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Oil price pass-through into inflation in Spain at national and regional level

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Abstract

Oil price showed sharp fluctuations in recent years which have revived the interest on its effect on inflation rates. In this paper we discuss the relationship between oil price and inflation in Spain. We adjust econometric models to predict the effect of oil price shocks on inflation both at national and regional level and under different scenarios. Our results show that almost half of inflation rates are explained by variations in oil price, that one-year ahead inflation will likely be moderate and that important differences across regions exist.

Keywords. inflation; deflation; oil price; forecasting; simulation

1 Introduction

The relevance of oil prices as a source of variations in prices was established as conventional wisdom after the oil shocks of the 1970s, when inflation reached two digits in most industrialized countries and around 25% in Spain. This view has been challenged in the last decades by several works documenting that the influence of oil price on inflation has decreased (Hooker, 2002);(DeGregorio et al., 2007). However, last years have been characterized by sharp variations in the oil price with yearly decreases around -50% and -30% in January 2015 and January 2016, followed by a sharp increase of 80% in January 2017. Our interest in studying the relationship between oil price and inflation stems from this new scenario. According to the Spanish Institute of Statistics (hereafter, INE), the

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annual change in the Consumer Price Index (CPI) in Spain stood at negative values during most 2016, with a minimum of -1.1% in April, while recovering during 2017 with a maximum of 3% in January and February. There was also a remarkable heterogeneity of inflation among the different regions,¹ with minima ranging from -1.5% in Castile La Mancha to -0.7% in the Basque Country. On the other hand, the Bank of Spain says “With regard to consumer prices, we expect that the slowdown in CPI since March, related to the evolution of the energy component, will be maintained during the rest of the year. Subsequently, inflation would rebound moderately, reflecting the cyclical strengthening of the activity. In this way, after growing by 2% in 2017, consumer prices will increase by 1.3% in 2018 and 1.6% in 2019.”²

We build on the hypothesis, consistent with the analysis from Bank of Spain, that there is a substantial ‘pass-through’ effect of changes in oil prices into inflation. On this basis, we measure and discuss this effect in Spain, both at national and region level. Accordingly, our main objectives are: (i) building econometric models for Spanish inflation as a function of oil prices, (ii) obtaining a quantitative measure of the influence of oil prices on the level and volatility of inflation, and (iii) forecasting inflation rates conditional to different scenarios for oil prices. The basic approach is similar to that in Castro et al. (2016), but it shows some important methodological novelties compared to previous work. First, it uses an interpolation method which is equally effective but much easier to replicate than the previous one. Second, it provides a variance decomposition method to analyze the ‘pass-through’ effect also in terms of volatility and, third, it provides the analysis both at the national and regional levels, revealing the existence of important differences across regions.

Main results show that (i) the value of inflation in any month is affected by annual changes in oil price in the current and previous month with 1 percent point increase in oil price variation leading to an expected 0.024 increase in inflation rate; (ii) when previous analysis is complemented with a variance decomposition approach, it is found that 41% of the variance of monthly changes of inflation were explained by the corresponding changes in Brent price; (iii) if extreme increases in oil price happen again next year, inflation rate in Spain will be well above 2% while extreme decreases may result in inflation rates very close to zero. However, if oil prices variations are closer to the positive or negative median variations in the analyzed period, inflation will be in the range 0.66-1.68; and (iv) important variations across regions are found. For example, the one-year ahead expected inflation under the ‘extreme increase’ scenario ranges from 1.93 (Ceuta) to 3.31 (Castile-La Mancha) while under the ‘extreme decrease scenario’ it goes from -0.65 (Castile-La Mancha) to 0.08 (Catalonia).

¹We have considered 17 autonomous regions (Andalusia, Aragón, Balearic Islands, Basque Country, Canary Islands, Cantabria, Castile-La Mancha, Castile-Leon, Catalonia, Comunidad Valenciana, Galicia, Extremadura, La Rioja, Madrid, Murcia, Navarra, Principado de Asturias) as well as two cities with a specific autonomy regime (Ceuta and Melilla).

²Source: “Proyecciones macroeconómicas de la economía española (2017-2019): Contribución del Banco de España al ejercicio conjunto de Proyecciones del Eurosistema de junio de 2017”, <http://www.bde.es>.

The structure of the paper is as follows: Section 2 describes the dataset and the econometric methods employed. Section 3 presents and discusses the main results for Spain, Section 4 does the same for its autonomous regions and cities and, finally, Section 5 provides some concluding remarks.

2 Data and methods

2.1 Description of the sample and data transformations

The dataset employed in this work includes the CPI in Spain and its regions (*Comunidades Autónomas*) provided by INE, as well as the Brent price published by the U.S. Energy Administration (hereafter, EIA). As crude oil prices are originally quoted in US Dollars (USD), we also used the USD/Euro exchange rate published by OECD. All the time series are observed in a monthly timescale from January 2002 (when Euro entered into circulation) to April 2018. Table 2.1 provides further details about this dataset.

Notation	Variable	Source
P_t^{SP}	CPI in Spain and 19 autonomous regions and cities	Spanish Institute of Statistics, INE. (http://www.ine.es)
O_t^{USD}	Brent oil price in USD	U.S. Energy Information Adm., EIA. (http://www.eia.gov)
ER_t	EUR/USD exchange rate	European Central Bank, ECB (http://www.ecb.europa.eu)
O_t^{EUR}	Brent oil price in EUR	EIA and ECB

Table 1: Definition of the dataset.

The original values of these variables were transformed to annual percent rates, which are the actual variables to be analyzed. To denote this transformation we consider that, for any variable, x_t , $r^{12}(x_t)$ is the corresponding annual rate, defined as: $r^{12}(x_t) = \left(\frac{x_t}{x_{t-12}} - 1\right) \times 100$.

Figure 1 displays the Spanish inflation and its first-order difference. Figure 2 does the same for the annual variation rate of oil prices in euros. Note that, in both cases, the annual rates are non-stationary and require an additional difference to display a stable mean.³ Therefore, the stationary transformation for all the variables considered in our dataset can be interpreted as the monthly acceleration of the annual growth rate.

Table 2 summarizes the main descriptive statistics of the stationary transformed series, as well as the p -values for the ADF and KPSS tests. Note that

³The series $r^{12}(O_t^{USD})$ and $r^{12}(TC_t)$ (not shown here by brevity) have the same properties.

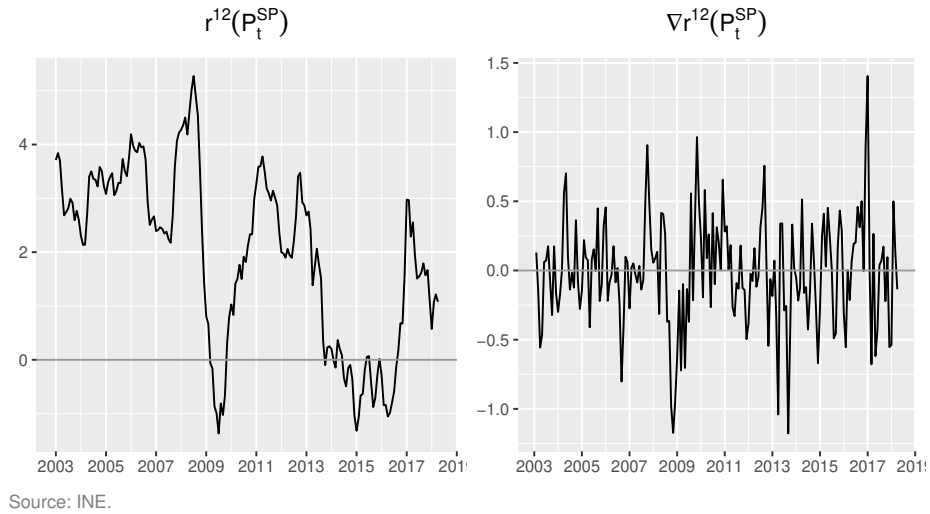


Figure 1: Annual percent changes for inflation in Spain $r^{12}(P_t^{SP})$ and its stationary series (acceleration) $\nabla r^{12}(P_t^{SP})$.

