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What the financial crisis started, commodity prices will finish: new challenges to monetary policy in the UK

What the financial crisis started, commodity prices will finish: new challenges to monetary policy in the UK.

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Abstract— **Consumer price inflation is increasingly tied to trends in commodity market prices and products imported from emerging economies and its nature is different from the past. Currently, the financial crisis and its negative consequences represent the primary problem for policy makers in stabilizing all economies. However, the food crisis should not be forgotten since the dynamic of the structural problems of commodity prices have accelerated recently. Therefore, looking beyond the present crisis, we can expect other challenges to emerge, one of which is a possible resurgence in increases in food and other commodity prices.**

Inspired by Boughton and Branson (1991), Sims (1992) and Hanson (2004), who identify the importance of the role of commodity prices in consumer price inflation in the USA during the 1980s, our study provides an up-to-date analysis of the ability of the food price index to improve inflation forecasts by reducing the forecast error over the period 1992 – 2012. The results of our stochastic model of the inflation forecast show that the inclusion of oil prices into the forecast significantly increases the forecast error while the inclusion of food prices reduces the forecast error.

This paper has potential implications for future studies of the challenges of forecasting inflation in the UK and may also contribute to a greater understanding of the importance of food prices in the UK by bringing commodity prices back into the discussion.

Keywords— **World food prices, crude oil prices, UK inflation forecast**

I. INTRODUCTION

In recent years, policy makers and researchers have paid considerable attention to the effect of oil prices on monetary policy and domestic price inflation (e.g. LeBlanc and Chinn 2004, Kaliam 2009, Trostle 2010) mostly via the dynamic of oil prices and a fast pass-through effect. These studies have shown that oil prices affect not only domestic inflation but also world food prices. However, insufficient attention has been paid to the effect of world food prices on domestic inflation in developed countries. Food prices are typically characterised by long-term relatively stable prices interrupted by short-term price spikes and a slower dynamic of the pass-through effect (Deaton and Laroque, 1992, Williams and Wright, 1991).

Even if rising world food prices transform into domestic retail prices relatively slowly, their effect cannot be ignored. Recent major fluctuations in food prices have been of particular concern. Given the large weight of food in households' consumption baskets (on average more than 10 per cent in the UK) and its limited substitutability by other goods, food price fluctuations often have a sizeable impact on overall consumer prices as well as on the terms of trade. Given the expectations of increasing world commodity prices and the greater volatility of those prices, an understanding of the long-run relationship between commodity prices and consumer price inflation is an important issue for policy makers, especially in terms of inflation forecasting in countries, such as the UK, which use inflation targeting as a policy instrument. There is a general agreement by economists on the importance for policy makers of inflation forecasting. However there is intense debate on the relevance of commodity prices as a leading indicator of inflation. The theoretical justifications for using commodity price inflation to predict future consumer price inflation is based on the way in which the commodities are purchased. Generally, commodities are purchased in spot markets and their prices are therefore flexible in contrast to final goods prices which are more likely to be sticky. In the event of a macroeconomic shock, commodity prices will be affected contemporaneously and will affect consumer prices only with a lag.

Boughton and Branson (1991) claim that commodity prices might serve as a useful leading indicator of inflation in developed countries as shocks in prices can occur in the market for certain commodities such as food or oil. Since these commodities are important for the domestic production of final goods, higher prices will be passed through to final goods prices. However the stickiness of the prices of final goods means that the acceleration of the prices of final goods will slow down.

According to Boughton and Branson (1991), commodity prices are determined in relatively flexible auction markets and as a result tend to respond quite quickly to disturbances. Nevertheless, their analysis of conventional trade-weighted commodity price indices shows no evidence of a long-run relationship between the levels of commodity prices and consumer prices in developed countries. However, the authors did not include exchange rates in their model. The relationship between commodity prices and inflation should be tested in a complete model with other variables, such as unemployment or exchange rates, as possible predictors of inflation.

According to Ferrucci et.al (2012) an empirical link between commodity prices and consumer prices may be difficult to detect since higher commodity prices may not be passed on fully to the consumers of final goods due to trade competition. The reason why the relevance of commodity prices to inflation forecasting is still unclear is that if consumer price inflation is subject to several offsetting shocks at the same time, the unconditional covariance between consumer prices and commodity prices tends to be small and insignificant. Indeed, the predictive ability of commodity prices would be small even if there is a theoretical link.

The forecasting ability of commodity prices was investigated by Sims (1992) via the inclusion of a commodity price index in a Vector Autoregression Model (VAR) and he claimed that the consecutive rise in the price level and short term interest rate was the result of an endogenous policy response to higher expected inflation and the proposed inclusion of a commodity price index in the inflation forecast. Since Sims's (1992) study, a commodity price index has been used in numerous VAR studies of monetary policy.

