BANCA D'ITALIA

EUROSISTEMA

Temi di Discussione

(Working Papers)

The trend-cycle decomposition of output and the Phillips curve: Bayesian estimates for Italy

by Fabio Busetti and Michele Caivano

November 2013

Number 941

BANCA D'ITALIA
EUROSISTEMA

Temi di discussione

(Working papers)

The trend-cycle decomposition of output and the Phillips curve: Bayesian estimates for Italy

by Fabio Busetti and Michele Caivano

Number 941 - November 2013

ISSN 1594-7939 (print)
ISSN 2281-3950 (online)

Printed by the Printing and Publishing Division of the Bank of Italy

THE TREND-CYCLE DECOMPOSITION OF OUTPUT AND THE PHILLIPS CURVE: BAYESIAN ESTIMATES FOR ITALY

by Fabio Busetti* and Michele Caivano*

Abstract

A standard model based trend-cycle decomposition of Italian GDP yields a likelihood function that is relatively flat and has two local maxima. A Bayesian estimation of the model identifies output gap and trend components that match the features of the Italian business cycle well. In a bivariate output and Phillips curve model it is found that: (i) the median value of the semi-elasticity of prices to the output gap is 0.5 after 20 quarters, (ii) the inflation cycle lags GDP on average by about 3 quarters.

JEL Classification: C30, C50, E50.
Keywords: Bayesian methods, potential output, unobserved components.

Contents

---

* Bank of Italy, Economic Research and International Relations.

1 Introduction

The identification of long-run and cyclical fluctuations in a time series leads to a fundamental trade-off in the degree of volatility assigned to each component. In the well-known Hodrick-Prescott (HP) filter the smoothness of the trend function is governed by a single bandwidth parameter, chosen in advance according to the observation frequency; the output gap is then defined as deviation of actual GDP from the HP trend. Similarly, band-pass filters as in Baxter and King (1999) are non-parametric methods aimed at extracting the time series fluctuations over given subsets of spectral frequencies, representing the long-run or the business cycle periodicity. These techniques have been widely adopted in empirical macroeconomic modelling but they have been also criticized as they might not properly account for the stochastic properties of the series. Harvey and Jaeger (1993) argue that stylized facts should better be based on models written in terms of components that have a direct interpretation. A model-based approach offers the further advantage of estimating the degree of trend smoothing. The dangers of using ad-hoc filtering are also examined in Canova (1998) and Marcet and Ravn (2004).

Economic interpretation of the extracted components calls for a sufficiently smooth trend function since its slope represents the growth of potential output, not driven by demand shocks. The output gap should then satisfactorily match the peaks and troughs of the fluctuations of economic activity over the business cycle.

This paper first considers the stochastic trend plus cycle unobserved components model proposed by Harvey (1989) for the series of Italian GDP. Maximum likelihood estimation of the model yields an objective function that is relatively flat and presents two local maxima. The optimization algorithm may converge to either maxima, depending on the initial conditions on the parameters. Interestingly, the local, but not global maximum, provides a trend-cycle decomposition that is very similar to that obtained by the HP filter. The output gap component implied by the global maximum instead appears more in line with the evidence provided by other business cycle indicators for the Italian economy.

In this context of a relatively flat likelihood function, Bayesian estimation appears a natural way to help with the identification of the components. A further advantage of the Bayesian approach is that it immediately yields measures of uncertainty surrounding the estimates and thus it allows to make probabilistic statements over the business cycle developments. We consider a Bayesian estimation algorithm that broadly corresponds to that in Harvey, Trimbur and Van Dijk (2007). A very mildly informative prior is adopted for the cyclical frequency parameter; full details of the convergence properties of the MCMC routine used in the estimation are provided. The median estimates of the parameters and the components are in line with the global maximum of the likelihood function.

Then a bivariate unobserved components model of GDP and inflation is estimated, to assess the relationship between output gap and price developments over the cycle. We find that: (i) the trend-cycle decomposition implied by this model is very close to that in the univariate case; (ii) the median response of prices to a 1% shock to the output gap is equal to 0.5 after 20 quarters; (iii) the inflation cycle lags the GDP cycle by about three quarters on average.

In summary, the paper proceeds as follows. Section 2 contains the classical and Bayesian estimation results for a univariate trend-cycle decomposition of Italian GDP. The bivariate model for output and inflation is considered in section 3. Section 4 provides concluding remarks and hints at possible extensions.

2 Univariate trend-cycle extraction for Italian GDP

We start by considering the univariate stochastic trend plus cycle model of Harvey (1989),

$$
\begin{aligned}
y_t &= \mu_t + c_t + \varepsilon_t, && (1)\\
\mu_t &= \mu_{t-1} + \beta_{t-1}, && (2)\\
\beta_t &= \beta_{t-1} + \omega_t, && (3)\\
\begin{bmatrix} c_t \\ c_t^* \end{bmatrix} &= \rho \begin{bmatrix} \cos(\lambda) & \sin(\lambda) \\ -\sin(\lambda) & \cos(\lambda) \end{bmatrix} \begin{bmatrix} c_{t-1} \\ c_{t-1}^* \end{bmatrix} + \begin{bmatrix} \kappa_t \\ \kappa_t^* \end{bmatrix}, && (4)\\
(\varepsilon_t, \omega_t, \kappa_t, \kappa_t^*)' &\sim NIID\left(0, diag\left(\sigma_\varepsilon^2, \sigma_\omega^2, \sigma_\kappa^2, \sigma_\kappa^2\right)\right), && (5)
\end{aligned}
$$

where the observable series, y_t, is the log of real GDP in Italy; the notation $NIID(0, \Sigma)$ stands for Gaussian disturbances that are independent and identically distributed with mean 0 and variance-covariance matrix Σ .

The trend component μ_t is an integrated random walk which, when estimated, tends to be relatively smooth. A more general form of the trend allows for a stochastic disturbance in the equation (2); however imposing some degree of smoothness is an advantage since the slope of the trend function is interpreted as the growth rate of potential output that supposedly should be slowly varying across time. The cyclical component c_t has an

ARMA (2,1) representation with complex roots; this is a stationary process if $\rho < 1$ with a peak in the spectrum at frequency λ, which determines the (pseudo) cyclical behaviour.[1] Harvey et al. (2007) consider Bayesian estimation of this model with application to US data. Clark (1987) estimates by maximum likelihood a similar model, but with an AR(2) cycle, for US GDP and industrial production; a Bayesian extension was considered by Planas, Rossi and Fiorentini (2008) as a model for output gap in the Euro area. Proietti (2009) illustrates a Bayesian procedure for the estimation of a bivariate model of GDP and inflation for the U.S. economy.

The trend and output gap components for the Italian GDP over the period 1982-2011 are extracted using model (1)-(5). The two subsections below deal with, respectively, maximum likelihood and Bayesian estimation of the model. The third subsection relates these estimates to the main features of the Italian business cycle.

2.1 Maximum likelihood estimation: local and global maxima

Maximum likelihood estimation of the model (1)-(5) yields an objective function that is relatively flat and presents two local maxima. The optimization algorithm may converge to either maxima, depending on the initial conditions on the parameters. The first two columns of table 1 reports the value of the model's parameters at the two maxima. At the global maximum the trend is smoother (σ_ω^2 is lower) while the output gap component is more persistent (higher ρ and lower λ). The period of the stochastic cycle, given by $P = 2\pi/\lambda$, is equal to 10.5 (6.4) years in the global (local) maximum. In the second column we report the posterior mode obtained through a Bayesian estimation of the unobserved component model.

Table 1 - Estimates for main parameters

	MLE		Bayesian*
	local	global	univariate
σ_ω - slope	.088	.030	.04
σ_κ - cycle	.455	.499	.82
λ - frequency	.244	.149	.133
ρ - persistence	.916	.962	.93

* posterior mode

[1]Harvey and Trimbur (2003) obtain a model-based representation of low pass and band pass filters by a similar, but more general, specification of the trend and cyclical components.

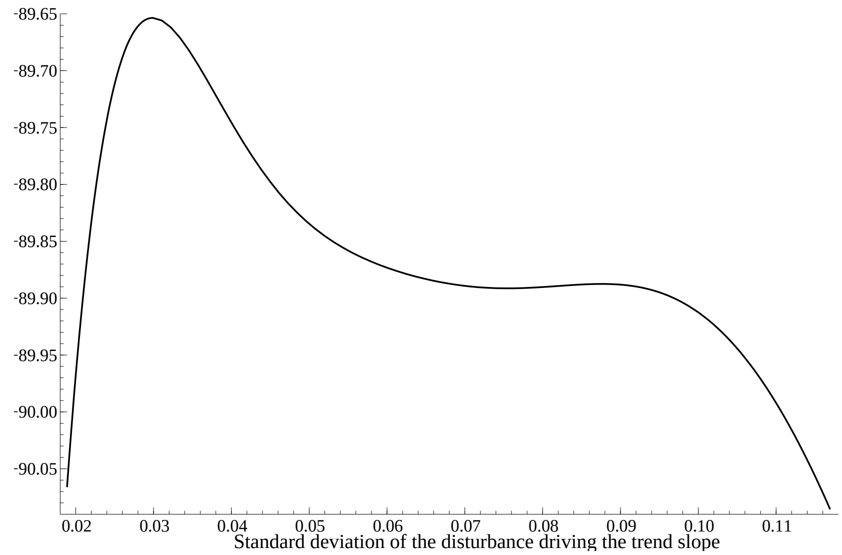

Figure 1: Likelihood function - σ_ω

Figure 1 shows a 'slice' of the likelihood function across the two maxima, projected into the σ_ω axis, that confirms the flatness of the function around the two maxima. The resulting trend-cycle decompositions are however rather different at the two maxima; the trend slope (which can be taken as a measure of potential output growth) and the output gap components are showed in figure 2 where the slope is given in annual terms. Interestingly, the local maximum corresponds to a decomposition similar to that implied by the HP filter. On the other hand the Bayesian estimation algorithm described in the next subsection identifies components that broadly match those corresponding to the global maximum. Although both trend-cycle decompositions appear reasonable, we will argue in subsection 2.3 that the global maximum provides a better description of the long-run and cyclical properties of the Italian economy.

2.2 Bayesian estimation

In the context of a flat likelihood function, Bayesian estimation can help identifying the components by specifying a prior distribution $p(\theta)$ for the parameter vector $\theta = [\rho, \lambda, \sigma_\varepsilon^2, \sigma_\omega^2, \sigma_\kappa^2]$. According to the Bayes rule, the posterior distribution of θ is $p(\theta|Y) = \frac{L(\theta|Y)p(\theta)}{\int L(\theta|Y)p(\theta)d\theta}$ where $L(\theta|Y)$ is the likelihood.

