Pawel Baranowski
National Bank of Poland and University of Lodz
pawel.baranowski@nbp.pl

Zbigniew Kuchta
University of Lodz
zbyszek.kuchta@gmail.com

Changes in nominal rigidities in Poland – a regime switching DSGE perspective[1]

Abstract:

In this paper, we estimate Erceg, Henderson and Levin's [2000] sticky price and sticky wage dynamic stochastic general equilibrium (DSGE) model while allowing for wage or price Calvo parameters regime switching and compare this with the constant-parameters model. Our results suggest that the model with price and wage rigidity switching is strongly favored by the data. However, we do not find significant evidence in support of independent Markov chains. Moreover, we identify historical periods when price and wage stickiness were low and show that during such periods, the economy reacts more strongly to structural shocks.

Keywords: nominal rigidities, Markov-switching DSGE models, Bayesian model comparison, regime switching.

JEL codes: C11, E31, E32, J30, P22.

[1] We acknowledge support received from the Polish National Science Centre under Grant DEC-2014/15/B/HS4/01996. The views presented here do not necessarily represent the views of the affiliated institutions.

Introduction

Dynamic stochastic general equilibrium models (DSGE) are the cornerstone of modern macroeconomics. These models have traditionally been based on microeconomic assumptions on the intertemporal optimizing behaviors of households and firms. Parameters that govern technology and preferences, macroeconomic policy or structural shocks are treated as time-invariant. This feature may limit constant-parameters model capacities to explain certain episodes (e.g., Great Moderation or disinflation processes occurring during the Volcker chairmanship). As an alternative to the constant-parameters approach, several authors have proposed DSGE models that allow one to switch structural parameters based on the actual state of the economy (MS-DSGE henceforth). Numerous studies have investigated monetary policy rules and/or shock parameters [see, among others: Schorfheide, 2005; Davig, Doh, 2008; Bianchi, 2012; Baele et. al., 2015]. Less attention has been placed on explicit changes in nominal rigidities, which play a key role in mechanisms of shock propagation and which often ensure the real effects of monetary policy.

As a transition economy, Poland experienced major structural changes during the early 1990s that resulted in high inflation rates and high levels of unemployment. Throughout its transition, the country experienced a long disinflation period that was accompanied by several abrupt structural changes (i.e., the adoption of inflation targets and a fully floating exchange rate regime, VAT changes, sectoral deregulation and EU accession). These factors exogenously change institutional frameworks or market conditions faced by firms, raising questions concerning possible nominal rigidity changes even more appealing.

In this paper, we estimate Erceg, Henderson and Levin's [2000] sticky price and sticky wage model with regime changes in the degree of nominal rigidities. The analysis is based on Bayesian model comparisons that involve monthly data on the Polish economy for 1996:8 to 2015:6. Like Rabanal and Rubio-Ramirez [2005, 2008] and Liu, Waggoner and Zha [2011], we use a modified harmonic mean estimator to find marginal data densities that reveal the model's fit with the data and performance in terms of one-step-ahead forecasting [An, Schorfheide, 2007].

A number of recent papers have analyzed changes in the degree of nominal rigidities based on micro data [e.g., Berradi et al., 2015; Chakraborty et al., 2015; for Poland: Macias, Makarski, 2013]. To our knowledge, only few papers have addressed switching degrees of nominal rigidities based on aggregate data [Eo, 2009; Liu, Mumtaz, 2011; Lhuisser, Zabelina, 2015]. However, none of these studies take wage rigidities into account. Hence, the present study is novel in that it allows for (and tests) both price and wage rigidity regime switches. Second, the paper compares independent regime changes in price and wage rigidity parameters to changes following common Markov process for both parameters. As nominal rigidities determine the slope of the Phillips curve, our work also contributes to the debate on the variations of this slope [e.g., Chortareas, Magonis, Panagiotidis, 2012; Vavra, 2014] and to the monetary policy transmission mechanism.

Using our proposed model, we identify two regimes even though we apply identical prior distributions across the regimes. The data strongly favor regime switching degree specifications of both price and wage rigidity, although they do not support the case of independent regime switching relative to common regimes for both nominal rigidities. The timing of these regimes appears to be intuitive, e.g., low levels of price rigidity occur during higher inflation. Moreover, we find that reactions to monetary policy and technological shock vary considerably across the regimes.

The paper proceeds as follows: next section presents MS-DSGE model and details of Markov-switching specifications, third section describes the particular model used in investigation, fourth section presents methodology and data, fifth section shows our main results and the last section concludes.

DSGE model

This section presents the New Keynesian DSGE model. The model applied here is largely based on a work by Erceg, Henderson and Levin [2000] (EHL henceforth) that includes Calvo [1983] sticky prices and wages. The EHL model is theoretically appealing, as it implies that strict inflation targeting may not be an optimal strategy. On the other hand, it can be considered empirically plausible as it allows one to explain inflation persistence owing to the sluggish responses of real marginal costs [see Rabanal, Rubio-Ramirez, 2005; 2008; Kuchta, 2014].

The economy includes a perfectly competitive final goods producer, a continuum of monopolistically competitive intermediate goods producers that are indexed by $j \in [0;1]$, and continuum of households that are indexed by $i \in [0;1]$ and a perfectly competitive labor agency. We assume that final goods producing firms combine intermediate goods using technology at a constant level of substitution elasticity [see Dixit, Stiglitz, 1977]:

$$Y_t = \left[\int_0^1 \left(Y_t^j\right)^{\frac{1}{1+\tau_p}} dj\right]^{1+\tau_p}$$

where Y_t represents the final product, Y_t^j is a quantity of intermediate goods and $\tau_P > 0$ represents the monopolistic mark-up on the goods market. Each final goods producer tends to maximize profits while taking prices of final and intermediate goods, P_t^j, as a given. As a result, the optimal demand for intermediate goods is given by:

$$Y_t^j = \left(\frac{P_t^j}{P_t}\right)^{-\left(\frac{1+\tau_p}{\tau_p}\right)} Y_t$$

for all $j \in [0;1]$ and where:

$$P_t = \left[\int_0^1 \left(P_t^j\right)^{-\frac{1}{\tau_p}} dj\right]^{-\tau_p}$$

is a final good price.

Each intermediate good j is produced by a firm j using the following constant return-to-scale technology:

$$Y_t^j = \varepsilon_t^a L_t^j$$

where L_t^j is labor input, ε_t^a is an identical among firms technology level from which the logarithm evolves according to a stationary first-order autoregressive process:

$$\ln\varepsilon_t^a = \rho_a \ln\varepsilon_{t-1}^a + \eta_t^a; \qquad \eta_t^a \sim iidN(0;\, \sigma_a^2)$$

and $\rho_a \in (0;1)$ is an autoregressive parameter. Each firm has access to a perfectly competitive labor market and pays the real wage w_t for a labor unit. The introduction of linear production technology implies that real marginal costs do not depend on the amount of produced goods and are identical among firms:

$$RMC_t^j = \frac{w_t}{\varepsilon_t^a}$$

We assume that prices are sticky according to Calvo [1983] and Yun [1996]; however the parameter of price stickiness follows a first-order discrete Markov process with two states and the transition matrix given by:

$$P^p = \begin{bmatrix} p_{11}^p & 1 - p_{11}^p \\ 1 - p_{22}^p & p_{22}^p \end{bmatrix}$$

where $p_{ii}^p = \Pr\left(s_t^p = i \middle| s_{t-1}^p = i\right)$. More specifically, we assume that during each period t, a portion of randomly chosen prices $1 - \theta_p\left(s_t^p\right) \in (0;1)$, $s_t^p = \{1,2\}$ can be set optimally in order to maximize the expected value of future discounted firm real profits, which are expressed by:

$$E_t\left\{\sum_{\tau=0}^{\infty} \theta_p\left(s_t^p\right)^{\tau} \beta^{\tau} \frac{\lambda_{t+\tau}}{\lambda_t}\left(\frac{P_t^*}{P_{t+\tau}} Y_t^j - RTC_{t+\tau}\left(Y^j\right)\right)\right\}$$

under the constraint given by final producer demand, where: P_t^* is an optimal price level, $\beta^{\tau}\frac{\lambda_{t+\tau}}{\lambda_t}$ is a stochastic discount factor, $\theta_p\left(s_t^p\right)^{\tau}$ measures the probability that price set in period t will not be reoptimized up until period $t+\tau$, E_t is a rational expectations operator and $RTC_t\left(Y^j\right)$ represents the real total cost depending on the quantity of goods produced. The first order condition for a firm that can set price optimally is given by:

$$E_t\left\{\sum_{\tau=0}^{\infty}\left[\beta\theta_p\left(s_t^p\right)\right]^{\tau} \frac{\lambda_{t+\tau}}{\lambda_t} Y_t^* \left[\left(1+\tau_p\right) RMC_{t+\tau} - \frac{P_t^*}{P_{t+\tau}}\right]\right\} = 0$$

This implies that each firm sets prices in order to equate expected average future marginal revenues to average future expected mark-ups over real marginal costs with weights given by the probability of non-reoptimizing prices and stochastic discount factors. The other prices, namely $\theta_p(s_t^p)$, remain unchanged. The real marginal cost is constant with respect to produced goods and is identical among firms, and all firms face the same demand constraints. Hence, all firms that can optimally choose prices during period t set it at the same level (P_t^*). As a result, we can rewrite the final goods price as:

$$P_t = \left[\left(1-\theta_p\left(s_t^p\right)\right)\left(P_t^*\right)^{-\frac{1}{\tau_p}} + \theta_p\left(s_t^p\right)P_{t-1}^{-\frac{1}{\tau_p}}\right]^{-\tau_p}$$