Subsequently commodity prices became one of the main areas of interest in inflation forecasting. Hanson (2004) adjusted the inclusion of the commodity price index in his inflation forecast by adding certain commodity price indices to a VAR forecasting model and found out that the inclusion of certain commodity prices into the forecast reduces the error in the consumer price inflation forecast by 35 per cent per annum. Blomberg and Harris (1995) found that commodity and producer price indices performed well in forecasting inflation in the 1970s and early 1980s. However, they lost their predictive ability after the mid-1980s due to the absence of significant food and oil price shocks during that period. Their results explain why Boughton and Branson (1991) could not identify a long-term relationship between commodity prices and consumer prices. These results were confirmed by Furlong and Ingenito (1996) who indicated that the ability of a non-oil commodity price index to Granger cause CPI inflation reduced the power of prediction in the mid-1980s. However, Cacchetti, Chu and Steindel (2000) came to a different conclusion. Instead of adding the commodity price indices and comparing the predicted outcome without commodity prices; they added a series of individual indicators of future inflation, such as exchange rates, interest rates and unemployment to the VAR model for a more complex comparison. Over the period 1975 – 1998, their results demonstrate that including certain commodity price indices (e.g. gold index, oil price index) improves the accuracy of the inflation forecast more than other indicators. Stock and Watson (2003) found that the use of forecasting models which include commodity price indexes between 1971 and 1984 increased the accuracy of the forecast for the change in monthly consumer price inflation relative to an autoregressive benchmark by 21 per cent. While this literature constitutes an important indication of the role of commodity prices in consumer price inflation, these papers focus on consumer price inflation in the USA during the 1980s when the ability of commodity price indices as a predictor of future inflation began to lose its power.

Previous studies in the UK have focused on the determinants of retail food price increases, rather than the ability of commodity prices to improve forecast inflation by reducing the forecast error. Hendry (2006) modelled UK inflation over the period 1875 – 1991 and included commodity prices, in order to test whether they accounted for the inflation. However the technical limitation of his study is that due to the unavailability of commodity data for the whole of the period, Hendry (2006) had to use the interpolation of data over period with missing data. Even though this is a standard statistical procedure for dealing with missing data, it may not capture the trend of data and might also contribute to Hendry's conclusion that commodity prices do not explain the UK's inflation shocks.

The lack of literature on the ability of commodity prices to improve the inflation forecast in the UK might be explained by the flow of inflation targeting. Monetary policy should respond if there is inflation, i.e. if there is a sustained increase in the general price level. However, it can be argued that high food prices often result from adverse supply shocks or large increases in input costs and it is not the intention of policy makers to react to short-term shocks since the conventional wisdom is that if inflation expectations are well anchored, monetary policy does not need to react to supply shocks. This premise is based on the assumption that the supply shocks are purely temporary. However, this assumption does not always hold. In the real world, supply shocks are often structural and lead to a permanent upward shift in prices. This is the case not only for oil prices but also for food prices. The substantial increases in commodity prices have recently been recognized and the argument that commodity prices are not significant indicators of inflation due to short-term shocks does not hold anymore.

Since there is agreement in the literature that commodity prices were good leading indicators of consumer price inflation during the 1970s and mid-1980s, this paper investigates the relationship in the UK over the period 1992 –

2012. This is the period since the Bank of England began inflation targeting and assumes that the BoE behaviour is described by the Taylor rule. This period seems to be ideal as during the last 20 years there has not been an event which could be compared to the oil price shocks or food price shocks of the 1960s and 1970s.

Previous studies have demonstrated that the inclusion of commodity prices in the forecast model did improve the inflation forecast; however the limitation of these studies relates to the fact that most authors include only commodity prices. However one should be aware of placing too much confidence in forecasts of inflation that rest on the signals from a single indicator. On the other hand, however, if too many indicators are included in the forecast it can lead to misleading results.

Therefore, the main aim of this paper is to measure the long-run equilibrium relationship between commodity prices and inflation and to identify whether the inclusion of commodity prices in our inflation forecasting model reduces the error associated with the inflation forecast in the UK.

II. Methodology

The non-stationary behaviour that characterises the CPI and its drivers, which was discussed in the previous section, gives rise to the possibility of cointegrated long-run relationships. To allow for the potential existence of these long run relationships, coupled with the potentially dynamic nature of the adjustment process, we develop an econometric model in a Vector Error Correction Model (VECM) framework.

This has an underlying form given by:

$$\Delta x_t = \alpha\beta' x_{t-1} + \sum_{i=t}^{p-1} \Gamma_i \Delta x_{t-i} + \Psi \mathrm{D_t} + \varepsilon_\mathrm{t} \qquad (1)$$

where the cointegrated relationships are explicitly parameterised by the matrix β, the coefficients provide estimates of the usual (long-run) response elasticity, given that the variables, world food prices, crude oil prices, UK CPI, the effective exchange rate and the official interest rate, are expressed in natural logs.