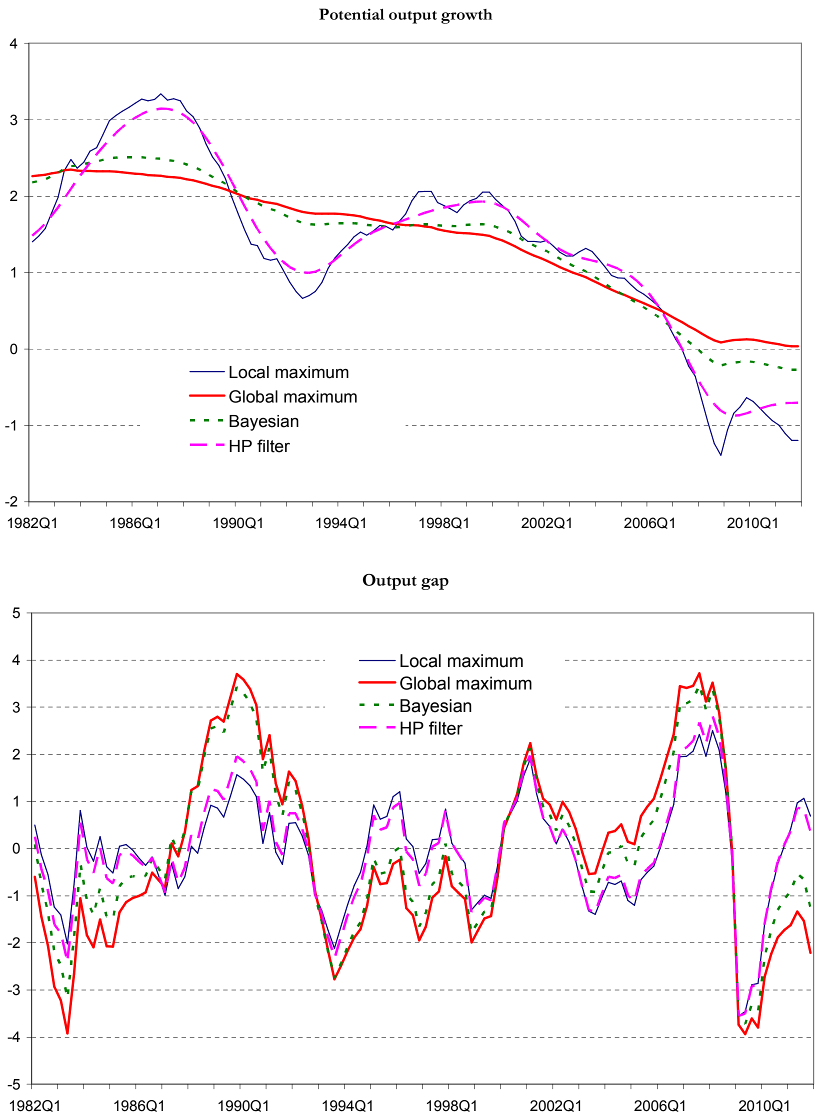

Figure 2: Components - ML estimation

We assume that all parameters are mutually independent *a priori*, that allows to write the prior distribution as $p(\theta) = p(\rho)p(\lambda)p(\sigma_\varepsilon^2)p(\sigma_\omega^2)p(\sigma_\kappa^2)$.

The prior distributions $p(\sigma_\varepsilon^2)$, $p(\sigma_\omega^2)$ and $p(\rho)$ are assumed to be uninformative; specifically, σ_ε^2 and σ_ω^2 are uniformly distributed over the interval $]0, +\infty[$, while ρ evolves according to a $Beta(a_\rho, b_\rho)$, with $a_\rho = b_\rho = 1$, which is equivalent to a uniform distribution restricted to the interval $[0, 1[$, in order to ensure stationarity of the cycle. The prior distribution for the frequency parameter λ is a $Beta(a_\lambda, b_\lambda)$, with $a_\lambda = 2$ and $b_\lambda = 6.37$, so that it has a mode corresponding to a cycle of 10 years but with a fairly large variance.[2] The distribution of σ_κ^2 is assumed to be an inverted gamma $IG(a_\kappa, b_\kappa)$, with $a_\kappa = 10$ and $b_\kappa = 50$; note that this guarantees that the variance of the stochastic cycle component is bounded away from zero.[3] Overall, these prior distributions reflect very loose restrictions, letting the data "speak".

The likelihood function $L(\theta|Y)$ can be calculated from the prediction error decomposition, using the output of the Kalman filter, applied to the state space model (1)-(5). Monte Carlo Markov Chain (MCMC) methods are used to simulate draws from the posterior distribution, which is not available in closed form. In particular, we use a Gibbs sampling, with a Metropolis step for λ and ρ.[4]

In figure 3 we show the marginal posterior distributions of ρ and λ, together with the priors; marginal posteriors for the variance parameters σ_ε^2, σ_ω^2 and σ_κ^2 are reported in figure 4. Whenever the prior distribution is uninformative it is not shown in the graph; for σ_κ^2 the prior distribution is such that it places a very tiny probability on small values (below 0.001) and it is almost flat for values between 0.001 and $+\infty$.

For all parameters, the posterior distributions are more concentrated than the corresponding priors, even in those cases where the latter have been chosen to be informative. The cycle is stationary, but quite persistent, with the posterior of the autoregressive parameter ρ peaking between 0.9 and 0.95. The density of the parameter λ is concentrated around the low frequencies and it displays a peak corresponding to a cycle of around 11 years. Posterior densities for the variance of the slope and the irregular components are

[2] The prior is consistent with the business cycle dating reported in the next subsection which point towards relatively long cycles.

[3] Compared with Harvey et al. (2007) we impose an informative prior on σ_κ^2; in our case this is needed in order to rule out outcomes that are too similar to the local ML maximum; note that imposing a prior on λ is not sufficient, due to the difficulty of separately identifying the parameters defining the variance of the cycle λ, ρ and σ_κ^2.

[4] See the Appendix for details.

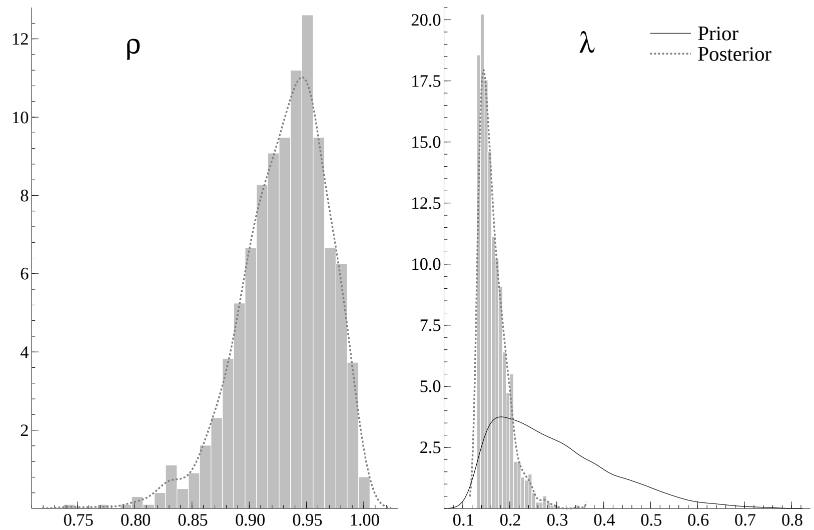

Figure 3: Posterior distributions of ρ and λ

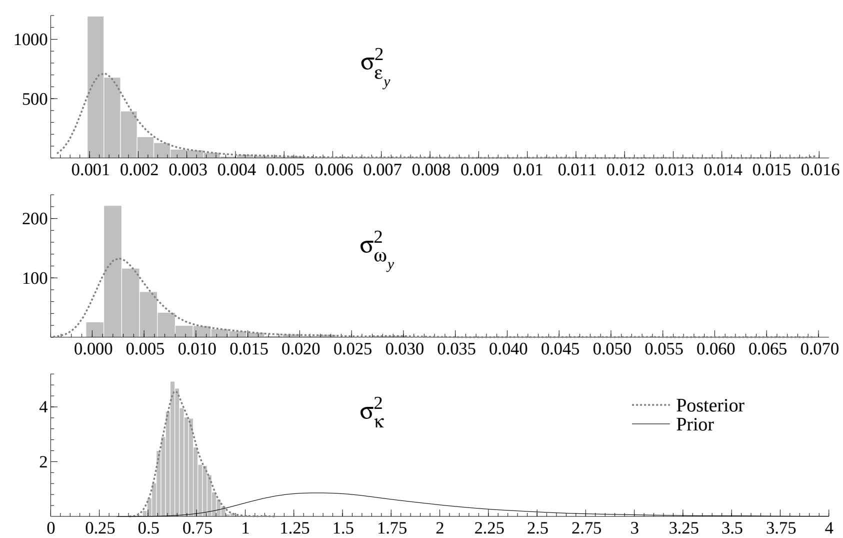

Figure 4: Posterior distributions of σ_{ε}^2, σ_{ω}^2 and σ_{γ}^2

asymmetric, concentrated near zero. The posterior distribution of the cycle component σ_κ^2, which is defined on a strictly positive support, appears on the other hand symmetric, signalling that prior restriction is not binding.

2.3 Characteristics of the Italian business cycle

The trend slope and the output gap components extracted by maximum likelihood estimation and by the Bayesian algorithm are graphed in figure 2: as anticipated in section 2.1, the Bayesian estimates are very close to those implied by the global maximum of the likelihood function, while the local maximum provides a decomposition similar to the HP filter. For the Bayesian case, figure 5 shows the smoothed estimate of the output gap together with the 68% and 90% posterior intervals.

In terms of economic interpretation of our estimates, the stochastic slope component changes very slowly at the global maximum (ranging from nearly 2.5% in the eighties to between 0 and 0.5% since the 2008-2009 recession) and thus it can be seen as a reasonable measure of potential growth; on the other hand, the large negative underlying growth rate of output in 2009-2011 obtained at the local maximum is not coherent with this interpretation. Furthermore, the sequence of peaks and troughs of the output gap component identified at the global maximum are more closely related to the ISCO-ISAE-ISTAT official dating of the Italian business cycle, that is based on several indicators; see ISTAT (2011) for details. Table 2 reports the complete cycles identified by the MLE's, by the Bayesian estimates and by ISCO-ISAE-ISTAT. According to the ISCO-ISAE-ISTAT dating, the Italian economy experienced four complete cycles, with troughs located at 1983Q1, 1993Q3, 1996Q4, 2003Q2 and 2009Q2. Four of them corresponds to the troughs identified at the global maximum (which however considers a single cycle the 10 year period 1993Q3-2003Q2), while the output gap implied by the local maximum finds two additional cycles of shorter periodicity (1991Q3-1993Q3 and 1999Q3-2003Q3). At the end of the sample the output gap remains negative at the global maximum, signalling that the Italian economy has not yet recovered from the deep recession of 2008-2009, while it already turns positive in the other case. Note that the dating based on the Bayesian estimate of the output gap is somewhat in between the dating based on the two MLE maxima. Overall, the model's parameters evaluated at the global maximum and at the Bayesian estimates seem to match more closely the official dating of the Italian business cycle than those at the local maximum.[5]

Table 2 - Dating of the Italian business cycle

MLE (global)		MLE (local)		Bayesian		ISCO-ISAE-ISTAT	
trough	peak	trough	peak	trough	peak	trough	peak
1983q2	1989q4	1983q2	1989q4	1983q2	1989q4	1983q1	1992q1
1993q3	-	1993q3	1996q1	1993q3	-	1993q3	1995q4
-	-	1996q4	1997q4	-	1997q4	1996q4	-
-	2001q4	1998q4	2001q4	1998q4	2001q1	-	2000q4
2003q2	2007q3	2003q3	2008q1	2003q2	2007q3	2003q2	2007q3
2009q2	-	2009q1	2011q3	2009q2	-	2009q2	-

The pseudo-real time estimates of the output gap component are also plotted in figure 5: in most cases they are within the 68% confidence band/posterior interval of the smoothed component. The higher variability of the smoothed estimates of the output gap reflects the fact that the corresponding potential output estimates are less volatile than the filtered ones. In order to appraise the extent to which the uncertainty is reduced when new data are used for the estimation, we have plotted in figure 6 the filtered and smoothed estimates of the Italian potential output and output gap in 2009Q4. The uncertainty surrounding the filtered estimates is quite large: the posterior density of the potential output growth ranges from positive numbers to very large negative ones. The output gap ranges from less than -5% to almost 0. Once new information becomes available, the uncertainty is considerably lower: the density of the smoothed estimate using information up to 2011Q4 is concentrated on the positive support, with potential output growth varying between 0.5 and -1.5% and the output gap in the range from -2.0 to -4.5%.

Further insights on the characteristics of the Italian business cycle can be gathered by looking at its amplitude. Figure 7 shows the average amplitude (across M draws) of the Italian cycle (together with 90% confidence bands), which for period t is computed, as in Harvey et al. (2007), by the following:

[5] A popular non-parametric approach to date the business cycle is the algorithm proposed in Bry and Boschan (1971); see the evidence for Italy reported in Bassanetti, Caivano and Locarno (2010). That method identifies a level cycle rather similar to the local maximum of the likelihood function of our model.

