EUROPEAN CENTRAL BANK

EUROSYSTEM

Food price pass-through in the euro area: the role of asymmetries and non-linearities(*)

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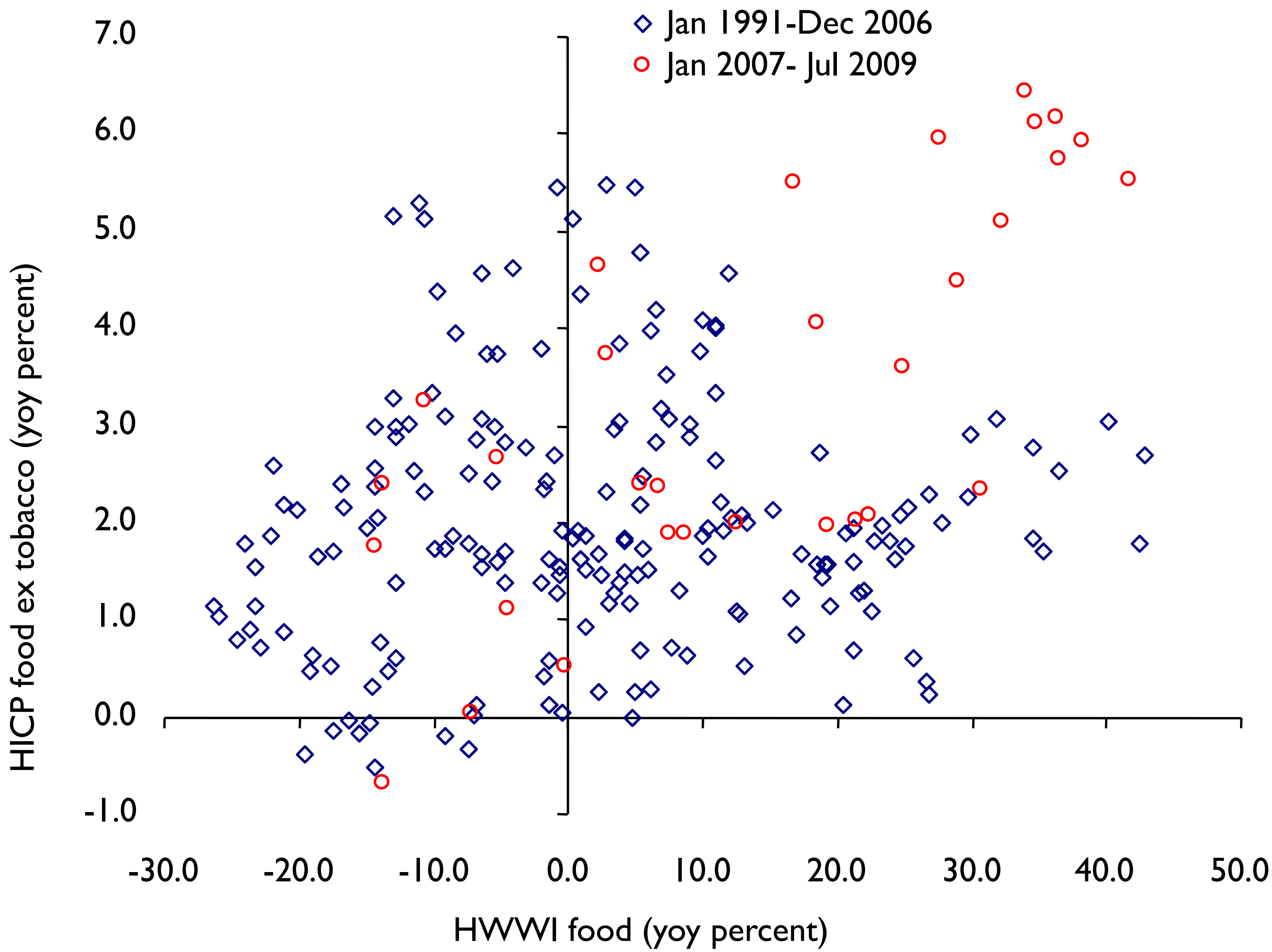
The views expressed in this presentation are those of the authors and do not necessarily reflect those of the European Central Bank

(*) The paper can be downloaded at: **http://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1168.pdf.**

