: %level refers to the monthly level of a variable expressed in percentage form

3.1.4 International Variables

International factors from the Euro Area and the US were included within the Open Economy model, due to their significant influence and prominence towards the UK's small open economy. The UK relies heavily on frequent trade with these large open economies, making them potentially important in shaping UK inflation dynamics. For the Euro Area and the US, the sourced slack measures largely mirror the domestic UK variables, to maintain a parsimonious approach. The only distinction lies in the exchange rate measures, where both the USD/GBP and EUR/GBP exchange rates are used to capture international currency strength relative to the UK.

Table 3.2: US Predictors – Data Sources and Types

Indicator	Description	Frequency	Variable Type	Source
Unemployment Rate	Unemployment rate (% of the total US labour force, age 16+ and currently reside in the US).	Monthly	%level, Seasonally Adjusted	St Louis Fed
Unemployment Gap	Estimated by taking the HP filter potential UE trend (with λ = 14400) away from the actual US UE data	Monthly	%level	St Louis Fed (Raw Data) & HP Filter Estimation
Industrial production	The total output of production industries across all US sectors. Index 2017=100	Monthly	%level, Seasonally Adjusted	St Louis Fed
Industrial production Gap	Estimated by taking the HP filter potential IP trend (with λ = 14400) away from the actual US IP data	Monthly	%level	St Louis Fed (Raw Data) & HP Filter Estimation
Interest Rate	Interest Rate (Federal Funds Effective Rate) – Set by the US Federal Reserve.	Monthly	%level	St Louis Fed
USD/GBP	U.S. Dollars to One UK Pound Sterling	Monthly	Nominal %level (Monthly Average Spot Rate)	St Louis Fed

Note: %level refers to the monthly level of a variable expressed in percentage form

Table 3.2: Euro Area Predictors – Data Sources and Types

Indicator	Description	Frequency	Variable Type	Source
Unemployment Rate	Unemployment rate (% of the total Euro Area labour force, age 15 to 74)	Monthly	%level, Seasonally Adjusted	ECB
Unemployment Gap	Estimated by taking the HP filter potential UE trend (with λ = 14400) away from the actual Euro Area UE data	Monthly	%level	ECB (Raw Data) and HP Filter Estimation
Industrial production	The total output of production industries across all Euro Area sectors (excluding construction). Index 2021=100	Monthly	%level, Seasonally Adjusted	ECB
Industrial production Gap	Estimated by taking the HP filter potential IP trend (with λ = 14400) away from the actual Euro Area IP data	Monthly	%level	ECB (Raw Data) and HP Filter Estimation
Interest Rate	Interest Rate (Main Refinancing Operation—set by the ECB)	Monthly	%level, Seasonally adjusted	ECB
EUR/GBP	EURO to One UK Pound Sterling	Monthly	Nominal %level (Monthly Average Spot Rate)	Bank of England

Note: %level refers to the monthly level of a variable expressed in percentage form

3.1.5 Data Sourcing

CPI and CPIH series, domestic unemployment and industrial production datasets were sourced from the Office for National Statistics (ONS). However, due to a lack of data availability, the domestic Interest Rate (IR) and the Real Broad Effective Exchange Rate (RBEER) series were sourced from the St Louis Fed. Likewise, all applied US variables were sourced from the St Louis Fed, whereas all utilised Euro Area variables were obtained from the European Central Bank (ECB)—aside from the EUR/GBP exchange rate series which was sourced from the Bank of England's database.

3.2 Out of Sample Forecasting Methodology

The full sample period will be between January 2000 until December 2022, within this the training sample will consist of 120 observations spanning from January 2000 to December 2009. Therefore, this study's forecast evaluation period will be from January 2010 until December 2022.

This study employs an expanding window out of sample approach to forecast CPI and CPIH year-on-year growth. This method involves utilising an initial training sample which is recursively expanded by adding one observation for every step ahead forecast, to generate the next step ahead forecast. For example, using the initial training sample between 2000M1 until 2009M12, the first inflation forecast will be for 2010M1. The training sample is then updated by the actual inflation observation of 2010M1, to now be fixed between 2000M1 until 2010M1, to generate the 2010M2 inflation forecast. Each time the training sample updates, the parameter estimates and autoregressive coefficients are re-estimated until the last out of sample inflation forecast for 2022M12.

3.2.1 Forecast Horizons

From utilising monthly data, this study will focus initially upon the one-month ahead forecast ($h=1$). This will then be expanded to a multi-period forecast horizon, including the three, six and twelve-month ahead inflation forecast ($h = 3$, 6 & 12).

At the one step ahead forecast ($h=1$), both direct and iterative forecasting methods are identical in estimation. However, when estimating a multiperiod ahead forecast ($h>1$) the two forecasting approaches will result in differences throughout forecast estimation. The iterative forecast iterates the one step ahead forecast within each next step ahead forecast, until the end of the evaluation period. Whereas a direct forecast involves creating a new model for each step ahead forecast, which is estimated using only the current values of the predictor variables.

Marcellino et al. (2006) notable comparison of the two forecasting methods highlights that iterative forecasts are associated with a lower MSFE than direct forecasts, provided the one step ahead forecast is correctly specified. However, direct forecasts are less prone to initial model misspecification. Ultimately, the authors conclude that the performance of the iterative forecasts significantly outweighs the direct forecast, and the predictive accuracy of iterative forecasting improves as the forecast horizon extends. Given the growing multiperiod forecast horizon adopted within this study, the iterative forecasting method has been utilised to account for these forecasting advantages.

Under this employed iterative approach, if T0 represents the end of the training sample and $h=1$, for the one step ahead forecast, the first out of sample forecast will be of T0+1. The result of this forecast will then be incorporated within the forecasting model when estimating the next forecast at T0+2. This iterative process will continue until the last out of sample forecast at Th, where T represents the final actual observation in the dataset.

3.2.2 Forecasting Models

The Workhorse model will incorporate only one lag of domestic inflation alongside one lag of domestic macroeconomic slack. The Open Economy model will remain identical in specification to the Workhorse model, only differing to include an additional lag of international slack to maintain parsimony. Furthermore, this study exclusively utilises univariate benchmarks to provide a strong model of comparison to the Phillips curve.

3.2.3 Benchmark Model

The main benchmark model will be a Naïve random walk, where inflation in the next period (π_{t+h}) is forecasted by its value within the previous period (π_t).

$$\pi_{t+h} = \pi_{t+h} \tag{3.1}$$

- π_t refers to the year-on-year growth rate of CPI or CPIH inflation at time t, therefore, π_{t+h} is the respective inflation rate at time t+h.

3.2.4 Competing Benchmark Model

The competing benchmark model is an autoregressive model of order one AR(1), which will be evaluated in forecasting performance relative to the random walk

$$\pi_{t+h} = \alpha_0 + \beta\pi_t + \varepsilon_{t+h} \tag{3.2}$$

- α_0 is the intercept term, β is the autoregressive parameter estimated from OLS and ε_{t+h} represents the error term. If β=1 & α_0= 0, then this model specification becomes a random walk

3.2.5 Workhorse Phillips Curve Model

Domestic inflation forecasts will be estimated utilising the widely applied Workhorse Phillips curve model.

$$\pi_{t+h} = \alpha_0 + \beta(L)\pi_t + \gamma(L)X_t + \varepsilon_{t+h} \tag{3.3}$$

- Xt is a measure of domestic slack at time t, $\beta(L)$ is the lag polynomial of inflation at time t and $\gamma(L)$ is the lag polynomial of domestic slack at time t. ε_{t+h} represents the error term. If Xt=0 and $\beta(L) = \beta(1)$, then this model specification becomes an AR(1) model.