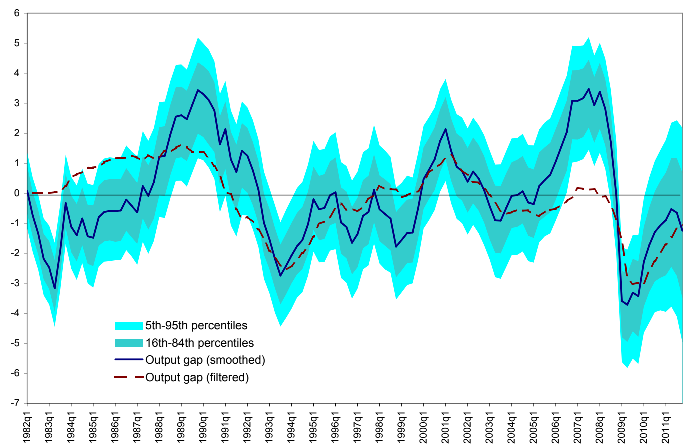

Figure 5: The Italian business cycle

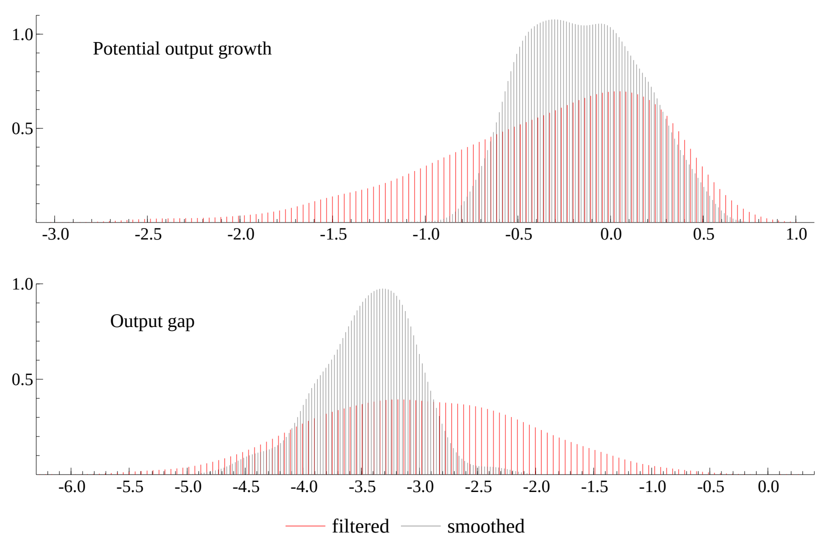

Figure 6: Smoothed and filtered estimates of potential output growth and of output gap in 2009Q4 - Italy

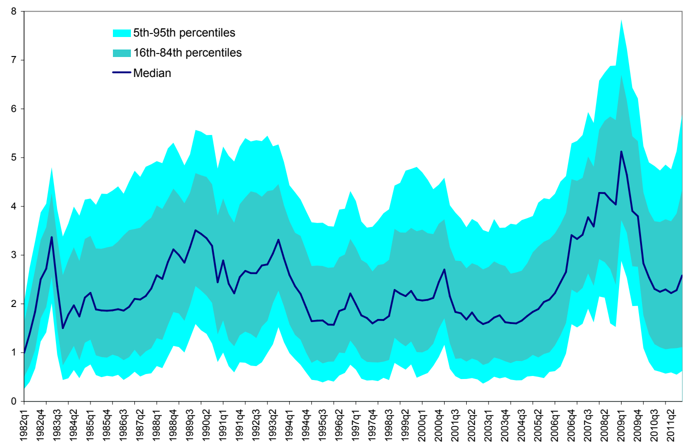

Figure 7: Amplitude of the Italian cycle

$$A_t = \frac{1}{M}\sum_{j=1}^{M}\sqrt{c_t^{2(j)} + c_t^{*2(j)}}. \tag{6}$$

The plot highlights a temporary increase in the amplitude of the business cycle during the 2008-09 recession, with a median estimate of around 4.5% (against values between 1.5 and 3.5% for the other periods).

3 Bivariate models of output gap and inflation

In this section the univariate trend-cycle decomposition of GDP is augmented with a model for inflation. We follow Harvey (2011) where inflation is modelled as the sum of a slowly changing component (trend) and a stationary cycle, the latter related to the GDP fluctuations[6]; a simpler univariate random walk plus noise model was considered in Stock and Watson (2007).

[6]Harvey (2011) shows that -under some conditions on the output gap process- this simple model for inflation is consistent with forward looking behaviour as in the hybrid New Keynesian Phillips curve of Gali and Gertler (1999).

Specifically, let y_t and π_t be the observed series of output (the logarithm of real GDP) and inflation (the change of the logarithm of the GDP deflator[7]). The model is as follows:

$$y_t = \mu_{y,t} + c_t + \varepsilon_{y,t}, \tag{7}$$

$$\pi_t = \mu_{\pi,t} + \delta c_t + \delta^* c_t^* + \varepsilon_{\pi,t}, \tag{8}$$

$$\mu_{y,t} = \mu_{y,t-1} + \beta_{y,t-1}, \tag{9}$$

$$\beta_{y,t} = \beta_{y,t-1} + \omega_{y,t}, \tag{10}$$

$$\mu_{\pi,t} = \mu_{\pi,t-1} + \zeta_{\pi,t}, \tag{11}$$

$$\begin{bmatrix} c_t \\ c_t^* \end{bmatrix} = \rho \begin{bmatrix} \cos(\lambda) & \sin(\lambda) \\ -\sin(\lambda) & \cos(\lambda) \end{bmatrix} \begin{bmatrix} c_{t-1} \\ c_{t-1}^* \end{bmatrix} + \begin{bmatrix} \kappa_t \\ \kappa_t^* \end{bmatrix} \tag{12}$$

$$(\varepsilon_{y,t}, \varepsilon_{\pi,t}, \omega_{y,t}, \zeta_{\pi,t}, \kappa_t, \kappa_t^*)' \sim NIID\left(0, diag\left(\sigma^2_{\varepsilon_y}, \sigma^2_{\varepsilon_\pi}, \sigma^2_{\omega_y}, \sigma^2_{\zeta_\pi}, \sigma^2_\kappa, \sigma^2_\kappa\right)\right). \tag{13}$$

Unlike Harvey (2011) our model allows for a phase shift in the inflation cycle with respect the GDP cycle if $\delta^* \neq 0$. This is measured by $\xi = -\lambda^{-1} atan(\frac{\delta^*}{\delta})$, where a positive (negative) value indicates that the inflation cycle leads (lags) the output cycle; see Runstler (2004) for the details. The cross-correlation between the inflation and output cycles at the lag s is given by $Corr(y, \pi|s) = \rho^{|s|} sign(\delta) cos(\lambda(s + \xi))$, where $sign(x) = 1$ if $x \geq 0$ and 0 otherwise.

The parameter vector of the model (7)-(13) is

$$\theta_{MV1} \equiv [\rho, \lambda, \delta, \delta^*, \sigma^2_{\varepsilon_y}, \sigma^2_{\varepsilon_\pi}, \sigma^2_{\omega_y}, \sigma^2_{\zeta_\pi}, \sigma^2_\kappa]'.$$

As in the univariate case, we specify prior distributions for the unknown parameters to be mutually independent and, for the most part, uninformative. All parameters are assumed to be uniformly distributed *a priori*, with the exception of λ, which again evolves according to a Beta(2,6.37) and σ^2_κ,

[7] We use the GDP deflator instead of consumer prices as a proxy for inflation in order to focus on domestic inflationary pressures, which are those directly related to the evolution of the output gap.

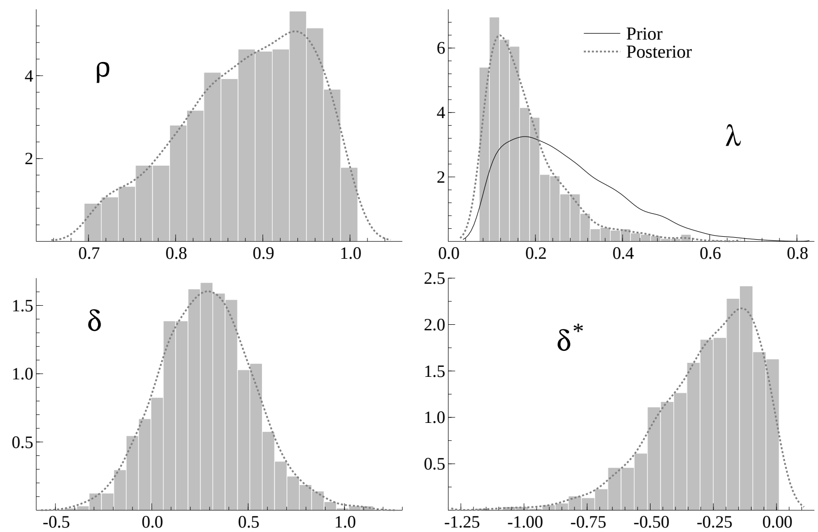

Figure 8: Posterior distributions: ρ, λ, δ, δ^*

which is distributed as an $IG(10, 90)$. [8] Prior restrictions on the remaining parameters have been imposed in the form of boundaries of the prior distributions, which, in the case of variances, are not allowed to take non-positive values and, in the case of the autoregressive parameter ρ, are restricted to the [0,1[interval.

As in the univariate case, we employ an MCMC routine to draw from the posterior distribution of the parameter vector. The estimated marginal posteriors are displayed in figures 8-10; a full set of convergence diagnostics of the MCMC routine is provided in the appendix.

It can be noticed that the estimates of the parameters governing the evolution of the cycle are not too different from the univariate case: the posterior distribution of λ still displays a peak at a frequency consistent with a cycle of about 11 years, but it is somehow more dispersed. The

[8] Parameter estimates are robust to changes in the prior distributions: robustness checks performed with an uninformative prior on λ yield a broadly unchanged posterior. Using a tighter prior does not change the results either, unless the mode of the prior distribution is considerably displaced from the one we have used in the baseline prior specification. Compared to the univariate model, the prior assumption for σ^2_κ is tighter; this is needed to rule out a too volatile potential output estimate (similar to the one obtained by ML at the local maximum), as it does not conform with the features of the Italian business cycle as described by independent estimates, such as the ISCO-ISAE-ISTAT indicator.

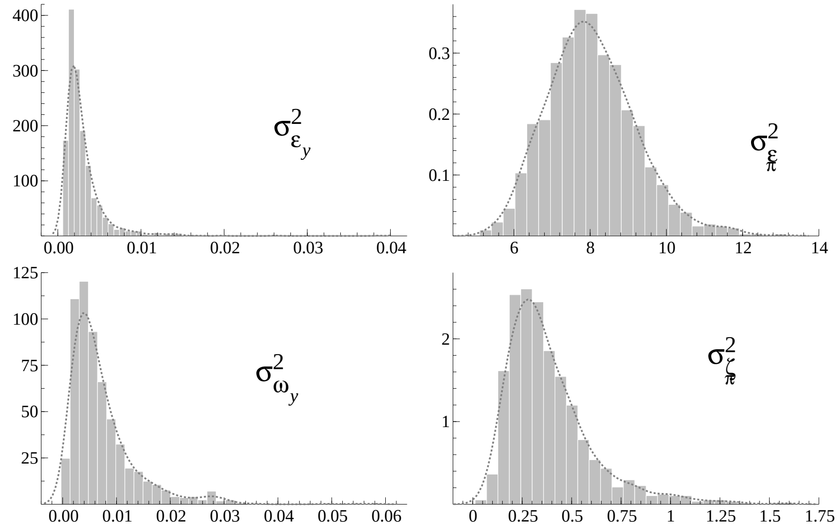

Figure 9: Posterior distributions: $\sigma^2_{\varepsilon_y}$, $\sigma^2_{\varepsilon_\pi}$, $\sigma^2_{\omega_y}$, $\sigma^2_{\zeta_\pi}$

persistence of the cycle is also similar to the univariate case. At the same time, the estimate of the variance of the innovation of the cycle process κ_t is somewhat larger, overall implying a higher variability of the GDP cycle. The parameter δ, measuring the co-movement between the GDP cycle and inflation, is positive, as expected, and turns out to be identified rather precisely. The average lag of inflation with respect to the output cycle exceeds 3 quarters, with a peak at around 2 quarters (fig 11, top panel); the cross-correlation between the two cycles is very high, with a peak at 1.

