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How do oil price forecast errors impact inflation forecast errors?

An empirical analysis from French and US inflation forecasts

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Abstract: This paper proposes an empirical investigation of the impact of oil price forecast errors on inflation forecast errors for two different sets of recent forecasts data: the median of SPF inflation forecasts for the U.S. and the Central Bank inflation forecasts for France. Mainly two salient points emerge from our results. First, there is a significant contribution of oil price forecast errors to the explanation of inflation forecast errors, whatever the country or the period considered. Second, the pass-through of oil price forecast errors to inflation forecast errors is multiplied by around 2 when the oil price volatility is large.

Keywords: Forecast errors; Inflation rate; Oil price; Threshold model.

JEL classification: C22, E31, E37.

Résumé: Cet article propose une évaluation empirique de l'impact des erreurs de prévision du prix du baril de pétrole sur les erreurs de prévision du taux d'inflation. Deux types de données récentes sont utilisées: la médiane des prévisions d'inflation du panel des prévisionnistes professionnels (Survey of Professional Forecasters) pour les Etats-Unis et les prévisions d'inflation de la Banque de France pour ce second pays. Deux principaux résultats émergent de cette étude. Tout d'abord, les erreurs de prévision du prix du baril de pétrole contribuent significativement à l'explication des erreurs de prévision du taux d'inflation, quels que soient le pays ou la période considérés. Ensuite, le coefficient de transmission des erreurs de prévision sur les prix pétroliers aux erreurs de prévision d'inflation est à peu près deux fois plus grand quand la volatilité des prix pétroliers est forte que quand elle est modérée.

Mots-clés: Erreurs de prévision; Taux d'inflation; Prix pétroliers; Modèle à seuil.

Codes JEL: C22, E31, E37.

Non-technical summary

The impact of oil price shocks on macroeconomic aggregates has been widely scrutinized both theoretically and empirically since the seventies. Empirical studies from the eighties pointed to a strong correlation between oil price shocks and recessions. However, this conclusion has been challenged over the last two decades by various studies whose results suggest that this correlation has decreased, if not vanished, from the eighties on. Such a weakening is also found in the pass-through of oil shocks to inflation, as measured e.g. by the core U.S. Personal Consumption Expenditures inflation or the U.S. GDP deflator. Unsurprisingly, the Consumer Price Index (CPI) seems to be a noticeable exception. Keeping in mind that the overall CPI inflation can be decomposed into the core CPI inflation and the food and energy components of inflation, this result is compatible with a stable core CPI: if core prices are sticky and/or correctly monitored by a non accommodating monetary policy, then oil price surprises are expected to affect headline inflation. This result supports a widespread belief among professional forecasters that overall inflation forecast errors are mainly due to oil price forecast errors. In its assessment of Euro system staff projections for Harmonized Index of Consumer Prices inflation in the Euro area during the period 2000-2012, the European Central Bank notes that: "In annual percentage deviation terms, the one-year-ahead oil price projections were, on average, 13% lower than the actual oil price over the sample period. This is vital to the explanation of why Euro area HICP inflation was underestimated." Indeed, if the impact of oil shocks on inflation was weak, so would be the impact of oil price forecast errors on inflation forecasts errors. To our knowledge, the pass-through of oil price forecast errors into inflation forecast errors has not been evaluated so far. The goal of our paper is to fill this gap.

To this end, we propose an empirical investigation of the impact of oil price forecast errors on inflation forecast errors for two different sets of recent quarterly forecasts data: the median of inflation forecasts from the Survey of Professional Forecasters for the U.S. and the Central Bank inflation forecasts for France. Mainly two salient points emerge from our results. First, from a standard linear framework, there is a significant contribution of oil price forecast errors to the explanation of inflation forecast errors, whatever the country or the period considered. The oil price forecast errors are found to explain around half of CPI error variance although they account for only 5% of CPI indices. Second, relaxing the linearity assumption reveals that the pass-through is not constant over time: it is found to be around twice as large during episodes of high oil price volatility as during calmer periods. This pass-through was particularly high during the last episode of high volatility during 2008-2009.

1 Introduction

The impact of oil price shocks on macroeconomic aggregates has been widely scrutinized both theoretically and empirically since the seventies. From a theoretical viewpoint, the models developed by e.g. Bruno and Sachs [1982], Phelps [1994], Ferdered [1996], Rotemberg and Woodford [1996] or more recently Blanchard and Gali [2010] are specifically devoted to this analysis. Only to mention the main effects, a raise in oil price is expected — from a traditional Keynesian view — to have a direct negative impact on aggregate demand due to the decrease in consumption following the real income reduction. The negative impact on aggregate demand can also stem from international wealth redistribution effects (oil exporting *vs* importing countries) and the decrease of consumers income due to the reduction of factors marginal productivity and hence remuneration. A direct negative impact on aggregate supply is also expected since oil is a production input: the increase of its price is expected to reduce firms profitability. Moreover, the decrease in real wage induced by the oil price shock could reduce labor supply and hence aggregate supply as well. From an empirical point of view, the seminal paper by Hamilton [1983] and his more recent empirical contribution in Hamilton [1996] both emphasize the correlation between oil shocks and recessions.[1] However, this conclusion is challenged by Hooker [1996], Blanchard and Gali [2010], Edelstein and Kilian [2009] or Valcarcel and Wohar [2013] whose results suggest that this correlation has decreased, if not vanished, from the eighties on. Such a weakening is also found in the pass-through of oil shocks to inflation, see e.g. Hooker [2002] for the core U.S. Personal Consumption Expenditures inflation or Herrera and Pesavento [2009] for the U.S. GDP deflator.[2] Nevertheless, the Consumer Price Index (CPI) is a noticeable exception as stressed in Blanchard and Gali [2010]: from a five-variable vector autoregression, they find a stable response on impact of

[1]A short run impact on production growth rate is also found for respectively European and Asian countries by Cunado and Perez de Gracia [2003] and Cunado and Perez de Gracia [2005].

[2]As emphasized by these authors, this suggests that “the less accommodative monetary policy of the Volcker-Greenspan era may have been more effective in controlling the expectations of higher inflation that follow an oil price shock".

U.S. CPI inflation to oil price shocks before and after 1984. As noticed by these authors, this is not surprising since part of the increase in oil prices is reflected mechanically in the oil component of the CPI. From their historical decomposition exercise, they even find that the contribution of oil price shocks to CPI inflation has increased in the recent period. Keeping in mind that the overall CPI inflation can be decomposed into the core CPI inflation and the food and energy components of inflation, this result is compatible with a stable core CPI: if core prices are sticky and/or correctly monitored by a non accommodating monetary policy, then oil price surprises are expected to affect headline inflation. This result supports a widespread belief among professional forecasters that overall inflation forecast errors are mainly due to oil price forecast errors. In its assessment of eurosystem staff projections for Harmonized Index of Consumer Prices inflation in the Euro area during the period 2000-2012, the ECB notes that: "In annual percentage deviation terms, the one-year-ahead oil price projections were, on average, 13% lower than the actual oil price over the sample period. This is vital to the explanation of why Euro area HICP inflation was underestimated."[3] Indeed, if the impact of oil shocks on inflation was weak, so would be the impact of oil price forecast errors on inflation forecasts errors. To our knowledge, the pass-through of oil price forecast errors into inflation forecast errors has not been evaluated so far. The goal of our paper is to fill this gap.

Beyond the empirical and operational interest of this topic, the microeconomic and macroeconomic consequences of such a link are as large as the number of economic decision rules which rely on inflation forecasts. At the microeconomic level, consequences of inflation forecast errors stem from the implied inefficiency of decisions made by agents whose perception of future relative prices is not correct.[4] A famous macroeconomic illustration is the forward Taylor rule first put forward by Clarida, Gali and Gertler [1998] and Clarida, Gali and Gertler [2000] which relate the interest rate fixed by the

[3]See p.76 of the ECB Monthly Bulletin of May 2013.