Trace and Maximal Eigen value statistics are used to assess the number of cointegrating relationships among the data. Equation (1) also defines a matrix of error correction coefficients α, elements of which load deviations from equilibrium into Δx_t for correction, thus quantifying the speed at which each variable adjusts to maintain equilibrium. Coefficients in Γ_i estimate the short-run effect of shocks to the variables on Δx_t and thereby allow the short and long-run responses to differ. Given the interest in the dynamics of inflation as well as the long-run impact of changes in the drivers of x_t, it is essential to use impulse response analysis in order to provide dynamic simulations of the effects of shocks of a known size and duration for each of the drivers of inflation discussed in the previous section. Based on the parameters estimated in (1), an impulse response function is used to produce the time path of the dependent variables to shocks from all the explanatory variables. Plots of the impulse response function over time provide a graphical illustration of the period-by-period simulation, describing the long-run effect on inflation in response to the shock. Coefficient variance decomposition is added in order to provide information on the eigenvector decomposition of the coefficient covariance matrix.

A stochastic model for the forecast of inflation is used, since time series are acting independently due to a certain level of random walk. However, at the same time there is evidence of a relationship between these variables.

Given the monthly frequency of our data, the VEC representation expresses the variables as $\%\Delta\ in\ x_t\ to\ x_{t-1}$ and the VEC model is expressed in log-levels. This is useful when we wish to evaluate the dynamic impact of shocks on the level of inflation.

III. Results and discussion

The six empirical VEC models contain variables (Δi_nom, Δcpi, Δoil, Δfood, Δeffect_exch, Δunemp and Δu_t) estimated by the least generalised variance estimator, with 504 monthly observations over the period 1992 to 2012.

In the model, there is no intercept in CE and VAR, a linear trend in CE which is included in the CE as a trend-stationary variable to take into account exogenous growth, assuming there is no trend in the shot-run relationship. There is no trend in VAR.

The results (Table 1) point to the presence of at least one cointegrating relationship indicated by a Trace statistic test and Max-Eigen value test at 0.5 levels of significance.

Therefore a VECM under assumption four is estimated. Table 1 shows the estimation outputs.

Table 1: Cointegration Test Statistics-Johansen Test

Sample: 1992M01 2012M01
Included observations: 228
Series: LOGCPI LOGUNEM
Lags interval: 1 to 4

Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept
	No Trend	No Trend	No Trend	Trend	Trend
Trace	1	0	1	1	1
Max-Eig	1	0	0	1	1

*Critical values based on MacKinnon-Haug-Michelis (1999)

Sample: 1992M01 2012M01
Included observations: 228
Series: LOGCPI LOGUNEM EFF
Lags interval: 1 to 4

Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept

	No Trend	No Trend	No Trend	Trend	Trend
Trace	1	1	3	1	2
Max-Eig	1	1	1	1	2

*Critical values based on MacKinnon-Haug-Michelis (1999)

Sample: 1992M01 2012M01
Included observations: 228
Series: LOGCPI LOGUNEM EFF O
Lags interval: 1 to 4

Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept
	No Trend	No Trend	No Trend	Trend	Trend
Trace	2	2	2	2	2
Max-Eig	2	2	2	2	2

*Critical values based on MacKinnon-Haug-Michelis (1999)

Sample: 1992M01 2012M01

Included observations: 231

Series: LOGCPI LOGUNEM EFF O F

Lags interval: 1 to 1

Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept
	No Trend	No Trend	No Trend	Trend	Trend
Trace	3	2	3	3	3
Max-Eig	3	2	2	3	3

*Critical values based on MacKinnon-Haug-Michelis (1999)

Sample: 1970M01 2012M05

Included observations: 228

Series: LOGCPI LOGUNEM EFF O F LOGI_NOM

Lags interval: 1 to 4

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept
	No Trend	No Trend	No Trend	Trend	Trend
Trace	3	2	1	2	2
Max-Eig	1	1	1	2	2

*Critical values based on MacKinnon-Haug-Michelis (1999)

When estimating the model of inflation, the period for VECM is 1992M12 to 2005M01. We chose a model with a linear trend with the intercept and a trend based on the results of a Johansen test. In order to test whether commodity prices improve the inflation forecast, we estimated unrestricted cointegrating vectors for six different equations (1) which are defined as:

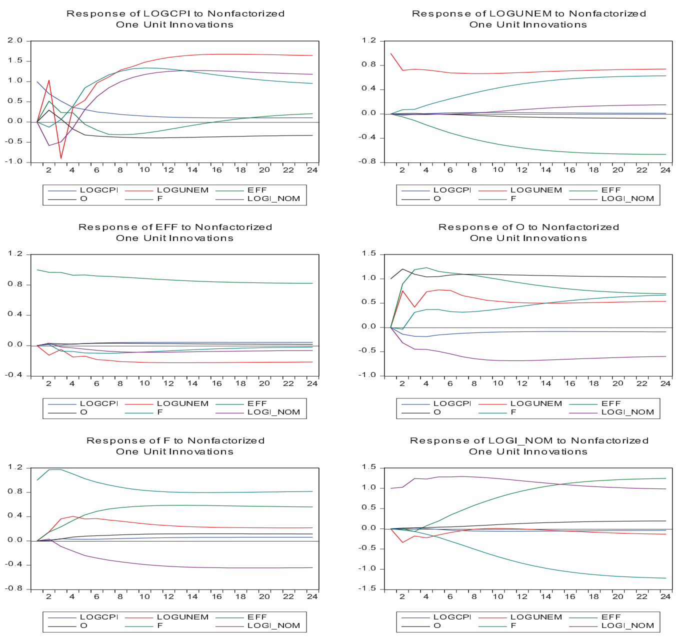
1. CPI f(unem,ε)
2. CPI f(unem,eff,ε)
3. CPI f(unem,eff,o,ε)
4. CPI f(unem,eff,o,f,ε)
5. CPI f(unem,eff,o,f,i_nom,ε)
6. CPI f(unem,eff, f,i_nom,ε)

The results (Appendix 1) provide an opportunity for economic interpretation which confirms the assumption that the UK's inflation depends positively on rising world food prices while a weak dependency can be seen in relation to oil prices.

To obtain a more complex picture of the dynamic effects of changes to the drivers, an impulse response analysis is applied to trace the effect of shocks of a specific size and duration on the UK's inflation.

Figure1 illustrates the dynamic effect of a unit one-period shock in each driver on consumer price inflation in the 24 months after the shock. Each impulse response function measures a separate shock, so they are plotted together merely for convenience.

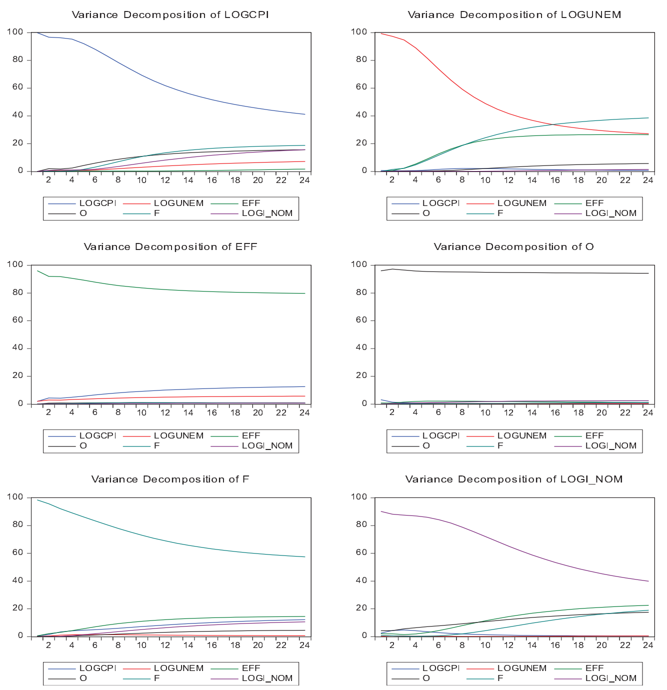
Figure 1: Impulse response function



A unit shock to world food price inflation is reflected in a decrease in consumer price inflation (upper left graph) in the months immediately following the shock and returns to zero in the second quarter, followed by a significant acceleration in consumer price inflation of approximately 120 basis points after one year. The initial (short-term) slowing down of inflation can be explained by the slower pass-through effect of world food prices into retail prices as discussed in section 2. In contrast to the shock to food prices, the shock to oil prices causes an initial acceleration in consumer price inflation, reflecting a faster pass through effect to retail prices in the short-term, in the long-term, however the opposite effect is observed. It is commonly assumed that increases in oil prices lead to increases in consumer price inflation. However Kilian (2009) shows that there is a significant difference in the reaction of consumer price inflation to shocks to oil prices depending on whether they are what he termed "political oil price shocks" or "other oil price shocks".

