MONETARY POLICY UNDER CONTINUOUS MARKET SENTIMENT REGIMES

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Abstract

In this article, an econometric method is proposed for the analysis of monetary policy under regimes that include unobserved agents' economic sentiments. In the non-linear LVSTAR model, market sentiments do not directly influence monetary policy, however, agents' actions may change over the sentiments providing different reactions to economic shocks. The results indicate differences in the effectiveness of the monetary policy between the high and low economic sentiment regimes, while both countries react in a similar way to the sentiment. In general, during the low level of economic sentiment conducting monetary policy can become more challenging as the reaction time for the economy increases and the changes in monetary policy need to be more vital to take effect.

Keywords: economic sentiments, non-linear, vector autoregression, monetary policy.

JEL codes: C01, C39, C57, E27, E52.

Introduction

In this article, the author discusses a new method to set up the SVAR model via smooth-regime switching with exogenous variables for monetary policies. In the paper, the usefulness of publicly accessible financial sentiment indices in monetary policy modelling is closely examined. Moreover, analyses are carried out regarding the effects of obtained sentiments on the monetary policy following a similar approach to (Nalban, 2016), who studied the Romanian monetary policy transmission mechanism under different regimes, identified on the basis of a synthetic, survey-based economic sentiment indicator (Economic Sentiment Indicator). The obtained results allow to state that asymmetry of the monetary policy transmission exists under those regimes.

The monetary transmission mechanism (MTM) in the United States is well-studied (see e.g. a survey), however, the topic concerning the effects of the economic

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sentiment on the monetary policy is less well-established. As far as the literature on the monetary transmission mechanism in Poland is concerned, it is already quite extensive. Recent contributions include (Chmielewski, 2016, 2018; Arratibel, 2014). Surveys regarding the MTM can be found in (Egert, 2009; Sznajderska, 2013). In the majority of studies, it has been found that a monetary policy shock is followed by a decrease in GDP (gross domestic product) and CPI (consumer price index), yet the evidence of these effects on the exchange rate is mixed. Nonetheless, non-linearities in the MTM in Poland remain explored only to a limited extent. The only study in which analysing MTM in Poland using non-linear VARs (vector autoregressions) is (Postek, 2011). He finds non-linearities of the effects of monetary policy shocks concerning phases of monetary policy and the business cycle. Other contributions related to non-linearities broad MTM context has been examined, albeit using different frameworks, can be found in (Łyziak, Demehuk, Przystupa, Sznajderska, & Wróbel, 2012; Chmielewski, 2016). Studies on asymmetries from some channels of the transmission mechanism of monetary policy include the following: (Chmielewski, 2018; Przystupa & Wróbel, 2011; Sznajderska, 2012).

It needs to be pointed out that regime-switching models based on sentiments can also be used in other applications. The concept is centred around the fact that sentiments can influence equilibrium in the general equilibrium framework (Angeletos, 2012; Benhabib, Wang, & Wen, 2013). Although (Fève & Guay, 2016) indicates that sentiments may have a limited effect on the macroeconomic fluctuations, while Chojnowski and Dybka (2017) have shown that economic sentiments can be used to forecast the exchange rate.

The contribution of this article to literature can be viewed from 2 angles. First, the estimation method of the LVSTAR model is presented, which, if possible, converges to stable solutions in both pure regimes. Such an assumption is consistent with the literature, in which it is stated that if sentiment reaches extreme values, the economy should be stable as everyone acts the same way (there is coordination among agents) (Taschereau-Dumouche & Schaal, 2015). The second area of our contribution is a more complex analysis of economic behaviour under the regimes defined by economic sentiment.

1. Global game approach

The foundations are set in the global games approach (Morris & Shin, 2000). Let us assume agents can perform 2 actions—to take credit or not. Even though agents are constraint to 2 actions, this game can be extrapolated to many other situations on the market. In the case of 2 players, if both invest the money they have borrowed, both get rewarded. If 1 of the players decides to restrain, s/he gets nothing, while the other one records a loss. Hence, if none of them invest, they gain nothing.

