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An empirical behavioral model of Russian households' deposit dollarization

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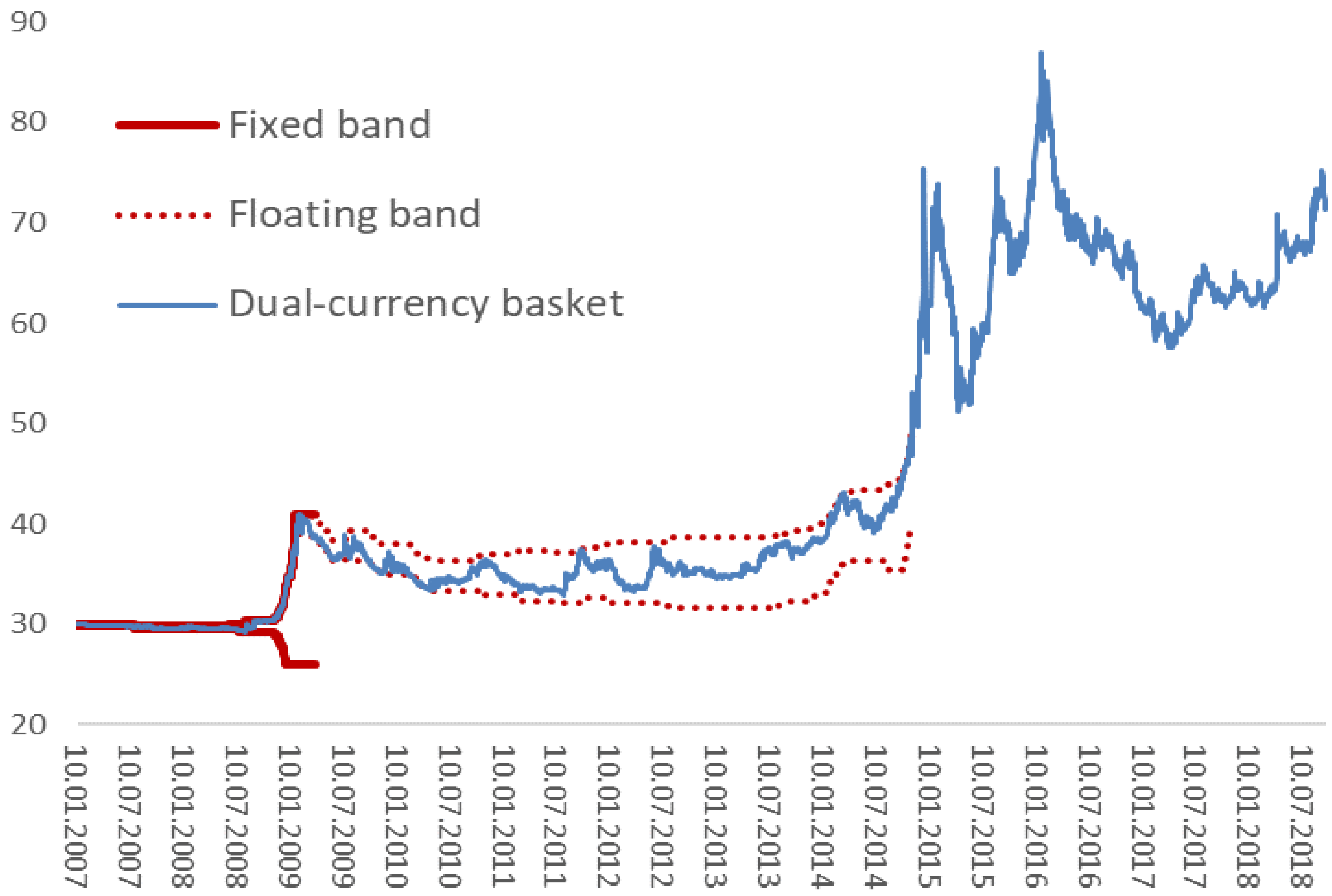
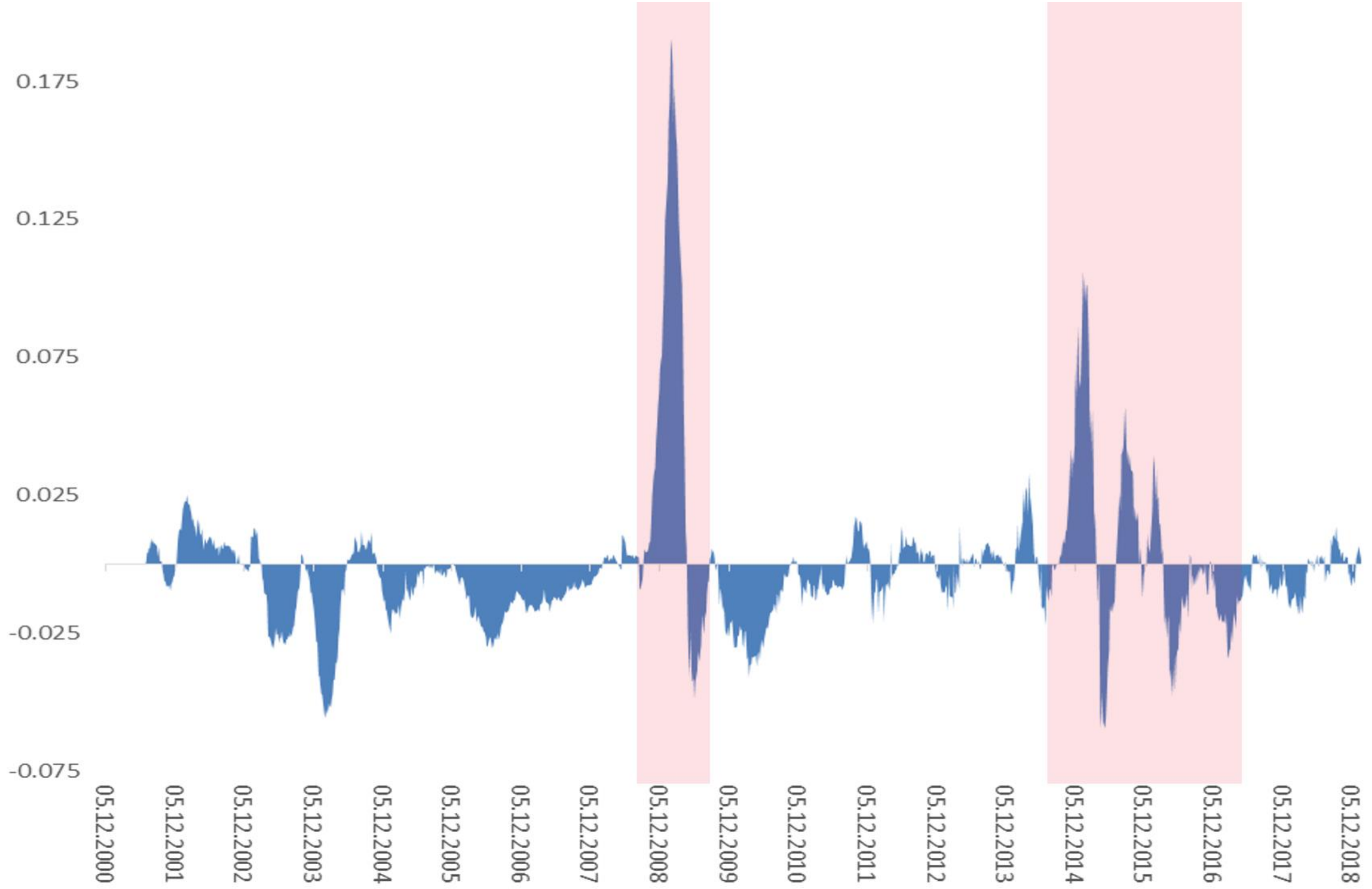
Motivation

