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Price discovery under crisis:

Uncovering the determinant factors of prices using efficient Bayesian model selection methods

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by

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Abstract

We seek to uncover the determinants of consumer prices in Greece by considering a large set of potential factors and accounting for delayed effects. To accomplish this we rely on recently presented Bayesian model selection methods which are efficiently adapted in the present context. Consumer prices drop significantly during the periods of discount sales, especially in the last two years; VAT changes are mostly absorbed (above 50%) by the producers; while a drop in retail sales affects prices with a significant lag (of 6 months). Evidence on the ways several other factors affect prices is also obtained.

Keywords

Prices; Taxes; Discount sales period; Retail sales; Variable selection; Population MCMC; Subspace Carlin and Chib (SCC).

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1. Background

Of all the countries that have been adversely affected by the recent economic crisis, the one that stands out is Greece. In the course of three years (from mid-2009 to mid-2012) the country's per capita Gross Domestic Product (GDP) fell by 13.2% and employee compensation by 27.4%, while the domestic Consumer Price Index (CPI) rose by 10.2%. This resulted in a drastic reduction in real incomes and, thus, purchasing power, giving rise to a central debate currently held in Greece and other European countries experiencing recession: Since demand falls, why prices are still rising? In an effort to shed some light on the issue, we consider a large set of possible predictors and try to identify the main factors that drive prices in the Greek market.

2. The model

In the international literature, national CPIs are often explained empirically in terms of international food price indices, crude oil, other commodity price indices, producer price indices, output, the money supply, exchange and interest rates (e.g., Askari and Krichene, 2010; Jail and Tamayo Zea, 2011; Alemu, 2012; Kamenik et al, 2013; and earlier authors sited therein).

In the pages that follow we consider a linear regression model for first differences (namely, monthly changes) in the CPI

$$Y_t = c + \sum_{k=1}^{K} a_k S_{k,t} + \sum_{i=1}^{I} \sum_{l_i=0}^{12} \theta_{i,l_i} Z_{i,t-l_i}, \quad e_t \sim N(0,\sigma^2),$$

(1)

where the terms $S_{k,t}$ correspond to K possible factors affecting the CPI's monthly change (Y_t) at the same time t, and the terms $Z_{i,t-l_i}$ correspond to I possible factors affecting the CPI's monthly change with lags (l_i) up to 12 months (see Table 1).

For a given model $m \in M$, the parameter space is defined as (suppressing index m)

$$\omega_m = \left\{k, i, l_i, c, a_k, \theta_{i,l_i}, \sigma^2\right\}, \quad k = 1,\ldots,K, \quad i = 1,\ldots,I, \quad l_i = 0,\ldots,12.$$

That is, we jointly estimate parameters $\left\{c, a_k, \theta_{i,l_i}, \sigma^2\right\}$ and engage in model selection with respect to the factors *k* and *i* that may affect the CPI both simultaneously and with lags, while taking into account that a factor may affect the CPI at a particular lag out of the l_i considered. As a result, the model space *M* includes $2^{K+(I*13)}$ possible models, which in our case corresponds to 2^{356} models, each with parameters ω_m to estimate.[1]

3. The data

The dataset considered hereinafter consists of monthly observations of the domestic CPI from January 2001 to August 2012 (140 observations). The potential determinant factors deemed to affect CPI are displayed in Table 1. These include: (a) the trend and technical factors such as the conventional subdivisions of the year (in the form of monthly categorical (dummy) variables), and the CPI revisions carried out by the statistical authority (also in the form of dummies)[2]; (b) discount sales periods,[3] and the VAT,[4] as any change in either of the two is likely to directly affect the CPI level; (c) new government formations (in the form of dummies) as election promises or shifts in policy orientation are likely to shape the CPI whether instantaneously or several months later; (d) the prices of agricultural inputs such as seeds, fertilizers, pesticides, veterinary medicines, animal feed and agricultural equipment of machinery as they indirectly affect retail prices through the supply chain; (e) the prices of buildings and building materials; (f) energy prices (involving electricity and heating oil); (g) transportation costs (namely gasoline prices, car prices, train, airline ship fares); (h) indices capturing the demand, supply and overall economic climate (namely, the industrial production

[1] Note that in the above formulation one could also incorporate other technical factors (besides the trend and monthly dummies) such as ARMA-GARCH effects. However, (a) the preliminary analysis showed that the first differences of the CPI (as well as the squares of these differences) do not exhibit statistical significant autocorrelations or partial autocorrelations, and (b) we are mainly interested to analyze the way considered factors affect the CPI and not in predictions.

[2] CPI revisions may affect the CPI level due to technical factors, since different products and services are taken into account in the calculation of the index. Furthermore, the weights of each sub-category change, resulting to changes in the general index. To the degree some subcategories are affected more by sales periods, we introduce also in the model cross-terms capturing the effect of sales periods before and after CPI revisions.

[3] Like elsewhere in the EU, in Greece sales are state-regulated and for the period under examination generally run twice a year: once in late summer and once in mid-winter. Department stores, boutiques, designer outlets, and even hardware shops clear out items from the previous season, gradually slashing prices over the course of the sales period.

[4] The value added tax (VAT) is calculated as a weighted average of all sub-indices of the CPI. Since a different VAT applies to different goods and services we have taken the weighted average of each sub-index (4 digit category), weighted by the weights used for the construction of the general CPI, as these are published by ELSTAT.

and overall retail sales figures, as well as interest rate spreads); (i) the international prices of commodities (meat, dairy products, cereals, oil, sugar), import-prices from EU and non-EU countries, and the euro-dollar exchange rate , all of which, as already mentioned, exist on a monthly basis.

Understandably, in the selection process of potential determinants there exist some limitations with respect to data availability. Several indicators pertaining to consumer demand and growth, such as the GDP and its proxies (wages, personal income), are only available on a quarterly basis. Considering the large number of potential predictors, any analysis based on data observed on lower frequencies (lower than monthly), would not be robust. Thus, besides the technical and other factors that directly affect prices (such as VAT changes and discount sales periods), we will only take into account the regressors which pertain to production cost, international prices, economic climate and consumer demand that are available on a monthly basis.