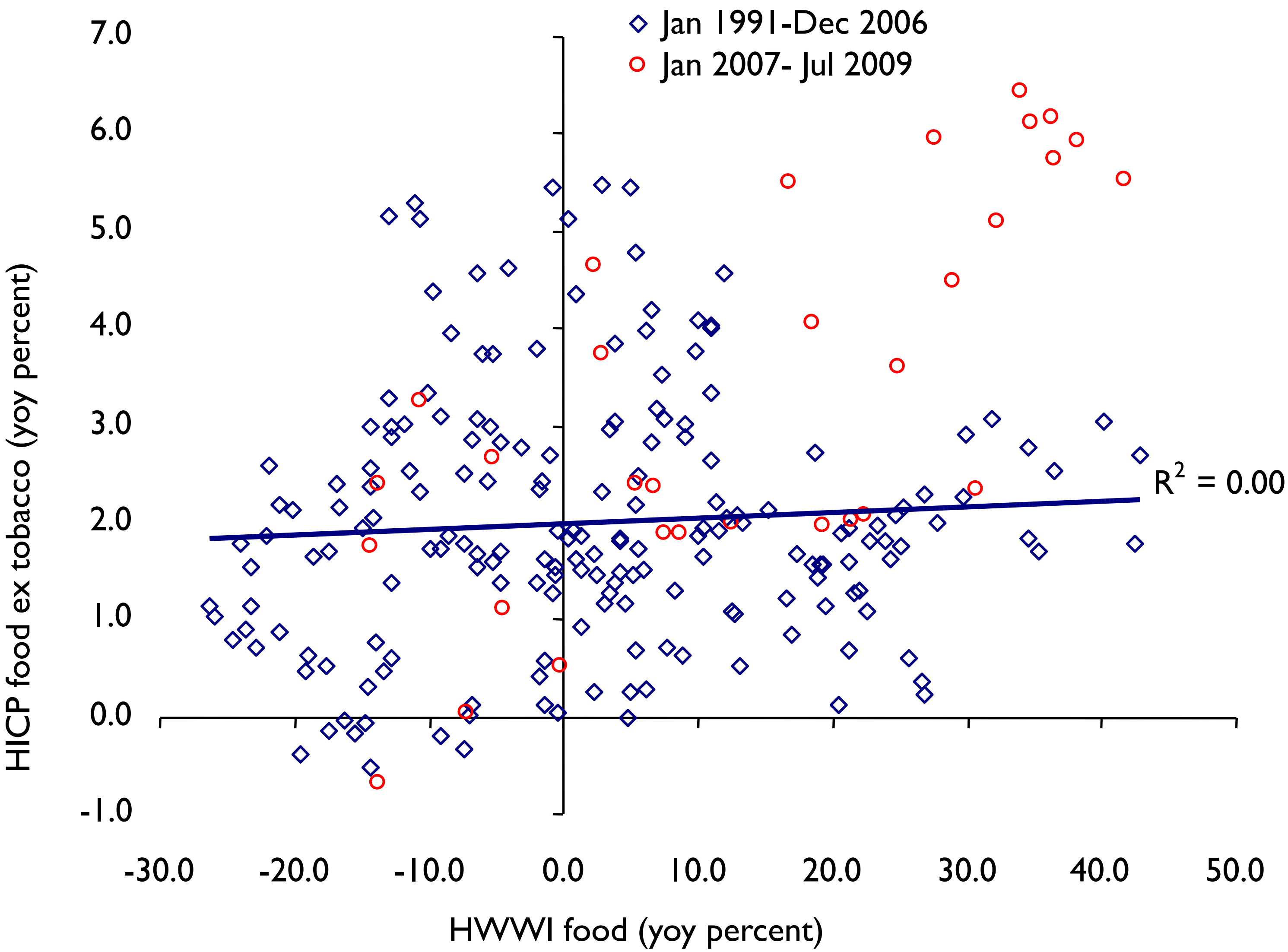
Outline

- **The paper's contributions:**
  - use of a new dataset to control for the CAP
  - accounting for non-linearities
- **Key findings**
- **Historical decomposition of the food price shock of 2007-09**

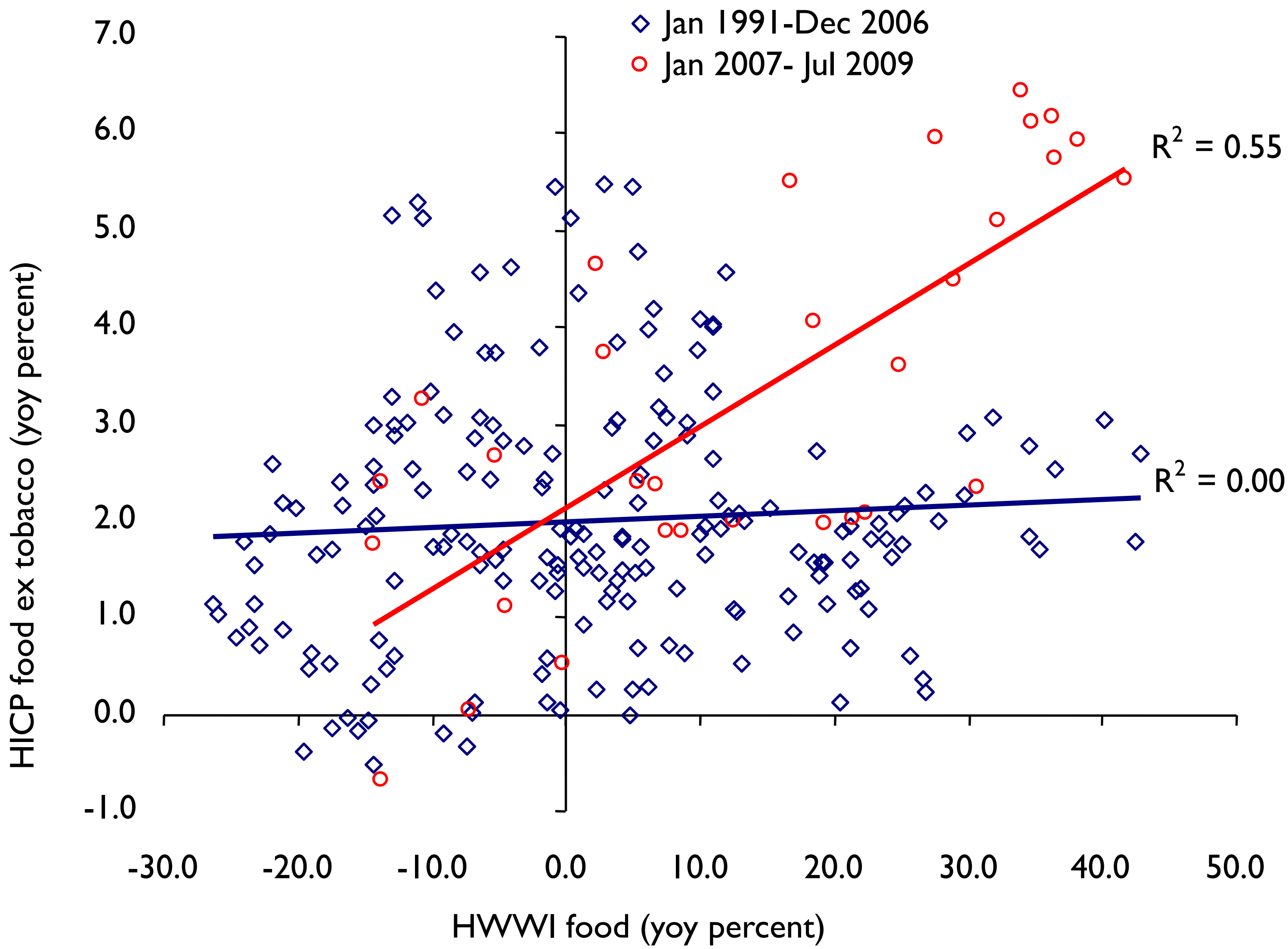
The food price puzzle: an illustration



The food price puzzle: an illustration



The food price puzzle: an illustration



Stylised facts from the earlier literature

- PT varies depending on the product
- PT varies across countries
- PT has changed over time
- PT to producer prices is higher than to consumer prices
- Pass-through is asymmetric and non-linear

For the euro area PT from international commodity prices is small and generally statistically insignificant

The food price puzzle

Conventional wisdom holds that commodity price shocks are transmitted to retail prices. Yet formal statistical tests struggle to find a robust pass-through (PT) for euro area food prices

Two hypotheses to explain this puzzle:

- **<u>Wrong data</u>: the international commodity prices at the heart of the existing PT studies neglect the distortions induced by the Common Agricultural Policy (CAP)**
- **<u>Wrong model</u>: PT may be non-linear, depending on the sign, size and volatility of the impulse**

Data issues

We use a new database of farm-gate and internal market prices of food commodities collected in the EU

Dataset takes implicitly into account the presence of the CAP in the EU

- **4 product groups covered (meat, crops, oils, dairy)**
- **Underlying series across the EU**
- **Monthly data, sample period starts in 1997**

Strong *prima facie* evidence that the CAP matters when assessing the PT in food production chain