3.2.6 Open Economy Phillips Curve Model

The model specification which will answer the research question of this study, will be an Open Economy Phillips curve. This model will integrate a set of international slack indicators, Vt, alongside the best performing set of domestic slack measures (Xt)—estimated using model (3.3).

$$\pi_{t+h} = \alpha_0 + \beta(L)\pi_t + \gamma(L)X_t + \delta(L)V_t + \varepsilon_{t+h} \tag{3.4}$$

- Vt is a measure of international slack at time t, δ(L) is the lag polynomial of an international slack measure at time t. ε_{t+h} is the error term. If V_t=0, then this model specification becomes a Workhorse Phillips curve model.

3.2.6 Applied Loss Functions & Evaluation Framework

For evaluating forecasting performance, this study applies the Mean Absolute Forecast Error (MAFE) and the Mean Squared Forecast Error (MSFE).

$$MAFE: \frac{1}{T-h-T0+1} \sum_{t=T0}^{T-h} |y_{t+h} - \hat{y}_{t+h|t}| \tag{3.5}$$

$$MSFE: \frac{1}{T-h-T0+1} \sum_{t=T0}^{T-h} \left(y_{t+h} - \hat{y}_{t+h|t}\right)^2 \tag{3.6}$$

- yt+h is the actual inflation value at time t+h and $\hat{y}_{t+h|t}$ is the h-step ahead inflation forecast—given the information up to time t. T0 represents the end of the training sample and T represents the last actual inflation observation within the dataset.

Both loss functions difference the model's forecast from the actual inflation data, to calculate the resulting forecasting loss. Therefore, greater forecasting accuracy is achieved when the

MAFE or MSFE values are closest to zero. The MAFE derives an absolute measure of the loss of a particular forecast, whereas the MSFE will square all forecasting losses. Subsequently, the MSFE will prefer smaller errors and punish larger errors significantly more than the MAFE.

4. Results

This section displays the forecasting results for CPI and CPIH measures of UK inflation, comparing the performance of the domestic Workhorse Phillips curve, Open Economy Phillips curve and univariate benchmarks. The primary benchmark model is a Naïve random walk (RW), and the main competing model is an autoregressive model of order one, AR(1), evaluated relative to the random walk—hereafter denoted as the 'AR(1)/RW' model.

The forecasting accuracy of the Workhorse, AR(1) and Open Economy models is evaluated using their relative MSFE and MAFE against the random walk benchmark. A relative MSFE or MAFE below 1 indicates that the random walk performs worse than the competing forecasting model, while a value greater than 1 suggests the random walk performs better. A relative MSFE or MAFE of exactly 1 implies that the compared inflation forecasting model performs as well as the random walk benchmark.

4.1 Competing Benchmark Model Results

Table 4.1: Competing Benchmark Results - CPI

Competing Benchmark Results - CPI				
AR(1)/RW:	MSFE (h=1)	MSFE (h=3)	MSFE (h=6)	MSFE (h=12)
	0.9972	0.9928	0.9888	0.9874
	MAFE (h=1)	MAFE(h=3)	MAFE (h=6)	MAFE (h=12)
	0.9961	0.9883	0.9785	0.9673

Table 4.2: Competing Benchmark Results - CPIH

Competing Benchmark Results - CPIH	MSFE (h=1)	MSFE (h=3)	MSFE (h=6)	MSFE (h=12)
AR(1)/RW:	0.997	0.9921	0.9872	0.9836
	MAFE (h=1)	MAFE(h=3)	MAFE (h=6)	MAFE (h=12)
	0.9947	0.985	0.973	0.9564

Table 4.1 & Table 4.2 display the results of the AR(1)/RW model in forecasting both CPI and CPIH series, across all estimated forecast horizons (1, 3, 6 and 12 months ahead). These results have been estimated using an iterative expanding window with a training sample of 120 observations. The AR(1) and RW forecasts were estimated utilising solely one lag of domestic inflation, of which the relative performance (MSFE & MAFE) of the AR(1) against the random walk is reported in the above tables.

The results shown in Tables (4.1) and (4.2) highlight that across the single and multi-period forecast horizons, for both CPI and CPIH series, the AR(1) model consistently improves over the Naïve random walk—establishing a strong competing model for evaluating the Phillips curve forecasts. The lowest MSFE of the AR(1)/RW is noted at 0.9921 at the 3-month ahead CPIH forecast, whilst its lowest MAFE is 0.9564 at the one-year ahead forecast of CPIH inflation.

Furthermore, Table (4.2) shows that the AR(1) model strengthens in predictive accuracy when forecasting CPIH inflation in comparison to CPI inflation. This difference in forecasting strength likely reflects the inclusion of owner-occupied housing costs within the CPIH series, possibly reducing inflation volatility by accounting for largely stable housing market trends. The relative stability of housing costs thus appears to enhance the AR(1) model's ability to distinguish persistent inflation dynamics from transient noise.

4.2 Workhorse Model Results

To aid in readability, the domestic Workhorse results, within Tables (4.3) and (4.4), are presented using a simple colour-coding structure. To explain, all Workhorse Phillips curve forecasts that outperform the random walk and the AR(1)/RW are highlighted in green, whereas Workhorse forecasts which do not beat the random walk and the AR(1)/RW are highlighted in red. Finally, Workhorse forecasts which improve over the random walk but are outperformed by the competing AR(1)/RW have been highlighted in grey. Any MSFE or MAFE of exactly 1 has been left blank.

Table 4.3: Workhorse Model Results for Forecasting CPI

CPI - Domestic Predictors (UK) - PC/RW	MSFE (h=1)	MAFE (h=1)	MSFE (h=3)	MAFE(h=3)	MSFE (h=6)	MAFE (h=6)	MSFE (h=12)	MAFE (h=12)
Unemployment Rate	0.9908	0.9918	0.9761	0.9762	0.9617	0.9598	0.9516	0.947
Interest Rate	0.9967	0.9966	0.991	0.9901	0.9844	0.9809	0.9766	0.9654
Industrial Production Index	0.9993	0.9989	0.9991	0.9963	1.009	0.9922	1.0089	0.9869
Real Broad Effective Exchange Rate	0.9987	0.9998	0.9977	0.9989	0.999	0.9994	1.0076	1.0066
Unemployment Gap	0.9987	1.0009	0.9977	1.0021	0.999	1.0054	1.0088	1.0199
Industrial Production Gap	1.0048	1.0021	1.0178	1.0055	1.0429	1.013	1.0988	1.0243

Table 4.3 reports the relative performance (MSFE & MAFE) of the Workhorse model against the Naïve random walk in forecasting CPI inflation, across all estimated forecast horizons (1, 3, 6 and 12 months ahead). Table (4.3) Workhorse results were estimated utilising an iterative expanding window with an initial training sample of 120 observations. From which, one lag of CPI inflation was utilised alongside one lag of domestic economic slack. All Workhorse inflation forecasts were calculated using equation (3.3).

Green – Workhorse model outperforms both AR(1)/RW & the random walk
Grey – Workhorse model improves over the random walk but not the AR(1)/RW
Red – Workhorse model does not improve over the random walk or the AR(1)/RW

Table (4.3) shows that additional domestic slack proxies beyond the unemployment rate, are not useful in capturing UK inflation dynamics. While applying the domestic interest rate, industrial production index and real broad effective exchange rate can improve the Workhorse model forecasts over the Naïve random walk, these specifications of the Workhorse model lack consistency in forecasting performance relative to the AR(1)/RW.

However, applying the unemployment rate within the Workhorse model leads to the model outperforming both the random walk and the AR(1)/RW across the entire forecast horizon. Furthermore, in comparison to all other examined proxies of domestic slack, applying the unemployment rate within the Workhorse model produces a lower relative MSFE and MAFE for each step-ahead CPI inflation forecast.

This result demonstrates the significant role of labour market slack shaping UK inflation dynamics, aligning with Phillips' (1958) original findings for the UK's small open economy. Therefore, as applying the unemployment rate within the Phillips curve model embodies a traditional Phillips curve relationship, these initial findings begin to indicate the presence of the Phillips curve in the UK—for this forecast evaluation period.