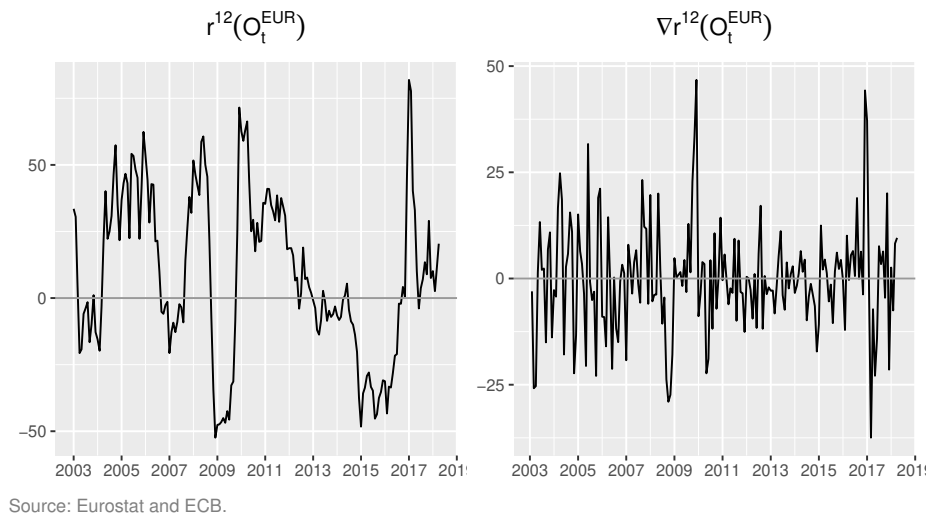


Figure 2: Annual percent changes for Brent price per barrel in euros $r^{12}(O_t^{EUR})$ and its stationary series (acceleration) $\nabla r^{12}(O_t^{EUR})$.

ADF rejects a unit root while KPSS does not reject stationarity. Therefore, both tests confirm that these series are stationary in the mean.⁴

	$\nabla r^{12}(P_t^{SP})$	$\nabla r^{12}(O_t^{EUR})$	$\nabla r^{12}(O_t^{USD})$	$\nabla r^{12}(ER_t)$
Mean	-0.01	-0.07	-0.12	0.02
Std. Dev.	0.39	12.8	13.78	3.44
Minimum	-1.18	-37.46	-39.06	-8.77
Maximum	1.41	46.75	44.5	10.25
<i>p</i> -value ADF	< 0.01	< 0.01	< 0.01	< 0.01
<i>p</i> -value KPSS	> 0.1	> 0.1	> 0.1	> 0.1

Table 2: Descriptive statistics for the stationary series for inflation in Spain $\nabla r^{12}(P_t^{SP})$, Brent price per barrel in euros $\nabla r^{12}(O_t^{EUR})$ and dollars $\nabla r^{12}(O_t^{USD})$ and exchange rates $\text{€}/\text{USD}$ $\nabla r^{12}(ER_t)$.

2.2 Causality analysis

Most works about oil price pass-through into inflation consider bi-directional causality between both variables and, therefore, use the popular VAR (Vector AutoRegressive) analytic framework. While this feedback may be reasonable when the inflation rate corresponds to a large economy producing oil, such as e.g. the U.S., it seems doubtful that inflation in Spain may affect oil prices at a global scale. Hence, a first step in our analysis consists in testing whether lagged relationships between Spanish inflation and oil price are one-way or bi-directional. In the latter case, a vector model would be needed for a full description of the system dynamics, while a scalar transfer function would be more efficient to describe one-way causality.

We compute the Granger (1969) test for a VAR model with one lag. After estimating the model by LS, the corresponding exclusion constraints are tested using standard results. This test consistently rejects the null that lagged oil price does not affect current inflation (*p-value*=0.432553) and, conversely, does not reject the null that lagged inflation does not affect oil price (*p-value*=0.000004). This result agrees with intuition, as Spain does not produce oil and its demand is relatively small in the international framework. Accordingly, Spanish macroeconomics do not affect oil markets.⁵

These results, which will be further confirmed in Section 3, suggest that a VAR specification would not be the best choice to model this dataset. In particular, a single-output transfer function model, (see Box et al., 2015) will be better suited because (i) it is an a flexible and efficient representation for a

⁴The null of ADF is that the series has a unit root, while KPSS test assumes that it is stationary. Statistic tests are more conclusive when rejecting the null and, because of this, these test supplement each other. In particular, ADF and KPSS are more decisive when the series is stationary and nonstationary, respectively.

⁵One may think that inflation could affect oil prices in euros though the effect of monetary policy over the EUR/USD exchange rate. Because of this, we computed the same tests using oil prices in USD and obtained the same conclusion.

single-direction causal relationship, (ii) which allows for instantaneous (0-lag) effects, and (c) seasonal autocorrelations, as those displayed by the inflation series analyzed. If intervention variables were required (see Box and Tiao, 1975) they could also be easily added to a transfer function, but not to a VAR model.

3 Empirical results for Spain

3.1 Univariate models and transfer function specification

Following Box et al. (2015) we (i) performed an univariate analysis of the inflation and oil price series; (ii) to filter them using the univariate model for the input (oil price) and then; (iii) computed the sample cross-correlation function between the series prewhitened in this way.

A standard univariate identification analysis suggested an $ARIMA(1, 1, 0) \times (0, 0, 1)_{12}$ specification for the series $r^{12}(P_t^{SP})$, $r^{12}(O_t^{USD})$ and $r^{12}(O_t^{EUR})$. The corresponding estimation results are shown in Table 3.

