

Inflation forecasts in the euro area: New insights from Phillips Curve estimates and quantile regressions

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Abstract

Accurate forecasts of inflation are of paramount importance for central banks, whose objective is to deliver price stability. Those last years in particular have put standard models into question given the systematic overprediction of inflation in a context of global disinflationary shocks, such as the sharp fall in oil prices. In this paper, we estimate Phillips curves to document the relative performance of a large number of global and domestic indicators for forecasting the euro area inflation. We highlight which indicators perform best depending on the macroeconomic context. While global factors such as commodity prices, import prices or global inflation improve our forecasts accuracy, we find little support for introducing global economic slack to the Phillips curve. We also rely on quantile regressions to document the impact of inflation covariates on the entire distribution of inflation. We provide evidence that quantile information can improve forecasts accuracy in periods of persistently low inflation.

Keywords: inflation, forecasting, Phillips curve, quantile regressions

JEL Classification: E31, E37, C22, C53

Motivation

- Use a large set of global and domestic factors to forecast inflation in the euro area (EA)
- Explore which indicators perform best depending on the macroeconomic context
- Explore whether quantile regressions improve forecast accuracy in periods of low inflation

Literature

- **Forecasting with Phillips curves:** forecast performance heavily depends on sample period, inflation series, benchmark models (for the US, see: Stock and Watson, 2008, Atkeson and Ohanian, 2001; for the EA, see: Banbura and Mirza, 2013, Ciccarelli and Osbat, 2017)
- **Importance of global factors in forecasting domestic inflation:** global inflation (Ciccarelli and Mojon, 2010); global economic slack and GVC (Borio and Filardo, 2007, Auer et al. 2017)
- **Quantile regressions (QR):** activity indicators are useful for forecasting the conditional distribution of inflation in the US (Manzam and Zerom, 2013); forecast superiority of QR over short forecast horizons for EA inflation (Buseti et al., 2015)

Methodology

Augmented Phillips curve (OLS)

$$\pi_t = \alpha + \sum_{l=1}^{MaxL=4} \rho_l \pi_{t-l} + \beta y_{t-1} + \sum_{i=1}^{MaxN=2} \sum_{l=1}^{MaxL=4} \gamma_{i,l} z_{i,t-l} + \varepsilon_t$$

- with π inflation at time t
- y domestic slack
- z an external factor

Benchmarks

- AR(1)
- backward-looking Phillips curve (PC): $\pi_t = \alpha + \rho \pi_{t-1} + \beta y_{t-1} + \varepsilon_t$

Forecast horizon: one-quarter ($h = 1$) and one-year ahead ($h = 4$)

Metrics

- Root-mean-squared forecasting error (RMSE)

- Biweighted RMSE (BRMSE, Stock and Watson, 2008) $BRMSE(t) = \sqrt{\frac{\sum_{s=t-7}^{t+7} K\left(\frac{s-t}{8}\right) (\pi_{s+h}^h - \pi_{s+h}^h)^2}{\sum_{s=t-7}^{t+7} K\left(\frac{s-t}{8}\right)}}$

where K is the biweight kernel: $K(x) = \frac{15}{16}(1-x^2)^2 \mathbb{I}_{\{|x| \leq 1\}}$

Data

- Quarterly data (1996-2016)
- **Dependent variables:** EA headline HICP, HICP excluding energy, HICP excluding food and energy
- **Domestic factors:** output gap; unemployment rate; unemployment gap; IPI
- **Global factors:** commodity prices; exchange rates; import prices; global inflation; global slack; EA foreign demand

OLS forecast performance

Main findings for headline inflation

- Out-of-sample, most specifications outperform the benchmarks
- For PC augmented with a single global factor, the best specifications include either oil prices, import prices or global inflation (OECD CPI excluding EA)

Diebold-Mariano test for pseudo out-of-sample forecasts

- H_0 : forecasts from model 1 (benchmark) perform at least as well as forecasts from model 2
- Forecasts from the best-performing one-factor models significantly outperform those from
 - the benchmarks (AR1, PC),
 - PC with other global factors (exchange rates, global slack),
 - a hybrid Phillips curve (M17)
- Forecasts from PC with two global factors (M18) outperform others