Table 4.4: Workhorse Model Results for Forecasting CPIH

CPIH - Domestic Predictors (UK) - PC/RW	MSFE (h=1)	MAFE (h=1)	MSFE (h=3)	MAFE(h=3)	MSFE (h=6)	MAFE (h=6)	MSFE (h=12)	MAFE (h=12)
Unemployment Rate	0.9901	0.9932	0.9733	0.9811	0.9541	0.967	0.9325	0.9551
Interest Rate	0.9976	0.9967	0.9938	0.9904	0.99	0.9818	0.9871	0.9682
Industrial Production Index	1.0006	0.9981	1.0024	0.9942	1.0065	0.9898	1.0173	0.983
Real Broad Effective Exchange Rate	0.9996	0.9988	0.9995	0.9967	1.0009	0.9945	1.0071	0.9937
Unemployment Gap	0.9962	0.9985	0.9909	0.9967	0.9877	0.9987	0.9929	1.0139
Industrial Production Gap	1.0069	1.002	1.0231	1.0016	1.0505	1.0064	1.1053	1.0123

Table 4.4 reports the relative performance (MSFE & MAFE) of the Workhorse model against the Naïve random walk in forecasting CPIH inflation, across all estimated forecast horizons (1, 3, 6 and 12 months ahead). Table (4.4) Workhorse results were estimated utilising an iterative expanding window with an initial training sample of 120 observations. From which, one lag of CPIH inflation was utilised alongside one lag of domestic economic slack. All Workhorse inflation forecasts were calculated using equation (3.3).

Green – Workhorse Phillips curve outperforms both AR(1)/RW & the random walk
Grey – Workhorse Phillips curve improves over the random walk but not the AR(1)/RW
Red – Workhorse Phillips curve does not improve over the random walk or the AR(1)/RW

Table (4.4) presents the Workhorse model forecasts of CPIH inflation. Evidently, most domestic indicators continue to struggle in providing any consistent forecasting gains over the competing univariate benchmarks, despite exhibiting lower MSFE and MAFE in comparison to the model's CPI forecasts. However, domestic unemployment remains an exception as its inclusion within the Workhorse model results in the model consistently outperforming the competing univariate models.

From the results displayed in both Tables (4.3) and (4.4), in comparison to applying any other domestic indicator within the Workhorse model, utilising the unemployment rate, when forecasting both CPI and CPIH measures of inflation, leads greatly in forecasting performance. Affirming that there is evidence to suggest that the traditional Phillips curve relationship remained prominent within the UK between January 2010 until December 2022, as this study's forecast evaluation period.

4.2.1 Workhorse Model Results – Summary

The results shown in Tables (4.3) and (4.4) highlight that an AR(1)/RW benchmark, which forecasts the one step ahead inflation rate iteratively with one lag of inflation, consistently outperforms the forecasting performance of Workhorse models that incorporate additional domestic slack proxies beyond the unemployment rate. This finding aligns with the works of Renberg and Westman (2023) on Swedish inflation, Banbura and Bobeica's (2023) on EU inflation and Faust and Wright (2013) on US inflation. These studies similarly concluded that incorporating various proxies of domestic slack within a Workhorse Phillips curve does not provide forecasting gains over univariate models.

Uniquely, this study finds that applying the domestic unemployment rate within the Workhorse Phillips curve, consistently enhances the forecasting performance of the Workhorse model relative to univariate benchmarks. This finding remains observed throughout the post-financial crisis period, where the presence of the Phillips curve relationship within the UK has been widely debated—see Castle and Hendry (2024). This study in comparison, finds that there is evidence to suggest that the traditional Phillips curve relationship remained in the UK.

Figure (4.1) visually demonstrates the forecasting performance of this observed traditional Phillips curve, highlighting how the Phillips curve strongly captures broad inflation trends from 2012 to 2019—across both CPI and CPIH series. In particular, the Workhorse model displays greater responsiveness in capturing the short-medium term fluctuations of CPI inflation, compared to the smoother and less reactive CPIH inflation trends. However, when comparing the forecasted values of the Workhorse model to actual CPI and CPIH outturns, within Figure (4.1), an episodic nature of the traditional Phillips curve is clear. In particular, the Phillips curve performs well in periods of demand-driven inflation but struggles in presenting accurate forecasts when supply side shocks and structural shifts drive UK inflation.

For instance, the Workhorse model underpredicts CPI and CPIH inflation during the post-financial crisis recovery period of 2010-2012, moving then to overpredict inflation levels for the remainder of this period (2012 – 2015). A period when low wage growth and the Bank of England's quantitative easing efforts kept inflation pressures subdued despite falling unemployment. This episodic pattern continues, as the Workhorse model overpredicts inflation following the immediate Brexit period of 2016 – 2017. This is likely due to the significant sterling depreciation at the time causing severe import cost pressures on the UK economy.

The episodic performance of the traditional Workhorse Phillips curve found within this study is consistent with the related literature, such as Ball and Mazumder (2011) and Forbes et al. (2017), in demonstrating the persistent challenges of observing a consistently stable Phillips curve relationship across the post-crisis period. Furthermore, the former Deputy Governor of the Bank of England once described this phenomenon as "*one of the key puzzles of the post recovery economy in the UK and in advanced economies*" (Sir Jon Cunliffe, 2017, p.4).

Figure 4.1: CPI & CPIH inflation forecasts from the Workhorse model against actual inflation outturns

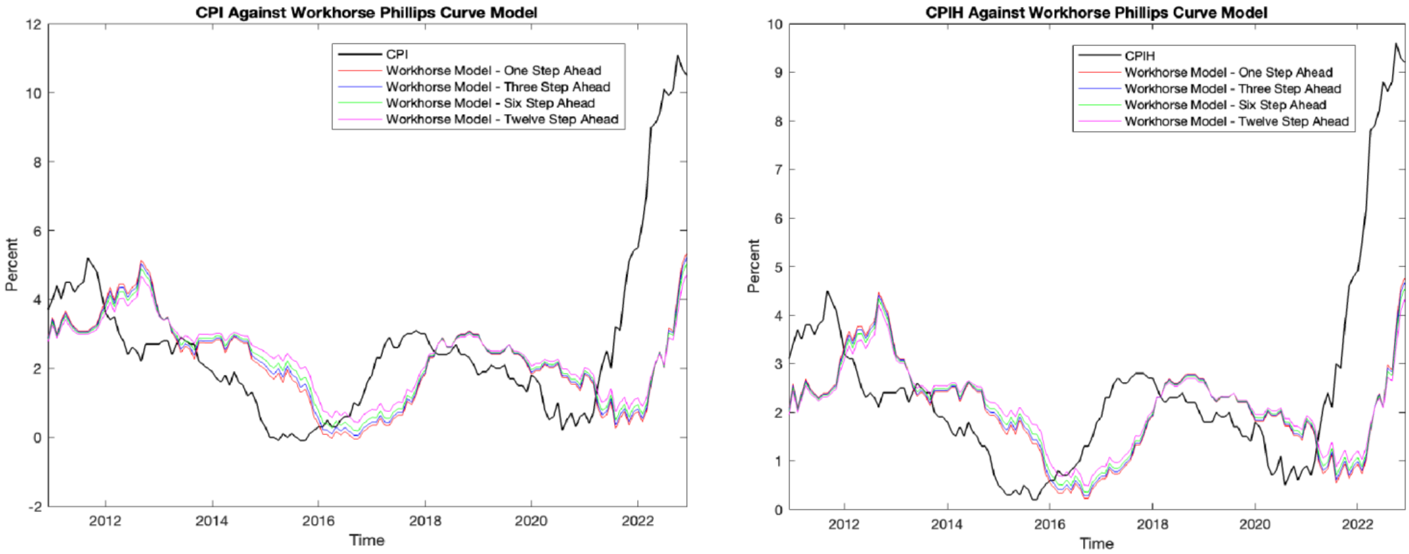


Figure 4.1 displays the out of sample forecasting performance of the Workhorse model, which is composed of one lag of CPI or CPIH inflation and one lag of the domestic unemployment rate, across the 1, 3, 6 and 12 month ahead forecast horizons. The Workhorse model in Figure 4.1 was estimated utilising an iterative expanding window, with an initial training sample of 120 observations.