There are 2 Nash equilibria for this set-up: both invest, or both do not. Thus, if both players undertake the same action, there is a stable solution. Therefore, this game is also commonly known as the coordination game.

Let us consider now that information is not fully accessible, and the agents have received signals, which are distorted. In such a scenario, they have to decide whether they take the credit, depending on how much they trust their signal. Hence, if the signal is strong, they will invest, otherwise, they will refrain from any action. As long as the agents know that other players have received signals, they must guess what signal they might have received. Additionally, the player knows the others will try to guess what signal the player has received. The latter situation corresponds to second-order beliefs over other economic signals (first-order beliefs). The game mentioned above can be easily extrapolated to more players, where returns depend on the number of agents who invest.

Additionally, in all the scenarios given above, let us assume there exogenous shock also exists, influencing second-order beliefs—market sentiment. If sentiments are high, then everyone believes that others received a high signal as well, so that they will invest; hence, the agent is eager to take on credit to invest as well. Analogically, when sentiments are low, no one tends to invest. Therefore, market sentiments can change one's action without influencing macroeconomic fundamentals. Such factors are known as economic sunspots. This framework corresponds to the method of how sentiments are implemented into economic models (Angeletos & La'o, 2013).

The first-order signals x' depend on the total productivity factor of the competitor, whereas the second-order signal x'' depends on the first-order signals. Both signals are distorted by a random i.i.d white noise (x' and x''). Second-order belief is additionally distorted by a market sentiment. In the paper, this idea is expanded for multiple agents on the market. The signal transmits information about economic well-being. Therefore, the first order belief is an aggregation of everyone else's Total Productivity Factor, while second-order belief is an aggregation of competitors' first-order signal. Market sentiment influences second-order beliefs in the same way as in the Angeletos method. Thus, this framework can be constrained to the following equations:

$$x'_{i,t} = \sum TFP_{j,t} + \varepsilon'_{i,t}$$
$$x''_{i,t} = \sum x'_{j,t} + \xi_t + \varepsilon''_{i,t}$$

The RBC model with market sentiments in second-order beliefs is further discussed by (Angeletos, Collard, & Dellas, 2018). Their model assumed the output (Y_t) is linearly dependent on equilibrium output level Y_t and market sentiments ξ_{-t}. In this article, the author proposes an econometric model that incorporates the aforementioned assumption by introducing regimes under which the economy operates.

2. Monetary policy model

Analysis of the monetary policy in the United States and Poland is based on the approach proposed by (Peersman & Smets, 2001). Let us consider the VAR model with the following variables:

$$Y_t = \begin{bmatrix} y_t \\ p_t \\ i_t \\ s_t \end{bmatrix}$$

where y_t denotes the output, p_t is the consumer price index, i_t refers to the monetary policy while s_t is the exchange rate. The identification strategy is based on the Cholesky decomposition with the ordering as in equation 3.

The LVSTAR model is used in the proposed approach with regimes identified based on sentiment values. There are 2 regimes: the high and the low sentiment value regimes. First, the author identifies that the low-sentiment regime under the underlying VAR model is stable (i.e. all the roots of the companion matrix lie within the unit circle). Monetary policy analysis started in January 1980.

3. LVSTAR model estimation

The logistic, smooth threshold vector autoregressive model (LVSTAR) expands the LSTAR model for multivariate data. This model assumes 2 independent processes: VAR(P_H)—high regime and VAR(P_L)—low regime. The outcome in each period is a mixture of those 2 regimes. The threshold variable defines how much of each occurs.

