DETERMINANTS OF FOOD PRICE INFLATION IN FINLAND

XAVIER IRZ, JYRKI NIEMI & LIU XING
MTT Agrifood Research, Economic Research Unit
Latokartanonkaari 9, 00790 Helsinki, Finland
Corresponding author: Xavier.irz@mtt.

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MTT Agrifood Research, Economic Research Unit
Latokartanonkaari 9, 00790 Helsinki, Finland
Xavier.irz@mtt.fi

Abstract: *The agricultural commodity crisis of 2006-8 and the recent evolution of commodity markets have reignited anxieties in Finland over fast-rising food prices and food security. Although the impact of farm commodity price shocks on the final consumer is mitigated by a large degree of processing as well as the complex structure of the food chain, little is known about the strength of the linkages between food markets and input markets. Using monthly series of price indices from 1995 to 2010, we estimate a vector error-correction (VEC) model in a co-integration framework in order to investigate the short-term and long-term dynamics of food price formation. The results indicate that a statistically significant long-run equilibrium relationship exists between the prices of food and those of the main variable inputs consumed by the food chain, namely agricultural commodities, labour, and energy. When judged by the magnitude of long-run pass-through rates, farm prices represent the main determinant of food prices, followed by wages in food retail and the price of energy. However, highly volatile energy prices are also important in explaining food price variability. The parsimonious VEC model suggests that the dynamics of food price formation is dominated by a relatively quick process of adjustment to the long-run equilibrium, the half life of the transitional dynamics being six to eight months following a shock.*

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Introduction

In recent years, food prices in Finland have received much attention from the media, policy makers and the general public. Perhaps the main concern relates to the potential consequences for Finnish consumers and Finnish living standards of the upward trend in and increasing variability of agricultural commodity prices, following the international food crisis of 2006-8. For instance, in the summer of 2010, speculations about the effect that a Russian grain export ban caused by forest fires might have on the price of Finnish bread made the news, which resulted in the Minister of Agriculture and Forestry issuing statements in order to reassure the public and market participants that the inflationary effect of the ban would, in fact, be limited. At a more fundamental level, however, legitimate concerns exist in relation to the growing scarcity and variability of supply of agricultural commodities in the medium to long term due to a conjunction of factors. Climate change is now expected to lower average yields and increase yield variability in many production areas of the world. The growing scarcity of fossil fuels and restrictions on greenhouse gas emissions will also raise the energy cost of agricultural production, while bio-energy production increasingly competes with food production for the use of scarce natural resources. Meanwhile, economic and population growth world-wide put constant pressure on the demand side of the global food balance equation. There is therefore little doubt that, in the medium to long term, prices of agricultural commodities traded on international markets are going to increase at a rate exceeding that of inflation.

Anticipating the impact that this evolution might have on retail food prices and the economic well-being of the Finnish population is difficult, however, because agricultural commodities receive a large amount of processing before reaching retail stores. Yet the extent to which food markets are linked to other markets, including commodity markets, remains largely unknown in Finland as in most other countries. This paper tackles that issue by investigating the dynamics of food price formation in relation to the prices of the inputs used intensively in the food chain, namely agricultural commodities, energy and labour. Put simply, we seek to establish to what extent and how quickly changes in input prices influence food prices.

Surprisingly perhaps given its current high profile in policy and media circles, food price inflation has not been the subject of much academic research in high-income countries such as Finland. A recent and largely descriptive report investigated Finnish food prices (Kotilainen et al., 2009), but its focus was mainly on a comparison of price levels with other EU countries and the related issue of competition within the food chain. More generally, the only examples of aggregate analysis of food price inflation in high-income countries of which we are aware originate from the United States. Hence, Lambert & Miljkovic (2010) used time series econometrics to analyse factors affecting U.S. food prices to conclude that farm prices and manufacturing wages were the main determinants, rather than consumer incomes or the price of other food production inputs such as energy. In a similar vein, Baek and Koo (2010) applied a cointegration framework to the same problem and found that agricultural commodity price and exchange rate played the key roles in determining the short and long-run movements of U.S. food prices, although in recent years there was also evidence of energy prices significantly affecting food prices in the long run.

Against this background, we develop a cointegration analysis of Finnish food prices to make an empirical contribution to the existing literature on the determinants of food price inflation in high-income countries.

Conceptual Framework and Data

Although we do not attempt to build a fully structural model of food prices, economic theory guides the selection of explanatory variables. At a fundamental level, food prices reflect equilibrium between supply and demand forces, and the model should therefore include the main shifters of supply and demand. On the supply side, a cursory analysis of the cost structure of the food industry indicates that, in addition to raw agricultural commodities, two other inputs are likely to have a major impact on retail food prices: labour, which is used in processing, wholesale and retail; and energy, which is required for both the transformation of the raw commodities, and the transportation of food to the final consumer. The state of the technology also influences the position of the industry supply curve, but the process of technological change is implicitly proxied by a time trend in the model. On the other side of the equilibrium relationship, demand is influenced by the average and distribution of disposable income as well as changes in the demographic composition of the population, but the latter are unlikely to be very large in a homogenous country such as Finland with little population growth and limited immigration. Ultimately, the empirical model attempts to explain retail food prices by the unit costs of agricultural raw materials, energy, and labour, while income is ignored due to the unavailability of monthly data (see below). Technological and preference changes are captured by trends in the model.