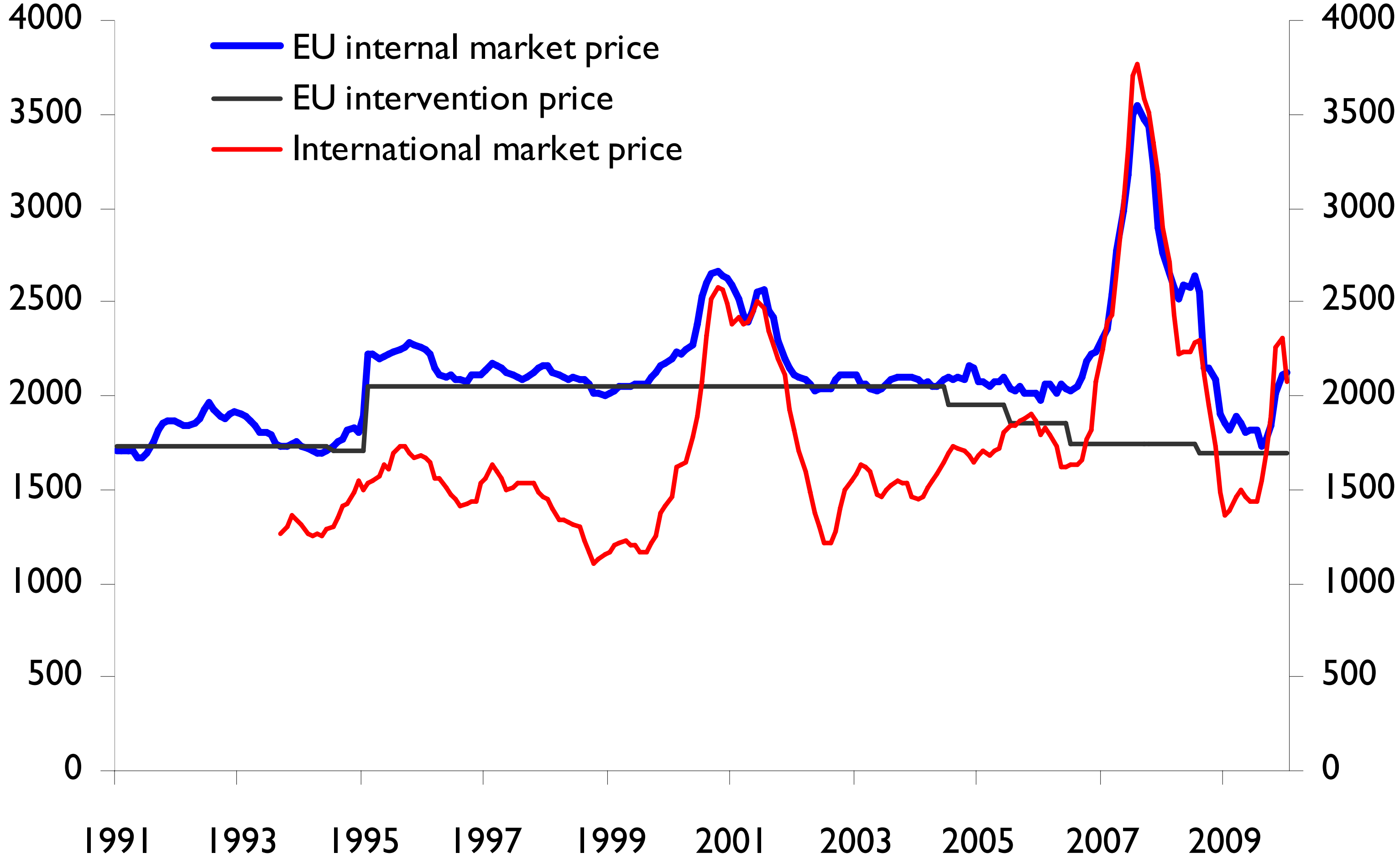
The DG-AGRI dataset: an overview

Cereals	*Dairy*	*Meat*	*Oil and fats*
Feed oats	*Skim milk powder (SMD)*	*Beef*	*Oil 2%*
Milling oats	*SMD - intervention quality*	*Joung beef*	*Extra vergin oil 0.5%*
Feed rye	*SMD - animal feed quality*	*Cow*	*Extra vergin oil 0.8%*
Breadmaking rye	*Butter*	*Young cow*	*Olive residue*
Durum wheat	*Cheddar*	*Pork*	*Olive residue 10%*
Feed wheat	*Edam*	*Chicken*	
Breadmaking wheat	*Eggs*		
Maize			
Malting barley			
Feed barley			

- 4 product groups and 28 price series covered
- Individual price series not weighted together within product groups

Milk prices and the role of the CAP

(euro per ton)

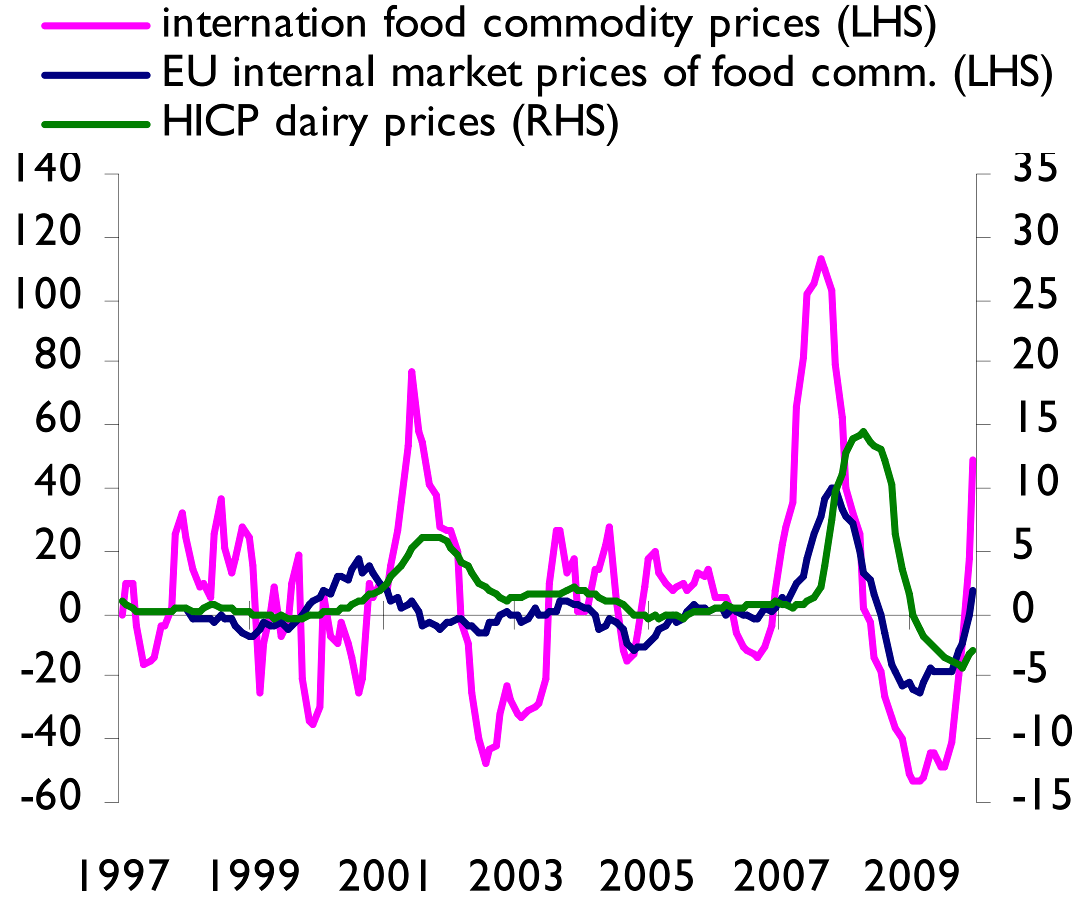


Sources: European Commission and USDA.

Note: monthly data; last observation December 2009.

Commodity and retail prices: dairy products

(annual percentage changes)



International food commodities significantly more volatile than EU internal market prices

EU internal market prices tend to correlate more closely with HICP food prices

EU commodity prices lead changes in HICP food prices

Sources: Eurostat, DG-AGRI and USDA.