Ruble / dual-currency basket exchange rate



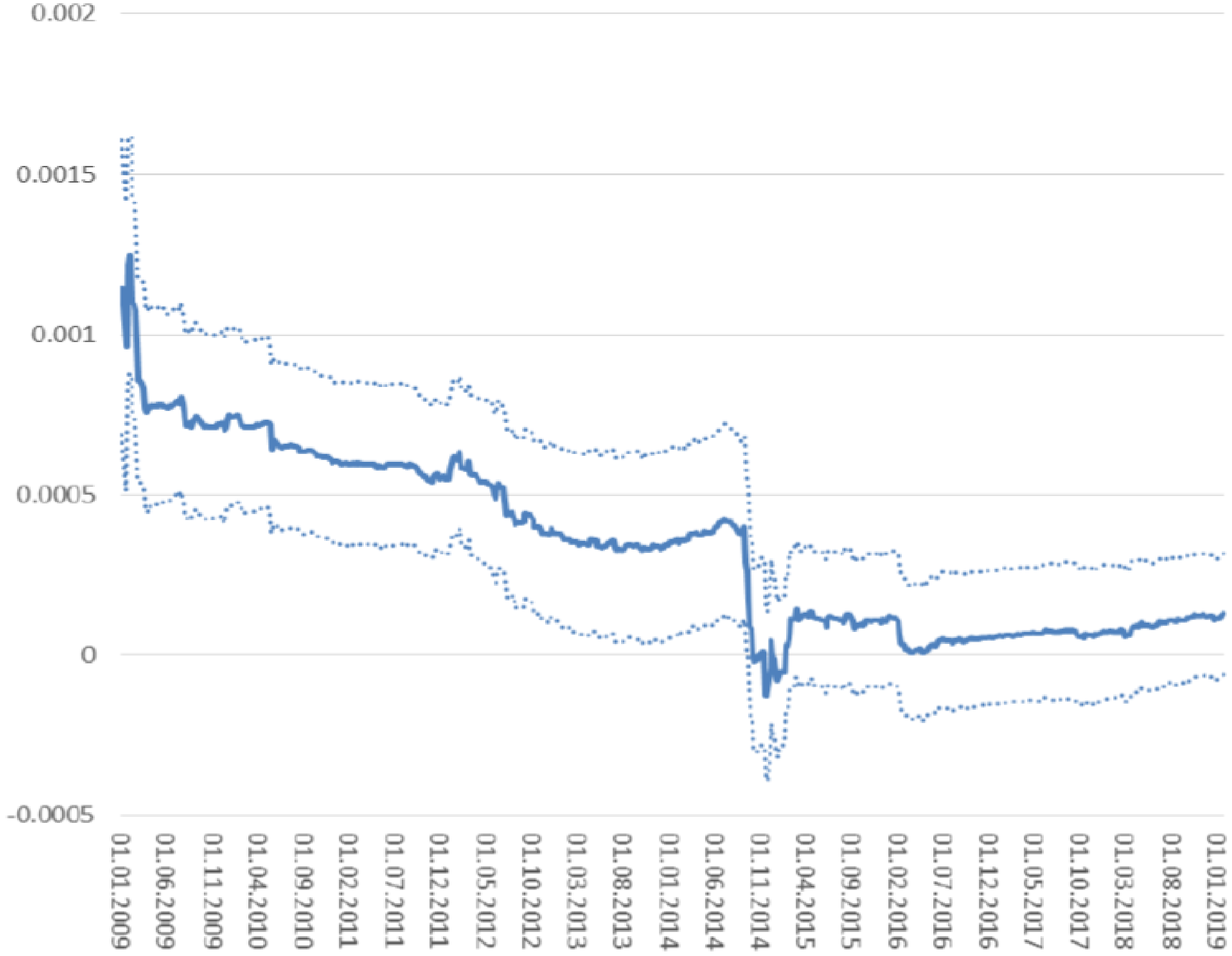
Motivation

3-month ‘excess’ inflows into households’ foreign currency deposits



Motivation

Time-varying sensitivity of changes in households' deposits dollarization to ruble depreciation rate (± 2 standard errors)



The concept

- Based on Westerhoff (2009) and Franke and Westerhoff (2012)
- **Fundamentalists' strategy:**

$$d_t^f = \varphi(e_{t-1}^* - e_{t-1})$$

- **Chartists' strategy:**

$$d_t^c = \chi(e_{t-1} - e_{t-2})$$

- **Strategies' fitness:**

$$w_t^j = \eta w_{t-1}^j + (e_{t-1} - e_{t-2}) d_{t-1}^j; \quad j = \{f, c\}$$

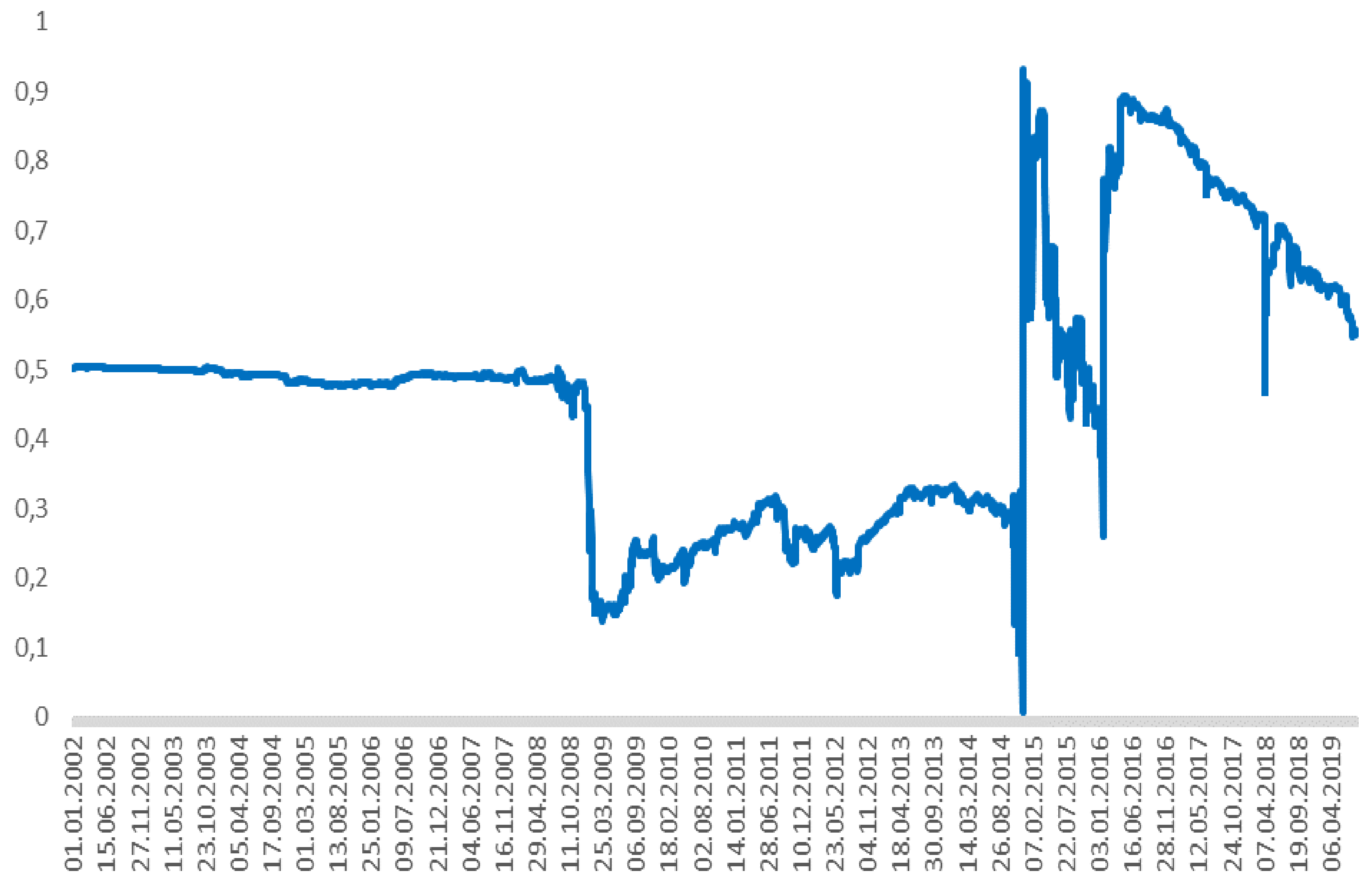
- **Fundamentalists' share:**

$$sf_t = \left(1 + \exp\left(-\beta\left(w_t^f - w_t^c\right)\right)\right)^{-1}$$

- *e* – log of exchange rate exchange
- *e** – moving average log of exchange rate exchange
- exchange rate depreciation and gap are standardized, $\varphi = \chi = 1,\ \eta = 1,\ \beta = 100$

