BANCO DE ESPAÑA
Eurosistema

Análisis y predicción de la inflación

Luis J. Álvarez

Desarrollos recientes y herramientas
para el análisis de la situación económica
Banco de España-CEMLA, Madrid, 5-7 junio

DG ECONOMICS, STATISTICS AND RESEARCH

Outline

A. Forecasting Álvarez and Sánchez (2019)

1. Some key ideas
    1. Usefulness of model-based expert forecasts
    2. Heterogeneity in price setting
    3. Accounting for changes in trend inflation

2. Three types of models
    1. Highly disaggregated univariate models
    2. Transfer function models
    3. Macro-founded models (e.g. Phillips curves)

B. Recent research

1. **Low inflation** Álvarez, Gadea and Gómez-Loscos (2019a)
2. **Inflation interdependence** Álvarez, Gadea and Gómez-Loscos (2019b)

Why model-based expert forecasts?

1. **Experts process a lot of information that is hard to endogenously include in a formal econometric model** (e.g. a future indirect tax change may be announced)
2. **Available evidence suggests that subjective inflation forecasts improve on a variety of model-based ones** (e.g. Faust and Wright (2013))
3. **Essentially, all models are wrong, but some are useful. Box and Draper (1987)**

Any model is just an imperfect stylized representation of the true world and some transmission channels may be modelled imperfectly or not at all

4. **Different models are useful to a different extent (forecasting, storytelling) so that a suite of models is to be preferred to just using a single one**

…and their relative merits may well depend on the nature of the shocks (e.g. changes in trend inflation**)**

Structural (behavioral) vs atheoretical (statistical) models

Structural models provide a theoretically sound explanation of relationships among variables, but are not very accurate for short term forecasting

Atheoretical models are much more reliable for the short term, but do not provide good explanations

Heterogeneity in price setting

Large heterogeneity in product markets in terms of:

1. **demand and supply elasticities**
2. **external competition**
3. **excise duties**
4. **government regulation**
5. **transitory shocks**

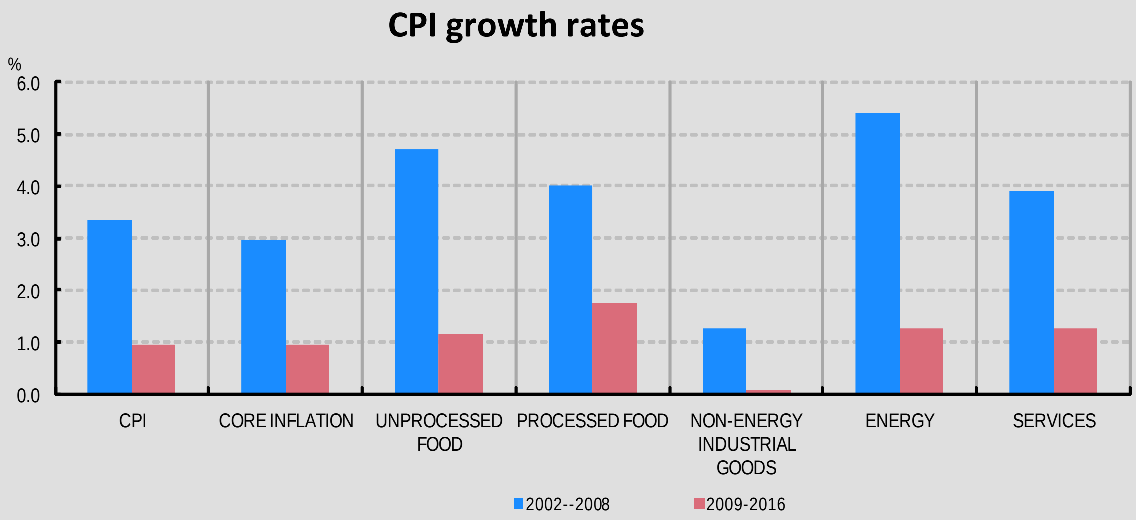
Price stickiness (Álvarez et al. (2006)**) and inflation persistence (**Lünnemann and Mathä (2004)**) are found to vary across goods and services**

This suggests a need to address heterogeneity

Enlarging the information set leads to improvements in the precision of forecasts (when the data generating process is known**)**

Changes in trend inflation

Stationary models of inflation following the Great Recession have tended to generate unreasonably high forecasts at longer horizons because inflation has been persistently above its full sample average. (These forecasts converge to the unconditional mean of inflation as the horizon gets large**)**



Some alternatives:

- **Breaks in mean (Hard to determine ex-ante; Not necessarily abrupt)**
- **Inflation gaps (Difference of inflation and a trend measure; Need to forecast trend inflation)**
- **Changes in inflation (Past inflation proxies trend inflation)**
- **Markov switching models**

1. Highly disaggregated univariate models

It is difficult to improve systematically upon simple univariate forecasting models, such as the Atkeson-Ohanian (2001) random walk model or the unobserved components model in Stock and Watson (2007). (IMA (1,1) representation**)**

We consider ARIMA(p,d,q)x(ps,ds,qs) models augmented with intervention analysis. For each of the COICOP 5 items (over 120 series), estimate by maximum likelihood models such as

$$\Delta^{d^i} \Delta_{12}{}^{d_s{}^i} \varphi^i(L)[p_t^i - \sum \alpha_j{}^i D_{jt}] = \theta^i(L)\epsilon_t$$

d^i and $d_s{}^i$ are the order of the product specific regular and seasonal difference operators

$\varphi^i(L)$ and $\theta^i(L)$ are product specific polynomial lag operators

D_{jt} are time dummies

This specification allows for heterogeneity and is able to capture changes in trend inflation

Model specification according to Gómez and Maravall (2001) algorithm

Gómez and Maravall (2001) algorithm

Determine the number of unit roots by estimating general mixed (regular and seasonal) models.

Roots are considered to be unit roots if their modulus is greater than a pre-specificed value

These estimators are consistent [Tiao and Tsay]

Classical unit root tests have low power when moving average components are important

Determine the order of autoregressive and moving average polynomials using a penalty function method à la Hannan-Rissanen [computationally cheap approximation to Bayesian information criterion] Parsimonious models are to be preferred

The algorithm allows for deterministic variables (outliers, Easter …) or regression effects

Model characteristics

	NUMBER OF MODELS WITH UNIT ROOTS (%			
	0	1	2	TOTAL
REGULAR UNIT ROOTS	2.4	84.7	12.9	100.0
SEASONAL UNIT ROOTS	33.1	66.9	0.0	100.0

77% of identified models imply non-stationary inflation. Most models have 1 regular and 1 seasonal unit root

Models are very parsimonious (Average number of AR and MA parameters is 2.4)

The modal model is ARIMA (0,1,1)x(0,1,1)$_{12}$ [23% of cases]

