DOES THE MONETARY TRANSMISSION MECHANISM CHANGE OVER TIME IN UKRAINE?

by

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Abstract

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The objective of this paper is to study a gradual change in the strength of transmission mechanism in Ukraine since the introduction of the IT regime. To find the evidence that the monetary transmission mechanism evolves over time, I estimate a time-varying parameter vector autoregression model with stochastic volatility. The study shows that responsiveness of Ukrainian economy to monetary policy shock in 2020 and 2022 has declined in comparison with 2016. Variability in values of shocks play the key role in causing the time-varying effect of the monetary policy transmission in Ukraine. The impact of exchange rate shock on Ukrainian economy from the first lockdown in 2020 to the beginning of 2022 was smaller than in previous years. Finally, I find no evidence for a change in transmission of a demand shock to prices over time. Robustness analysis shows that my results are consistent under alternative model's specifications.

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LIST OF ABBREVIATIONS

ARIMA. Autoregressive integrated moving average.

CB. Central Bank.

CPI. Consumer price index.

FAVAR. Factor-augmented vector autoregression.

GDP. Gross Domestic Product.

IT. Inflation targeting.

MTM. Monetary transmission mechanism.

NBU. National Bank of Ukraine.

NEER. Nominal effective exchange rate.

SSSU. State Statistics Service of Ukraine.

ToT. Terms of trade index.

TRAMO-SEATS. Time series Regression with ARIMA noise, Missing values and Outliers - Signal Extraction in ARIMA Time Series.

TVP–VAR. Time-varying parameter vector autoregression.

UIIR. Ukrainian Index of Interbank Rates.

UONIA. Ukrainian OverNight Index Average.

VAR. Vector autoregression.

Chapter 1

INTRODUCTION

The NBU adopted the inflation targeting regime in the second half of 2015. Since then, the policymaker seeks to understand and quantify the potential impact of the monetary policy as well as internal and external shocks on the economy of Ukraine. In this thesis, I seek to understand whether the monetary transmission mechanism has changed over time.

The process through which monetary policy actions affect the economy is described by a transmission mechanism of monetary policy. The monetary transmission mechanism in Ukraine is usually described as a two-step process (Zholud, Lepushynskyi, and Nikolaychuk 2019). In the first stage, the CB changes the key policy rate. Then the interest rate affects economic activity and the level of inflation, which is the main goal of the monetary policy under the IT regime. There are different channels through which monetary policy impacts real economic variables (Mishkin 1995). Zholud et al. show that only two of them are significant in Ukraine: the interest rate channel and the exchange rate channel. Therefore, I focus only on these two channels in this thesis.

The strength of monetary transmission mechanism is the scale of a signal that transmits from the key rate to economic decisions that drive changes in the output and prices. It is not constant over time and depends on a number of time-varying factors within any economy. These factors vary from a current monetary framework to the structure of an economy. On the one hand, the Central Bank is continuously improving its monetary instruments to pursue its goals. Such changes in instruments may strengthen a monetary policy transmission mechanism. On the other hand, large external events like the COVID-19 pandemic create destabilizing effects on the global economy that potentially can result in drastic changes to the elements of the transmission mechanism in small open economies. Therefore, it is important to study how the response of the economy to monetary policy shocks evolve over time.

The contribution of this thesis is that, to the best of my knowledge, it is the first attempt to use time-varying estimation framework to study monetary transmission mechanism in Ukraine. Particularly, I use TVP-VAR framework for monetary policy analysis in Ukraine and investigate the impact of exchange rate shock during the COVID-related economic recession on the monetary transmission mechanism.

The research question is whether there was a gradual change in the strength of transmission mechanism in Ukraine since the introduction of the IT regime. To answer the question, I estimate the responsiveness of the Ukrainian economy to monetary policy shocks allowing for possible time variation in both shocks and transmission. There are three main hypothesis that I test in the thesis.

The first hypothesis is that the Ukrainian economy has become less responsive to monetary policy shocks over time. Formally it means that there is a statistically significant difference in the impulse responses to a monetary policy shock at different time periods starting from 2016M1. The interest rate shock is assumed to be the monetary policy shock. A weakening of MTM is a common result in the literature (Arratibel and Michaelis, 2014). There are two possible explanations to this finding. First, an economy can become more stable as the result of inflation targeting, because shocks decrease in magnitude that means lower variance in economic variables (Svensson 1997). Second, a decrease in responsiveness of the economy can indicate diminishing efficiency of interventions made by the CB due to rigidity of its monetary decisions and slow adjustment to a state of the real world (Morgan 2009). It is important to distinguish between these two origins of resilience because each of them implies a different policy response. If it is the first reason, then policy makers can reduce the frequency of policy interventions to increase a level of certainty for economic agents. If it is the second reason, then a central banker must compensate the reduction in responsiveness by the increase in magnitudes of interventions.

The second hypothesis is that the impact of exchange rate shock on the economy has increased during the COVID-related recession. This hypothesis comes from the assumption that the magnitude of shock hitting economy is larger during a crisis compared to normal times

(Justiniano and Primicery 2005; Arias, Hansen and Ohanian 2006). To test the hypothesis, I check whether the responsiveness of economy to exchange rate shocks at 2020M4 – that is the first full month when Ukraine was under a total lockdown — is greater in absolute value than at 2016M4 and 2022M1.

The third hypothesis is that the response of inflation to demand shock is diminishing over time. In the empirical literature it is usually associated with a change in the nature of inflation process (Riggi and Santoro 2015; Szafranek 2017). Statistically, it means that differences in the impulse responses to a demand shock between earlier and latter time periods decrease over time.

To find the evidence that the monetary transmission mechanism evolves over time, I estimate a time-varying parameter vector autoregression model with stochastic volatility. There are three types of shocks in the model: demand shock, nominal effective exchange rate shock, and interest rate shock. Then I compute median impulse responses to these shocks at different time periods. I consider three time periods: 2016M4 — the first period for which it is possible to estimate the impulse response function given that the model has three lags; 2020M4 — the first full month under the lockdown in Ukraine; 2022M1 — the last observation in the sample and the last period before the war started. To test the hypotheses, I analyze the posterior probability for the difference in the time-specific impulse responses at periods mentioned above. If the values of probabilities are close to 50% it indicates an insignificant difference in the response of the economy to a shock. Simply, it means no evidence for time-variation in MTM. Conversely, posterior probability values above or below 50% imply the difference in levels of responsiveness over time (Arratibel and Michaelis 2014). Finally, I perform Wilcoxon test to find whether there is a statistically significant difference between median impulse responses for selected pairs of time points on five horizons (one, six, twelve, twenty-two and thirty-six months since a shock).

The paper is organized as follows. In Chapter 2, I review the literature on the peculiarities of the monetary transmission mechanism in Ukraine and the available frameworks for time-varying monetary policy analysis using TVP-VAR models. In Chapter 3, I discuss the econometric specification of the time-varying parameter vector autoregression model with stochastic volatility. In Chapter 4, I provide a data overview. Chapter 5 provides the estimation results, probabilities calculation, and robustness checks. Chapter 6 concludes.

Chapter 2

LITERATURE REVIEW

The classical VAR approach is well-discussed in literature for studying multivariate time series in relation to the monetary policy analysis. Generally, researchers try to find out all possible transmission channels in an economy. It is common in literature to analyze their properties as being constant in time. Topics of interest include following: significance of links between an impulse and a response, rate of transmission, direction, duration, and magnitude of a response. Depending on a country under a scope, researchers concentrate on specific subjects of the MTM. Literature on developing countries pays relatively more attention to the role of risk premiums in the monetary transition, while the exchange rate channel plays an important role in research on small open economics like Ukraine. In contrast, researchers began to study a monetary transmission mechanism in dynamics only two decades ago (Cogley and Sargent 2001), due to advances in both theoretical econometrics and computing power. The amount of research in this field is still limited and is mostly concentrated on large economies as the US and the EU. Therefore, this chapter is divided into two parts. The first one explores general trends on research of MTM in open economies. The second part presents successes and failures of application of the time-varying framework to a monetary policy research.

2.1. Empirical studies on the monetary transmission mechanism in small open economies

My paper is related to the literature studying the responsiveness of open economies to monetary policy shocks. Stojanović (2016) estimates the strength of the monetary transmission mechanism in Serbia. The paper is constrained by a relatively short span of data used during analysis (from 2009M1 to 2013M12). Nevertheless, the author obtained statistically significant results through the structural VAR model. The study finds the exchange rate and credit channels to be dominant in the Serbian MTM.

Chmielewski et al. (2020) provide an extensive overview of general features of the MTM in Poland based on pieces of evidence from both VAR and structural New-Keynesian models. Disregarding the specific type of models, all of them provide evidence for the existence of the following channels: the interest rate, exchange rate, credit, risk-taking, and cash-flow channels. The authors conclude that the exchange rate channel and the interest rate channel provide the greatest shares of transmission of a monetary impulse to inflation.

My paper contributes to the literature that studies responses of the Ukrainian economy to monetary policy shocks. Zholud, Lepushynskyi, and Nikolaychuk (2019) examined the monetary transmission mechanism from a perspective of five main channels: the interest rate, exchange rate, expectations, credit, asset prices channels. The researchers find that only the first three are effective. It is important to notice that the effectiveness of each channel was examined using different approaches due to data limitations. The interest rate channel was analyzed in the greatest detail based on the date from 2015M12 to 2018M12. Using the autoregressive-distributed lag approach the authors find the interest rate channel pass-through is statistically significant from zero and lies in the range of 15-30%. For other channels, like exchange rate and expectation ones, the analysis is limited by examination of related literature, graphical description, economic rationale, and simple correlation analysis. Thus, the overall results about significance are to be treated with caution due to the absence of conformity in the applied methodology.

Borsuk (2021) has used a more sophisticated and consistent approach based on the Bayesian structural autoregressive model to provide empirical evidence for the existence of the credit channel in Ukraine. In particular, the author uses the supplement VAR model to examine the presence of two main subparts of the broad credit channel — the balance sheet and the bank lending channels. The researcher shows they are functioning, which contrasts with the results of Zholud et al. However, neither of papers accounts for a possibility of a time-varying monetary transmission mechanism, creating the actuality for my thesis.