The concept

Fundamentalists' share



Data

- **Frequency:** 5-day
- **Time Period:**
  - Train sample: 20.03.2002 – 30.01.2010
  - Test sample: 05.02.2010 – 20.01.2019

- **Data :**

$$dd_t = \frac{FD_t - FD_{t-1} \times \frac{E_t}{E_{t-1}} - \frac{FD_{t-1}}{TD_{t-1}} \times \Delta D_t}{TD_{t-1}},$$

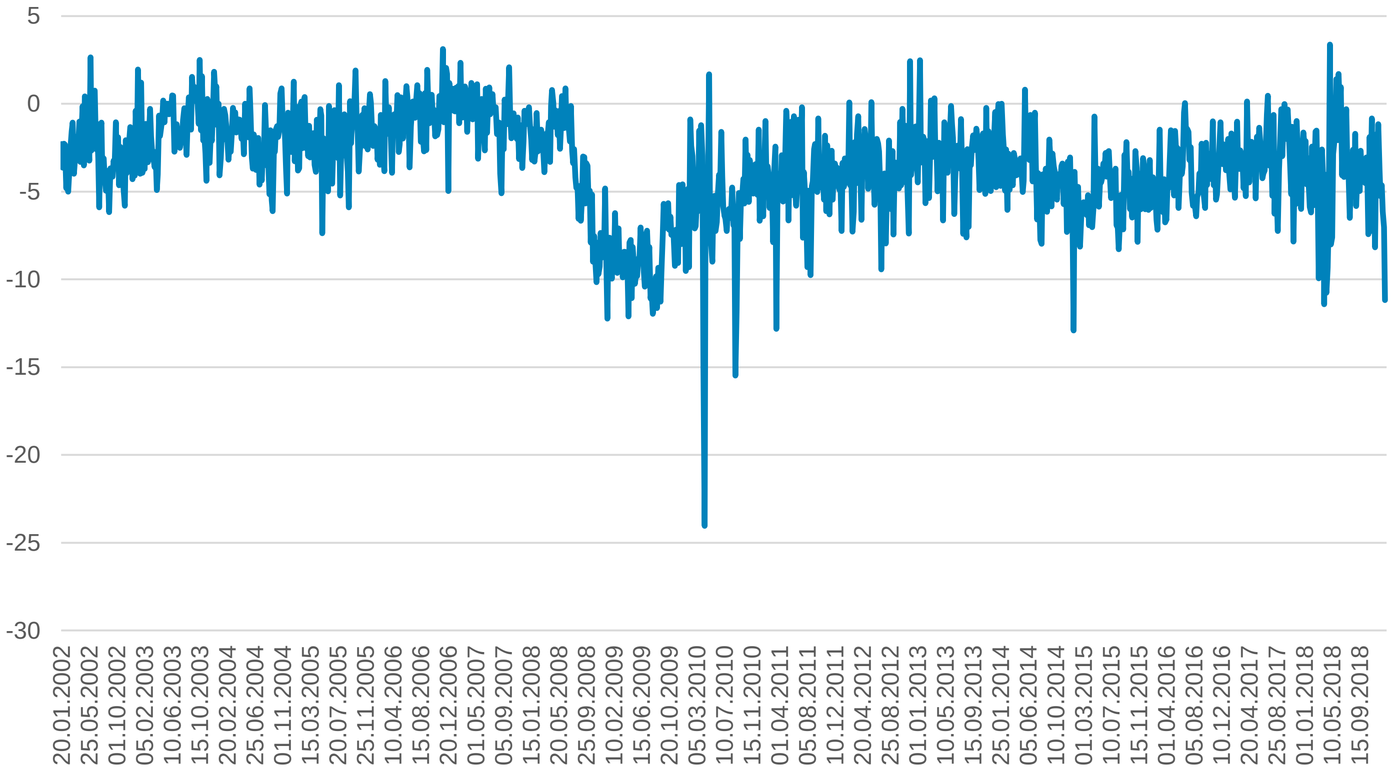
$$\Delta D_t = \Delta RD_t + FD_t - FD_{t-1} \times \frac{E_t}{E_{t-1}},$$

TD_t — total households deposits, FD_t — ruble value of households deposits denominated in foreign currency, RD_t — households deposits denominated in rubles, E_t — ruble/USD exchange rate value.

- e_t – Log nominal exchange rate USD/RUB
- π_t^{oil} – Oil price inflation
- s_t – News sentiment index

Sentiment Index

- Based on LDA text analysis of news, associated with ‘Currency’ and ‘Exchange rate dynamics’
- The higher the index, the ‘better’ are news => sentiment is higher



Variable	Pearson’s correlation [P-Value]
Exchange Rate	-0.195 *** [0.001]
Log Exchange Rate	-0.216 *** [0.001]
Diff Log Exchange Rate	-0.071 *** [0.009]

0.039*"рубль" + 0.023*"курс" + 0.023*"ставка" + 0.022*"рынок" + 0.020*"валюта" + 0.019*"доллар" + 0.016*"валютный" + 0.015*"цб" + 0.013*"евро" + 0.009*"неделя" + 0.009*"день" + 0.007*"пункт" + 0.007*"рублевый" + 0.005*"годовой" + 0.005*"снижаться" + 0.005*"фрс" + 0.005*"вырастать" + 0.005*"девальвация" + 0.005*"нефть" + 0.004*"падение" + 0.004*"уровень" + 0.004*"центробанк" + 0.004*"промсвязьбанк" + 0.004*"финанс" + 0.004*"вклад" + 0.004*"ищенко" + 0.004*"подорожать" + 0.004*"индекс" + 0.004*"конец" + 0.003*"последний" + 0.003*"покупка" + 0.003*"подешеветь" 0.003*"улюкаев" + 0.003*"начало" + 0.003*"копа" + 0.003*"аналитик" + 0.003*"снижение" + 0.003*"укрепление" + 0.003*"российский" + 0.003*"после" + 0.003*"операция" + 0.003*"сша" + 0.003*"доходность" + 0.003*"25" + 0.003*"процентный" + 0.003*"ослабление" + …

Behavioral model of deposit dollarization

- Fundamentalists' dollarization strategy:

$$d_t^f = \alpha^f + \varphi(e_t^* - e_t) + \sum_{j=1}^{p} (b_{oil.j}^f \pi_{t-j}^{oil} + b_{sent.j}^f s_{t-j}) + v_t^f$$

$$v_t^f \sim N\left(0, \sigma_f^2\right)$$

- Chartists' dollarization strategy:

$$d_t^c = \alpha^c + \chi(e_t - e_{t-1}) + \sum_{j=1}^{p} (b_{oil.j}^c \pi_{t-j}^{oil} + b_{sent.j}^c s_{t-j}) + v_t^c$$

$$v_t^c \sim N(0, \sigma_c^2)$$

$$\chi \geq 0; \qquad \varphi \geq 0$$

Behavioral model of deposit dollarization

- Strategy's fitness:

$$w_t^j = \eta w_{t-1}^j + (1-\eta)(e_{t-1} - e_{t-2})d_{t-1}^j; \quad j = \{f, c\}$$

$$0.9 \leq \eta \leq 1$$

$$w_0^c = w_0^f$$

$$a_t = \left(w_t^f - w_t^c\right)$$

- Alternative specification with "herding"

$$a_t = \left(w_t^f - w_t^c\right) + \rho_{herd}\left(w_{t-1}^f - w_{t-1}^c\right)$$

$$sf_t = (1 + \exp(-\beta a_t))^{-1}$$

Behavioral model of deposit dollarization

- There is a share of fundamentalists in the economy sf_t. Hence, the total dollarization in the economy is defined as:

$$\bar{d}_t = sf_t d_t^f + (1 - sf_t) d_t^c$$

- We fit the 5-day change in dollarization:

$$dd_t = \bar{d}_t - \bar{d}_{t-5d}$$

Estimation method:

Khabibullin and Seleznev (2020)

Stochastic Gradient Variational Bayes and Normalizing Flows for Estimating Macroeconomic Models