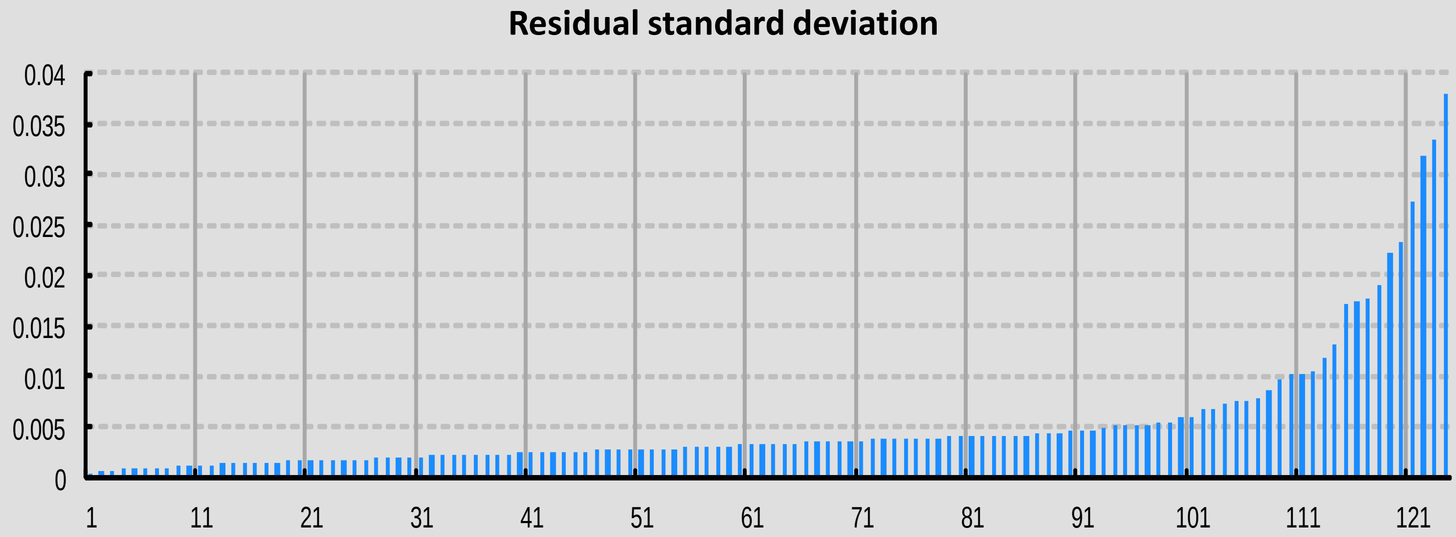
	ORDER OF REGULAR POLYNOMIALS			
	1	2	3	TOTAL
PURE AUTOREGRESSIVE	17.7	7.3	4.8	29.8
PURE MOVING AVERAGE	29.8	1.6	2.4	33.9
MIXED MODEL	9.7	2.4	6.5	18.5
NO POLYNOMIAL				17.7

No clear pattern for regular polynomials

	ORDER OF SEASONAL POLYNOMIALS			
	1	2	3	TOTAL
PURE AUTOREGRESSIVE	13.7	0.0	0.0	13.7
PURE MOVING AVERAGE	58.9	0.0	0.0	58.9
MIXED MODEL	13.7	0.0	0.0	13.7
NO POLYNOMIAL				13.7

Seasonal polynomials are predominantly of the moving average type

Large heterogeneity in product price predictability



Harder to forecast prices correspond to energy (Electricity, gas, fuels) and unprocessed food (e.g. beef, poultry, potatoes..)

…but also some services (Hotels and travel packages)

Most other services prices are typically easy to forecast (Rents, health insurance …), in the sense that their models have low residual standard deviations

2. Transfer function models

$$p_t^i = \sum \alpha_j{}^i D_{jt} + \sum \beta^i(L) x_{jt}^i \quad + N_t^i{}_t$$

$$N_t^i \quad = \frac{\theta^i(L)}{\Delta^{d^i} \Delta_{12}{}^{d_s{}^i} \varphi^i(L)} \; \epsilon_t^i$$

x_{jt}^i are explanatory variables (e.g producer prices, oil price)

Forecasts from these models do not necessarily converge to the unconditional mean. This will depend on regular and seasonal unit roots in the series and in explanatory variables

Need to forecast explanatory variables

We consider a less detailed breakdown than for univariate models

Indicators used

	Indicators	Dummies	
		VAT	Regulated prices
Unprocessed food			
Fruits and vegetables	Fruits and vegetables agricultural prices		
Meat, and fish	Meat agricultural prices		
Processed food	Industrial and import prices	Tobacco taxes	
Non energy industrial goods			
Clothing and footwear	Industrial prices	VAT	
Rest	Industrial prices	VAT	Regulated prices
Energy	Oil prices		Regulated prices
Services	Unit labour costs	VAT	Regulated prices

Indicators of domestic and external prices are built by CPI-weighting disaggregated data on indicators

VAT rises were not significant for food and energy; Neither excise duties on alcohol

Import prices do not have explanatory power on non-energy industrial goods

Forecasting energy

❿

$$\Delta P_t^C = \alpha \Delta P_t^O + \beta \Delta P_{t-1}^O + \gamma P_t^O \Delta P_t^O$$

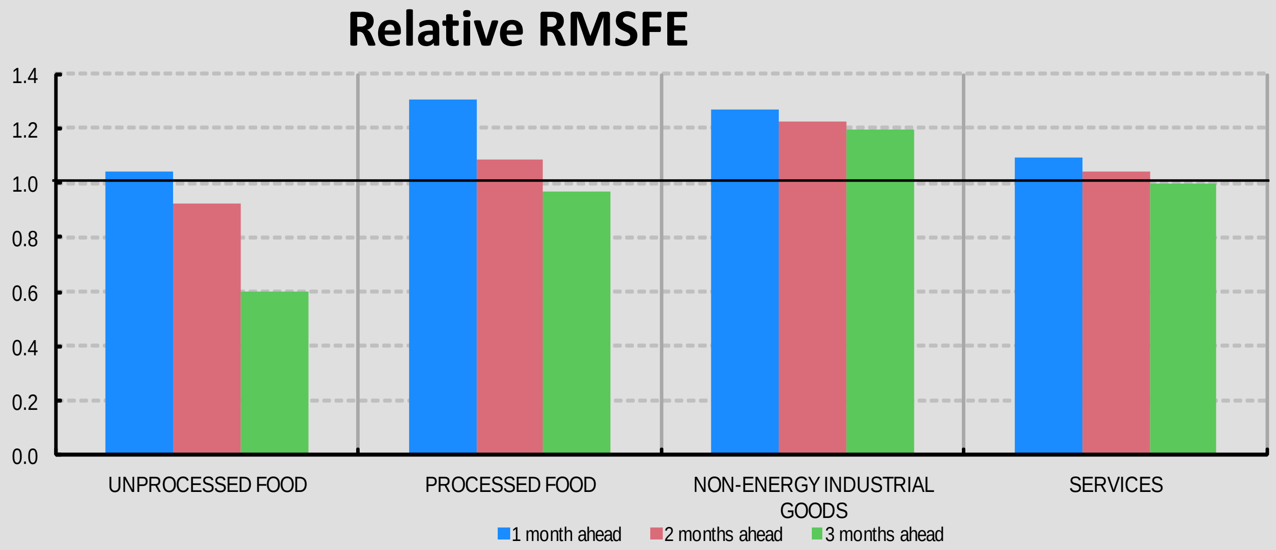
For transport and heating fuels, we use non-linear models that allow the elasticity to depend on the oil price

Nowcasts are made using weekly retail price data

For electricity prices, we use information on wholesale markets to nowcast

For natural gas and butane gas prices, we consider information on announced changes, since they are regulated

Real time forecast evaluation



Bottom up univariate forecasts tend to perform worse than transfer function models (Relative RMSFE higher than 1)

Forecast gains diminish the further the horizon, reflecting difficulties in forecasting indicators

Small gains for services and unprocessed food

Hybrid New Keynesian Phillips Curve Models

$$\pi_t = \pi_t^e + \alpha h_t + e_t$$

$$\pi_t^e = \gamma \pi^o + (1-\gamma)\frac{1}{4}(\pi_{t-1} + \pi_{t-2} + \pi_{t-3} + \pi_{t-4})$$