The threshold variable is transformed by the transition function: g(·): $\theta \rightarrow [0,1]$. Then, the final model assumes following form:

$$Y_t = g(\theta_t)\left(\sum_{\tau=1}^{P_H} A_{(H,\tau)} Y_{(t-\tau)}\right) + \left(1 - g\left(\theta_t\right)\right)\left(\sum_{\tau=1}^{P_L} A_{(L,\tau)} Y_{(t-\tau)}\right)$$

Although the algorithm is still developing in the literature, which guarantees stable VARs in both regimes, in this article, the author takes advantage of the fact that the threshold variable is known as extracted market sentiment ($\theta = \xi$). Let us define function g as a cumulative normal distribution function with the mean $\overline{\mu}$ and standard deviation $\overline{\sigma}$. Hence $g = \Phi(\xi, \overline{\mu}, \overline{\sigma})$. For the given values of $\overline{\mu}$ and $\overline{\sigma}$ transition function value is known, hence, the LVSTAR model becomes:

$$Y_t = \Phi\left(\xi_t, \bar{\mu}, \bar{\sigma}\right)\left(\sum_{\tau=1}^{P_H} A_{(H,\tau)} Y_{(t-\tau)}\right) + \left(1 - \Phi\left(\xi_t, \bar{\mu}, \bar{\sigma}\right)\right)\left(\sum_{\tau=1}^{P_L} A_{(L,\tau)} Y_{(t-\tau)}\right)$$

Let us further define $Y_{H,t} = \Phi(\xi_t, \bar{\mu}, \bar{\sigma})Y_t$ and $Y_{L,t} = (1 - \Phi(\xi_t, \bar{\mu}, \bar{\sigma}))Y_t$. Then Y_t is a mixture of 2 VAR models:

$$Y_t = \left(\sum_{\tau=1}^{P_H} A_{(H,\tau)} Y_{(t-\tau)}\right) + \left(\sum_{\tau=1}^{P_L} A_{(L,\tau)} Y_{(t-\tau)}\right)$$

Moreover, VAR models can be solved row-by-row, leading to a linear model for each endogenous variable. Because values vary over time, it is unlikely that Y_H and Y_L are collinear. Hence, OLS can be used to estimate A_H and A_L. Let us set up an algorithm, which for given pairs of $\bar{\mu}$ and $\bar{\sigma}$ results in the sum of squared residuals. Then, by creating a grid, one can minimise the error of the LVSTAR model to obtain the optimal transition function.

As the algorithm mentioned above requires little computing power, it is possible to impose additional constraints that would satisfy theoretical assumptions.

The author has shown that extracted market sentiments can be used as a proxy variable, which divides the population into 2 groups. Recalling the game from section 2, it can be assumed that high regime represents a population that is likely to invest, hence, A_H represents how this population interprets the past. Then, the low regime represents the population, who does not like to invest, and analogically, A_L represents how those people interpret the past. Thus, if all people tend to either invest or not to invest, the economy is expected to be in Nash equilibrium and, by the second welfare theorem, in Pareto equilibrium. Therefore, VAR models defined by A_H and A_L should be stable and convergent.

Moreover, it is unlikely that all populations will choose the same action. Hence, a grid range can be limited, so transition function values are bounded from below (b) and above ($1 - b$). Then, the algorithm assumes the following form:

$$\left(\bar{\mu}, \bar{\sigma}, A_H^*, A_L^*\right) = \underset{\mu, \sigma, A_H, A_L}{\arg\max} \sum_{t=1}^{T} \left\| y_t - \tilde{y}_t \right\|$$

$$\forall_k y_t^k = \frac{Y_t}{sd\left(Y_t^k\right)}$$

$$\tilde{y}_t = \sum_{\tau=1}^{P_H} A_{H,\tau} Y_{t-\tau} + \sum_{\tau=1}^{P_L} A_{L,\tau} Y_{t-\tau}$$

$$Y_{H,t} = \Phi\left(\xi_t, \bar{\mu}, \bar{\sigma}\right) Y_t$$

$$Y_{L,t} = \left(1 - \Phi\left(\xi_t, \bar{\mu}, \bar{\sigma}\right)\right) Y_t$$

$$\forall_{r\in\{H,L\}} \max\left(roots\left(A_r\right)\right) < 1$$
$$\forall_{r\in\{H,L\}} rank\left(Y_r\right) \geq \kappa$$
$$\forall_t b \leq \Phi\left(\xi_t, \mu, \sigma\right) \leq 1-b$$

For a given value of ξ_{-t}, it is possible to derive an IRF function by adding matrices A_H and A_L.