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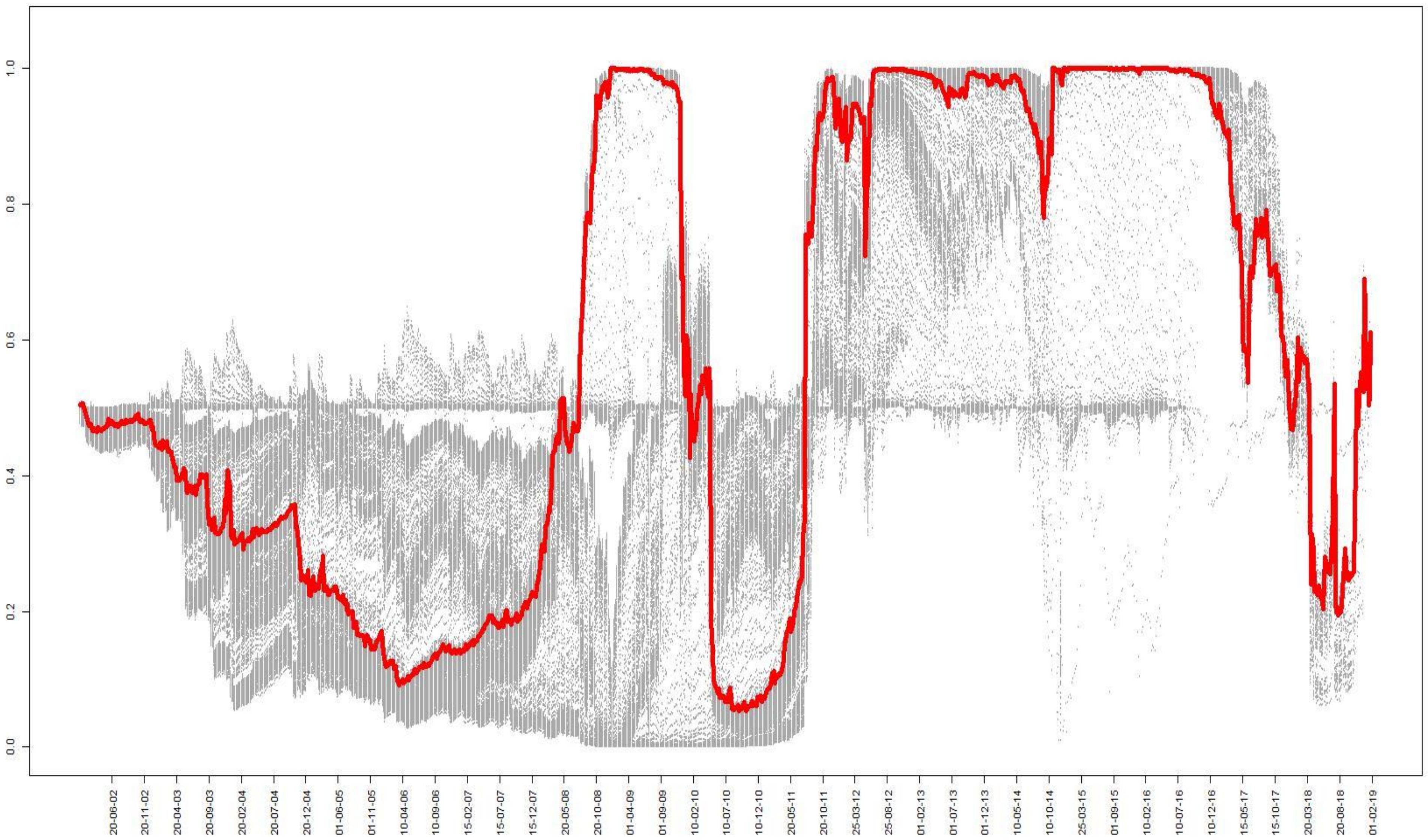
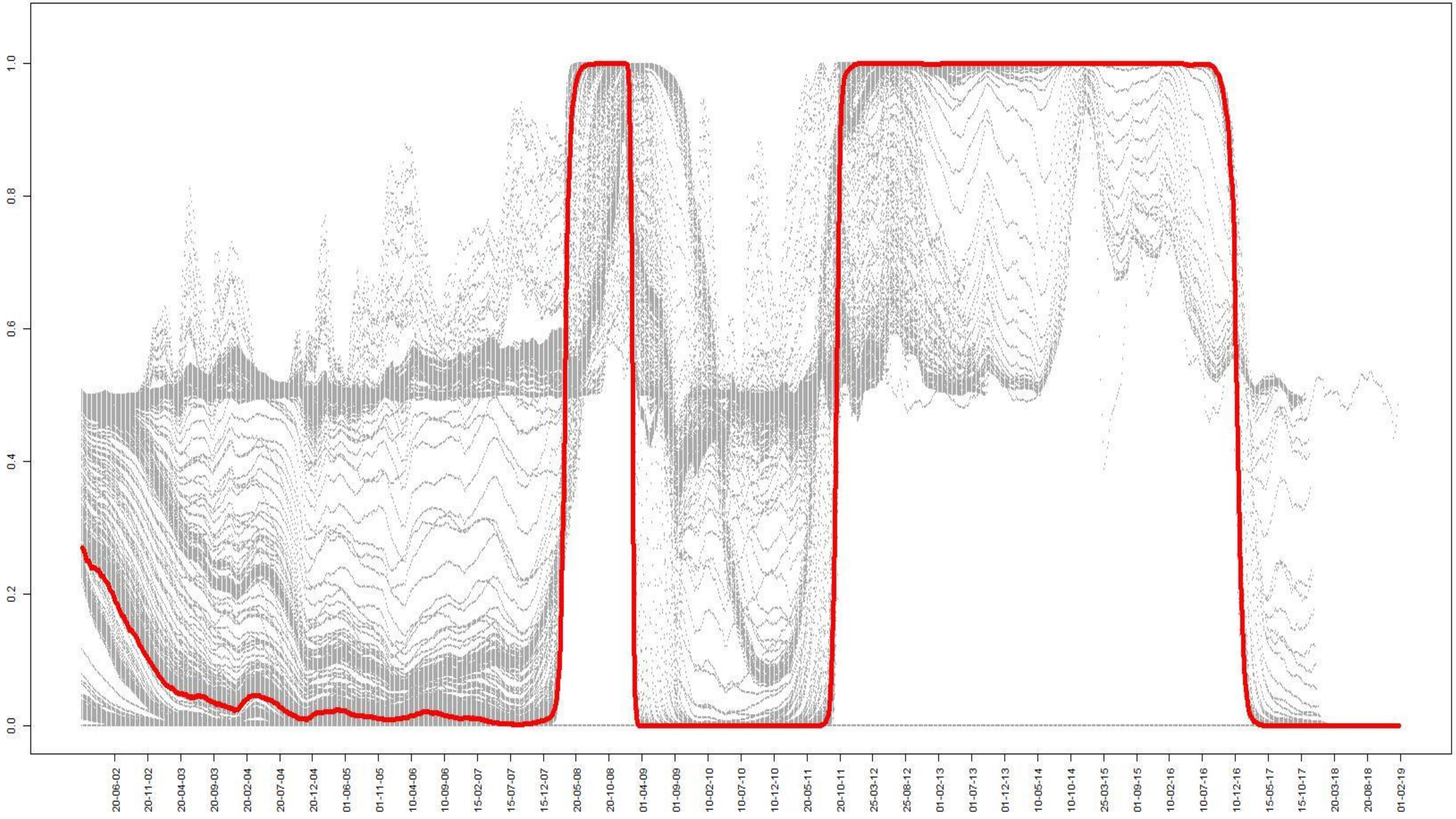
Results: real-time fundamentalists share estimates



Results: real-time fundamentalists share estimates (HERD)



Benchmark models: models with changes in regime

We compare our model with commonly used econometric models with regime shifts:

1. TVP
2. Markov-switching
3. Threshold (naïve recursive share as a threshold variable)
4. Smoothed-transition (naïve recursive share as a transition variable)

RMSE of the alternative models (as ratio to the RMSE of ARX)