All variables, except for the dummies, the trend, and the discount sales periods are converted to indices the base value of which (100) has been set at the 2009 average in order to simplify the inference procedure and prior assignment, as well as the interpretation of the model's parameters. Then, the first differences (i.e., the monthly changes) of these indices are employed so as to reduce the correlation among the 356 candidate variables.

4. Inference

In such a complex model space we need a powerful inference tool to obtain the posterior quantities of interest, i.e. model probabilities and parameters ω_m . So we rely on Bayesian inference and construct a Population Markov Chain Monte Carlo (MCMC) algorithm that efficiently samples from both the model and parameter space.

A. Prior specification

Considering that the likely explanatory variables have been converted to monthly changes in indices, we make use of typical vague proper priors, $\left\{c, a_k, \theta_{i,l_i}\right\} \sim N(0,10^2)$, $\sigma^2 \sim IG(10^{-6},10^{-6})$. For the model *m*, we place a prior on the model size $(k + i \times l_i)$ and given the model size, the prior is taken to be uniform among models with the same number of

parameters. Since we want to identify a limited number of variables affecting the CPI, we set $p(m) \sim \text{Poisson}(1)$. Furthermore, we present the results (prior sensitivity analysis) under two alternative priors, i.e. a Poisson with mean 5, and a Beta-Binomial (Kohn et al., 2001) with a mean and standard deviation 5.

B. The model selection algorithm

Given the large number of explanatory variables and the incumbent correlation structure, we need an effective inference tool to obtain the posterior summaries of interest. It is important to note that in our case a typical Reversible Jump (RJ) algorithm (Green, 1995) fails to sample efficiently from the posterior, even after 10 million iterations (see Section 5 for further evidence). In this respect, we make use of recent techniques, namely the Subspace Carlin and Chib (SCC) algorithm (Petralias and Dellaportas, 2012) which is designed to sample efficiently under high dimensional spaces. Furthermore, we augment this algorithm to a Population framework, so that several parallel chains of the SCC algorithm run in parallel under different temperatures, exchanging information in an efficient way.

To simplify the notation we may think of each $Z_{i,t-l_i}$ as a distinct variable for each lag l_i and, hence, denote (a) the set of explanatory variables as $X_{m,t} = \{S_{k,t}, Z_{i,t-l_i}\}$ for a model *m*, (b) the set of associated parameters to estimate as $b_m = \left\{c, a_k, \theta_{i,l_i}\right\}$, (c) the (normal) likelihood with $f(y \mid b_m, m)$, (d) the prior densities with $f(b_m, m) = f(b_m \mid m) f(m)$; and define the pseudoprior densities for the parameters b_j which do not belong to the model *m* as $f(b_j \mid j \neq m)$. The latter are not prior densities, but conveniently chosen linking densities required to generate parameters for variables that do not belong to the model *m*, which could be added in the next step of the algorithm. Thus, they are like proposal densities used in a RJ algorithm. In our application, bearing in mind that all data are taken as monthly changes of indices, and after inspecting descriptive summaries of the variables, the pseudopriors (proposals) are specified as $f(b_j \mid j \neq m) \underset{iid}{\sim} N(0,1)$.[5]

[5] We tested the algorithm using pseudo prior densities obtained from pilot Gibbs runs on each explanatory variable, and inflating their standard deviation by a factor of two or three. This strategy

We also denote with (a) $S_m = \{S_m^-, S_m^0, S_m^+\}$ the neighborhood of model *m* which includes all models that can be formed by deleting, replacing or adding a variable in relation to those present in the model, where $\{S_m^-, S_m^0, S_m^+\}$ represents the respective deletion, replacement and addition subspace; and (b) $Q_m = \{q_m^-, q_m^0, q_m^+\}$ the respective proposal probabilities for selecting each subspace. These are taken to be uniform in our application. Then the SCC algorithm proceeds as follows:

The SCC algorithm

- *Generate parameters* b_j *from the full conditionals*

$$f(b_j \mid b_{-j}, m, y) \sim \begin{cases} f(y \mid b_m, m) f(b_m, m), & j = m \\ f(b_j \mid j \neq m), & j \neq m \end{cases}$$

(2)

- *Choose a subspace, say* S_m^+, *with probability* q_m^+ .
- *Propose a new model* m' *with probability*

$$g(m, m') = \frac{A_{m'}}{\sum_{s \in S_m^+} A_s}$$

(3)

where A_m *is the posterior up to a constant*

$$A_m = f(y \mid b_m, m) f(b_m, m) \prod_{j \neq m} f(b_j \mid j \neq m) \ .$$

(4)

- *Accept the move with probability*

turned to provide equally well mixing ability of the algorithm, as the plain proposals (pseudopriors) suggested above.

$$\alpha = \min\left(1, \frac{q_{m'}^{-} \sum_{s \in S_m^{+}} A_s}{q_m^{+} \sum_{s \in S_{m'}^{-}} A_s}\right),$$

(5)

which is the ratio of the posterior mass of the proposed (addition) subspace to the inverse (deletion) subspace. Thus via expression (3) we propose easily more probable models within a subspace, and the move is accepted if the subspace we are moving to has higher posterior mass than the inverse subspace (see expression (5)). For the replacement move we suggest using a simple RJ step, in view of the large number of densities A_m that require evaluation at every iteration (Petralias and Dellaportas, 2012).

The above algorithm is enriched by applying a population algorithm. (See Jasra et al., 2007, for applications in the transdimensional space.) We denote with π the SCC invariant distribution with states (b_m, m). We also construct tempered auxiliary distributions π^{ζ_λ} with ζ_λ denoting the inverse temperature parameter of chain λ; and propose to use just three parallel chains: One with $\zeta=1$ for the central untempered sampling chain; one with $\zeta>1$ which jumps among models that have higher posterior density; and one with $\zeta<1$ (a flatter density) which explores less probable models and improves the mixing ability of the algorithm. In our application we set ζ_1 =0.8 and ζ_3=1.2, so that the acceptance rate of the exchange move may be about 0.5 (Liu, 2001). Considering the efficiency of the underlying SCC algorithm and the large number of models it explores at every iteration, the use of just two auxiliary chains proves to be adequate, at least in this application.[6]

The Population SCC algorithm

- *Run λ=3 parallel Markov chains with target densities π^{ζ_λ} where*
  $\zeta_1 < 1, \zeta_2 = 1, \zeta_3 > 1$.
- *At every iteration choose randomly between:*

[6] The Population SCC algorithm run for 300,000 iterations with additional 100,000 iterations used for the burn-in period. It needed about sixteen hours to run in an Intel Corei 7 CPU. It is coded in Matlab and is available upon request from the first author.