Note: monthly data; last observation Dec 2009.

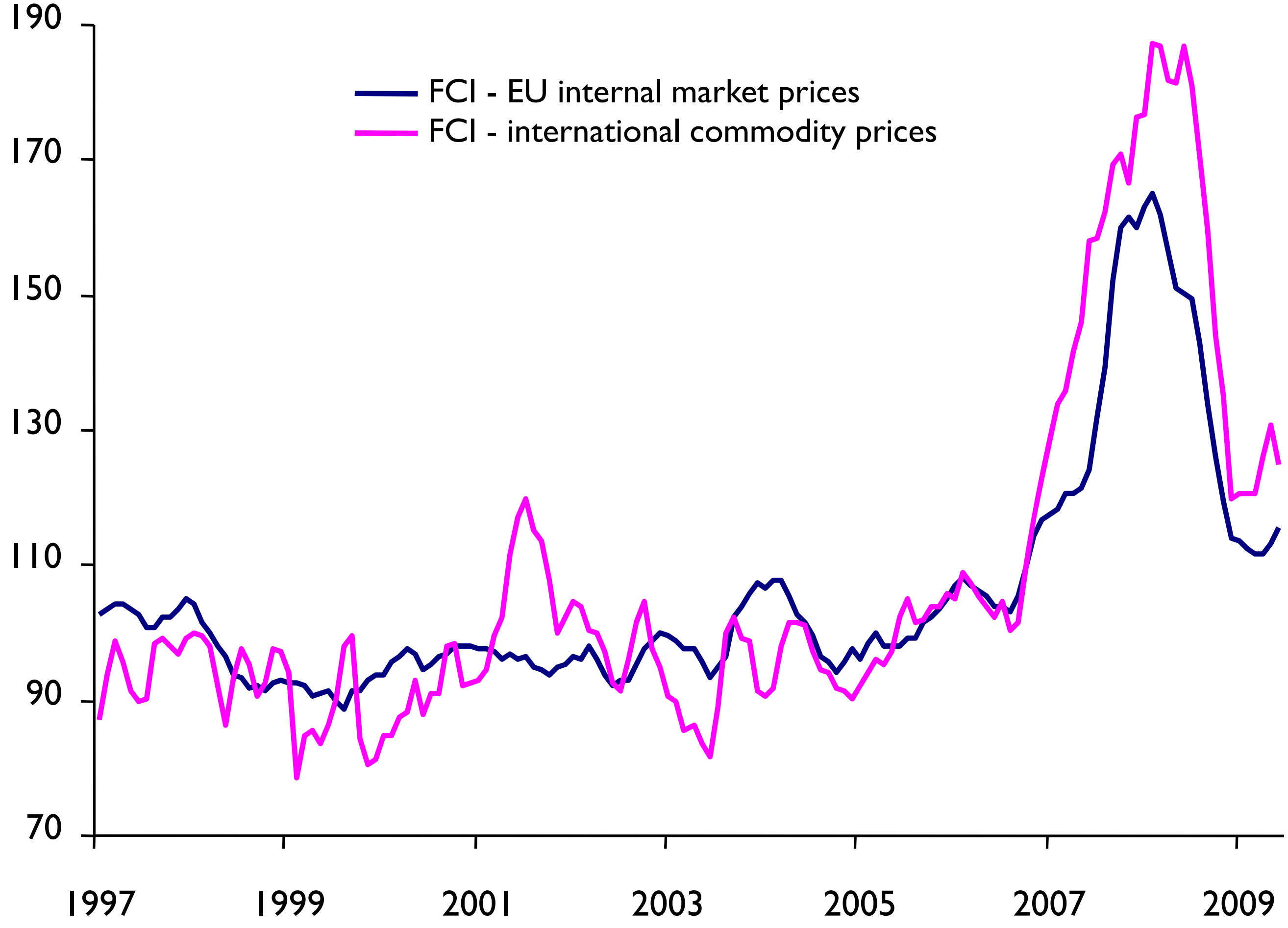
A new Food Commodity Index (FCI)

Individual series can be combined in a FCI including:

- **EU internal market prices for the commodities that are produced domestically in the EU (e.g. wheat, milk)**
- **international prices for those commodities that are not subject to CAP intervention prices (e.g. cocoa, coffee)**

Prices are weighted using use-based weights

International vs EU internal market prices



Sources: DG-AGRI, HWWI, and ECB calculations.

VAR analysis in a food price chain

Estimate VARs in a price chain framework

EU farm-gate → PPI food → HICP food

Pass-through measured by impulse responses

Estimation performed both on food aggregates and on sub-components

Focus on selected food items representing ~ 50% of the euro area HICP food consumption basket (fish, fruit, vegetables, soft drinks, alcoholic beverages and tobacco are excluded)

Asymmetries and non-linearities

Estimate five different VARs on monthly data:

1) <u>Linear:</u>

$$y_t = k + \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t$$

y_t is (n x 1) vector of endogenous variables
k is (n x 1) intercept vector
A_i is (n x n) matrix of AR coefficients (i = 1, 2, ..., p)
ε_t is (n x 1) vector of white noise processes

$$y_t = (hicp\_food_t, ppi\_food_t, comm\_food_t)'$$

Asymmetries and non-linearities

Estimate five different VARs on monthly data:

2) Asymmetric: separate positive and negative shocks

$$c_t^+ = \begin{cases} c_t \; if \; c_t > 0 \\ 0 \; if \; c_t \leq 0 \end{cases}$$

$$c_t^- = \begin{cases} c_t \; if \; c_t < 0 \\ 0 \; if \; c_t \geq 0 \end{cases}$$

Then estimate two separate VARs

$$y_t = (hicp\_food_t, ppi\_food_t, c_t^+)'$$

$$y_t = (hicp\_food_t, ppi\_food_t, c_t^-)'$$

Asymmetries and non-linearities

Estimate five different VARs on monthly data:

3) <u>Net 1</u>: considers commodity prices increases that exceed the maximum value over the previous 12 months

$$NCPI_t = \max\left(0, c_t - \max\left\{c_{t-1}, \ldots, c_{t-12}\right\}\right)$$

4) <u>Net 2</u>: considers commodity prices increases that exceed the maximum value over the previous 24 months

Asymmetries and non-linearities

Estimate five different VARs on monthly data:

5) <u>Scaled</u>: AR(12) GARCH(1,1) specification, to account for volatility

$$c_t = \alpha_0 + \alpha_1 c_{t-1} + \ldots + \alpha_{12} c_{t-12} + e_t$$

$$e_t \left| I_{t-1} \right. \sim N(0, h_t)$$

$$h_t = \gamma_0 + \gamma_1 e_{t-1}^2 + \gamma_2 h_{t-1}^2$$

$$SCPI_t = \max\left(0, c_t / \sqrt{\hat{h}_t}\right)$$

Persistence of a 1% commodity price shock

Length of pass-through to HICP

(number of months)

	Linear	Asymmetric	Net 1	Net 2	Scaled
Bread	10	7	7	7	8
Coffee	8	7	9	8	7
Dairy	8	9	10	10	10
Fats	9	9	10	4	10
Meat	7	2	2	2	7
Sugar	-	-	c	c	-
FCI	9	8	8	8	9