Forecast horizon	TVP AR	TVAR E	TVAR SW	LSTAR E	LSTAR SF	MSBVAR	BEH WG	BEH HERD
1	1.156	1.078	1.088	1.409	1.532	1.028	1.116	1.088
2	1.151	1.081	1.131	1.285	1.470	1.094	1.119	1.043
3	1.144	0.995	1.015	1.478	1.318	**0.950**	1.054	1.034
4	1.187	0.995	1.059	1.229	1.417	**0.968**	1.003	1.012
5	1.188	1.018	1.053	1.231	1.307	**0.989**	1.067	1.021
6	1.235	0.990	1.016	1.187	1.200	**0.959**	0.983	0.980
7	1.240	0.970	1.014	1.175	1.265	**0.942**	0.968	0.983
8	1.250	0.961	1.002	1.121	1.230	0.969	**0.961**	0.980
9	1.279	0.971	0.985	1.254	1.133	0.961	**0.927**	0.976
10	1.311	0.974	0.989	1.050	1.237	0.961	**0.907**	0.968
11	1.296	0.981	0.992	1.026	1.089	0.982	**0.925**	0.967
12	1.347	0.981	0.974	0.980	1.018	1.023	**0.884**	0.945

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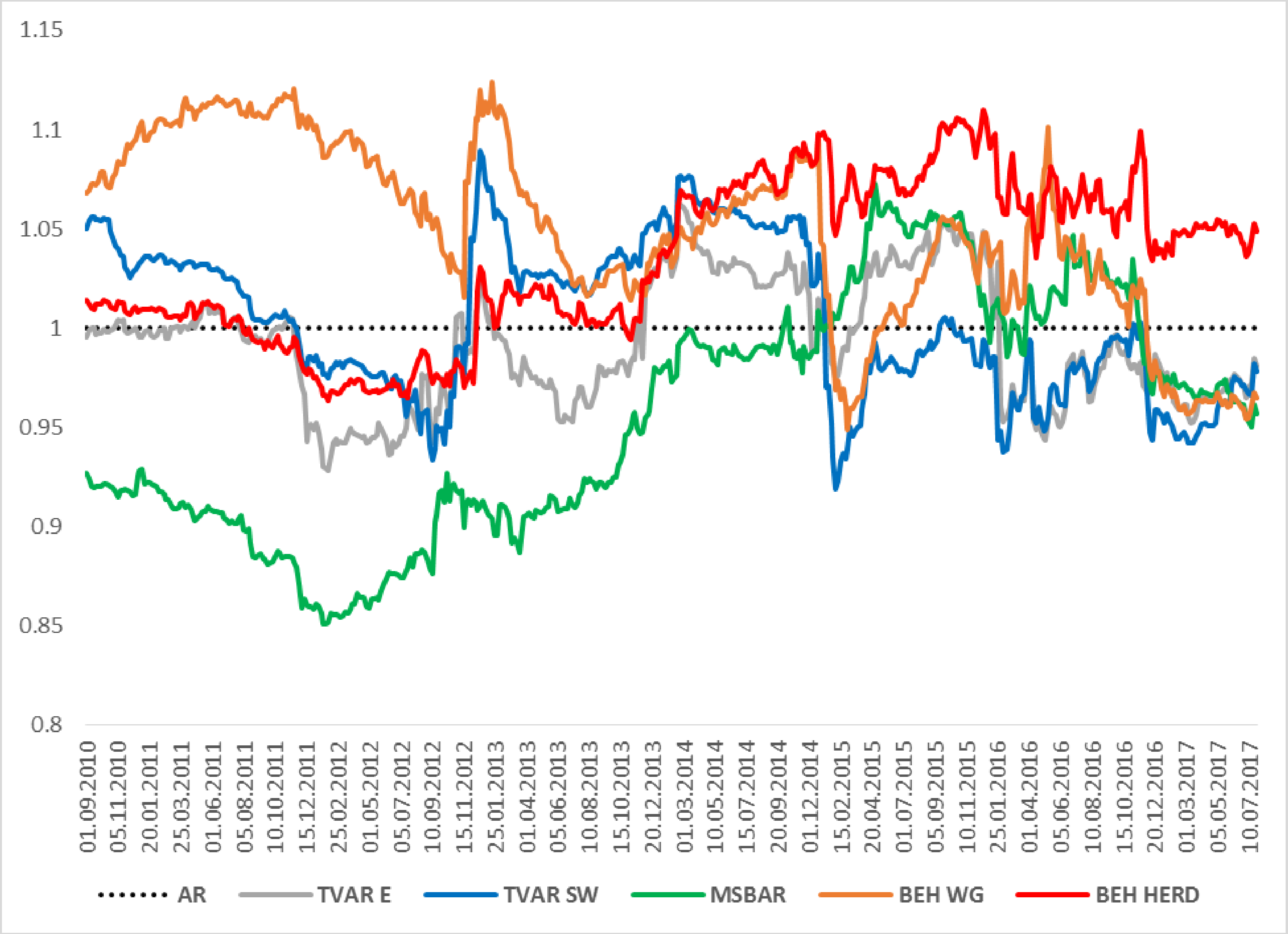
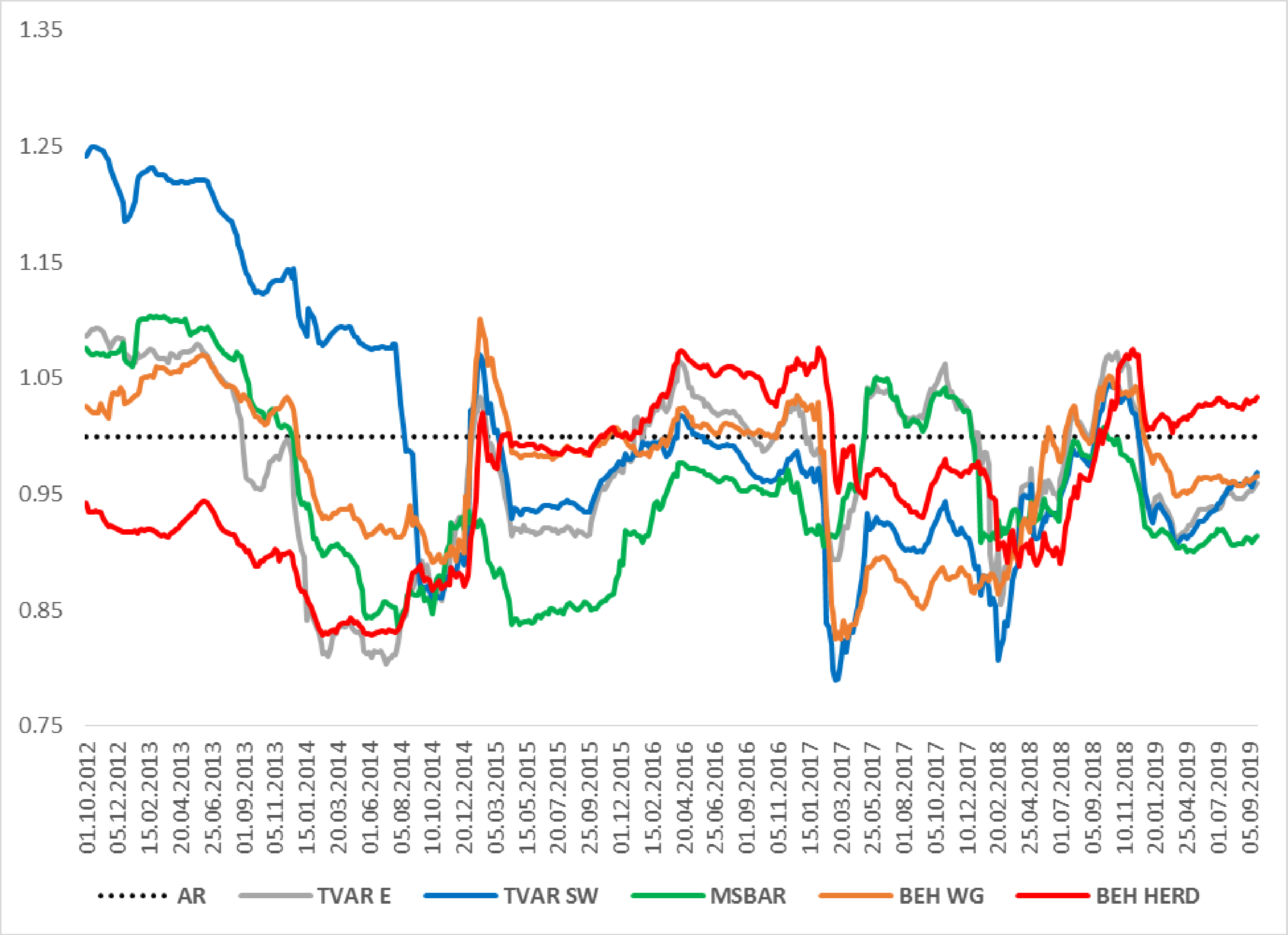
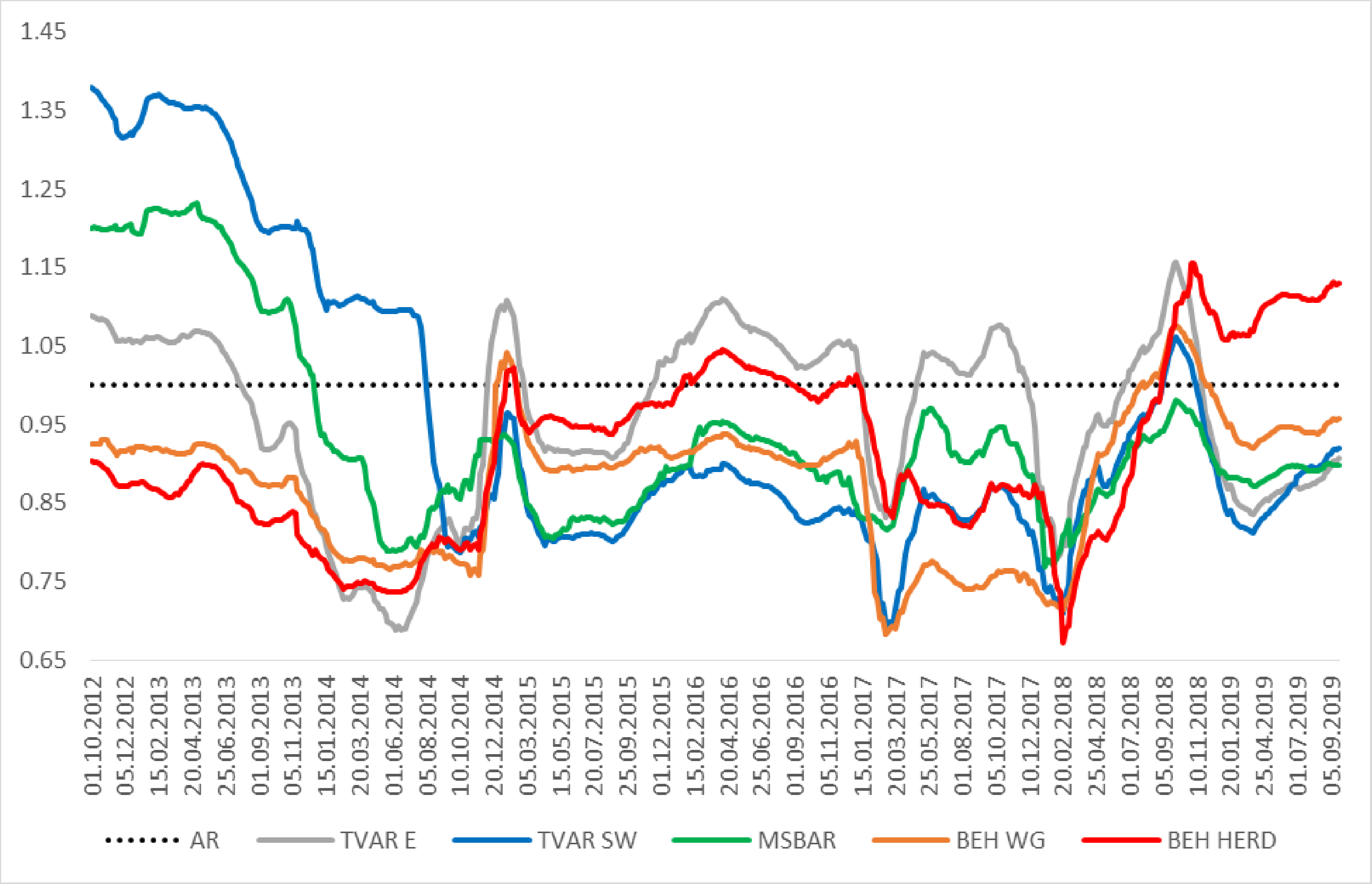
Relative Recursive RMSE (forecast horizon = 3)