- *An exchange move which changes the states between a randomly chosen tempered chain and the central untempered chain. The Metropolis-Hastings acceptance rate used to swap the values of chain 1 with chain 2, is of the form*

$$\alpha = \min\left(1, \frac{\pi^{\zeta_1}(\beta_{m_2}, m_2)\pi^{\zeta_2}(\beta_{m_1}, m_1)}{\pi^{\zeta_1}(\beta_{m_1}, m_1)\pi^{\zeta_2}(\beta_{m_2}, m_2)}\right) \quad (6)$$

A mutation move which updates all chains according to the SCC algorithm.

5. Results

Economic results

Table 2 presents the four most probable models visited under each prior specification, along with their parameter estimates, the posterior probability in the Population SCC sample, and the latter's Monte Carlo Standard Error[7]. Since different prior specifications are associated to different model sizes, variables that are present in all specifications, have higher probability to be indeed the strongest factors affecting CPI. The first best model visited under the Poisson (1) and Beta-Binomial (5) priors is the same, featuring a rather large posterior probability (6.1% and 26% respectively) considering the dimension of the model space (2^{356}), signaling that this is a dominant model over the others explored in the model space The model includes (i) a monthly dummy variable associated with a seasonal CPI drop in June, (ii) the changes in the average VAT, (iii) the discount sales periods, the coefficient of which suggest a CPI drop of about 1.6% (2.9% after the CPI revision of January 2011), (iv) changes in the gasoline price index, which appear to affect the CPI by about 4%, and (v) changes in the domestic index of retail sales, which appear to affect the CPI after a time lag of 6 months by about 1.7%.

In view of these results the following comments are in order: (a) The coefficient associated with the VAT is estimated to 0.59 in most probable models. (As the reader may recall the VAT vector is converted to an index, the based period of which is set to the 2009 average.) In

[7] The Monte Carlo Standard Error which is used to estimate the variability due to simulation, is calculated based on the batch mean method (Geyer, 1992) of dividing the sample to $\sqrt{N}$ batches (each with size $\sqrt{N}$), where N denotes the total number of the iterations of the Population SCC algorithm.

view of the fact that the average VAT rate weighted across all products, services and regions, was equal to 12.2% in 2009 and to 16.6% in 2012, a marginal increment of 1%, from 12.2% to 13.2% (or from 16.6% to 17.6%) is expected to have affected (or to affect) a CPI increment of 0.48% (or 0.44%.) This suggests that, *ceteris paribus*, a significant portion (above 50%) of the VAT rate change is absorbed by the producers. (b) It seems that the discount sales period effect is larger post January 2011. However, it is unclear whether this is due to the CPI revision or the deepening of the economic recession or both. (c) The relatively small effect associated with domestic retail sales reflects considerable price inflexibility with respect to changes in demand. For instance, a 10% fall in retail sales is expected to reduce the CPI by 0.17%, six months later.

Moving on to the other probable models, it is interesting to note the positive effect of changes in the prices of imports from the EU onto the CPI (by 29.5% according to the second best model under the Poisson (5) prior), and the negative impact of (new) government formation onto the CPI four months after swearing in (by 0.33% according to the fourth best model under the Poisson (5) prior).

Table 3 lists the variables according to their marginal probability of inclusion[8] under each prior specification. The fourteen variables with the highest probability of inclusion are the same under the Poisson (1) and Beta-Binomial (5) priors, and also feature among the top 20 variables visited under the Poisson (5) prior and in the four best models of Table 2 alongside the index of fertilizer prices (lag 5). Therefore, there is considerable confidence that they are indeed among the most probable factors likely to affect the CPI, with the discount sales periods, the gasoline price index, and the VAT appearing as the primary factors.

It is interesting to note that variables such as industrial production (related to growth) and government bond spread (related to economic climate) were not found important at any lag, signaling that domestic prices are more associated to international prices rather than

[8] A measure usually employed in order to help identify important variables in high dimensional spaces is the marginal probability of inclusion (see Barbieri and Berger, 2004). This is calculated as the percentage of times a variable is observed in the transdimensional MCMC sample. If we denote with $\hat{f}(m|y)$ the estimated posterior probability of a model m, then the probability of inclusion of a variable *i* is given as

$$p_i = \sum_{m \in M^i} \hat{f}(m|y)$$

where M^i denotes all the models visited by the algorithm in which the variable is present.

production. Furthermore, the Euro-dollar exchange rate and import prices from non-EU countries were not found important, as opposed to imports from EU countries that were found important at lag 2 (see Table 3), indicating that Greece is more dependent to within-EU trade. Finally apart from gasoline prices, price indices related to the means of transport (cars purchase, airplanes, ships, trains fees) were not found important.

Figure 1 displays the estimated CPI monthly changes which are based on (a) all models visited by the algorithm (through model averaging), and (b) the best model under the Poisson (1) prior. In both cases the estimates seem to lie close to the observed CPI monthly changes, with similar Root Mean Squared Error, equal to 0.2273 under the model averaging approach and 0.2286 when the estimates are based only on the best model. Similar results are obtained via the other prior specifications.