Monthly price indices from Statistics Finland are used to build a data set from the time Finland joined the EU (January 1995) to February 2010 (the latest month available when the study started), giving a total of 182 observations. The decision to ignore data preceding Finland's entry into the EU is made for two reasons: first, EU entry was a major structural break for Finnish food markets, with the years preceding entry characterized by sharp price adjustments; and, second, Finland had to operate many changes in its collection and calculation of statistics so as to harmonise its system with that of the EU, which makes it difficult to merge pre- and post-entry data.

Food prices are measured by the component of the Consumer Price Index (CPI) corresponding to food and non-alcoholic beverages. Farm prices are measured by the price index of agricultural goods output, including fruits and vegetables but excluding fur skins. Labour unit cost in food retail is measured by a seasonally-adjusted wage index for retail sales in non-specialised stores, with food, beverages and tobacco dominating. Finally, energy prices are drawn from the database on prices of the means of agricultural production for the input category labelled 'Energy and lubricants'. Unfortunately, there are no monthly statistics on disposable income available in Finland and the variable is therefore ignored in subsequent analysis[1].

The data rescaled to a 1995 base year is presented in Figure 1, from which a few remarks are in order. Overall food prices in Finland have increased since 1995 at the economy-wide rate of inflation, but the period since mid-2007 has seen a particularly fast rise in food prices, followed by a significant decline. The recent food crisis has therefore had a visible impact on retail Finnish food markets. However, food prices are also much more stable than those of commodities, with energy prices in particular showing large volatility. By contrast, wages in food retail have grown almost linearly at a rate close to that of per capita income, with the exception of a brief break in trend around 2008. Finally, we note the clear seasonality of agricultural prices, which is addressed in the econometric model by including monthly dummies.

Overview of time-series analysis

The first step of the analysis focuses on the stochastic properties of the series by testing for the presence of unit roots. This allows for the identification of stationary and non-stationary time series, which in turn permits the specification of a model that should not produce spurious results. Provided that the variables are non-stationary as is usually the case with time-series of prices, the existence of a long-run equilibrium among variables is then tested by applying the Johansen approach, which starts with the specification of a vector autoregression (VAR) model of order k:

$$z_t = \mu + A_1 z_{t-1} + \ldots + A_k z_{t-k} + \varepsilon_t \qquad (1)$$

In equation (1), z_t denotes the (4 x 1) vector of indices of food prices, farm prices, energy prices, and wages in food retail, while ε_t denotes the white-noise error term. A key feature of the VAR model is that it does not impose any a *priori* restriction on the exogeneity of variables, which is attractive in the present context because of the possibility of bi-directional causality. For instance, given that labour is an important input in food processing and retail, the wage rate is likely to influence food prices. However, high food prices could also give food manufacturers and retailers more room when negotiating wages with employees.

[1] The figure below plots the income series extrapolated from annual data.

The idea behind the approach proposed by Johansen (1995) is to reformulate the VAR model so as to impose and test the validity of cointegrating constraints in the following equation:

$$\Delta z_t = \mu + \Gamma_1 \Delta z_{t-1} + \ldots + \Gamma_{k-1} z_{t-k+1} + \Pi z_{t-k} + \varepsilon_t \qquad (2)$$

The (4 x 4) matrices Γ_i (i=1,…k-1) guide the short-run dynamics of the model, while any long-run relationships are captured by the (4 x 4) matrix Π. The full dynamics of the system is better understood by re-writing model (2) in vector error-correction (VEC) form, which involves, when possible, decomposing matrix Π into the product αβ'. Each vector of the (4 x r) matrix β describes a stationary co-integration linear relationship that holds among the variables in the long-run equilibrium, while the (4 x r) matrix α gathers the coefficients that dictate the speed of adjustment of z_t to the long-run equilibrium. The method proposed by Johansen (1995) to establish whether this decomposition is possible relies on a test of the rank $r \leq 4$ of matrix Π. If $r = 0$, no cointegration relationship exists, while if $r = 4$ all the variables in z_t are stationary. More usually, matrix Π has reduced rank r corresponding to the number of cointegration relationships.

Empirical results

Unit Root tests

The empirical analysis starts with the presentation of unit root tests for the logarithm of all four time series included in the model. We report the results of the Augmented Dickey-Fuller (ADF) test, which remains popular because of its simplicity and generality, as well as the Phillips-Perron (PP) test, which has been proposed as an alternative. Both tests use the same null hypothesis of non-stationarity, but it has been established in the literature that they also have low power (i.e., they under-reject the null hypothesis when the series are, in fact, stationary). For that reason, it is also interesting to report the results of the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test that relies on the opposite null hypothesis of stationarity of the series.