[4]This view has been popularized by the monetarist and new classical schools of Chicago, with the respective influential contributions of Friedman and Schwartz [1963], Lucas [1972] and Sargent and Wallace [1975].

central banker to the expected output and inflation gaps : regarding the latter, the expected overall — *i.e.* including energy — inflation gap is typically taken into account. For instance, the European Central Bank explicitly aims at inflation rates of below, but close to, 2% over the medium term, where the inflation rate is measured by the Harmonized Index of Consumer Prices (HICP) which includes energy prices. For the Bank of England, the inflation target of 2% is expressed in terms of an annual rate of inflation based on the CPI while the Federal Open Market Committee of the Federal Reserve Bank targets a rate of 2% for inflation as measured by the annual change in the price index for personal consumption expenditures : those price indices include energy.[5] Hence, a better understanding of inflation forecast errors is called for to investigate if *i)* there is room for improvement in the inflation forecasting exercise and *ii)* if so, along which dimensions. As a starting point to address these questions, this paper will focus on oil price forecast errors as a potential source of inflation forecast errors. To this end, recent quarterly data are used for inflation forecasts errors from France and the United States, coming respectively from Banque de France (BdF) and the Survey of Professional Forecasters (SPF).

In a first step, the empirical analysis is held in a standard linear framework. It reveals that the contemporaneous correlation of these data with oil price forecasts errors turns out to be strong for both countries. This suggests that inflation forecast errors are due to oil price forecast errors to the extend that oil price forecast errors may be considered as exogenous with respect to national price index forecast errors. Even though this condition may be challenged for such a large country as the U.S.[6], it is more likely to hold in such a relatively small country as France. This first result confirms the widely held view among professional forecasters. Yet, it is not very useful since the crude oil prices are very difficult to forecast for the kind of projection horizons typically considered by Central Banks, i.e. no longer than one year ahead. As discussed to great extent in Alquist et al.

[5] As noticed in Blanchard and Gali [2010] *inter alia*, oil price shocks have often been followed by a tightening of the monetary policy in order to contain upwards inflationary pressure.

[6] See e.g. Kilian [2008] or Alquist, Kilian and Vigfusson [2013].

[2013], the no-change forecast[7] of the nominal price of oil is not outperformed by any of the more sophisticated alternative approaches they consider in their paper. Even though the headline inflation point forecast can hardly be improved from this first finding, it is still possible to use the relationship between the oil price and headline inflation forecast errors to refine the measure of inflation forecast uncertainty, i.e. the predictive density.

This is done in a second step, where the relationship between inflation and oil price forecast errors is allowed to be regime-dependent. Actually, relaxing the linearity assumption reveals that the pass-through is not constant over time : it is found to be more than twice as large during episodes of high oil price volatility as during calmer periods. It was particularly high during the last episode of high volatility during 2008-2009. This feature is exploited to built regime-dependent bootstrapped fan charts for inflation forecasts. It turns out that the uncertainty surrounding overall inflation forecasts is much reduced in low oil price volatility times compared to large volatility periods: the width of the 90%-confidence interval of the one-year ahead inflation forecast is divided by two in both countries. For instance, as of say the last quarter of 2013 — which belongs to the low oil price volatility regime — our model predicts a very low deflation risk over 2014 in the U.S. and an even lower deflation risk in France where it does not belong to the 90%-confidence interval.

The remainder of the paper is organized as follows. Section 2 presents some preliminary descriptive statistics for our forecast errors data. Section 3 presents the first piece of evidence, found from a linear framework, of the close relationship between oil price and inflation forecast errors. Section 4 extends this setup to allow for a nonlinear relationship and illustrates the relevance of such an approach by proposing regime-dependent fan charts of inflation forecasts. Section 5 concludes.

[7] i.e. the forecast stemming directly from a random-walk process.

2 Forecast errors data for inflation and oil price

In this paper, we propose to explore French and U.S. inflation forecast errors because the data we have found for these two countries are very different by nature, as are the characteristics of the countries themselves. Indeed, France can be considered as a small oil importing country, for which the oil price can be safely considered as given exogenously for all agents. By contrast, the U.S. are of course a large country whose oil demand can influence the oil market price — see for instance Alquist et al. [2013] on this point. Moreover this is also an oil-producing country.

For France, the inflation forecast data used here are made by a large national economic institution, namely the Banque de France. Each quarter, an inflation forecasting exercise is performed along the lines defined by the European System of Central Banks (ESCB). It consists in providing monthly inflation projections over a 1-year horizon. So, thirteen *monthly* Harmonized Index of Consumer Prices inflation (HICP) forecasts are performed by Banque de France. Those projections are calculated on a quarterly basis, in the middle of each quarter.[8] To simplify notations and comparison with other forecasts, we will consider only the end-of-quarter forecasts.[9] We denote with a subscript $h = 0$ the forecast for the last month of the current quarter (the so-called nowcast), $h = 3$ the forecast for the last month of the following quarter (or one-quarter horizon), and so on for h =6, 9 and 12 (two- to four-quarter horizons). Regarding oil price forecasts, Banque de France uses the ones common to all the central banks belonging to the Eurosystem for each quarterly forecast exercise. More precisely, the ESCB assumptions about the development of oil prices are based on the futures prices of Brent crude oil. In this approach, the $h-$period forecast of the price of oil is given by the price of the oil futures

[8]To fix ideas on the timing, quarterly forecast exercises are respectively closed in February, May, August and November and the HICP is released around the 15th of next month. For instance, the HICP for February is only released mid-March.

[9]The analysis below has been performed for all existing h and these results will also be commented sometimes. They are available upon request from the authors.

contract at maturity h.[10] The primary inflation forecasts made by Banque de France result from the aggregation of around 50 monthly sectoral price forecasts. Even though the forecast object are quarter-on-quarter growth rates, inflation forecasts are finally released as one-year percentage changes and this is also how the forecast errors are evaluated. For this reason, we will accordingly express the oil price forecast and its corresponding error in terms of one-year percentage change. The sample for these French data starts on the first quarter of 2005 only, because the ESCB oil price projections series are not available before this date. They are plotted in Fig. 6 in Appendix.

For the U.S., inflation forecast data from the Survey of Professional Forecasters (SPF) are used. More precisely, the median of the survey forecasts of the Consumer Price Index is retained. The survey question explicitly refers to the quarter-on-quarter rate of change in the quarterly average headline CPI level (in annualized percentage points). The series corresponding to the nowcast (CPI2), the 1-quarter ahead (CPI3) and up to 4-quarter ahead forecasts (CPI6) are retained. To compute the forecast errors series, we use the quarter-on-quarter rate of change in the observed quarterly (seasonally adjusted) CPI data downloadable from the Federal Reserve Bank of Saint-Louis website. Then, by contrast with Europe, the U.S. forecasters focus more on the West Texas Intermediate (WTI) crude oil price than on the Brent crude oil price. Accordingly, our measure of the oil price forecast errors will rely on WTI price. Then, since data on oil price forecasts are not available in the SPF database, they will be approximated by a series of forecasts analogue to the one used at Banque the France, i.e. based on the price of the WTI crude oil futures contract at maturity h corresponding to the forecast horizon.[11] As emphasized in the ECB Monthly Bulletin (May 2013), many other central banks (e.g. the Federal Reserve System, the Bank of England and the Bank of Canada) and international organizations (e.g. the IMF) use oil futures prices as predictors of spot

[10] See the ECB Monthly Bulletin (May 2013) for more details.

[11] Here, we hope that the median of oil price forecasts from SPF is close to this quite standard measure. This is of course a simplifying assumption since each forecaster surveyed has presumably his own oil price forecast.

prices in their macroeconomic projections. Our U.S. data sample begins in 1992q1 and ends up in 2013q4.