Diagnostics of the model selection algorithm

Figure 2 displays the number of variables which are included in the posterior sample of the Population SCC algorithm under the different prior specifications. We observe that under the Poisson (1) prior most of the visited models include five to ten variables; under the Beta-Binomial (5) prior, again five to ten models, but with higher frequency models featuring six variables; and under the Poisson (5) prior models involving eight to 17 variables, with higher frequency models featuring eleven variables. This is typical in high dimensional models spaces with incumbent correlation structures, in which actual model size may be affected by prior beliefs. Nevertheless, this Figure is geared towards depicting the probability of the model size. This is not to be confused with the probability of specific models (shown in Table 2). Indeed, it is a usual phenomenon for model selection algorithms to visit often higher dimension spaces, and for the most probable models to include a comparatively small number of variables.

The effectiveness and accuracy of the SCC algorithm in relation to several widely used model selection methods has been demonstrated in Petralias and Dellaportas (2012). Thus, here we only comment on the need to use such a technique compared to a standard sampler. As depicted in Figure 3, a standard RJ sampler fails completely to converge even after 10 million iterations and displays significant drift in the ergodic probability estimates of most probable models, whereas the

Population SCC algorithm seems to sample efficiently within only 300 thousand iterations. Furthermore, the Monte Carlo Standard Error for the four best models is significantly higher

for the RJ algorithm, i.e. equal to 0.0031, 0.0023, 0.0010 and 0.0011, as opposed to 0.0022, 0.0016, 0.0008 and 0.0006 respectively, in the case of the Population SCC (Poisson (1) prior. Similar differences observed for other prior specifications) signal higher accuracy in model probability estimates. The enhanced mixing ability of the Population SCC algorithm is also depicted in the multiple times higher (addition/deletion) acceptance rate, which is equal to 0.569 (central chain; Poisson (1) prior), as opposed to 0.037 for the RJ.

6. Conclusions and policy implications

Two of the most important factors identified as likely to affect prices are the VAT rate(s) and the gasoline price index. Of these, the weighted average (across products and regions) VAT rate has been tweaked (revised upwards) a number of times in recent years, from 12.2% in 2009 to 16.6% in September 2011, and left untouched for the remaining period under examination (Table 4). The gasoline price index has risen by approximately 80% since 2009 (Figure 4), mostly as a result of successive excise tax hikes, to the extent by 2012 taxes accounted for more than 60% of the retail price people pay for gasoline. By subtracting the effects of VAT revisions and gasoline price changes, one can easily infer that the CPI in August 2012 lied close to the 2009 average (see Figure 5). Furthermore, prices seem to drop considerably during discount sales periods, more so in recent years, thus affecting increased seasonal variability in the CPI around sales periods.

Our proposed model selection framework aims to capture which of the considered variables (and at which lag) are associated to CPI changes. Of course other variables can be associated to the formation of prices, such as GDP, wages, unemployment rate, not taken into account in the present analysis. The impact of the economic downturn and overall environment in Greece is taken into account in our model by other variables, such as the change in retail sales and in industrial production, as well as government bond spreads (the latter two not found important at any lag). However the fact that the results are quite robust under different prior specifications (and model sizes) with respect to the most important variables in forming CPI, indicates that even if additional variables were to be included in the model, the ones identified in our analysis would still have high probability of inclusion.

Furthermore it was interesting to find that CPI can be predicted (see Figure 2 and the associated small Root Mean Squared Errors in Section V) based on technical factors, sales

periods, VAT and market place conditions, as reflected by changes in retail sales, with considerable lag (6 months), as well as gasoline prices and the prices of imports. The latter suggests that the Greek market depends extensively on imports and less on domestic production.

In view of the above, if the objective is to improve real incomes along with people's well-being, and competitiveness in the economy through price reductions, it might make sense to (a) expand or multiply discount or high sales periods; (b) reduce the VAT; (c) lower indirect fuel taxes while stepping up fuel market checks; and (d) bring down dependence on imports while raising domestic production.

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Figure 2: Number of variables visited by the PopulationSCC algorithm under each prior specification

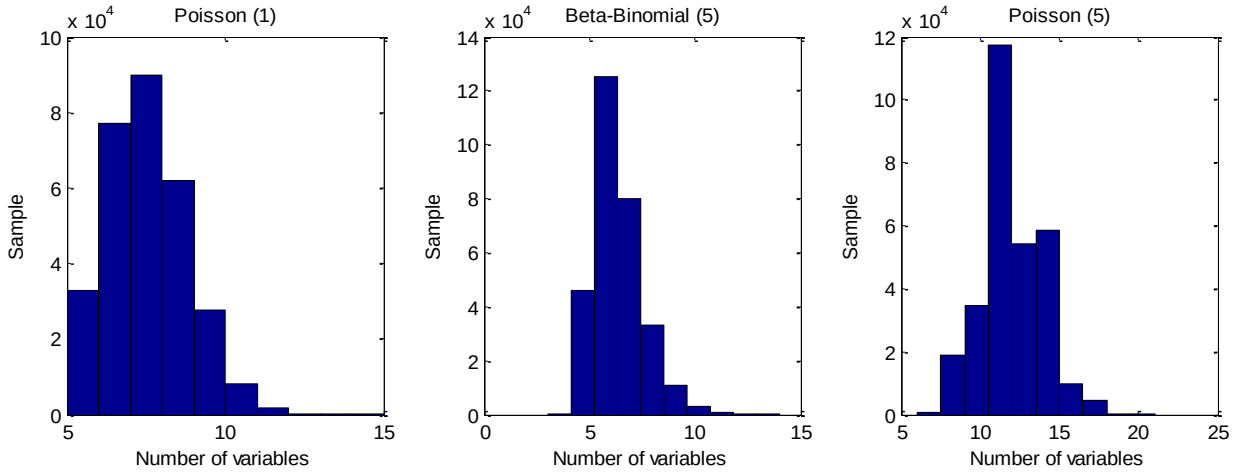
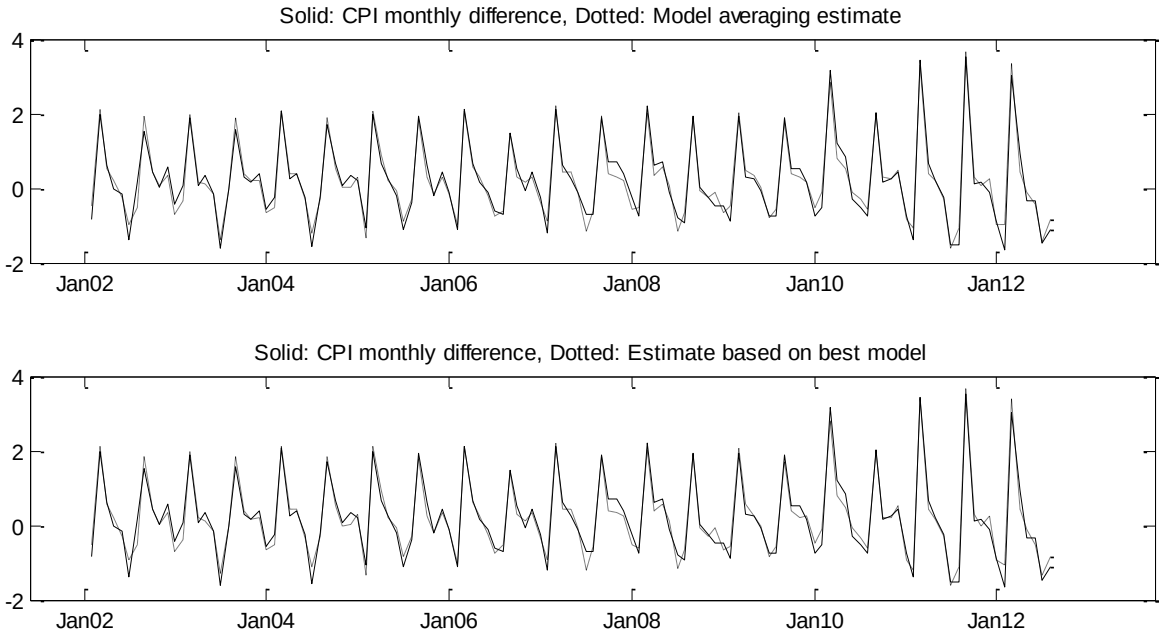