We assume that all households maximize utility obtained through consumption, C_t^i, and labor effort. Each household supplies differentiated and imperfect substitutive labor services, L_t^i, to labor agency which combine them into homogeneous labor input and which sells them to firms. Labor agency aggregates household labor services using following formula:

$$L_t = \left[\int_0^1 \left(L_t^i\right)^{\frac{1}{1+\tau_w}} di\right]^{1+\tau_w}$$

where $\tau_w > 0$ represents a monopolistic household's mark-up. Labor agency maximizes profits based on the nominal wage of each household, W_t^i, and market nominal wages are taken as a given. As a result, the optimal demand for labor is given by:

$$L_t^i = \left(\frac{W_t^i}{W_t}\right)^{-\frac{1+\tau_w}{\tau_w}} L_t$$

for all $i \in [0;1]$ and where:

$$W_t = \left[\int_0^1 \left(W_t^i\right)^{-\frac{1}{\tau_w}} di\right]^{-\tau_w}$$

is a nominal wage in the economy. Finally, a household's lifetime utility function is given by:

$$E_t\left\{\sum_{\tau=0}^{\infty}\beta^{\tau}\,\varepsilon_{t+\tau}^{b}\left[\frac{\left(C_{t+\tau}^i\right)^{1-\delta_c}}{1-\delta_c} - \varepsilon_{t+\tau}^{l}\frac{\left(L_{t+\tau}^i\right)^{1+\delta_l}}{1+\delta_l}\right]\right\}$$

where $\beta \in (0; 1)$ is a discount factor, $\delta_c > 0$ is a relative risk averse parameter and $\delta_l > 0$ denotes inverse Frisch elasticity. The utility function is affected by two disturbances, a preference shock, ε_t^b, and a labor supply shock, ε_t^l. We assume that these shocks follow a first-order autoregressive process:

$$\ln\varepsilon_t^b = \rho_b \ln\varepsilon_{t-1}^b + \eta_t^b; \qquad \eta_t^b \sim iidN(0;\ \sigma_b^2)$$

$$\ln\varepsilon_t^l = \rho_l \ln\varepsilon_{t-1}^l + \eta_t^l; \qquad \eta_t^l \sim iidN(0;\ \sigma_l^2)$$

where $\rho_b \in (0; 1)$ and $\rho_l \in (0; 1)$ are autoregressive parameters.

Households receive income from labor; from financial investments, B_{t-1}^i, represented by one-period riskless nominal bonds; and from shares from firms that produce intermediate goods, d_t, assuming equal shares among particular households. Moreover, each household participates in state-contingent securities, D_t^i, which protect them from risks related to staggered wage settings. Hence, budget constraints in real terms can be expressed as:

$$\frac{B_t^i}{R_t P_t} + C_t^i = \frac{B_{t-1}^i}{P_t} + \frac{W_t^i}{P_t} L_t^i + D_t^i + d_t$$

where R_t is the short-term gross nominal interest rate.

Each household determines consumption and the quantity of bonds. The household's first order condition is given by a standard Euler equation with respect to consumption:

$$\varepsilon_t^b \left(C_t^i\right)^{-\delta_c} = \beta E_t \left\{ \varepsilon_{t+1}^b \left(C_{t+1}^i\right)^{-\delta_c} \frac{R_t}{\pi_{t+1}} \right\}$$

Moreover, the standard transversality condition should hold in each period:

$$\lim_{t\to\infty} \beta^t \varepsilon_t^b \left(C_t^i\right)^{-\delta_c} B_t^i = 0$$

We assume that each household can choose nominal wage conditionally according to the Calvo scheme. Like firm problems, we assume that during every period, a randomly chosen set of households of measure $1 - \theta_w(s_t^w)$, $s_t^w = \{1, 2\}$ can reoptimize wages while tending to maximize the lifetime utility function:

$$\max_{W_t^*} E_t \left\{ \sum_{s=0}^{\infty} \left(\beta \theta_w(s_t^w)\right)^s \varepsilon_{t+s}^b \left[\frac{\left(C_{t+s}^i\right)^{1-\delta_c}}{1-\delta_c} - \varepsilon_{t+s}^l \frac{\left(L_{t+s}^i\right)^{1+\delta_l}}{1+\delta_l} \right] \right\}$$

under budget constraints:

$$\frac{B_{t+s}^{i}}{R_{t+s}P_{t+s}} + C_{t+s}^{i} = \frac{B_{t+s-1}^{i}}{P_{t+s}} + \frac{W_t^*}{P_{t+s}} L_{t+s}^{i} + D_{t+s}^{i} + d_{t+s}$$

and labor agency demand function:

$$L_{t+s}^{*} = \left(\frac{W_t^*}{W_{t+s}}\right)^{-\frac{1+\tau_w}{\tau_w}} L_{t+s}$$

where W_t^* represents the optimal nominal wage. The rest of the wages, of measure $\theta_w(s_t^w)$, remain unchanged. Like price stickiness, for wages, we allow for parameter switching by assuming that parameter $\theta_w(s_t^w)$ is governed by a first-order discrete Markov process with two states and the transition matrix given by:

$$P^{w} = \begin{bmatrix} p_{11}^{w} & 1 - p_{11}^{w} \\ 1 - p_{22}^{w} & p_{22}^{w} \end{bmatrix}$$

where $p_{ii}^{w} = \Pr(s_t^w = i | s_{t-1}^w = i)$. The first order condition for wage choice is given by:

$$\sum_{s=0}^{\infty} \left(\beta\theta_w(s_t^w)\right)^s E_t \left\{ L_{t+s}^* \left[(1+\tau_w) MUL_{t+s}^* - \lambda_{t+s}^{i} \frac{W_t^*}{P_{t+s}} \right] \right\} = 0$$

According to this condition, wages are chosen in order to ensure that the expected stream of future marginal revenues is equal to the expected stream of future mark-ups over marginal costs, which are represented in this case by the marginal disutility of labor (MUL_t), where both are weighed by the future expected labor demand.

The introduction of state-contingent securities causes each household to be homogenous with respect to income regardless of the results of the Calvo lottery. Moreover, the utility function is separable with respect to consumption and labor efforts, and labor demand depends only on wages that are chosen by a household. Hence, we can limit ourselves to an investigation of symmetric equilibrium whereby all households that are able to set the wage optimally will select it at the same level.[2] This property allows us to rewrite the aggregate nominal wage in the economy as:

$$W_t = \left[\theta_w(s_t^w) W_{t-1}^{-\frac{1}{\tau_w}} + \left(1 - \theta_w(s_t^w)\right) (W_t^*)^{-\frac{1}{\tau_w}} \right]^{-\tau_w}$$

[2] State-contingent securities also ensure equilibrium symmetry.

In the remainder of this paper, we consider the equilibrium on labor and goods markets. In particular, we assume that the following conditions hold in every period:

$$\frac{1}{\Delta_p}\int_0^1 Y_t^j \, dj = Y_t$$

$$\frac{1}{\Delta_w}\int_0^1 L_t^i \, di = L_t$$

where $\Delta_p \equiv \int_0^1 \left(\frac{P_t^j}{P_t}\right)^{-\frac{1+\tau_p}{\tau_p}} dj \geq 1$ and $\Delta_w \equiv \int_0^1 \left(\frac{W_t^i}{W_t}\right)^{-\frac{1+\tau_w}{\tau_w}} di \geq 1$ measure the price and wage dispersion, respectively, which in both cases are directly related to staggered wage and price mechanisms [see e.g., Yun, 1996, p. 355]. As we are interested in a closed economy model without capital accumulation, the aggregate demand equation is given by:

$$Y_t = C_t$$

The model is closed by a monetary policy rule according to Taylor [1993] with interest rate smoothing of the following form:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho} \left(\left(\frac{\pi_t}{\pi}\right)^{\phi_\pi} \left(\frac{Y_t}{Y}\right)^{\phi_Y}\right)^{1-\rho} \exp(\eta_t^R)\,; \qquad \eta_t^R \sim iid\ N(0; \sigma_R^2)$$

where $\rho \in (0;1)$ is a smoothing parameter and where $\phi_\pi > 0$ and $\phi_Y > 0$ measure interest rate reactions with respect to inflation and the output gap, respectively. While the Taylor principle holds in our model with time-invariant parameters, we do not assume that central bank reactions to inflation must be always greater than one, as we are also interested in parameter vectors that allow for indeterminacy in one regime even when the linear rational expectations model solution exists and is unique.

Estimated models

The presented model allows us to consider five different specifications. In the first specification (CONSTANT), we assume that all parameters are time-invariant. This model is treated throughout our analysis as a benchmark specification. In the second specification (PRICES), we allow for Markov switching in the Calvo probability for prices $\theta_p(s_t^p)$, assuming that parameter $\theta_w(s_t^w)$ is time-invariant while estimating p_{11}^p and p_{22}^p probabilities. The third specification (WAGES) introduces the Markov switching mechanism for the Calvo wages parameter, $\theta_w(s_t^w)$, while imposing the price stickiness as time-invariant. As a consequence, we estimate p_{11}^w and p_{22}^w probabilities. In the fourth specification (SYNCHRONISED), we assume that both Calvo probabilities, namely $\theta_p(s_t^p)$, $\theta_w(s_t^w)$, are time-dependent according to the discrete first order Markov process while also assuming that both are governed by the same Markov chain. In this specification, we also estimate the transition probabilities for a common chain. In our last specification (INDEPENDENT), we relax the assumption on synchronized changes in price and wage rigidity and consider a model wherein both Calvo probabilities are governed by two independent Markov chains. In this specification, we also estimate the p_{11}^p, p_{22}^p, p_{11}^w, and p_{22}^w transition probabilities.[3]

Data and methods

Bayesian techniques are widely used to estimate DSGE models. These methods allow one to incorporate prior knowledge into statistical inferences while performing reliable model comparisons. The popular approach is based on state-space representations of linear rational expectation model (LRE) solutions; the Kalman filter, which is used to evaluate the likelihood function; and the MCMC algorithm, which is used to find posterior distribution draws [see, among others, An, Schorfheide, 2007; Fernandez-Villaverde, 2010; Guerron-Quintana, Nason, 2012].