4.2 Open Economy Results

This section displays the main results of this study, whether the inclusion of international factors improves UK inflation forecasting. In answering this question, this study combines all sourced international slack indicators with the best performing set of domestic indicators. This will determine if the contribution of international factors can improve the forecasting accuracy of the strongest domestic Workhorse models.

For each Workhorse model specification, the best performing domestic slack indicators to combine with each international indicator were selected by the criterion of the lowest average MSFE and MAFE across the full forecast horizon. Applying the domestic unemployment rate, interest rate and industrial production index provided the lowest average forecasting errors when utilised in the Workhorse model. Therefore, these domestic indicators were incorporated within the Open Economy model, in combination with international factors.

The competing benchmark of the Open Economy model remains as the AR(1)/RW [8]. The forecasting loss difference, measured by the MSFE and MAFE, between the Workhorse and Open Economy models will serve as the primary metric for assessing the comparative performance of both models—conditional on both models using the same domestic slack proxy. The result of this comparison will be the key indicator to determine if an Open Economy model improves UK inflation forecasting accuracy.

For ease of readability, the below Open Economy result Tables (4.5) (4.6), (4.7) and (4.8), display only the best performing domestic indicators that improved the most in forecasting accuracy when combined with a variety of Euro Area and US slack indicators[9]. For the US, Tables (4.5) and (4.6) display the results of combining the domestic unemployment rate, to forecast CPI inflation, and the domestic interest rate, to forecast CPIH inflation, with US slack indicators. For the Euro Area, Tables (4.7) and (4.8) present the results of combining the domestic interest rate with a variety of Euro Area slack, for forecasting both CPI and CPIH inflation.

Within Tables (4.5) (4.6), (4.7) and (4.8), all Open Economy forecasts that improve over the Workhorse model, when applied with the same domestic indicator, have been placed in bold. Moreover, any Open Economy forecast which performs the same as the AR(1)/RW benchmark has been left blank. The remaining interpretation of the Open Economy results against the benchmark models will be identical to the colour coding structure of the Workhorse model results[10].

[8] See the competing benchmark results, within Tables (4.1) and (4.2).
[9] If needed for future study, Appendix A & B contains the full set of the best performing Open Economy model results.
[10] See Tables (4.3) and (4.4) for a simple explanation of this colour structure

Table 4.5: (US) Open Economy Model Results for Forecasting CPI Inflation with Domestic Unemployment

(CPI) US Open Economy Model - PC/RW:	MSFE (h=1)	MAFE (h=1)	MSFE (h=3)	MAFE(h=3)	MSFE (h=6)	MAFE (h=6)	MSFE (h=12)	MAFE (h=12)
US Unemployment Rate	0.991	0.992	0.9766	0.9768	0.9621	0.96	**0.9511**	**0.9468**
US Interest Rate	**0.9891**	**0.9913**	**0.9715**	**0.975**	**0.9534**	**0.9575**	**0.9481**	**0.9426**
US Industrial Production Index	**0.9892**	**0.9908**	0.9769	0.9763	0.9724	0.9669	0.9812	0.9707
USD/GBP	0.9953	**0.9765**	1.0502	0.9875	1.2179	1.1235	1.6104	1.4024
US Unemployment Gap	**0.9882**	**0.9897**	**0.9717**	**0.9716**	**0.9596**	**0.9552**	0.9599	0.95
US Industrial Production Gap	**0.9845**	**0.9836**	**0.9717**	**0.962**	0.9803	**0.957**	1.0333	1.0173

Table 4.5 reports the relative MSFE & MAFE of the Open Economy model against the Naïve random walk in forecasting CPI inflation, across the 1,3,6 and 12-month forecast horizons. Table (4.5) Open Economy results were estimated utilising an iterative expanding window with an initial training sample of 120 observations. From which, one lag of CPI inflation was applied alongside one lag of domestic unemployment and one lag of US slack. Table 4.5 Open Economy inflation forecasts were calculated using equation (3.4).

Bold – Open Economy model outperforms the Workhorse model, when both models utilise the same domestic slack indicator
Green – Open Economy model improves over AR(1)/RW and the random walk
Grey – Open Economy model improves over the random walk but not the AR(1)/RW
Red – Open Economy model does not improve over the random walk or the AR(1)/RW

As shown in Table (4.5), the predictive accuracy of the observed traditional Phillips curve improves when applied with a variety of US indicators to forecast CPI inflation. In particular, the combination of the US interest rate with domestic unemployment results in forecasting gains over the domestic Workhorse model, for each step ahead forecast.

However, combining US unemployment alongside domestic unemployment maintains a similar performance to the Workhorse model for the short-term CPI forecast. However, this Open Economy combination enhances in forecasting performance as the horizon grows, ultimately outperforming the Workhorse model at the one year ahead forecast. This indicates that US unemployment trends are more useful in capturing medium-long term UK inflation dynamics rather than the short-term. Overall, the strong observed forecasting performance of the traditional Phillips curve appears to be largely improved upon when combined with US slack indicators.

Table 4.6: (US) Open Economy Model Results for Forecasting CPIH Inflation with the Domestic Interest Rate

(CPIH) US Open Economy Model - PC/RW :	MSFE (h=1)	MAFE (h=1)	MSFE (h=3)	MAFE(h=3)	MSFE (h=6)	MAFE (h=6)	MSFE (h=12)	MAFE (h=12)
US Unemployment Rate	**0.9928**	**0.9924**	**0.9811**	**0.9794**	**0.9687**	**0.9626**	**0.9571**	**0.9389**
US Interest Rate	**0.9961**	0.9989	**0.9894**	0.9968	**0.9819**	0.9943	**0.9741**	0.9911
US Industrial Production Index	**0.9927**	0.9998	**0.9887**	1.0046	0.9983	1.0184	1.0372	1.0602
USD/GBP	1.0123	**0.9899**	1.0491	**0.9775**	1.1228	0.9822	1.2897	1.0578
US Unemployment Gap	**0.9932**	**0.9954**	**0.9853**	**0.9881**	**0.9827**	**0.9815**	0.9911	0.9814
US Industrial Production Gap	**0.9916**	**0.9926**	**0.9803**	**0.9797**	**0.9728**	**0.9666**	**0.9731**	**0.9546**

Table 4.6 reports the relative MSFE & MAFE of the Open Economy model against the Naïve random walk in forecasting CPIH inflation, across the 1,3,6 and 12-month forecast horizons. Table (4.6) Open Economy results were estimated utilising an iterative expanding window with an initial training sample of 120 observations. From which, one lag of CPIH inflation was applied alongside one lag of the domestic interest rate and one lag of US slack. Table 4.6 Open Economy inflation forecasts were calculated using equation (3.4).

Bold – Open Economy model outperforms the Workhorse model, when both models utilise the same domestic slack indicator
Green – Open Economy model improves over AR(1)/RW and the random walk
Grey – Open Economy model improves over the random walk but not the AR(1)/RW
Red – Open Economy model does not improve over the random walk or the AR(1)/RW

Introducing US slack proxies alongside the domestic interest rate within an Open Economy model, as shown in Table 4.6, greatly improves upon the forecasting performance of the Workhorse model, the random walk and the AR(1)/RW. The lowest reported MAFE of this combination is 0.9389, and the lowest MSFE is 0.9571, at the one year ahead CPIH forecast. Furthermore, this Open Economy specification consistently surpasses the forecasting accuracy of the Workhorse model, across all estimated forecast horizons, when combining the domestic interest rate with either the US unemployment rate or the US industrial production gap.