Ball and Mazumder (2011)

Models just for core inflation

We also control for changes in VAT, regulated prices and external prices

Models using GDP growth and the change in the unemployment rate are used

These models involve stationary inflation, which limits their usefulness as forecasting models

ASYMMETRIC MODELS

Equation [2]. Model with asymmetrical response to GDP and forward- and backward-looking inflation expectations		
Inflation expectations (γ)	0.24	0.005
GDP growth (α)	0.06	0.063
Recession dummy(α_r)	0.27	0.001
Adjusted R^2	0.70	

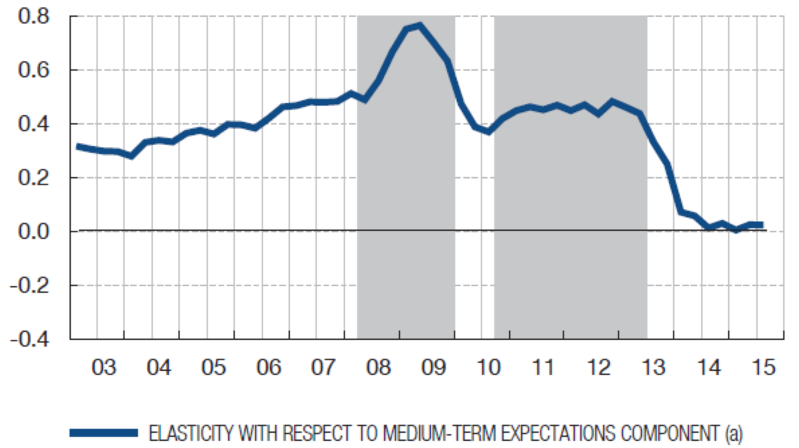
$$\pi_t = \pi_t^e + \alpha h_{t-1} + \alpha_r h_{t-1} d_r + e_t$$

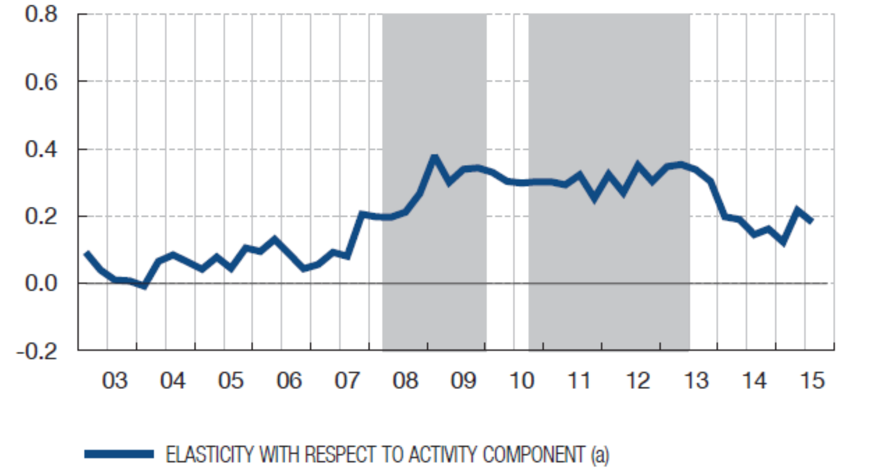
$$\pi_t^e = \gamma \pi^o + (1-\gamma)\frac{1}{4}(\pi_{t-1} + \pi_{t-2} + \pi_{t-3} + \pi_{t-4})$$

- **We generalize Ball and Mazumder (2011) to allow for asymmetries**
- **The sensitivity of inflation depends on the business cycle: the response is significantly higher in recessions than in expansions**
- **This asymmetry is in line with survey results in Álvarez and Hernando (2007) and Izquierdo and Jimeno (2015)**

ASYMMETRIES AND THE ROLE OF EXPECTATIONS

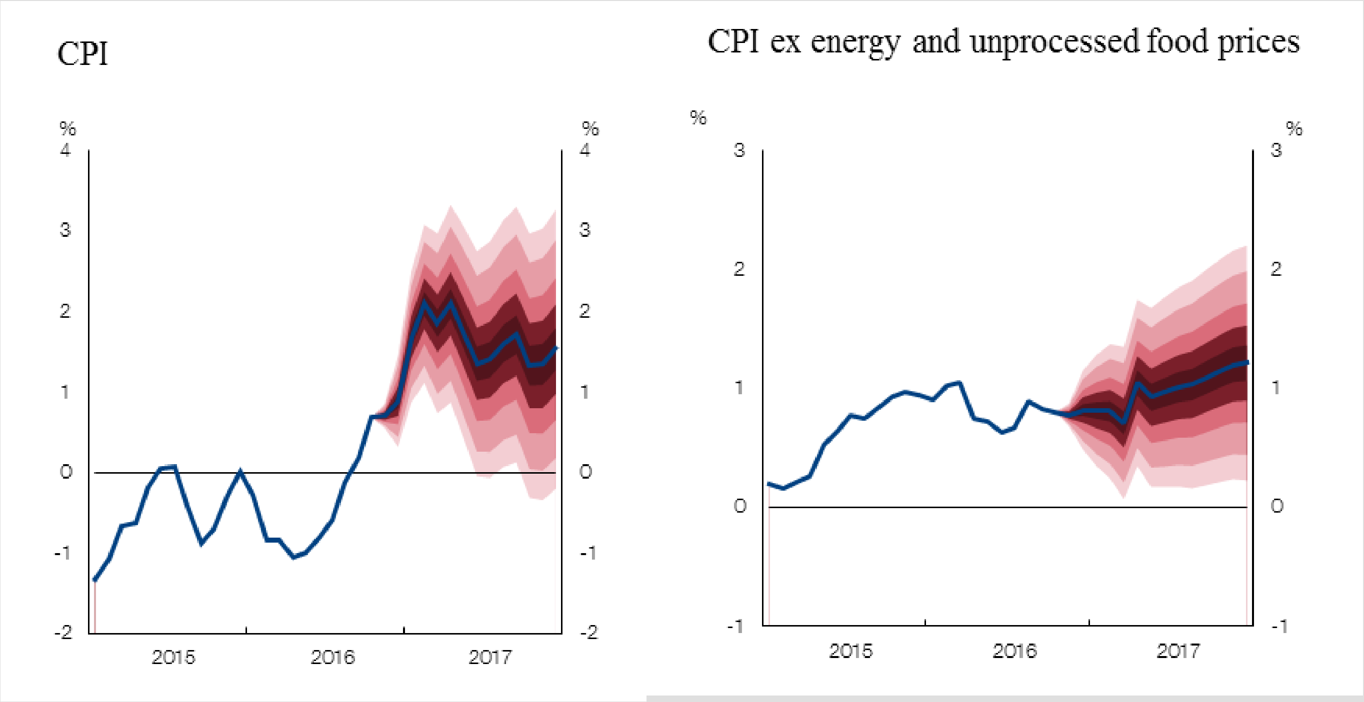
ELASTICITY OF INFLATION TO ITS DETERMINANTS