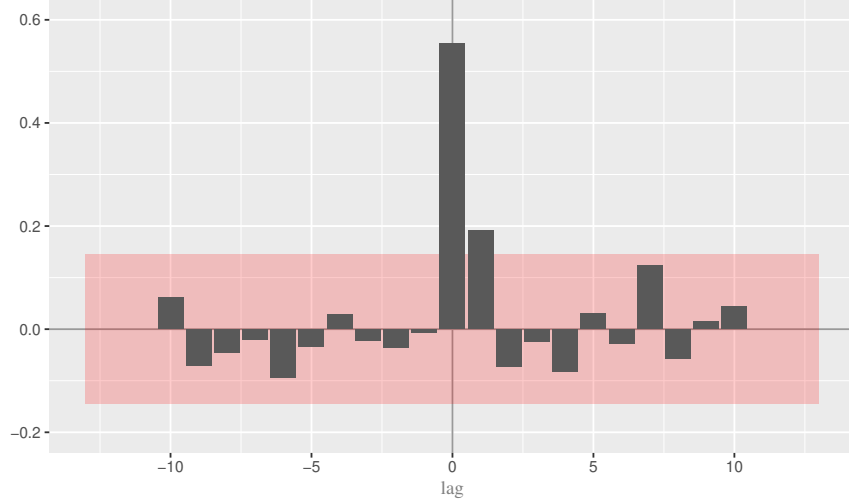
Variable	$\nabla r^{12}(O_t^{EUR})$	$\nabla r^{12}(O_t^{USD})$	$\nabla r^{12}(P_t^{SP})$
ϕ_1	0.196 (0.072)	0.254 (0.071)	0.412 (0.067)
Θ_1	-0.621 (0.066)	-0.642 (0.065)	-0.83 (0.059)
σ_a	10.941	11.481	0.274
$Q(39)(p\text{-value})$	35.077 (0.559)	39.87 (0.262)	16.088 (0.999)

Note: The figures in parentheses are the standard errors unless otherwise indicated. The $Q(39)$ statistic is the Ljung-Box portmanteau test for the null of no residual autocorrelation, computed with the first 39 residual autocorrelations.

Table 3: ARIMA modelling results corresponding to $ARIMA(1, 1, 0) \times (0, 0, 1)_{12}$ process for $r^{12}(x_t)$.

Note that the residual standard deviations in the oil price models are 40 times larger than those in the model for inflation. This clearly illustrates the fact that oil prices are extremely volatile and, in practice, means that they cannot be predicted with a reasonable uncertainty. The analytic approach suggested in Subsection 3.5 addresses this issue.

We have: (i) filtered the series $\nabla r^{12}(P_t^{SP})$ to shocks in $\nabla r^{12}(O_t^{EUR})$ using the model for the latter which, given the results in the previous causality analysis, is the potential input of the relationship, and then (ii) computed the sample cross-correlation function (CCF) between both series, which is shown in Figure 3. The cross-correlations corresponding to positive lags are proportional to the impulse response function of $\nabla r^{12}(P_t^{SP})$ to shocks in $\nabla r^{12}(O_t^{EUR})$, see Box et al. (2015). Negative lags correspond to the inverse causality relationship. This CCF:



The shaded area is approximate 5% significance limits for each individual correlation.

Figure 3: Cross correlations between the prewhitened series of inflation in Spain, $\nabla r^{12}(P_t^{SP})$ and the lagged annual variation rate of Brent prices in euros. Note that negative lags are actually leads for $\nabla r^{12}(O_t^{EUR})$.

1. ...has no significant values in the negative lags, which confirms the causality analysis in Subsection 2.2 and,
2. ...under the reasonable assumption that the instantaneous (0-lag) correlation corresponds to the effect of oil price over HICP, suggests that a shock in $\nabla r^{12}(O_t^{EUR})$ has a positive and significant effect over $\nabla r^{12}(P_t^{SP})$ and $\nabla r^{12}(P_{t+1}^{SP})$.

3.2 The response of Spanish inflation to shocks in Brent price

Previous results suggest a transfer function specification relating inflation: (i) with the contemporary and first lagged values of the annual variation of oil prices, and (ii) an error term with the $ARIMA(1, 1, 0) \times (0, 0, 1)_{12}$ structure of the endogenous variable. The main estimation results for this specification are:

$$r^{12}(P_t^{SP}) = \underset{(0.0016)}{0.0146} + \underset{(0.0016)}{0.0085L} r^{12}(O_t^{EUR}) + \hat{N}_t^{EUR} \quad (1)$$

$$(1 - \underset{(0.073)}{0.278L}) \nabla \hat{N}_t^{EUR} = (1 - \underset{(0.058)}{0.65L^{12}}) \hat{a}_t^{EUR} \quad (2)$$

$$\hat{\sigma}_P = 0.224 \quad \log\text{-lik} = 10.488$$

where L denotes the lag operator and log-lik is the (log) value of the Gaussian likelihood function on convergence.

All the parameters in (1)-(2) are significant and its residuals do not show relevant correlations, either with the lags of the model input or with its own past, so we can consider it to be statistically adequate. On the other hand, its information criteria values⁶ were consistently smaller than those of the alternative specifications considered, so it was chosen as final model⁷

3.3 Time series decomposition

The transfer function (1) implies that: (i) the value of inflation in any month is affected by the annual change in Brent price in the same and previous month; (ii) the effect of changes in oil prices over inflation is transient⁸; and (iii) the expected total response of inflation to a 1 percent point increase in $r^{12}(O_t^{EUR})$ would be $\hat{g} = 0.015 + 0.009 = 0.024$ percentage points. Obviously this total

⁶Besides the *AIC*, we also considered Schwarz (1978) and Hannan and Quinn (1979) Information Criteria, which values are not shown for simplicity.

⁷The input to the transfer function (1) is expressed in euros, while original oil prices are quoted in USD. Therefore, this specification may confound variations in oil prices and exchange rates. Following Castro et al. (2016), we separated both effects by means of the approximation:

$$r^{12}(O_t^{EUR}) \simeq r^{12}(O_t^{USD}) + r^{12}(TC_t). \quad (3)$$

and estimated a variation of model (1)-(2) separating the change in inflation due to oil price from that due to exchange rate fluctuations. Estimation results for this model were:

$$\begin{aligned} r^{12}(P_t^{SP}) = & \left(\begin{matrix} 0.0135 & 0.008 \\ (0.0015) & (0.0016) \end{matrix} L \right) r^{12}(O_t^{US\$}) \\ & + \left(\begin{matrix} 0.0037 & 0.0034L \\ (0.007) & (0.007) \end{matrix} \right) r^{12}(ER_t) + \hat{N}_t \end{aligned} \quad (4)$$

$$(1 - \begin{matrix} 0.3164L \\ (0.073) \end{matrix}) \nabla \hat{N}_t = (1 - \begin{matrix} 0.6659 L^{12} \\ (0.06) \end{matrix}) \hat{a}_t \quad (5)$$

$$\hat{\sigma}_P = 0.226 \quad \log\text{-lik} = 8.887$$

so the effect of the exchange rate is not statistically significant, being this result coincident with the findings of Castro et al. (2016) for the Eurozone. Following these authors, we conclude that the variability of oil price in USD is so large than it dominates the influence of the exchange rate which, therefore, becomes non-significant.

The last step in this modeling sequence consisted in dropping the exchange rate variation from the specification, yielding a final model which relates directly the inflation rate with oil price in USD. The corresponding estimation results were:

$$r^{12}(P_t^{EA}) = \left(\begin{matrix} 0.0133 & 0.0077L \\ (0.0015) & (0.0015) \end{matrix} \right) r^{12}(O_t^{US\$}) + \hat{N}_t^P \quad (6)$$

$$(1 - \begin{matrix} 0.3205L \\ (0.072) \end{matrix}) \nabla \hat{N}_t^P = (1 - \begin{matrix} 0.6785 L^{12} \\ (0.057) \end{matrix}) \hat{a}_t^P \quad (7)$$

$$\hat{\sigma}_P = 0.226 \quad \log\text{-lik} = 8.631$$

so the model fit, measured both, through the residual standard deviation and the AIC, are worse than those of model (1)-(2).

⁸To test for persistent effects we tried alternatives to model (1) allowing for a rational transfer function. The estimated polynomial in the denominator did not have unit roots and was, in fact, non-significant.