Table: One-sided Diebold-Mariano test for headline HICP (P-values)

Benchmark	h	AR1	PC	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M17
M1 (Oil price)	1	0.02	0.03	0.30	0.02	0.01	0.49	0.46	0.01	0.03	0.01	0.02	0.03	
	4	0.06	0.01	0.35	0.04	0.01	0.55	0.36	0.01	0.01	0.00	0.01	0.05	
M2 (Relative import prices)	1	0.01	0.01	0.70	0.00	0.01	0.88	0.61	0.00	0.06	0.00	0.01	0.02	
	4	0.06	0.00	0.65	0.01	0.00	0.88	0.44	0.00	0.00	0.00	0.00	0.02	
M5 (Import prices)	1	0.01	0.02	0.51	0.12	0.00	0.01	0.46	0.01	0.03	0.01	0.02	0.02	
	4	0.03	0.01	0.45	0.12	0.00	0.00	0.30	0.00	0.00	0.00	0.00	0.02	
M6 (OECD CPI ex. EA)	1	0.02	0.03	0.54	0.39	0.03	0.03	0.54	0.02	0.00	0.02	0.03	0.03	
	4	0.06	0.02	0.64	0.56	0.03	0.05	0.70	0.02	0.00	0.01	0.01	0.07	
M18 (Oil, OECD CPI ex. EA)	1	0.01	0.02	0.06	0.09	0.02	0.01	0.10	0.04	0.01	0.00	0.01	0.02	
	4	0.00	0.02	0.07	0.09	0.02	0.02	0.09	0.03	0.01	0.00	0.01	0.03	

Comparison with a BVAR

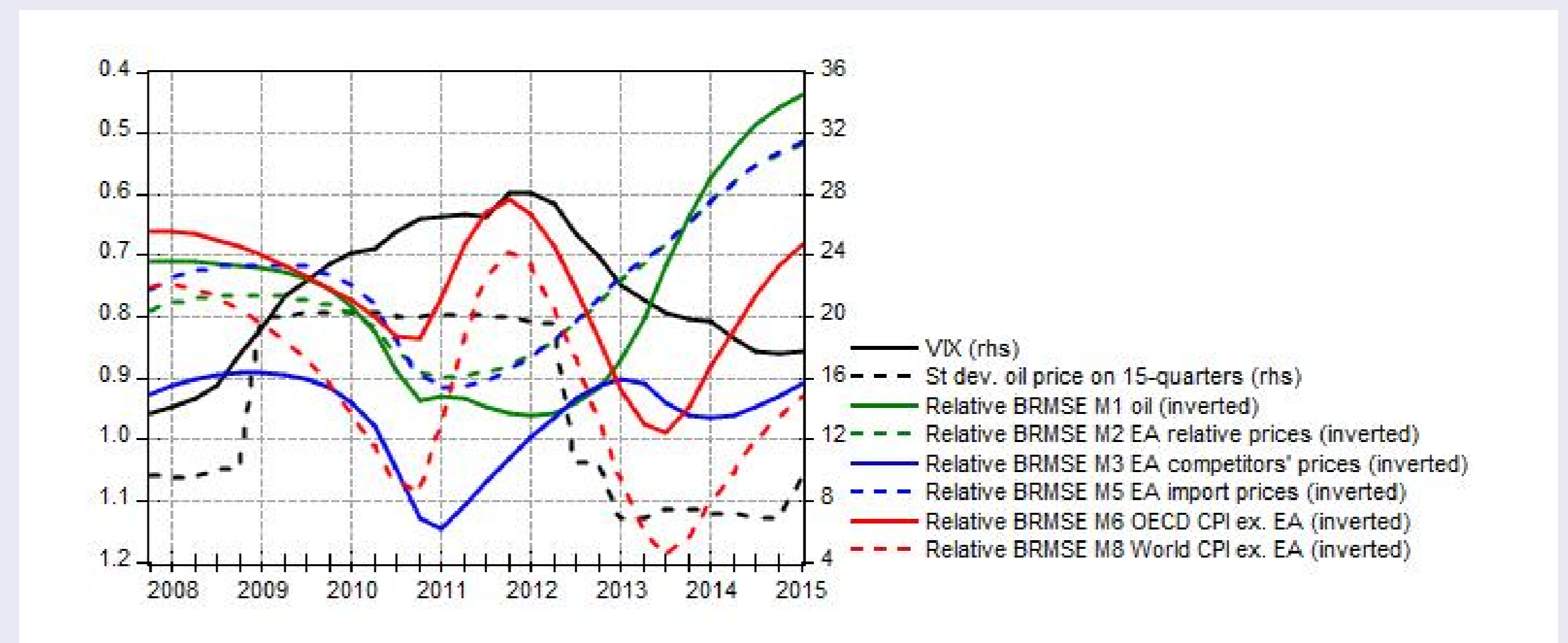
Augmented PC perform almost as well as a more sophisticated model