Introducing Markov switching causes the estimation procedure to become much more complicated than it is in the constant-parameter case. This issue is twofold. First, Markov-switching linear rational expectation system solutions are much more complicated, as agents must consider that existing regime can change in the future. Moreover, a rational equilibrium can always be indeterminate in certain regimes, even if the solution of an entire system is unique [see Farmer, Waggoner, Zha, 2005]. As a

[3] We also account for switching: policy parameters, shocks' variances, and parameters governing persistence (corresponding results are shown in Appendix C).

consequence, popular methods of solving LRE that have been introduced, among others, by Blanchard and Kahn [1980], Klein [2000] and Sims [2001] cannot be used. Second, likelihood values must account for the fact that regimes can change in a sample. Hence, likelihood is dependent on possible state histories, causing the number of possible paths to grow exponentially.[4] As a result, the Kalman filter is difficult to apply [see Blagov, 2013; Alstadheim, Bjørnland, Maih, 2013].

Through our Bayesian estimations of MS-DSGE, we are interested in the vector of structural parameters, $\boldsymbol{\omega}$, in the vector of transition probabilities, $\boldsymbol{\varphi}$, and in states of the system, $\mathbf{S^T}$. These vectors are estimated together using the following Bayes theorem [see Schorfheide, 2005, p. 401]:

$$\mathrm{p}(\boldsymbol{\omega}, \boldsymbol{\varphi}, \mathbf{S^T} | \mathbf{Y^T}, \mathrm{M_i}) = \frac{\mathrm{p}(\mathbf{Y^T} | \boldsymbol{\omega}, \boldsymbol{\varphi}, \mathbf{S^T}, \mathrm{M_i}) \mathrm{p}(\mathbf{S^T} | \boldsymbol{\varphi}, \mathrm{M_i}) \mathrm{p}(\boldsymbol{\varphi}, \boldsymbol{\omega}, \mathrm{M_i})}{\mathrm{p}(\mathbf{Y^T}, \mathrm{M_i})}$$

where $\mathrm{p}(\mathbf{Y^T} | \boldsymbol{\omega}, \boldsymbol{\varphi}, \mathbf{S^T}, \mathrm{M_i})$ is the likelihood function of model $\mathrm{M_i}$, $\mathrm{p}(\mathbf{S^T} | \boldsymbol{\varphi}, \mathrm{M_i})$ denotes the prior distribution of the state, $\mathrm{p}(\boldsymbol{\varphi}, \boldsymbol{\omega}, \mathrm{M_i})$ is the prior for vectors of the structural parameters $\boldsymbol{\omega}$, and state probabilities $\boldsymbol{\varphi}$ and $\mathrm{p}(\mathbf{Y^T}, \mathrm{M_i})$ denote the marginal data density, which is given by:

$$\mathrm{p}(\mathbf{Y^T}, \mathrm{M_i}) = \int \mathrm{p}(\mathbf{Y^T} | \boldsymbol{\omega}, \boldsymbol{\varphi}, \mathbf{S^T}, \mathrm{M_i}) \mathrm{p}(\mathbf{S^T} | \boldsymbol{\varphi}, \mathrm{M_i}) \mathrm{p}(\boldsymbol{\varphi}, \boldsymbol{\omega}, \mathrm{M_i}) \, d(\boldsymbol{\omega}, \boldsymbol{\varphi}, \mathbf{S^T})$$

Marginal data density measures the model fit to the data and one-step-ahead forecasting performance [An, Schorfheide, 2007, p. 144-147] and is used in our Bayesian model comparisons. It is defined as an integral over whole parameters and state spaces, and it averages particular likelihoods treating priors for state probabilities and structural parameters as weights. It is thus sensitive to parameter dimensions and state spaces, and it punishes the model with more parameters when parameters are empirically irrelevant. As a consequence, a more complex model should not necessary be evaluated as better than a simpler model [see Rabanal, 2007, p. 924-925].

We estimate the models examined over several steps. In the first step, we log-linearize equilibrium conditions around the deterministic steady state with at a zero

[4] For example, if we consider a model with two possible states and evaluate likelihood function using 10 observations, the number of possible paths is equal to 2^{10}.

inflation rate.[5] We consider the non-inflationary long-run equilibrium, as it ensures that steady state in our model is time- and state-independent even when Calvo probabilities switch between particular regimes.[6] As a consequence, the steady state does not depend on particular system states.[7] In the second step, we apply perturbation methods with first-order approximation in order to find the solution to the Markov-switching linear rational expectation system. This solution allows us to find the transition equation for state space representation of the DSGE model. Next, we apply Kim and Nelson [1999] filter in order to evaluate the likelihood function. Finally, the MCMC algorithm with adaptation and delayed rejection is used to find draws from posterior distribution. Obtained draws are then used in order to obtain moments of marginal posterior distributions and to evaluate marginal data densities using the Modified Harmonic Mean Estimator (MHM) proposed by Geweke [1998].

MS-DSGE model Bayesian estimations allow us to compare different model specifications. It is worth noting that the comparison results are consistent, even when the models compared are misspecified or nonnested. Performed comparisons are based on the Posterior Odds Ratio given by:

$$POR_{i,j} = \frac{\mathrm{p}(\mathrm{M_i})}{\mathrm{p}(\mathrm{M_j})}\frac{\mathrm{p}(\mathbf{Y^T}, \mathrm{M_i})}{\mathrm{p}(\mathbf{Y^T}, \mathrm{M_j})}$$

where $\frac{\mathrm{p}(\mathrm{M_i})}{\mathrm{p}(\mathrm{M_j})}$ is a prior odds ratio and where $\frac{\mathrm{p}(\mathbf{Y^T},\mathrm{M_i})}{\mathrm{p}(\mathbf{Y^T},\mathrm{M_j})}$ is a Bayes factor. In evaluating a particular model, we apply Jeffreys' rules [see Kass, Raftery, 1995]. Accordingly, we treat model $\mathrm{M_i}$ as favored by the data when the posterior odds ratio is greater than 20 and as strictly favored by the data when the posterior odds ratio is greater than 150. Moreover, a posterior odds ratio of less than 3 is interpreted as an insignificant difference between compared models.

---

[5] The log-linear form of the EHL model is presented in Appendix A.

[6] Note that this approach excludes the possibility to analyze changes in inflation targeting and determines data filtering methods.

[7] It is theoretically interesting to consider a model with steady state depending on a particular system state. We omit this possibility, as the considered model is time-consuming to compute, even when we only consider a Markov chain with two states.

The models presented in the previous section are estimated using monthly data for the Polish economy for 1996:8 to 2015:6. Although most of the DSGE models are estimated using quarterly data, we prefer to use more frequently recorded data for two reasons. First, such data allow us to capture not only long- and medium-term regime changes but also short-term regime changes that cannot be found using quarterly data. Second, monthly data allow us to increase the number of observations, as DSGE model estimations for the Polish economy seem to suffer from a limited number of observations relative to similar studies on the U.S. economy or Eurozone. Our dataset includes[8] (i) monthly CPI inflation, (ii) industrial production volumes, (iii) money market interest rates measured based on WIBOR 1M and (iv) real wages. Before estimation, all of the series were filtered.

All variables in the theoretical model are expressed as a percentage deviation from the steady state. Moreover, the theoretical model does not exhibit a balanced growth path or inflation in the long run equilibrium. As a consequence, all series should be transformed prior to estimation.[9] Our approach was conducted as follows. First, all series (with the exception of interest rates) were seasonally adjusted using TRAMO/SEATS. Second, we removed trends from the logs of real variables using a Hodrick-Prescott (HP) filter.[10] Rather than excluding deterministic trends, the HP filter does not require explicit assumptions on the growth paths of potential outputs. We also exclude the first order difference filter, as it causes observables to be much more volatile, thus potentially generating very frequent and biased estimates of regime changes (especially when using monthly data). Moreover, we decided to remove deterministic trends of nominal variables for 1996:8 to 2003:12. During this period, Poland underwent a disinflation process, and the inflation target gradually declined. These processes appear difficult to explain using a model with constant long-run in-

[8] All data were collected from the Reuters DataStream database,

[9] Means of transforming data are always a source of controversy. Interesting discussions on this issue are provided in Canova [2009] and Chiaie [2009], among others.

[10] When we apply the HP filter, we use $\lambda = 129600$ as proposed by Ravn and Uhlig [2002].

flation rates[11], rendering regime changes rare and biased. Finally, we demeaned all of the series.

Priors

Before carrying out estimations, it is necessary to specify prior distributions for estimated parameters. Smets and Wouters [2003] proposed to dividing a vector of parameters into two groups. The first group includes these parameters, which are calibrated and treated as a constant in the estimation. The second group includes parameters that are estimated. We follow this approach and calibrate[12] the discount factor, β; the inverse of the labor supply elasticity level, δ_l; and household and firm monopolistic mark-up levels denoted by τ_w and τ_p, respectively. We use a value of 0.997 for the parameter β, implying that the annual steady-state real interest rate is equal to 4%. This value appears to be consistent with previous quarterly DSGE model estimations for the Polish economy. For the δ_l parameter, we select a value of 1.25, which lies between micro- and macro-evidence [see Peterman, 2012]. The steady-state firm mark-up level τ_P is set as 0.1, which is slightly above Hagemejer and Popowski's [2014] estimated value. The same value was selected for the τ_w parameter. Both imply that the elasticities of labor and good demand are equal to 11.

The rest of the parameters were estimated. Our prior distribution selections are presented in Table 1. It is worth noting that chosen priors are the same for both regimes. Hence, we do not impose any ex ante restrictions, allowing us to identify two different regimes. Moreover, chosen priors seem to be rather diffuse in comparison to priors used in previous studies.

[11] As noted above, we decided to analyze the model without considering steady state inflation rate as this allowed us to assume that long-run equilibrium is independent of regime switching mechanisms.
[12] Chosen parameters are the least important in the transmission mechanism on one hand and difficult to identify empirically in the DSGE model on the other.

Table 1. Prior distributions.