The key distinction between my paper and the abovementioned studies is that I focus on time-varying effect of the monetary policy transmission in Ukraine. To my best knowledge, a gradual change in the strength of MTM in Ukraine has been never analysed with a use of a Bayesian TVP–VAR model with stochastic volatility. In my paper, I attempt to do in for the first time for Ukraine.

2.2. Time-varying monetary policy transmission

Time-variant approach used in this thesis is based on Primiceri (2005). He is the first to incorporate a time-variant approach into the analysis of monetary policy using the U.S. postwar data. He studied responses of inflation and unemployment to monetary policy shocks assuming that both coefficients in vector autoregression and the variance-covariance matrix of shocks can vary over time. The effect is achieved by allowing drifting coefficient in the VAR model and adding multivariate stochastic volatility. In the paper, he provides the estimation framework that is incorporated into this thesis. Primiceri concludes that there is evidence of time variation in the US monetary transmission, but not large enough to explain all fluctuations in variables.

Mumtaz, Zabczyk, and Ellis (2011) estimate the time-varying factor-adjusted VAR model (FAVAR) for the UK on quarterly data from 1975 to 2005. Its key difference from the TVP-VAR model is that it includes a large number of variables considering the economic activity (up to one hundred various variables) to account for the noisiness of data. However, a large number of parameters will make any VAR model unidentifiable, so they are summarized by principal components and only after are used in model estimation. The authors found that with every consecutive year since 1992, monetary policy shocks were increasing their impact on inflation, equity prices, and the exchange rate. The accounting for the time-variable framework is favorable however its implications on the optimal monetary policy and the country's welfare are yet to be determined.

The question of changes in MTM with time is also addressed by Babecka-Kucharčuková et al (2013). The researchers estimate the Bayesian VAR and TVP-VAR model on the quarterly data for the Czech Republic from mid-1990 to the end of 2010 and conclude that there is no clear evidence of significant changes to the transmission of monetary policy after the crisis of 2008 in the long run. The weakening of the transmission has taken place only during the crisis and in a couple of following years.

Important evidence of the applicability of a time-variant approach to the study of the transmission mechanism in a context of a small open economy was made by Arratibel and Michaelis (2014). The authors found that output and consumer prices in Poland were more responsive to interest rate shocks between 2000 and 2007 compared to 2012. They also calculate the posterior probability for the differences in time-specific impulse responses to provide clear evidence for the change in the transmission mechanism in Poland over time. I use their methodology to estimate a significance in changes of MTM in Ukraine over time in my thesis.

Chapter 3

METHODOLOGY

3.1. The setup of the TVP-VAR model

To account for the time-varying effect of the transmission mechanism the thesis incorporates the time-varying parameter VAR model with stochastic volatility. The key difference of this model from the standard vector autoregressive models is that TVP-VAR implies that both coefficients and the variance-covariance matrix of shocks can change over time. In this model each element of the matrix of coefficients and the lower-triangular matrix of errors is assumed to be a random walk without a drift. Therefore, the model can capture potential heteroskedasticity of the shocks.

I follow Primiceri (2005) to estimate the TVP-VAR model of a form:

$$Y_t = C_t + B_{1,t}Y_{t-1} + \cdots + B_{k,t}Y_{t-k} + u_t, \tag{1}$$

where $t = 1, \dots T$; Y_t is the vector of endogenous variables; C_t is the vector of time-varying coefficients multiplied by the vector of constants; $B_{i,t},\ i = 1, \dots, k,$ are matrices of time-varying coefficients with k lags; and u_t are unobservable heteroscedastic shocks with the variance-covariance matrix Ω_t. The TVP-VAR model estimates are based on monthly data starting from 2016M1 until 2022M1.

To allow time variation of shocks, consider the following factorization of the matrix Ω_t:

$$Var(u_t) = \Omega_t = A_t^{-1}\Sigma_t\Sigma_t'(A_t^{-1})', \tag{2}$$

where A_t and Σ_t are respectively time-varying lower triangular and diagonal matrices:

$$\Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \sigma_{n,t} \end{bmatrix} \quad \mathrm{A}_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{n1,t} & \cdots & \alpha_{n(n-1),t} & 1 \end{bmatrix} \tag{3}$$

Referring to the forecited reduction of the covariance matrix and storing time-variable coefficient into new matrix $\bar{B}_t$ the TPV-VAR model can be restated as:

$$Y_t = X_t'\bar{B}_t + A_t^{-1}\Sigma_t\varepsilon_t, \tag{4}$$

where $X_t = I_n \otimes [1, Y_{t-1}', \dots, Y_{t-k}']$, $\bar{B}_t = [C_t, B_{1,t}, \dots, B_{k,t}]$, $Var(\varepsilon_t) = I_n$.

Finally, setup (4) allows a time-variant effect in endogenous variables via $\bar{B}_t$. Also, A_t implies that innovation to the one variable has a non-constant effect on the other variables. Practically, the effect of variation in time is achieved by setting parameters $\bar{B}_t$, α_t, and σ_t as random walk with a drift:

$$\bar{B}_t = \bar{B}_{t-1} + \nu_t, \tag{5}$$

$$\alpha_t = \alpha_{t-1} + \xi_t, \tag{6}$$

$$log\sigma_t = log\sigma_{t-1} + \eta_t \tag{7}$$

It is important to notice that while elements $\bar{B}_t$ and α_t are derived from known parameters, the standard deviations σ_t are generated by unobservable variables (Shepard 1996). All types of shocks in the model are jointly normally distributed with mean zero and variance V that obey assumptions (8):

$$V = \begin{bmatrix} I_n & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix}, \tag{8}$$

where I_n is an identity matrix, Q, S, and W are some positive definite matrices called state space system matrices. Such specification of V is reasoned by the high number of parameters in the model. I restrict the matrix V by equating non-diagonal to zero for reducing the computational complexity of the estimation.

3.2. Bayesian inference

I use Bayesian estimation approach to address several common problems that present with estimation of classical VAR models. First, due to the high frequency of the data (the model is based on monthly observations) resulting in a large level of noise, the estimation results could be statistically insignificant. Second, time-varying models experience an exponential growth in a number of free parameters at state space system matrices as the number of endogenous variables and lags increases. Thus, it makes precise estimates an impossible task. To overcome the limitations the Bayesian methods of estimation are used in this thesis. This approach allows estimating the posterior distributions of parameters $\bar{B}_t$, A_t, Σ_t and V using their prior values obtained from the data.

Following the literature (Primiceri 2005 and Mumtaz et al. 2011), priors are obtained by estimating the ordinary fixed-coefficient VAR model on a subset from the available data. However, due to a time period (only 73 data points are present), I use the entire sample as in Arratibel and Michaelis (2014). As in the literature, priors $\bar{B}_0$ and A_0 are set to follow the normal distribution with means corresponding to the respective OLS point estimates $\hat{B}_{OLS}$ and $\hat{\mathrm{A}}_{OLS}$, and variances that are four times ones from time-invariant VAR. For $log\sigma_0$ mean corresponds to the natural logarithm of the OLS estimate and variance is the identity matrix multiplied by four. The value of multiplier comes from the relevant literature (Primiceri 2005, Cogley and

Sargent 2005, Arratibel and Michaelis 2014). The hyperparameters — parameters of prior distribution in Bayesian statistics — Q, W and S are chosen to follow the inverse-Wishart distribution after the literature (Cogley and Sargent 2005). The distribution of the priors is summarised in the table below.

Table 1. Selected priors.

Parameter	**Description**	**Prior Family**	**Coefficients**
$\boldsymbol{B_0}$	Initial betas	$N\left(\hat{B}_{OLS}, k_B \cdot Var(\hat{B}_{OLS})\right)$	$k_B = 4$
$\boldsymbol{A_0}$	Initial covariance	$N\left(\hat{A}_{OLS}, k_A \cdot Var(\hat{A}_{OLS})\right)$	$k_A = 4$
$\boldsymbol{log\sigma_0}$	Initial log volatility	$N(log\hat{\sigma}_{OLS}, k_\sigma \cdot I_n)$	$k_\sigma = 1$
$\boldsymbol{Q}$	VCM of shocks to B_t	$IW(k_Q^2 \cdot \tau \cdot Var(\hat{B}_{OLS}), \tau)$	$k_Q = 0.01$, $\tau = 73$
$\boldsymbol{W}$	VCM of shocks to $log\sigma_t$	$IW(k_W^2 \cdot (1 + \dim(W)) \cdot I_n, (1 + \dim(W)))$	$k_W = 0.1$, $\dim(W) = 5$
$\boldsymbol{S_j}$, where $\boldsymbol{j = 1, \dots, n-1}$	VCM of shocks to A_t	$IW\left(k_S^2 \cdot (1 + \dim(S)) \cdot Var(\hat{A}_{OLS}), (1 + \dim(S))\right)$	$k_S = 0.01$, $\dim(S) = 4$

For coefficients k_B, k_A, k_σ I follow Primiceri (2005). τ is the size of the training sample (in our case it equals the size of full sample). Values k_W, k_S are set after Arratibel and Michaelis (2014). They describe an amount of uncertainty put on shocks to volatility and covariance respectively. Coefficient k_Q specify prior beliefs about time variation in estimates of the coefficients. The value is selected to minimize the deviance information criterion. More information on the optimal model selection is present in the next section. Once prior values are calculated, the posterior parameters are obtained by a variant of the Markov chain Monte Carlo algorithm called Gibbs sampler (Del Negro and Primiceri 2015).