The lag length in the auto-regression forming the basis of the ADF test is chosen by maximising the Akaike information criterion, with a maximum lag of 13. The results (Table 1) indicate that food prices, energy prices, and the wage rate are integrated of order one (e.g., I(1)), whether a deterministic trend is included or not in the test equation. However, the null hypothesis of non-stationarity of farm prices is strongly rejected, although this conclusion is not robust to the choice of test, with both the PP and KPSS tests suggesting, instead, that farm prices are I(1). This lack of consistency across tests is also observed for the energy price and wage series when a deterministic trend is allowed. Altogether, the weight of the evidence points to the non-stationarity of the series for farm, food, and energy prices. It is more difficult to conclude in the case of the wage series, which is not entirely surprising given its near linearity (Figure 1), and the finding in the literature that, in finite samples, any trend-stationary process can be approximated arbitrarily well by a unit root process and, conversely, that any unit root process can be approximated by a trend-stationary process (Harris and Sollis, 2003, p. 54). However, because the statistical consequences of treating a non-stationary variable as stationary are so severe, we opt on the side of caution by considering in subsequent analysis that the wage series is integrated of order one.

Cointegration test

Before we can apply the Johansen procedure to test for the existence of co-integration relationships among the four variables, it is necessary to establish the length of the lag in equation (2), which is achieved by optimising the value of an information criterion in the unrestricted VAR model (1). Table 2 reports the results for four such criteria, namely the Akaike (AIC), Schwarz (SC), Hannan-Quinn (HQ) criteria as well as the final prediction error (FPE). A lag length of only two months is chosen on the basis of all four criteria, and this conclusion is also reached by applying lag-exclusion Wald tests (not reported).

Johansen (1988) has established that testing for the existence of $r \leq 3$ co-integration relationships among the four variables of the model is equivalent to testing the hypothesis that the rank of matrix Π in equation (2) is at most r. Reduced-rank regression can then be used to form a likelihood ratio test of that hypothesis on the basis of the so called *trace* statistic, or alternatively, the maximum eigenvalue statistic. Lutkepohl et al. (2001) investigated the small sample properties of both tests to conclude to the slight superiority of the trace test, which we therefore favour in our analysis. The last issue to be resolved before the cointegration test can be performed is whether to include constants and trends in both the short-run and long-run parts of equation (2). Three models can realistically be considered (Harris & Sollis, 2003, p. 133):

- Model 1 introduces only constants in the long-run model (i.e., in the cointegration vectors β) to account for unit of measurement of the variables in $\mathbf{z}_t$. This is appropriate if there are no linear trends in the levels of the data.
- Model 2 allows for such linear trends by adding a constant to the first-difference short-run component of Model 1. However, the two constants are not uniquely identified and it is therefore assumed that the they add up to provide an overall intercept in the short-run model.
- Model 3 further adds a time trend to the cointegration vectors to allow for long-run linear growth not accounted for in Model 2.

Unfortunately, there is no easy way to determine a priori which model should be used to test for cointegration, which introduces a serious difficulty given that the result of the test depends on the chosen model. Johansen (1992) proposes a solution to that conundrum that involves applying the Pandula principle to the joint hypothesis of a maximum rank of Π and combination of deterministic variables (i.e., constant and trends) entering the model. This is applied to the problem at hand and Table 3 reports the results, in the form of the p-values of the different hypotheses. The most stringent hypothesis of no cointegration relationship in Model 1 is strongly rejected, and giving more flexibility to the model by adding deterministic components (i.e. moving to models 2 and 3) also leads to rejection of the hypothesis of absence of cointegration. Moving from left to right, then top to bottom of the table, the first non-rejection of the null at the 5% level corresponds to the hypothesis of a single cointegration relationship in Model 2 (i.e.. constants in both short-run and long-run model), and this specification is therefore selected.

The long-run cointegration relationship

The normalised long-run cointegration relationship among the four variables estimated by the Johansen technique is as follows:

$$\ln P_{food} = \underset{(5.64)}{0.312}{*}\ln P_{ag} + \underset{(1.75)}{0.055}\ln{*}P_{en} + \underset{(7.04)}{0.258}{*}\ln P_w + 1.692 \qquad (3)$$

In equation (3), P_{food}, P_{ag}, P_{en} and P_w denote respectively the price indices of food, agricultural commodities and energy as well as the wage rate in food retail, while *t*-ratios of the estimated coefficients are reported in parentheses. Ignoring the constant which has no economic meaning and simply reflects units of measurement, the estimated coefficients have the expected positive sign, indicating a positive long-run relationship between food prices and the three major production factors used in the food chain. Further, the long-run relationships between food and input prices are statistically significant, very strongly so in the case of agricultural commodities and wages, but only at the 8% level in the case of energy. Given the log-log nature of the estimated equation, the coefficients can be interpreted as pseudo-elasticities reflecting the relative influence of each variable on food prices. On that basis, the estimation results indicate that agricultural prices represent the main determinant of food prices, with any 10% increase in price at the farm gate eventually resulting in a more than 3% increase in food prices at retail level. Next comes the wage rate in food retail, with a pseudo-elasticity, or pass-through rate, of just over a quarter, and finally energy, with a relatively small coefficient equal to 0.06.