Parameter	Symbol	Support	Distribution	Mean	S.D.
Calvo probability for prices	$\theta_P(s_t^p)$	$[0; 1]$	Beta	0.5	0.2
Calvo probability for wages	$\theta_w(s_t^w)$	$[0; 1]$	Beta	0.5	0.2
Relative risk aversion	δ_C	$\mathbb{R}^+$	Normal	4	1.5
Monetary policy reaction to inflation	ϕ_π	$\mathbb{R}^+$	Normal	1.5	0.25
Monetary policy reaction to output	ϕ_Y	$\mathbb{R}^+$	Normal	0.042	0.02
Interest rate smoothing	ρ	$[0; 1]$	Beta	0.5	0.254
Technological shock persistence	ρ_a	$[0; 1]$	Beta	0.5	0.254
Preference shock persistence	ρ_b	$[0; 1]$	Beta	0.5	0.254
Labor supply shock persistence	ρ_l	$[0; 1]$	Beta	0.5	0.254
Technological shock variance	σ_a^2	$\mathbb{R}^+$	Inverse Gamma	0.0174*	–
Preference shock variance	σ_b^2	$\mathbb{R}^+$	Inverse Gamma	0.0174*	–
Labor supply shock variance	σ_l^2	$\mathbb{R}^+$	Inverse Gamma	0.0174*	–
Monetary policy shock variance	σ_R^2	$\mathbb{R}^+$	Inverse Gamma	0.0174*	–
Transition probability for prices	$1 - p_{11}^p$	$[0; 1]$	Beta	0.0452	0.0285
Transition probability for prices	$1 - p_{22}^p$	$[0; 1]$	Beta	0.0452	0.0285
Transition probability for wages	$1 - p_{11}^w$	$[0; 1]$	Beta	0.0452	0.0285
Transition probability for wages	$1 - p_{22}^w$	$[0; 1]$	Beta	0.0452	0.0285

* - distribution modes.

To reflect the theoretical restrictions, we impose a beta distribution for all parameters contained in the interval $[0; 1]$. For price and wage stickiness parameters, we set the mean value to 0.5 and the standard deviation to 0.2. For the other structural parameters (ρ, ρ_a, ρ_b and ρ_l), we use a slightly looser prior, as we are using more frequently recorded data than are typically used. The priors of the transition probabilities imply an average duration (90% HPD) of between 10 and 100 months. For the monetary policy reaction parameters, we choose a normal distribution with means comparable to Taylor's [1993] initial calibration. Chosen priors do not restrict the parameter space to those values that ensure equilibrium determinacy. We do this to reflect the fact that for the MS-DSGE model, indeterminacy can be achieved in some regimes, even when a system is unique overall. For all of the shock variances, we use an inverse gamma distribution in line with the existing literature.

Results

This section presents the results of the Bayesian estimation models considered. We begin with a short description of the posterior estimates with an emphasis on differences between the particular regimes. We then identify regimes using smoothed probabilities and perform Bayesian model comparisons to determine the empirical importance of Markov-switching for the Polish economy. Finally, we analyze the differences between impulse response functions that can occur when we assume that parameters contained with nominal rigidities are time-dependent.

All of the results presented in this section are based on an MCMC algorithm with 2 chains with 400,000 draws each and where the last 200,000 draws are used to find posterior distributions for each model. We use the RISE package for this task.

Marginal posteriors for the estimated parameters are presented in Table 2.[13] We focus on the posterior mean and on a 90% HPD. Overall, the posteriors are far more concentrated than the priors, confirming that most of the parameters were heavily affected by the data during the estimation. The exceptions were parameters δ_c, ϕ_π and ϕ_Y. However, the posteriors obtained for these parameters seem to be comparable to those of previous results for the Polish economy [see, among others: Kolasa, 2008; Kuchta, 2014], especially considering the fact that we used more frequently recorded data than are typically used. Moreover, most of "non-switching" parameters do not vary considerably across particular models, even if we assume that the parameters governing nominal rigidities were time-dependent. This implies a substantial degree of interest rate smoothing, moderate monetary policy reaction to output gap and very limited reaction to inflation, which seems to be close to indeterminacy region of the parameter space.

[13] A graphical comparison between the priors and posteriors is presented in Appendix B.

Table 2. Posterior statistics across the models (means and 90% HPD in parentheses)

	INDEPEND-ENT	**SYNCHRO-NISED**	**PRICES**	**WAGES**	**CONSTANT**
$\theta_P(s_t^p = 1)$	0.904 [0.871 0.933]	0.896 [0.864 0.923]	0.914 [0.886 0.935]	0.936 [0.913 0.951]	0.937 [0.922 0.949]
$\theta_P(s_t^p = 2)$	0.941 [0.925 0.957]	0.935 [0.919 0.950]	0.946 [0.931 0.959]		
$\theta_w(s_t^w = 1)$	0.731 [0.629 0.816]	0.739 [0.663 0.811]	0.844 [0.793 0.876]	0.87 [0.813 0.903]	0.854 [0.802 0.877]
$\theta_w(s_t^w = 2)$	0.856 [0.809 0.898]	0.851 [0.809 0.891]		0.76 [0.653 0.825]	
δ_C	5.005 [3.003 7.036]	4.969 [2.981 7.096]	4.571 [2.51 6.731]	4.399 [0.396 6.843]	4.525 [2.376 6.675]
ϕ_π	1.348 [1.013 1.838]	1.397 [1.021 1.915]	1.279 [0.996 1.748]	1.171 [0.996 1.608]	1.214 [0.986 1.621]
ϕ_Y	0.043 [0.016 0.07]	0.043 [0.014 0.071]	0.043 [0.014 0.071]	0.038 [0.013 0.064]	0.041 [0.014 0.068]
ρ	0.935 [0.902 0.961]	0.941 [0.912 0.964]	0.928 [0.9 0.954]	0.912 [0.879 0.947]	0.92 [0.889 0.948]
ρ_a	0.568 [0.462 0.677]	0.532 [0.423 0.641]	0.549 [0.439 0.649]	0.465 [0.366 0.565]	0.449 [0.349 0.544]
ρ_b	0.764 [0.696 0.831]	0.763 [0.693 0.831]	0.756 [0.687 0.824]	0.776 [0.702 0.848]	0.767 [0.692 0.836]
ρ_l	0.016 [0.002 0.042]	0.017 [0.002 0.041]	0.015 [0.002 0.043]	0.016 [0.002 0.047]	0.018 [0.002 0.048]
σ_a^2	0.207 [0.109 0.360]	0.198 [0.110 0.325]	0.269 [0.15 0.575]	0.298 [0.173 0.465]	0.363 [0.212 0.537]
σ_b^2	0.103 [0.063 0.143]	0.103 [0.063 0.146]	0.094 [0.053 0.137]	0.096 [0.054 0.143]	0.093 [0.051 0.138]
σ_l^2	4.647 [2.351 8.678]	3.960 [2.194 6.971]	6.614 [3.881 9.359]	5.193 [2.672 8.878]	7.12 [3.795 9.522]
σ_R^2	0.00089 [.00089 .00089]	0.00088 [.00089 .00089]	0.00089 [.00088 .00090]	0.00089 [.00088 .00090]	0.00089 [.00089 .00090]
$1 - p_{11}^p$	0.064 [0.023 0.118]	0.069 [0.037 0.106]	0.039 [0.015 0.071]	N.A.	N.A.
$1 - p_{11}^w$	0.116 [0.061 0.183]		N.A.	0.115 [0.059 0.183]	N.A.
$1 - p_{22}^p$	0.039 [0.016 0.070]	0.148 [0.083 0.224]	0.058 [0.021 0.109]	N.A.	N.A.
$1 - p_{22}^w$	0.042 [0.018 0.074]		N.A.	0.044 [0.019 0.075]	N.A.

We identify two different regimes: (i) one with high price and wage rigidities and (ii) one with low price and wage rigidities.[14] For the high rigidity regimes, the average price duration was evaluated for a period of between 14 and 23 months when two independent Markov chains were considered (INDEPENDENT) and for a period of between 12 and 20 months[15] when only one Markov chain was introduced for both rigidities (SYNCHRONISED). For the low rigidity regime, these intervals were estimated for values recorded within periods of 8 and 14 months and 7 and 13 months, respectively. Similar results were obtained when wage rigidity was assumed to be time-invariant.

We found wage rigidities to be lower than price rigidities in all of the estimated models, even when we assumed wage stickiness to be time-dependent. However, this may be somewhat counterintuitive, similar results hold for a variety of DSGE models when constant returns to scale are considered [see Smets, Wouters, 2003]. In the model with two independent Markov chains, wage rigidity was evaluated for a period of between 3 and 6 months for the low rigidity regime and for a period of between 5 and 10 months for the high rigidity regime. These results do not change substantially when we introduce only one Markov process that governs both rigidities and when we assume that price rigidity is time-invariant.

In contrast to these results, the model with fixed parameters identifies only high levels of rigidity for both wage and price stickiness. Our estimates suggest that the average durations were evaluated for a period of between 13 and 20 months in the case of prices and for a period of between 5 and 8 months in the case of wages. These intervals are consistent with the high rigidity regime.