Here I provide a sketch for the algorithm. Let's denote the entire range of time-varying that parameter can take by B^T, Σ^T, A^T for the coefficient, time-varying diagonal, and lower triangular matrices respectively, let $V = [Q, S, W]$ — the collection of variance-covariance matrices of independent and identically distributed shocks $\{\nu_t, \xi_t, \eta_t\}$, combine parameters and VCMs into one vector $\theta = [B^T, A^T, V]$. Finally, define $s^T = [s_1, \dots, s_T]', T = 73,$ the matrix of indicator variables selecting at every point of time which mixture of normal approximations should be used for each log-squared error that is used to draw a volatility state for a period $t.$ It follows that the Gibbs sampler proposed by Del Negro and Primiceri (2015) takes the form:

1. Initialize A^T, Σ^T, s^T and V.
2. Sample B^T from $p\left(B^T|\theta^{-B^T}, \Sigma^T\right)$ using the algorithm by Carter and Kohn (1994).
3. Sample Q from inverse Wishart distribution $p(Q|B^T)$.
4. Sample A^T from $p\left(A^T|\theta^{-A^T}, \Sigma^T\right)$ using the Carter and Kohn algorithm.
5. Sample blocks $S_j, j = 1, \dots, n-1$ from $p\left(S_j|\theta^{-S_j}, \Sigma^T\right)$.
6. Sample the indicator variables s^T from $p(s^T|\Sigma^T, \theta)$ as described in Kim, Shephard and Chib (1998).
7. Sample Σ^T from $p(\Sigma^T|\theta, s^T)$ using the Carter and Kohn algorithm again.
8. Sample W from inverse Wishart distribution $p(W|\Sigma^T)$.
9. Go to Step 2.

Steps 2–9 from the algorithm above are repeated 40,000 times. First 20,000 iterations are dropped because they are used to establish the convergence of a sampler. To resolve a problem of autocorrelation between consequent iterations, I keep only each 10^{th} draw in the final sample following Arratibel and Michaelis (2014). As the result, I obtain distributions of B, Σ, A, V for all points of time in the sample $t = 1, \dots, T-k$, each containing 2,000 values, where T — number of time periods and k — number of lags.

3.3. Model selection

The variables of interest can be divided into two types: levels (IPI, NEER, TOT) and rates (CPI, monetary policy rate) — more on them in the next chapter. Presence of data based on different scales can result into unsignificant results and produce meaningless impulse responses.

Therefore, every model discussed in this thesis was estimated on normalized data. I demeaned every time series presented in Figure 1 and divided them by respective variable's standard deviation. Using scaled data, I estimate the model (4) using values of parameters presented in Table 1. However, there is a one parameter yet to choose. As long as I deal with a type of a vector autoregressive model, it is important to specify a number of lags used. To select the number of lags to be included in TVP-VAR estimation I use deviance information criterion (henceforth, DIC). This is hierarchical modeling generalization of the Akaike information criterion used for specification selection under the Bayesian framework. In the essence, DIC rewards the best fit of estimated parameters to the data and penalizes model complexity at the same time. The DIC is defined as

$$DIC = \overline{D(\theta)} + p_D, \tag{9}$$

where $\overline{D(\theta)}$ is the posterior mean of the deviance, $p_D = \overline{D(\theta)} - D(\bar{\theta})$ is an effective number of model's parameters, and θ was defined in previous section a collection of parameters $[B^T, A^T, V]$. $\overline{D(\theta)}$ is calculated as minus two multiplied by the natural logarithm of the integrated likelihood function

$$\overline{D(\theta)} = -2\mathrm{E}_\theta[\ln p(Y|\theta)\,|\theta] \tag{10}$$

It is important to notice that the direct calculation of (10) is impossible due to a model complexity, so it is approximated using improved cross-entropy method proposed by Chan and Eisenstat (2018).

Chapter 4

DATA OVERVIEW

The variables of interest are GDP, CPI, nominal effective exchange rate (NEER), average overnight interest rate, and terms of trade index. All data except terms of trade are obtained from the NBU database. The statistics on the import price index and export price index to form the terms of trade variable are taken from SSSU. GDP, overnight interest rates, and CPI are used in the model to proxy the interest rate channel: it shows how the shock in a monetary policy will transfer to changes in the inflation by affecting the market interest rates first, then these changes will influence the aggregate demand, resulting in changes in CPI. Similarly, the exchange rate channel can be approximated as follows: the policy shock is transferred to the CPI through the market interest rates, the exchange rate, and the aggregate demand. Moreover, I account for possible external shocks using terms of trade index.

The main problem is related to the fact that the data on GDP is not available on monthly basis. However, it is solved by approximating the monthly GDP time series with the index of industrial production. Also, there is no unified source on values of interbank interest rates. The NBU's methodology on the calculation interbank rates was revisited several times in 2019 and 2020. Thus, the values for the average overnight interest rate are obtained by merging UIIR, Pre-UONIA, and UONIA data sets. Index of industrial production and NEER are stated in relative terms with 2016 being the reference level. The terms of trade index shows a ratio of export and import price indexes compared with the respective period of the previous year. Interbank interest rate is determined as a monthly average for the overnight interest rate in the banking system. Inflation is defined by calculating a percentage change of the consumer price index to corresponding month of the previous year.

To allow for better model fit, all variables are tested for the presence of seasonal patterns. None of them showed signs of seasonality, thus the seasonal adjustment is unnecessary. The resulting data is depicted in Figure 1.

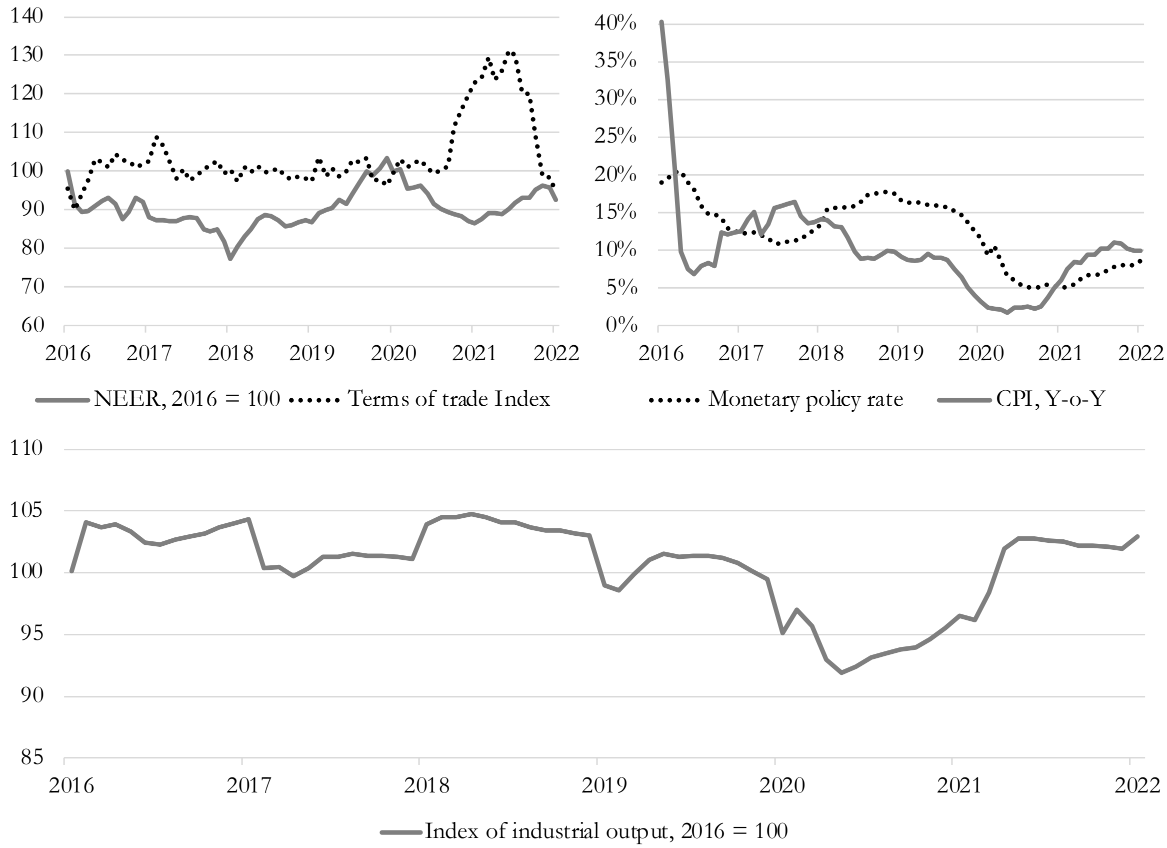

Figure 1. Variables of interest 2016M1–2022M1.

Source: author's calculations on the data from NBU and SSSU

In this paper I use monthly data that covers a horizon from 2016M1–2022M1. All variables but inflation rate and monetary policy rate are used in levels. Data is already noisy and limited, there are 73 observations in total, so any kind differencing will result in a loss of a precious information. It is important to notice that a potential presence of the unit root in time series is not an obstacle for estimation of a TVP–VAR model because it relies on a marginal likelihood estimation, that in its turn is unaffected by a potential unstationarity of variables (Arratibel and Michaelis 2014).

The IPI is present is a form of a monthly index (2016 = 100), seasonally adjusted by NBU using the TRAMO-SEATS method (Gomez and Maravall 1996). The level of industrial production was outstanding the base level up to late 2019, however a dip in the IPI occurred from 2019M12 to 2021M3 because of a COVID-19 related recession. The inflation is measured as a year-to-year change in the CPI. Consumer price index decreased dramatically in the beginning of the sample and plummeted from 40.3% in 2016M1 to 9.8% three months after. The pace of inflation increased it following periods and a CPI topped in September of 2019 reaching 16.4%. Throughout 2020 a level of inflation was under NBU's 5% level, but in the next year it has slowly went up to a 10% rate. Speaking about the short-term interest rate in the economy, it is approximated with an average overnight interbank interest rate and present in monthly average percent. The variable is used as a proxy for monetary policy rate in this paper. Interest rate was declining all over the observed time horizon, reaching 8.67% on average in January of 2022. Nominal effective exchange rate is given as a monthly index with a base in 2016. After reaching he trough in 2018M1 that indicates a depreciation of a Ukrainian currency against a basket of foreign currencies, UAH was slowly recovering its value up to a January of 2021. However, the Ukrainian currency reached only a 95% of its value in the base period by the beginning of 2022. The last variable of interest is terms of trade depicted as a monthly index of a current value to corresponding month of the previous year. From 2020M10 to 2020M10 a value of index has significantly overstated a 100% meaning export prices were up to 31% greater than import ones during this period.

Chapter 5

ESTIMATION RESULTS

This chapter provides optimal specification selection, estimation results, significance tests and robustness checks for the TVP-VAR model. Sections 5.2, 5.3, and 5.4 present a detailed analysis of a time-varying transmission of monetarily policy, nominal effective exchange rate and demand shocks. In Section 5.5, I conduct impulse response analysis of a monetary policy shock assuming the elements in error matrix fixed at the sample averages. Alternative parameter configurations for a TVP-VAR model are discussed in Section 5.6. Figures describing consumer price index and terms of trade index shocks are depicted in Appendixes A and B.