Table: RMSE from BVAR (median) and augmented PC for headline π

Forecast horizon	BVAR	Model 1	Model 2	Model 5	Model 18
h=1	0.20	0.22	0.27	0.26	0.20
h=4	0.22	0.25	0.28	0.27	0.20

Time stability

Figure: BRMSE ratios over 15-quarters rolling forecast windows for $h = 1$



Relative BRMSE show the ratio of BRMSE from a model to those of the benchmark Phillips curve, realized over a 15-quarters rolling forecast period.

Quantile regressions

Motivation:

- Estimate the relationship between inflation and a set of covariates on the entire distribution of inflation
- Assess how conditional quantiles $q_\tau(\pi|X)$ of the dependent variable π change with respect to changes in the set of explanatory variables X
- Allow for heterogenous impacts of the covariates on specific areas of π conditional distribution

Specification:

$$q_\tau(\pi_t|x_t) = \alpha^{(\tau)} + \sum_{l=1}^{Max=4} \rho_l^{(\tau)} \pi_{t-l} + \delta^{(\tau)} y_{t-1} + \sum_{i=1}^{Max=2} \sum_{l=1}^{Max=4} \gamma_{i,l}^{(\tau)} z_{i,t-l} + \varepsilon_t^{(\tau)}$$

with $x_t = (1, \pi_{t-l}, y_{t-1}, z_{i,t})'$ the set of explanatory variables: π_{t-l} , lagged inflation, y_{t-1} lagged domestic slack, and $z_{i,t}$ the set of global factors.

Quantile slopes

- Inflation more persistent in the lowest quantiles of the distribution
- Lower impact of oil prices for the lowest quantiles
- Higher impact of import prices for the highest quantiles

Figure: Quantile slopes for the set of covariates of M1 (oil price)