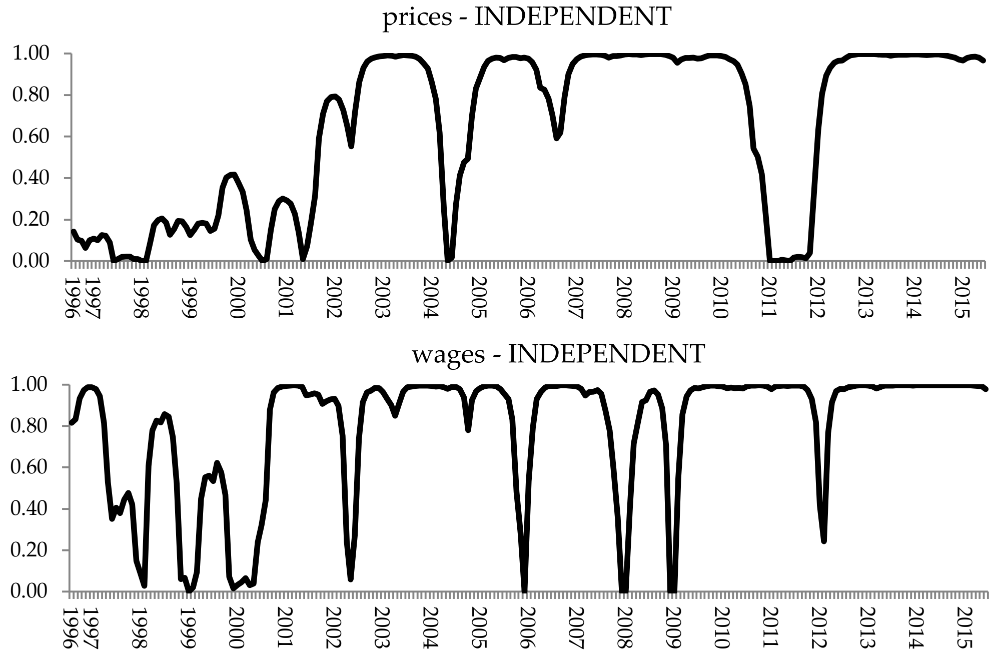
By introducing switching between the regimes, we were able to identify low rigidity regimes that cannot be observed in a constant-parameters model. Figure 1 presents

[14] It is worth noting that we identify both regimes using the same priors which means that we do not impose any ex ante restrictions.

[15] It should be stressed that four different regimes were included in the INDEPENDENT model, as we used two independent Markov chains.

the smoothed probability of the Polish economy remaining in a higher price or wage rigidity regime from 1996:8 to 2015:8. The presented values were evaluated using two independent Markov chains, with one assigned to each form of rigidity.

Figure 1. Estimated probability of higher nominal rigidity regimes (i.e., $s_t^w = 2$ and $s_t^p = 2$):



The probabilities shown in Figure 1 allow us to highlight several results that seem to be fairly intuitive, especially for prices. First, lower price rigidity degree were found to be more probable at the beginning of the sample, when Poland experienced a high inflation period (before 2002). Second, throughout the historically low inflation period in Poland occurring after 2004 (and through deflation since the mid-2014), the high price rigidity regime has dominated. This result seems reasonable, as during high inflation periods, non-adjusting price costs, which are represented for example by changes in relative prices, seemed to be much higher than they were during the low inflation periods. In such a case more frequent price adjustments (i.e. lower price rigidity) is consistent with a wide variety of models based on the menu cost approach. Third, short-lived switching from higher to lower price rigidity degree occurred at almost the same time as two significant institutional changes: May 2004, when Poland joined European Union, and January 2011, when VAT rates increased.[16]

In contrast to the price stickiness results, the high wage rigidity regime seems to dominate the sample. Exceptions include the periods of 1996 – 1997 and 1999 – 2000, when lower wage rigidities were more probable that higher wage rigidities. For the rest of the sample, only short-lived switches are observable. Smoothed probabilities seem to be less predictable than those of high price rigidity regime. One may expect that during high inflation periods, nominal wages change more often than they do during low inflation periods, as real wages decrease faster. However, our results can be justified as follows. First, our estimates suggest that real wages in the regime of low wage rigidity are rather flexible, as the average duration is no longer than half a year. Second, during high inflation periods, unemployment rates were higher than 10%, potentially alleviating pressures to increase wages even when inflation rates were high.[17]

Table 3. Bayesian model comparisons (MHM logarithm of marginal data density)[18]

	log (MDD)	**Posterior Odds Ratio***	**Posterior Odds Ratio****
PRICES	-587.477	$9.92 * 10^{6}$	$1.080 * 10^{-17}$
WAGES	-572.599	$2.870 * 10^{13}$	$3.125 * 10^{-11}$
SYNCHRONISED	-548.410	$9.182 * 10^{23}$	1
INDEPENDENT	-547.118	$3.344 * 10^{24}$	3.642
CONSTANT	-603.587	1	$1.089 * 10^{-24}$

*,** Posterior Odds Ratios were evaluated by treating model M_j as CONSTANT and SYNCHRONISED.

Next, we evaluate the empirical importance of introducing Markov-switching for prices and wages by conducting Bayesian model comparisons.[19] The results are presented in table 3. The posterior odds ratios strongly support models with Markov-switching when they are compared to a model with time-invariant parameters. More-

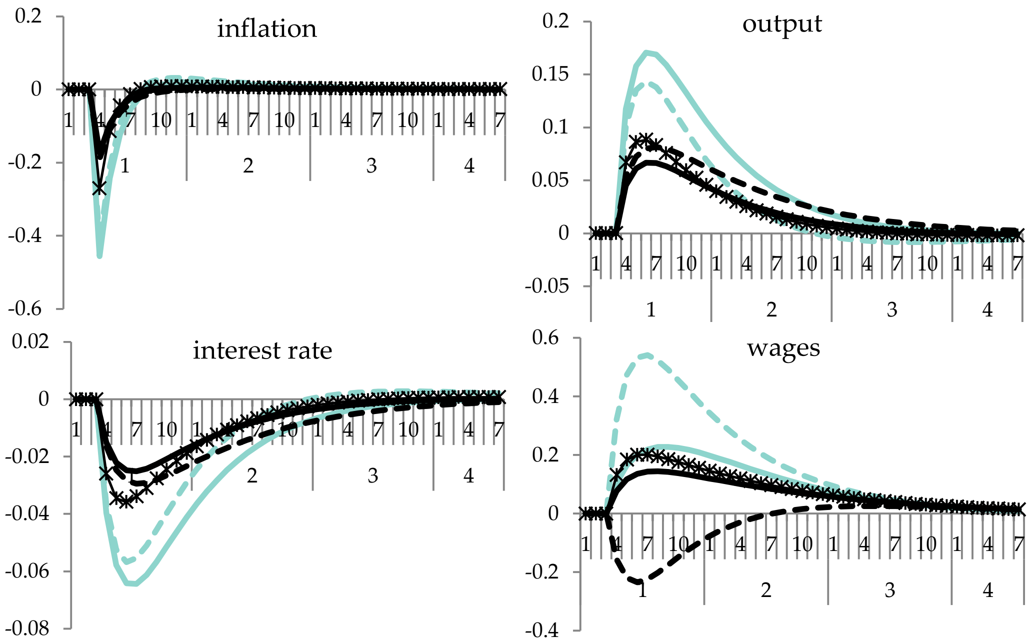
[16] Note that during Poland's accession to the European Union, Polish VAT rates also changed substantially.
[17] Similar explanations can be given for the entire period. For example, we do not find strong evidence of low wage rigidity regime from mid-2002 to the end of 2004. During this period, unemployment rates were higher than 18%.
[18] Applying Laplace approximations did not change the model's rank.
[19] In Appendix C, we present the results of our Bayesian model comparisons, when taking into account regime changes in monetary policy rule, structural shock persistence and shock volatility.

over, the models with Markov-switching for both rigidities are strongly favored by the data over model PRICES or WAGES. However, the empirical difference between the model with one chain (SYNCHRONISED) and that with two independent chains (INDEPENDENT) is negligible, whereas the difference between PRICES and WAGES is extremely significant,[20] and the model with wage switching is favored.

Finally, we determine how the economy reacts to disturbances when we allow for price and wage rigidity switching. In particular, we compare impulse response functions obtained from the model with time-invariant parameters (denoted in Figures 2 and 3 as a solid black line with asterisks) with those that can be obtained from the INDEPENDENT model. Figure 2 presents the impulse response functions for observables in the case of technological shock. The dynamics of this model is determined by four different regimes: i) low price and wage rigidity regime denoted as solid gray lines, ii) low price and high wage rigidity regime denoted by dashed gray lines, iii) high price and low wage rigidity regime denoted by dashed black lines, and iv) high price and wage rigidity regime denoted by solid black lines. All of these impulse response functions presented were computed from posterior distribution means, which are shown in Table 1.

[20] The posterior odds ratio is equal to $3.27 * 10^6$ and favors model WAGES with respect to PRICES.

Figure 2. Impulse response functions for observables – technological shock



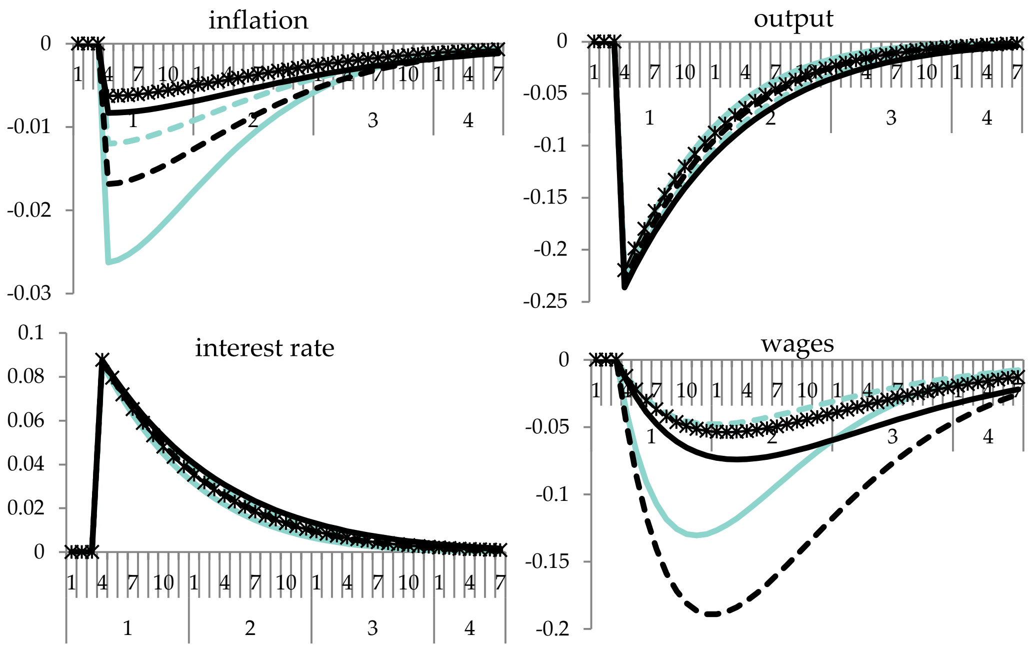
Solid gray lines denote low price and wage rigidity regime, dashed gray lines denote low price rigidity and high wage rigidity regime, black dashed lines denote high price rigidity and low wage rigidity regime, black solid lines denote high price and wage rigidity regime, and black lines with asterisks denote model with constant parameters.