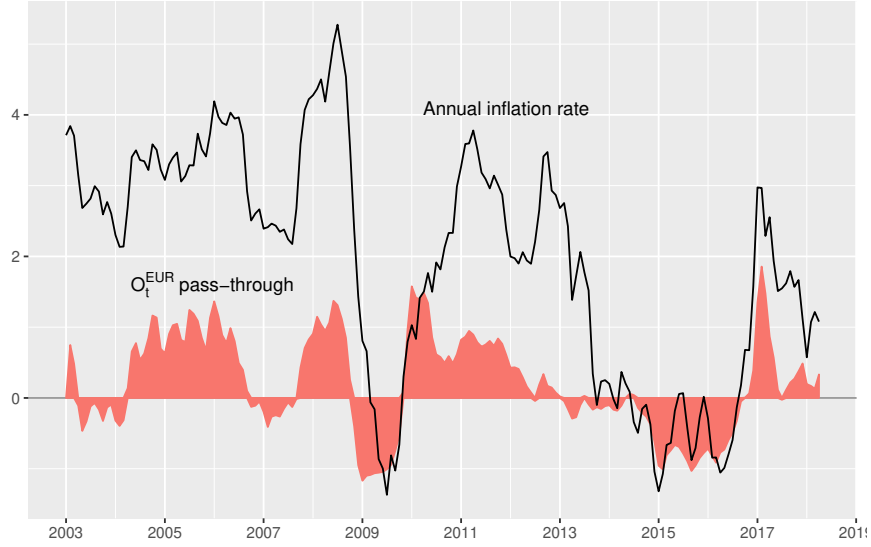


Figure 4: Annual inflation rates in Spain vs. the estimated oil price pass-through.

response, which is known in the literature as the as “gain”, provides a measure of the sensitivity of the inflation level to changes in oil prices.

This sensitivity parameter may seem small, but one should take into account that the expected pass-through effect is given by the product of the parameters in model (1) times the corresponding changes in oil prices, that is:

$$r^{12}(\hat{P}_t^O) = 0.0146 r^{12}(O_t^{EUR}) + 0.0085 r^{12}(O_{t-1}^{EUR}) \quad t = 2, \dots, n \quad (8)$$

so the part due to other factors F would be:

$$r^{12}(\hat{P}_t^F) = r^{12}(P_t^{SP}) - r^{12}(\hat{P}_t^O). \quad (9)$$

Figure 4 displays the profile of the Spanish inflation versus the pass-through component computed according to (8). Note that: (i) both series display a high degree of comovement (their sample correlation is 0.729), (ii) the contribution of oil prices to inflation ranges from +1.8 to -1.2 points in some months, and (iii) the oil price pass-through is a major determinant of the deflation spells observed in 2009 and 2014-2016. As noted before, the effect of oil prices over inflation is transient, so the duration of these spells is due relatively long streaks of negative shocks in oil prices. After the end of these streaks, and in absence of other deflationary factors, inflation rates recover positive values.

3.4 Variance decomposition

Variance decomposition in a dynamic model is difficult because one should take into account the dynamic influence of the inputs on the output. However, the value of $r^{12}(\hat{P}_t^O)$ given by (9) accumulates all these effects into and, therefore, can be used to compute a simplified variance decomposition for the stationary transformation of inflation.

Re-ordering the terms in (9) and multiplying both sides by the regular difference operator ∇ , we obtain:

$$\nabla r^{12}(P_t^{SP}) = \nabla r^{12}(\hat{P}_t^O) + \nabla r^{12}(\hat{P}_t^F), \quad (10)$$

...where all the variables are stationary, so they have stable means and variances.

As the addends in the right-hand-side term of (10) are theoretically independent, we could perform the decomposition of variance using this expression. However, we found more practical the following regression-based procedure.

The percentage of the variance of $\nabla r^{12}(P_t^{SP})$, which is explained by $\nabla r^{12}(\hat{P}_t^O)$, would be the determination coefficient of a linear regression of the former variable on the latter. In our case, the main LS results are:

$$\nabla r^{12}(P_t^{SP}) = \underset{(0.022)}{-0.016} + \underset{(0.093)}{1.028} \nabla r^{12}(\hat{P}_t^O) + \hat{\epsilon}_t \quad R^2 = 0.401 \quad (11)$$

Then, in the sampling period considered, 40.1% of the variance of monthly changes of inflation were explained by the corresponding changes in Brent price.

Note that:

1. The R^2 in model (11) can be computed directly as the squared value of the sample correlation between $\nabla r^{12}(P_t^{SP})$ and $\nabla r^{12}(\hat{P}_t^O)$. The variance decomposition percentages shown in the remainder of this paper are computed using this simplified procedure.
2. Taking into account the standard errors for the parameters in (11), this expression is statistically equivalent to (10), so the results provided by both expressions would be very similar. The practical advantage of the regression-based procedure is that it assures the orthogonality of the addends in the right-hand-side of (11) so it provides a 'cleaner' decomposition.

3.5 Conditional inflation forecasts

As shown in previous subsection, fluctuations in oil prices have significant effects on inflation and are therefore relevant to forecast short-term inflation. On the other hand, anticipating future oil price movements is very difficult, since this variable is very volatile and mainly determined by a set of factors, including global or oil-specific demand, oil supply and financial movements. As highlighted in the introduction, changes in oil prices have been quite abrupt recently. Due to the unpredictable and recent fluctuations of oil price, we considered five different scenarios for the rate of change of the crude price, see Table

4. They are two extreme scenarios (upward and downward), two 'moderate' (increase and decrease) scenarios and a stable scenario. The criteria to quantify the values for the different scenarios were the following: extreme increase and decrease just replicate the maximum (positive and negative) annual changes in Brent prices observed during the period while moderate scenarios use the median (conditional on positive and negative) variations in Brent prices observed during the period. Finally, the stable scenario assumes there is no variation in oil prices. For each of them we compute the corresponding inflation forecasts.

	Annual variation rate	Assumed price
Extreme increase	81.9	106.85
Moderate increase	31.4	77.19
Stable	0.0	58.74
Moderate decrease	-13.2	50.99
Extreme decrease	-52.4	27.96

Table 4: Scenarios for Brent prices (EUR/Barrel) in April 2019 .

In this framework, conditional forecasting for Brent prices consists in computing the most likely trajectory: (a) linking the past of the time series O_t^{EUR} (January 2002 to April 2018, in this case), (b) with the terminal values for April 2019 defined in Table 4, (c) taking into account the dynamics of the time series, as described by the models in Table 3. Therefore, it reduces to computing model-based interpolations for eleven missing values (May 2018 to March 2019) in a time series. Castro et al. (2016) solved this problem using a state-space procedure known as 'fixed-interval smoothing', (see Anderson and Moore, 1979). This method is precise, fast and efficient, but requires specialized software. Because of this, here we use an alternative approach inspired in Box and Tiao (1975) intervention analysis. It consists in:

1. Building three artificial variables combining (a) the past history of O_t^{EUR} , with (b) eleven null values, and (c) each of the terminal conditions defined in Table 4.
2. Estimating an intervention model for each of these variables including: (a) eleven impulse-type intervention variables⁹, each one of them corresponding to one of the months which values were set to zero, and (b) an error model with the ARIMA structure given in Table 3.