In contrast, Table 4.4 revealed that the domestic Workhorse model, when utilised only with the domestic interest rate, failed to outperform the AR(1)/RW benchmark at any forecast horizon. This stark difference in forecasting performance begins to highlight the inherent limitations of domestic-focused inflation forecasting models and the subsequent importance of including international variables to improve UK inflation forecasting accuracy.

Table 4.7: (Euro Area) Open Economy Model Results for Forecasting CPI Inflation with the Domestic Interest Rate

(CPI) Euro Area Open Economy Model - PC/RW:	MSFE (h=1)	MAFE (h=1)	MSFE (h=3)	MAFE(h=3)	MSFE (h=6)	MAFE (h=6)	MSFE (h=12)	MAFE (h=12)
Euro Area Unemployment Rate	**0.9939**	1.0051	0.9916	1.0179	1.0069	1.0495	1.0782	1.1286
Euro Area Interest Rate	0.9968	1.003	0.9918	1.0085	0.9872	1.0171	0.9853	1.0335
Euro Area Industrial Production Index	**0.9887**	0.9988	**0.9742**	0.9988	**0.9665**	1.0081	0.9773	1.0456
EUR/GBP	**0.9729**	**0.9936**	**0.9394**	0.9913	**0.9246**	1.0119	**0.9561**	1.0752
Euro Area Unemployment Gap	**0.9946**	**0.9944**	**0.9859**	**0.9838**	**0.977**	**0.9701**	**0.9692**	**0.9503**
Euro Industrial Production Gap	**0.9942**	**0.9875**	**0.9863**	**0.9654**	**0.9811**	**0.9393**	0.9834	**0.9066**

Table 4.7 reports the relative MSFE & MAFE of the Open Economy model against the Naïve random walk in forecasting CPI inflation, across the 1,3,6 and 12-month forecast horizons. Table (4.7) Open Economy results were estimated utilising an iterative expanding window with an initial training sample of 120 observations. From which, one lag of CPI inflation was applied alongside one lag of the domestic interest rate and one lag of Euro Area slack. Table 4.7 Open Economy inflation forecasts were calculated using equation (3.4).

Bold – Open Economy model outperforms the Workhorse model, when both models utilise the same domestic slack indicator
Green – Open Economy model improves over AR(1)/RW and the random walk
Grey – Open Economy model improves over the random walk but not the AR(1)/RW
Red – Open Economy model does not improve over the random walk or the AR(1)/RW

Table 4.8: (Euro Area) Open Economy Model Results for Forecasting CPIH Inflation with the Domestic Interest Rate

(CPIH) Euro Area Open Economy Model - PC/RW:	MSFE (h=1)	MAFE (h=1)	MSFE (h=3)	MAFE(h=3)	MSFE (h=6)	MAFE (h=6)	MSFE (h=12)	MAFE (h=12)
Euro Area Unemployment Rate	**0.9889**	1.002	**0.9818**	1.0128	0.9981	1.0415	1.0813	1.1339
Euro Area Interest Rate	**0.996**	1.003	**0.9897**	1.0091	**0.9833**	1.0196	**0.9789**	1.0405
Euro Area Industrial Production Index	**0.9838**	**0.9981**	**0.9677**	1.0039	**0.9683**	1.029	1.0052	1.0776
EUR/GBP	**0.9822**	**0.9942**	**0.9568**	0.9871	**0.9378**	0.9909	**0.9401**	1.0174
EU Unemployment Gap	**0.9935**	**0.9918**	**0.9838**	**0.9776**	**0.9751**	**0.9616**	**0.9702**	**0.9428**
EU Industrial Production Gap	**0.991**	**0.9817**	**0.9796**	**0.9509**	**0.9738**	**0.916**	**0.9814**	**0.8771**

Table 4.8 reports the relative MSFE & MAFE of the Open Economy model against the Naïve random walk in forecasting CPIH inflation, across the 1,3,6 and 12-month forecast horizons. Table (4.8) Open Economy results were estimated utilising an iterative expanding window with an initial training sample of 120 observations. From which, one lag of CPIH inflation was applied alongside one lag of the domestic interest rate and one lag of Euro Area slack. Table 4.8 Open Economy inflation forecasts were calculated using equation (3.4).

Bold – Open Economy model outperforms the Workhorse model, when both models utilise the same domestic slack indicator
Green – Open Economy model improves over AR(1)/RW and the random walk
Grey – Open Economy model improves over the random walk but not the AR(1)/RW
Red – Open Economy model does not improve over the random walk or the AR(1)/RW

Tables 4.7 and 4.8 display the forecasting performance of applying the domestic interest rate jointly with Euro Area slack variables to forecast CPI and CPIH inflation. Comparable to the US Open Economy results, presented in Tables 4.5 and 4.6, the inclusion of Euro Area slack indicators demonstrates that international factors can greatly enhance the forecasting accuracy of both CPI and CPIH inflation series, relative to the domestic Workhorse model.

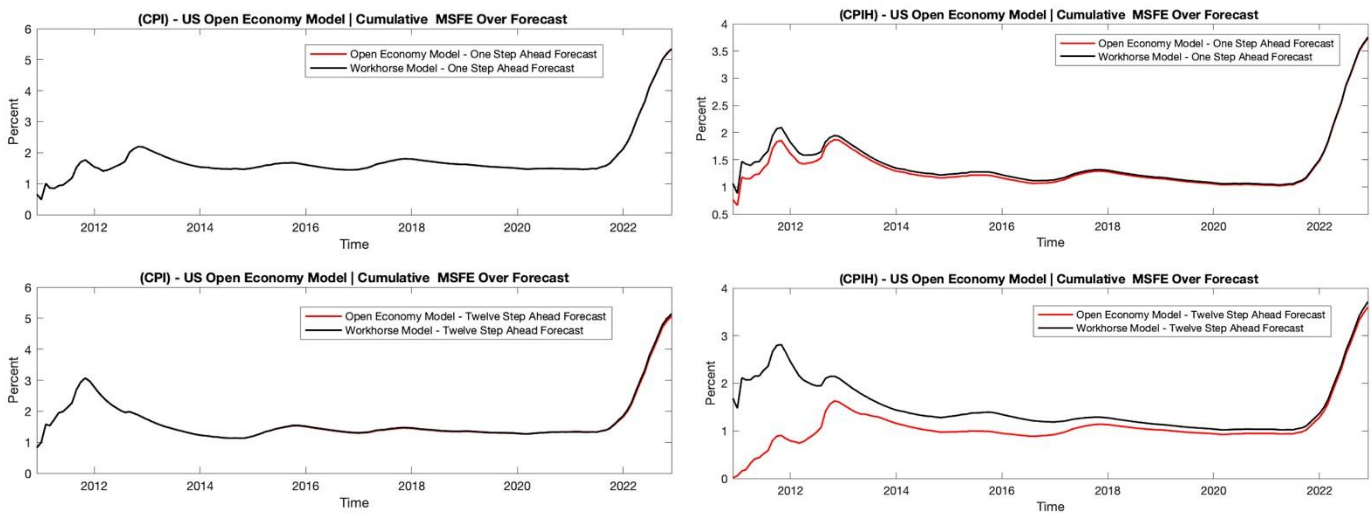
Notably, combining the Euro Area unemployment gap and industrial production gap with the domestic interest rate outperforms the forecasting accuracy of the Workhorse model across all estimated forecast horizons. The lowest MAFE of this combination is 0.8771 at the one year ahead forecast. However, the Euro Area Open Economy specification with the lowest MSFE of 0.9378, combines the EUR/GBP exchange rate alongside the domestic interest rate.