5.1. Results of model selection

Table 2 presents the estimated DIC for the time-varying models with different combination of lags and prior beliefs about time variation in estimates of the coefficients.

Table 2. DIC estimates for various TVP-VAR models (standard errors in parenthesis). The best fit indicated by the lowest DIC and highlighted with bold font.

k_Q	**Lags**			
	1	**2**	**3**	**4**
0.01	156.2 (0.83)	192 (0.89)	**123.7 (2.18)**	144.6 (2.21)
0.02	155.9 (1.58)	145.2 (0.53)	156.7 (1.10)	139.9 (2.08)
0.03	162.3 (0.73)	145.0 (0.94)	193.0 (0.97)	238.2 (1.44)
0.04	162.8 (0.57)	168.0 (0.78)	125.4 (2.24)	281.9 (1.15)
0.05	181.1 (0.68)	215.8 (0.90)	262.6 (1.01)	322.1 (0.82)

The model with three lagged variables and 1% uncertainty around betas produces the lowest value of a deviance information criterion, so I choose this specification for the further estimation.

5.2. Transmission of monetary policy shocks to economic variables

A special feature of TVP-VAR model is that IRFs can be estimated starting any specific point of time inside the sample. For the impulse response analysis, I estimate the impact of one standard deviation shock of the error term ε_t. The other elements of the equation (4) are kept at their time values at the period t following Arratibel and Michaelis (2014). In other words, I allow both shocks (elements of Σ_t) and parameters that determine transmission (elements of $\bar{B}_t$ and A_t) to change over time.

Figure 2 depicts median impulse responses to one standard deviation of the contractionary monetary policy shock at 2016M4, 2020M4 and 2022M1. Also, the IRFs from a simple VAR model with three lags are added as a benchmark. Each impulse response function has an expected direction of a reaction despite the fact that sign restrictions were not imposed. In general, we see that median impulse response functions in 2020 and 2022 are similar and smaller compared to the responses in 2016. Simple VAR IRFs are close to 2016 responses of GDP and ToT and approximately inbetween of the IRFs of CPI and NEER for displayed periods.

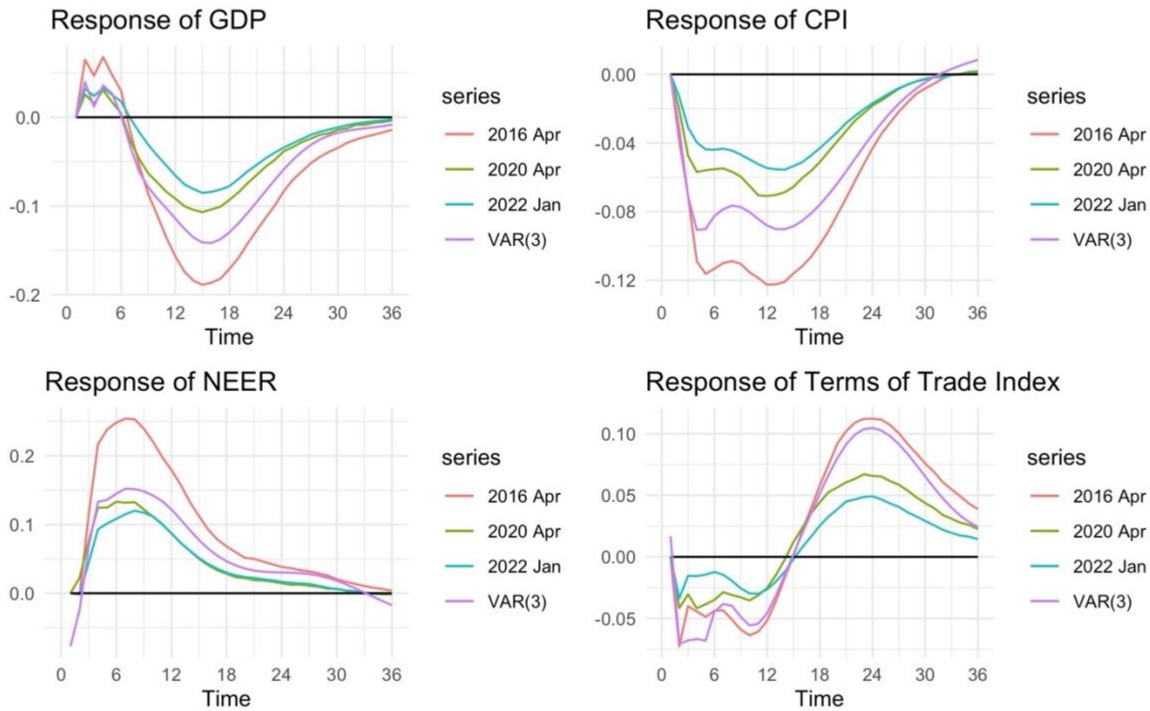

Figure 2. Median impulse responses to one standard deviation of the contractionary monetary policy shock at 2016M4, 2020M4 and 2022M1 versus the benchmark; self-response excluded.

The main finding is that the monetary transmission mechanism was weakening over time. For example, a contractionary monetary policy shock, defined as an unexpected increase of the interest rate by one standard deviation, led to 0.12 standard deviation decrease of CPI 2016M4 in 12 months after the shock (which is the peak of the response function). In 2020M4, same one-standard-deviation increase in interest rate caused a decrease in CPI by 0.07 standard deviations. The similar pattern is observed for the other variables.

Figure 3 presents time-varying median impulse responses to one standard deviation of the contractionary monetary policy shock for all dates. In general, we see that responses were decaying over time, what is in line with Arratibel and Michaelis' (2014) impulse response analysis for Poland. It is clearly seen from the plot that variables are comparatively more responsive to monetary policy shock prior to a mid-2018. In 2018, Ukrainian economy recovered from 2014-

2015 economic crisis that was caused by the annexation of Crimea and the Donbas Conflict. Consumer inflation returned to downward trend due to successful NBU's monetary policy. Overall, economic situation has become more stable since 2018. At the end of a sample, the absolute values of responses are relatively lower, meaning the economy became more resistant to deviations of the interest rate.

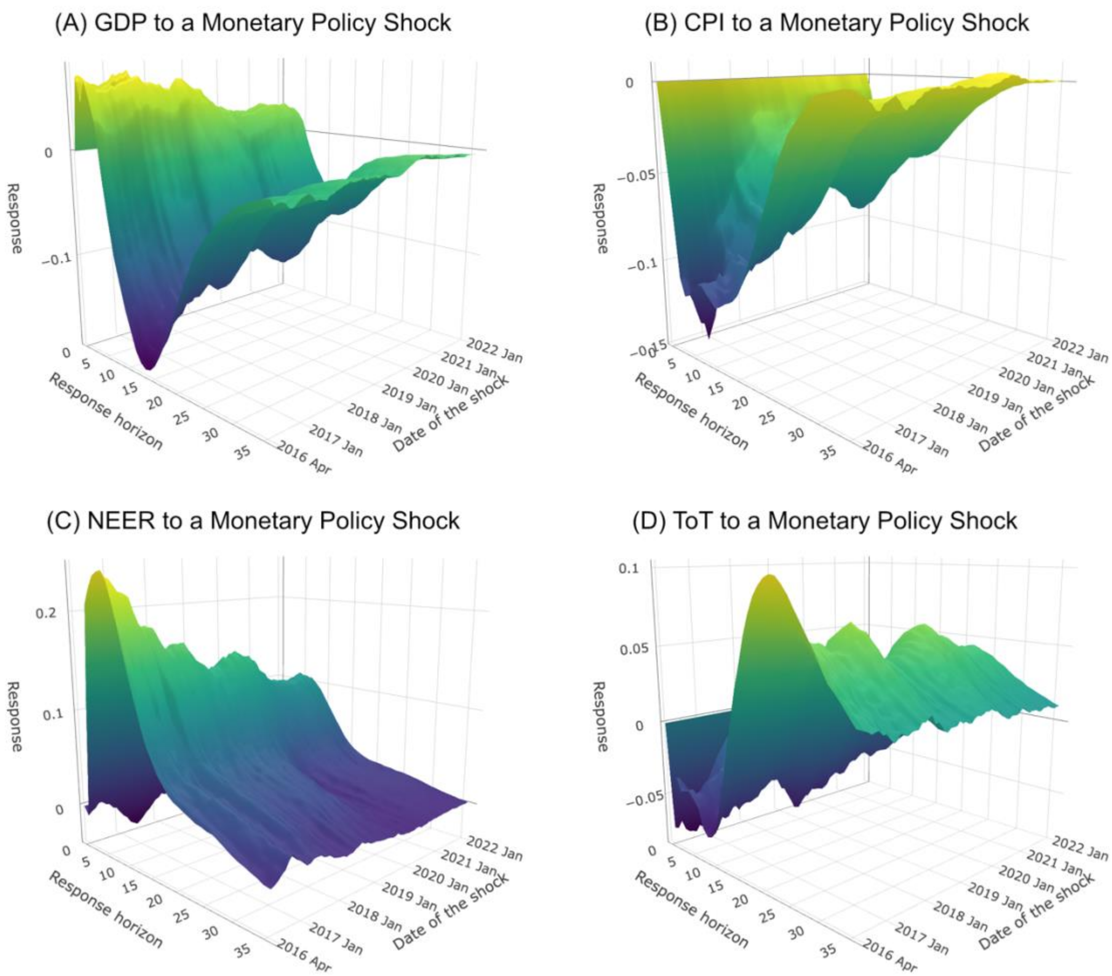

Figure 3. Time-varying median impulse responses to one standard deviation of the contractionary monetary policy shock.

An alternative way to identify the presence of time-varying impulse responses to a monetary policy shock is to study the dynamics of responses to a monetary policy shock in 6, 12, and 24 months after the shock. The results are presented in Appendix C. In this analysis, since the data is noisy, I use 68% confidence interval. This choice is consistent with the majority of the papers that use TVP–VAR models (Primiceri 2005; Baumeister et al 2010; Arratibel and Michaelis 2014; Bijsterbosch and Falagiarda 2014).