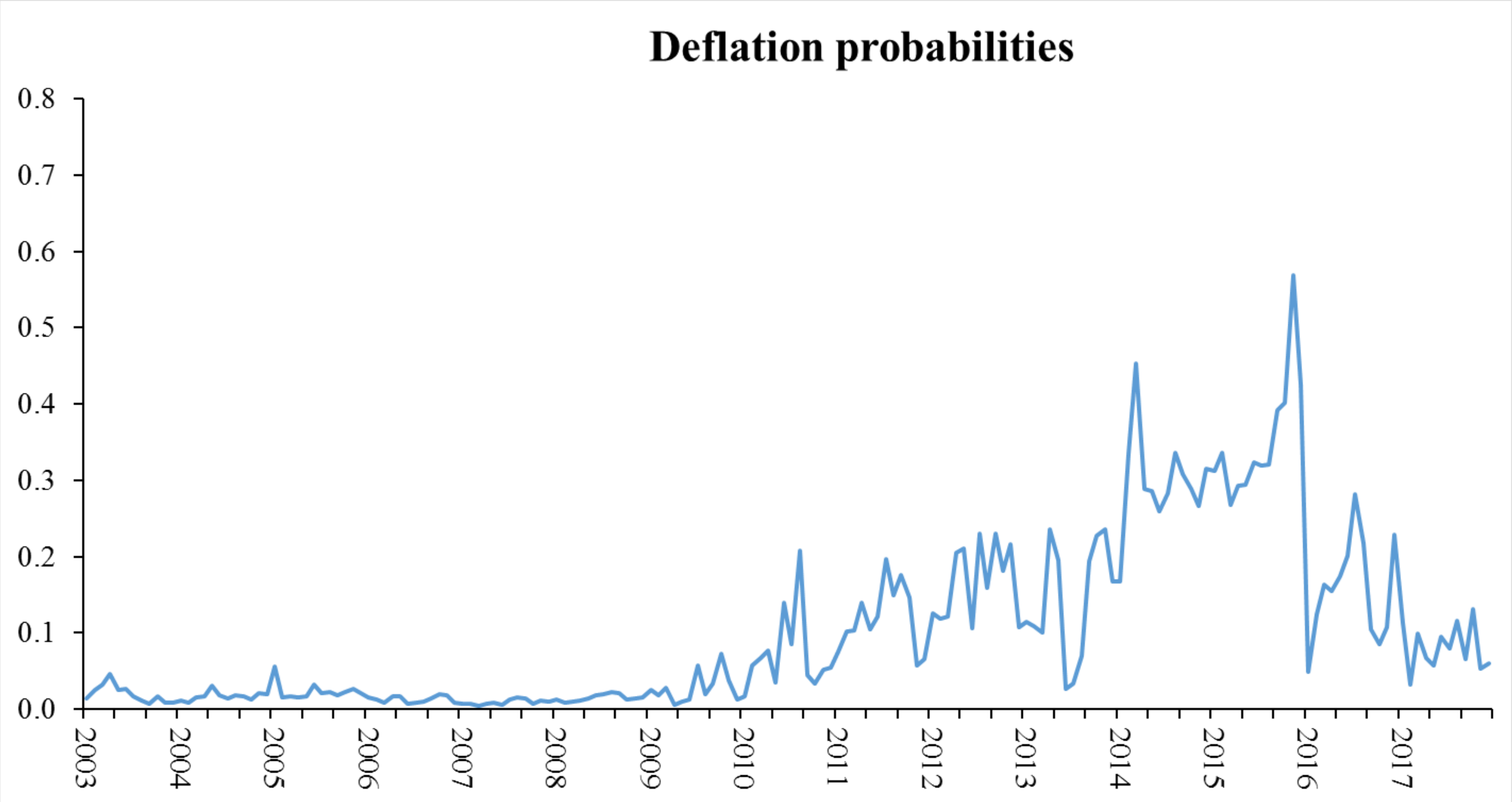
- **Time-varying estimates point to a loss of weight of the forward looking component in the determination of inflation expectations ¿Deanchoring?**
- **This result is in line with Busetti at al. (2015)**
- **Time-varying estimates also show that the responsiveness of inflation in recessions is higher than in expansions**

Some illustrations: 1. Fan charts



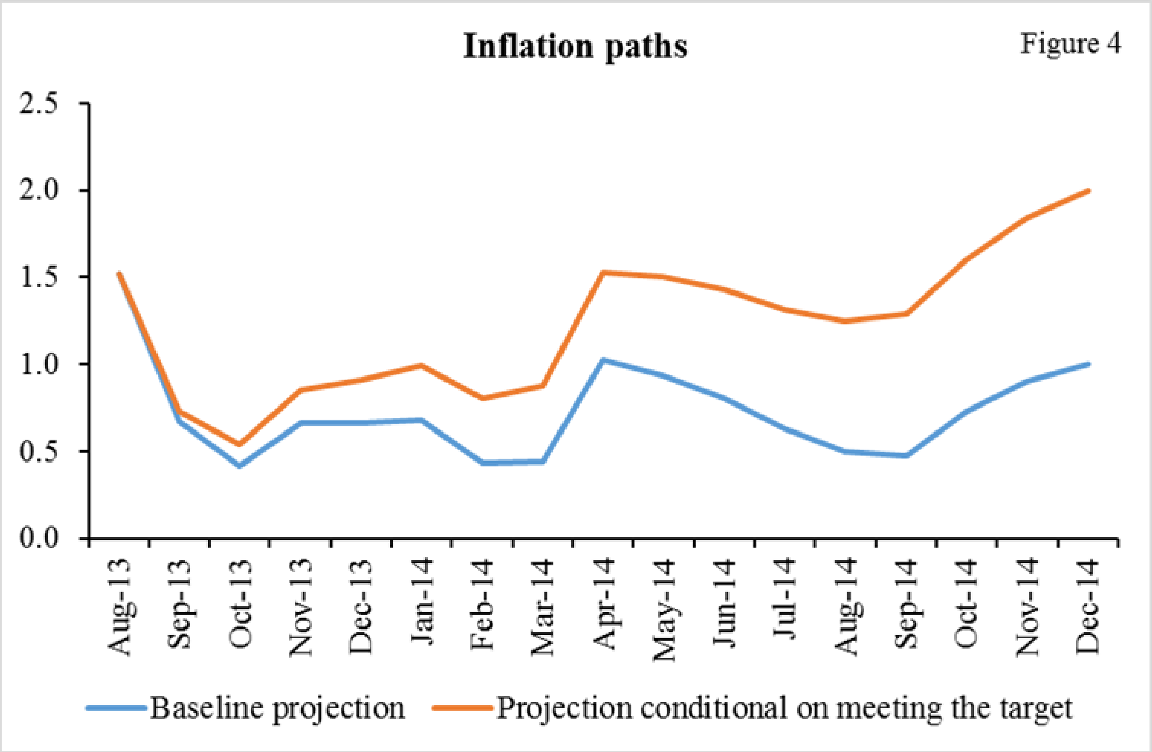
Uncertainty around the central projection. Intervals with probabilities of 20%, 40%, 60%, 80% and 90%, respectively

Some illustrations: 2. Deflation probabilities



Real time exercise of the probability of deflation one-year ahead using the distribution of final projections