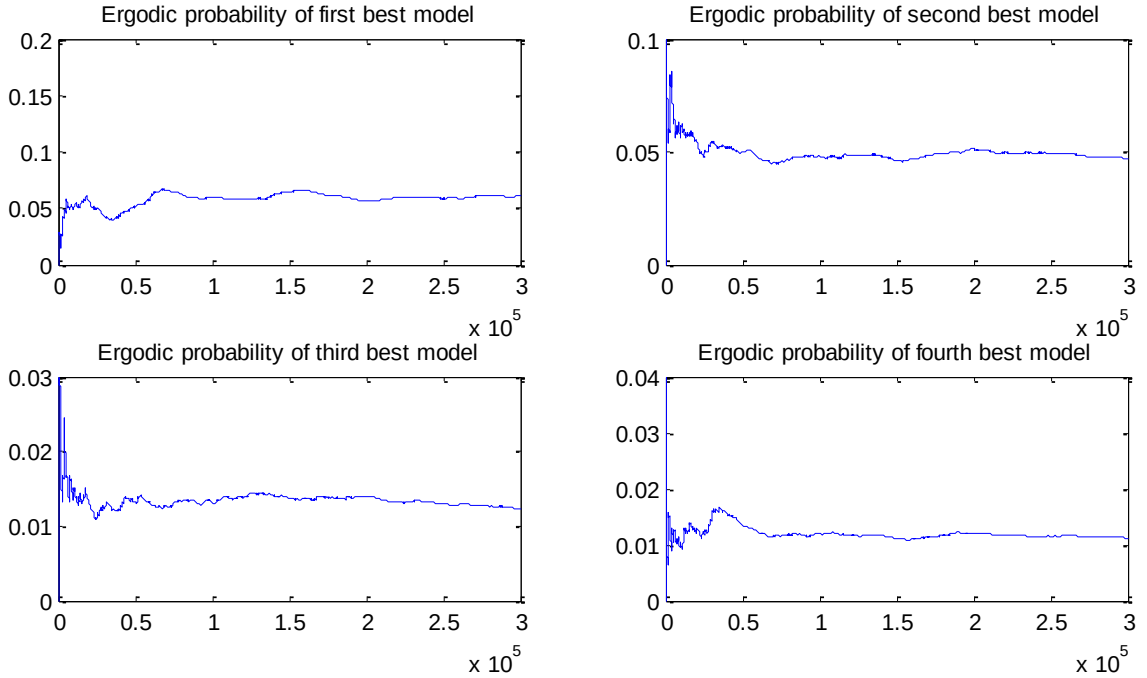
Figure 1: Model fit: Estimated CPI monthly changes based on all models (model averaging) and the best model under the Poison 91) prior



Note: The high seasonality is primarily attributed to the periods of discount sales.

Figure 3: Ergodic probability plots of the four best models estimated across the sample via the PopulationSCC and the RJ algorithms under the Poisson (1) prior.

PopulationSCC (300 thousand iterations without thinning)



Reversible Jump (10 million iterations; thinning per 10 iterations)