- Full PT to consumer prices takes between 7 and 10 months
- Finding of a slow PT in line with earlier studies
- Heterogeneity
- Slower than PT to PPI

Impact of a 1% shock in commodity prices

Linear model – by HICP food component

(percentage point)

	Bread	Coffee	Dairy	Fats	Meat	Sugar
contemporaneous	-0.0014	0.0056	0.0307	-0.0019	0.0477	0.0016
1 quarter	0.0614	0.0429	0.2369	0.0960	0.1391	0.0052
2 quarters	0.1413	0.0767	0.5361	0.1548	0.1939	0.0094
3 quarters	0.2152	0.0930	0.7103	0.1762	0.2303	0.0125
4 quarters	0.2583	0.1011	0.7383	0.1829	0.2487	0.0144
5 quarters	0.2714	0.1051	0.6918	0.1849	0.2554	0.0153
6 quarters	0.2650	0.1071	0.6412	0.1855	0.2564	0.0157

- Differences in PT by component appear significant
- In principle, bottom-up approach is preferable as it allows a more flexible modelling of idiosyncratic components

Impact of a 1% shock in commodity prices

Linear model – Aggregate versus disaggregate

(percentage point)

	Weighted sum	FCI	FCI INTERNATIONAL
contemporaneous	0.0233	0.0285	-0.0001
1 quarter	0.1226	0.1767	0.0070
2 quarters	0.2317	0.3246	0.0295
3 quarters	0.3029	0.4259	0.0488
4 quarters	0.3270	0.4727	0.0600
5 quarters	0.3229	0.4846	0.0649
6 quarters	0.3108	0.4819	0.0661

– Differences between aggregate and disaggregate approach: use of FCI leads to overestimation

– When global commodity prices are used PT becomes minuscule

Impact of a 1% shock in commodity prices

HICP food prices – differences across models

(percentage point)

	Linear	*Asymmetric*	*Net 1*	*Net 2*	*Scaled*
Panel A: Weighted sum					
contemporaneous	*0.0233*	*0.0327*	*0.0156*	*0.0150*	*0.0144*
1 quarter	*0.1226*	*0.2133*	*0.1335*	*0.1375*	*0.1023*
2 quarters	*0.2317*	*0.3927*	*0.2547*	*0.2607*	*0.2200*
3 quarters	*0.3029*	*0.5052*	*0.3402*	*0.3409*	*0.3041*
4 quarters	*0.3270*	*0.5496*	*0.3817*	*0.3776*	*0.3468*
5 quarters	*0.3229*	*0.5531*	*0.3910*	*0.3835*	*0.3589*
6 quarters	*0.3108*	*0.5419*	*0.3840*	*0.3750*	*0.3561*

- Asymmetries are important – PT of negative shocks is nil
- Impact of "exceptional" shocks is not much different from linear case
- Scaling the shock by its volatility also yields similar PT as linear case

Historical decomposition

Compute a historical decomposition (Sims, 1980) to gauge the impact of commodity price shocks on retail food prices

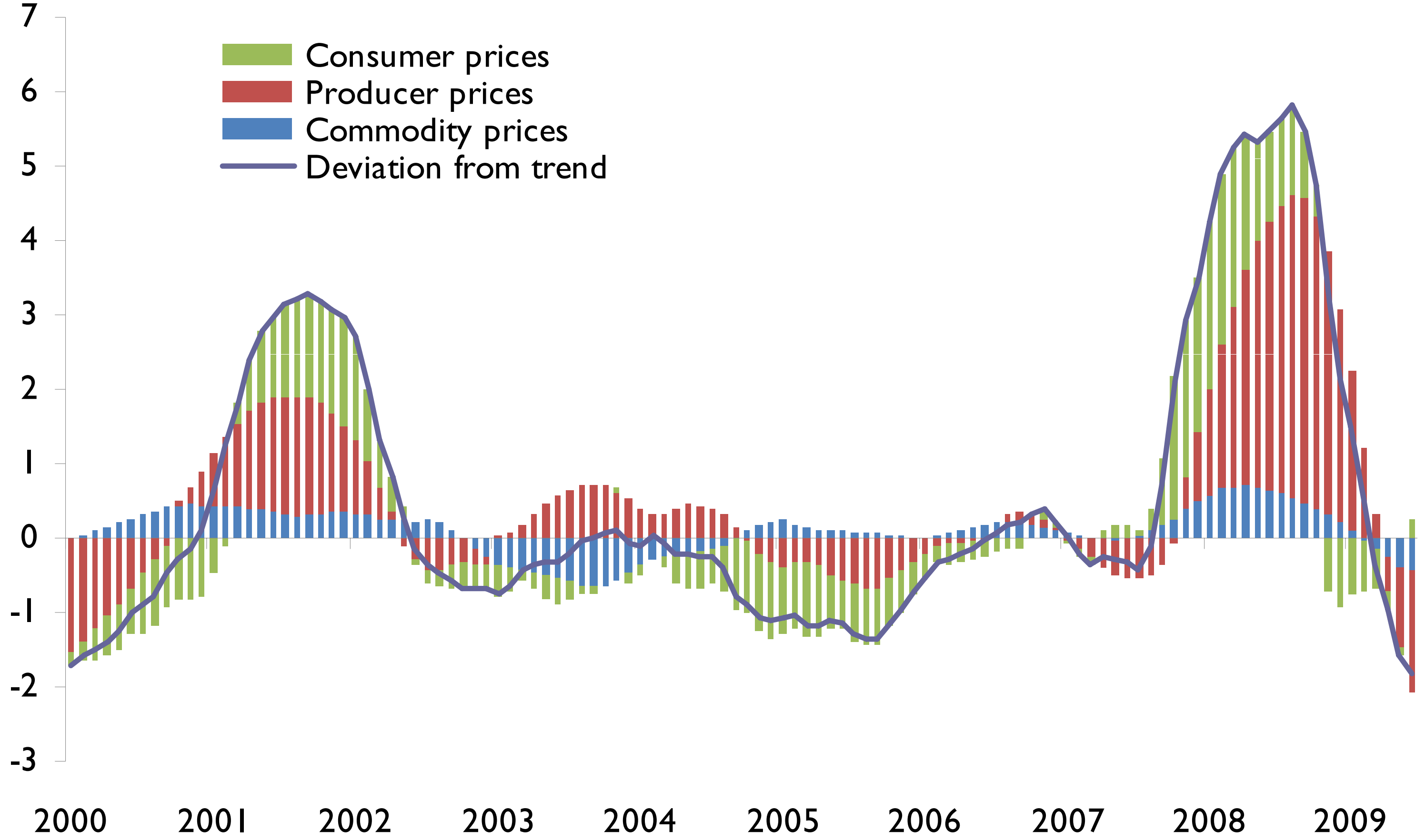
Decomposition shows how much of the deviation from trend in HICP food prices is attributed to shocks at various stages of the food supply chain