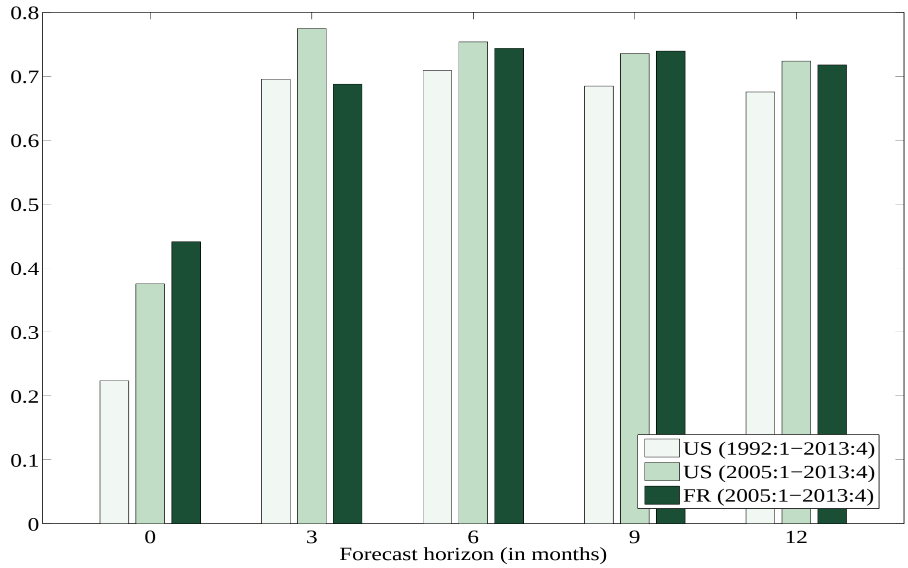
Let us denote by $\varepsilon^{\pi}_{h,t}$ the forecast errors on inflation defined by the difference between the actual inflation (HICP for France and CPI for the U.S.) rate at time t and the forecast made for this variable h months ago, for $h \in \{0, 3, 6, 9, 12\}$. This corresponds respectively to nowcast, one-quarter ahead forecast and so on up to one-year ahead forecast. $\varepsilon^{oil}_{h,t}$ denotes the similarly defined forecast error on Brent or WTI oil price change at time t. Table 4 in Appendix reports the mean bias and the Root Mean Square Forecast Error of the data. It reveals that overall inflation and crude oil price forecasts were under-estimated over the recent period (2005q1-2013q4) in both countries. The link between these two biases is not obvious since when the full sample is considered in the U.S., the crude oil price remains under-estimated whereas the overall inflation is over-estimated (negative bias) for all forecast horizons $h \geq 6$. Finally, the median of SPF individual forecasts appears more accurate over the whole sample (1992q1-2013q4) than over the last sub-sample: it has gotten worse since 2005q1.

3 Are inflation forecast errors imputable to oil price forecast errors?

3.1 How correlated are these errors?

Fig. 1 below represents the correlation between U.S. CPI forecast errors and WTI crude oil forecast errors based on futures over the full sample (first bar) and the 2005q1-2013q4 sub-sample (second bar). The third bar corresponds to the French analogue — correlation between HIPC forecast errors and Brent crude oil forecast errors based on futures — as of 2005q1 to 2013q4. For forecast horizons ranging from one to four quarters ahead, the correlation patterns are very similar across countries: they reach 70% or more over the last sub-sample and are only very slightly below when the whole sample is considered for the U.S.. Expectedly, the inflation nowcasts are less correlated with oil price nowcast

Figure 1: Correlation between inflation and oil future price forecast errors



errors because the latest news regarding oil price are incorporated in the inflation nowcast.

Of course, inflation forecast errors could also stem from other forecast errors, such as *e.g.* real GDP forecast errors. Since the latter are available from the same sources over the same samples, we will also consider them as a potential source of inflation forecast errors. Again, they are expressed in year-on-year and quarter-on-quarter percent changes respectively for French and US data.[12] They are plotted in Fig. 6 and 7 in Appendix. A look at the correlation between the inflation errors and those errors reveals a weaker link than with the crude oil price errors, as can be seen from Table 1 below. When considering the largest sample for the US, this correlation reaches a maximum of 10% for three-quarter ahead forecasts. The maximum is 28% if only the past eight years are considered. Over the latter period, the correlation for French forecast errors ranges from 39% to 60%. In all cases, this is quite less than the 75% typically reached by the

[12]We will use the series corresponding to the nowcast (DRGDP2), the 1-quarter ahead (DRGDP3) and up to 4-quarter ahead forecasts (DRGDP6) from SPF database.

Table 1: Correlation between inflation and real GDP forecasts errors

horizon (in months)	0	3	6	9	12
US$^{(a)}$	-0.03	0.03	0.08	0.10	0.09
US$^{(b)}$	-0.01	0.15	0.25	0.28	0.28
FR$^{(b)}$	0.39	0.60	0.56	0.53	0.57

(a): 1992q1-2013q4. (b): 2005q1-2013q4.

correlation with crude oil price errors. Nevertheless, these real GDP forecast errors will be included among the right-hand side variables in the subsequent empirical analysis so as to avoid a potential omitted variable issue.

3.2 A simple regression model

To explore further the link between inflation forecast errors and oil price errors, we will first consider the simple regression model (1) below:

$$\varepsilon^{\pi}_{h,t} = \mu + \beta\varepsilon^{oil}_{h,t} + \gamma\varepsilon^{gdp}_{h,t} + u_t \tag{1}$$

Note that when forecasts horizon is larger than the forecast exercise frequency — for instance one-year ahead forecasts made on a quarterly basis — the estimated residuals $\hat{u}_t$'s are expected to be serially correlated. This in turn implies an under-estimation of the estimated coefficients standard errors. To get robust standard errors estimates, we use the Newey and West [1987] general covariance estimator which is consistent in the presence of both heteroskedasticity and autocorrelation of unknown form.[13] The results are reported in Table 2. The similarity of the conclusions across samples and countries is worth noticing: the main determinant of inflation forecast errors is the crude oil price errors, with a pass-through coefficient of 0.03 in the United States whatever the sample considered and of 0.02 in France over the past eight years. These figures are unsurprisingly of the same order of magnitude as the share of gasoline and oil products

[13]It is computed using a Bartlett kernel with a bandwidth selected following Andrews [1991].

Table 2: Estimation results

horizon (in months)	0	3	6	9	12
			US$^{(a)}$		
μ	-0.01	-0.28	-0.40^{**}	-0.46^{**}	-0.51^{**}
	(0.13)	(0.20)	(0.19)	(0.19)	(0.19)
β	0.02^{*}	0.03^{**}	0.03^{**}	0.03^{**}	0.03^{**}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
γ	-0.03	-0.03	-0.00	0.03	0.03
	(0.04)	(0.06)	(0.07)	(0.07)	(0.07)
R^2-adj	0.03	0.47	0.50	0.46	0.45
AIC	3.21	3.56	3.57	3.63	3.65
			US$^{(b)}$		
μ	0.07	0.14	-0.18	-0.22	-0.51^{**}
	(0.24)	(0.32)	(0.33)	(0.35)	(0.19)
β	0.03^{**}	0.04^{**}	0.03^{**}	0.03^{**}	0.03^{**}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
γ	-0.07	-0.14	0.02	0.06	0.03
	(0.09)	(0.10)	(0.13)	(0.14)	(0.07)
R^2-adj	0.10	0.59	0.57	0.52	0.45
AIC	3.73	4.05	4.19	4.22	3.65
			FR$^{(b)}$		
μ	-0.00	0.06	0.09	-0.03	-0.07
	(0.01)	(0.05)	(0.03)	(0.11)	(0.15)
β	0.01^{**}	0.01^{**}	0.02^{**}	0.02^{**}	0.02^{**}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
γ	0.03	0.17^{*}	0.03	0.02	-0.01
	(0.05)	(0.09)	(0.13)	(0.11)	(0.11)
R^2-adj	0.19	0.64	0.62	0.58	0.51
AIC	-2.01	0.14	1.22	1.91	2.25

(a): 1992q1-2013q4. (b): 2005q1-2013q4.

Standard Errors into parenthesis.

Superscripts * and ** denote 10- and 5-percent levels respectively.