Kilian (2009) found that other oil supply disruptions significantly lower the price level in the long-run while political oil supply shocks do not have a significant effect on consumer price inflation in the short or long term. Therefore, it could be assumed that the insignificant reaction of inflation to oil price shocks in our case can be explained by the political nature of the shock. It is also possible that there is more information which we have not included in order to explain the reaction. The results from the impulse response function show that a unit shock to the unemployment rate has a very significant and volatile initial effect on inflation. However, in the long-term (after the first year) it leads to an acceleration of consumer price inflation of approximately 150 basis points. The reaction of the CPI to a unit shock of unemployment supports the assumption that unemployment can be used as a strong indicator of future inflation, together with world food prices and nominal interest rates. Indeed, a shock to the effective exchange rate does not have a significant impact on inflation while a shock to nominal interest rates does so. This is not surprising since policy in the UK is clearly oriented towards a form of inflation targeting in which the main policy tool is the interest rate.

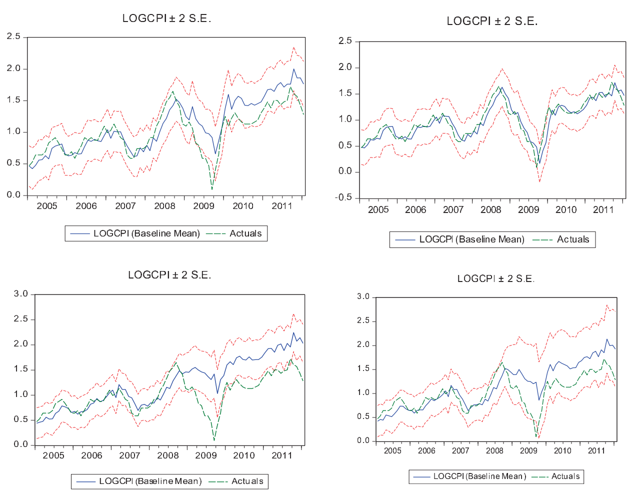
Figure 2: Variance decomposition of CPI and RPI



From the variance decomposition functions presented in Figure 2, it can be observed that as usual, the majority of the percentage of the errors that is attributable to own shocks can be found in all cases. Nearly 20 per cent of the forecast error variance of a CPI is explained by innovations to world food prices, oil prices and nominal interest rates in the long term. In the case of other variables, where nearly the whole forecast error of a variable is explained by itself, interesting results came from analysing unemployment. About 40 per cent of the forecast error variance of unemployment is explained by innovations to world food prices and more than 30 per cent by the effective exchange rate.

A good inflation forecast should meet two criteria. First of all, a forecast must be unbiased; thus the forecast errors must average out to zero over time. In other words, positive and negative errors must cancel each other out in the long-term. Therefore in the long-term the forecast error is either equal to or close to zero. Second, the forecast must be efficient, meaning that…*"forecasters must use all the relevant information at their disposal in forming the forecast* (Croushore, 1996). The forecast results of the six VEC models are presented in Figure 3 and Figure 4 presents the forecast error. Model 1, where the forecast inflation is based on an indicator of the status of the real economy, indicated by the rate of unemployment, and thus based on an original Philips curve, shows an underestimation of inflation from 2005 to 2007 by 6 per cent on average. This is the period before the financial crisis when inflation had been about 2.5 per cent on average and unemployment had been declining. Declining unemployment is usually a sign of accelerating inflation as rising productivity leads to increases in wages and prices. However, during this period inflation was not accelerating but rather slowing. A contrary effect might be explained by the action of policy makers in keeping the inflation target in mind. The inflation rate moving close to 3 per cent over 2 years does not represent an anchored expectation. This could be the reason for the increase in interest rates during this period. However, our first model could not predict this movement since it does not include this criterion. The forecast error of Model 1 has been increasing since 2008 due to the fact that since the financial crisis, unemployment and inflation have both increased rapidly. With increasing unemployment, our model estimated slowing inflation. During this period we observed a contrary reaction by inflation until late 2009 and early 2010 when its rate slowed down. However, during these years our model 1 over-predicted inflation on average by 23 per cent. The inaccuracy of the inflation forecast from Model 1 can be observed graphically in Figure 3.

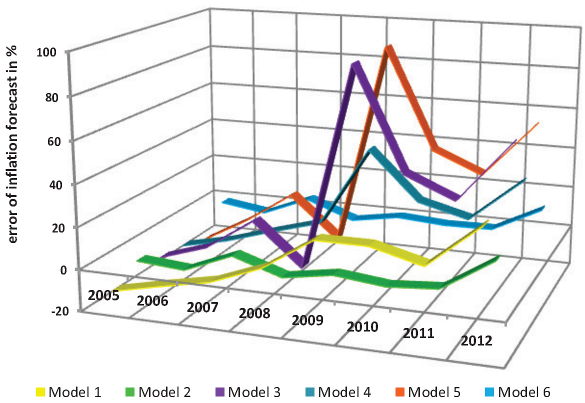
Figure 3: Inflation forecast



Whereas Model 1 bases the forecast of inflation on an indicator of the status of the real economy (unemployment), in Model 2 we also add a financial indicator - the effective exchange rate. While unemployment reflects what is happening in the economy within a country, the effective exchange rate shows the position of the country in an international context.