The median response of the output to one standard deviation contractionary monetary policy shock at the 6th month is not different from zero (Figure 10, Appendix C.1.). As for the inflation rate, the median response is estimated to be around -0.11 standard deviations up to October 2017. It has decreased to -0.05 deviation by mid-2018 and remained at this level till the end of the observable window. The median response of the exchange rate was gradually decreasing from 0.27 standard deviations from the mean to approximately 0.1 at 2022M1. The confidence interval for the terms of trade response includes a zero level live throughout a whole sample, thence the effect on the terms of trade is unsignificant at the 6th month from shock.

Impulse responses show different patterns at the 12th month. Responses of GDP are now significant, slowly increasing from -0.18 standard deviations to -0.075 (Figure 11, Appendix C.2.). Effects on CPI change more gradually but remain in the same range. The impact on the exchange rate decreased to 0.15 deviations in the 2014M4 with a minimum of 0.085 units in January of 2022. As for ToT, its effects remained unchanged. Responses of all variables at 24th month since the initial monetary policy shock are close to zero (Figure 12, Appendix C.3.).

The visual interpretation can be misleading so statistical testing is used. To check a significance in differences of responses at specific points in time I compute the posterior probability for the difference in the impulse responses at chosen period (Table 3). Probability is evaluated as a share of impulse responses that are smaller in value at the first period. Specifically, I use distributional properties of the estimated response functions and compare values of impulses fix at five horizons since the initial shock pairwise: 2016M4 vs 2020M4, 2016M4 vs 2022M1 and 2020M4 vs 2022M1. Values close to 50% indicate a weak difference between the two periods. Interpretation of non-50% values vary for effects with different signs. If the shock has contractionary effect on the response variable (↓), values above 50% mean that the first response in greater in magnitude (absolute value) than the second response and vice versa. If the shock has positive effect on the response variable (↑), values above 50% imply that the first response in smaller in absolute value than the second response and vice versa.

Table 3. Probability for the differences in the responses to a monetary policy shock at different horizons ahead after the initial shock.

Horizon	1 M	6 M	12 M	24 M	36 M
GDP (↓)					
2016/2020	13.5%	44.1%	72.4%	66.2%	55.1%
2016/2022	20.3%	55.5%	84.5%	67.8%	51.7%
2020/2022	58.5%	63.5%	70.8%	49.6%	45.7%
CPI (↓)					
2016/2020	68.1%	78.6%	71.7%	63.4%	51.9%
2016/2022	66.3%	83.8%	83.5%	63.4%	46.8%
2020/2022	50.6%	59.1%	64.7%	48.0%	45.1%
NEER (↑)					
2016/2020	67.7%	13.3%	23.5%	37.4%	46.6%
2016/2022	56.6%	8.1%	22.4%	42.9%	48.5%
2020/2022	34.5%	35.2%	49.8%	56.3%	53.9%
ToT (↑)					
2016/2020	71.3%	52.4%	60.5%	35.7%	39.1%
2016/2022	77.4%	62.7%	61.5%	25.7%	37.6%
2020/2022	62.9%	62.7%	51.1%	38.7%	49.6%

Considering the output, the monetary policy shock resulted in lower contraction of GDP at the horizons of one and six month in 2016 relatively 2020. However, the impulse has caused greater decline in output since one and two years after shock in 2016. The pattern is different when comparing 2020M4 and 2022M. Earlier period is characterized with higher level of absolute response in GDP to the shock from one to twelve month.

Responses of the inflation rate in 2016 are significantly greater in absolute value then in 2020 and 2022 at the horizon up to 24 months. In contrast, the differences in a pair 2020/2022 are mostly unsignificant over all available horizons but six and twelve months.

Considering the effect of the monetary policy shock to the exchange rate, the response of NEER was considerably greater in 2016 compared to the other periods at horizons from 6^{th} to 24^{th} month. Comparing 2020M4 and 2022M1, the first period's response was larger up to a half of the year since a shock, and slightly lower in the January of 2022 in a medium term.

Regarding the impact on the terms of trade index, the estimated response pattern is unformal for all pairs of periods. Precisely, responses in the first period are higher up to the one year after the shock, and smaller afterwards.

Overall, the strong difference in pairs 2016/2020, 2016/2022 is present at all horizons but the last. Generally, there is a little difference at responses to the monetary policy shocks at the 36^{th} month since the initial shock because economy fully converges back to the steady state after three years past the initial shock. Additionally, a Wilcoxon test for equal distribution of medians between selected pairs of periods is provided it Table 4. Symbol $\neq$ indicates that the null hypothesis about the medians are from similar distributions is rejected at the 1% significance level. Symbol $=$ means the hypothesis can't be rejected at the same significance level.

In general, Wilcoxon test shows that the statistically significant change in responses to the monetary policy shock is present when allowing for over-time variation in both shocks and model coefficients in (4). However, the result on CPI and NEER responses stands out slightly. Considering the effect of the inflation rate, responses at 36^{th} month since the initial shock are unsignificant. Visual examination on Figures 2 and 3 indicates that values of impulse response functions simply return to the steady state by this time. So, it takes 3 years for the CPI rate to return to its pre-shock levels no matter at what point of time Ukrainian economy undergo an unexpected increase in the monetary policy rate. The impact on NEER has no time-varying effect at 36^{th} month, too. Additionally, in a 2020/2022 pair, the time difference in an exchange rate response to a monetary policy shock is unsignificant starting from one year after it.

Table 4. Wilcoxon rank sum test for equal medians of two distributions for the responses to a monetary policy shock at different horizons ahead after the initial shock.

Horizon	**1 M**	**6 M**	**12 M**	**24 M**	**36 M**
GDP					
2016/2020	≠	≠	≠	≠	≠
2016/2022	≠	≠	≠	≠	≠
2020/2022	≠	≠	≠	=	=
CPI					
2016/2020	≠	≠	≠	≠	=
2016/2022	≠	≠	≠	≠	=
2020/2022	≠	≠	≠	=	=
NEER					
2016/2020	≠	≠	≠	≠	=
2016/2022	=	≠	≠	≠	=
2020/2022	≠	≠	=	=	=
ToT					
2016/2020	≠	≠	≠	≠	≠
2016/2022	≠	≠	≠	≠	≠
2020/2022	≠	≠	≠	≠	≠

Table 4 shows strong evidence for a presence of a difference in responsiveness of GDP, CPI, NEER and ToT to monetary policy shocks at 2016M4, 2020M4 and 2022M1. Moreover, results from Table 3 state that absolute values of responses were greater in the beginning of the sample at horizons from 6^{th} to 24^{th} month since the shock. Therefore, the first hypothesis on the graduate decrease in responsiveness of Ukrainian economy is confirmed. A discussion on whether it is the case of a stabilization of the economy or a decrease in effectiveness of NBU policies is provided in Section 5.5.

5.3. Transmission of exchange rate shocks to economic variables

Figure 4 depicts median impulse responses to one standard deviation of the exchange rate shock that is presented as an unexpected change in the nominal exchange rate. Each impulse response function has an expected direction. This time base impulse responses from VAR(3) model systematically overestimate results from a time-varying model.

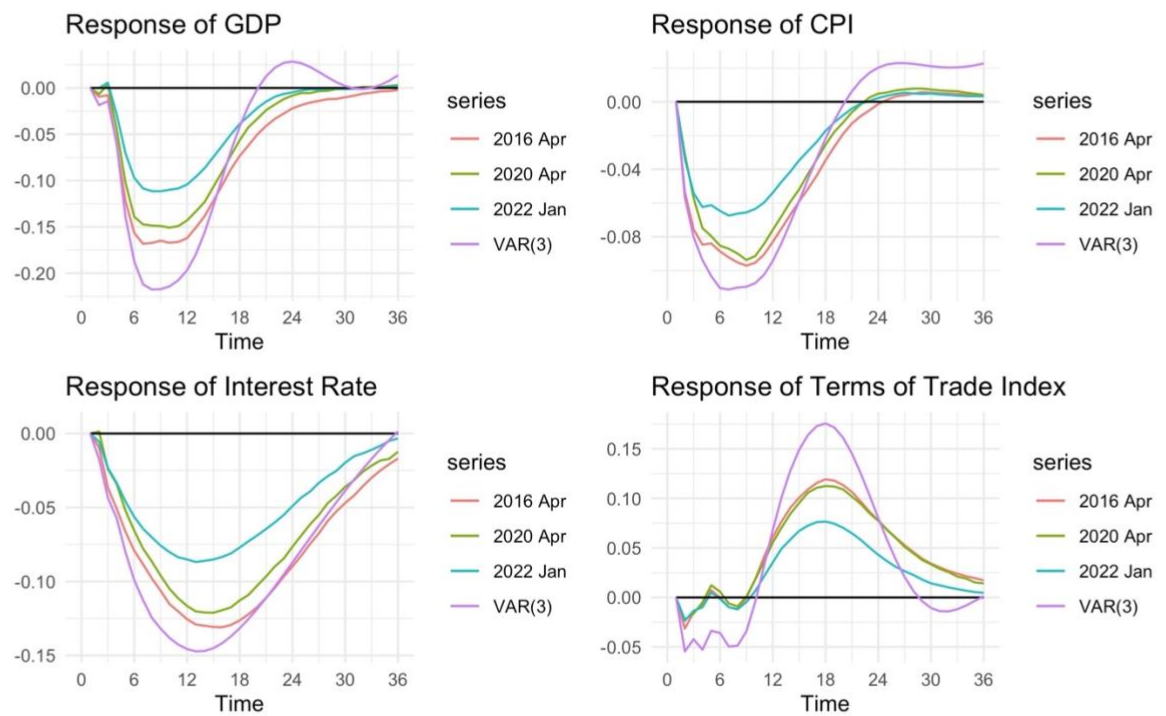

Figure 4. Median impulse responses to one standard deviation of the nominal effective exchange rate shock at 2016M4, 2020M4 and 2022M1 versus the benchmark; self-response excluded.