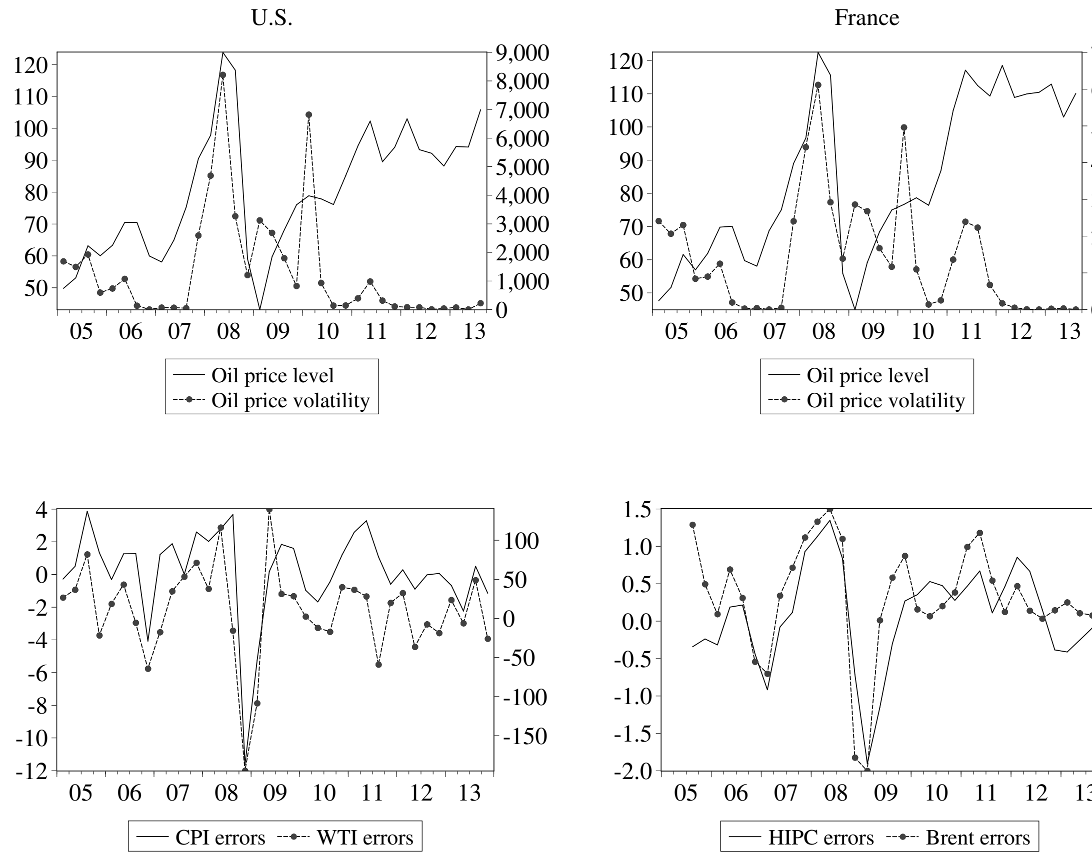
in the CPI. In the latter country, despite the correlation found between inflation and real GDP forecast errors, no significant impact is found from the latter to the former. Expectedly, this result holds for the US data where the correlation between these two kinds of forecast errors was found to be quite weak already. Also remarkable is the level of the coefficients of determination, as soon as the horizon is greater or equal to 1 quarter: they range from 0.45 (4-quarter ahead forecast horizon in the US) to 0.64 (1-quarter ahead forecast in France). Hence, oil price forecast errors are an essential cause of CPI forecast errors: they explain around half of CPI error variance although they account for only 5% of CPI indices.

4 A Regime-dependent model for inflation forecast errors

A widespread belief amongst professional forecasters is that a high Brent oil price volatility makes it difficult to predict inflation accurately. The top panel of Fig. 2 above plots the crude oil price in levels together with its volatility as measured by the square of its year-on-year percent change, for the U.S. and France over their common sample 2005q1-2013q4.[14] The bottom panel of Fig. 2 shows the two-quarter ahead forecast errors for inflation and oil prices in these countries for the same sub-sample. A quick glance at these data reveals that the periods before 2008 and after 2009 both correspond to a relatively small oil price volatility, but while the oil price level stays relatively low before 2008, with values typically below 80 USD per barrel, it becomes quite high after 2009 with values ranging between 80 and 110 to 120 USD. Then, when looking at the inflation and oil price forecasts errors plotted below for the same sub-sample, it turns out that

[14] The square of the WTI year-on-year percent change is retained here even though the inflation forecasts data from the U.S. SPF are expressed in quarter-on-quarter percent change. Indeed, as also noticed by e.g. Blanchard and Gali [2010], the year-on-year percent change series is smoother than its quarter-on-quarter analogue and is therefore more likely to capture epochs of volatility instead of isolated points of volatility.

Figure 2: Crude oil price: level and volatility



Note: The solid line (left scale) is the oil price in levels. The dotted line (right-scale) is its volatility, as approximated by the square of its y-o-y percent change.

the correlation between the two series is large not so much when the Brent price level is high but rather when its volatility is large.

4.1 The model

To account for this dynamics which seems to depend on the volatility of oil price, we propose to explore the relationship between inflation and oil price forecast errors in a setup which allows for different regimes. More precisely, we consider a framework which allows the closeness of this relationship to depend on the state the volatility of oil price is in, namely high or normal/low. Even though there is not much evidence supporting the effect of GDP forecast errors on inflation forecast errors from the linear analysis above, one cannot exclude *a priori* that this relationship is nonlinear. Hence, both oil price and GDP forecast errors will still be considered in the subsequent analysis. With σ_t^{oil} denoting time t volatility of oil price approximated by the square of its time t year-on-year change, the regime-dependent model considered here for inflation forecast errors is a threshold-type model given by:

$$\varepsilon_{h,t}^{\pi} = \mu + s_t(\beta^h \varepsilon_{h,t}^{oil} + \gamma^h \varepsilon_{h,t}^{gdp}) + (1 - s_t)(\beta^\ell \varepsilon_{h,t}^{oil} + \gamma^\ell \varepsilon_{h,t}^{gdp}) + u_t \quad (2)$$

with

$$s_t = 1(\sigma_t^{oil} > \lambda), \quad (3)$$

where λ is a positive real-valued threshold parameter and $1(\cdot)$ is the indicator function which takes on value 1 if the condition into parenthesis is satisfied and zero otherwise. Hence, Equation (2) is piecewise linear: it implies that the relation between $\varepsilon_{h,t}^{\pi}$ and $\varepsilon_{h,t}^{oil}$ (resp. $\varepsilon_{h,t}^{gdp}$) is characterized by coefficient β^h (resp. γ^h) if $\sigma_t^{oil} > \lambda$ and by coefficient β^ℓ (resp. γ^ℓ) if $\sigma_t^{oil} \leq \lambda$. In accordance with Fig. 2, β^h is expected to be larger than β^ℓ.

The estimation of model (2)-(3)'s parameters μ, β^h, γ^h, β^ℓ and γ^ℓ would be straightforward if the threshold parameter value, λ, were known. However, this is not the case here and λ has to be estimated as well. To this end, the grid-search estimation approach which is commonly used in the threshold models literature is retained. It consists in estimating model (2)-(3) by nonlinear least squares for all possible values of $\lambda \in \Lambda$, where Λ is a grid interval of the ordered values of the threshold variable σ_t^{oil}. The boundaries of $\Lambda = [\lambda_{inf}, \lambda_{sup}]$ are chosen so as to leave at least 10% of the observations in each regime. Then, the threshold estimate, $\hat{\lambda}$, is the value in Λ which minimizes the sum of squared residuals, i.e. which maximizes the model's likelihood. Then, $\hat{\mu}$, $\hat{\beta}^h$, $\hat{\gamma}^h$, $\hat{\beta}^\ell$ and $\hat{\gamma}^\ell$ are obtained by least squares estimation of equation (2) with $\hat{s}_t = 1(\sigma_t^{oil} > \hat{\lambda})$.

4.2 The estimation results

Before presenting the threshold model estimates, let us first note that model (2)-(3) shrinks to a linear model if:

$$H_0 : \beta^h = \beta^\ell = \beta \text{ and } \gamma^h = \gamma^\ell = \gamma. \tag{4}$$

Obviously, the threshold parameter is unidentified under this linear null hypothesis. Consequently, the linearity hypothesis is tested using a SupLR statistics calculated along the lines described by Davies [1987], and whose p-value is bootstrapped following Hansen [1996] with 5,000 replications. Both linearity SupLR test bootstrapped p-values and estimation results are reported in Table 3 below.[15] From the formers, evidence for a nonlinear relationship between inflation, crude oil price and/or GDP growth forecast errors is found in both countries. When considering the whole sample in the U.S., the SupLR linearity test p-values range from 0.2% for the one-year forecast horizon to 6% for the one-quarter forecast horizon. Of course, the power of this test decreases when the sample size decreases too, so that linearity is rejected less often in the restricted sample, but still, the bootstrapped p-values range here from 7% to 12.4% for one- to four-quarter ahead forecasts horizons. The relationship is found to be much weaker for inflation nowcasts as can be seen from the corresponding R^2 values, and there is no evidence of nonlinearity at this horizon. In this country for longer horizons, the estimated threshold value implies that the CPI inflation forecast errors process switches from low to high volatility regime as soon as there is a change in the WTI crude oil price of around 30%. Again, the latest news regarding oil price and/or output growth are expected to be already incorporated in the inflation nowcast. In France, it is only for forecasts errors corresponding to horizons strictly greater than one-quarter that our SupLR test results mildly reject the linear null: for forecast horizons from two quarters to one year, this test p-values range from

[15] The constant term has been withdrawn from these models since it was found to be non significantly different from zero. More statistics about the estimated models are gathered in Tables 5 and 6 in Appendix.