Although the specification of the long-run relationship was selected on the basis of statistical tests, it is worth exploring the robustness of the results to the inclusion of deterministic variables in the cointegration equation. The following equation reports estimates of vector β when a linear trend is allowed to enter the long-run relationship:

$$\ln P_{food} = \underset{(5.28)}{0.272^*} \ln P_{ag} + \underset{(1.89)}{0.055} \ln^* P_{en} + \underset{(3.39)}{0.742^*} \ln P_w - \underset{(2.13)}{0.002^*} t - 0.350 \qquad (4)$$

While the coefficients associated with farm and energy prices remain close to those estimated in equation (3), the pseudo-elasticity associated with the wage rate in food retail is almost three times larger. Clearly, the model has difficulties separating the effects of the trend from those of wages, which seems intuitive given the high level of collinearity between the two variables already evident in Figure 1. Equation (4) also reports a negative monthly trend in food prices which translates into a 2.4% annual decrease, possibly due to technological and deflationary structural changes within the food chain.

Weak exogeneity and Granger causality tests

In order to better understand the dynamic relationships among the four variables and refine the model, we present the results of weak exogeneity tests of the null hypothesis that all adjustment parameters (i.e., rows of matrix α) associated with a given variable z_j are equal to zero. An exogenous variable, although it may enter the long-run equilibrium, is not itself caused by the other variables of the VAR (or VEC) model, and there is therefore no loss of information in not modelling its determinants (i.e., not including Δz_{jt} as a left-handside variable of the model). Instead, the model can then more simply be conditioned on that variable by introducing it as a right-hand-side variable (in first difference Δz_{jt}).

The results reported in Table 4 indicate that the prices of food and agricultural commodities should be treated as endogenous to the system at any reasonable level of significance, whereas the null of weak exogeneity of the price of energy and wages cannot be rejected. This suggests that the dynamics of the four variables is driven primarily by the wage rate in food retail as well as the price of energy, and that hypothesis can be analysed further through Granger causality tests, as reported in Table 5 for different lag lengths. Focusing first on the variable of primary interest, we can see that the price of food is Granger caused by the three remaining variables of the model, hence giving support to our broad logical framework[2]. Agricultural prices are themselves Granger caused by food and energy prices but not by the wage rate in food retail, which conforms to intuition. Turning to the two variables that have previously been characterised as weakly exogenous, the wage rate in food retail and the price of energy are not Granger caused by any of the variables in the model, and there is therefore here consistency between the two sets of tests (although the test results that food prices does not Granger cause energy prices change when the lag length is extended).

Vector Error Correction Model

Based on the two sets of tests, we specify a conditional VEC that includes food and agricultural prices as endogenous variables, with energy prices and wages treated as exogenous variables that enter the short-run model (contemporaneously and in lagged form) as well as the long-run model. Further, in search of a more parsimonious specification, F-tests of nullity of the two coefficients associated with each variable are carried out and reported in Table 6.

This shows that, of the conditioning variables, only one-month lagged energy prices are significant in the VEC model, while both endogenous variables (agricultural and food prices) are also only significant in the short-run model with a lag of one month. Most seasonal dummies are significant, although there are exceptions (e.g., February, May, June, and November). Altogether, this series of tests suggests that the short-run dynamics of the VEC model is captured by a very parsimonious specification that includes only energy prices and both endogenous variables with a single lag. However, estimation of that model reveals some serious problems of residual autocorrelation and heteroskedasticity, and trade-offs therefore exist between parsimony and robustness of the model. Through trial and error, we identified a preferred specification that includes two lags of the endogenous variables, all seasonal dummies, and both conditioning

[2] We note, however, that the hypothesis that energy prices Granger cause food prices is rejected when the lag length is extended to 12.

variables with a single lag. The estimation results are presented in Table 7 for that model as well as more general specifications mentioned previously.

Focusing on the preferred specification, we first note that the model, overall, has satisfactory explanatory power with a R-square equal to one half for the food price equation, and 0.58 for the agricultural price equation. The speed of adjustment coefficients associated with the error correction (EC) terms have the expected negative sign that is required for the model to return to its long run equilibrium following a shock. Further, the coefficients are highly statistically significant in both equations, and their magnitudes indicate a rather speedy process of adjustment back to equilibrium: the half-lives of the transitory dynamics describing food prices and agricultural prices are 3.8 months and two months, respectively.