These results suggest that the anticipation of Brexit weakening economic ties, reducing trade flows, and diminishing the UK's sensitivity to Euro Area business cycles, put forward by Dhingra et al. (2017), has not fully materialised when focusing on the co-movements of UK and Euro Area inflation dynamics. As the results shown in Tables (4.7) and (4.8) highlight, the Euro’s currency strength as well as cyclical deviations from long-run Euro Area economic trends can help to capture UK inflation volatility and thus improve UK inflation forecasting accuracy. Thus, strengthening the deep economic interdependence between the Euro Area and the UK, despite the long-lasting structural shift expected under Brexit.

Overall, the results from the Euro Area and US Open Economy models indicate that an increasingly globalised macroeconomy, between both large open economies and small open economies, can lead to gains in UK inflation forecasting. Thus, reinforcing Forbes (2019), who highlights the growing influence of global factors in shaping UK inflation dynamics.

To demonstrate the stability of the Phillips curve models, Figures (4.2) and (4.3) display the cumulative MSFE of the best performing Open Economy combinations relative to the Workhorse model. In these plots, the MSFE of both models are summed over the forecast evaluation period to illustrate the cumulative forecasting losses over time. These plots focus on the one and twelve-month ahead forecast, to compare the stability and inflation forecasting accuracy of the Open Economy and Workhorse models across the short to medium-long term horizon. This forecast horizon is particularly relevant for the Bank of England, which prioritises the short to medium-long term inflation forecast to guide the implementation of appropriate monetary policy for the UK[11].

Figure 4.2: Cumulative MSFE Comparison of the Workhorse and US Open Economy Phillips curve model against actual inflation



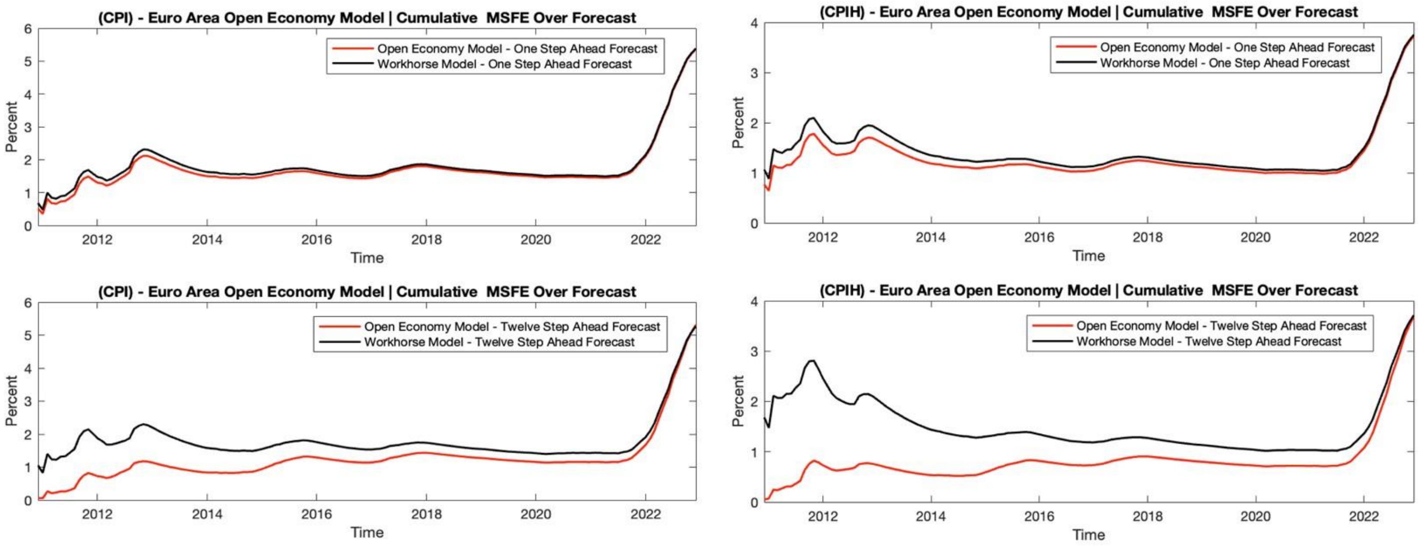
The left-hand side Open Economy plots have been estimated with one lag of domestic unemployment, one lag of CPI inflation, alongside one lag of the US interest rate. The comparing Workhorse plot is produced using one lag of domestic unemployment and one lag of CPI inflation. The right-hand side Open Economy plots have been estimated with one lag of the US unemployment rate, one lag of the domestic interest rate and one lag of CPIH inflation. The Workhorse model is then produced using one lag of the domestic interest rate and one lag of CPIH inflation

[11] The Bank of England's medium-long term inflation targeting horizon to help guide the 2% CPI target is discussed in Bernanke (2024) and consistently referenced in the Bank's monetary policy framework; see Bank of England (2023)

While the resulting relative MSFE and MAFE across all forecast horizons, shown in Table 4.5, indicate consistent improved forecasting accuracy from combining the US interest rate alongside the domestic unemployment rate to forecast UK inflation. These forecasting gains appear minimal and are not visually apparent within the cumulative MSFE plots of this same combination. This reflects the dominant predictive power of domestic unemployment within the Workhorse model, consistent with the presence of a traditional Phillips curve relationship within this study.

However, when combining the domestic interest rate with the US unemployment rate, as displayed on the right hand side plot within Figure 4.2, the US Open Economy model consistently produces a lower cumulative MSFE at the one year ahead forecast. Underscoring the significant improvements an Open Economy model can introduce to the domestic Workhorse forecasts, when an alternative measure of domestic slack is utilised aside from the unemployment rate.

Figure 4.3: Cumulative MSFE Comparison of the Workhorse and Euro Area Open Economy Phillips curve model against actual inflation



Both Open Economy plots (for CPI and CPIH) have been plotted by applying one lag of the domestic interest rate alongside one lag of the Euro Area industrial production gap and one lag of either inflation series. The Workhorse model in both graphs (for both CPI and CPIH) is produced using one lag of the domestic interest rate and one lag of inflation.

Figure (4.3) highlights that the Euro Area Open Economy model, which combines the domestic interest rate alongside the Euro Area industrial production gap, provides a more consistent and stable forecast than that of the domestic Workhorse model. Similar to Figure (4.2) for the US, the forecasting improvement of the Euro Area Open Economy model is strongly apparent at the 12-month horizon, compared to the one month ahead forecast. This signifies that international spillover effects, to the UK's small open economy are associated with delayed transmission.

Regarding the episodic performance of the Workhorse model, both the best performing Euro Area and US Open Economy models yield a lower cumulative MSFE across the post-financial crisis and Brexit periods compared to the Workhorse model. This suggests that the inclusion of international factors contributes to a more stable medium-long term forecast of UK inflation throughout periods of global uncertainty.

This study has shown that only when the domestic unemployment rate is solely applied within the Workhorse model does its cumulative MSFE and forecasting performance match that of the best-performing Open Economy models. This underscores the observed persistent relationship between unemployment and inflation dynamics in the UK throughout this study's forecast evaluation period. Thus, supporting the presence of an observed Phillips curve relationship within this paper, which remains difficult to significantly improve in forecasting accuracy through the inclusion of international factors.

5. Conclusion

This study has examined whether including international factors in parsimonious Phillips curve models can improve the forecasting accuracy of the UK's year-on-year CPI and CPIH inflation series. All forecasts were generated using an expanding window approach, with a forecast horizon which captures the UK's short to medium-long term inflation dynamics.

The initial finding of this study is that the inclusion of domestic slack indicators, outside of the unemployment rate, within a Workhorse Phillips curve model is outperformed by univariate models in forecasting UK inflation. However, crucially, this study finds that incorporating the domestic unemployment rate within the Workhorse model greatly improves forecasting accuracy relative to univariate models. This indicates a presence of the traditional Phillips curve relationship within the UK, which this study has observed across January 2010 to December 2022.