4. Data

In this research, models were estimated based on monthly data. All except for financial market variables are seasonally and, if necessary, calendar-adjusted.

Although the data for the United States are available for a very long period of time, the author decided to start analysis in 1980, after the collapse of the Bretton Woods system, that can be viewed as a new monetary policy era. The inflation rate measure is calculated with the Personal Expenditures excluding food and energy price index obtained from the Federal Reserve Economic Data (FRED) database. Next, the elective federal funds rate was used as the monetary policy measure (FRED), including the shadow rates computed by the Reserve Bank of New Zealand for the periods when non-standard monetary policy measures were used. The industrial production index was used as an output measure (FRED), and the Real Eleective Exchange Rate from the Bank for International Settlements was used. Last but not least, the Michigan Consumer Index was applied as an economic sentiment indicator.

It should be noted that both models with stationary and non-stationary variables are used in studies on the effects of monetary policy shocks employing VARs. In using the latter approach, the author follows (Sims, 1990), who indicates that even in the case of non-stationarity, classical methods give consistent estimates of VAR parameters. Furthermore, the author finds residuals to be stationary, suggesting long-run relationships in our set of variables. This makes using VARs in (log-)levels appropriate (Canova, 2007).

5. Results

In this section, results are presented regarding changes in inflation rate stemming from monetary policy and other macroeconomic variables under two different regimes: low and high economic sentiments. Results denoted as control show the standard VAR model without the thresholds as a reference point for our results.

In Figure 1, the probability is shown that, across time, the economy is in the higher regime. The results indicate clear signs of the dire economic sentiment on the US market in the early 1990s and during the Great Recession. A more extended period of high market sentiment can be seen during the "dot-com" bubble, switching between regimes after the bubble burst. The contrary happened during the Great Recession. Prolonged, low market sentiments kept the economy in the almost pure, "lower" regime.

Interestingly, the "neutral" value of high regime probability is within interval 0.6-0.8, which suggests the higher-regime is most prominent.

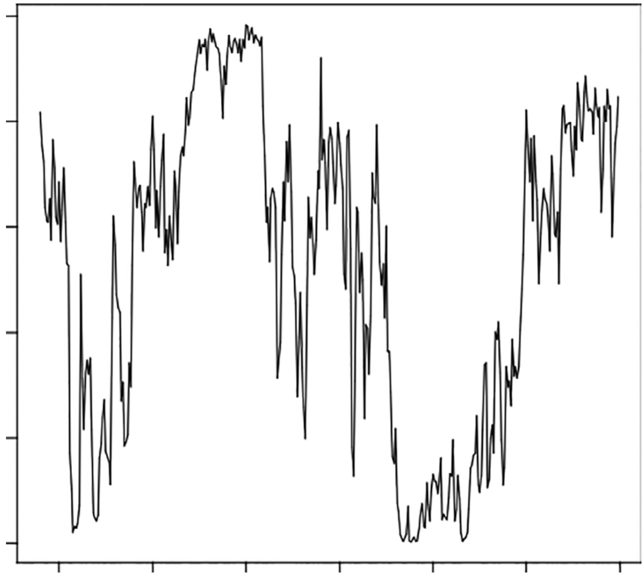

Figure 1. Probability of the higher regime
Source: Own research.

Let us examine the pure regimes. In Figure 2, the impact is presented of tightening of monetary policy on prices. In the "control" scenario, one can record a heavy price puzzle—after 6 months, there is a significant drop in prices. That behaviour is counter-intuitive and was discussed broadly in the with (e.g. Uhlig, 2005). In this article, we tackle the problem from a sentiment angle.

In the low, "recessionary" regime, the impact is more aligned with theory. Contrary to the control scenario, prices do not bounce back after a drop. However, the price puzzle is present in the high regime for all the examined scenarios. The results might suggest that consumer/investor sentiment can influence the effectiveness of the monetary policy, as the high regime overlaps with periods of over-optimism (e.g. dot-com bubble). More insight on irregularities of the CPI behaviour is noted by the GDP response.