The appearance of positive technological shock increases output and marginal product of labor. Moreover, changes in technology and real wage affect real marginal cost and encourage a decline in prices. In turn, inflation rate declines. As interest rate is set according to the Taylor rule, they also fall. Marginal product of labor increase allows for changes in real wages. However, while reaction signs are regime-dependent and are not observed when prices are sticky, wages are relatively flexible.[21]

Introducing time-dependent price and wage stickiness substantially increases response magnitudes. While high price rigidity regimes (denoted by black lines) appear to be comparable to constant-parameter models (denoted by a line with asterisks), accounting for low price rigidity regimes causes economy to react more strongly to aggregate supply disturbances. Moreover, reaction magnitudes do not depend heavily on wage stickiness, though real wage reactions are an exception.

[21] This result can be justified as follows. When prices are sticky, very few firms can reoptimize their prices while the rest remain unchanged, but all labor units become more productive. Hence, the demand for goods produced by firms that cannot optimize declines and as a consequence, labor demand also falls, decreasing real wages, even when positive technological shocks are observable in the economy.

Figure 3. Impulse response functions for observables – monetary policy shock



Solid gray lines denote low price and wage rigidity regime, dashed gray lines denote low price rigidity and high wage rigidity regime, black dashed lines denote high price rigidity and low wage rigidity regime, black solid lines denote high price and wage rigidity regime, and black lines with asterisks denote model with constant parameters.

Figure 3 presents impulse response functions for the observables in the case of monetary policy shocks. The appearance of monetary policy shock increases interest rates and causes output and real wages to fall as a result of decreased aggregate demand levels. Hence, inflation also falls. Interest rate and output responses are comparable between particular models, and notable differences are observed in the case of inflation and real wages. Our results seem to be fairly intuitive and suggest that the most severe inflation reactions occur during regimes characterized by more flexible wages and prices, whereas regimes with high degree of nominal rigidity are similar to model with constant parameters. The wage response results show that the constant-parameter model is similar to high nominal wage rigidity regimes, whereas the strongest reactions are observed in the regimes with the low wage rigidity. These results suggest that the economy reacts more strongly on monetary policy shocks during regimes characterized by low wage rigidities. Moreover, in contrast to technological shock, response magnitudes seem to be governed by wage stickiness switches, whereas changes in price stickiness appear to be rather unimportant.

Conclusions

In this paper, we examined changes in the degree of nominal rigidity in Poland. Using monthly data for 1996-2015, we estimated a set of sticky price and wage models while allowing for Markov switching in Calvo price and/or wage stickiness parameters. We compared four variants (varying in terms of switching parameters) to the model without regime changes (which was treated as a benchmark). Our findings are as follows.

First, the data reveal two regimes and strongly prefer models with switching degrees of both price and wage rigidity. The model with two independent Markov chains that govern price and wage rigidity is rather not preferred than the model with synchronized price and wage rigidity changes.

Second, the timing of the estimated rigidity changes is fairly intuitive. The model identifies a low price stickiness regime during the transition period when inflation rates were rather high, which is consistent with the menu cost interpretation. The model also switches in May 2004 when Poland joined the European Union and in January 2011 when VAT rates increased. However, we do not find similar results in the case of wages, potentially due to high unemployment rates occurring during the transition period. Surprisingly, we do not find significant changes in either regime during the last financial crisis.

Third, our comparison of impulse response functions shows that during periods of low rigidity, the economy reacts stronger to structural shocks. The magnitudes of responses to technological shock are largely driven by changes in price stickiness, whereas wage stickiness switches are rather unimportant. In contrast to the effects of technological shock, we find that the economy reacts stronger to monetary policy shock during low wage rigidity regimes, and the magnitudes of responses are largely driven by changes in wage stickiness.

Literature

1. Alstadheim, R., Bjørnland, H.C., & Maih, J. (2013). Do central banks respond to exchange rate movements? A Markov-switching structural investigation. *Norges Bank Research Working Paper*, *24*.
2. An, S., & Schorfheide, F. (2007). Bayesian analysis of DSGE models. *Econometric reviews*, *26*(2-4), 113-172.
3. Baele, L., Bekaert, G., Cho, S., Inghelbrecht, K., & Moreno, A. (2015). Macroeconomic regimes. *Journal of Monetary Economics*, *70*, 51-71.
4. Berradi N., Gautier E., & Bihan H. (2015). More Facts about Prices: France Before and During the Great Recession. *Journal of Money, Credit and Banking*, 47(8), 1465–1502.
5. Bianchi, F. (2012). Regime switches, agents' beliefs, and post-world war ii us macroeconomic dynamics. *The Review of Economic Studies*, rds032.
6. Blagov, B. (2013). Financial Crises and Time-Varying Risk Premia in a Small Open Economy: A Markov-Switching DSGE Model for Estonia. *Eesti Pank. Working Paper Series, 8/2013.*
7. Blanchard, O.J., & Kahn, Ch.M. (1980). The Solution of Linear Difference Models under Rational Expectations. *Econometrica, 48(5)*, 1305-1312.
8. Calvo, G.A. (1983). Staggered Prices in a Utility-Maximizing Framework, *Journal of Monetary Economics*, *12*, 383-398.
9. Canova, F. (2009). Bridging cyclical DSGE models and the raw data. *manuscript*
10. Chakraborty R., Dobson P.W., Seaton J., Waterson M. (2015), Pricing in inflationary times: The penny drops, *Journal of Monetary Economics*, 76, 71-86.
11. Chiaie, S.D. (2009). The sensitivity of DSGE models' results to data detrending. *Working Paper*, *157*, Oesterreichische Nationalbank.
12. Chortareas, G., Magonis, G., & Panagiotidis, T. (2012). The asymmetry of the New Keynesian Phillips Curve in the euro-area. *Economics Letters*, 114(2), 161-163.
13. Davig, T., & Doh, T. (2008). Monetary Policy Regime Shifts and Inflation Persistence. *Research Working Papers*, *08-16*, The Federal Reserve Bank of Kansas City, Economic Research Department.
14. Dixit, A.K., & Stiglitz, J.E. (1977). Monopolistic competition and optimum product diversity. *The American Economic Review*, 297-308.
15. Eo, Y. (2009). Bayesian analysis of DSGE models with regime switching. Available at SSRN 1304623.
16. Erceg, C. J., Henderson, D. W., & Levin, A. T. (2000). Optimal monetary policy with staggered wage and price contracts. *Journal of Monetary Economics*, *46*(2), 281-313.
17. Farmer, R.E.A, Waggoner, D.F., & Zha, T. (2005). Understanding Markov-switching rational expectations models, *Journal of Economic Theory*, *144*, 1849-1867.
18. Fernandez-Villaverde, J. (2010). The econometrics of DSGE models. *SERIEs Journal of the Spanish Economic Association*, *1*, 3-49.

19. Geweke, J. (1998). Using Simulation Methods for Bayesian Econometric Models: Inference, Development, and Communication. *Research Department Staff Report, 249*, Federal Reserve Bank of Minneapolis.
20. Guerrón-Quintana, P.A., & Nason, J.M. (2012). Bayesian Estimation of DSGE Models. *Working Paper*, *12-4*, Research Department, Federal Reserve Bank of Philadelphia.
21. Hagemejer, J., & Popowski, P. (2014). The distribution of monopolistic markups in the Polish economy. *Eastern European Economics, 52*(6), 3-31.
22. Kass, R.E., & Raftery, A.E. (1995). Bayes Factors. *Journal of the American Statistical Association*, *90 (430)*, 773-795.
23. Kim, Ch-J., & Nelson, Ch.R. (1999). Has the U.S. Economy Become More Stable? A Bayesian Approach Based on a Markov-Switching Model of the Business Cycle. *The Review of Economics and Statistics*, *81 (4)*, 608-616.
24. Kolasa, M. (2009). Structural heterogeneity or asymmetric shocks? Poland and the euro are through the lens of a two-country DSGE model. *Economic Modelling, 26*, 1245-1269.
25. Klein, P. (2000). Using the generalized Schur form to solve a multivariate linear rational expectations model. *Journal of Economic Dynamic & Control*, *24*, 1405-1423.
26. Krajewski, P. (2014). Comparison of Nominal and Real Rigidities: Fiscal Policy Perspective. *Comparative Economic Research*, 17(1), 61-76.
27. Kuchta, Z. (2014). Nominal wage rigidities in small-scale DSGE models: An empirical analysis for the Polish economy [in Polish: Sztywność płac nominalnych w modelach DSGE małej skali. Analiza empiryczna dla Polski]. *Gospodarka Narodowa*, (6), 31-56.
28. Lee, J., & Nelson, C. R. (2007). Expectation horizon and the Phillips curve: The solution to an empirical puzzle. *Journal of Applied Econometrics, 22*(1), 161-178.
29. Lhuissier, S. & Zabelina, M. (2015). On the Structural Nature of Pricing Parameters. *Journal of Economic Dynamics & Control*, *57*, 77–95.
30. Liu, P., & Mumtaz, H. (2011). Evolving macroeconomic dynamics in a small open economy: An estimated markov switching DSGE model for the UK. *Journal of Money, Credit and Banking, 43*(7), 1443-1474.
31. Liu, Z., Waggoner, D. F., & Zha, T. (2011). Sources of macroeconomic fluctuations: A regime-switching DSGE approach. *Quantitative Economics*, *2*(2), 251-301.
32. Macias, P. & Makarski K. (2013), Stylised facts on consumer prices in Poland [in Polish: Stylizowane fakty o cenach konsumenta w Polsce], *NBP Working Papers*, 268.
33. Peterman, W. (2012). Reconciling micro and macro estimates of the Frish labor supply elasticity. *Finance and Economics Discussion Series*, *2012-75*, Board of Governors of the Federal Reserve System.
34. Rabanal, P. & Rubio-Ramírez, J.F. (2005). Comparing New Keynesian models of the business cycle: A Bayesian approach. *Journal of Monetary Economics, 52*(6), 1151-1166