The idea consists, therefore, in treating the null values as if they were outliers, so the coefficients for their impulse variables are estimates of their most

⁹An impulse-type variable has a unit value in the date of the potentially outlying value to be intervened, and zeros in the rest of positions. The corresponding coefficient can therefore be interpreted as the correction required to transform the outlying value into the expected value for the time series. In this case, the values to be intervened are null, so the coefficients for the corresponding impulse variables can be interpreted as estimates of the expected value for the time series given the past history, the terminal condition and the ARIMA model for the error.

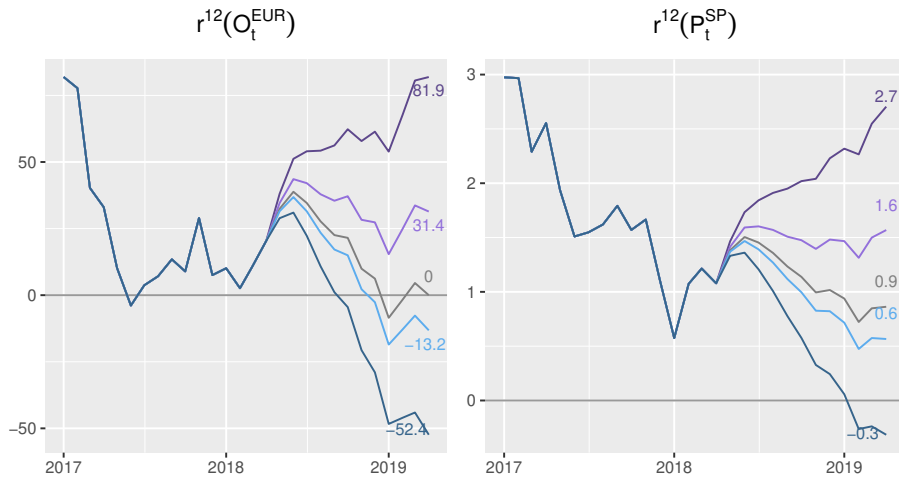


Figure 5: Forecasts in five scenarios for annual rate of Brent price in April 2019 and their corresponding scenarios for Spanish annual inflation.

likely value. After computing these interpolations, the augmented January 2002-April 2018 series in fed as input to the transfer function (1)-(2) to compute the corresponding inflation forecasts.

Figure 5 shows the Spanish inflation forecasts computed in this way. Note that:

1. Under the stable scenario, positive inflation rates are expected although they are well below the 2% inflation which is considered “adequate” by the ECB.
2. Under the moderate increase scenario, inflation projections are again below the 2% (the higher rate would be 1.93% in July, 2018). However, under the extreme increase scenario a maximum inflation rate of 2.88% will be expected in October and April 2018.
3. Under the moderate decrease scenario, our results show that inflation rates will be always positive (minimum of 0.63 in January, 2018) but very low. However, under the extreme decrease scenario a negative inflation rate of -0.2 will be expected in April 2018.

4 The response of inflation in Spanish regions to shocks in Brent price

Table 5 displays: (i) a summary of the estimation results for the regional transfer function models, which in all cases have the same specification and the Spanish

inflation model (1)-(2), (ii) the corresponding long-term-gain, as well as (iii) the variance decomposition described in Subsection 3.4. This Table is sorted according to the values of the gain and includes for reference the statistics of the Spanish model.

Note that the smaller sensitivities of inflation to shocks in oil prices measured both, by the gain and % variance correspond to relatively small and isolated geographic spaces, such as Melilla, Balearic Islands, Canary Islands and Ceuta, where the effect of road transport costs is probably smaller than that of maritime transportation. Differences in regional taxation, as well as the special fiscal regimes of Ceuta, Melilla and Canary islands, could also explain this result.

	Instantaneous effect	Lagged effect	Long-term gain	Variance
Spain	0.015	0.009	0.023	40.1
Castile-La Mancha	0.019	0.011	0.030	45.2
Cantabria	0.016	0.012	0.028	43.7
Castile-Leon	0.018	0.011	0.028	44.8
Galicia	0.017	0.010	0.026	43.1
Aragon	0.015	0.009	0.025	39.7
Murcia	0.016	0.009	0.025	36.1
Asturias	0.015	0.009	0.024	40.2
Navarra	0.016	0.009	0.024	35.7
La Rioja	0.016	0.008	0.024	33.1
Andalusia	0.014	0.008	0.023	38.2
Comunitat Valenciana	0.014	0.008	0.023	36.0
Extremadura	0.014	0.009	0.023	36.4
Catalonia	0.014	0.008	0.022	35.4
Basque Country	0.014	0.008	0.022	37.3
Balearic Islands	0.012	0.008	0.021	33.8
Madrid	0.014	0.008	0.021	34.9
Melilla	0.010	0.011	0.021	33.8
Canary Islands	0.009	0.011	0.020	32.4
Ceuta	0.007	0.009	0.016	27.0

Note: The shaded area shows the mean of the long term gain (0.0235) \pm one standard deviation (0.0034) for the Spanish regions.

Table 5: Summary of estimation and sensitivity results from the regional transfer function models. The regions are sorted according to the long term gain.

The maps and tables in the Appendix report the detailed results of the conditional forecasts analysis for the different regions and autonomous cities. We can see important regional differences in the different scenarios.

1. Under the stable scenario, the final inflation rate varies from 1.24% in Catalonia to 0.62% in Ceuta. That is, the inflation rate of the most inflationary region double the inflation rate of the less inflationary region.

2. Under the moderate increase scenario, the final inflation rate varies from 1.93% in Catalonia and the 1.13% in Ceuta. Obviously, the differences are even larger under the extreme increase scenario. Inflation in Castile-La Mancha will reach the 3.31% while inflation in Ceuta will remain under 2%.
3. Under the moderate decrease scenario, the final inflation rate varies from 0.95% in Catalonia to 0.41% in Ceuta. Finally, in the extreme decrease scenario only two regions remain with positive inflation rate (Catalonia and Balearic Islands) while the higher deflation takes place in Castile-La Mancha (-0.68%)

Note that the final inflation rate depends on the current inflation rate and on the effect of oil price variation on inflation. As Castile-La Mancha shows the highest gain, it is the more affected by the extreme scenarios, being the more inflationary region under a 'extreme increase' scenario (despite showing lower current inflation rate than, for example, Catalonia) and the more deflationary one under a 'extreme decrease' scenario (despite showing higher current inflation rate than, for example, Murcia)

5 Concluding remarks

Sharp fluctuations of oil price in recent years have revived the interest on its effect on inflation. In this paper we adjust econometric models to analyze the effect of oil price shocks on the Spanish inflation rate and to forecast it under different scenarios of oil price variations. The analysis is developed both at the national and regional level.

Main results have shown that 41% of the variance of monthly changes of inflation were explained by the corresponding variations in oil price. More precisely, inflation rate in any month is affected by annual changes in oil price in the current and previous month, with a expected total response of inflation to a 1 percent change of oil price variation leading to a 0.024 change in inflation rate. Regarding inflation forecasts, we found that, if oil prices variation are in the median of their past history, inflation rate for Spain will be in the range 0.67-1.5%. However, under the extreme increase scenario inflation rate in Spain will be well above the 2% while under the extreme decrease scenario it will be very close to zero. Finally, we found important variations across regions, being the Castiles and Cantabria those regions where inflation was more dependent on oil price variation and the islands (Balearic and Canarias) and the autonomous cities (Ceuta and Melilla) those less dependent. The determinants of these regional differences are not the goal of this study but constitute an interesting topic for further research.