Table 3: Threshold model estimation results

horizon (in months)	0	3	6	9	12
			US$^{(a)}$		
β^ℓ	0.002 (0.011)	0.013** (0.004)	0.014** (0.004)	0.013** (0.005)	0.012** (0.005)
β^h	0.030** (0.014)	0.032** (0.007)	0.028** (0.007)	0.027** (0.007)	0.027** (0.008)
γ^ℓ	−0.047 (0.044)	−0.148** (0.055)	−0.158** (0.056)	−0.152** (0.060)	−0.148** (0.057)
γ^h	0.116 (0.094)	0.115 (0.087)	0.209* (0.112)	0.236** (0.060)	0.235** (0.116)
R^2-adj	0.08	0.58	0.56	0.53	0.51
AIC	3.21	3.45	3.47	3.53	3.55
SupLR p-val.	68.8%	6.0%	3.5%	2.1%	0.2%
$\sqrt{\lambda}$	32.76	31.33	32.76	32.76	32.76
			US$^{(b)}$		
β^ℓ	0.018 (0.013)	0.027** (0.010)	0.023** (0.009)	0.023** (0.009)	0.021** (0.008)
β^h	0.064** (0.020)	0.044** (0.010)	0.033** (0.009)	0.031** (0.009)	0.030** (0.010)
γ^ℓ	−0.114 (0.082)	−0.592** (0.172)	−0.284** (0.092)	−0.258** (0.098)	−0.233** (0.094)
γ^h	0.376* (0.201)	0.004 (0.149)	0.315** (0.148)	0.312** (0.156)	0.313 (0.171)
R^2-adj	0.16	0.69	0.65	0.62	0.60
AIC	3.69	3.81	3.96	4.00	4.05
SupLR p-val.	55.3%	7.0%	7.1%	8.35%	12.4%
$\sqrt{\lambda}$	32.76	28.33	32.76	31.33	32.76
			FR$^{(b)}$		
β^ℓ	−0.031** (0.014)	0.010** (0.003)	0.013** (0.003)	0.008 (0.005)	0.001 (0.007)
β^h	0.011** (0.002)	0.018** (0.004)	0.029** (0.001)	0.028** (0.002)	0.031** (0.004)
γ^ℓ	−1.175** (0.378)	0.373** (0.139)	—	—	—
γ^h	0.162** (0.064)	0.213 (0.165)	—	—	—
R^2-adj	0.51	0.60	0.67	0.60	0.62
AIC	-0.845	0.765	1.27	1.87	1.97
SupLR p-val.	45.9%	74.0%	6.9%	17.7%	10.4%
$\sqrt{\lambda}$	2.24	48.87	48.87	37.21	37.21

Notes: See Table 2.

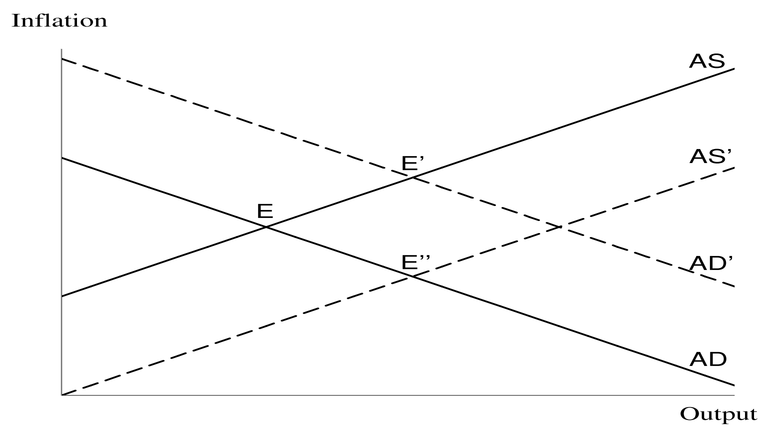
6.9% to 17.7%.[16] Here, the estimated values of the threshold parameter suggest that when the Brent crude oil price changes by more than 49% (respectively 37%), then the 2-quarter (respectively 3 and 4-quarters) HICP inflation forecast errors process switches to the high volatility regime.

The common feature shared by both countries and samples is that as expected, the role of oil price forecast errors is much stronger in the regime corresponding to high oil price volatility than in the low volatility regime. For instance, when considering the large U.S. sample, the value of β^{ℓ} is around 0.013 for all horizons greater than nowcast while the one of β^{h} is close to 0.030. In France, when the linear model is rejected in favor of the regime-switching one (*i.e.* from 2-quarters ahead on), β^{ℓ} is typically found to be not significantly different from zero whereas β^{h} is still close to 0.03 as in the U.S.. One possible explanation of this finding is that in the low volatility regime, oil price news are perceived as more persistent by central bankers than in the high volatility regime. Yet, it is now quite well established that the maximum impact of monetary policy on real U.S. activity is lagged by a few quarters. As a result, by trying to accommodate oil price changes which are not likely to be persistent, as in the high volatility regime, the monetary policy could lead to pro-cyclical, destabilizing macroeconomic impact. By contrast, thanks to a lower level of uncertainty in the low than in the high oil price volatility regime, these news are more likely to be efficiently corrected by monetary policy. Hence, their transmission to inflation is expected to be muted in the low volatility regime.

For these nonlinear French models, the output forecast errors coefficients were also found to be non significant whatever the regime, confirming the conclusion drawn from the linear analysis. These coefficients were accordingly set to zero. This is in sharp contrast with the U.S. results where once their influence is allowed to be regime-specific, the output forecast errors significantly affect the inflation forecast errors — negatively

[16] Again, the small size of this sample reduces the power of the test and the null is hence not rejected often enough. This is why we consider the nonlinear alternative models here despite unconventional levels of rejection.

Figure 3: Correlation between inflation and output forecast errors



in the low volatility regime and positively otherwise. This could be rationalized from a standard aggregate supply (AS) and aggregate demand (AD) theoretical framework where both signs are possible depending on which side of the market is over-estimated. As can be seen from Figure 3, starting from a macroeconomic equilibrium at the intersection of AS and AD curves in E, the output can be over-estimated either because the aggregate demand is over-estimated in location AD' (point E') or because the aggregate supply is over-estimated in location AS' (point E''): depending on this, the inflation rate will be either over-estimated (E') and the parameter γ is hence expected to be positive, or under-estimated (E'') and then the parameter γ is expected to be negative. The results in Table 3 suggest an interpretation of the two regimes in the U.S. case along these lines. In the low oil price volatility regime, which corresponds to a 'normal' regime to which most of the observations belong[17], the estimated value of γ^{ℓ} is around -0.15 for the longest sample and between -0.23 and -0.59 for the shortest one, which indicates an over-estimation of the aggregate supply, *caeteris paribus*. This regime would hence be dominated by aggregate supply shocks. On the contrary, the high oil price volatility regime is typically associated with a positive estimate of γ^h which points to a prevalence of aggregate demand shocks.

[17] See the additional results gathered in Appendix, Table 5.

It is worth noticing that the latter regime is the one capturing the most recent U.S. recession which has been characterized by a drop in the aggregate demand of unexpected magnitude.[18] Yet, it can be seen from Fig.7 in Appendix that during the subprime crisis episode, the output growth was over-estimated while the inflation rate was under-estimated: this reveals the predominant role of oil price forecast errors which has more than compensated the effect of output growth forecast errors.