Model 2 seems to be a better model of the inflation forecast than Model 1, as the forecast error stays quite low during the forecast period (Figure 4). The improvement in the forecast error compared to Model 1 can be explained by a decline in the exchange rate. A decline in the exchange rate is a signal of accelerating inflation. Even though Model 2 shows a much smaller forecast error (Figure 4), it cannot be classified as an efficient forecast, since it does not include all information in forming the forecast. In addition, as was noted earlier, one should be careful not to place too much confidence in forecasts of inflation that rest on the signals from a single indicator. On the other hand, the fact that the inclusion of an effective exchange rate into the forecast model improved the forecast error significantly (Figure 4) provides a signal that the UK's inflation might be more influenced by external factors. Indeed, the objective of this paper is to investigate whether the inclusion of commodity prices improves the inflation forecast by lowering the forecast error. Therefore Model 3 includes world crude oil prices since an increase in commodity prices is often linked to higher inflation. Surprisingly however, the forecast results are worse than before (Figure 3). The forecast error is similar to Model 2 in the first two years of the forecast. However, from 2008, Model 3 over-estimates inflation during the financial crisis by approximately 91 per cent (Figure 4). Indeed, the large forecast error could be predicted from the results of the impulse response function which signals a weak response of inflation to the shock to oil prices. Therefore although oil prices have been responsible for high inflation in the past, our results indicate a weakening relationship. As noted earlier, this may be due to the nature of the oil price shock. Kilian (2009) found that other oil supply disruptions significantly lower the price level in the long run while political oil supply shocks do not have a significant effect on consumer price inflation in the short or long term. Therefore it could be assumed that the weaker relationship between inflation and oil prices can be explained by the political nature of the shocks during the period in question. Since early 2009 the forecast error has decreased however it remains over 40 per cent. Therefore, from Model 3 it can be concluded that the inclusion of oil prices does not improve the UK's inflation forecast. Our results are in a contrast with the findings of previous studies of inflation in the USA. However, the inclusion of world food prices in Model 4 shows an improvement in the inflation forecast (Figure 3) as the forecast error of Model 4 compared to Model 3 decreases by 13 per cent (as an average percentage calculated for the whole forecasting period). However, even if the forecast error of Model 4 is smaller than the forecast error of Model 3 it is still too high to be considered as a good forecast model. A large increase in the forecast error is noted in early 2009 when the forecast error of Model 4 increased by 38 per cent compared to the forecast error in 2008 (Figure 4). Indeed, Model 4 over-estimates inflation from 2008 till 2012. Therefore, neither the inclusion of oil prices nor the inclusion of food prices improves the forecast. However, the inclusion of oil prices in Model 3 significantly worsens the forecast error while the inclusion of food prices in Model 4 improves the forecast error. The results of the impulse response function indicate that oil prices should not be included in the inflation forecast model.

Figure 4: Inflation forecast error



It is assumed that adding interest rates into the inflation forecast model will improve the inflation forecast error. Therefore, Model 5 includes not only commodity prices and indicators of the real economy, but also two financial indicators – the exchange rate and the interest rate. Surprisingly, the results are however worse than in previous models (Figure 4). Indeed, the forecast error is as high as in Model 3. It is clear that none of the series in our model seems to react significantly to the shock to oil prices; therefore it might be a reason why the inclusion of oil prices worsens the forecast error. Therefore the last model of the inflation forecast, Model 6, excludes the oil price (Figure 3).

The exclusion of the oil price from the forecast model significantly decreases the forecast error (Figure 4) and shows a relatively small forecast error even during the financial crisis. As in the case of all the models, the forecast error increases in the final year of the forecast. This is probably due to insufficient data for the final year.

IV. Conclusion

There is an agreement in the literature that commodity prices were good leading indicators of consumer price inflation during the 1970s and mid-1980s. However there is a lack of empirical evidence for the 2000s, especially for the UK. This paper provides a comprehensive analysis of the predictive ability of the world food price index and the world oil price index between 1992 and 2012.

Our results show that the inclusion of oil prices in the inflation forecast significantly worsens the forecast error while the inclusion of food prices improves the forecast error.

The results of our six stochastic models for the inflation forecast show that the world food price index improves the accuracy of the CPI while by contrast the crude oil price index is not useful for forecasting the CPI.

To conclude, our findings show that a forecasting model which includes food prices is superior to models which include oil prices. The model establishes an empirical link between world food prices, world oil prices and inflation in the UK for the 2000s.