Shocks are assumed to follow the same order as the food price chain:

commodity prices → PPI food → HICP food

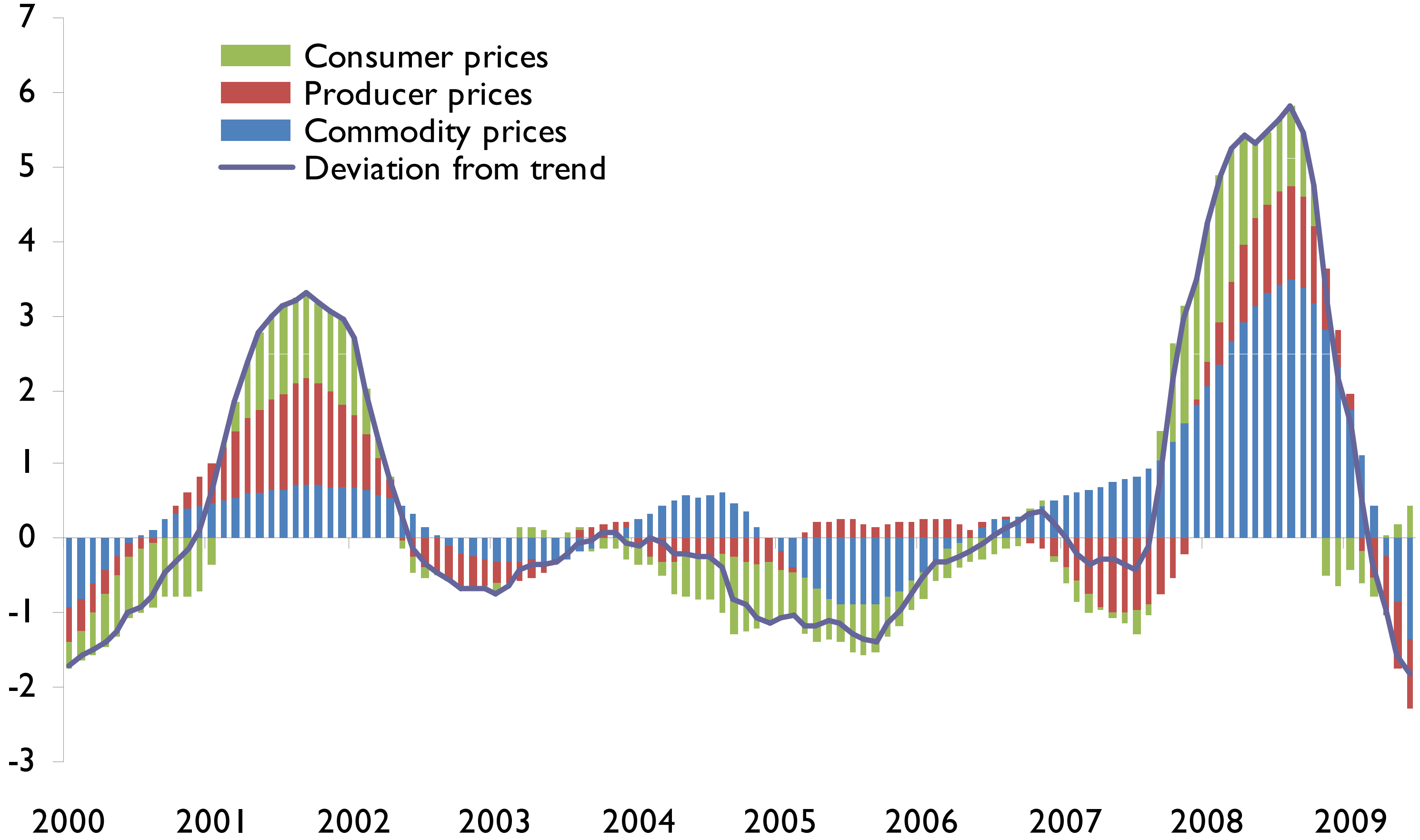
Historical decomposition (1)

Linear VAR + International commodity prices



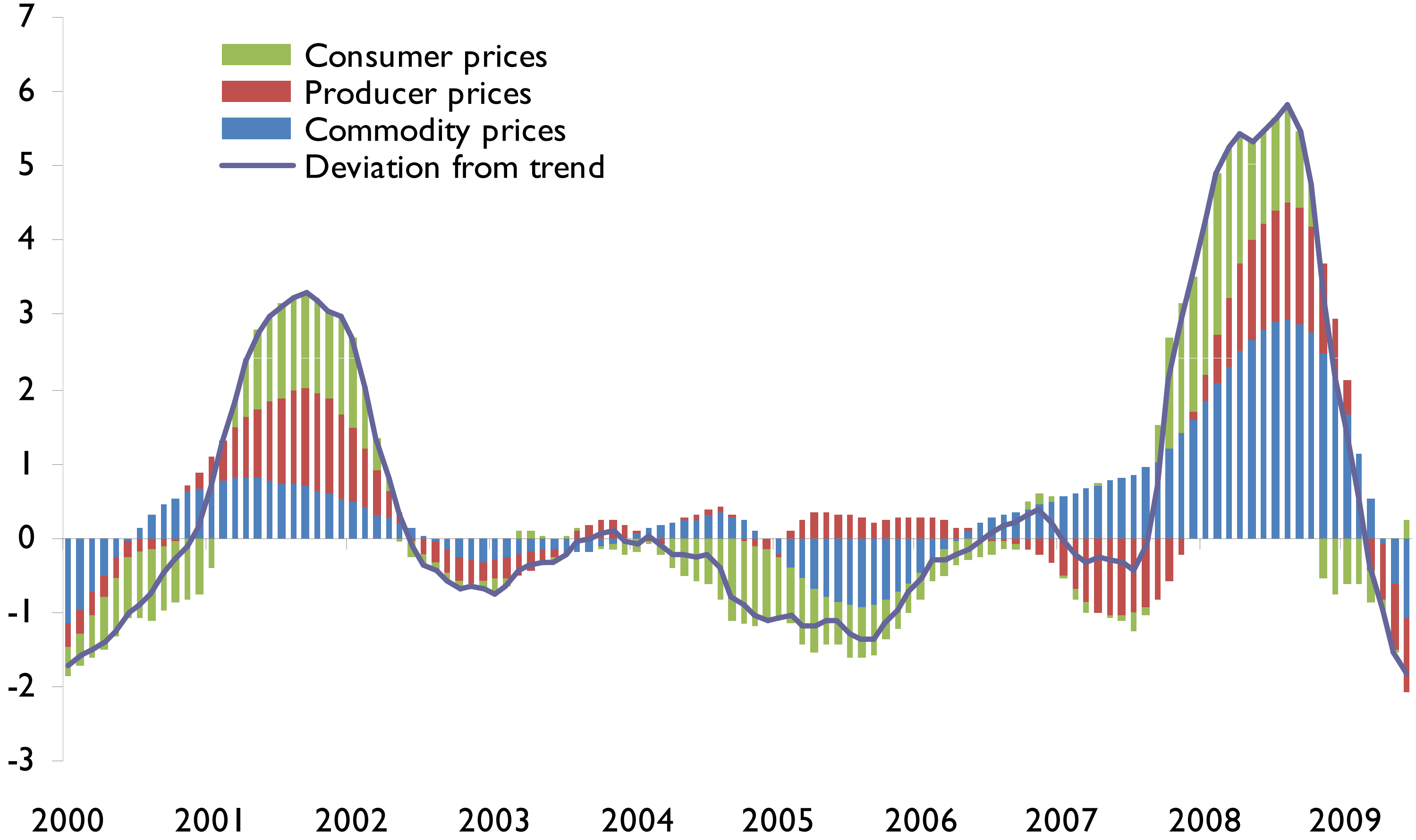
Historical decomposition (2)