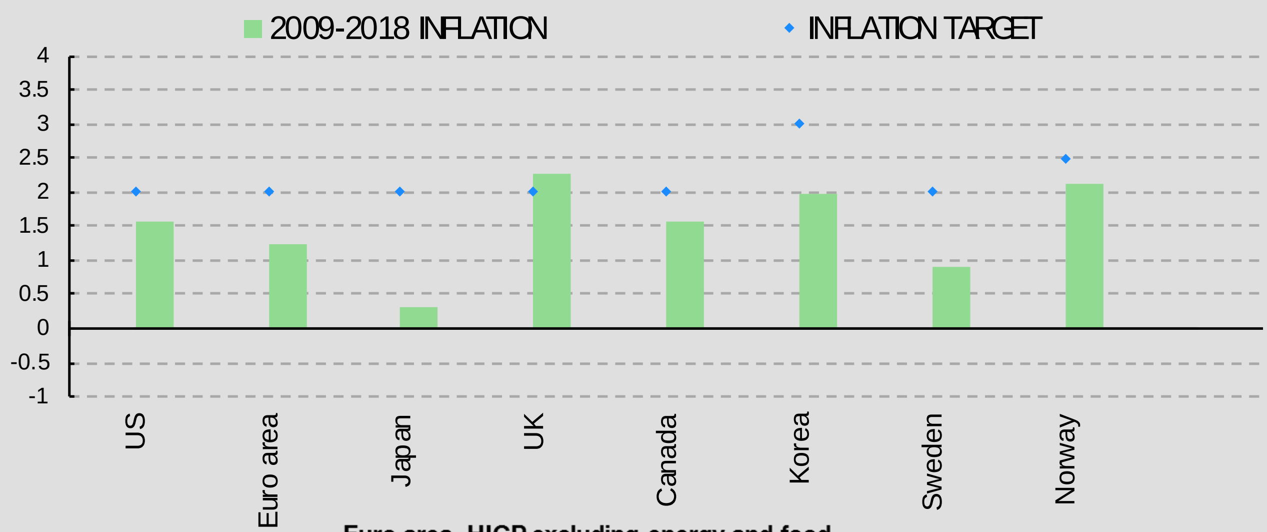
Some illustrations: 3. Inflation targets

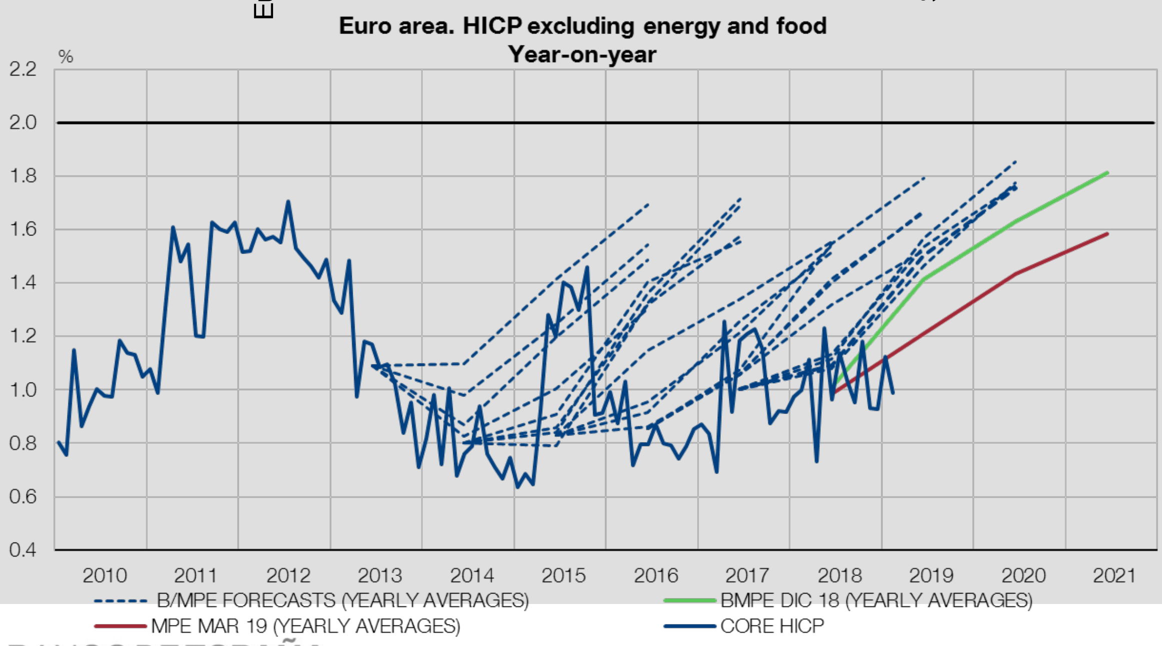


Álvarez *et al.* (1997) procedure considering a target of 2% at the end of 2014

LOW INFLATION. MOTIVATION

AVERAGE INFLATION AND INFLATION TARGETS





Protracted period of low inflation. Not only headline but also core inflation. Particularly so in the euro área

In many countries, actual inflation below Central Banks' targets

… despite very expansionary monetary policy and recovery in activity

- What we intend to learn from this project:
  - Have there been changes in inflation regimes? Is it a global phenomenon? Are there sectoral differences? *Markov switching models/Breaks*

$$\pi_t = \mu_{S_t} + \varepsilon_t$$

  - What are the drivers of inflation in the low/high inflation regimes (asymmetries)? ULCs, external prices, slack, inflation expectations… $\pi_t = \mu_{S_t} + x_t\beta_{S_t} + \varepsilon_t$

    Markov switching models with state dependent means: low and high inflation

  - What determines the probability of remaining in low inflation?, what is the expected duration of a low inflation episode? $\Pr(s_t = j|s_{t-1} = i) = p_{ij} = f(x_{t-1}; \beta_{S_{t-1}})$

    Markov switching models with state dependent probabilities: low and high inflation

LOW INFLATION. MARKOV SWITCHING MODELS. HEADLINE HICP

INFLATION REGIMES IN ADVANCED ECONOMIES

Countries	μ_1	μ_2	σ	p	q
Advanced economies	2.68	1.30	0.46	0.96	0.97
	(0.089)	(0.067)	(0.045)	(0.006)	(0.003)
European Union	2.16	0.60	0.32	0.99	0.95
	(0.046)	(0.092)	(0.030)	(0.003)	(0.013)
Euro area	2.26	0.82	0.28	0.98	0.98
	(0.050)	(0.061)	(0.027)	(0.000)	(0.001)
Austria	2.44	1.16	0.32	0.96	0.97
	(0.083)	(0.066)	(0.030)	(0.005)	(0.003)
Belgium	2.76	1.13	0.53	0.95	0.97
	(0.105)	(0.084)	(0.050)	(0.010)	(0.004)
Finland	2.88	1.01	0.31	0.96	0.98
	(0.071)	(0.046)	(0.029)	(0.005)	(0.002)
France	2.04	0.64	0.27	0.98	0.97
	(0.056)	(0.064)	(0.026)	(0.000)	(0.004)
Germany	1.95	0.70	0.24	0.97	0.96
	(0.046)	(0.052)	(0.023)	(0.003)	(0.004)
Ireland	3.13	0.06	1.24	0.98	0.99
	(0.110)	(0.124)	(0.117)	(0.001)	(0.003)
Italy	2.37	0.58	0.32	0.99	0.98
	(0.043)	(0.069)	(0.029)	(0.008)	(0.002)
Luxembourg	3.10	0.86	0.72	0.97	0.97
	(0.095)	(0.110)	(0.070)	(0.003)	(0.004)
Netherlands	3.43	1.34	0.59	0.96	0.99
	(0.083)	(0.032)	(0.055)	(0.005)	(0.001)
Portugal	2.77	0.41	0.62	0.99	0.98
	(0.061)	(0.088)	(0.058)	(0.008)	(0.005)
Spain	2.78	-0.15	0.58	0.99	0.96
	(0.056)	(0.108)	(0.054)	(0.003)	(0.005)
Cyprus	2.89	-0.25	1.20	0.98	0.97
	(0.090)	(0.129)	(0.115)	(0.002)	(0.005)
Greece	3.51	-0.08	1.03	0.99	0.98
	(0.080)	(0.118)	(0.096)	(0.007)	(0.002)
Latvia	8.45	1.77	4.98	0.98	0.99
	(0.287)	(0.174)	(0.463)	(0.001)	(0.004)
Lithuania	8.89	1.74	3.34	0.97	0.99
	(0.336)	(0.127)	(0.310)	(0.004)	(0.004)
Malta	3.14	1.10	0.51	0.96	0.95
	(0.073)	(0.079)	(0.050)	(0.006)	(0.012)
Slovakia	7.96	1.95	4.18	0.98	0.99
	(0.226)	(0.158)	(0.390)	(0.002)	(0.004)
Canada	1.89	-0.19	0.60	1.00	0.85
	(0.050)	(0.393)	(0.056)	(0.008)	(0.115)
Denmark	2.31	0.71	0.30	0.97	0.96
	(0.052)	(0.062)	(0.028)	(0.003)	(0.004)
Japan	1.87	-0.27	0.42	0.94	0.98
	(0.118)	(0.048)	(0.039)	(0.022)	(0.001)
Poland	10.05	2.00	3.99	0.99	1.00
	(0.297)	(0.143)	(0.370)	(0.008)	(0.014)
Sweden	2.05	0.79	0.32	0.97	0.97
	(0.059)	(0.060)	(0.030)	(0.003)	(0.003)
United Kingdom	2.92	1.24	0.43	0.98	0.98
	(0.140)	(0.089)	(0.040)	(0.002)	(0.001)
United States	3.24	1.46	0.68	0.95	0.97
	(0.125)	(0.081)	(0.066)	(0.011)	(0.003)