The pattern of response is similar for all variables. IRFs that are drawn from 2016M4 and 2020M4 nearly overlay, while the absolute values of responses in January of 2022 are smaller (Figure 4). The effect of GDP response peaks at 8th month since the initial shock with 0.15 standard deviation decrease from the mean level in 2016 and 2020. For a comparison, a contraction of the output reached only 0.11 standard deviations in 2022. Regarding the impact on the inflation rate, the decrease of CPI reached -0.09 standard deviations at its minimum on the third quarter since shock for the IRF drawn at 2016M4.

Overall, there is a little difference in responses in 2016M4 and 2020M4 for each variable, however both are substantially larger in the absolute value than responses at periods in-between, as well as at the end of a sample (Figure 5).

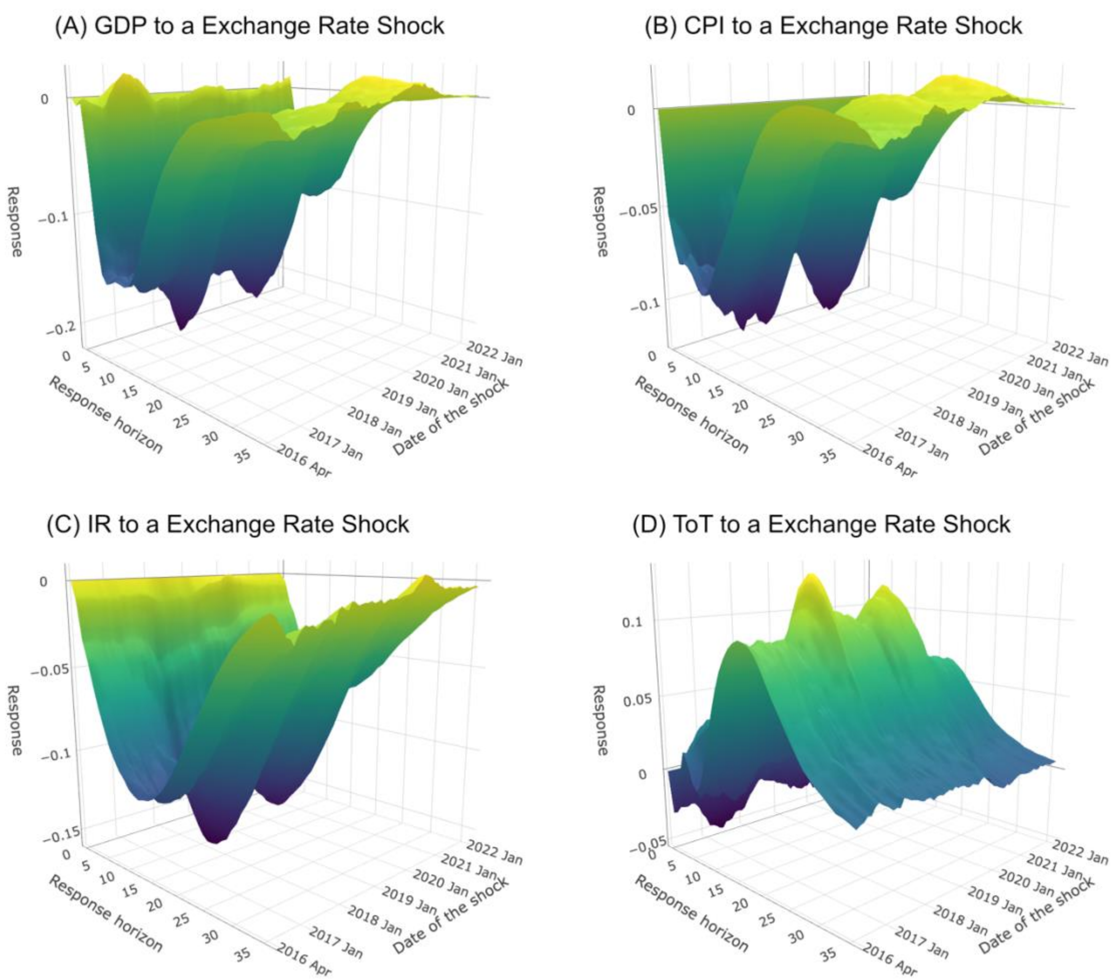

Figure 5. Time-varying median impulse responses to one standard deviation of the nominal effective exchange rate shock.

A time-varying effect of variable to the exchange rate shock is present at fixed horizons, too. Considering responses at the 6^{th} month, the median response of output was holding at -0.165 standard deviation from the mean level prior to the beginning of 2020 (Figure 13, Appendix D.1.). The effect started to decrease in absolute value around a first couple of months of the COVID lockdown in Ukraine and flattened out in August around -0.1 standard deviations. The similar pattern with decrease in responsiveness to exchange rate shocks at a start of the pandemic is observed for both CPI and interest rate responses. The effect on terms of trade is not different from zero on the entire interval.

Impulse responses at the 12^{th} month nearly mirror prior ones. The only difference is that the responses of ToT became marginally significant at 68% confidence interval (Figure 14, Appendix D.2.). The impact of the exchange rate shock to terms of trade was positive and exhibited a downward trend, declining form 0.07 standard deviations in 2016M1 to 0.05 in 2022M1. However, the effect may be considered as economically insignificant. As for a one year since shock, responses of output and inflation rate returned to their mean levels, while impacts of interest rate and ToT are practically non-zero, but statistically they are close to unsignificant ones (Figure 15, Appendix D.3.).

The calculations of the posterior probability in differences for responses to exchange rate shock show ambiguous pattern (Table 5). In terms of the output, the shock has resulted in greater contraction of GDP in both 2016 and 2020 relatively to 2022 for 1^{st}, 6^{th} and 12^{th} month. In the pair 2016/2020, shocks were smaller in 2016M4 only for 1^{st} and 12^{th} month and larger in remaining periods. Such sign alteration of differences may indicate overall insignificance of time variation for responses between these periods.

The same holds for both effects on prices and interest rate for 1^{st}, 6^{th} and 12^{th} month in pairs 2016/2022 and 2020/2022. The effect on CPI and NEER was larger in absolute value only for 1^{st} month and marginally significant at two and three years since shock. As for the terms of trade, all difference in its response to the exchange rate shock but for 12^{th} and 24^{th} month are close to unsignificant.

Table 5. Probability for the differences in the responses to an exchange rate shock at different horizons ahead after the initial shock.

Horizon	1 M	6 M	12 M	24 M	36 M
GDP (↓)					
2016/2020	44.6%	53.1%	46.7%	60.0%	54.5%
2016/2022	59.7%	77.0%	71.8%	53.8%	48.9%
2020/2022	62.8%	77.1%	74.2%	43.9%	44.7%
CPI (↓)					
2016/2020	72.0%	40.6%	48.4%	57.5%	52.8%
2016/2022	71.2%	64.3%	68.9%	47.9%	47.7%
2020/2022	48.8%	72.0%	68.3%	42.1%	45.8%
I (↓)					
2016/2020	73.5%	50.5%	43.8%	52.2%	56.2%
2016/2022	60.8%	69.8%	70.0%	64.4%	52.5%
2020/2022	35.8%	72.0%	76.3%	60.8%	46.1%
ToT (↑)					
2016/2020	56.0%	48.2%	47.1%	51.6%	44.7%
2016/2022	54.5%	44.9%	36.9%	35.3%	46.4%
2020/2022	49.4%	49.5%	39.2%	35.9%	51.8%

Impulse responses of the output and the interest rate to one standard deviation exchange rate shock have statistically significant differences in median at all possible period combinations and horizons. Concerning the inflation rate, IRFs return to their long-term levels by the second year from shock. A time changing effect of transmission is present at the remaining intervals. As for terms of trade, impacts from an exchange rate shock for 24th and 36th month in 2016/2020 pair are statistically equal. Comparing 2016M4 and 2022M1, the only unsignificant difference in response is present at 6M. Lastly, there was no significant contrast in impact on terms of trade for both 1st and 6th month between 2020M4 and 2022M1.

Table 6. Wilcoxon rank sum test for equal medians of two distributions for the responses to an exchange rate shock at different horizons ahead after the initial shock.

Horizon	1 M	6 M	12 M	24 M	36 M
GDP					
2016/2020	≠	≠	≠	≠	=
2016/2022	≠	≠	≠	≠	=
2020/2022	≠	≠	≠	=	=
CPI					
2016/2020	≠	=	≠	=	=
2016/2022	≠	≠	≠	=	=
2020/2022	≠	≠	≠	=	=
I					
2016/2020	≠	≠	≠	≠	=
2016/2022	≠	≠	≠	≠	≠
2020/2022	≠	≠	≠	≠	≠
ToT					
2016/2020	≠	≠	≠	=	=
2016/2022	≠	=	≠	≠	≠
2020/2022	=	=	≠	≠	≠

I can conclude that there is a change in transmission of an exchange rate shock in Ukraine, most notably it has been present since 2020. In other words, the difference in responsiveness of Ukrainian economy to exchange rate shocks during the COVID-related recession is proven. However, the estimated direction of change is different from my assumption. Specifically, responses to exchange rate shocks have become less in absolute value for the majority of horizons since the initial shock. For that reason, the second hypothesis is rejected.

5.4. Transmission of demand shock to inflation

To confirm or deny the hypothesis on a diminishing response of inflation to demand shock over time I study only a link between output and CPI.

Figure 6 depicts median impulse responses to one standard deviation of the demand shock that is presented as an unexpected change in the proxy for GDP — the index of industrial output. The IRFs have an expected sign for the first 12 month after which the response becomes negative. The value of an effect after a sign change is not greater than -0.025 standard deviation, so it is practically no different from a zero. Impacts on inflation rate drawn in 2016M4, 2020M4 and 2022M1 are similar in both shape and absolute values, although an impulse response in April of 2020 peaked at higher value of 0.072 standard deviations.