Figure 12 shows the smoothed estimate of the Italian potential output (top-left panel), of core inflation (top-right panel), of the potential output growth (bottom-left panel) and of the output and inflation cycles (bottom-right panel), computed on the basis of the posterior median of the parameters. The trend cycle decomposition of GDP is not too different from that of the univariate model, although both the potential output and the output gap are somewhat less smooth, with the latter displaying larger swings, especially at the end of the sample.

Finally, figure 13 shows the cyclical response of inflation to a 1% temporary increase in the output gap innovation. On impact, the effect on inflation (top panel) is given by the parameter δ, which has an average value of about 0.3; the effect of the shock dies out after 16 quarters. The impact on the

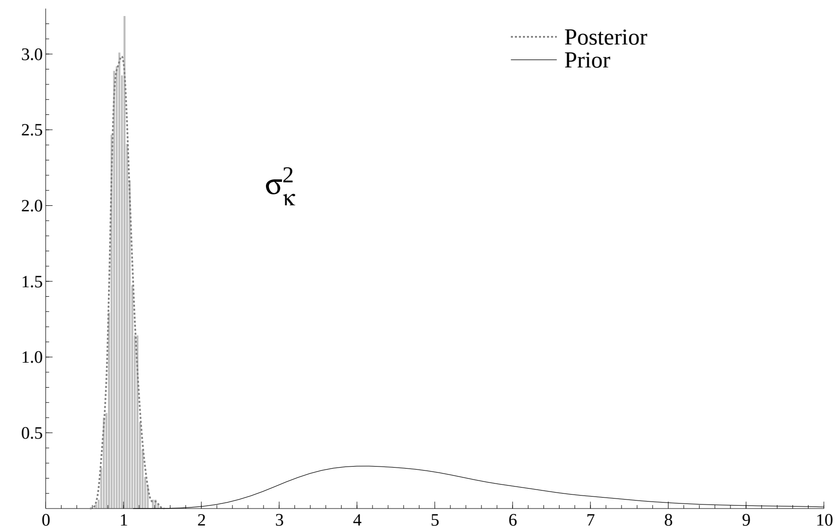

Figure 10: Posterior distributions: σ_κ^2

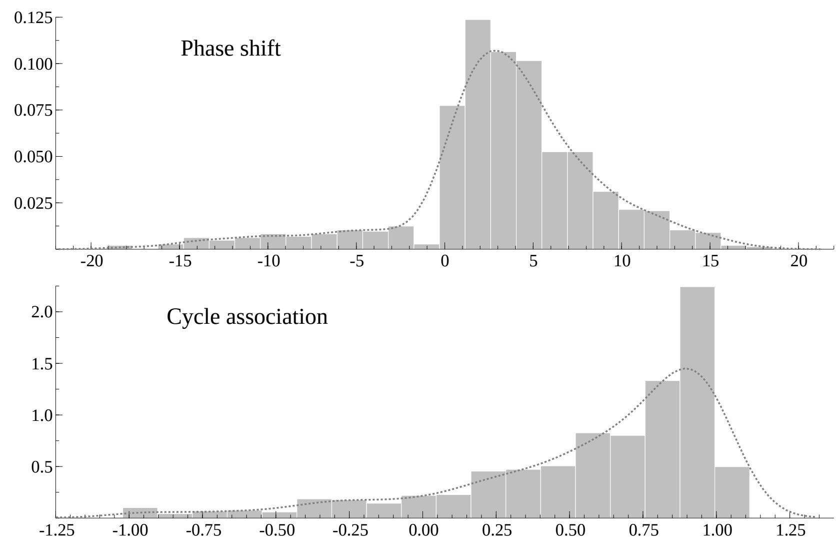

Figure 11: Posterior distributions: cycle phase shift and cross-correlation

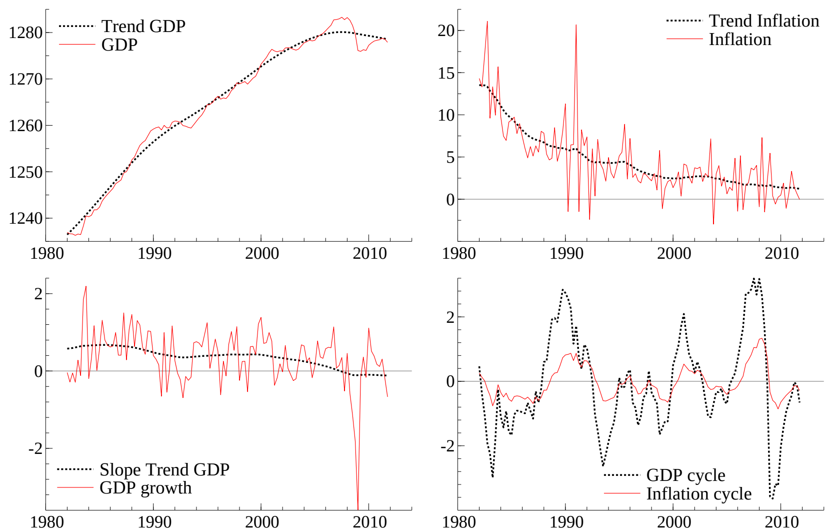

Figure 12: Components - Median of the parameters

price level can be appraised in the bottom panel, where it is shown that the price semi-elasticity to the output gap is 0.5% after 20 quarters.[9]

4 Conclusion

Unobserved component models for output and inflation have been estimated for the Italian economy. We have showed that the adoption of a Bayesian perspective is effective in the context of a flat likelihood function and it helps in formulating probabilistic statements regarding business cycle developments. Our estimates broadly match the official dating of the business cycle. The estimation of a bivariate model highlighted the features in the transmission of output gap shocks to prices.

The analysis carried out in this paper could be further extended in at least two directions. First, it could take into account additional variables that may help identifying long run and cyclical components and provide additional insights on the link between the output and inflation. Second, the models could be extended to allow for structural changes in the long run and/or the cyclical components, such as the possibility of a trend break at

[9]The response of the price level is given by the partial cumulated sums of the response of inflation rescaled by the cumulated response of the output gap.

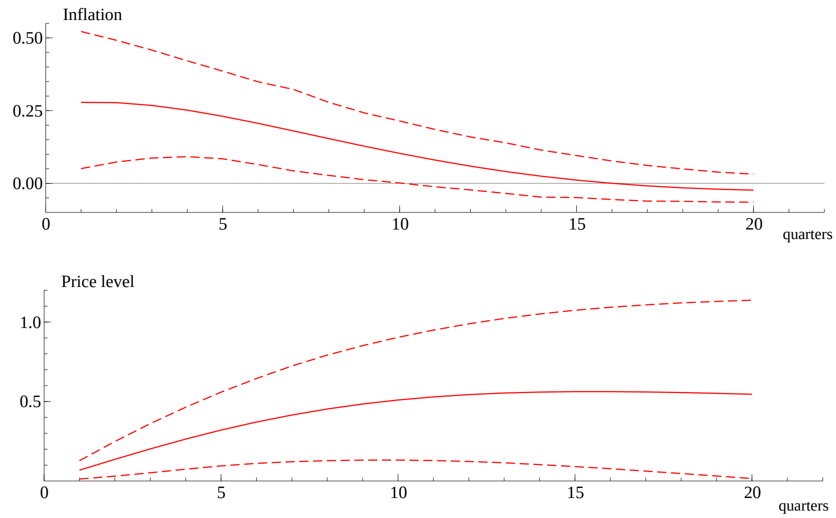

Figure 13: Response of inflation and prices to a 1% temporary increase in the output gap; dashed lines: 68% posterior bands

the time of the Great Recession of 2009. We leave these issues for future research.

References

Bassanetti, A., Caivano, M. and Locarno, A. (2010). Modeling italian potential output and the output gap, *Temi di discussione 771*, Banca d'Italia.

Baxter, M. and King, R. G. (1999). Measuring business cycles: Approximate band-pass filters for economic time series, *The Review of Economics and Statistics* **81**(4): pp. 575–593.

Brooks, S. P. (1998). Quantitative convergence diagnosis for mcmc via cusums, *Statistics and Computing* **8**: 267–274.

Bry, G. and Boschan, C. (1971). Cyclical analysis of time series: Selected procedures and computer programs, *Technical paper 20*, NBER.

Canova, F. (1998). Detrending and business cycle facts, *Journal of Monetary Economics* **41**(3): 475–512.

Clark, P. K. (1987). The cyclical component of u.s. economic activity, *The Quarterly Journal of Economics* **102**(4): 797–814.

Durbin, J. and Koopman, S. J. (2002). A simple and efficient simulation smoother for state space time series analysis, *Biometrika* **89**(3): 603–615.

Gali, J. and Gertler, M. (1999). Inflation dynamics: A structural econometric analysis, *Journal of Monetary Economics* **44**(2): 195–222.

Geweke, J. (1992). Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments, *Bayesian Statistics*, Oxford University Press, pp. 169–193.

Harvey, A. C. (1989). *Forecasting, Structural Time Series Models and the Kalman Filter*, Cambridge University Press, Cambridge.

Harvey, A. C. (2011). Modelling the phillips curve with unobserved components, *Applied Financial Economics* **21**(1-2): 7–17.

Harvey, A. C. and Jaeger, A. (1993). Detrending, stylized facts and the business cycle, *Journal of Applied Econometrics* **8**(3): pp. 231–247.

Harvey, A. C. and Trimbur, T. M. (2003). General model-based filters for extracting cycles and trends in economic time series, *The Review of Economics and Statistics* **85**(2): 244–255.

Harvey, A. C., Trimbur, T. M. and Van Dijk, H. K. (2007). Trends and cycles in economic time series: A bayesian approach, *Journal of Econometrics* **140**(2): 618–649.

ISTAT (2011). *Rapporto annuale - La situazione del Paese nel 2010*, Istituto nazionale di statistica.

Marcet, A. and Ravn, M. O. (2004). The hp-filter in cross-country comparisons, *CEPR Discussion Papers 4244*.

Planas, C., Rossi, A. and Fiorentini, G. (2008). Bayesian analysis of the output gap, *Journal of Business & Economic Statistics* **26**: 18–32.

Proietti, T. (2009). Structural time series models for business cycle analysis, *in* T. C. Mills and K. Patterson (eds), *Palgrave Handbook of Econometrics*, Vol. 2: Applied Econometrics, Palgrave Macmillan.

Runstler, G. (2004). Modelling phase shifts among stochastic cycles, *Econometrics Journal* **7**(1): 232–248.

Stock, J. H. and Watson, M. W. (2007). Why has u.s. inflation become harder to forecast?, *Journal of Money, Credit and Banking* **39**(1): 3–33.

Yu, B. and Mykland, P. (1998). Looking at markov samplers through cusum path plots: a simple diagnostic idea, *Statistics and Computing* **8**(3): 275–286.

Appendices

A The Bayesian estimation algorithm

In this appendix we illustrate the details of our Bayesian estimation algorithm for the bivariate model (7)-(13).