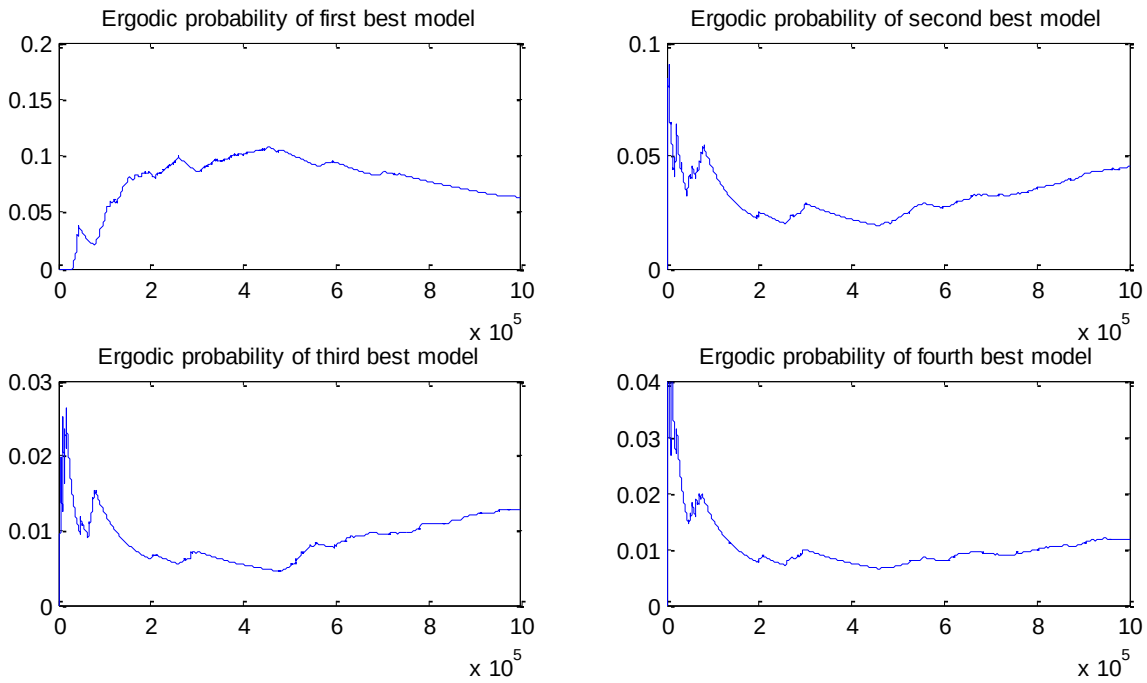
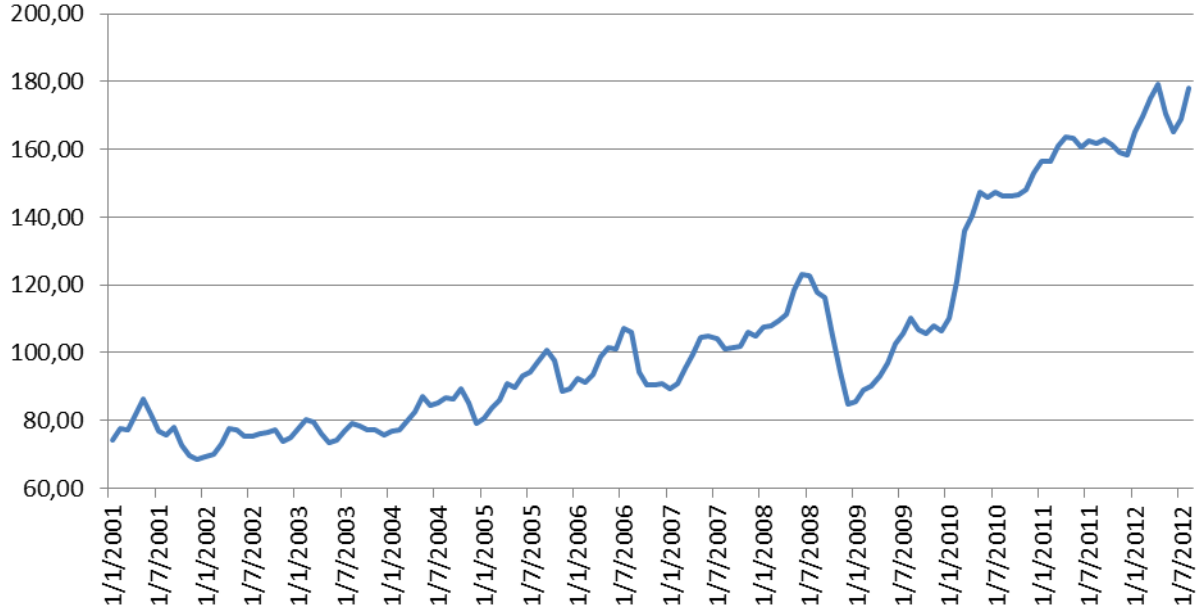
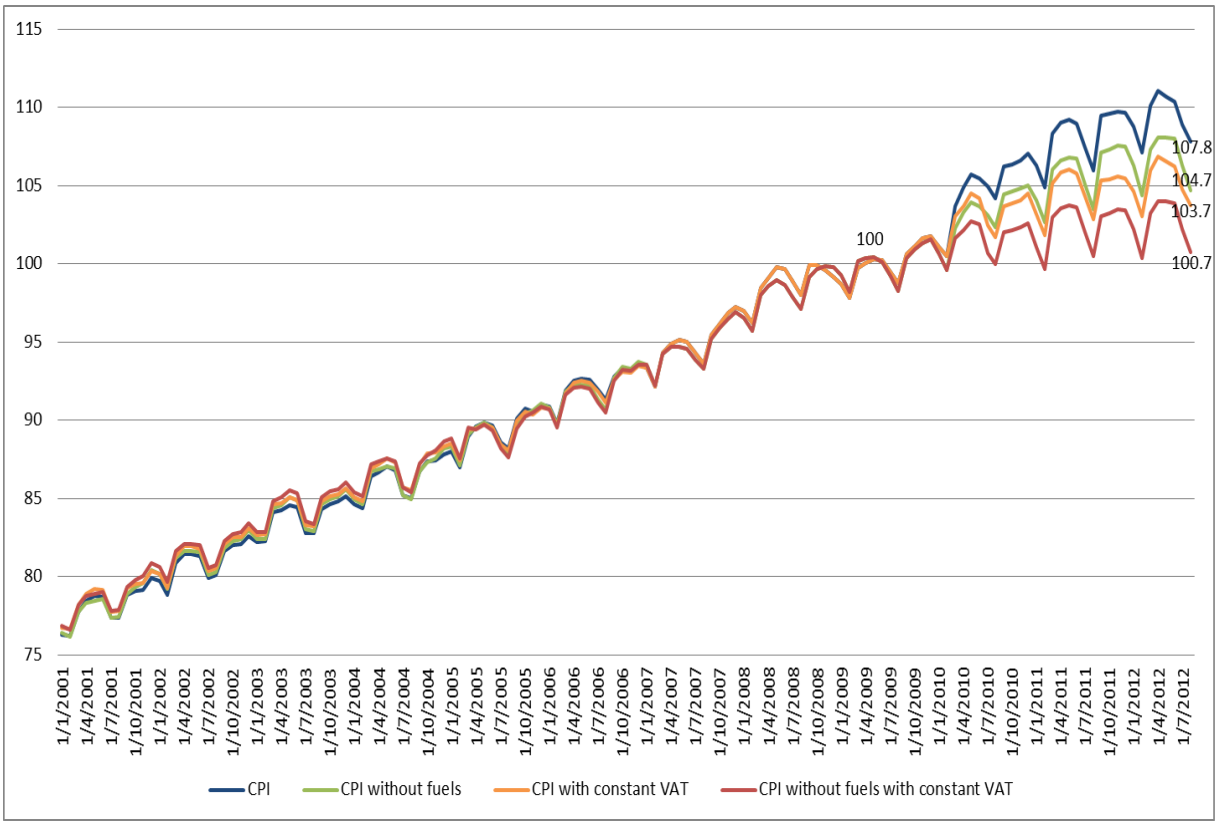