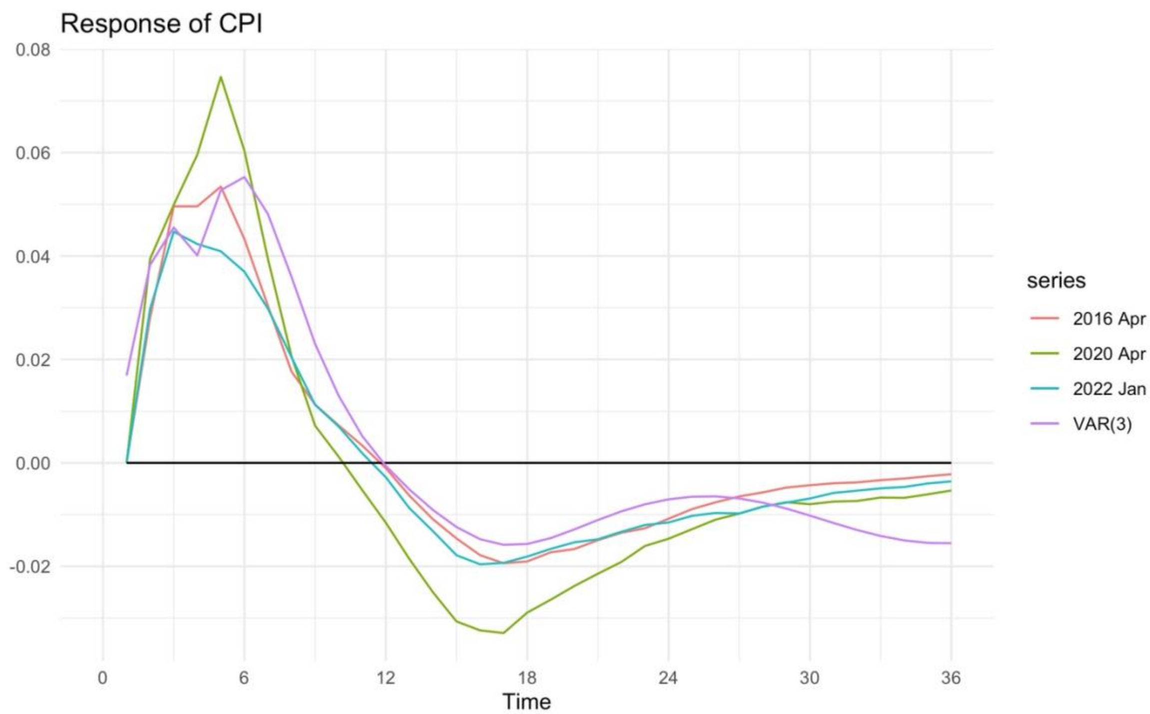

Figure 6. Median impulse responses of CPI to one standard deviation of the demand shock at 2016M4, 2020M4 and 2022M1 versus the benchmark.

Regarding the effect of a demand shock on price changes at every available point of time, there are two periods that stand out with comparatively higher responses (Figure 7). These periods include a time frame from the beginning of the sample to the end of 2016, when the inflation targeting was still a relatively new tool for the NBU and around a winter of 2020, the time

Ukrainian economy faced a first wave of COVID-19. Importantly, the variation in time is present mostly at 6th month of shock and becomes nearly unsignificant since the 12th month of the innovation.

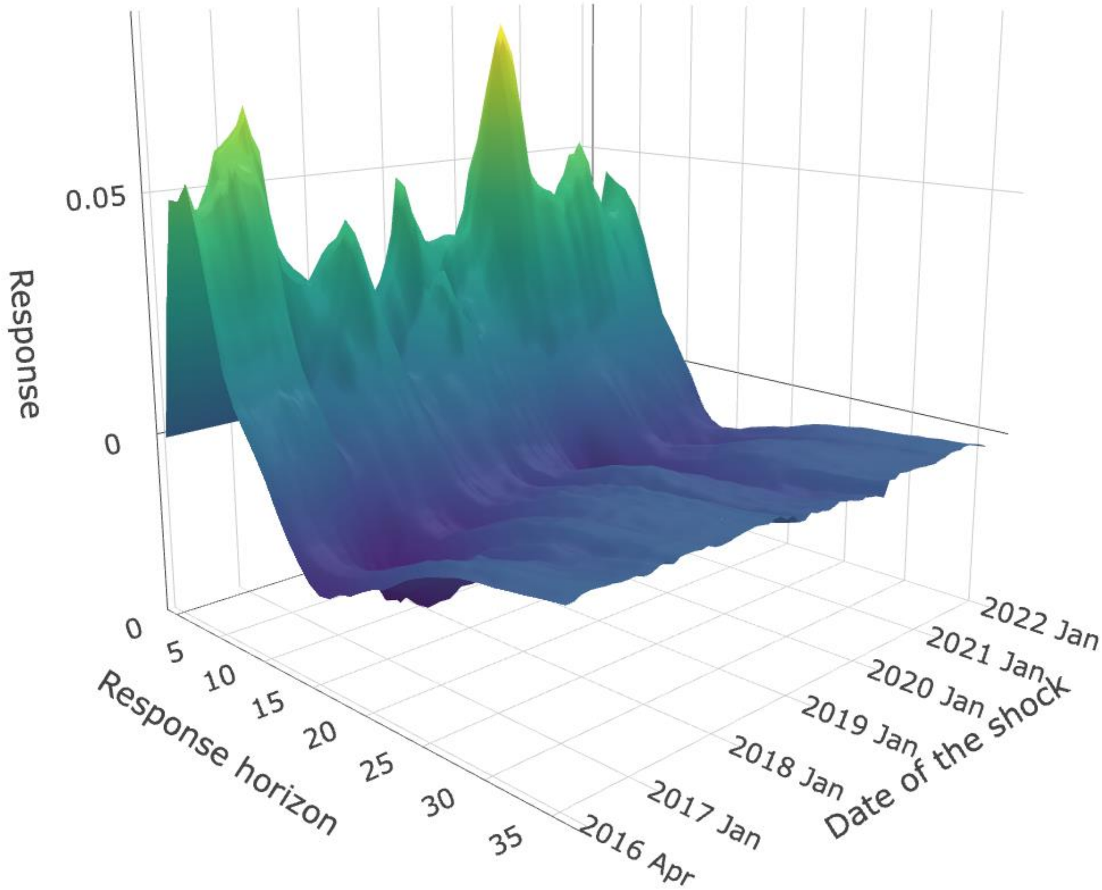

Figure 7. Time-varying median impulse responses of CPI to one standard deviation of the demand shock.

The insignificance of the impact of a demand shock on prices is obvious form the dynamics of responses at 6th, 12th, and 24th month with 68% confidence interval (Appendix E). Median responses of price changes are practically not significant as confidence intervals fully contain a zero-point line for each fixed horizon since the initial demand shock.

As for the probability calculation, the majority of CPI responses to the demand shock set in the close interval to 50%, indicating that there is neither significant decrease in the response of inflation, nor increase.

Table 7. Probability for the differences in the responses of CPI to a demand shock at different horizons ahead after the initial shock.

Horizon	**1 M**	**6 M**	**12 M**	**24 M**	**36 M**
CPI (↑)					
2016/2020	59.3%	55.2%	41.1%	48.6%	47.1%
2016/2022	51.9%	48.9%	48.1%	49.8%	48.4%
2020/2022	41.7%	43.9%	55.9%	51.2%	50.2%

Wilcoxon rank sum test shows that median impulse responses of CPI on a demand shock between selected period are mostly from the same continuous distributions (Table 7). The difference is present between 2016M4 and 2020M4, and 2020M4 and 2022M1 for 1st, 6th and 12th month. However, Table 7 shows that the difference are practically small and considered to be economically unsignificant.

Table 8. Wilcoxon rank sum test for equal medians of two distributions for the responses of CPI to a demand shock at different horizons ahead after the initial shock.

Horizon	**1 M**	**6 M**	**12 M**	**24 M**	**36 M**
CPI					
2016/2020	≠	≠	≠	=	≠
2016/2022	=	=	=	=	=
2020/2022	≠	≠	≠	=	=

Overall, responses of CPI to a demand shock are insignificant at every point of time in the sample. Tests show that medians of IRF distributions belong to the same distributions in majority of cases. Moreover, changes in transmission of a demand shock to prices are not present over time. I find no evidence to support the hypothesis on a diminishing response of inflation to demand shock over time.

5.5. Impulse response analysis with fixed shocks

The baseline TVP-VAR model estimated in previous sections account for time variation in two ways simultaneously. First, it allows for a magnitude of shock hitting the economy to change with time by setting elements of Σ_t in (4) at the respective periods t. Second, the elements of $\bar{B}_t$ and A_t are free to vary over time, too. Latter means that values of coefficients that determine a transmission mechanism itself are subject to time changes. In this subsection I fix the elements of Σ_t to their average values over the period from 2016M4 to 2022M1 and repeat the impulse response analysis from Section 5.2 to find what is driving the decrease in responsiveness of Ukrainian economy since the beginning of inflation targeting.

Figure 8 depicts median impulse responses to one standard deviation of the sample average monetary policy shock at selected points of time. It is clearly visible that time variation between periods nearly has gone after I set the shock to be constant. Posterior IRFs become extremely close in values and shapes to prior ones that are drawn from simple VAR(3) model. However, impulse responses form TVP-VAR model converge to the steady state better and don't have ill-behaved outliers. By contrast, responses of NEER from VAR(3) model at the first and the second periods don't follow assumed restriction on zero-valued shock at initial period. The other significant change in the impulse responses after setting shocks to a mean level is that the responses became smaller in absolute values compared to IRFs form Figure 2. Visual analysis of impulse responses to a monetary policy shock shows that time variation in elements of $\bar{B}_t$ and A_t have a little effect on the overall variability of the monetary policy transmission in Ukraine over time.