A.1 Priors

The unknowns of the model are represented by the sequence of unobserved components $\{\alpha_t\}_{t=1}^T \equiv \{\mu_{y,t}, c_t, c_t^*, \mu_{\pi,t}, \beta_t\}_{t=1}^T$ and by the parameters $\sigma^2_{\varepsilon_y}$, $\sigma^2_{\varepsilon_\pi}$, σ^2_ω, σ^2_ζ, σ^2_κ, λ, ρ, δ and δ^*.

We now define the set $\Psi \equiv \{\{\alpha_t\}_{t=1}^T, \sigma^2_{\varepsilon_y}, \sigma^2_{\varepsilon_\pi}, \sigma^2_\omega, \sigma^2_\zeta, \sigma^2_\kappa, \lambda, \rho, \delta, \delta^*\}$ and denote by Ψ_j the j-th element of Ψ and by Ψ_{-j} all elements of Ψ but the j-th.

We assume that the prior distributions of the elements of Ψ are mutually independent, i.e. that $p(\Psi) = \prod_j p(\Psi_j)$. The prior distributions for the time-invariant parameters are as follows:

$$\lambda \sim Beta(a_\lambda, b_\lambda), \tag{14}$$

$$\rho \sim Beta(a_\rho, b_\rho), \tag{15}$$

$$\delta \sim N(\mu_\delta, \sigma^2_\delta), \tag{16}$$

$$\delta^* \sim N(\mu_{\delta^*}, \sigma^2_{\delta^*}), \tag{17}$$

$$\sigma^2_\kappa \sim IG(a_\kappa, b_\kappa), \tag{18}$$

and the prior distributions of all other variance parameters are assumed to be $U(\epsilon, S)$, with ϵ and S being small and large values, respectively, that ensure that the variance remains positive and bounded.

The prior distribution of the sequence $\{\alpha_t\}_{t=1}^T$ is implicitly defined by the priors on the time-invariant parameters and by that on the initial condition of the sequence, which is assumed to be diffuse.

A.2 The MCMC routine

The posterior distribution $p(\Psi|Y)$ can be obtained by Bayes rule combining the data density $p(Y|\Psi)$ with the prior $p(\Psi)$: $p(\Psi|Y) = \dfrac{p(Y|\Psi)p(\Psi)}{\int p(Y|\Psi)p(\Psi)d\Psi}$. Given the form of the model and the assumptions about prior distributions, such posterior cannot be derived in closed form and needs to be simulated using an MCMC routine. We implement a Gibbs algorithm with Metropolis steps for the parameters λ and ρ. Given our prior assumptions it can be showed that the conditional posteriors needed to implement the Gibbs sampler are as follows: draws from the conditional density $p({\alpha_t}_{t=1}^T|\Psi_{\alpha_t})$ can be obtained using the simulation smoother of Durbin and Koopman (2002). For time-invariant parameters:

$$p(\sigma^2_{\varepsilon_y}|Y, \Psi_{-\sigma^2_{\varepsilon_y}}) \propto IG(\tilde{a}_{\sigma_y}, \tilde{b}_{\sigma_y}) \tag{19}$$

where $\tilde{a}_{\sigma_y} = \frac{T}{2} - 1$ and $\tilde{b}_{\sigma_y} = \frac{\sum_{t=1}^T \hat{\varepsilon}^2_{y,t}}{2}$.

$$p(\sigma^2_{\varepsilon_\pi}|Y, \Psi_{-\sigma^2_{\varepsilon_\pi}}) \propto IG(\tilde{a}_{\sigma_\pi}, \tilde{b}_{\sigma_\pi}), \tag{20}$$

with $\tilde{a}_{\sigma_\pi} = \frac{T}{2} - 1$ and $\tilde{b}_{\sigma_\pi} = \frac{\sum_{t=1}^T \hat{\varepsilon}^2_{\pi,t}}{2}$.

$$p(\sigma^2_{\omega}|Y, \Psi_{-\sigma^2_{\omega}}) \propto IG(\tilde{a}_{\sigma_\omega}, \tilde{b}_{\sigma_\omega}), \tag{21}$$

with $\tilde{a}_{\sigma_\omega} = \frac{T}{2} - 1$ and $\tilde{b}_{\sigma_\omega} = \frac{\sum_{t=1}^T \hat{\omega}^2_{t}}{2}$.

$$p(\sigma^2_{\zeta}|Y, \Psi_{-\sigma^2_{\zeta}}) \propto IG(\tilde{a}_{\sigma_\zeta}, \tilde{b}_{\sigma_\zeta}), \tag{22}$$

with $\tilde{a}_{\sigma_\zeta} = \frac{T}{2} - 1$ and $\tilde{b}_{\sigma_\zeta} = \frac{\sum_{t=1}^T \hat{\zeta}^2_{t}}{2}$.

$$p(\sigma^2_{\kappa}|Y, \Psi_{-\sigma^2_{\kappa}}) \propto IG(\tilde{a}_{\sigma_\kappa}, \tilde{b}_{\sigma_\kappa}), \tag{23}$$

with $\tilde{a}_{\sigma_\kappa} = T + a_{\sigma_\kappa}$ and $\tilde{b}_{\sigma_\zeta} = \frac{\hat{K}}{2} + b_{\sigma_\kappa}$.

$$p(\delta|Y, \Psi_{-\delta}) \propto N\left(\left[\frac{\sum_t \hat{\pi}_{1,t}\hat{c}_t}{\sigma^2_{\varepsilon_\pi}} + \frac{\mu_\delta}{\sigma^2_\delta}\right] s, s\right), \tag{24}$$

where $\hat{\pi}_{1,t} \equiv \pi_t - \hat{\mu}_{\pi,t} - \delta^* \hat{c}^*_t$ and $s \equiv \left(\frac{\sum_t \hat{c}^2_t}{\sigma^2_{\varepsilon_\pi}} + \frac{1}{\sigma^2_\delta}\right)^{-1}$.

$$p(\delta^*|Y, \Psi_{-\delta^*}) \propto N\left(\left[\frac{\sum_t \hat{\pi}_{2,t}\hat{c}^*_t}{\sigma^2_{\varepsilon_\pi}} + \frac{\mu_{\delta^*}}{\sigma^2_{\delta^*}}\right] s^*, s^*\right), \tag{25}$$

where $\hat{\pi}_{2,t} \equiv \pi_t - \hat{\mu}_{\pi,t} - \delta\hat{c}_t$ and $s^* \equiv \left(\frac{\sum_t \hat{c}_t^{*2}}{\sigma^2_{\varepsilon_\pi}} + \frac{1}{\sigma^2_{\delta^*}}\right)^{-1}$.

For λ and ρ it is not possible to derive a conditional posterior distribution in closed form, as their prior are Beta distribution (which are not conjugate with the conditional likelihood); furthermore, λ enters the model in a non-linear fashion. Therefore, for those parameters we resort to a Metropolis step with random walk proposal. We ran the MCMC routine for 1000000 draws in the case of the univariate model and for 2000000 draws for the multivariate model.

A.3 Convergence diagnostics

Provided that certain regularity conditions are satisfied, with MCMC techniques it is possible to sample from the posterior distribution of the parameters, after an initial burn-in period; while there is no certain answer to whether the Markov chain defined by algorithm has converged to its stationary distribution (i.e. to the joint posterior), a number of diagnostics can be performed.

Simple diagnostics, such as a visual inspection of the path of the draws, are often used to determine whether the draws resemple those that would have been generated by an iid process. As this type of check is at best subjective, in this paper we resort to more formal statistics to assess the convergence properties of our chain. In particular, we use the Brooks (1998) convergence diagnostics to determine the burn-in period and refine the sample of draws used for inference and double-check the results of the Brooks' diagnostics by the Geweke (1992) stationarity test.

Brooks (1998) test is based upon the CUSUM diagnostics proposed by Yu and Mykland (1998). The latter diagnostics is computed as follows:

- for a chain of N draws choose a statistics $g(\Psi_j)$ and after a burn-in period of $N_0 < N$ iterations compute the mean $\mu_N = \frac{\sum_{i=N_0+1}^{N} g(\Psi_j^{(i)})}{N-N_0}$;
- for $l = N_0+1, N_0+2, ..., N$ compute the so-called CUSUM quantity $CS_l = \sum_{i=N_0+1}^{l}[g(\Psi_j^{(i)}) - \mu_N]$.

Yu and Mykland (1998) suggest to visually inspect the way it converges to the total sum. Note that $CS_N = 0$ by construction; however, for a well-mixing chain CS_l should converge to 0 fast and be displaying small random fluctuations around 0. Any clear pattern in the plot of CS_l against l would on the contrary be an indication of a slow-mixing chain. Brooks (1998) proposes a formal statistics to give a quantitative assessment of the indications provided by the CUSUM series of partial sums. In particular, Brooks (1998) suggests to compute:

$$d_t = \begin{cases} 1 & \text{if } \; CS_{l-1} < CS_l > CS_{l+1} \text{ or } CS_{l-1} > CS_l < CS_{l+1} \\ 0 & \text{otherwise} \end{cases}$$

for all $t = n_0 + 1, ..., n - 1$ (with n_0 representing the burn-in period and n the total number of draws). Then, the quantity

$$D_n = \frac{1}{n - n_0} \sum_{t=n_0+1}^{n-1} d_t$$

can be treated as a binomial random variable with mean $\frac{1}{2}$ and variance $\frac{1}{4(n-n_0)}$. For large n_0 this will approach a normal random variable with the same mean and variance, so a lack of convergence could be detected if the absolute value of D_n lies outside the interval $\frac{1}{2} \pm z_{\alpha/2}\sqrt{\frac{1}{4(n-n_0)}}$. The latter result would hold if the draws were effectively iid and generated by a symmetric distribution. This is not the case for many of our parameters as the draws are by construction autocorrelated (they are the outcome of a Markov chain) and are likely to lead in many cases to asymmetric distributions. In addition, the length of the burn-in period is not known *a priori*. Brooks (1998) suggests to deal with the asymmetry problem by computing the CS quantities with respect to the sample median instead of the sample mean μ_N, while the autocorrelation can be removed by "thinning" the sample of draws, i.e. by selecting draws so that in the chain they are distanced by a "thin" factor H. Brooks' statistics can be used both for determining the burn-in period and the most appropriate value for the "thin" factor H. Brooks (1998) shows that a necessary condition for convergence is that the statistics D_n remains stable for different values of n. Therefore, we have computed the statistics for 100 samples of draws of length n, with burn-in $n_0 = n/2$, with $n = 500000, 505000, 510000, ..., 1000000$ for the univariate model and $n = 1000000, 1010000, 1020000, ..., 2000000$ for the multivariate model. The results are shown in the figures (14)-(15).

For all models, the D_n statistics appears to stabilize around the 60th sample, corresponding to burn-in of 400000 draws for the univariate model and 800000 for the multivariate ones.

The draws remaining after burn-in still display a considerable autocorrelation, as it can be checked by the correlograms reported in figures (16)-(17).