Compliance with Ethical Standards

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The authors declare that: (a) they have no conflict of interest, (b) this article does not contain any studies with human participants or animals performed by any of the authors, and (c) they fully adhere to the principles in Springer's Guide on Publishing Ethics.

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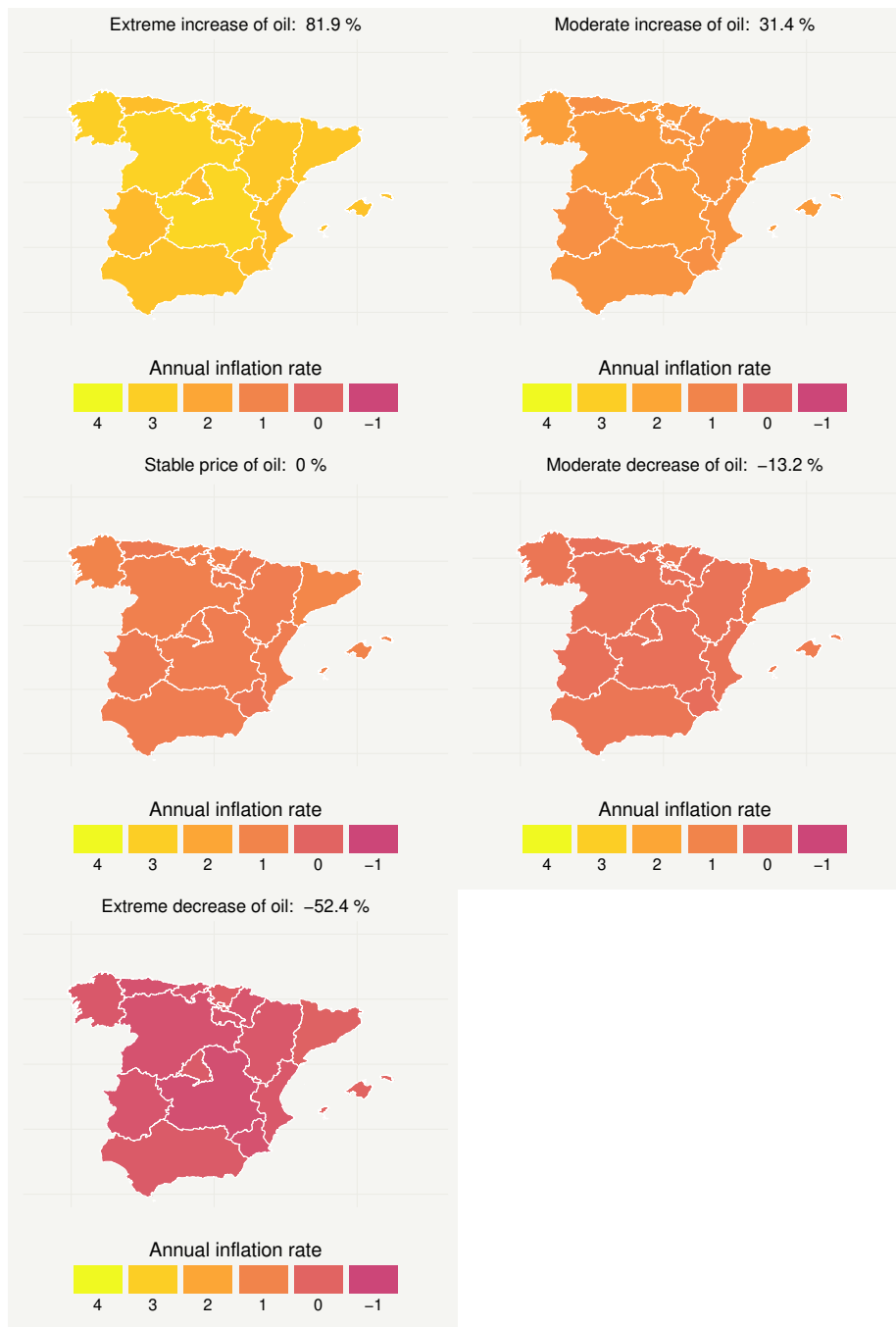


Figure 6: Conditional forecast analysis for the annual inflation rate by Spain's regions according to five scenarios of oil price in April 2019 .

	May-18	Jun-18	Jul-18	Aug-18	Sep-18	Oct-18	Nov-18	Dec-18	Jan-19	Feb-19	Mar-19	Apr-19
Spain	1.47	1.73	1.84	1.91	1.95	2.02	2.04	2.23	2.32	2.27	2.55	2.70
Castile-La Mancha	1.73	2.05	2.18	2.27	2.34	2.39	2.44	2.66	2.68	2.75	3.09	3.21
Castile-Leon	1.50	1.86	2.06	2.16	2.28	2.32	2.37	2.61	2.62	2.67	3.01	3.12
Cantabria	1.66	2.05	2.24	2.12	2.21	2.37	2.39	2.55	2.73	2.64	2.94	3.09
Galicia	1.60	1.98	2.07	2.12	2.26	2.38	2.30	2.56	2.66	2.67	2.98	3.04
Catalonia	1.60	1.82	1.85	1.89	1.96	2.07	2.12	2.34	2.40	2.33	2.59	2.82
Aragon	1.50	1.73	1.88	1.99	2.03	2.01	2.04	2.29	2.34	2.27	2.59	2.75
Balearic Islands	1.45	1.68	1.81	1.83	1.89	1.96	2.01	2.18	2.38	2.37	2.65	2.69
Navarra	1.36	1.68	1.75	1.90	2.03	2.00	2.02	2.26	2.20	2.19	2.49	2.67
La Rioja	1.18	1.55	1.70	1.87	1.94	1.93	2.08	2.35	2.24	2.14	2.45	2.67
Andalusia	1.44	1.74	1.85	1.92	1.92	1.93	1.93	2.14	2.28	2.21	2.53	2.65
Basque Country	1.41	1.75	1.76	1.80	1.89	2.01	2.08	2.23	2.33	2.24	2.48	2.64
Comunitat Valenciana	1.48	1.73	1.80	1.89	1.92	1.95	1.96	2.13	2.27	2.16	2.44	2.61
Murcia	1.11	1.47	1.70	1.76	1.90	1.94	1.92	2.09	2.17	2.12	2.39	2.60
Asturias	1.28	1.55	1.59	1.57	1.69	1.79	1.86	2.02	2.11	2.11	2.40	2.59
Extremadura	1.24	1.53	1.73	1.82	1.88	1.89	1.88	2.11	2.23	2.20	2.44	2.54
Madrid	1.43	1.64	1.82	1.90	1.80	1.93	1.97	2.07	2.13	2.14	2.34	2.51
Melilla	1.08	1.35	1.38	1.48	1.55	1.58	1.62	1.80	1.97	1.86	2.27	2.38
Canary Islands	1.29	1.47	1.65	1.85	1.93	1.89	1.80	2.03	2.08	1.85	2.23	2.34
Ceuta	0.44	0.67	0.73	0.92	1.02	1.06	1.15	1.33	1.51	1.37	1.58	1.72
Std. Dev.	0.29	0.31	0.32	0.29	0.29	0.31	0.29	0.31	0.29	0.33	0.34	0.33
Range	1.30	1.38	1.50	1.35	1.32	1.33	1.29	1.33	1.22	1.38	1.51	1.49
IQ range	0.24	0.25	0.17	0.14	0.14	0.13	0.20	0.26	0.24	0.22	0.22	0.22

Table 6: Conditional forecast analysis for the annual inflation in Spain and its regions for the **extreme increase** scenario for oil price in April 2019 , (year-on-year growth of 81.9 %). The regions are sorted according to the forecast in April 2019 .