We have estimated two-state Markov switching models for 27 economies

For advanced economies, inflation in the high inflation state has a mean above 2.5% and around 1.3% in the low inflation state

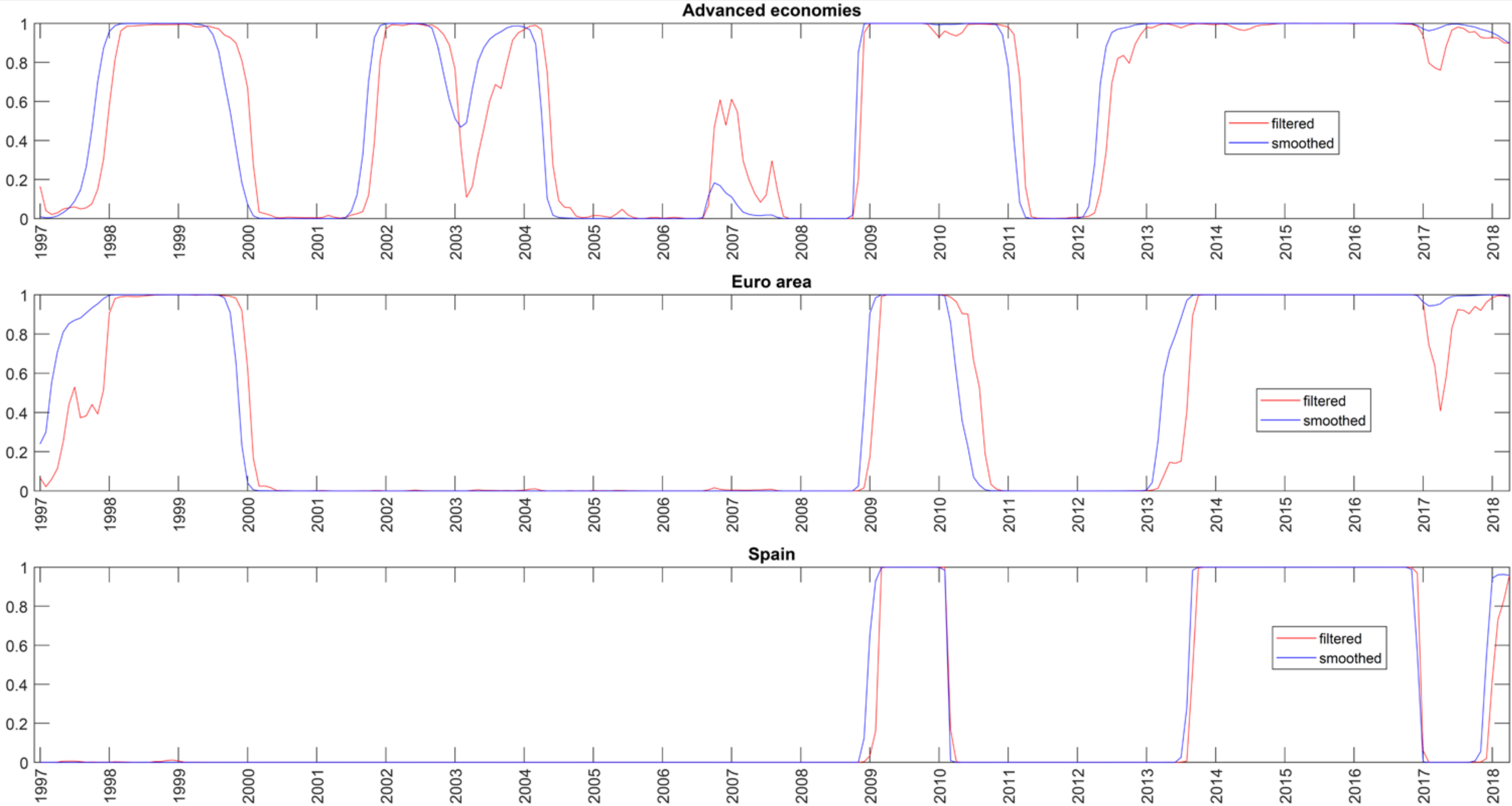
For the euro area, inflation has a mean slightly above 2% in the high inflation state and around 0.8% in the low inflation state

Inflation in the low/high inflation state is lower in the euro area than in the US.

Former Communist economies have higher inflation rates both in low and high inflation periods. They also show higher volatility

Inflation is quite persistent (the probability of remaining in low inflation is high)