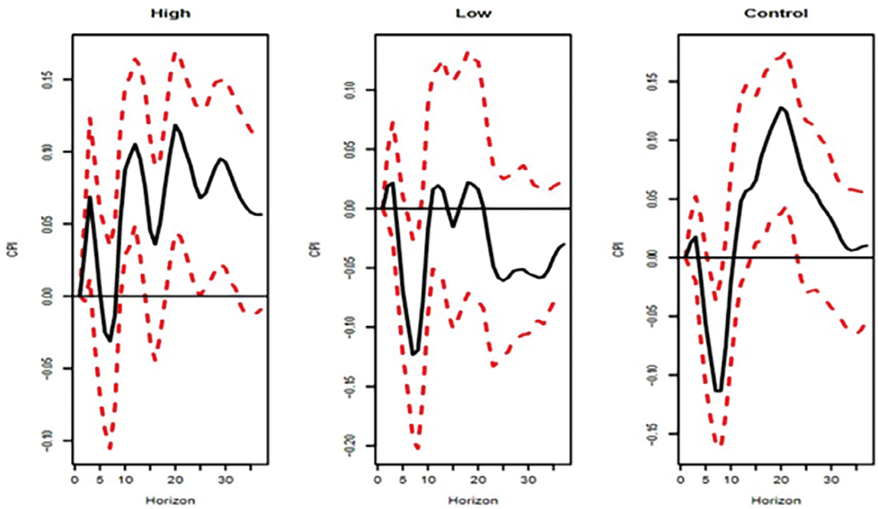

Figure 2. Impact of monetary policy shock on prices: 3-years projection
Source: Own research.

A similar story can be told by examining the impact of monetary policy on output (see Figure 3). In low regime tightening, the monetary policy harms the economy, whereas the opposite can be recorded during the high regime of over-optimism.

More research needs to be done to explain this phenomenon confidently. There are several potential culprits, however. The first might suggest that monetary models need to be extended to include more variables, which theoretical models did not involve. Considering that the anomaly occurs during waves of optimism, expectations may play an essential role in shaping the final action of the agents. Additionally, the irrationality of agents causes misinterpretation of the interest rate increase implications.

Another explanation might come from the timing of the decision. When optimism starts to fade, and the cycle reaches its peak in business cycles, FED might prolong the prosperity period by lowering the interest rate. Nonetheless, the output falls because the pessimism error occurs, disregarding FED actions. Therefore, a VAR model picks the lowering interest rate to decrease GDP growth, which implies that increasing interest rate would further increase GDP.

The LSTVAR model provides analysis of the monetary policy impact of "pure" regimes and allows to analyse this influence in a "mixed" regime, given by any market sentiment values.

For graphical representation, the author uses 3-dimensional IRFs. On the x-axis, the time horizon is set, on the y-axis, the probability of a higher regime is labelled, and the value is represented by colours—the brighter the green, the higher the values; the brighter the red, the lower they are. For values close to zero, white or pale colour is plotted.

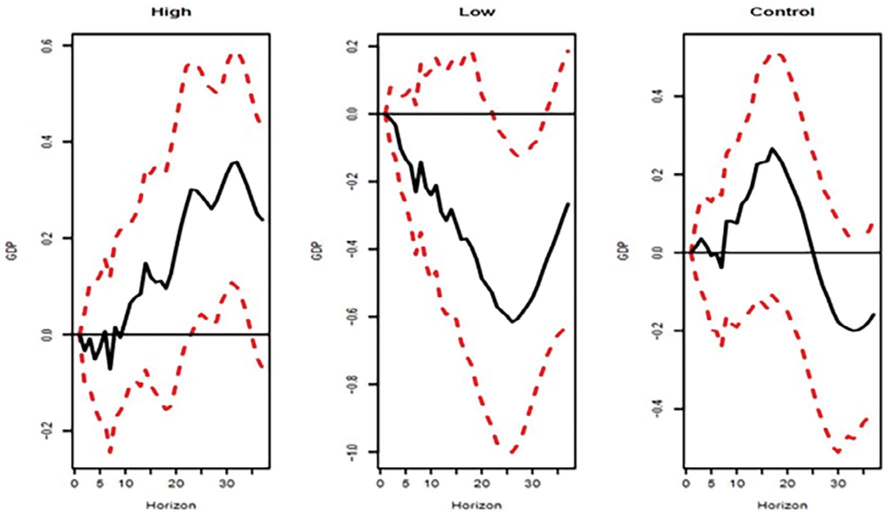

Figure 3. IRF—impact of monetary policy shock on output: 3-year projection
Source: Own research.