We therefore thin the sample of draws by a thin factor of H, which will be determined, again, on the basis of the D_n statistics. The optimal

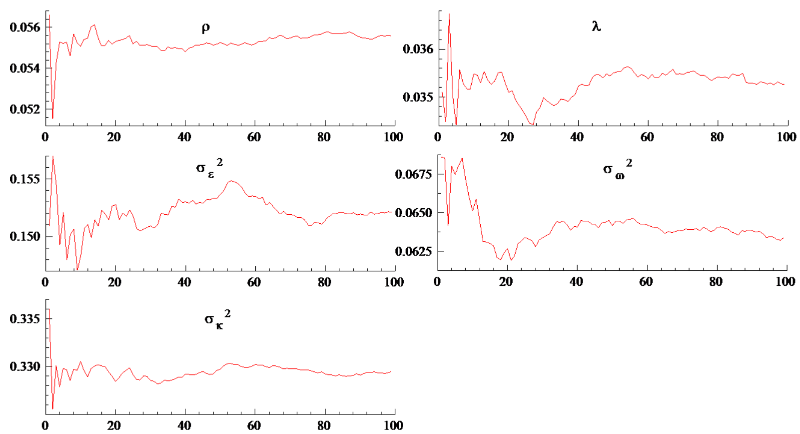

Figure 14: D_n statistics - univariate model - Italy

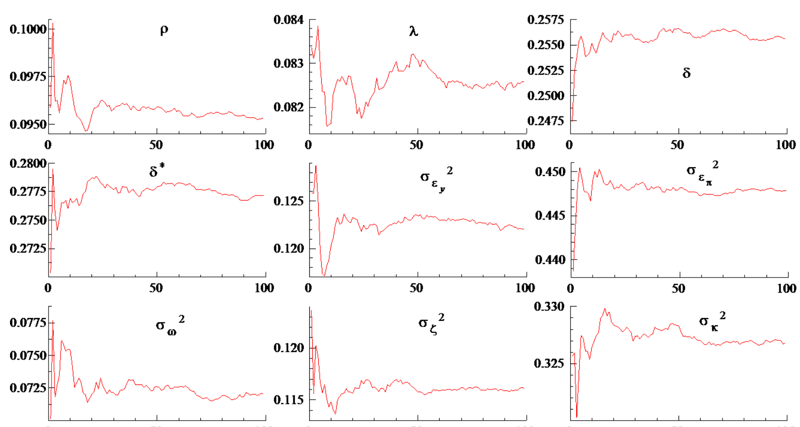

Figure 15: D_n statistics - multivariate model - Italy

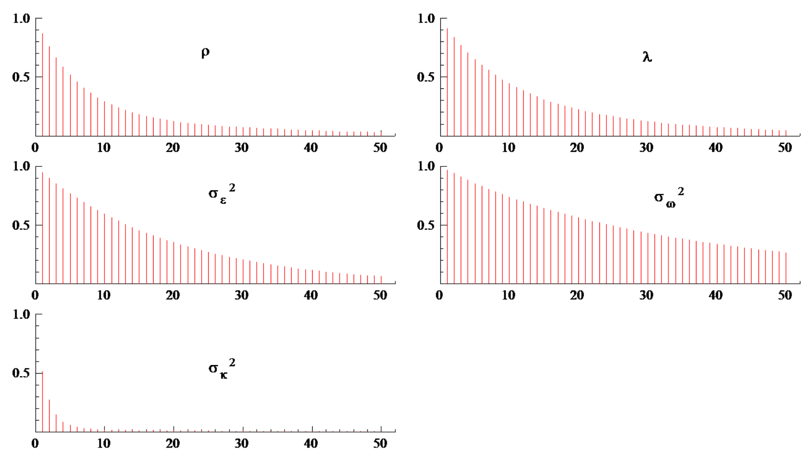

Figure 16: Correlogram - univariate model - Italy

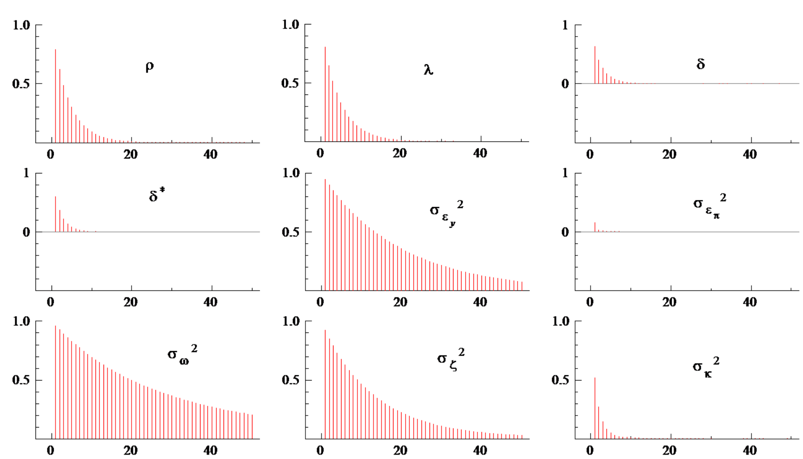

Figure 17: Correlogram - multivariate model - Italy

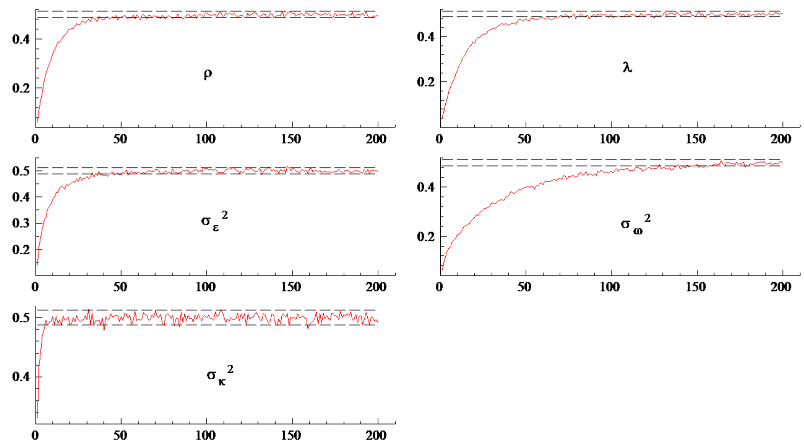

Figure 18: D_n statistics for different thin factors - univariate model - Italy

thin factor will be such that the statistics remain inside the 95% bounds of a normal random variable with mean $\frac{1}{2}$ and variance $\frac{1}{4(n-n_0)}$, given by $\frac{1}{2} \pm z_{\alpha/2}\sqrt{\frac{1}{4(n-n_0)}}$. In figures (18)-(19) we plot D_n against the thin factor H, with $H = 1, 2, ..., 200$. In order to keep the width of the 95% confidence interval constant, we compute the D_n statistics over samples of equal length. So, for instance, in the case of the univariate model, when $H = 1$ we compute D_n for the sample of 3000 draws from the 400001th to the 403000th, when H=2 we pick one draw out of 2 from the 400001th to the 406000th, and so on. A similar procedure is applied to the multivariate model.

For almost all parameters a thin factor of 100 appears to be sufficient for the D_n statistics to remain inside the asymptotic 95% interval and only in a few cases a thin factor of 200 is required. We choose the latter factor for all parameters, which implies that the total number of draws we retain for inference is 3000 for the univariate model and 6000 for the multivariate one.

As a further check of the convergence of the chain we compute, for the samples of draws selected above, the convergence diagnostics suggested by Geweke (1992). Geweke's test of stationarity of the distribution aims at comparing the behavior of the chain at the beginning and at the end of the sample (after burn-in); according to Geweke (1992), if we have a sequence of

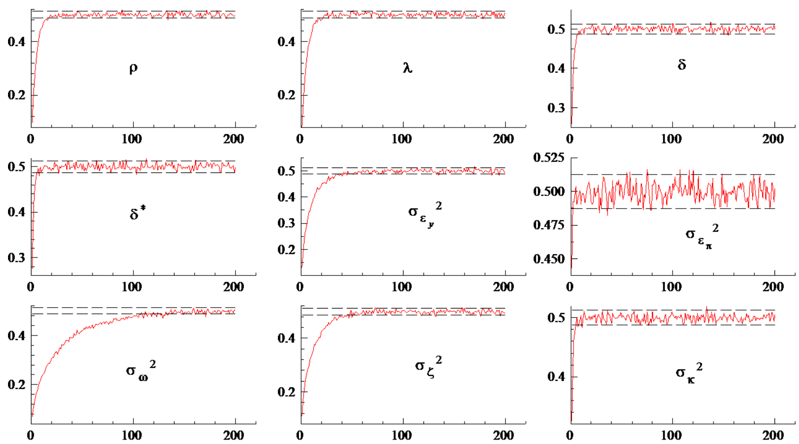

Figure 19: D_n statistics for different thin factors - multivariate model - Italy

$N = n - n_0$ draws (i.e. N draws after burn-in n_0) for the parameter Ψ_j, given a function $g(\Psi_j)$ we can construct mean values of the function for the first n_A and the last n_B draws $\bar{g}_A = \frac{\sum_{1=1}^{n_A} g(\Psi_j^{(i)})}{n_A}$ and $\bar{g}_B = \frac{\sum_{1=n_B+1}^{n} g(\Psi_j^{(i)})}{n_B}$ and get consistent estimates of the variance of $\bar{g}_A$ and $\bar{g}_B$ by their spectral densities at the 0 frequency $S_A(0)$ and $S_B(0)$, respectively. Then, if $n_A + n_B < N$ the distribution of the statistics

$$d = \frac{\bar{g}_A - \bar{g}_B}{\sqrt{\frac{S_A(0)}{n_A} + \frac{S_B(0)}{n_B}}}, \tag{26}$$

approaches a standard normal as $N \to \infty$. Geweke (1992) suggests to use $n_A = .1N$ and $n_B = .5N$.

We compute Geweke's statistics for the mean of the parameters and report the results in table A.1. As it can be easily checked for all parameters the statistics are well inside the 95% bounds of a standard normal ± 1.96, thus providing further evidence in favour of the fact that our chain has converged.

Table A.1 - Geweke's statistics				
	Univariate model		Multivariate model	
sample	whole	thinned	whole	thinned
ρ	-0.016	0.023	-0.026	-0.017
λ	0.012	0.102	-0.018	-0.011
δ	-	-	0.005	-0.108
δ^*	-	-	-0.004	0.074
$\sigma^2_{\varepsilon_y}$	-0.008	0.086	0.017	0.098
$\sigma^2_{\varepsilon_\pi}$	-	-	-0.004	0.040
σ^2_{ω}	0.003	0.035	0.013	0.031
σ^2_{ζ}	-	-	0.015	0.056
σ^2_{κ}	0.006	-0.005	0.007	0.008

RECENTLY PUBLISHED "TEMI" (*)

N. 916 – *The effect of organized crime on public funds*, by Guglielmo Barone and Gaia Narciso (June 2013).

N. 917 – *Relationship and transaction lending in a crisis*, by Patrick Bolton, Xavier Freixas, Leonardo Gambacorta and Paolo Emilio Mistrulli (July 2013).

N. 918 – *Macroeconomic effects of precautionary demand for oil*, by Alessio Anzuini, Patrizio Pagano and Massimiliano Pisani (July 2013).

N. 919 – *Skill upgrading and exports*, by Antonio Accetturo, Matteo Bugamelli and Andrea Lamorgese (July 2013).

N. 920 – *Tracking world trade and GDP in real time*, by Roberto Golinelli and Giuseppe Parigi (July 2013).

N. 921 – *Should monetary policy lean against the wind? An analysis based on a DSGE model with banking*, by Leonardo Gambacorta and Federico M. Signoretti (July 2013).

N. 922 – *Marshallian labor market pooling: evidence from Italy*, by Monica Andini, Guido de Blasio, Gilles Duranton and William C. Strange (July 2013).

N. 923 – *Do euro area countries respond asymmetrically to the common monetary policy?*, by Matteo Barigozzi, Antonio M. Conti and Matteo Luciani (July 2013).

N. 924 – *Trade elasticity and vertical specialisation*, by Ines Buono and Filippo Vergara Caffarelli (July 2013).

N. 925 – *Down and out in Italian towns: measuring the impact of economic downturns on crime*, by Guido de Blasio and Carlo Menon (July 2013).

N. 926 – *The procyclicality of foreign bank lending: evidence from the global financial crisis*, by Ugo Albertazzi and Margherita Bottero (July 2013).

N. 927 – *Macroeconomic and monetary policy surprises and the term structure of interest rates*, by Marcello Pericoli (September 2013).

N. 928 – *Central bank refinancing, interbank markets, and the hypothesis of liquidity hoarding: evidence from a euro-area banking system*, by Massimiliano Affinito (September 2013).

N. 929 – *Forecasting aggregate demand: analytical comparison of top-down and bottom-up approaches in a multivariate exponential smoothing framework*, by Giacomo Sbrana and Andrea Silvestrini (September 2013).