4.3 Implications for inflation forecast fan charts

One consequence of the nonlinear representation of the inflation forecast errors given in Eq. (2) is that the corresponding forecast uncertainty is also regime-dependent. Some kind of asymmetry in inflation forecasts uncertainty has already been explicitly taken into account by e.g. the Bank of England. This institution publishes its forecasts in the form of a probability distribution since February 1996 for inflation and November 1997 for GDP growth. By doing so, it has popularized the use of fan charts to present GDP growth or inflation forecasts. As emphasized in Britton, Fisher and Whitley [1998], this new presentation aims at making clearer the "Bank's subjective assessment of medium-term inflation pressures, without suggesting a degree of precision that would be spurious". The Bank of England fan chart for inflation forecasts is built from a 'two-piece' normal probability distribution function which allows for skewness and hence asymmetry. The value of the parameters of this distribution is discussed at each projections exercise by the Monetary Policy Committee with the advice from Bank staff. By contrast, the French National Institute for Statistics and Economic Studies (INSEE) assumes that forecast errors follow, at each date, a zero mean Gaussian distribution whose variance, σ_h, depends on the forecast horizon h.[19] Over the past decade, there has been almost as many methods proposed to build these fan charts as articles or notes devoted to that topic. More generally, the confidence interval of future inflation at the $\alpha\%$ bilateral level,

[18] See for instance Hamilton [2009] on this point.

[19] See e.g. the INSEE's "Note de Conjoncture", June 2008.

denoted $CI^{\pi}_{1-\alpha}$, may be computed from the inflation forecast error probability given by:

$$\begin{aligned} P\left[C_h\left(1-\frac{\alpha}{2}\right) \leq \varepsilon^{\pi}_{h,\tau} < C_h\left(\frac{\alpha}{2}\right)\right] &= 1-\alpha \\ \Longleftrightarrow P\left[C_h\left(1-\frac{\alpha}{2}\right) \leq \pi_{\tau} - \pi^{f}_{\tau|\tau-h} < C_h\left(\frac{\alpha}{2}\right)\right] &= 1-\alpha, \end{aligned}$$

where $C_h(1-\frac{\alpha}{2})$ denotes the value such that $\varepsilon^{\pi}_{h,\tau}$ is greater with probability $(1-\frac{\alpha}{2})$, $\forall h$ and $\pi^{f}_{\tau|\tau-h}$ stands for the h-period ahead forecast of time τ inflation, whose realization is denoted π_{τ}. Finally, the confidence interval is obtained as:[20]

$$CI^{\pi}_{1-\alpha} = \left\{\pi^{f}_{\tau|\tau-h} + C_h\left(1-\frac{\alpha}{2}\right); \pi^{f}_{\tau|\tau-h} + C_h\left(\frac{\alpha}{2}\right)\right\}.$$

In this paper, we will depart from existing works in two ways. First, we will not impose any functional form for the distribution of the forecast errors but will bootstrap it instead. Second, we will use a wild bootstrap method which keeps any heteroskedasticity features potentially present in the data in the bootstrapped sample. To this end, the bootstrapped residuals (denoted $\hat{u}^{b}_{t}$) are computed by multiplying the estimated residuals $\hat{u}_t$ of Eq. (1) or (2) by random draws of an *i.i.d.* process η_t which has a Rademacher distribution[21], i.e. a discrete probability distribution where a random variate X has a 50% chance of being either +1 or -1.[22] From these bootstrapped residuals, we create S bootstrapped series of inflation forecast errors, $\varepsilon^{\pi,b}_{h,t}$ using the estimated values of the parameters both from the linear model:

$$\varepsilon^{\pi,b}_{h,t} = \hat{\mu} + \hat{\beta}\varepsilon^{oil}_{h,t} + \hat{\gamma}\varepsilon^{gdp}_{h,t} + \hat{u}^{b}_{t},$$

[20] Note that this interval is centered on the realization of inflation π_{τ} instead of its forecast. Consequently, any forecast bias will make the forecast value $\pi^{f}_{\tau-h|\tau}$ depart from the middle of this confidence interval. For instance, Laurent and Kozluk [2012] present fan charts for the German GDP growth where the forecast not only is not in the middle of the interval but also can be outside of it. To overlook this issue, some authors, as e.g. Elder, Kapetanios, Taylor and Yates [2005], just do not report the forecast value in their fan charts.

[21] Note that if the η_t's were drawn in a Gaussian distribution, then moments of order greater than 2 would be magnified mechanically. Since the tails of the distribution are of particular interest in this application, we use a Rademacher distribution which keeps moments of order 3 and 4 as in the estimated residuals sample.

[22] Acknowledging that the residuals in Eq. (2) are serially correlated for most of the French models (see Table 6 in Appendix), the Dependent Wild Bootstrap method described in Davidson and Monticini [2014] is used in these cases.

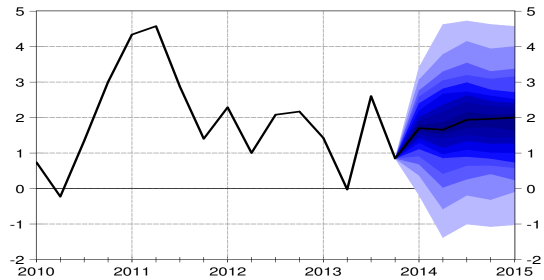
and regime-specific ones for the threshold model:

$$\varepsilon_{h,t}^{\pi,b} = \begin{cases} \hat{\mu} + \hat{\beta}^h \varepsilon_{h,t}^{oil} + \hat{\gamma}^h \varepsilon_{h,t}^{gdp} + \hat{u}_t^{hb}, \text{ if } s_t = 1 \\ \hat{\mu} + \hat{\beta}^\ell \varepsilon_{h,t}^{oil} + \hat{\gamma}^\ell \varepsilon_{h,t}^{gdp} + \hat{u}_t^{\ell b}, \text{ if } s_t = 0 \end{cases}$$

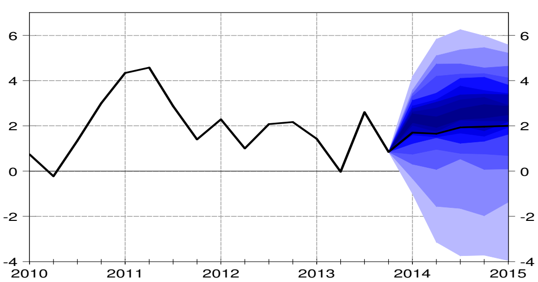
Then, the empirical quantiles of these bootstrapped series are used to compute the values of $C_h(1-\frac{\alpha}{2})$ and $C_h(\frac{\alpha}{2})$ which define the confidence interval bounds. Mainly two reasons motivate the regime-specific computation of the fan charts from the nonlinear models. First, the threshold variable which governs the regime switches is assumed to be exogenous. Indeed, modelling the crude oil price volatility in such a way that accurate forecasts could be performed is particularly difficult, see e.g. Alquist et al. [2013] and beyond the scope of this paper. Second, unless there are good reasons to put a high probability on a regime switch over the next year, allowing for random regime switches in the bootstrap process would yield fan charts similar to those obtained from the linear model: the latter is in fact more or less a weighted average of the two regimes, the weights corresponding roughly to the relative percentage of observations lying in each regime. Hence, the advantage of the regime-specific modelling for the assesment of the predictive density would be lost. In Fig. 4 and 5 below, the $CI_{1-\alpha}^{\pi}$ are computed for $\alpha \in \{10\%, 20\%, \ldots, 90\%\}$ and represented from darker to clearer shaded areas. The black line represents the inflation forecasts. A quick look at these graphs reveals that whatever the model and/or oil price volatility regime, the uncertainty found around the inflation forecasts is almost twice as big in the U.S. as in France. For instance, the width of the 90% confidence intervals is around 5.5 percent points for the U.S. linear model and reaches more than 9 in the high volatility regime of the threshold model from two-quarter horizons on. The French analogues are only around 3 and 5 percent points respectively. It is also worth noticing that in both countries, the confidence intervals are wider (respectively narrower) when obtained from the threshold model high (respectively low) oil price volatility regime than those obtained from the linear model estimates. The interest of the regime-dependent approach developed here is even clearer for French inflation forecasts. The possibility of deflation in Europe and especially in France is currently widely debated among pol-