Whilst the presence of a domestic Phillips curve relationship remains observed for the UK, this study has shown that its associated forecasting performance is episodic—consistent with the findings of Forbes et al (2017) and Stock and Watson (2007). By incorporating international factors alongside domestic slack indicators, within an Open Economy Phillps curve model, this study finds that inflation forecasting accuracy consistently outperforms the domestic-focused Workhorse model. Thus, illustrating that international spillover effects and global linkages contribute significantly to the UK's small open economy.

However, this observed international contribution in improving forecasting performance is largely present in Workhorse Phillips curve variants that include domestic slack measures beyond the staple unemployment rate—especially for the one-year ahead inflation forecast. Importantly, although the forecasting performance of the traditional Phillips curve improves when combined with international slack, this improvement is largely minimal across the short to medium-long term inflation forecast. Reinforcing the presence of a strong traditional Phillips curve relationship in this study, which is difficult to enhance in forecasting accuracy through the inclusion of international factors.

When focusing on periods of global and national economic uncertainty, the Open Economy model continues to provide clear forecasting gains relative to the domestic Workhorse model. This is apparent throughout the post-crisis, Brexit and early pandemic periods, suggesting that adopting a parsimonious global approach improves UK inflation forecasting accuracy during volatile economic periods without adding to model complexity. Therefore, the Bank of England should consider a similar simple modelling approach when forecasting national inflation. This could serve as an alternative to the currently applied sophisticated COMPASS model which, as Bernanke's (2024) review recommends, should be replaced.

In terms of limitations, this paper focuses on the UK, a single small open economy, meaning the observed findings may not be generalisable to other small open economies. Furthermore, while this paper ensures that a complete parsimonious forecasting approach is maintained, a comparison of parsimonious forecasts against more complex modelling may have presented further completeness in this paper's findings.

This paper’s limitations highlight the potential for future research within this field of inflation forecasting. This could involve expanding the international regions considered to a wider global scope or trial in estimation with longer forecast horizons to test the long-term stability of the Phillips curve relationship. It could also be beneficial for future research to simultaneously investigate the difference in UK inflation forecasting accuracy between simple and more sophisticated forecasting models—such as machine learning methods compared to a simple Phillips curve.

To conclude, this paper’s findings add to the limited body of literature on the significance of incorporating international factors and applying simple modelling when forecasting inflation of small open economies.

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Appendix

Appendix A presents the full set of results tables for the best-performing US Open Economy model combinations that were not included in the main body of the dissertation. Appendix B provides the equivalent results for the Euro Area Open Economy models, also omitted from the final write-up for brevity. All Open Economy results tables included in the Appendix follow the same colour structure used for Tables 4.5, 4.6, 4.7 & 4.8 within the main text—see Chapter 4.3 (Open Economy results) for a detailed explanation.

Appendix A – Best Performing US Open Economy Combinations

Table A: (Forecasting CPI) Domestic Interest Rate Combined with US Slack

(CPI) US Open Economy Model - PC/RW :	MSFE (h=1)	MAFE (h=1)	MSFE (h=3)	MAFE(h=3)	MSFE (h=6)	MAFE (h=6)	MSFE (h=12)	MAFE (h=12)
US Unemployment Rate	0.9927	0.9889	0.982	0.97	0.9735	0.9481	0.9739	0.9398
US Interest Rate	0.9972	0.9976	0.9925	0.9932	0.9873	0.9874	0.9816	0.9779
US Industrial Production Index	0.9982	0.9994	0.9995	0.9991	1.0084	1.0045	1.035	1.028
USD/GBP	1.007	0.9914	1.033	0.9798	1.0904	0.9819	1.2265	1.0361
US Unemployment Gap	0.9963	0.9953	0.9907	0.987	0.9858	0.9764	0.9827	0.9619
US Industrial Production Gap	0.9957	0.9945	0.99	0.9847	0.9862	0.9723	0.9873	0.9621

Table A1 reports the relative performance (MSFE & MAFE) of the Open Economy model against the Naïve random walk in forecasting CPI inflation, across the full estimated forecast horizon (1, 3, 6 and 12 months ahead). These Open Economy results were estimated utilising an iterative expanding window with a training sample of 120 observations. From which one lag of CPI inflation was applied alongside one lag of the domestic interest rate and one lag of US slack. Table A1 Open Economy inflation forecasts were calculated using equation (3.4).

Table A2: (Forecasting CPI) Domestic Industrial Production Combined with US Slack

(CPI) US Open Economy Model - PC/RW :	MSFE (h=1)	MAFE (h=1)	MSFE (h=3)	MAFE(h=3)	MSFE (h=6)	MAFE (h=6)	MSFE (h=12)	MAFE (h=12)
US Unemployment Rate	0.999	0.9907	1.0031	0.9755	1.0199	0.9637	1.0729	0.9716
US Interest Rate	0.9968	0.9971	0.9924	0.991	0.9893	0.9826	0.9922	0.9744
US Industrial Production Index	1.0059	1.005	1.0199	1.0153	1.0441	1.0315	1.0943	1.0658
USD/GBP	0.9962	0.9812	1.0185	0.9634	1.0983	0.9968	1.316	1.163
US Unemployment Gap	0.9998	0.999	1	0.9968	1.0016	0.9934	1.0075	0.974
US Industrial Production Gap	0.9989	0.9989	0.9975	0.9964	0.971	0.993	1.0005	0.9893

Table A2 reports the relative performance (MSFE & MAFE) of the Open Economy model against the Naïve random walk in forecasting CPI inflation, across the full estimated forecast horizon (1, 3, 6 and 12 months ahead). These Open Economy results were estimated utilising an iterative expanding window with a training sample of 120 observations. From which one lag of CPI inflation was applied alongside one lag of the domestic industrial production index and one lag of US slack. Table A2 Open Economy inflation forecasts were calculated using equation (3.4).

Table A3: (Forecasting CPIH) Domestic Unemployment Rate Combined with US slack

(CPIH) US Open Economy Model - PC/RW :	MSFE (h=1)	MAFE (h=1)	MSFE (h=3)	MAFE(h=3)	MSFE (h=6)	MAFE (h=6)	MSFE (h=12)	MAFE (h=12)
US Unemployment Rate	0.9906	0.9943	0.9748	0.9842	0.9571	0.9727	0.9388	0.967
US Interest Rate	**0.9876**	**0.9922**	**0.9662**	**0.9782**	**0.9415**	**0.9619**	**0.9124**	**0.9467**
US Industrial Production Index	**0.9877**	**0.9927**	**0.9718**	0.9837	0.9621	0.9813	0.9685	1.0031
USD/GBP	0.9984	**0.9792**	1.0306	**0.9693**	1.1324	1.0405	1.3942	1.2489
US Unemployment Gap	**0.9859**	0.9885	**0.9642**	**0.9698**	**0.9437**	**0.9528**	**0.9283**	**0.9446**
US Industrial Production Gap	**0.9843**	**0.9818**	**0.9664**	**0.9579**	0.9607	**0.9436**	0.9792	0.9767

Table A3 reports the relative performance (MSFE & MAFE) of the Open Economy model against the Naïve random walk in forecasting CPIH inflation, across the full estimated forecast horizon (1, 3, 6 and 12 months ahead). These Open Economy results were estimated utilising an iterative expanding window with a training sample of 120 observations. From which one lag of CPIH inflation was applied alongside one lag of the domestic unemployment rate and one lag of US slack. Table A3 Open Economy inflation forecasts were calculated using equation (3.4).