N. 930 – *Uncertainty and heterogeneity in factor models forecasting*, by Matteo Luciani and Libero Monteforte (September 2013).

N. 931 – *Economic insecurity and fertility intentions: the case of Italy*, by Francesca Modena, Concetta Rondinelli and Fabio Sabatini (September 2013).

N. 932 – *The role of regulation on entry: evidence from the Italian provinces*, by Francesco Bripi (September 2013).

N. 933 – *The management of interest rate risk during the crisis: evidence from Italian banks*, by Lucia Esposito, Andrea Nobili and Tiziano Ropele (September 2013).

N. 934 – *Central bank and government in a speculative attack model*, by Giuseppe Cappelletti and Lucia Esposito (September 2013).

N. 935 – *Ita-coin: a new coincident indicator for the Italian economy*, by Valentina Aprigliano and Lorenzo Bencivelli (October 2013).

N. 936 – *The Italian financial cycle: 1861-2011*, by Riccardo De Bonis and Andrea Silvestrini (October 2013).

N. 937 – *The effect of tax enforcement on tax morale*, by Antonio Filippin, Carlo V. Fiorio and Eliana Viviano (October 2013).

(*) Requests for copies should be sent to:
Banca d'Italia – Servizio Studi di struttura economica e finanziaria – Divisione Biblioteca e Archivio storico – Via Nazionale, 91 – 00184 Rome – (fax 0039 06 47922059). They are available on the Internet www.bancaditalia.it.

2010

A. PRATI and M. SBRACIA, *Uncertainty and currency crises: evidence from survey data*, Journal of Monetary Economics, v, 57, 6, pp. 668-681, **TD No. 446 (July 2002).**

L. MONTEFORTE and S. SIVIERO, *The Economic Consequences of Euro Area Modelling Shortcuts*, Applied Economics, v. 42, 19-21, pp. 2399-2415, **TD No. 458 (December 2002).**

S. MAGRI, *Debt maturity choice of nonpublic Italian firms* , Journal of Money, Credit, and Banking, v.42, 2-3, pp. 443-463, **TD No. 574 (January 2006).**

G. DE BLASIO and G. NUZZO, *Historical traditions of civicness and local economic development,* Journal of Regional Science, v. 50, 4, pp. 833-857, **TD No. 591 (May 2006).**

E. IOSSA and G. PALUMBO, *Over-optimism and lender liability in the consumer credit market,* Oxford Economic Papers, v. 62, 2, pp. 374-394, **TD No. 598 (September 2006).**

S. NERI and A. NOBILI, *The transmission of US monetary policy to the euro area,* International Finance, v. 13, 1, pp. 55-78, **TD No. 606 (December 2006).**

F. ALTISSIMO, R. CRISTADORO, M. FORNI, M. LIPPI and G. VERONESE, *New Eurocoin: Tracking Economic Growth in Real Time,* Review of Economics and Statistics, v. 92, 4, pp. 1024-1034, **TD No. 631 (June 2007).**

U. ALBERTAZZI and L. GAMBACORTA, *Bank profitability and taxation,* Journal of Banking and Finance, v. 34, 11, pp. 2801-2810, **TD No. 649 (November 2007).**

L. GAMBACORTA and C. ROSSI, *Modelling bank lending in the euro area: a nonlinear approach,* Applied Financial Economics, v. 20, 14, pp. 1099-1112 ,**TD No. 650 (November 2007).**

M. IACOVIELLO and S. NERI, *Housing market spillovers: evidence from an estimated DSGE model,* American Economic Journal: Macroeconomics, v. 2, 2, pp. 125-164, **TD No. 659 (January 2008).**

F. BALASSONE, F. MAURA and S. ZOTTERI, *Cyclical asymmetry in fiscal variables in the EU*, Empirica, **TD No. 671**, v. 37, 4, pp. 381-402 **(June 2008).**

F. D'AMURI, GIANMARCO I.P. OTTAVIANO and G. PERI, *The labor market impact of immigration on the western german labor market in the 1990s,* European Economic Review, v. 54, 4, pp. 550-570, **TD No. 687 (August 2008).**

A. ACCETTURO, *Agglomeration and growth: the effects of commuting costs,* Papers in Regional Science, v. 89, 1, pp. 173-190, **TD No. 688 (September 2008).**

S. NOBILI and G. PALAZZO, *Explaining and forecasting bond risk premiums,* Financial Analysts Journal, v. 66, 4, pp. 67-82, **TD No. 689 (September 2008).**

A. B. ATKINSON and A. BRANDOLINI, *On analysing the world distribution of income*, World Bank Economic Review , v. 24, 1 , pp. 1-37, **TD No. 701 (January 2009).**

R. CAPPARIELLO and R. ZIZZA, *Dropping the Books and Working Off the Books,* Labour, v. 24, 2, pp. 139-162 ,**TD No. 702 (January 2009).**

C. NICOLETTI and C. RONDINELLI, *The (mis)specification of discrete duration models with unobserved heterogeneity: a Monte Carlo study,* Journal of Econometrics, v. 159, 1, pp. 1-13, **TD No. 705 (March 2009).**

L. FORNI, A. GERALI and M. PISANI, *Macroeconomic effects of greater competition in the service sector: the case of Italy,* Macroeconomic Dynamics, v. 14, 5, pp. 677-708, **TD No. 706 (March 2009).**

Y. ALTUNBAS, L. GAMBACORTA and D. MARQUÉS-IBÁÑEZ, *Bank risk and monetary policy,* Journal of Financial Stability, v. 6, 3, pp. 121-129, **TD No. 712 (May 2009).**

V. DI GIACINTO, G. MICUCCI and P. MONTANARO, *Dynamic macroeconomic effects of public capital: evidence from regional Italian data,* Giornale degli economisti e annali di economia, v. 69, 1, pp. 29-66, **TD No. 733 (November 2009).**

F. COLUMBA, L. GAMBACORTA and P. E. MISTRULLI, *Mutual Guarantee institutions and small business finance,* Journal of Financial Stability, v. 6, 1, pp. 45-54, **TD No. 735 (November 2009).**

A. GERALI, S. NERI, L. SESSA and F. M. SIGNORETTI, *Credit and banking in a DSGE model of the Euro Area,* Journal of Money, Credit and Banking, v. 42, 6, pp. 107-141, **TD No. 740 (January 2010).**

M. AFFINITO and E. TAGLIAFERRI, *Why do (or did?) banks securitize their loans? Evidence from Italy*, Journal of Financial Stability, v. 6, 4, pp. 189-202, **TD No. 741 (January 2010).**

S. FEDERICO, *Outsourcing versus integration at home or abroad and firm heterogeneity,* Empirica, v. 37, 1, pp. 47-63, **TD No. 742 (February 2010).**

V. DI GIACINTO, *On vector autoregressive modeling in space and time,* Journal of Geographical Systems, v. 12, 2, pp. 125-154, **TD No. 746 (February 2010).**

L. FORNI, A. GERALI and M. PISANI, *The macroeconomics of fiscal consolidations in euro area countries,* Journal of Economic Dynamics and Control, v. 34, 9, pp. 1791-1812, **TD No. 747 (March 2010).**

S. MOCETTI and C. PORELLO, *How does immigration affect native internal mobility? new evidence from Italy,* Regional Science and Urban Economics, v. 40, 6, pp. 427-439, **TD No. 748 (March 2010).**

A. DI CESARE and G. GUAZZAROTTI, *An analysis of the determinants of credit default swap spread changes before and during the subprime financial turmoil,* Journal of Current Issues in Finance, Business and Economics, v. 3, 4, pp., **TD No. 749 (March 2010).**

P. CIPOLLONE, P. MONTANARO and P. SESTITO, *Value-added measures in Italian high schools: problems and findings*, Giornale degli economisti e annali di economia, v. 69, 2, pp. 81-114, **TD No. 754 (March 2010).**

A. BRANDOLINI, S. MAGRI and T. M SMEEDING, *Asset-based measurement of poverty*, Journal of Policy Analysis and Management, v. 29, 2 , pp. 267-284, **TD No. 755 (March 2010).**

G. CAPPELLETTI, *A Note on rationalizability and restrictions on beliefs,* The B.E. Journal of Theoretical Economics, v. 10, 1, pp. 1-11,**TD No. 757 (April 2010).**

S. DI ADDARIO and D. VURI, *Entrepreneurship and market size. the case of young college graduates in Italy*, Labour Economics, v. 17, 5, pp. 848-858, **TD No. 775 (September 2010).**

A. CALZA and A. ZAGHINI, *Sectoral money demand and the great disinflation in the US*, Journal of Money, Credit, and Banking, v. 42, 8, pp. 1663-1678, **TD No. 785 (January 2011).**

2011

S. DI ADDARIO, *Job search in thick markets*, Journal of Urban Economics, v. 69, 3, pp. 303-318, **TD No. 605 (December 2006).**

F. SCHIVARDI and E. VIVIANO, *Entry barriers in retail trade*, Economic Journal, v. 121, 551, pp. 145-170, **TD No. 616 (February 2007).**

G. FERRERO, A. NOBILI and P. PASSIGLIA, *Assessing excess liquidity in the Euro Area: the role of sectoral distribution of money,* Applied Economics, v. 43, 23, pp. 3213-3230, **TD No. 627 (April 2007).**

P. E. MISTRULLI, *Assessing financial contagion in the interbank market: maximun entropy versus observed interbank lending patterns,* Journal of Banking & Finance, v. 35, 5, pp. 1114-1127, **TD No. 641 (September 2007).**

E. CIAPANNA, *Directed matching with endogenous markov probability: clients or competitors?*, The RAND Journal of Economics, v. 42, 1, pp. 92-120, **TD No. 665 (April 2008).**

M. BUGAMELLI and F. PATERNÒ, *Output growth volatility and remittances*, Economica, v. 78, 311, pp. 480-500, **TD No. 673 (June 2008).**

V. DI GIACINTO e M. PAGNINI, *Local and global agglomeration patterns: two econometrics-based indicators,* Regional Science and Urban Economics, v. 41, 3, pp. 266-280, **TD No. 674 (June 2008).**

G. BARONE and F. CINGANO, *Service regulation and growth: evidence from OECD countries,* Economic Journal, v. 121, 555, pp. 931-957, **TD No. 675 (June 2008).**

P. SESTITO and E. VIVIANO, *Reservation wages: explaining some puzzling regional patterns*, Labour, v. 25, 1, pp. 63-88, **TD No. 696 (December 2008).**

R. GIORDANO and P. TOMMASINO, *What determines debt intolerance? The role of political and monetary institutions*, European Journal of Political Economy, v. 27, 3, pp. 471-484, **TD No. 700 (January 2009).**

P. ANGELINI, A. NOBILI e C. PICILLO, *The interbank market after August 2007: What has changed, and why?*, Journal of Money, Credit and Banking, v. 43, 5, pp. 923-958, **TD No. 731 (October 2009).**

G. BARONE and S. MOCETTI, *Tax morale and public spending inefficiency,* International Tax and Public Finance, v. 18, 6, pp. 724-49, **TD No. 732 (November 2009).**

L. FORNI, A. GERALI and M. PISANI, *The Macroeconomics of Fiscal Consolidation in a Monetary Union: the Case of Italy,* in Luigi Paganetto (ed.), Recovery after the crisis. Perspectives and policies, VDM Verlag Dr. Muller, **TD No. 747 (March 2010).**

A. DI CESARE and G. GUAZZAROTTI, *An analysis of the determinants of credit default swap changes before and during the subprime financial turmoil*, in Barbara L. Campos and Janet P. Wilkins (eds.), The Financial Crisis: Issues in Business, Finance and Global Economics, New York, Nova Science Publishers, Inc., **TD No. 749 (March 2010).**

A. LEVY and A. ZAGHINI, *The pricing of government guaranteed bank bonds,* Banks and Bank Systems, v. 6, 3, pp. 16-24, **TD No. 753 (March 2010).**