The short-run dynamics are more difficult to interpret but a clear pattern emerges regarding the seasonality of the first endogenous variable: as compared to their December level, food prices are higher from January to July, and lower from August to November, with a particularly noticeable monthly hike in January (more than 1%). The seasonality of agricultural prices is less obvious, although there is evidence of relatively low prices in the first quarter of the year, and relatively high prices in July and August.

The short-run impact of the lagged endogenous variables are unclear as the coefficients associated with the one-month and two-month lags often have opposite signs and similar magnitudes. For instance, rather counter-intuitively the short-run effect of a ten percent increase in agricultural prices is to lower food prices by 0.4% the following month, but half of that increase then disappears in month two. Similarly, the two coefficients associated with lagged food prices in the agricultural price equation almost offset each other. Meanwhile, the coefficients of the weakly exogenous variables (wages in food retail and energy prices) are not very significant in the agricultural price equation, and have a negative sign that is difficult to interpret in the food price equation. Finally, we note that the constant is equal to zero (food price equation) or small and insignificant (agricultural price equation), which indicates the absence of linear structural change affecting producer technology and/or consumer preferences. All in all, the dynamics of food price formation is dominated by the relatively speedy adjustment to a long-run equilibrium as well as seasonal effects.

The statistical properties of the model are based on the assumption that the residuals in equation (2) are white noise, which was tested ex-post. Table 8 reports the result of autocorrelation tests for lag lengths of up to 12 months. The null hypothesis of absence of autocorrelation cannot be rejected for any lag length, except in the case of the LM-test with 12 lags. Note, however, that the Portmanteau test produces a different conclusion, whether based on the Q statistic or its adjusted version. We therefore conclude that the model does not suffer seriously from autocorrelation. Next, heteroskedasticiy is tested through the extension of White's (1980) test to systems of equations as discussed by Kelejian (1982) and Doornik (1995). The estimated LM chi-square statistics is 398.4 with 369 degrees of freedom, leading to a p-value of 0.14 that indicates that the null of absence of heteroskedasticity cannot be rejected. Finally, normality is tested through the multivariate extension of the Jarque-Bera test that compares the third and fourth moments of the residuals to those of the normal distribution. Normality is unfortunately rejected at the 5% level on the basis of either the skewness or kurtosis of the residuals. Altogether, we conclude that the estimated model is consistent with the underlying assumption of homoskedasticity and absence of autocorrelation, but violates the normality assumption. That last result, while not entirely satisfactory, is however rather commonly encountered in empirical applications of long time series.

Finally, Figure 2 presents the impulse response functions describing how food prices react to shocks affecting the three other variables of the model, hence providing a better understanding of how long-run model, short-run model, and volatility of time-series all contribute to the formation of food prices. Somewhat surprisingly in light of the relatively large adjustment coefficients reported previously, but in line with much of the literature on the subject, the figure indicates that food prices only stabilise after a significant period of time following a shock, with some adjustment still visible

24 months after the perturbation. Food prices respond the most to shocks affecting agricultural prices, which we explain by the importance of that variable in the long-run equilibrium (3) combined with its large variability evident in Figure 1. Next come energy prices, the relatively small influence of that variable on the long-run equilibrium being somewhat offset by its extreme volatility. The opposite explanation applies to the wage rate in food retail: although wages have a large influence on food prices in the long-run, as shown in equation (3), their limited variability implies that food prices respond little to a typical shock affecting that variable.

Discussion and Conclusion

This paper has used time-series econometrics to investigate the dynamics of food price formation in Finland. We have established the existence of a long-run equilibrium relationship between the prices of food and those of the main elements of the food marketing bill, namely agricultural commodities, energy and labour. Further, a simple vector auto-correction model shows that, after controlling for seasonal effects, those three variables alone explain about half of the variability in food prices since Finland joined the EU in 1995. Following a shock, convergence to the long-run equilibrium takes more than two years, although half of the adjustment typically occurs within 6-8 months (Figure 2).

In modern food-chains, large quantities of non-agricultural inputs are added to raw commodities in order to produce the final products that consumers ultimately purchase from retail stores. Our results indicate, however, that agricultural prices remain, quantitatively, the main determinant of food prices in Finland, with a long-run pass-through rate of nearly one third. Meanwhile, energy prices play a significant but quantitatively more limited role in determining the equilibrium level of food prices, although they are important in explaining food price variability. These findings are consistent with those reported for the US by Baek & Koo (2010) as well as Lambert and Miljkovic (2010)[3]. Although they confirm the existence of strong linkages between agricultural and energy markets, they also suggest that the role of energy prices in driving food price inflation should not be exaggerated.