	May-18	Jun-18	Jul-18	Aug-18	Sep-18	Oct-18	Nov-18	Dec-18	Jan-19	Feb-19	Mar-19	Apr-19
Spain	1.41	1.59	1.60	1.57	1.51	1.48	1.40	1.48	1.47	1.31	1.50	1.57
Galicia	1.55	1.82	1.80	1.74	1.76	1.76	1.57	1.71	1.69	1.59	1.79	1.76
Catalonia	1.55	1.69	1.62	1.56	1.53	1.55	1.50	1.62	1.59	1.42	1.59	1.74
Castile-La Mancha	1.67	1.86	1.87	1.82	1.76	1.68	1.60	1.68	1.57	1.51	1.73	1.73
Castile-Leon	1.44	1.69	1.77	1.75	1.74	1.66	1.58	1.70	1.58	1.50	1.72	1.73
Cantabria	1.60	1.89	1.95	1.72	1.68	1.72	1.62	1.66	1.71	1.50	1.68	1.72
Balearic Islands	1.41	1.55	1.60	1.53	1.50	1.48	1.44	1.52	1.62	1.53	1.72	1.68
Basque Country	1.36	1.62	1.53	1.48	1.48	1.50	1.48	1.53	1.54	1.35	1.50	1.58
Aragon	1.45	1.58	1.63	1.63	1.56	1.44	1.35	1.50	1.44	1.26	1.48	1.55
Andalusia	1.39	1.61	1.62	1.58	1.49	1.40	1.30	1.40	1.45	1.27	1.50	1.54
Comunitat Valenciana	1.43	1.59	1.56	1.55	1.48	1.41	1.32	1.40	1.43	1.22	1.41	1.49
Navarra	1.30	1.53	1.49	1.53	1.56	1.43	1.33	1.47	1.30	1.18	1.38	1.47
La Rioja	1.12	1.40	1.44	1.50	1.47	1.36	1.39	1.55	1.34	1.14	1.34	1.47
Madrid	1.38	1.50	1.60	1.58	1.39	1.43	1.37	1.37	1.34	1.26	1.37	1.46
Extremadura	1.19	1.39	1.49	1.49	1.44	1.35	1.24	1.37	1.39	1.26	1.40	1.41
Asturias	1.22	1.40	1.34	1.21	1.23	1.22	1.19	1.24	1.22	1.12	1.31	1.41
Murcia	1.06	1.32	1.44	1.39	1.43	1.36	1.24	1.30	1.27	1.11	1.28	1.39
Canary Islands	1.26	1.36	1.47	1.58	1.57	1.44	1.26	1.41	1.37	1.05	1.35	1.38
Melilla	1.05	1.24	1.18	1.19	1.17	1.11	1.06	1.15	1.22	1.02	1.34	1.38
Ceuta	0.41	0.58	0.58	0.69	0.72	0.69	0.72	0.82	0.93	0.72	0.86	0.94
Std. Dev.	0.28	0.29	0.29	0.25	0.24	0.24	0.22	0.22	0.19	0.22	0.22	0.20
Range	1.26	1.30	1.37	1.13	1.03	1.07	0.90	0.89	0.78	0.87	0.93	0.82
IQ range	0.24	0.26	0.17	0.13	0.13	0.17	0.24	0.22	0.26	0.33	0.29	0.29

Table 7: Conditional forecast analysis for the annual inflation in Spain and its regions for the **moderate increase** scenario for oil price in April 2019 , (year-on-year growth of 31.4 %). The regions are sorted according to the forecast in April 2019 .

	May-18	Jun-18	Jul-18	Aug-18	Sep-18	Oct-18	Nov-18	Dec-18	Jan-19	Feb-19	Mar-19	Apr-19
Spain	1.38	1.50	1.45	1.36	1.23	1.14	0.99	1.02	0.94	0.72	0.85	0.86
Catalonia	1.52	1.60	1.48	1.35	1.27	1.23	1.12	1.17	1.08	0.85	0.96	1.06
Balearic Islands	1.38	1.48	1.47	1.34	1.26	1.18	1.08	1.11	1.15	1.00	1.14	1.05
Galicia	1.51	1.72	1.63	1.50	1.44	1.38	1.12	1.19	1.10	0.92	1.06	0.96
Basque Country	1.33	1.54	1.39	1.28	1.22	1.19	1.10	1.10	1.04	0.80	0.90	0.92
Cantabria	1.56	1.79	1.78	1.47	1.36	1.32	1.14	1.10	1.08	0.79	0.90	0.87
Castile-Leon	1.40	1.58	1.58	1.49	1.40	1.24	1.09	1.13	0.93	0.78	0.92	0.87
Andalusia	1.36	1.52	1.47	1.37	1.22	1.07	0.91	0.95	0.93	0.69	0.86	0.85
Castile-La Mancha	1.63	1.75	1.67	1.55	1.40	1.24	1.08	1.08	0.88	0.74	0.88	0.81
Madrid	1.35	1.42	1.46	1.39	1.13	1.12	1.00	0.94	0.86	0.71	0.77	0.81
Aragon	1.42	1.49	1.47	1.41	1.27	1.08	0.93	1.01	0.88	0.64	0.79	0.80
Comunitat Valenciana	1.40	1.50	1.42	1.34	1.21	1.08	0.93	0.94	0.91	0.64	0.76	0.79
Canary Islands	1.24	1.30	1.35	1.41	1.35	1.16	0.93	1.03	0.93	0.56	0.81	0.79
Melilla	1.02	1.17	1.05	1.01	0.93	0.81	0.71	0.74	0.76	0.50	0.77	0.76
Navarra	1.27	1.44	1.33	1.31	1.27	1.07	0.91	0.97	0.74	0.55	0.69	0.72
La Rioja	1.09	1.30	1.28	1.28	1.18	1.00	0.97	1.06	0.78	0.51	0.65	0.72
Extremadura	1.16	1.31	1.35	1.28	1.17	1.01	0.84	0.90	0.86	0.67	0.76	0.71
Asturias	1.19	1.31	1.18	0.99	0.94	0.87	0.77	0.76	0.67	0.50	0.63	0.67
Murcia	1.03	1.23	1.28	1.17	1.14	1.01	0.81	0.81	0.71	0.48	0.59	0.64
Ceuta	0.39	0.53	0.48	0.55	0.54	0.46	0.45	0.51	0.57	0.31	0.42	0.46
Std. Dev.	0.27	0.28	0.28	0.23	0.21	0.21	0.18	0.17	0.16	0.17	0.17	0.14
Range	1.23	1.26	1.29	0.99	0.90	0.92	0.69	0.68	0.59	0.69	0.72	0.60
IQ range	0.23	0.25	0.17	0.13	0.16	0.20	0.21	0.18	0.22	0.25	0.18	0.15

Table 8: Conditional forecast analysis for the annual inflation in Spain and its regions in the **stable** scenario for oil price in April 2019 , (year-on-year growth of 0 %). The regions are sorted according to the forecast in April 2019 .