G. BARONE, R. FELICI and M. PAGNINI, *Switching costs in local credit markets,* International Journal of Industrial Organization, v. 29, 6, pp. 694-704, **TD No. 760 (June 2010).**

G. BARBIERI, C. ROSSETTI e P. SESTITO, *The determinants of teacher mobility: evidence using Italian teachers' transfer applications*, Economics of Education Review, v. 30, 6, pp. 1430-1444, **TD No. 761 (marzo 2010).**

G. GRANDE and I. VISCO, *A public guarantee of a minimum return to defined contribution pension scheme members,* The Journal of Risk, v. 13, 3, pp. 3-43, **TD No. 762 (June 2010).**

P. DEL GIOVANE, G. ERAMO and A. NOBILI, *Disentangling demand and supply in credit developments: a survey-based analysis for Italy,* Journal of Banking and Finance, v. 35, 10, pp. 2719-2732, **TD No. 764 (June 2010).**

G. BARONE and S. MOCETTI, *With a little help from abroad: the effect of low-skilled immigration on the female labour supply,* Labour Economics, v. 18, 5, pp. 664-675, **TD No. 766 (July 2010).**

S. FEDERICO and A. FELETTIGH, *Measuring the price elasticity of import demand in the destination markets of italian exports,* Economia e Politica Industriale, v. 38, 1, pp. 127-162, **TD No. 776 (October 2010).**

S. MAGRI and R. PICO, *The rise of risk-based pricing of mortgage interest rates in Italy*, Journal of Banking and Finance, v. 35, 5, pp. 1277-1290, **TD No. 778 (October 2010).**

M. TABOGA, *Under/over-valuation of the stock market and cyclically adjusted earnings*, International Finance, v. 14, 1, pp. 135-164, **TD No. 780 (December 2010).**

S. NERI, *Housing, consumption and monetary policy: how different are the U.S. and the Euro area?*, Journal of Banking and Finance, v.35, 11, pp. 3019-3041, **TD No. 807 (April 2011).**

V. CUCINIELLO, *The welfare effect of foreign monetary conservatism with non-atomistic wage setters*, Journal of Money, Credit and Banking, v. 43, 8, pp. 1719-1734, **TD No. 810 (June 2011).**

A. CALZA and A. ZAGHINI, *welfare costs of inflation and the circulation of US currency abroad,* The B.E. Journal of Macroeconomics, v. 11, 1, Art. 12, **TD No. 812 (June 2011).**

I. FAIELLA, *La spesa energetica delle famiglie italiane*, Energia, v. 32, 4, pp. 40-46, **TD No. 822 (September 2011).**

R. DE BONIS and A. SILVESTRINI, *The effects of financial and real wealth on consumption: new evidence from OECD countries,* Applied Financial Economics, v. 21, 5, pp. 409–425, **TD No. 837 (November 2011).**

F. CAPRIOLI, P. RIZZA and P. TOMMASINO, *Optimal fiscal policy when agents fear government default*, Revue Economique, v. 62, 6, pp. 1031-1043, **TD No. 859 (March 2012).**

2012

F. CINGANO and A. ROSOLIA, *People I know: job search and social networks*, Journal of Labor Economics, v. 30, 2, pp. 291-332, **TD No. 600 (September 2006).**

G. GOBBI and R. ZIZZA, *Does the underground economy hold back financial deepening? Evidence from the italian credit market*, Economia Marche, Review of Regional Studies, v. 31, 1, pp. 1-29, **TD No. 646 (November 2006).**

S. MOCETTI, *Educational choices and the selection process before and after compulsory school*, Education Economics, v. 20, 2, pp. 189-209, **TD No. 691 (September 2008).**

P. PINOTTI, M. BIANCHI and P. BUONANNO, *Do immigrants cause crime?*, Journal of the European Economic Association , v. 10, 6, pp. 1318–1347, **TD No. 698 (December 2008).**

M. PERICOLI and M. TABOGA, *Bond risk premia, macroeconomic fundamentals and the exchange rate*, International Review of Economics and Finance, v. 22, 1, pp. 42-65, **TD No. 699 (January 2009).**

F. LIPPI and A. NOBILI, *Oil and the macroeconomy: a quantitative structural analysis,* Journal of European Economic Association, v. 10, 5, pp. 1059-1083, **TD No. 704 (March 2009).**

G. ASCARI and T. ROPELE, *Disinflation in a DSGE perspective: sacrifice ratio or welfare gain ratio?,* Journal of Economic Dynamics and Control, v. 36, 2, pp. 169-182, **TD No. 736 (January 2010).**

S. FEDERICO, *Headquarter intensity and the choice between outsourcing versus integration at home or abroad*, Industrial and Corporate Chang, v. 21, 6, pp. 1337-1358, **TD No. 742 (February 2010).**

I. BUONO and G. LALANNE, *The effect of the Uruguay Round on the intensive and extensive margins of trade,* Journal of International Economics, v. 86, 2, pp. 269-283, **TD No. 743 (February 2010).**

S. GOMES, P. JACQUINOT and M. PISANI, *The EAGLE. A model for policy analysis of macroeconomic interdependence in the euro area,* Economic Modelling, v. 29, 5, pp. 1686-1714, **TD No. 770 (July 2010).**

A. ACCETTURO and G. DE BLASIO, *Policies for local development: an evaluation of Italy's "Patti Territoriali",* Regional Science and Urban Economics, v. 42, 1-2, pp. 15-26, **TD No. 789 (January 2006).**

F. BUSETTI and S. DI SANZO, *Bootstrap LR tests of stationarity, common trends and cointegration,* Journal of Statistical Computation and Simulation, v. 82, 9, pp. 1343-1355, **TD No. 799 (March 2006).**

S. NERI and T. ROPELE, *Imperfect information, real-time data and monetary policy in the Euro area,* The Economic Journal, v. 122, 561, pp. 651-674, **TD No. 802 (March 2011).**

G. CAPPELLETTI, G. GUAZZAROTTI and P. TOMMASINO, *What determines annuity demand at retirement?,* The Geneva Papers on Risk and Insurance – Issues and Practice, pp. 1-26, **TD No. 805 (April 2011).**

A. ANZUINI and F. FORNARI, *Macroeconomic determinants of carry trade activity,* Review of International Economics, v. 20, 3, pp. 468-488, **TD No. 817 (September 2011).**

M. AFFINITO, *Do interbank customer relationships exist? And how did they function in the crisis? Learning from Italy*, Journal of Banking and Finance, v. 36, 12, pp. 3163-3184, **TD No. 826 (October 2011).**

R. CRISTADORO and D. MARCONI, *Household savings in China,* Journal of Chinese Economic and Business Studies, v. 10, 3, pp. 275-299, **TD No. 838 (November 2011).**

P. GUERRIERI and F. VERGARA CAFFARELLI, *Trade Openness and International Fragmentation of Production in the European Union: The New Divide?,* Review of International Economics, v. 20, 3, pp. 535-551, **TD No. 855 (February 2012).**

V. DI GIACINTO, G. MICUCCI and P. MONTANARO, *Network effects of public transposrt infrastructure: evidence on Italian regions,* Papers in Regional Science, v. 91, 3, pp. 515-541, **TD No. 869 (July 2012).**

A. FILIPPIN and M. PACCAGNELLA, *Family background, self-confidence and economic outcomes,* Economics of Education Review, v. 31, 5, pp. 824-834, **TD No. 875 (July 2012).**

2013

F. CINGANO and P. PINOTTI, *Politicians at work. The private returns and social costs of political connections*, Journal of the European Economic Association, v. 11, 2, pp. 433-465, **TD No. 709 (May 2009).**

F. BUSETTI and J. MARCUCCI, *Comparing forecast accuracy: a Monte Carlo investigation*, International Journal of Forecasting, v. 29, 1, pp. 13-27, **TD No. 723 (September 2009).**

D. DOTTORI, S. I-LING and F. ESTEVAN, *Reshaping the schooling system: The role of immigration*, Journal of Economic Theory, v. 148, 5, pp. 2124-2149, **TD No. 726 (October 2009).**

A. FINICELLI, P. PAGANO and M. SBRACIA, *Ricardian Selection*, Journal of International Economics, v. 89, 1, pp. 96-109, **TD No. 728 (October 2009).**

L. MONTEFORTE and G. MORETTI, *Real-time forecasts of inflation: the role of financial variables*, Journal of Forecasting, v. 32, 1, pp. 51-61, **TD No. 767 (July 2010).**

E. GAIOTTI, *Credit availablility and investment: lessons from the "Great Recession"*, European Economic Review, v. 59, pp. 212-227, **TD No. 793 (February 2011).**

A. ACCETTURO e L. INFANTE, *Skills or Culture? An analysis of the decision to work by immigrant women in Italy,* IZA Journal of Migration, v. 2, 2, pp. 1-21, **TD No. 815 (July 2011).**

A. DE SOCIO, *Squeezing liquidity in a "lemons market" or asking liquidity "on tap"*, Journal of Banking and Finance, v. 27, 5, pp. 1340-1358, **TD No. 819 (September 2011).**

M. FRANCESE and R. MARZIA, *is there Room for containing healthcare costs? An analysis of regional spending differentials in Italy,* The European Journal of Health Economics (DOI 10.1007/s10198-013-0457-4), **TD No. 828 (October 2011).**

G. BARONE and G. DE BLASIO, *Electoral rules and voter turnout,* International Review of Law and Economics, v. 36, 1, pp. 25-35, **TD No. 833 (November 2011).**

E. GENNARI and G. MESSINA, *How sticky are local expenditures in Italy? Assessing the relevance of the flypaper effect through municipal data,* International Tax and Public Finance (DOI: 10.1007/s10797-013-9269-9), **TD No. 844 (January 2012).**

A. ANZUINI, M. J. LOMBARDI and P. PAGANO, *The impact of monetary policy shocks on commodity prices*, International Journal of Central Banking, v. 9, 3, pp. 119-144, **TD No. 851 (February 2012).**

S. FEDERICO, *Industry dynamics and competition from low-wage countries: evidence on Italy*, Oxford Bulletin of Economics and Statistics (DOI: 10.1111/obes.12023), **TD No. 879 (September 2012).**

FORTHCOMING

A. MERCATANTI, *A likelihood-based analysis for relaxing the exclusion restriction in randomized experiments with imperfect compliance*, Australian and New Zealand Journal of Statistics, **TD No. 683 (August 2008).**

M. TABOGA, *The riskiness of corporate bonds*, Journal of Money, Credit and Banking, **TD No. 730 (October 2009).**

F. D'AMURI, *Gli effetti della legge 133/2008 sulle assenze per malattia nel settore pubblico,* Rivista di Politica Economica, **TD No. 787 (January 2011).**

E. COCOZZA and P. PISELLI, *Testing for east-west contagion in the European banking sector during the financial crisis,* in R. Matoušek; D. Stavárek (eds.), Financial Integration in the European Union, Taylor & Francis, **TD No. 790 (February 2011).**

R. BRONZINI and E. IACHINI, *Are incentives for R&D effective? Evidence from a regression discontinuity approach,* American Economic Journal : Economic Policy, **TD No. 791 (February 2011).**

F. NUCCI and M. RIGGI, *Performance pay and changes in U.S. labor market dynamics*, Journal of Economic Dynamics and Control, **TD No. 800 (March 2011).**

O. BLANCHARD and M. RIGGI, *Why are the 2000s so different from the 1970s? A structural interpretation of changes in the macroeconomic effects of oil prices*, Journal of the European Economic Association, **TD No. 835 (November 2011).**

F. D'AMURI and G. PERI, *Immigration, jobs and employment protection: evidence from Europe before and during the Great Recession,* Journal of the European Economic Association, **TD No. 886 (October 2012).**

R. DE BONIS and A. SILVESTRINI, *The Italian financial cycle: 1861-2011,* Cliometrica, **TD No. 936 (October 2013).**