Figure 4: Domestic price index of gasoline from January 2011 to August 2012 (2009=100)



Source: ELSTAT.
Note: The excise fuel tax has risen seven times in the last decade, from € 296 per 1000 litres in January 2002 to € 670 in May 2010. Standard VAT is applied on top. As a result, by the end of 2012, approximately 60% of the retail gasoline price was attributed to taxes.

Figure 5: Variants of the monthly CPI from January 2011 to August 2012 (2009 average =100)



Source: ELSTAT. The indices are calculated based on ELSTAT's weights as well as the gasoline price index series and the VAT series.

Table 1: Factors considered as likely to affect prices

Factors (*K=18*) affecting prices at the same time: $S_{k,t}, \quad k = 1,...,K$

1-11	Monthly dummies (D1, D2,….D11) capturing abnormal prices changes in the corresponding months (January-November. Reference: December).
12	Trend
13	VAT: The series is constructed as a weighted average of the VAT rates that apply to each (4-digit) subcategory of the CPI each month. The subgroup weights are those used by the National Statistical Service of Greece (NSSG) up to 2010 and its successor, ELSTAT, subsequently. (See Table 4.)
14	Discount sales: The percentage of each month (i.e. portion of days out of the monthly total) which corresponds to a discount sales period (based on formal sales periods as announced (declared) by the Ministry of Development from 2001 to 2012).
15	CPI revision by the NSSG in January 2005: Dummy variable taking the value of one from Jan. 2005 to December 2010 and zero otherwise.
16	CPI revision by ELSTAT in January 2011: Dummy variable taking the value of one from Jan. 2011 onwards and the value of zero otherwise.
17	Variable #14 × variable #15 in order to capture additional effects on the CPI during the sales period after the 2005 revision.
18	Variable #14 × variable #16 in order to capture additional effects on the CPI during the sales period after the 2010 revision.

Factors (*I=26*) affecting prices with possible lags up to 12 months: $Z_{i,t-l_i}, \quad i = 1,...,I, \quad l_i = 0,...,12$

1	New government: Dummy for the month a new government is formed.
2	Domestic index of seed prices
3	Domestic index of fertilizer prices
4	Domestic index of pesticide prices
5	Domestic index of veterinary medicine prices
6	Domestic index of animal feed prices
7	Domestic index of agricultural equipment and machinery prices
8	Domestic index of buildings and building material prices
9	Domestic index of electricity prices
10	Domestic index of heating oil prices
11	Domestic index of gasoline prices (Fig.6)
12	Domestic index of purchased car prices
13	Domestic index of train fares
14	Domestic index of airline fares
15	Domestic index of ship fares
16	Domestic indes of industrial production
17	Domestic index of retail sales
18	Price index of imports from the EU
19	Price index of imports from non EU countries
20	International meat price index
21	International dairy price index
22	International cereal price index
23	International oils price index
24	International sugar price index
25	Euro-dollar exchange rate
26	Ten year Greek government bond yield compared to the German bond yield

Notes: With the exception of the dummies, the trend and discount sales, the remaining variables correspond to monthly changes (first difference) of indices the base period of which is set to mid-2009.

Data sources for the domestic indices and import prices: ELSTAT; for the International price indices: FAO; for the Bond spreads and euro-dollar exchange rate: Eurostat.

Table 2: Estimated parameters of the variables included in the four best (highest posterior probability) models under each prior specification. The standard deviations are supplied in parentheses