Table A4: (Forecasting CPIH) Domestic Industrial Production Combined with US slack

(CPIH) US Open Economy Model - PC/RW :	MSFE (h=1)	MAFE (h=1)	MSFE (h=3)	MAFE(h=3)	MSFE (h=6)	MAFE (h=6)	MSFE (h=12)	MAFE (h=12)
US Unemployment Rate	1.001	**0.9954**	1.0043	**0.9868**	1.0112	**0.977**	1.029	**0.9627**
US Interest Rates	**0.9966**	**0.9972**	**0.9914**	**0.9921**	**0.9872**	**0.9863**	0.9878	**0.9825**
Industrial Production	1.0026	1.0062	1.0154	1.0235	1.045	1.0503	1.1114	1.1001
USD/GBP	1.0017	**0.9801**	1.0321	**0.96**	1.119	0.9945	1.3397	1.1618
US Unemployment Gap	1	1.0004	**1.001**	1.0012	**1.0042**	1.004	**1.0142**	1.0099
US Industrial Production Gap	0.9977	**0.9975**	**0.9943**	**0.9933**	**0.9917**	**0.989**	**0.993**	0.9859

Table A4 reports the relative performance (MSFE & MAFE) of the Open Economy model against the Naïve random walk in forecasting CPIH inflation, across the full estimated forecast horizon (1, 3, 6 and 12 months ahead). These Open Economy results were estimated utilising an iterative expanding window with a training sample of 120 observations. From which one lag of CPIH inflation was applied alongside one lag of the domestic industrial production index and one lag of US slack. Table A4 Open Economy inflation forecasts were calculated using equation (3.4).

Appendix B - Best Performing Euro Area Open Economy Combinations:

Table B1: (Forecasting CPI) Domestic Unemployment Rate Combined with Euro Area Slack

(CPI) Euro Area Open Economy Model - PC/RW:	MSFE (h=1)	MAFE (h=1)	MSFE (h=3)	MAFE(h=3)	MSFE (h=6)	MAFE (h=6)	MSFE (h=12)	MAFE (h=12)
Euro Area Unemployment Rate	0.9892	1.0028	0.9829	1.0165	0.993	1.0577	1.0771	1.1651
Euro Area Interest Rate	1.0023	1.0031	1.0074	1.0086	1.016	1.0166	1.0347	1.0305
Euro Area Industrial Production Index	0.9911	1.0017	0.9809	1.0087	0.979	1.0322	1	1.079
EUR/GBP	1.0006	1.0045	1.0057	1.014	1.0192	1.0356	1.0544	1.0791
Euro Area Unemployment Gap	0.9963	0.9961	0.9912	0.9883	0.9882	0.9791	0.9921	0.9747
Euro Industrial Production Gap	0.9978	0.9924	0.9957	0.9779	0.9972	0.9605	1.0101	0.9414

Table B1 reports the relative performance (MSFE & MAFE) of the Open Economy model against the Naïve random walk in forecasting CPI inflation, across the full estimated forecast horizon (1, 3, 6 and 12 months ahead). These Open Economy results were estimated utilising an iterative expanding window with a training sample of 120 observations. From which one lag of CPI inflation was applied alongside one lag of the domestic unemployment rate and one lag of Euro Area slack. Table B1 Open Economy inflation forecasts were calculated using equation (3.4).

Table B2: (Forecasting CPI) Domestic Industrial Production Combined with Euro Area Slack

(CPI) Euro Area Open Economy Model - PC/RW:	MSFE (h=1)	MAFE (h=1)	MSFE (h=3)	MAFE(h=3)	MSFE (h=6)	MAFE (h=6)	MSFE (h=12)	MAFE (h=12)
Euro Area Unemployment Rate	0.9806	0.9859	0.9519	0.9647	0.928	0.9551	0.9196	0.9595
Euro Area Interest Rate	0.9949	0.998	0.9868	0.9945	0.9793	0.9901	0.9751	0.9878
Euro Area Industrial Production Index	0.981	0.9767	0.9655	0.9483	0.9706	0.9419	1.005	0.9733
EUR/GBP	1.0088	1.0149	1.0456	1.0582	1.1295	1.1458	1.3275	1.3066
Euro Area Unemployment Gap	0.9861	0.9805	0.9668	0.9467	0.9536	0.913	0.957	0.8931
Euro Industrial Production Gap	0.9908	0.9731	1.0003	0.9406	1.053	0.9431	1.1914	1.0357

Table B2 reports the relative performance (MSFE & MAFE) of the Open Economy model against the Naïve random walk in forecasting CPI inflation, across the full estimated forecast horizon (1, 3, 6 and 12 months ahead). These Open Economy results were estimated utilising an iterative expanding window with a training sample of 120 observations. From which one lag of CPI inflation was applied alongside one lag of the domestic industrial production index and one lag of Euro Area slack. Table B2 Open Economy inflation forecasts were calculated using equation (3.4).

Table B3: (Forecasting CPIH) Domestic Unemployment Rate Combined with Euro Area Slack

(CPIH) Euro Area Open Economy Model - PC/RW:	MSFE (h=1)	MAFE (h=1)	MSFE (h=3)	MAFE(h=3)	MSFE (h=6)	MAFE (h=6)	MSFE (h=12)	MAFE (h=12)
Euro Area Unemployment Rate	0.9793	0.9863	0.949	0.9666	0.9246	0.9601	0.9198	0.9733
Euro Area Interest Rate	0.9931	0.9996	0.9833	1.0003	0.9763	1.0043	0.9808	1.0223
Euro Area Industrial Production Index	0.98	0.978	0.9581	0.9515	0.9507	0.9428	0.9683	0.9474
EUR/GBP	1.0015	1.0135	1.0305	1.055	1.1176	1.1382	1.3613	1.341
Euro Area Unemployment Gap	0.9838	0.9792	0.9583	0.9443	0.9326	0.9064	0.908	0.8694
Euro Industrial Production Gap	0.9918	0.9692	0.9979	0.9281	1.0374	0.9152	1.1414	0.9824

Table B3 reports the relative performance (MSFE & MAFE) of the Open Economy model against the Naïve random walk in forecasting CPIH inflation, across the full estimated forecast horizon (1, 3, 6 and 12 months ahead). These Open Economy results were estimated utilising an iterative expanding window with a training sample of 120 observations. From which one lag of CPIH inflation was applied alongside one lag of the domestic unemployment rate and one lag of Euro Area slack. Table B3 Open Economy inflation forecasts were calculated using equation (3.4).

Table B4: (Forecasting CPIH) Domestic Industrial Production Combined with Euro Area Slack

(CPIH) Euro Area Open Economy Model - PC/RW:	MSFE (h=1)	MAFE (h=1)	MSFE (h=3)	MAFE(h=3)	MSFE (h=6)	MAFE (h=6)	MSFE (h=12)	MAFE (h=12)
Euro Area Unemployment Rate	0.9877	1.0013	0.9781	1.0154	0.9927	1.059	1.0846	1.1691
Euro Area Interest Rate	1.0029	1.0031	1.009	1.0085	1.019	1.0177	1.0396	1.0329
Euro Area Industrial Production Index	0.9876	1.002	0.9783	1.0186	0.988	1.0564	1.0376	1.1131
EUR/GBP	1.0009	1.0017	1.0044	1.0064	1.0129	1.0157	1.0356	1.0439
Euro Area Unemployment Gap	0.996	0.993	0.991	0.9813	0.9887	0.9689	0.9943	0.9617
Euro Industrial Production Gap	0.9974	0.9874	0.996	0.9654	1.0005	0.9412	1.0213	0.9176

Table B4 reports the relative performance (MSFE & MAFE) of the Open Economy model against the Naïve random walk in forecasting CPIH inflation, across the full estimated forecast horizon (1, 3, 6 and 12 months ahead). These Open Economy results were estimated utilising an iterative expanding window with a training sample of 120 observations. From which one lag of CPIH inflation was applied alongside one lag of the domestic industrial production index and one lag of Euro Area slack. Table B4 Open Economy inflation forecasts were calculated using equation (3.4).