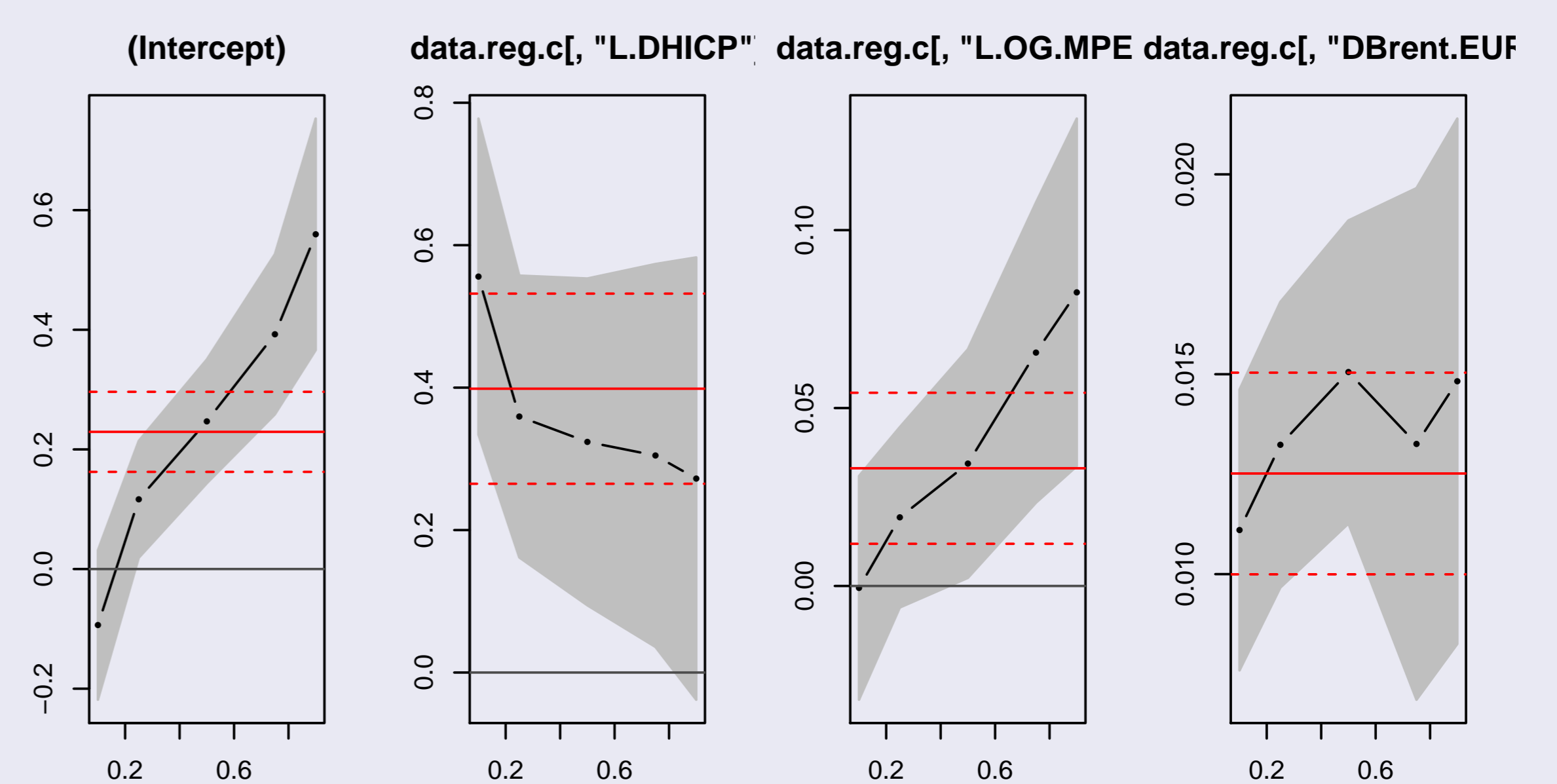
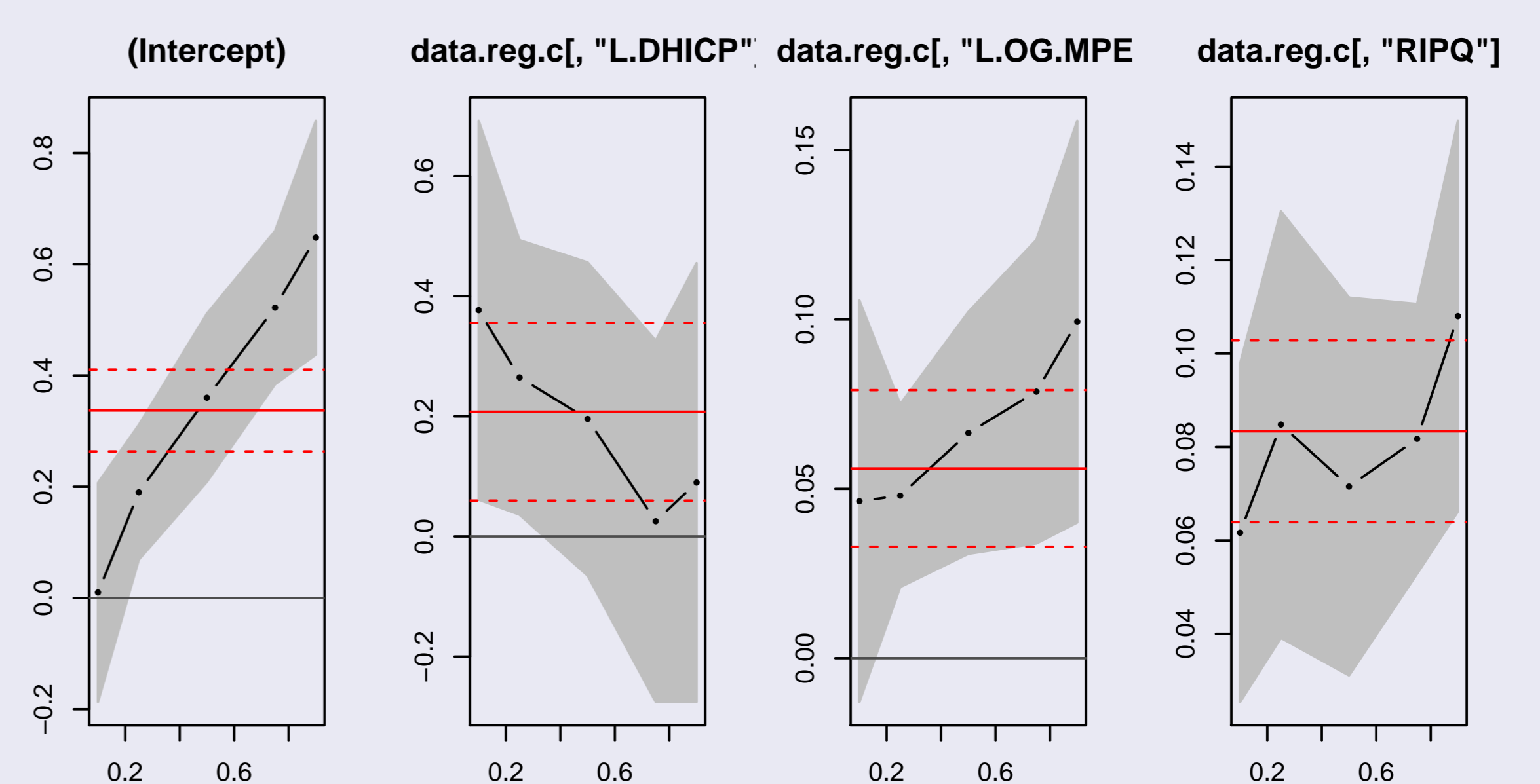