	May-18	Jun-18	Jul-18	Aug-18	Sep-18	Oct-18	Nov-18	Dec-18	Jan-19	Feb-19	Mar-19	Apr-19
Spain	1.37	1.47	1.39	1.27	1.12	1.00	0.83	0.82	0.72	0.47	0.57	0.57
Balearic Islands	1.37	1.44	1.42	1.26	1.15	1.05	0.93	0.93	0.96	0.78	0.90	0.79
Catalonia	1.50	1.57	1.42	1.27	1.16	1.09	0.96	0.99	0.87	0.61	0.70	0.78
Basque Country	1.32	1.50	1.34	1.20	1.11	1.06	0.95	0.92	0.84	0.57	0.64	0.64
Galicia	1.50	1.68	1.56	1.40	1.31	1.22	0.93	0.97	0.84	0.64	0.75	0.62
Andalusia	1.35	1.48	1.41	1.29	1.10	0.93	0.74	0.75	0.71	0.45	0.60	0.56
Canary Islands	1.24	1.27	1.30	1.34	1.25	1.05	0.79	0.86	0.75	0.35	0.58	0.54
Madrid	1.34	1.39	1.40	1.31	1.03	0.98	0.85	0.76	0.65	0.48	0.52	0.53
Cantabria	1.55	1.74	1.70	1.36	1.22	1.15	0.94	0.87	0.81	0.49	0.57	0.51
Castile-Leon	1.38	1.54	1.51	1.38	1.26	1.07	0.88	0.89	0.66	0.47	0.59	0.50
Comunitat Valenciana	1.38	1.46	1.35	1.26	1.10	0.94	0.76	0.75	0.69	0.39	0.50	0.50
Melilla	1.02	1.14	1.00	0.94	0.83	0.69	0.56	0.57	0.56	0.28	0.53	0.49
Aragon	1.40	1.45	1.40	1.31	1.14	0.93	0.75	0.80	0.64	0.38	0.50	0.49
Castile-La Mancha	1.61	1.70	1.59	1.43	1.25	1.05	0.86	0.82	0.59	0.41	0.52	0.43
Extremadura	1.14	1.27	1.28	1.19	1.05	0.87	0.68	0.71	0.64	0.42	0.48	0.42
La Rioja	1.07	1.26	1.22	1.18	1.05	0.85	0.79	0.85	0.55	0.25	0.36	0.41
Navarra	1.25	1.40	1.27	1.22	1.14	0.92	0.73	0.77	0.50	0.29	0.40	0.41
Asturias	1.18	1.27	1.12	0.90	0.82	0.72	0.59	0.55	0.44	0.24	0.35	0.36
Murcia	1.01	1.19	1.22	1.07	1.01	0.86	0.63	0.60	0.47	0.22	0.30	0.33
Ceuta	0.39	0.51	0.44	0.50	0.46	0.37	0.33	0.37	0.41	0.14	0.23	0.25
Std. Dev.	0.27	0.27	0.27	0.22	0.20	0.19	0.16	0.16	0.15	0.16	0.16	0.14
Range	1.22	1.24	1.26	0.94	0.85	0.85	0.63	0.61	0.54	0.63	0.67	0.53
IQ range	0.23	0.25	0.18	0.14	0.15	0.19	0.20	0.15	0.22	0.20	0.15	0.14

Table 9: Conditional forecast analysis for Spain and its regions in the **moderate decrease** scenario for oil price in April 2019 , (year-on-year growth of -13.2 %). The regions are sorted according to the forecast in April 2019 .

	May-18	Jun-18	Jul-18	Aug-18	Sep-18	Oct-18	Nov-18	Dec-18	Jan-19	Feb-19	Mar-19	Apr-19
Spain	1.33	1.36	1.21	1.01	0.78	0.58	0.33	0.24	0.06	-0.26	-0.24	-0.32
Balearic Islands	1.33	1.35	1.25	1.03	0.85	0.68	0.49	0.42	0.37	0.12	0.17	0.00
Catalonia	1.47	1.46	1.24	1.02	0.83	0.69	0.48	0.43	0.24	-0.09	-0.08	-0.07
Basque Country	1.28	1.40	1.16	0.95	0.80	0.66	0.48	0.38	0.22	-0.12	-0.12	-0.18
Canary Islands	1.21	1.19	1.16	1.13	0.97	0.70	0.38	0.38	0.20	-0.27	-0.10	-0.20
Madrid	1.31	1.29	1.23	1.06	0.71	0.60	0.38	0.23	0.04	-0.20	-0.24	-0.28
Melilla	0.99	1.05	0.85	0.71	0.54	0.33	0.13	0.07	-0.02	-0.37	-0.19	-0.29
Andalusia	1.31	1.38	1.23	1.03	0.77	0.52	0.25	0.19	0.06	-0.28	-0.20	-0.31
Ceuta	0.37	0.44	0.32	0.32	0.24	0.08	-0.01	-0.02	-0.03	-0.36	-0.33	-0.35
Comunitat Valenciana	1.34	1.36	1.17	1.00	0.76	0.53	0.27	0.18	0.04	-0.33	-0.30	-0.37
Galicia	1.45	1.55	1.35	1.10	0.93	0.75	0.37	0.31	0.10	-0.19	-0.17	-0.37
Aragon	1.36	1.34	1.21	1.04	0.78	0.49	0.22	0.19	-0.05	-0.41	-0.36	-0.45
Extremadura	1.11	1.16	1.10	0.93	0.72	0.45	0.18	0.14	-0.01	-0.31	-0.32	-0.46
La Rioja	1.03	1.15	1.02	0.90	0.69	0.40	0.26	0.24	-0.15	-0.53	-0.50	-0.53
Navarra	1.21	1.29	1.07	0.94	0.78	0.47	0.20	0.15	-0.20	-0.49	-0.46	-0.53
Cantabria	1.51	1.62	1.49	1.05	0.81	0.64	0.34	0.17	0.02	-0.39	-0.40	-0.54
Asturias	1.14	1.16	0.93	0.63	0.46	0.28	0.07	-0.05	-0.25	-0.53	-0.50	-0.56
Castile-Leon	1.34	1.41	1.28	1.06	0.84	0.55	0.27	0.18	-0.15	-0.43	-0.41	-0.58
Murcia	0.97	1.08	1.02	0.80	0.65	0.41	0.10	-0.02	-0.23	-0.56	-0.57	-0.61
Castile-La Mancha	1.56	1.56	1.35	1.09	0.81	0.50	0.21	0.07	-0.27	-0.55	-0.54	-0.72
Std. Dev.	0.27	0.26	0.25	0.20	0.17	0.17	0.14	0.15	0.18	0.18	0.19	0.19
Range	1.19	1.18	1.16	0.80	0.74	0.66	0.49	0.48	0.64	0.69	0.74	0.72
IQ range	0.23	0.24	0.20	0.14	0.12	0.22	0.18	0.18	0.23	0.23	0.25	0.25

Table 10: Conditional forecast analysis for Spain and its regions in the **extreme decrease** scenario for oil price in April 2019 , (year-on-year growth of -52.4 %). The regions are sorted according to the forecast in April 2019 .