Further, the analysis indicates that other economy-wide factors, which tend not to attract much attention from policy-makers and the media, are also very important in determining food price inflation (if not volatility). Hence, it follows from the estimated co-integration relationship that wages in food retail have a strong influence on Finnish food prices. The finding that those wages are themselves weakly exogenous to the model suggests that their determination lies largely outside of the food chain and results from an equilibrium on the Finnish labour market.

The analysis presented above could be extended in many directions in order to increase the robustness of the results and improve our understanding of food price formation in Finland. At a methodological level, it is for instance possible that the price dynamics is fundamentally different in periods of price stability and periods of price instability, and it would therefore seem interesting to test for the presence of structural breaks and/or the existence of different regimes of food price formation[4]. At an empirical level, it seems also likely that, as shown by Leibtag (2009) for the US, the dynamics of food price formation varies substantially for the different sub-sectors and links of the food chain. Hence, further insights would be gained from disaggregation of the analysis across food industries (e.g., meat, dairy) and the explicit investigation of price formation at the wholesale level. Finally, a comparative study of price formation in the different countries of the EU or the Baltic region would help in deriving general conclusions regarding the efficiency with which Finnish food markets operate.

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[3] To the best of our knowledge, the dynamics of food price inflation has not been analysed econometrically in any EU country, which gives novelty to our work but makes comparison difficult.

[4] However, the limited size of the dataset makes this inquiry difficult.

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Figure 1: Price indices of food and related variables (1995=100)

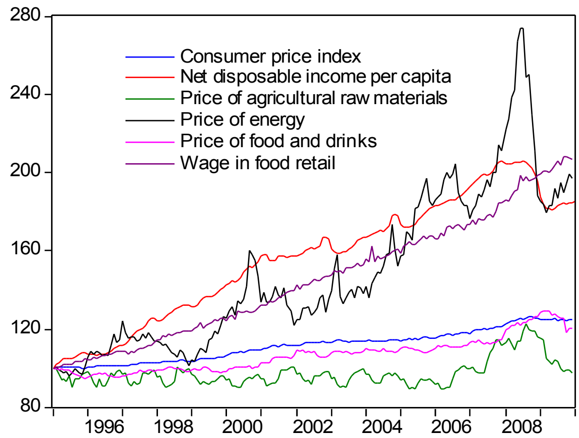

Figure 2: Impulse response functions

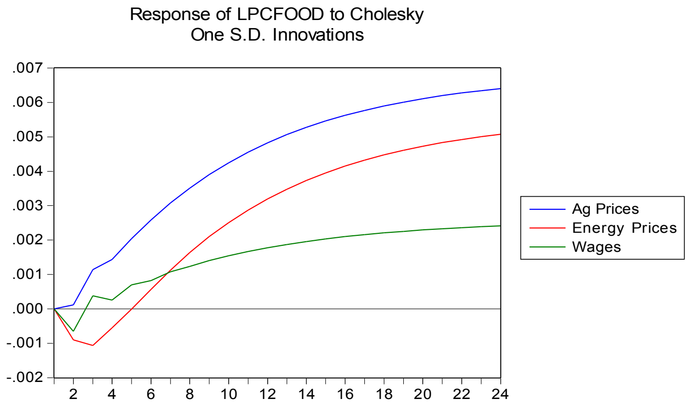

Table 1: Results of unit root tests

		ADF					PP				KPSS		
Variable	Exogenous	Stat. (level)	p-val.	Lag	Stat. (1st dif.)	p-val.	Stat. (level)	p-val.	Stat. (1st dif.)	p-val.	Stat. (level)	CV 5%	Stat. (1st dif.)
Farm Price	Cst	**-4.49**	**0.000**	12			-2.61	0.092	-12.99	0.000	0.65	0.46	0.05
	Cst & trend	**-4.54**	**0.002**	12			-3.3	0.069	-12.95	0.000	0.20	0.15	0.04
Food Price	Cst	-0.42	0.901	2	-7.62	0.000	-0.29	0.920	-14.44	0.000	1.55	0.46	0.12
	Cst & trend	-3.25	0.077	2	-7.64	0.000	-3.11	0.106	-14.46	0.000	0.18	0.15	0.05
Energy Price	Cst	-1.11	0.708	0	-12.72	0.000	-1.18	0.683	-12.74	0.000	1.58	0.46	0.04
	Cst & trend	-2.7	0.239	0	-12.69	0.000	-3.1	0.109	-12.7	0.000	**0.10**	0.15	
Wages	Cst	0.29	0.977	1	-24.33	0.000	0.61	0.990	-30.34	0.000	1.74	0.46	0.22
	Cst & trend	-3.3	0.069	1	-24.29	0.000	**-6.01**	**0.000**		0.000	**0.08**	0.15	