Linear VAR + EU internal market prices



Historical decomposition (3)

Non-linear VAR + EU farm gate prices



Conclusions

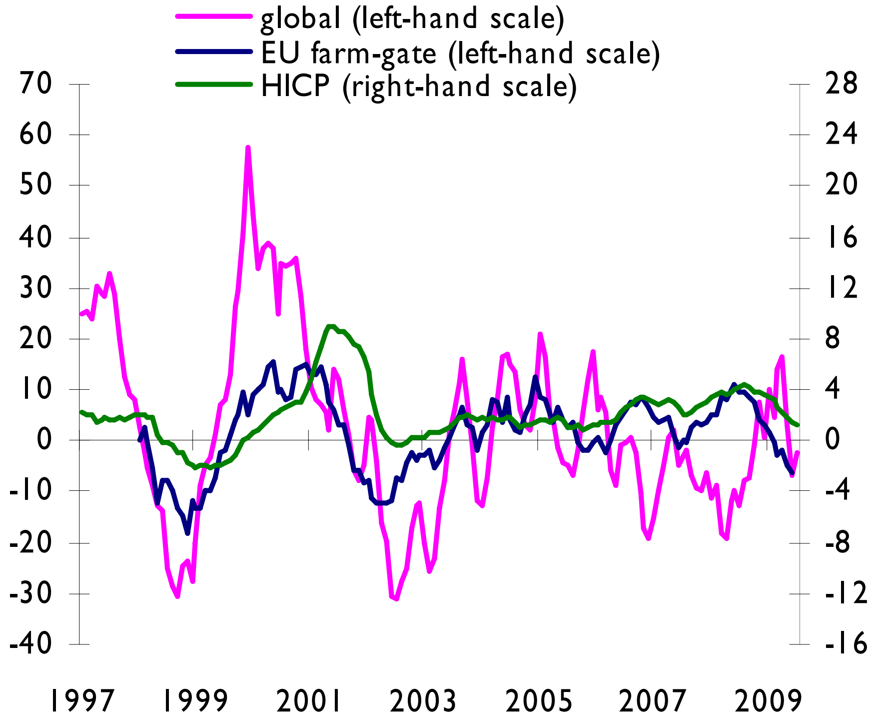
- **We have measured PT elasticities in the food supply chain using a VAR and impulse responses**
- **EU farm-gate prices perform well – unlike international commodities**
- **Asymmetries and non-linearities appear to be statistically and economically significant**
- **The disaggregate approach allows more flexible modelling of idiosyncratic components, this can be an advantage for short time forecasting**

Thank you for your attention!

Consumer and commodity prices

Meat

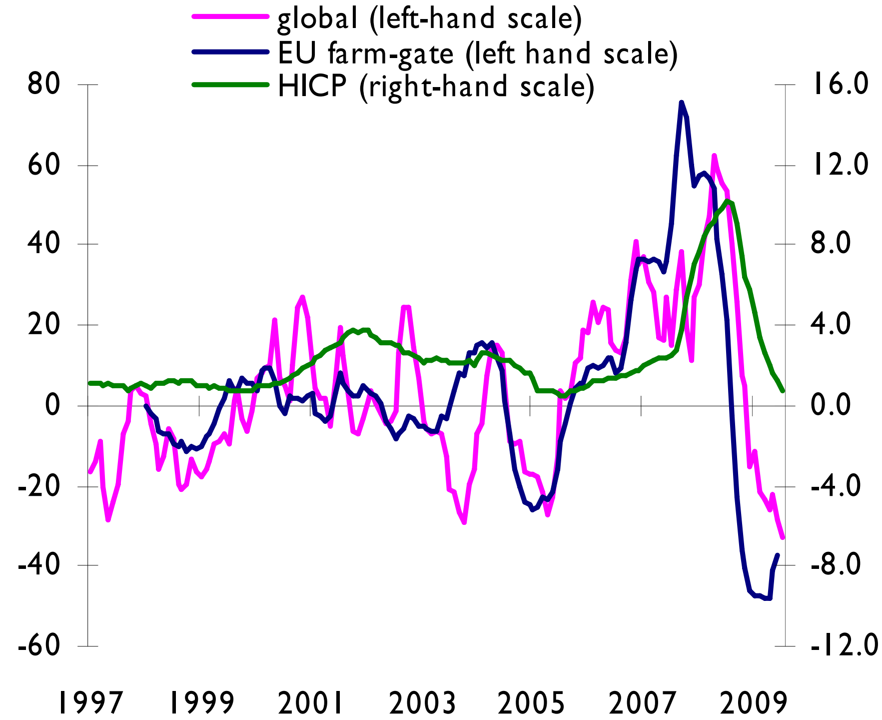
(annual percentage change)



Sources: Eurostat, DG-AGRI and Bloomberg.

Bread and cereals

(annual percentage change)

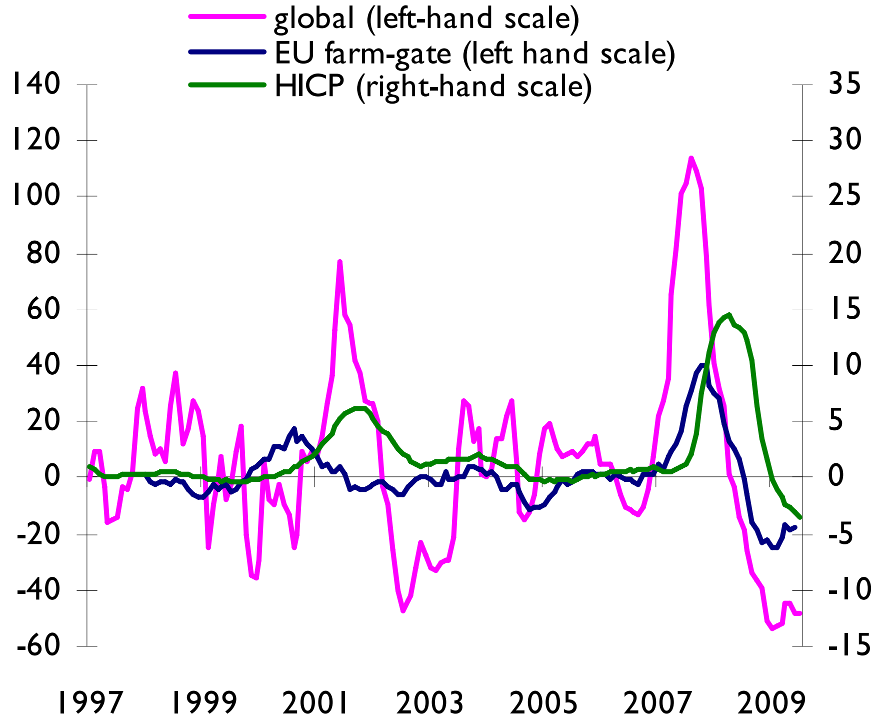


Sources: Eurostat, DG-AGRI and OECD.