Figure 4: U.S. CPI forecasts bootstrapped fan charts

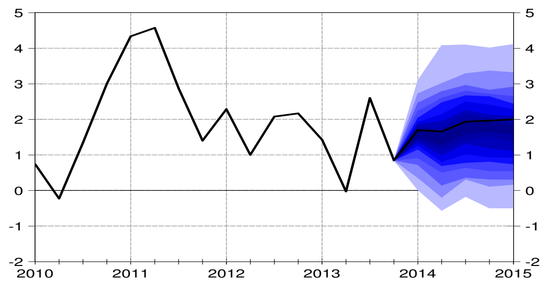
((a)) Linear model



((b)) High regime



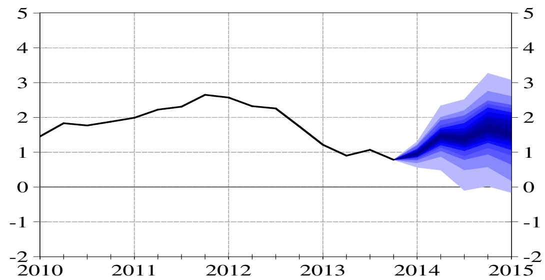
((c)) Low regime



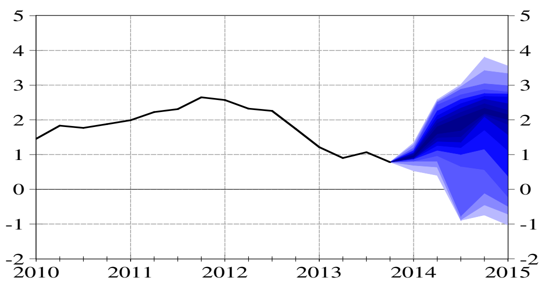
icy makers and economists, in a context of restrictive policies and wage costs decreases performed in Europe particularly since the Greek government-debt crisis. In early April 2014, Olivier-Jean Blanchard, now International Monetary Fund's chief economist, urged the European Central Bank to act soon to counter extremely low inflation, which could impede the euro area's rebound. At the same moment, European Central Bank executive board member Yves Mersch noted that the ECB sees "no imminent risk of deflation" and that its current forecasts for inflation still point to a slow return to a level closer to 2%, which the central bank considers appropriate. From the 2013Q4 perspective, a slight raise in HICP was expected during 2014, as can be seen from Fig. 5. Nevertheless, deflation could not have been ruled out in France according to the 80 and 90% confidence intervals from 2014q2 on, had the high oil price volatility regime prevailed (panel (b)). By contrast, in the low volatility regime, the deflation risk could have been ruled out

Figure 5: France HICP forecasts bootstrapped fan charts

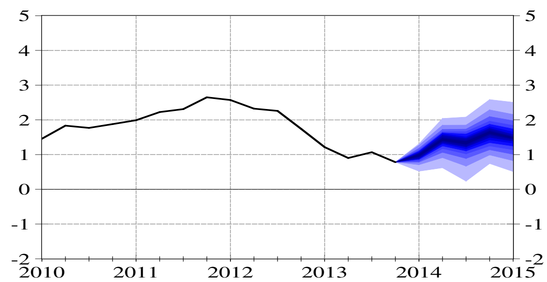
((a)) Linear model



((b)) High regime



((c)) Low regime



even at the 90%-level (panel (c) of Fig. 5).

5 Conclusion

This paper proposes an empirical investigation of the impact of oil price forecast errors on inflation forecast errors for two different sets of recent forecasts data: the median of SPF inflation forecasts for the U.S. and the Central Bank inflation forecasts for France.

Mainly two salient points emerge from our results. First, there is a significant contribution of oil price forecast errors to the explanation of inflation forecast errors, whatever the country or the period considered. Second, in most of the cases it is better accounted for by a threshold nonlinear model where the oil price volatility is the regime-switching variable than by its linear constrained version. Once the regime-dependent nature of the relationship is explicitly taken into account, it turns out that the pass-through of oil price forecast errors to inflation forecast errors is multiplied by around 1.5 or 2 when the oil price volatility is large compared to when it is low. Development of a theoretical model that accounts for this regime-dependent pass-through remains on the agenda for future research.

Finally, the interest of the nonlinear approach developed here is illustrated by the construction of bootstrapped regime-dependent inflation forecast fan charts. As of the end of 2013, the fan chart built from the linear model could not exclude a deflation risk in 2014 at the 90%-level for France, whereas it was clearly excluded from the regime-dependent fan chart assuming that 2014 could be safely classified as a low oil price volatility period.

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Appendix

Table 4: Inflation and crude oil price (%, yoy, futures) forecasts errors descriptive statistics

	ε_0^{π}	ε_3^{π}	ε_6^{π}	ε_9^{π}	ε_{12}^{π}	ε_0^{oil}	ε_3^{oil}	ε_6^{oil}	ε_9^{oil}	ε_{12}^{oil}
					Mean Bias					
US$^{(a)}$	0.01	0.01	-0.05	-0.14	-0.19	1.79	10.43	12.93	13.06	13.51
US$^{(b)}$	0.13	0.17	0.13	0.09	0.07	0.46	4.23	9.52	12.08	13.20
FR$^{(b)}$	0.01	0.09	0.11	0.15	0.20	0.25	2.01	5.91	9.77	11.20
					Root Mean Square Forecast Error					
US$^{(a)}$	1.20	1.93	1.97	1.97	1.95	17.47	51.51	53.04	52.78	52.51
US$^{(b)}$	1.57	2.72	2.76	2.73	2.70	19.58	54.42	59.16	60.43	60.66
FR$^{(b)}$	0.21	0.53	0.78	0.94	1.03	10.24	23.42	29.71	32.57	32.49

(a): 1992q1-2013q4. (b): 2005q1-2013q4.

Table 5: Descriptive statistics by regime

horizon (in months)	0	3	6	9	12
			US$^{(a)}$		
Obs. regime ℓ	60	58	60	60	60
Obs. regime h	24	26	24	24	24
mean ϵ_ℓ^π	-0.105	-0.145	-0.167	-0.255	-0.302
mean ϵ_h^π	0.301	0.390	0.300	0.234	0.189
$\sigma^2(\epsilon_\ell^\pi)$	0.777	1.671	1.703	1.74	1.711
$\sigma^2(\epsilon_h^\pi)$	3.376	9.029	10.284	9.989	9.822
			US$^{(b)}$		
Obs. regime ℓ	24	20	24	23	24
Obs. regime h	12	16	12	13	12
mean ϵ_ℓ^π	0.096	0.041	0.228	0.146	0.159
mean ϵ_h^π	0.197	0.321	-0.056	-0.02	-0.113
$\sigma^2(\epsilon_\ell^\pi)$	0.933	2.387	2.587	2.647	2.528
$\sigma^2(\epsilon_h^\pi)$	6.017	14.644	19.475	17.422	18.566
			FR$^{(b)}$		
Obs. regime ℓ	5	28	27	23	22
Obs. regime h	31	7	7	10	10
mean ϵ_ℓ^π	-0.076	0.023	0.056	0.054	0.155
mean ϵ_h^π	0.023	0.27	0.317	0.333	0.287
$\sigma^2(\epsilon_\ell^\pi)$	0.031	0.209	0.28	0.323	0.333
$\sigma^2(\epsilon_h^\pi)$	0.047	0.552	1.987	2.315	2.84