Table 2: Lag-length selection criteria in unrestricted VAR model

Lag	FPE	AIC	SC	HQ
0	3.89E-10	-10.3	-9.4	-10.0
1	3.46E-15	-21.9	-20.8	-21.5
2	2.44e-15*	-22.3*	-20.8*	-21.7*
3	2.61E-15	-22.2	-20.5	-21.5
4	2.92E-15	-22.1	-20.0	-21.3
5	3.04E-15	-22.1	-19.7	-21.1
6	3.33E-15	-22.0	-19.3	-20.9
7	3.20E-15	-22.1	-19.1	-20.9
8	3.46E-15	-22.0	-18.7	-20.7
9	3.55E-15	-22.0	-18.4	-20.5
10	3.91E-15	-21.9	-18.0	-20.3
11	3.82E-15	-22.0	-17.8	-20.3
12	3.75E-15	-22.0	-17.5	-20.2

* indicates lag order selected by the criterion
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 3: Results of cointegration tests

Number of cointegrating equations	Deterministic components Model 1	Model 2	Model 3
0	0.0000	0.0001	0.0000
At most 1	0.0000	**0.0589**	0.0032
At most 2	0.0458	0.2861	0.0025
At most 3	0.1769	0.9756	0.1373

Table 4: Results of exogeneity tests

Ho: Weakly exogenous variable(s)	Chi-squared	P-value
Price of food	18.75	0.000
Price of ag commodities	11.25	0.001
Price of energy	0.00	0.997
Wages in food retail	0.68	0.411
Price of energy & wages in food retail	0.69	0.708

Table 5: Results of Granger causality tests

Lag length	k=2		k=5		k=12	
Hypothesis	**F-Statistic**	**Prob.**	**F-Statistic**	**Prob.**	**F-Statistic**	**Prob.**
ln(P_{ag}) does not Granger cause ln(P_f)	11.44	0.000	4.00	0.002	6.07	0.000
ln(Pf) does not Granger cause ln(Pag)	2.51	0.084	2.76	0.020	2.65	0.003
ln(Pen) does not Granger cause ln(P_f)	10.40	0.000	5.77	0.000	3.17	0.001
ln(Pf) does not Granger cause ln(Pen)	0.77	0.466	0.64	0.668	3.02	0.001
ln(Pw) does not Granger cause ln(P_f)	5.20	0.006	3.31	0.007	1.46	0.147
ln(Pf) does not Granger cause ln(Pw)	1.38	0.255	1.27	0.279	0.88	0.568
ln(Pen) does not Granger cause ln(P_{ag})	3.68	0.027	2.04	0.075	1.25	0.254
ln(Pag) does not Granger cause ln(Pen)	1.36	0.258	0.86	0.506	1.37	0.187
ln(Pw) does not Granger cause ln(P_{ag})	1.45	0.238	1.05	0.392	0.68	0.767
ln(Pag) does not Granger cause ln(Pw)	1.16	0.315	0.87	0.500	0.97	0.477
ln(Pw) does not Granger cause ln(Pen)	2.50	0.085	1.34	0.248	1.51	0.128
ln(Pen) does not Granger cause ln(Pw)	0.71	0.494	0.82	0.535	0.88	0.572

Table 6: Results of F-test of Ho: coefficients of variable in left column are both equal to zero. In bold: rejections at 10% level of significance.

	Chi-Squared Statistics			P-values		
Lag	0	1	2	0	1	2
EC	**43.55**			**0.000**	-	-
P_e	0.39	4.78	2.28	0.822	**0.092**	0.320
P_w	0.87	2.49	0.49	0.648	0.288	0.782
P_f	-	**5.30**	2.49	-	**0.070**	0.288
P_a	-	**12.05**	4.23	-	**0.002**	0.121
SD_{Jan}	**22.98**	-	-	**0.000**	-	-
SD_{Feb}	3.32	-	-	0.190	-	-
SD_{Mar}	23.90	-	-	**0.000**	-	-
SD_{Apr}	4.98	-	-	**0.083**	-	-
SD_{May}	4.46	-	-	0.108	-	-
SD_{Jun}	0.45	-	-	0.798	-	-
SD_{Jul}	**27.97**	-	-	**0.000**	-	-
SD_{Aug}	**23.85**	-	-	**0.000**	-	-
SD_{Sep}	**5.24**	-	-	**0.073**	-	-
SD_{Oct}	**7.89**	-	-	**0.019**	-	-
SD_{Nov}	3.45	-	-	0.178	-	-

Table 8: Autocorrelation tests

	Portmenteau test				LM-test	
Lags	Q-Stat	P-value	Adj Q-Stat	P-value	LM-Stat	P-value
1	0.275	NA*	0.276	NA*	3.436	0.488
2	0.470	NA*	0.474	NA*	2.073	0.722
3	2.508	0.643	2.547	0.636	2.761	0.599
4	8.021	0.431	8.187	0.415	5.590	0.232
5	9.820	0.632	10.039	0.613	1.804	0.772
6	12.452	0.712	12.763	0.690	2.899	0.575
7	14.844	0.785	15.253	0.762	3.173	0.529
8	20.511	0.667	21.189	0.628	7.488	0.112
9	24.356	0.663	25.240	0.615	4.798	0.309
10	26.508	0.741	27.520	0.693	2.627	0.622
11	28.430	0.812	29.570	0.767	2.308	0.679
12	36.813	0.615	38.562	0.535	11.067	0.026

*The test is valid only for lags larger than the VAR lag order.