Prior distribution	Poisson (1)				Beta-Binomial (5)				Poisson (5)			
Model	First best	Second best	Third best	Fourth best	First best	Second best	Third best	Fourth best	First best	Second best	Third best	Fourth best
Probability % (Monte Carlo Standard Error)	6.10 (0.22)	4.71 (0.16)	1.23 (0.08)	1.12 (0.06)	25.98 (0.65)	11.90 (0.46)	3.86 (0.22)	3.31 (0.22)	0.069 (0.011)	0.065 (0.011)	0.047 (0.011)	0.046 (0.012)
February dummy		-0.295 (0.079)	-0.339 (0.077)				-0.296 (0.079)		-0.344 (0.077)	-0.240 (0.075)	-0.287 (0.072)	-0.323 (0.071)
June dummy	-0.800 (0.096)	-0.470 (0.072)	-0.484 (0.070)	-0.437 (0.077)	-0.800 (0.096)	-0.777 (0.103)	-0.470 (0.073)	-0.450 (0.082)	-0.493 (0.067)	-0.456 (0.071)	-0.467 (0.070)	-0.463 (0.064)
July dummy		-0.521 (0.080)	-0.531 (0.078)	-0.449 (0.084)			-0.520 (0.080)	-0.400 (0.087)	-0.533 (0.077)	-0.512 (0.076)	-0.510 (0.076)	-0.503 (0.074)
October dummy										0.230 (0.073)		
VAT	0.059 (0.013)	0.056 (0.013)	0.059 (0.013)	0.058 (0.014)	0.059 (0.013)		0.056 (0.013)		0.059 (0.013)	0.058 (0.013)	0.056 (0.013)	0.052 (0.012)
Discount sales	-1.634 (0.049)	-1.618 (0.049)	-1.598 (0.048)	-1.685 (0.048)	-1.634 (0.049)	-1.647 (0.052)	-1.617 (0.049)	-1.694 (0.052)	-1.597 (0.049)	-1.617 (0.045)	-1.618 (0.052)	-1.576 (0.043)
Discount sales occurring after January 2011	-1.275 (0.114)	-1.243 (0.113)	-1.250 (0.111)	-1.236 (0.120)	-1.275 (0.114)	-1.345 (0.120)	-1.243 (0.111)	-1.307 (0.125)	-1.240 (0.111)	-1.197 (0.103)	-1.244 (0.098)	-1.359 (0.103)
Index of gasoline prices	0.039 (0.005)	0.044 (0.005)	0.044 (0.005)	0.041 (0.005)	0.039 (0.005)	0.043 (0.006)	0.044 (0.005)	0.045 (0.006)	0.045 (0.005)	0.045 (0.005)	0.044 (0.005)	0.047 (0.005)
Price index of imports from the EU (lag 2)										0.295 (0.102)		
New government formation dummy (lag 4)												-0.329 (0.108)
International dairy price index (lag 5)												0.013 (0.003)
Domestic index of retail sales (lag 6)	0.017 (0.003)				0.017 (0.003)	0.016 (0.003)						
Domestic index of agricultural equipment and machinery prices (lag 9)			0.163 (0.053)						0.170 (0.055)			0.194 (0.051)
Constant	0.251 (0.023)	0.292 (0.025)	0.268 (0.025)	0.259 (0.024)	0.251 (0.023)	0.265 (0.024)	0.292 (0.025)	0.272 (0.026)	0.266 (0.024)	0.222 (0.030)	0.291 (0.023)	0.260 (0.022)
Standard deviation of errors	0.231	0.228	0.220	0.241	0.231	0.249	0.228	0.257	0.220	0.214	0.228	0.202

Table 3: Marginal probability of inclusion of variables under each prior specification. The top twenty variables visited under each prior specification, irrespectively of model

Poisson (1)			Beta-Binomial (5)			Poisson (5)		
Variable	Probability	Monte Carlo Standard Error	Variable	Probability	Monte Carlo Standard Error	Variable	Probability	Monte Carlo Standard Error
Discount sales (DS)	1.000	0.000	Discount sales (DS)	1.000	0.000	Discount sales (DS)	1.000	0.000
DS after January 2011	1.000	0.000	DS after January 2011	1.000	0.000	DS after January 2011	1.000	0.000
Index of gasoline prices	1.000	0.000	Index of gasoline prices	1.000	0.000	Index of gasoline prices	1.000	0.000
June dummy	0.991	0.002	June dummy	1.000	0.000	June dummy	0.997	0.001
VAT	0.824	0.009	Index retail sales (lag 6)	0.691	0.012	VAT	0.908	0.007
July dummy	0.615	0.009	VAT	0.640	0.010	July dummy	0.891	0.009
Index retail sales (lag 6)	0.391	0.009	July dummy	0.310	0.011	February dummy	0.608	0.011
February dummy	0.389	0.008	February dummy	0.156	0.006	Ind. agric. eq. etc. (lag 9)	0.359	0.010
Index EU imports (lag 2)	0.137	0.005	Index EU imports (lag 2)	0.050	0.002	October dummy	0.348	0.010
October dummy	0.130	0.005	New gov. dummy (lag 4)	0.049	0.001	New gov. dummy (lag 4)	0.296	0.007
New gov. dummy (lag 4)	0.097	0.003	October dummy	0.035	0.002	Index EU imports (lag 2)	0.269	0.009
Ind. agric. eq. etc. (lag 9)	0.088	0.004	Index fertilizer pr. (lag 5)	0.030	0.002	August dummy	0.161	0.007
Int'l dairy index (lag5)	0.054	0.004	Int'l dairy index (lag5)	0.021	0.002	Index retail sales (lag 6)	0.118	0.009
Index fertilizer pr. (lag 5)	0.042	0.003	Ind. agric. eq. etc. (lag 9)	0.021	0.001	DS after January 2005	0.109	0.005
New gov. dummy (lag 7)	0.038	0.001	Ind. train fares (lag 7)	0.020	0.002	Int'l dairy index (lag5)	0.108	0.007
Ind. buildings etc. (lag 3)	0.038	0.002	Int'l cereal pr. Ind. (lag5)	0.019	0.001	Ind. seed prices (lag 8)	0.104	0.006
Ind. seed prices (lag 8)	0.037	0.002	New gov. dummy (lag 7)	0.016	0.001	New gov. dummy (lag 7)	0.103	0.003
New gov. dummy (lag 3)	0.033	0.001	Ind. buildings etc. (lag 3)	0.014	0.001	Ind. buildings etc. (lag 3)	0.101	0.005
Ind. train fares (lag 7)	0.033	0.003	Ind. seed prices (lag 8)	0.013	0.001	April dummy	0.098	0.005
Int'l cereal pr. Ind. (lag5)	0.032	0.003	New gov. dummy (lag 5)	0.013	0.001	Index fertilizer pr. (lag 5)	0.096	0.006

Note: Underlines denote the same fourteen variables with the highest probability in the Poison (1) and Beta-Binomial priors.

Table 4: VAT rates from 1992 to 2012

Time period (from - to)		Aegean islands			Rest of Greece		
(dd/mm/yyyy)		standard	reduced	lowest	standard	reduced	lowest
8/8/1992	31/3/2005	13%	6%	3%	18%	8%	4,0%
1/4/2005	14/3/2010	13%	6%	3%	19%	9%	4,5%
15/3/2010	30/6/2010	15%	7%	4%	21%	10%	5,0%
1/7/2010	31/12/2010	16%	8%	4%	23%	11%	5,5%
1/1/2011		16%	9%	5%	23%	13%	6,5%
1/9/2011		The VAT on food products served outdoors (restaurants, hotels, taverns etc.) and non-alcoholic beverages increased from the reduced rate to the normal rate.					

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