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VI. APPENDIX

Results of VEC model

	Model 1		Model 2			
Error correction	D(LOGCPI)	D(LOGUNEM)	D(LOGCPI)	D(LOGUNEM)	D(EFF)	
D(LOGCPI(-1))	0.022527 (0.08628)	-0.012892 **(0.00790)**	-0.102210 (0.08576)	-0.015745 **(0.00693)**	0.006388 **(0.01293)**	
D(LOGCPI(-2))	0.010334 (0.08435)	-0.006657 (0.00773)	-0.084380 (0.08655)	-0.009864 (0.00699)	-0.023803 (0.01305)	
D(LOGUNEM(-1))	1.058617 (0.89067)	0.012152 (0.08159)	1.206393 (1.03894)	-0.171753 (0.08390)	-0.250723 (0.15668)	
D(LOGUNEM(-2))	-1.348061 (0.88052)	0.230164 (0.08066)	-1.292492 (1.04302)	0.034805 (0.08423)	-0.108221 (0.15730)	
D(EFF(-1))	-	-	-0.123487 (0.55998)	0.021269 (0.04522)	0.028332 (0.08445)	
D(EFF(-2))	-	-	-0.631396 (0.54342)	-0.012586 (0.04388)	0.035486 (0.08195)	
	Model 3					
Error correction	D(LOGCPI)	D(LOGUNEM)	D(EFF)	D(O)		
D(LOGCPI(-1))	0.027883 (0.08758)	-0.014163 (0.00775)	0.007340 (0.01452)	-0.067280 (0.05833)		
D(LOGCPI(-2))	0.091599 (0.08669)	-0.008759 (0.00768)	-0.016667 (0.01437)	-0.001912 (0.05773)		
D(LOGUNEM(-1))	0.204295 (0.98127)	-0.200171 (0.08688)	-0.269613 (0.16271)	0.231588 (0.65350)		
D(LOGUNEM(-2))	-2.319292 (0.97526)	0.010916 (0.08635)	-0.137021 (0.16172)	-0.517101 (0.64950)		
D(EFF(-1))	0.043700 (0.51503)	0.020546 (0.04560)	0.036155 (0.08540)	0.820968 (0.34300)		
D(EFF(-2))	-0.754658 (0.50674)	-0.010355 (0.04486)	0.016357 (0.08403)	0.215302 (0.33747)		
D(O(-1))	0.355014 (0.12833)	0.005879 (0.01136)	0.030449 (0.02128)	0.220952 (0.08546)		
D(O(-2))	-0.138708 (0.12983)	0.007018 (0.01149)	-0.007340 (0.02153)	-0.097174 (0.08646)		
	Model 4					
Error correction	D(LOGCPI)	D(LOGUNEM)	D(EFF)	D(O)	D(F)	
D(LOGCPI(-1))	0.016064 (0.08963)	-0.019388 (0.00761)	0.012930 (0.01458)	-0.050335 (0.05983)	0.015858 (0.01694)	
D(LOGCPI(-2))	0.085079 (0.08836)	-0.013859 (0.00750)	-0.010731 (0.01438)	0.013536 (0.05898)	0.022060 (0.01670)	
D(LOGUNEM(-1))	0.199189 (0.98464)	-0.203618 (0.08363)	-0.261182 (0.16020)	0.237113 (0.65722)	0.015819 (0.18615)	
D(LOGUNEM(-2))	-2.328731 (0.97871)	-0.001265 (0.08312)	-0.130140 (0.15924)	-0.470157 (0.65326)	0.102718 (0.18502)	
D(EFF(-1))	0.169206 (0.53533)	0.062178 (0.04547)	-0.026235 (0.08710)	0.713289 (0.35731)	0.065648 (0.10120)	
D(EFF(-2))	-0.543171 (0.53138)	0.026701 (0.04513)	-0.039198 (0.08645)	0.109957 (0.35468)	-0.035301 (0.10046)	
D(O(-1))	0.352239 (0.13008)	0.012572 (0.01105)	0.022877 (0.02116)	0.200965 (0.08682)	-0.000858 (0.02459)	
D(O(-2))	-0.122209 (0.13308)	0.015868 (0.01130)	-0.019385 (0.02165)	-0.121867 (0.08882)	0.004473 (0.02516)	
D(F(-1))	-0.629344 (0.46250)	-0.014150 (0.03928)	0.078636 (0.07525)	-0.014244 (0.30871)	0.295331 (0.08744)	
D(F(-2))	-0.252022 (0.47507)	-0.071061 (0.04035)	0.007968 (0.07729)	0.357721 (0.31710)	0.078077 (0.08981)	
	Model 5					
Error correction	D(LOGCPI)	D(LOGUNEM)	D(EFF)	D(O)	D(F)	D(logi_nom)
D(LOGCPI(-1))	-0.003201 (0.08739)	-0.019065 (0.00750)	-0.000254 (0.01495)	-0.082839 (0.06013)	0.004063 (0.01662)	0.033377 (0.01718)
D(LOGCPI(-2))	0.079897 (0.08827)	-0.013498 (0.00757)	-0.019956 (0.01510)	-0.003254 (0.06074)	0.014616 (0.01678)	0.014152 (0.01735)
D(LOGUNEM(-1))	0.199189 (0.98464)	-0.203618 (0.08363)	-0.261182 (0.16020)	0.237113 (0.65722)	0.015819 (0.18615)	-0.409539 (0.18887)
D(LOGUNEM(-2))	-2.328731 (0.97871)	-0.001265 (0.08312)	-0.130140 (0.15924)	-0.470157 (0.65326)	0.102718 (0.18502)	-0.012641 (0.19202)
D(EFF(-1))	0.169206 (0.53533)	0.062178 (0.04547)	-0.026235 (0.08710)	0.713289 (0.35731)	0.065648 (0.10120)	-0.117748 (0.10564)
D(EFF(-2))	-0.543171 (0.53138)	0.026701 (0.04513)	-0.039198 (0.08645)	0.109957 (0.35468)	-0.035301 (0.10046)	-0.208687 (0.10529)
D(O(-1))	0.352239 (0.13008)	0.012572 (0.01105)	0.022877 (0.02116)	0.200965 (0.08682)	-0.000858 (0.02459)	-0.007118 (0.02609)
D(O(-2))	-0.122209 (0.13308)	0.015868 (0.01130)	-0.019385 (0.02165)	-0.121867 (0.08882)	0.004473 (0.02516)	0.009127 (0.02694)
D(F(-1))	-0.629344 (0.46250)	-0.014150 (0.03928)	0.078636 (0.07525)	-0.014244 (0.30871)	0.295331 (0.08744)	0.033891 (0.08890)
D(F(-2))	-0.252022 (0.47507)	-0.071061 (0.04035)	0.007968 (0.07729)	0.357721 (0.31710)	0.078077 (0.08981)	0.063609 (0.08841)
D(LOGI_NOM(-1))	-0.902682 (0.42291)	-0.034690 (0.03629)	0.047520 (0.07234)	-0.359685 (0.29101)	0.060943 (0.08041)	0.039214 (0.08313)
D(LOGI_NOM(-2))	-0.286608 (0.39888)	-0.012547 (0.03423)	-0.019791 (0.06822)	-0.197360 (0.27447)	-0.091214 (0.07584)	0.237668 (0.07840)
	Model 6					
Error correction	D(LOGCPI)	D(LOGUNEM)	D(EFF)	D(F)	D(logi_nom)	
D(LOGCPI(-1))	-0.010808 (0.07010)	-0.015411 (0.00699)	0.007904 (0.01236)	-0.016774 (0.01676)	0.018589 (0.02476)	
D(LOGCPI(-2))	-0.014371 (0.07053)	-0.008935 (0.00703)	-0.021342 (0.01243)	0.004515 (0.01686)	0.032512 (0.02491)	
D(LOGUNEM(-	1.022575	0.053028	-0.139299	-0.146662	-1.020601	