Relative Recursive RMSE (forecast horizon = 6)



Relative Recursive RMSE (forecast horizon = 12)



Conclusions

- The concept of chartists vs. fundamentalists behavioral model appears to be applicable to the developments of dollarization in Russia

- The estimates of population shares are informative and economically interpretable. The increase in the volatility if followed by the increase in the share of fundamentalists. This property reveals the time-varying nature of links between dollarization and exchange rate dynamics.

- The model can be applied in practice for real-time forecasting

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Thank you for your attention!

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Brief Estimation Details

Model estimation: Variational Bayes with Normalizing Flows

To estimate model parameters and hidden states, we use novel Variational Bayes with Normalizing Flows method.

Aim: Choose an approximate function $q(\cdot)$ for model parameters and the vector of prior hyperparameters φ to maximize the Evidence Lower Bound (ELBO):

$$\log p(y|x,\varphi) = \log\left(\int \frac{p(y,\theta|x,\varphi)}{q_\psi(\theta)} q_\psi(\theta)d\theta\right) \geq \int \big(\log p(y,\theta|x,\varphi) - \log q_\psi(\theta)\big) q_\psi(\theta)d\theta$$

$$= L(q,\varphi)$$

$$L(q,\varphi) = \log p(y|x,\varphi) - KL\big(q(\theta)||p(\theta|y,x,\varphi)\big) \rightarrow \max_{q,\varphi},$$

where $KL(f(\theta)||g(\theta))$ — Kullback–Leibler divergence, $\log p(y\,|x,\varphi)$ — marginal likelihood, ψ — parameters of the approximate density

Standard VB Algorithms

Mean field (MF) approximation using independent Gaussian approximate densities is the standard VB procedure (Blei et al, 2017):

$$q_{\psi}(\theta) = q_{\psi_1}(\theta^1) q_{\psi_2}(\theta^2) \ldots q_{\psi_D}(\theta^D)$$

$$q_{\psi_d}(\theta^d) \sim \mu_d + \sigma_d N(0,1), \qquad d = 1, \ldots, D$$

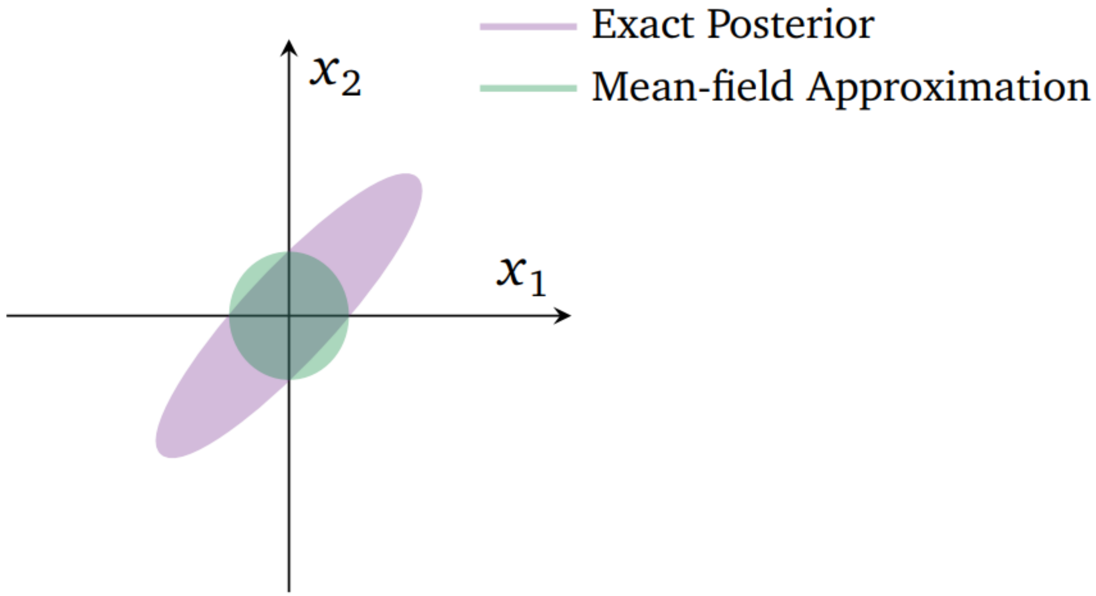
or: $q_{\psi}(\theta) \sim N(\bar{\theta},\ \overline{V_{\theta}})$

However, this technique is prompt to the issue of poor choice of the approximate density family.