In Figure 4, the prominent price puzzle can be recorded for probability values of 0.15 and higher. Additionally, in this figure, the proper negative impact of monetary policy on output is also shown for a similar interval (0.15 or lower).

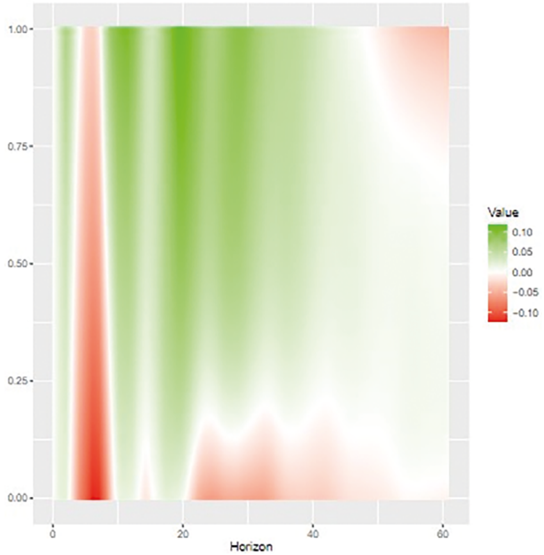

Figure 4. 3-D IRF—impact of interest rate on CPI: 5-year projection
Source: Own research.

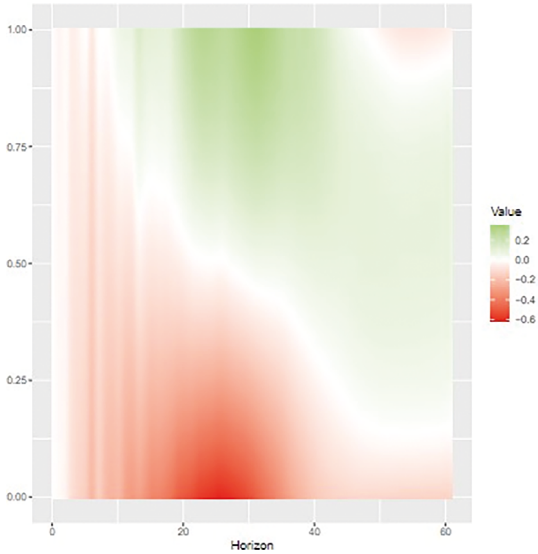

Figure 5. 3-D IRF—impact of interest rate on GDP: 5-year projection
Source: Own research.

Henceforth, for most periods, the economy demonstrates abnormal behaviour. The results suggest that a relatively small fraction of optimistic agents in the economy may deviate from the theoretical behaviour. However, more evidence needs to be claimed to prove such a statement, as mentioned earlier.

Conclusions

In this article, a novel method is presented for implementing market sentiments in monetary policy literature. The preliminary results show that tightening the monetary policy has varying impact on the economy, depending on values of customer confidence index. The proposed model differentiates 2 regimes—"high", which overlaps with expansion periods of the business cycle, and „low", overlapping with recession. During periods of recession, economic behaviours align with new-Keynesian theory models, whereas in higher regimes, they act counter-intuitively. The results may allow to suggest that the irrationality of economic agents can play a significant role in monetary policy effectiveness.

Moreover, the price puzzle also seems to be connected with market sentiments. In the lower regimes, the impact of interest rates on prices is negative. However, the higher probability of a "high" regime, the more persistent the price puzzle becomes.

Although the results presented in this article are preliminary and should be considered with caution, more research on this topic may bring more insight to policy planning and recession recovery programmes.

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