1))	(0.67786)	(0.06759)	(0.11951)	(0.16206)	(0.23940)
D(LOGUNEM(-2))	-0.538616 (0.69011)	0.188372 (0.06881)	0.072325 (0.12167)	-0.127823 (0.16499)	-0.017127 (0.24372)
D(EFF(-1))	-0.254507 (0.39658)	0.100932 (0.03954)	-0.111901 (0.06992)	-0.156631 (0.09481)	-0.182810 (0.14006)
D(EFF(-2))	-0.851470 (0.38989)	0.016775 (0.03888)	0.038877 (0.06874)	0.062608 (0.09321)	-0.131669 (0.13770)
D(F(-1))	0.080443 (0.29067)	0.001821 (0.02898)	0.076527 (0.05125)	0.394045 (0.06949)	0.261341 (0.10266)
D(F(-2))	0.647499 (0.29852)	-0.040797 (0.02977)	0.054543 (0.05263)	0.019006 (0.07137)	0.030502 (0.10543)
D(LOGI_NOM(-1))	0.131893 (0.19497)	-0.032295 (0.01944)	0.045948 (0.03437)	-0.027618 (0.04661)	0.337889 (0.06886)
D(LOGI_NOM(-2))	-0.039165 (0.18398)	0.004573 (0.01834)	-0.083365 (0.03244)	-0.069450 (0.04399)	0.069104 (0.06498)