35. Rabanal, P. (2007). Does inflation increase after a monetary policy tightening? Answers based on an estimated DSGE model. *Journal of Economic Dynamics & Control*, *31*, 906-937.
36. Rabanal, P., & Rubio-Ramírez, J.F. (2008). Comparing new Keynesian models in the Euro area: a Bayesian approach. *Spanish Economic Review, 10*(1), 23-40.
37. Ravn, M.O., & Uhlig H. (2002). On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations. *The Review of Economics and Statistics*, 84(2), 371-380.
38. Schorfheide, F. (2005). Learning and monetary policy shifts, *Review of Economics Dynamics*, *8*, 392-419.
39. Sims, Ch.A. (2001). Solving Linear Rational Expectations Models. *Computational Economics*, *20*, 1-20.
40. Smets, F., & Wouters, R. (2003). An Estimated Dynamic Stochastic General Equilibrium Model of the Euro Area. *Journal of the European Economic Association*, *1(5)*, 1123-1175.
41. Taylor, J.B. (1993). Discretion versus policy rules in practice. In *Carnegie-Rochester conference series on public policy,39*, December, 195-214.
42. Vavra, J.S. (2014). Time-Varying Phillips Curves. *National Bureau of Economic Research Working Paper, 19790*.
43. Yun, T. (1996). Nominal price rigidity, money supply endogeneity, and business cycles. *Journal of Monetary Economics*, *37*, 345-370.

Appendix A:

This appendix presents a log-linear representation of the theoretical model. It is given by the following equations:

$$\hat{y}_t = E_t\{\hat{y}_{t+1}\} - \frac{1}{\delta_c} E_t\{\hat{r}_t - \hat{\pi}_{t+1} + \hat{\varepsilon}^b_{t+1} - \hat{\varepsilon}^b_t\}$$

$$\hat{\pi}_t = \frac{\left(1-\theta_p(s^p_t)\right)\left(1-\beta\theta_p(s^p_t)\right)}{\theta_p(s^p_t)} \widehat{rmc}_t + \beta E_t\{\hat{\pi}_{t+1}\}$$

$$\widehat{w}_t = \frac{\left(1-\theta_w(s^w_t)\right)\left(1-\beta\theta_w(s^w_t)\right)}{\theta_w(s^w_t)} \frac{b_w\tau_w}{\delta_l(1+\tau_w)+\tau_w} \widehat{mrs}_t + b_w\beta E_t\{\hat{\pi}_{t+1} + \widehat{w}_{t+1}\} - b_w\hat{\pi}_t + b_w\widehat{w}_{t-1}$$

$$\widehat{rmc}_t = \widehat{w}_t - \hat{\varepsilon}^a_t$$

$$\widehat{mrs}_t = \hat{\varepsilon}^l_t + (\delta_c + \delta_l)\hat{y}_t - \delta_l\hat{\varepsilon}^a_t$$

$$\hat{r}_t = \rho\hat{r}_{t-1} + (1-\rho)(\phi_\pi\hat{\pi}_t + \phi_Y\hat{y}_t) + \eta^R_t; \quad \eta^R_t \sim iid\ N(0,\sigma^2_R)$$

$$\hat{\varepsilon}^a_t = \rho_a\hat{\varepsilon}^a_{t-1} + \eta^a_t; \quad \eta^a_t \sim iid\ N(0,\sigma^2_a)$$

$$\hat{\varepsilon}^b_t = \rho_b\hat{\varepsilon}^b_{t-1} + \eta^b_t; \quad \eta^b_t \sim iid\ N(0,\sigma^2_b)$$

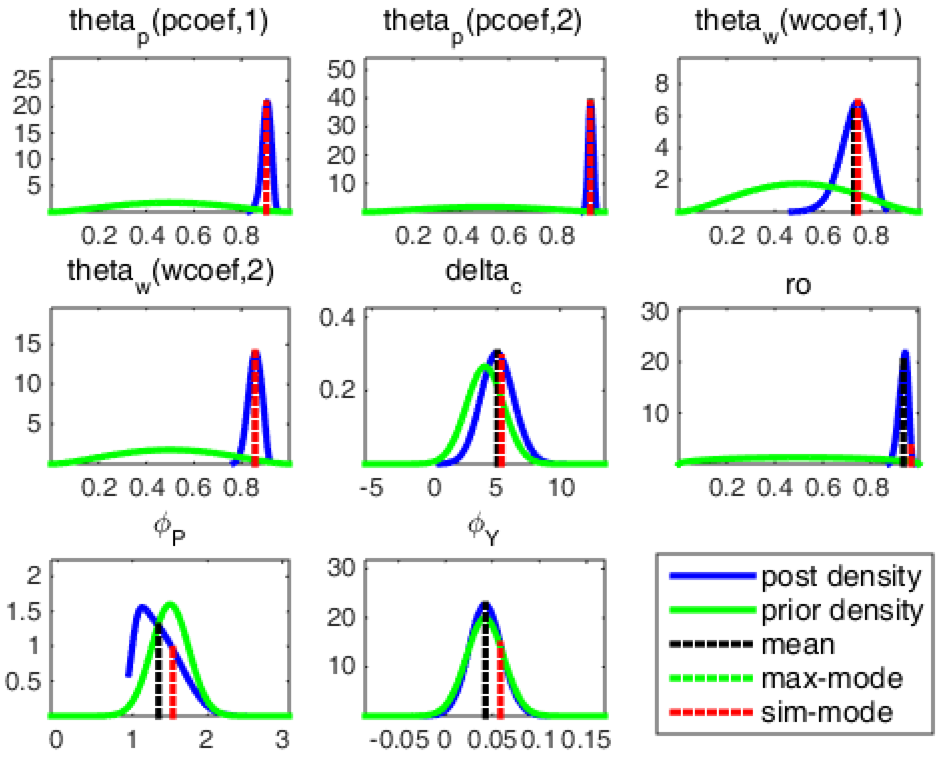
$$\hat{\varepsilon}^l_t = \rho_l\hat{\varepsilon}^l_{t-1} + \eta^l_t; \quad \eta^l_t \sim iid\ N(0,\sigma^2_l)$$

where $b_w \equiv \frac{\theta_w(s^w_t)[\delta_l(1+\tau_w)+\tau_w]}{\delta_l(1+\tau_w)+\tau_w-\left(1-\beta\theta_w(s^w_t)\right)\left(1-\theta_w(s^w_t)\right)\delta_l(1+\tau_w)+\beta\theta_w(s^w_t)^2[\delta_l(1+\tau_w)+\tau_w]} > 0$ is a parameter, $\hat{y}_t$ is the output, $\hat{r}_t$ is the nominal interest rate, $\hat{\pi}_t$ denotes inflation, $\widehat{rmc}_t$ is the real marginal cost, $\widehat{mrs}_t$ is the marginal rate of substitution between consumption and labor, $\widehat{w}_t$ is the real wage, $\hat{\varepsilon}^a_t$ denotes technological shock, $\hat{\varepsilon}^b_t$ denotes preference shock, $\hat{\varepsilon}^l_t$ denotes labor supply shock, $\theta_p(s^p_t) \in [0;1]$ is the price stickiness parameter, $s^p_t = \{1,2\}$ represents the discrete Markov chain for the price stickiness parameter, $\theta_w(s^w_t) \in [0;1]$ is the wage stickiness parameter, $s^w_t = \{1,2\}$ represents the discrete Markov chain for the wage stickiness parameter, $\delta_c > 0$ is the relative risk aversion parameter, $\delta_l > 0$ is the inverse of labour supply elasticity, $\beta \in [0;1]$ is the discount factor, $\tau_w > 0$ is the wage mark-up, E_t is the rational expectation operator and all variables denoted by "^" represent the percentage deviation from a steady state defined for variable "x_t" as:

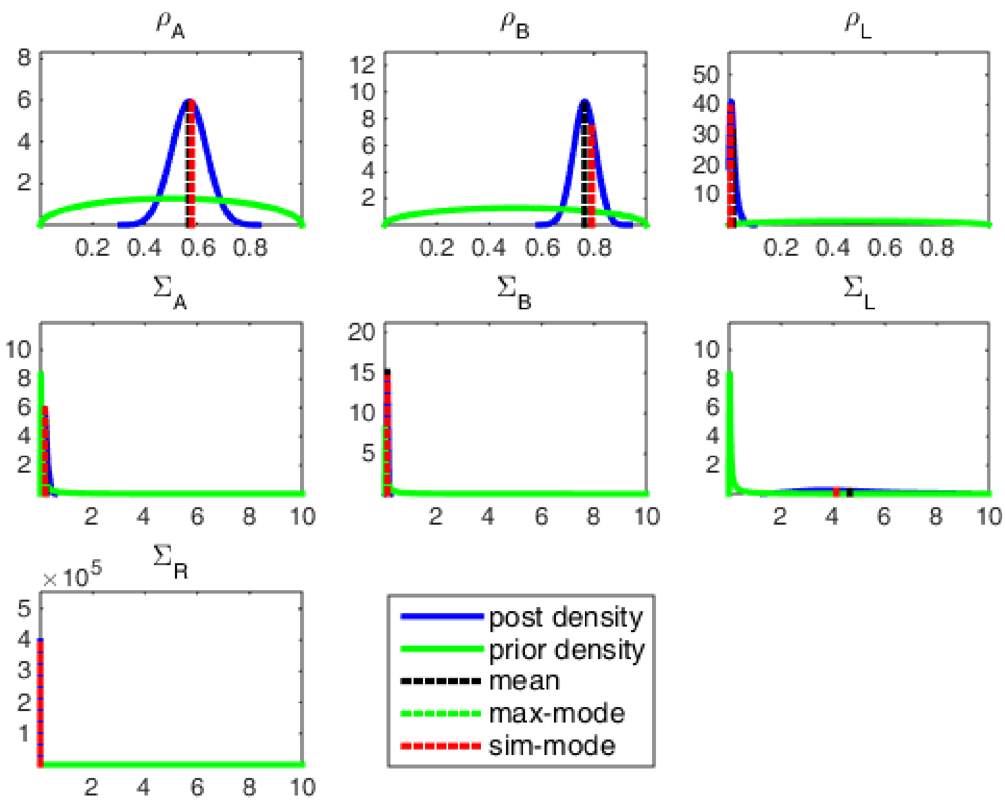
$$\hat{x}_t = \ln\left(\frac{x_t}{\bar{x}}\right)$$