Table 7: Estimated VEC models

	Full VEC		Conditional VEC		Preferred VEC	
	ΔP_f	ΔP_a	ΔP_f	ΔP_a	ΔP_f	ΔP_a
EC	-0.176	-0.282	-0.178	-0.285	-0.165	-0.285
	[-5.44]	[-3.70]	[-5.44]	[-3.72]	[-5.23]	[-3.88]
ΔP_e	-	-	0.001	0.022	-	-
			[0.07]	[0.62]		
$\Delta P_e(-1)$	-0.032	0.015	-0.033	0.013	-0.032	0.016
	[-2.11]	[0.42]	[-2.15]	[0.36]	[-2.09]	[0.46]
$\Delta P_e(-2)$	-0.022	0.002	-0.023	-0.002	-	-
	[-1.46]	[0.05]	[-1.51]	[-0.04]		
ΔP_w	-	-	0.042	0.091	-	-
			[0.68]	[0.63]		
$\Delta P_w(-1)$	-0.115	0.107	-0.088	0.166	-0.112	0.062
	[-1.92]	[0.76]	[-1.23]	[0.99]	[-2.24]	[0.53]
$\Delta P_w(-2)$	-0.007	0.083	0.000	0.102	-	-
	[-0.12]	[0.58]	[0.00]	[0.70]		
$\Delta P_f(-1)$	-0.160	-0.141	-0.161	-0.126	-0.146	-0.153
	[-2.22]	[-0.83]	[-2.18]	[-0.73]	[-2.05]	[-0.92]
$\Delta P_f(-2)$	0.098	0.166	0.095	0.162	0.099	0.178
	[1.33]	[0.96]	[1.28]	[0.93]	[1.35]	[1.04]
$\Delta P_a(-1)$	-0.043	-0.276	-0.045	-0.286	-0.042	-0.274
	[-1.18]	[-3.18]	[-1.21]	[-3.25]	[-1.15]	[-3.17]
$\Delta P_a(-2)$	0.019	-0.166	0.019	-0.170	0.021	-0.168
	[0.52]	[-1.96]	[0.51]	[-1.99]	[0.59]	[-1.99]
C	0.002	-0.001	0.000	-0.006	0.000	-0.005
	[2.80]	[-0.74]	[-0.03]	[-1.19]	[0.17]	[-1.09]
SD_{Jan}	0.011	-0.018	0.011	-0.019	0.011	-0.018
	[3.94]	[-2.83]	[3.83]	[-2.89]	[4.17]	[-2.87]
SD_{Feb}	0.006	0.005	0.006	0.004	0.006	0.005
	[1.80]	[0.65]	[1.75]	[0.51]	[1.81]	[0.67]
SD_{Mar}	0.002	-0.039	0.002	-0.040	0.002	-0.039
	[0.65]	[-4.83]	[0.61]	[-4.85]	[0.50]	[-4.92]
SD_{Apr}	0.003	-0.016	0.003	-0.016	0.002	-0.016
	[0.76]	[-2.06]	[0.76]	[-2.10]	[0.61]	[-2.05]
SD_{May}	0.006	0.011	0.006	0.010	0.005	0.011
	[1.69]	[1.40]	[1.67]	[1.29]	[1.51]	[1.44]
SD_{Jun}	0.002	0.003	0.002	0.003	0.001	0.003
	[0.56]	[0.49]	[0.54]	[0.40]	[0.46]	[0.46]
SD_{Jul}	0.005	0.036	0.005	0.036	0.004	0.036
	[1.69]	[5.14]	[1.66]	[5.02]	[1.52]	[5.23]
SD_{Aug}	-0.004	0.033	-0.004	0.033	-0.004	0.034
	[-1.35]	[4.79]	[-1.30]	[4.70]	[-1.52]	[4.86]
SD_{Sep}	-0.001	0.017	-0.001	0.017	-0.001	0.017
	[-0.29]	[2.32]	[-0.26]	[2.27]	[-0.35]	[2.31]
SD_{Oct}	-0.006	0.011	-0.006	0.011	-0.007	0.011
	[-2.33]	[1.66]	[-2.30]	[1.61]	[-2.41]	[1.68]
SD_{Nov}	-0.002	0.011	-0.002	0.011	-0.002	0.011
	[-0.58]	[1.73]	[-0.56]	[1.77]	[-0.67]	[1.72]
R^2	0.504	0.581	0.506	0.583	0.497	0.580
Adj. R^2	0.441	0.527	0.435	0.523	0.440	0.532