Consumer and commodity prices

Dairy

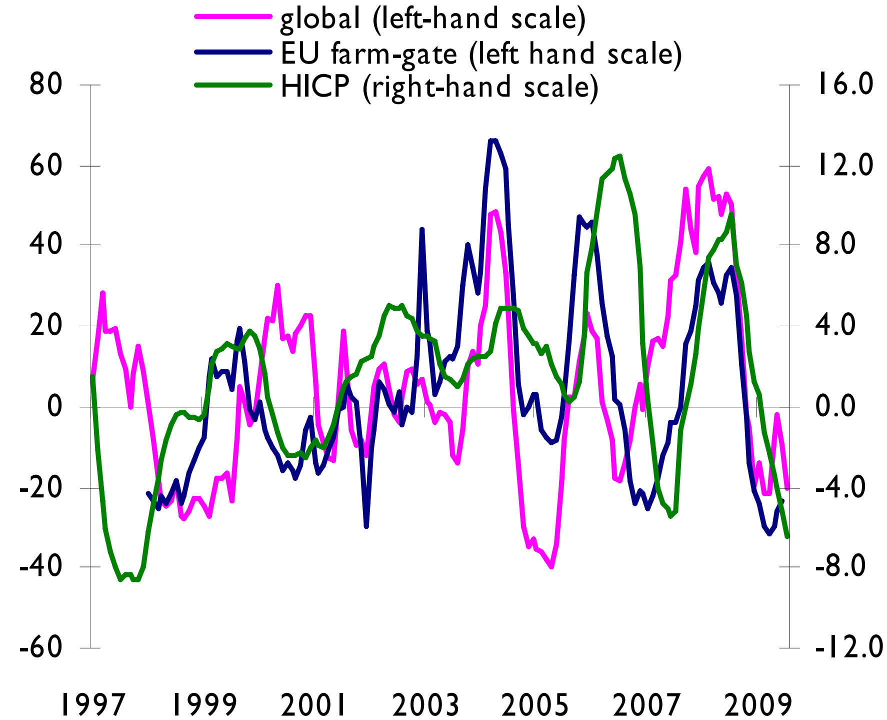
(annual percentage change)



Sources: Eurostat, DG-AGRI and Bloomberg.

Oil and fats

(annual percentage change)



Sources: Eurostat, DG-AGRI and OECD.

Euro area HICP food prices by component

	Food item	Weight in overall HICP food
UNPR	Meat	18.8
PR	Bread and cereals	13.3
PR	Milk, cheese and eggs	11.8
PR	Sugar, jams, honey, chocolate and confectioneries	4.9
PR	Oil and fats	2.8
PR	Coffee	1.9
	Total of included items	**53.5**
UNPR	Fish	5.9
UNPR	Fruit	6.2
UNPR	Vegetables	8.1
PR	Mineral waters, soft drinks, fruit and vegetable juices	4.9
PR	Alcohol beverages	7.5
PR	Tobacco	11.6
PR	Food products n.e.c.	2.2
	Total of excluded items	**46.4**

Impact of a 1% shock in commodity prices

HICP food prices

(percentage point)

	Linear	Asymmetric	Net 1	Net 2	Scaled
Panel A: Weighted sum					
contemporaneous	0.0233	0.0327	0.0156	0.0150	0.0144
1 quarter	0.1226	0.2133	0.1335	0.1375	0.1023
2 quarters	0.2317	0.3927	0.2547	0.2607	0.2200
3 quarters	0.3029	0.5052	0.3402	0.3409	0.3041
4 quarters	0.3270	0.5496	0.3817	0.3776	0.3468
5 quarters	0.3229	0.5531	0.3910	0.3835	0.3589
6 quarters	0.3108	0.5419	0.3840	0.3750	0.3561
Panel B: FCI					
contemporaneous	0.0285	0.0456	0.0190	0.0200	0.0234
1 quarter	0.1767	0.3194	0.2045	0.2018	0.1597
2 quarters	0.3246	0.5306	0.3438	0.3412	0.2831
3 quarters	0.4259	0.6516	0.4241	0.4182	0.3602
4 quarters	0.4727	0.7042	0.4606	0.4499	0.3959
5 quarters	0.4846	0.7200	0.4727	0.4580	0.4071
6 quarters	0.4819	0.7207	0.4743	0.4572	0.4078
Panel C: FCI international					
contemporaneous	-0.0001	-0.0018	-0.0025	-0.0026	0.0015
1 quarter	0.0070	0.0074	0.0065	0.0055	0.0005
2 quarters	0.0295	0.0446	0.0335	0.0470	0.0078
3 quarters	0.0488	0.0746	0.0555	0.0824	0.0140
4 quarters	0.0600	0.0932	0.0700	0.1047	0.0179
5 quarters	0.0649	0.1038	0.0791	0.1161	0.0202
6 quarters	0.0661	0.1097	0.0848	0.1199	0.0216

Persistence of a 1% commodity price shock

Length of pass-through to PPI

(number of months)

	Linear	*Asymmetric*	*Net 1*	*Net 2*	*Scaled*
Bread	*8*	*5*	*5*	*5*	*7*
Coffee	*7*	*5*	*8*	*7*	*5*
Dairy	*7*	*7*	*8*	*8*	*8*
Fats	*5*	*4*	*3*	*2*	*4*
Meat	*3*	*1*	*c*	*c*	*3*
Sugar	*-*	*-*	*-*	*-*	*-*
FCI	*7*	*6*	*6*	*6*	*7*

- Full PT to the consumers takes between 7 and 10 months. Finding from earlier studies of a slow PT broadly confirmed by the VAR analysis
- Heterogeneity
- Slower than PT to PPI

Historical decomposition: conceptual

Compute a historical decomposition to gauge the impact of commodity price shocks on retail food prices

Theory:

Write the VAR

$$A(L)y_t = \varepsilon_t$$

in moving average form

$$y_t = [A(L)]^{-1}\varepsilon_t = \sum_{i=0}^{\infty} M_t \varepsilon_{t-i}$$

where M_t is a diagonal matrix

Historical decomposition: conceptual

Assume $$\varepsilon_t = Sv_t$$

Where v_t is a vector of orthogonal random variables such that

$$Evv' = I \quad \textbf{and} \quad SS' = \Sigma$$

is the covariance matrix of ε_t

As there is more than one factorisation *SS'* of Σ, assume a Choleski decomposition where *S* is lower triangular

Historical decomposition: empirical

In practice:

Decomposition constructed via a succession of in-sample forecasts, as a layer cake:

First project y_t assuming $\varepsilon_t = 0$ (→ trend in y_t)

Then add the shocks ε_t one by one, assuming the same ordering as the price chain:

commodity prices → PPI food → HICP food

Pairwise difference measures how much of the deviation from trend in HICP food prices is attributed to shocks at various stages of the food supply chain

Historical decomposition: caveat

Ordering matters when using Choleski

- does the ordering make sense economically?
- (Granger) test for one way causality
- robustness test