HEADLINE HICP. PROBABILITIES OF BEING IN A LOW INFLATION STATE

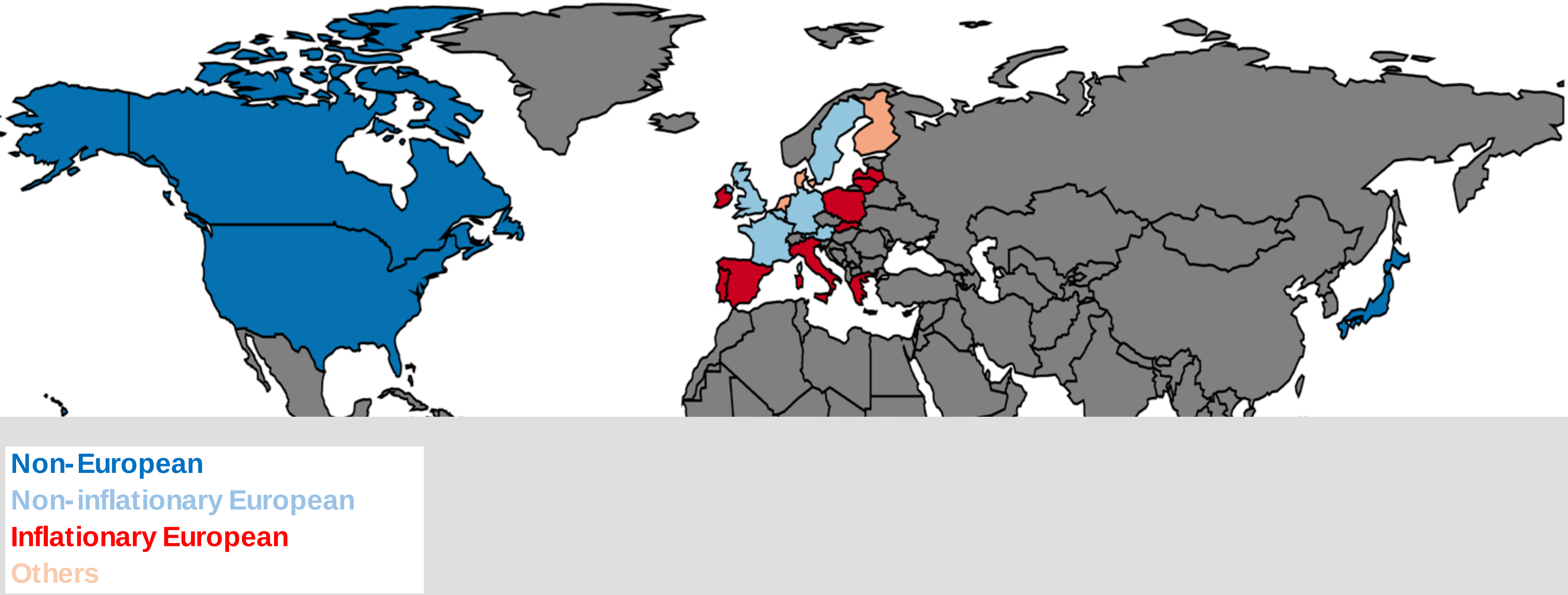


1. Different chronology of inflation regimes among main economic areas
2. Increase of synchronization since the Great Recession, in line with Alvarez, Gadea, Gomez-Loscos (2019a)

INFLATION CLUSTERS. HEADLINE HICP

FINITE MIXTURE MARKOV SWITCHING MODELS

1. We endogenously identify 4 groups of countries, taking into account all MS parameters
2. Non-European countries are clearly split from European ones
3. In Europe, we distinguish core (those with price stability, such as Germany) and peripheral countries (traditionally inflationary countries, such as Spain)



HEADLINE INFLATION. EURO AREA. STATE DEPENDENT MODEL. NEW KEYNESIAN PHILLIPS CURVE MODEL

EA	Model 1		Model 2	
	param	std	param	std
Mu. High inflation	2.177	0.0701	1.7297	0.2331
Mu. Low inflation	0.3666	0.132	0.4245	0.0944
sigma	0.2368	0.0426	0.056	0.0101
p	0.9653	0.0057	0.859	0.0622
q	0.8803	0.0617	0.9438	0.0188
Inflation expectations. High inflation			0.3678	0.1491
Inflation expectations. Low inflation			0.7332	0.0667
GDP. High inflation			0.0813	0.0457
GDP. Low inflation			-0.0053	0.0288
External prices. High inflation			0.1418	0.0224
External prices. Low inflation			0.1142	0.0169

In the low inflation state, inflation seems more responsive to inflation expectations, but less less responsive to GDP and external prices

- **Aim**
  - Analysis of inflation interdependence in advanced economies
  - In contrast with GDP, scant literature on inflation comovements

- **Some channels driving inflation interdependence**

  Conceptual framework: open-economy New Keynesian Phillips Curve

  - Common macroeconomic shocks (e.g. oil prices)
  - GDP comovements may bring about inflation interdependence due to Phillips curve mechanisms
  - Globalization: growing economic and financial integration
  - In the case of the euro area, common monetary policy

MORAN-STOCK-WATSON INDEX OF COMOVEMENT

$$\widehat{I}_i = \frac{\sum_{i=1}^{N} \sum_{j=1}^{i-1} \widehat{cov(y_{it}, y_{jt})} / N(N-1)/2}{\sum_{i=1}^{N} \widehat{var(y_{it})} / N}$$

$$\widehat{cov(y_{it}, y_{jt})} = \frac{1}{k} \sum_{s=t-int(k/2)}^{t+int(k/2)} (y_{is} - \overline{y_{it}})(y_{js} - \overline{y_{jt}})$$

$$\widehat{var(y_{it})} = \frac{1}{k} \sum_{s=t-int(k/2)}^{t+int(k/2)} (y_{is} - \overline{y_{it}})^2$$

$$\overline{y_{it}} = \frac{1}{k} \sum_{s=t-int(k/2)}^{t+int(k/2)} y_{is}$$

Stock and Watson (2008) modification of Moran's spatial correlation index

Summary measure of comovements across countries
over time taking into account rolling cross correlations

Here we use a window of 5 years, but results are robust to other lengths

Perfect positive correlation implies a value of the index of 1

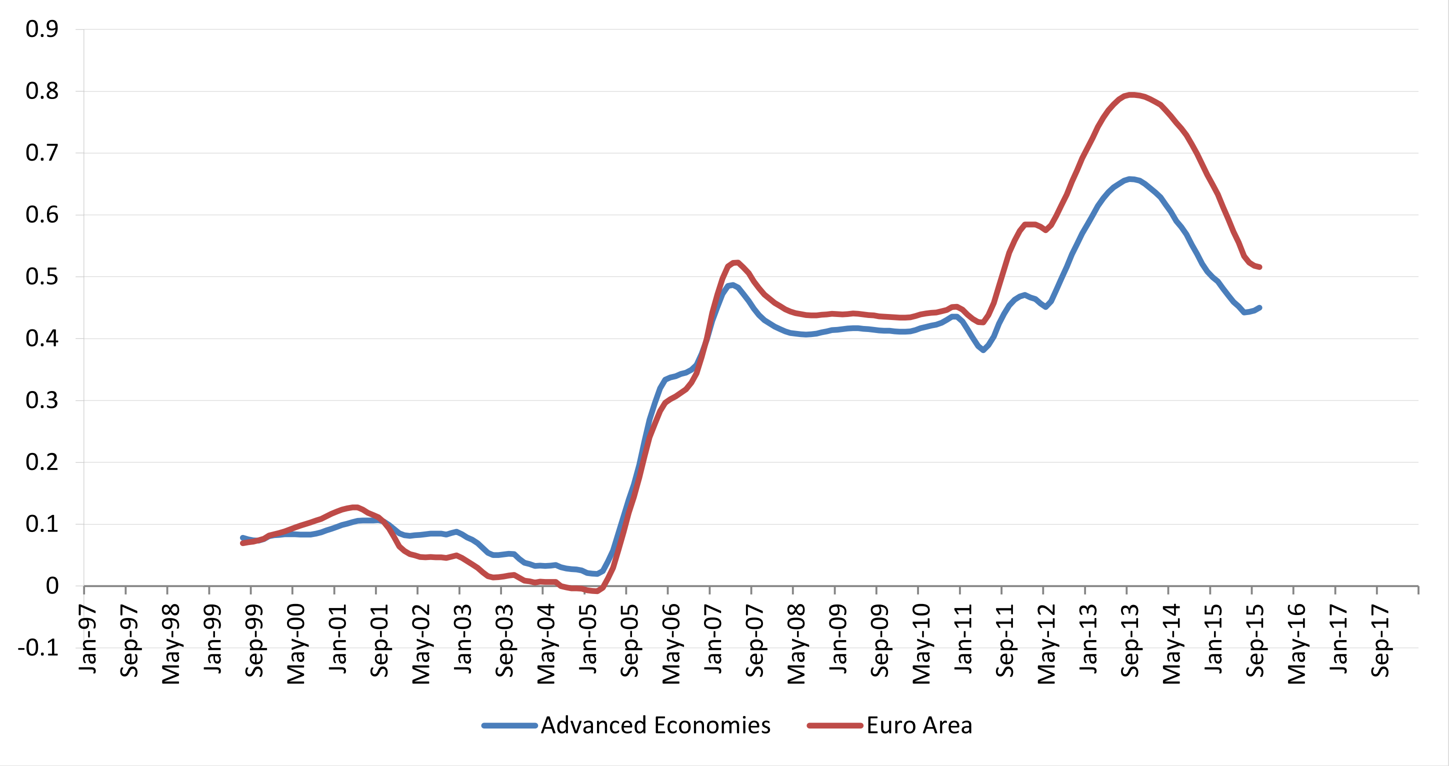
3. MAIN RESULTS (I)