Mean Field Approximation

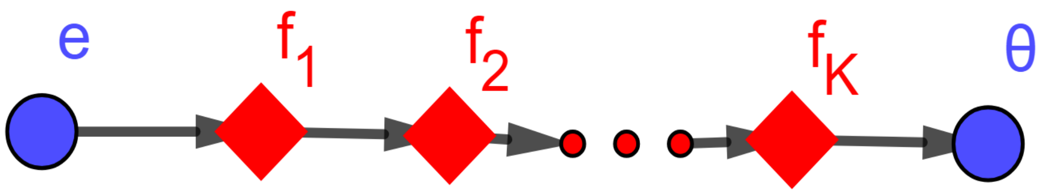
Poor choice of the approximate density family.

For instance, in the simplest case of multivariate normal distribution (Blei, et al, 2017). Independent MF-VB usually incorrectly estimates the posterior distribution moments of order >1:



Normalizing Flows (NF)

- To handle this problem we use the following parameter transformation:



$$\theta_K = g_\psi(e) = f^K_{\psi_K}\left(f^{K-1}_{\psi_{K-1}}\left(\ldots\left(f^1_{\psi_1}(e)\right)\right)\right),$$

where $f^k_{\psi_k}$ — transformation function for the k-th step of transformation. In the ML literature there are several types of such transformations. Following (Kingma, Welling, 2018), we used Sylvester NF (Berg, et al, 2018) as one of the most flexible:

$$f^k_{\psi_k}(z) = z + Ah(Bz + b)$$

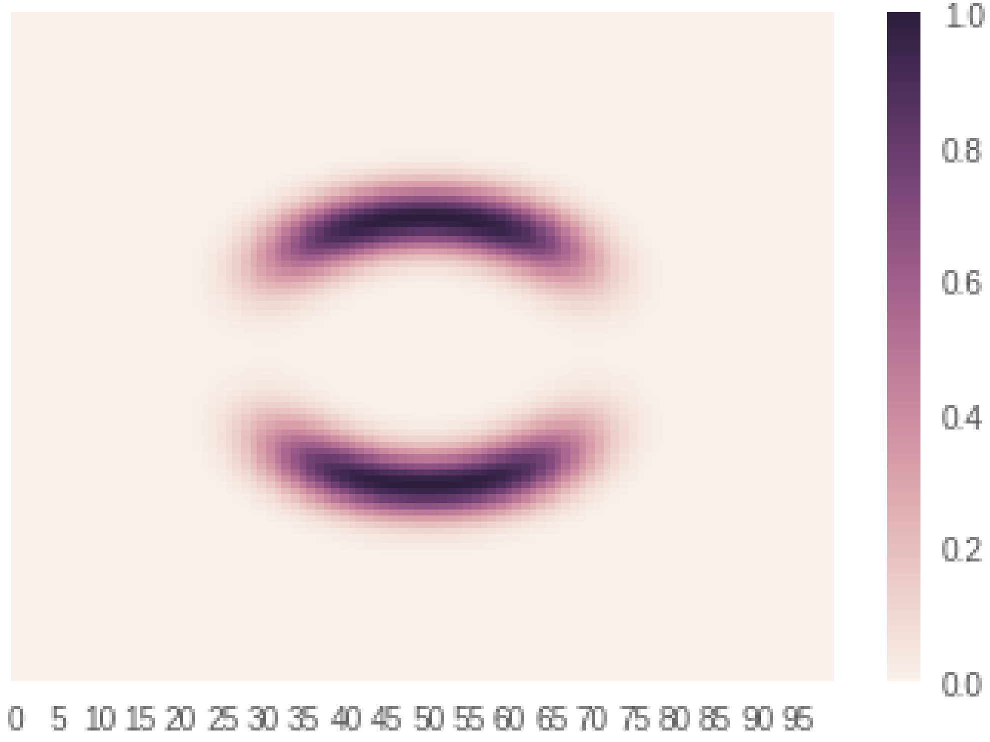
where A, B and b are $D \times M$, $M \times D$ и $M \times 1$ matrices, $h(\cdot)$ – activation function (we used $\tanh(\cdot)$). Hence, approximate density parameters are:

$$\psi_k = \{A, B, b\}$$

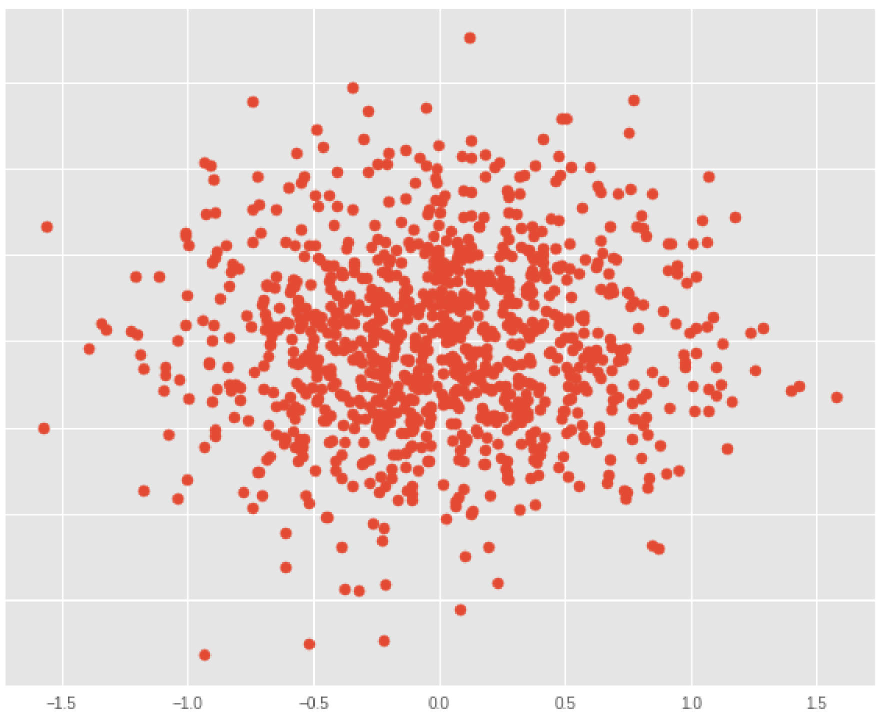
Normalizing Flows (NF)

To illustrate the performance of SGVB-NF let us assume the following experiment (similar to Kingma, Welling, 2018). Suppose that the true posterior is of the form:

True posterior density



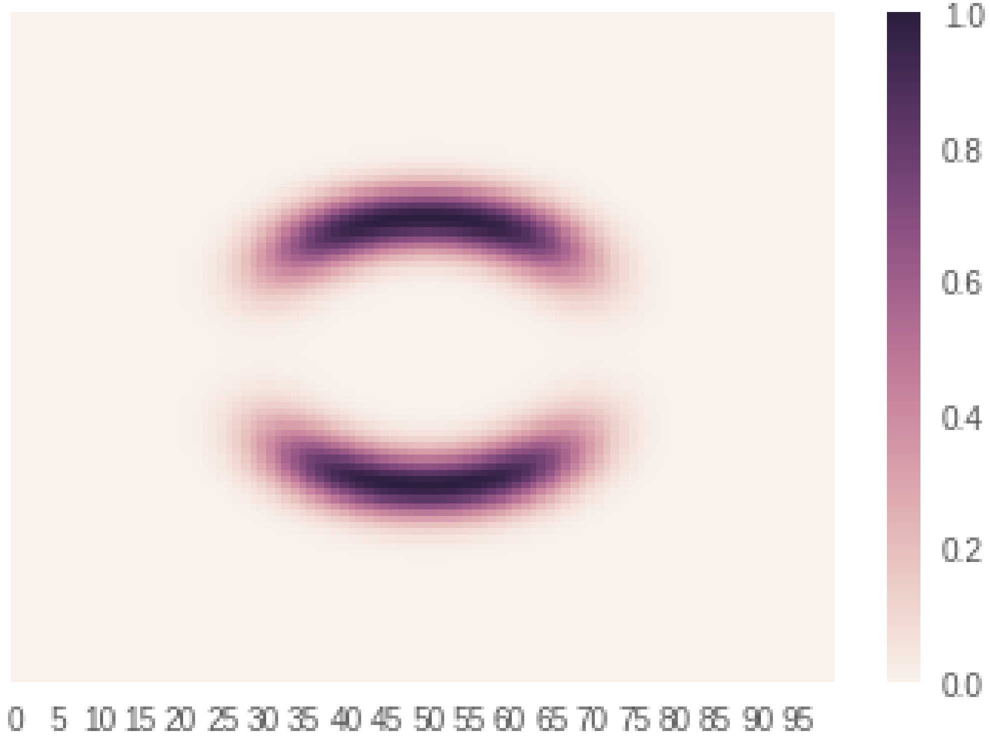
VB-MF approximation



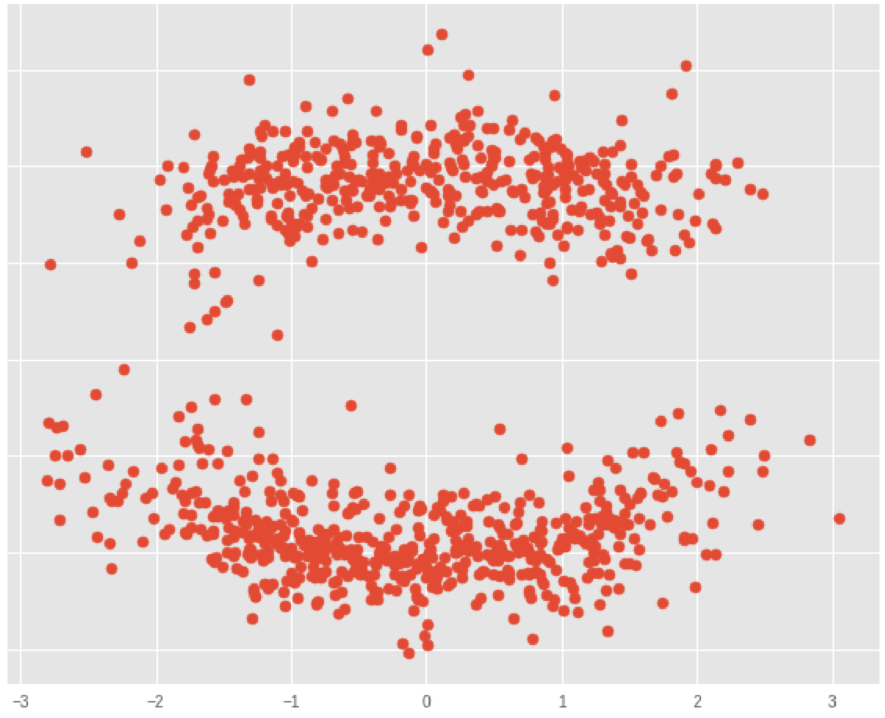
Normalizing Flows (NF)

SGVB-NF gains more accurate approximation. Here we used $K = 50$ sequential transformations.

True posterior density



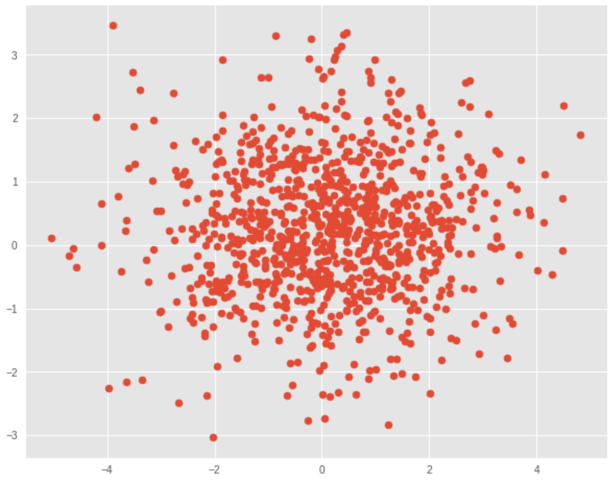
SGVB-NF approximation



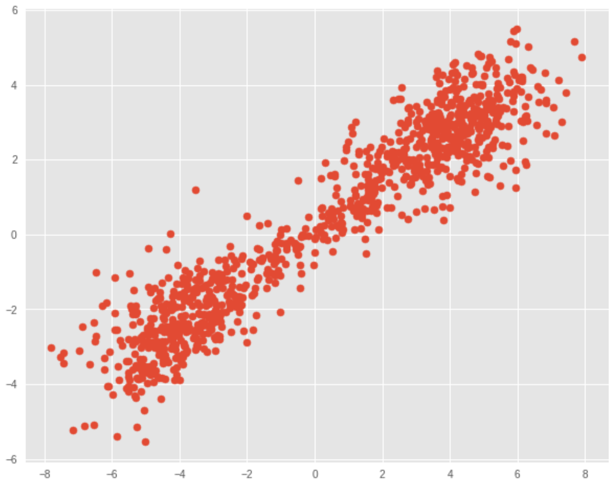
Normalizing Flows (NF)

SGVB-NF gains more accurate approximation. Here we used $K = 50$ sequential transformations.

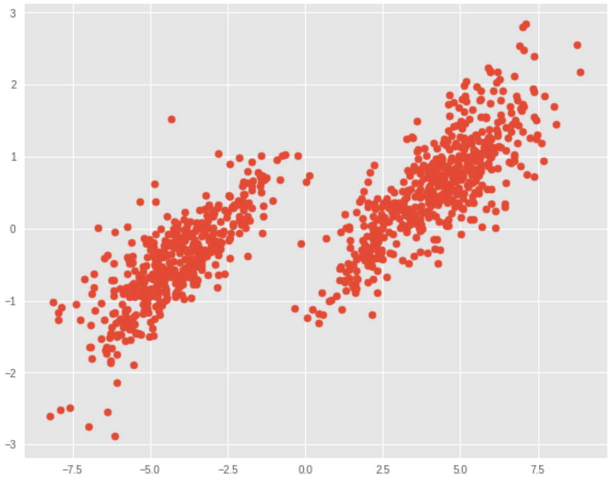
k=0



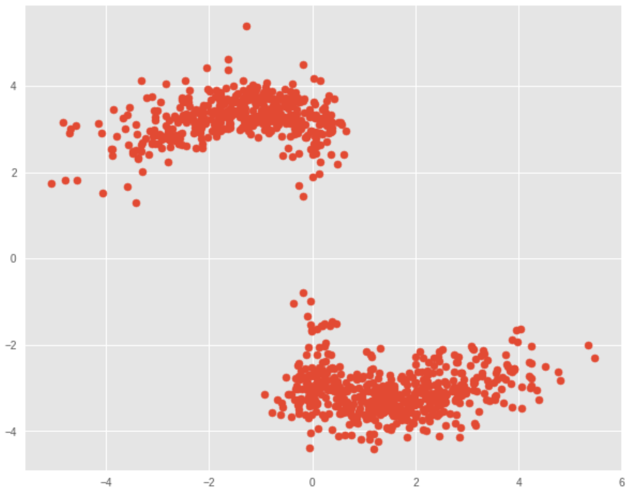
k = 10



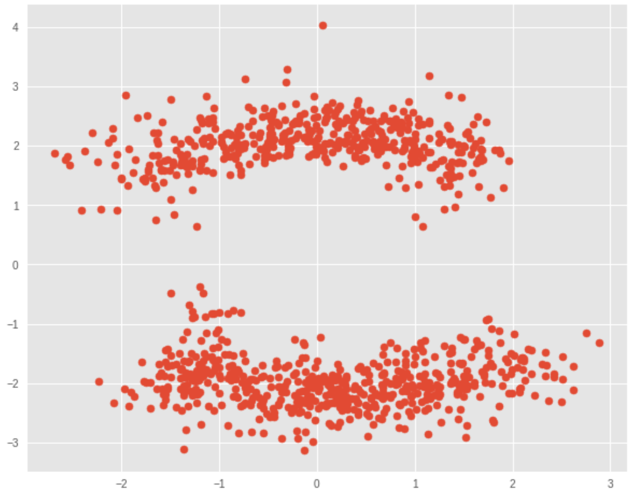
k = 20



k =40



k = 45



k = 50