Appendix B:

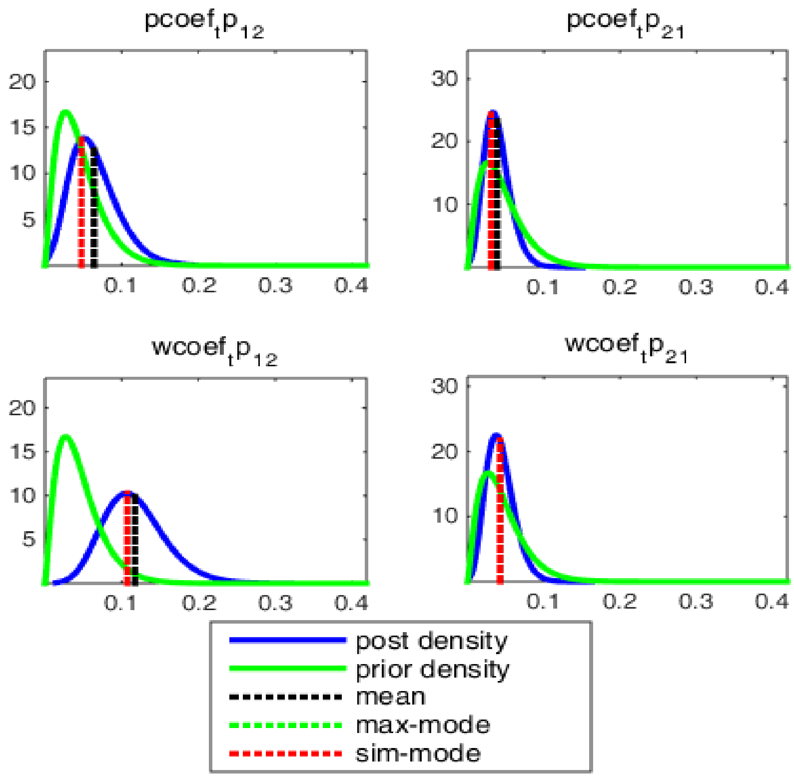
Figure B1. Prior and posterior marginal distributions (INDEPENDENT)
(part 1: structural parameters)



(part 2: shocks persistence and variance parameters)



(part 3: transition probabilities)



Appendix C:

This appendix presents the result of Bayesian model comparison for a model with time-varying parameters of monetary policy rule (POLICY), shock's persistence and interest rate smoothing (PERSISTENCE) and shock's variances (VOLATILITY). The results provide additional support for the models with switching nominal rigidities (INDEPENDENT and SYNCHRONISED).

Table C1.

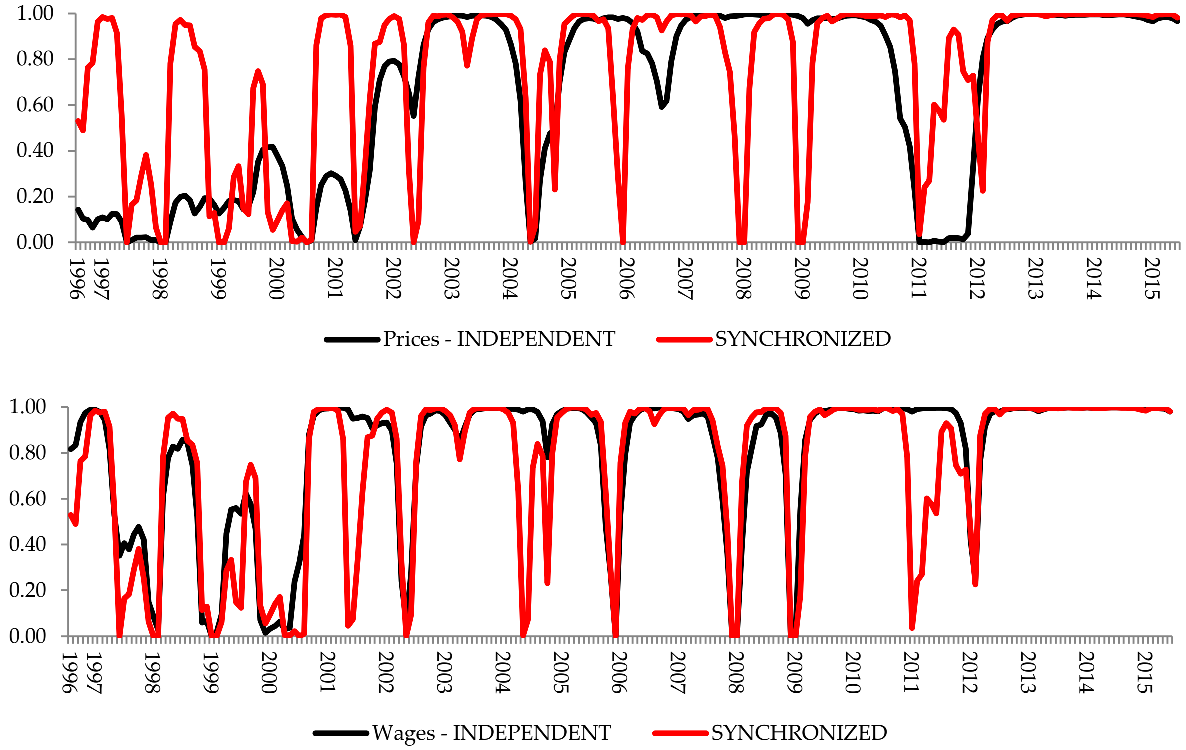
	log(MDD)	**Posterior Odds Ratio***	**Posterior Odds Ratio****
POLICY	-614.818	$1.326 * 10^{-5}$	$1.445 * 10^{-29}$
PERSISTENCE	-623.789	$1.684 * 10^{-9}$	$1.834 * 10^{-33}$
VOLATILITY	-645.770	$4.789 * 10^{-19}$	$5.216 * 10^{-43}$
SYNCHRONISED	-548.410	$9.182 * 10^{23}$	1
INDEPENDENT	-547.118	$3.344 * 10^{24}$	3.642
CONSTANT	-603.587	1	$1.089 * 10^{-24}$

*,** Posterior Odds Ratios were evaluated by treating model $\mathrm{M_j}$ as CONSTANT and SYNCHRONISED.

Appendix D:

This appendix presents the results of comparisons made between estimated probabilities in the model with two independent Markov chains (INDEPENDENT) denoted by black lines and the model with only one Markov chain, which governs switches in both price and wage rigidity (SYNCHRONISED) (denoted by the red line). Probabilities are presented in Figure D1 and should be treated as smoothed probabilities.

Figure D1. Estimated probabilities of higher nominal rigidity (INDEPENDENT vs. SYNCHRONIZED)



Drawing comparisons allows us to show that the introduction of only one Markov chain seems to serve as a compromise between price and wage rigidity switches. This effect is especially evident for the period following 2001, during which price and wage rigidity switches identified from the INDEPENDENT model have been rather uncorrelated. Prior to 2001, the common chain switches was similar to those of wage rigidity Markov chain. Consequently, the low price rigidity period is difficult to identify using a model with only one Markov chain.

Appendix E:

This appendix presents the summary of estimations with alternative priors on Calvo parameters. More specifically we assumed prior distribution with 90% HPD ranging from 0.668 to 0.99 (identical for price and wage rigidity, and for both regimes). This intervals are consistent the belief that price and wage expected duration ranges from 3 months to 100 months. The remaining prior distributions was set as in the baseline (see Table 1 and Priors section). In the Table E1 posterior distribution for the parameters of interest are presented, while in the Table E2 – the Bayesian model comparison results. Overall this sensitivity analysis show that posterior distribution was only little affected by change of the priors. The most notable difference is that the model with two independent regimes (INDEPENDENT) is now performing significantly better than the SYNCHRONISED, as posterior odd ratio exceeds 40.

Table E1. Posterior statistics across the models (Calvo parameters only; means and 90% HPD in parentheses)

	INDEPENDENT	**SYNCHRONISED**	**CONSTANT**
$\theta_P(s_t^p = 1)$	0.920 [0.896 0.942]	0.913 [0.886 0.939]	0.946 [0.935 0.957]
$\theta_P(s_t^p = 2)$	0.950 [0.936 X.963	0.944 [0.929 0.960]	
$\theta_w(s_t^w = 1)$	0.786 [X.629 X.816]	0.784 [0.711 0.838]	0.879 [0.870 0.887]
$\theta_w(s_t^w = 2)$	0.882 [0.848 0.908]	0.876 [0.833 0.907]	

Table E2. Bayesian model comparisons (MHM logarithm of marginal data density)

	log (MDD)	**Posterior Odds Ratio***	**Posterior Odds Ratio****
SYNCHRONISED	-535.822	$1.599 * 10^{33}$	1
INDEPENDENT	-532.061	$6.870 * 10^{34}$	42.957
CONSTANT	-612.277	1	$6.253 * 10^{-34}$

*,** Posterior Odds Ratios were evaluated by treating model M_j as CONSTANT and SYNCHRONISED.

1