Figure: Quantile slopes for M2 (relative import prices)



Forecast performance: OLS vs Quantile regressions

Do QR provide better forecasts than OLS in periods of subdued inflation (2014-2015)?

- We compare forecasts for $t+h$ from OLS and the QR model corresponding to the inflation quantile in t (using the historical distribution of inflation up to t) with usual metrics (RMSE)
- H_0 : forecasts from model 1 (OLS) perform at least as well as forecasts from model 2 (QR)

Table: One-sided Diebold-Mariano test for headline HICP for OLS against QR (P-values)

Benchmark	M1 OLS	M2 OLS	M3 OLS	M5 OLS	M6 OLS	M18 OLS
Forecast horizon	h=1	h=4	h=1	h=4	h=1	h=4
M1 QR (Oil price)	0.64	0.90	0.20	0.45	0.06	0.17
M2 QR (Relative imp. prices)	0.12	0.98	0.03	0.52	0.03	0.14
M3 QR (Competitors' prices)	0.52	0.98	0.05	0.75	0.03	0.13
M5 QR (Import prices)	0.13	0.98	0.02	0.50	0.02	0.11
M6 QR (OECD CPI ex. EA)	0.26	0.90	0.08	0.61	0.04	0.32
M18 QR (Oil, OECD CPI ex. EA)	0.63	0.91	0.20	0.29	0.05	0.09

Conclusion

- PC remains a valuable forecasting tool, even compared to more sophisticated models
- Commodity prices and import prices perform better than global inflation or global slack
- Forecasts from quantile regressions might be useful in periods of persistently high or low inflation