1. Inflation interdependence is quite relevant
2. Core inflation interdependence is much lower than headline inflation interdependence (common shocks).
3. There is marked heterogeneity in the degree of synchronization across sectors (highest in energy, due to oil price shocks)
4. Inflation interdependence among OEA countries is higher than for EA countries, which is higher than for advanced economies (role of common monetary policy)

Countries	HICP	Energy	Food	Core	Non energy	Services	GDP
Advanced economies	0.30	0.60	0.32	0.15	0.09	0.19	0.42
	(0.00)	(0.00)	(0.00)	(0.01)	(0.07)	(0.00)	(0.00)
Euro area (EA)	0.36	0.65	0.36	0.20	0.14	0.22	0.42
	(0.00)	(0.00)	(0.00)	(0.02)	(0.06)	(0.01)	(0.01)
Original EA countries (OEA)	0.59	0.84	0.51	0.29	0.18	0.31	0.55
	(0.00)	(0.00)	(0.00)	(0.04)	(0.14)	(0.03)	(0.00)

3. MAIN RESULTS (II)

1. Interdependence is higher in the euro area than for advanced economies as a whole (common monetary policy and trade relationships)
2. Inflation interdependence has tended to increase over our sample period (globalization, growing trade integration and common monetary policy)



TREND, CYCLICAL AND SHORT RUN INFLATION (I)

Inflation can be decomposed into frequency bands using a band-pass filter

$$\pi_t = \pi_t^T + \pi_t^{BC} + \pi_t^{SR}$$

π_t^T: Trend inflation (Long-run fluctuations). Cycles over 5 years

π_t^{BC}: Business cycle inflation. Cycles between 2 and 5 years

π_t^{SR}: Short-run fluctuations. Cycles less than 2 years

Different band-pass filters can be used to carry out this decomposition. For instance, Christiano and Fitzgerald or Baxter and King. We use Christiano and Fitzgerald since the BK filter involves losing observations at the start and end of the sample

Unobserved component models are not explicit about frequency bands considered and, in general, will vary across countries and components

TREND, CYCLICAL AND SHORT RUN INFLATION (II)

1. Trend inflation shows a sizable degree of interdependence
2. For business cycle frequencies, synchronization is highest, when the Phillips curve mechanism is strongest
3. The degree of interdependence across countries for high frequencies is quite low, except in the case of energy, reflecting the relevance of transitory country-specific shocks (e.g. VAT rises)

Countries	HICP	Energy	Food	Core	Non energy	Services
		TREND				
Advanced economies	0.26	0.63	0.29	0.15	0.10	0.20
	(0.00)	(0.00)	(0.00)	(0.01)	(0.06)	(0.00)
Euro area (EA)	0.33	0.69	0.31	0.20	0.15	0.24
	(0.00)	(0.00)	(0.00)	(0.02)	(0.06)	(0.01)
Original EA countries (OEA)	0.58	0.89	0.47	0.30	0.20	0.34
	(0.00)	(0.00)	(0.00)	(0.03)	(0.10)	(0.02)
		BUSINESS CYCLE				
Advanced economies	0.40	0.61	0.42	0.20	0.07	0.18
	(0.00)	(0.00)	(0.00)	(0.00)	(0.13)	(0.00)
Euro area (EA)	0.45	0.67	0.48	0.23	0.14	0.22
	(0.00)	(0.00)	(0.00)	(0.01)	(0.07)	(0.01)
Original EA countries (OEA)	0.65	0.83	0.62	0.33	0.16	0.36
	(0.00)	(0.00)	(0.00)	(0.02)	(0.16)	(0.01)
		SHORT-RUN				
Advanced economies	0.28	0.50	0.12	0.03	0.00	0.02
	(0.00)	(0.00)	(0.03)	(0.34)	(0.55)	(0.38)
Euro area (EA)	0.26	0.51	0.14	0.03	0.01	0.03
	(0.00)	(0.00)	(0.06)	(0.38)	(0.53)	(0.42)
Original EA countries (OEA)	0.45	0.72	0.20	-0.01	-0.03	0.02
	(0.00)	(0.00)	(0.11)	(0.61)	(0.71)	(0.52)

DRIVERS OF INFLATION INTERDEPENDENCE (I)

- To shed some light on the macroeconomic drivers of the degree of inflation interdependence, we consider a number of variables suggested by open economy new keynesian Phillips curve and mark-up pricing models.
- We assess the distance between correlation matrices using a matrix norm. Specifically, we use the Frobenius norm.

$$||P_{\pi} - P_{x^i}||_F = \sqrt{Tr[(P_{\pi} - P_{x^i})(P_{\pi} - P_{x^i})']}$$

where is the cor rix of a potential driving variable and ***Tr*** is the trace operator.

P_{π} P_{x^i}

- The lower (higher) is the value of this norm, the closer (farther) are two matrices. In the extreme case in which the two matrices are identical, the Frobenius distance between them is equal to zero.

DETERMINANTS OF INFLATION INTERDEPENDENCE (IV)

Variables	AE	EA	OEA
Inflation expectations	8.50	5.01	2.04
	(0.00)	(0.00)	(0.00)
Business cycles	7.78	4.34	1.92
	(0.00)	(0.00)	(0.00)
External prices	8.52	4.74	2.67
	(0.00)	(0.00)	(0.00)
Unit labour costs	8.18	5.60	4.06
	(0.00)	(0.00)	(0.00)
Compensation per employee	9.16	7.44	5.92
	(0.04)	(1.00)	(1.00)
Productivity	10.21	7.73	5.56
	(1.00)	(1.00)	(0.97)
Mark-up	9.04	6.27	3.30
	(0.01)	(0.03)	(0.00)

Note. p-values in parentheses.

Standard variables in open economy new Keynesian Phillips curve models explain inflation interdependence:

- Inflation expectations
- Business cycles
- External prices

Unit labor costs and mark-ups interconnectedness also explains inflation interdependence.

Drivers have a higher explanatory power in the euro area than in advanced economies as a whole and even more so in the case of original euro area countries.

Some references

Alvarez, Luis J.; J.C. Delrieu and J. Jareño (1997) "Restricted forecasts and economic target monitoring: An application to the Spanish Consumer Price Index," *Journal of Policy Modeling*, 19(3), 333-349.

Álvarez, L. J; M.D. Gadea and A. Gómez-Loscos (2019a) Low inflation in advanced economies, work in progress

Álvarez, L. J; M.D. Gadea and A. Gómez-Loscos (2019b) Inflation interdependence in advanced economies, Banco de España, Working paper

Alvarez, L. J. and I. Sánchez (2019) “Inflation projections for monetary policy decision making”, *Journal of Policy Modeling*, forthcoming

THANKS FOR YOUR ATTENTION