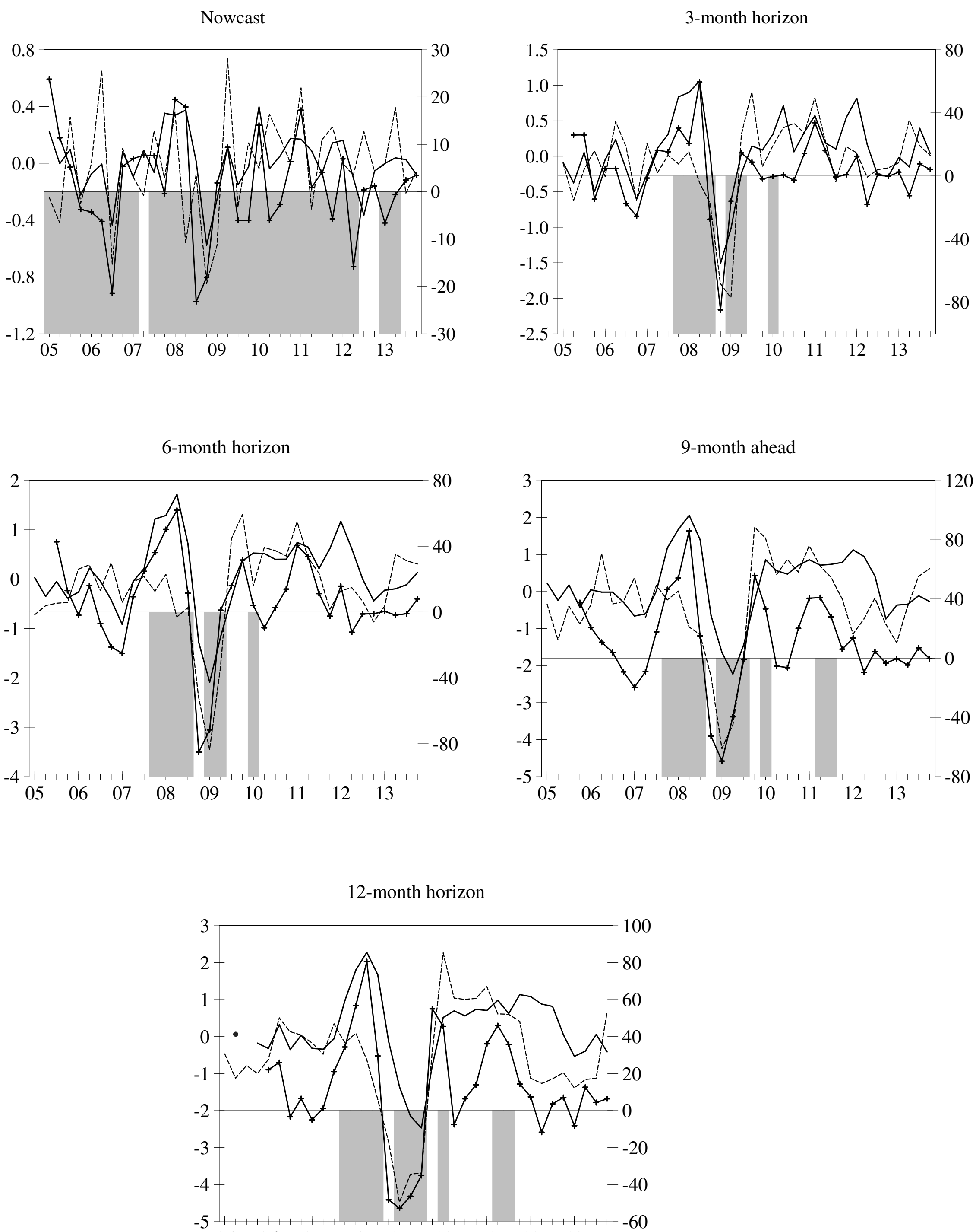
(a): 1992q1-2013q4. (b): 2005q1-2013q4.

Table 6: Residual statistics and specification tests

horizon (in months)	0	3	6	9	12
			US$^{(a)}$		
$\sigma^2(u_t)$	1.337	1.634	1.64	1.718	1.729
Q(4) p-val.	14.8%	69.8%	56.5%	46.8%	25.8%
ARCH(4) p-val.	95.3%	15.7%	6.7%	11.7%	7.0%
			US$^{(b)}$		
$\sigma^2(u_t)$	1.922	2.157	2.529	2.627	2.74
Q(4) p-val.	20.7%	12.7%	20.1%	68.2%	38.2%
ARCH(4) p-val.	76.6%	23.3%	58.6%	64.1%	55.2%
			FR$^{(b)}$		
$\sigma^2(u_t)$	0.021	0.100	0.191	0.346	0.382
Q(4) p-val.	20.5%	1.3%	0.1%	0.8%	2.1%
ARCH(4) p-val.	37.5%	93.6%	61.9%	10.2%	2.1%

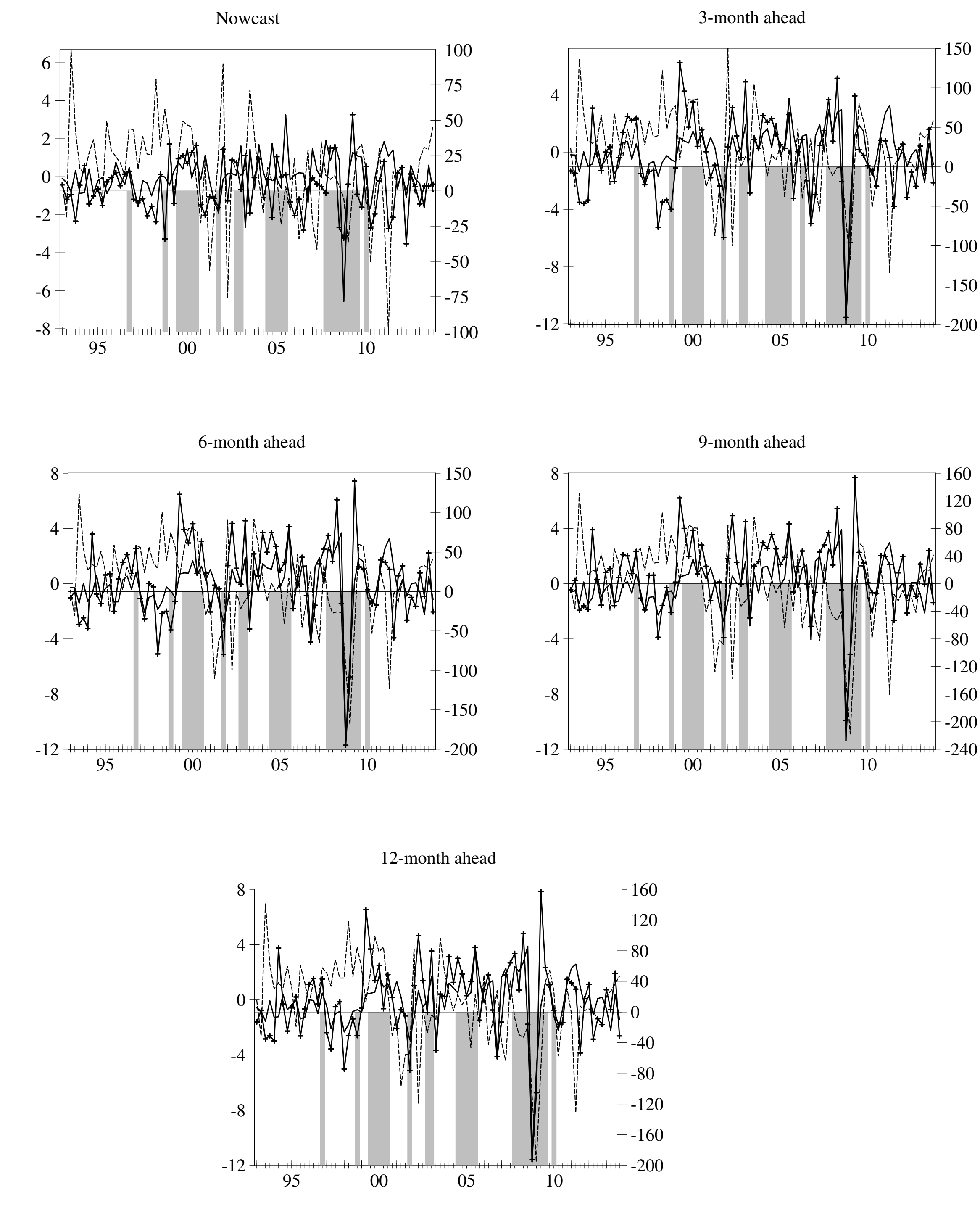
(a): 1992q1-2013q4. (b): 2005q1-2013q4.

Figure 6: French HICP, GDP and Brent future price forecast errors



Note: % y-o-y errors, HICP in solid line, GDP in dotted line (left scale), Brent in line and + (right-scale).

Figure 7: U.S. CPI, GDP and WTI future price forecast errors



Note: % y-o-y errors, CPI in solid line, GDP in dotted line (left scale), WTI in line and + (right-scale).

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