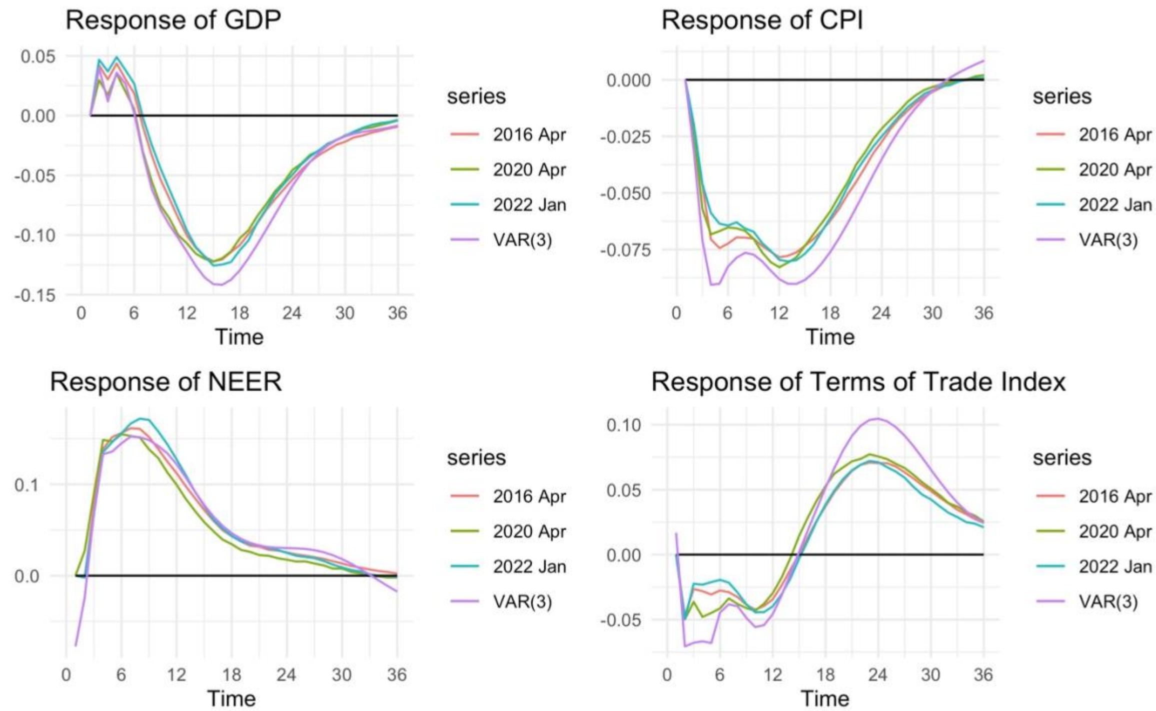

Figure 8. Median impulse responses to one standard deviation of the sample average monetary policy shock at 2016M4, 2020M4 and 2022M1 versus the benchmark; self-response excluded.

Posterior differences for all variables of interest to an averaged monetary policy shock between 2016M4, 2020M4 and 2022M1 are weak as probabilities at different horizons are close to 50% with few exceptions (Table 9). The result of Wilcoxon test also changed in comparison with a model that allows time-varying shocks. Difference in median responses of CPI is present only for 6th, 12th and 24th month in 2016/2020 pair, 1st and 6th month between 2016M4 and 2022M1 and 1st month in the remaining pair of periods (Table 10, Appendix F). Regarding the impact on the exchange rate, medians are from different continuous distributions only between April of 2020 and January of 2022. Concerning the output, there is no difference in median responses for 12th month in each considered time period.

Table 9. Probability for the differences in the responses to the sample average monetary policy shock at different horizons ahead after the initial shock.

Horizon	1 M	6 M	12 M	24 M	36 M
GDP (↓)					
2016/2020	33.8%	33.9%	44.1%	53.8%	54.5%
2016/2022	56.0%	53.2%	48.8%	52.4%	53.3%
2020/2022	67.0%	63.2%	53.9%	48.2%	49.5%
CPI (↓)					
2016/2020	49.4%	53.5%	46.7%	55.2%	51.2%
2016/2022	54.8%	54.1%	46.6%	49.6%	49.3%
2020/2022	52.6%	50.6%	50.6%	46.0%	49.0%
NEER (↑)					
2016/2020	75.2%	48.8%	45.5%	44.7%	46.9%
2016/2022	50.7%	53.7%	54.9%	50.7%	48.8%
2020/2022	32.1%	54.6%	58.6%	54.8%	52.4%
ToT (↑)					
2016/2020	45.4%	44.7%	56.9%	52.0%	50.5%
2016/2022	46.1%	53.4%	47.1%	49.8%	47.7%
2020/2022	49.9%	58.4%	43.4%	47.7%	48.4%

Summing up, variability in values of shocks play the key role in causing the time-varying effect of the monetary policy transmission in Ukraine. After I set up the elements of Σ_t to their average values over the sample period, differences in impulse responses of economic variables to monetary policy shocks became both statistically and economically insignificant in majority of cases. It means that the effectiveness of the monetary transmission mechanism itself (that determines values of coefficients in matrix $\bar{B}_t$) neither increased nor decreased since adoption of the inflation targeting regime. The reason for decline of responsiveness of Ukrainian economy to monetary policy shocks is that the magnitude of these shocks has decreased over time as the economy become more predictable and stable due to introduction of inflation targeting by the NBU.

5.6. Robustness checks

I consider two alternatives to the TVP-VAR model considered in previous sections. For the first alternative, I train priors and estimate the model on the data from 2016M5 to 2022M1. This time window excludes a period of extremely high inflation (up to 40.3% year-to-year change in January of 2016) that is present in original sample. Second alternative incorporates different values of hyperparameters used to form prior distributions. In particular, I set coefficients k_B, k_A, k_σ, k_W, k_S, and k_Q following Del Negro and Primiceri (2015). Figures and Tables describing impulse response analysis under alternative model specifications are depicted in Appendixes G and H. These specifications give similar results to the original model and conclusions of research hypotheses remain unaltered, too. Only difference is that alternative models produce slightly smaller impulse responses in their absolute values.

Chapter 6

CONCLUSIONS AND POLICY IMPLICATIONS

In this thesis, I applied the TVP–VAR model by Primiceri (2005) to study an evolution of the monetary policy transmission mechanism in Ukraine over time. Overall, there is strong evidence that the reaction of Ukrainian economy to monetary policy shocks has changed since 2016 and mixed evidence for a variation in responses to exchange rate shocks.

There are four key findings of this paper: 1) responsiveness of Ukrainian economy to monetary policy shock in 2020 and 2022 has declined in comparison with 2016; 2) variability in values of shocks play the key role in causing the time-varying effect of the monetary policy transmission in Ukraine, not the change in effectiveness of the monetary transmission mechanism itself; 3) the impact of exchange rate shock on Ukrainian economy from the first lockdown in 2020 to the beginning of 2022 was smaller than in previous years; 4) changes in transmission of a demand shock to prices are not present over time, indicating there is no evidence for a change is the nature of inflation process in Ukraine from 2016 to 2022.

Considering the first finding, the result of impulse response analysis supports a hypothesis for a presence of a diminishing responsiveness of GDP, CPI, NEER and ToT to monetary policy shocks from 2016M4 to 2022M1. In particular, one standard deviation monetary policy shock that occurred in 2016M4, leads to CPI decrease by 0.12 standard deviations from the mean in one year after the initial innovation. This effect has weaker impact at the end of a sample, since the negative impact on CPI from the shock in January of 2020 is estimated to reach only 0.07 standards deviation. As for the same monetary policy shock on GDP, the decrease in size of innovation in 2016M4 is expected to peak at 0.19 standard deviations, while in 2022 the negative effect on the output is only 0.09 standard deviation from the mean. The result that the economy became more resistant to monetary shocks over time since introduction of the inflation targeting regime is consistent with study on Polish economy (Arratibel and Michaelis 2014).

Second, estimation of impulse response functions with errors fixed at their sample averages shows that time variation in impact of a monetary policy shock between periods has gone after innovations are set to constant value. Posterior IRFs become extremely close in values and shapes to functions that are drawn from a simple VAR(3) model. Time variation in elements of coefficient matrix, that determine a transmission mechanism itself, have a little effect on the overall variability of the monetary policy transmission in Ukraine over time. Therefore, the time-varying effect of the MTM is mostly caused by changes in magnitude of shocks hitting the economy. Size of these shocks has decreased over time as the economy become more predictable and stable due to introduction of inflation targeting by the NBU.

Third, time-varying impulse responses to a nominal effective exchange rate shock provide no evidence to the hypothesis that the impact of exchange rate shock on the economy has increased during the COVID-related recession. Despite there is a statistically significant difference in responsiveness of Ukrainian economy to exchange rate shocks in 2020 as compared to previous periods, an impact on macroeconomic variables became less in the absolute value. More specifically, the effect of GDP response peaks at the 8^{th} month since the initial shock in both 2016 and 2020 with 0.15 standard deviation decrease from the mean level. For a comparison, a contraction of the output reached only 0.11 standard deviations in 2022. The similar pattern of a decrease in size of responses at the end of a sample is typical for CPI, ToT and interest rate, too.

Finally, I find no evidence to support the hypothesis that the response of inflation to demand shock is diminishing over time in Ukraine. Impacts of a demand shock to CPI rate are insignificant at every point of time form 2016 to early-2022. Moreover, Wilcoxon rank sum test shows that medians of IRF distributions for CPI responses belong to the same distribution in majority of cases. I conclude that changes in transmission of a demand shock to prices are not present over time.

Results are robust under alternative model's specifications. Checks for consistency include estimation of the model on a narrower data sample and different specification of hyperparameters for underlying prior distributions. Only difference is that alternative models produce slightly smaller impulse responses in their absolute values, however the significance of results for hypothesis testing remain unchanged.

The results of this study are potentially useful for the NBU, as the information on the existence of time-varying transmission in Ukraine may help the regulator with better understanding on how their past monetary policy decisions resulted into efficiency of inflation targeting. Additionally, the accounting for possible time effects in MTM can help the CB to choose instruments that will help to pursue current monetary policy goas more effectively. For example, it is shown in this thesis that values of shocks play the key role in causing the time-varying effect of the monetary policy transmission in Ukraine. As Ukraine is currently at war, we can expect sizes of shock influencing macroeconomic variables to be huge till the end of 2022 at least. Therefore, one can expect that the responsiveness of Ukrainian economy will increase to the values of 2016 and even more. For the regulator it means that it may avoid abrupt and sizable interventions during periods of the high responsiveness of the economy to monetary policy shocks.

Further research in this area may include an estimation of TVP-VAR model for Ukraine using different set priors. One may seek to implement Minnesota priors or optimal prior selection using Bayesian shrinkage methods and compare results with ones that present is this thesis, as TVP-VAR models are usually vulnerable to overfitting and sensitive to selection of priors.

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APPENDIX A

MEDIAN IMPULSE RESPONSES TO A CONSUMER PRICE INDEX SHOCK AT 2014M4, 2020M4, 2022M1

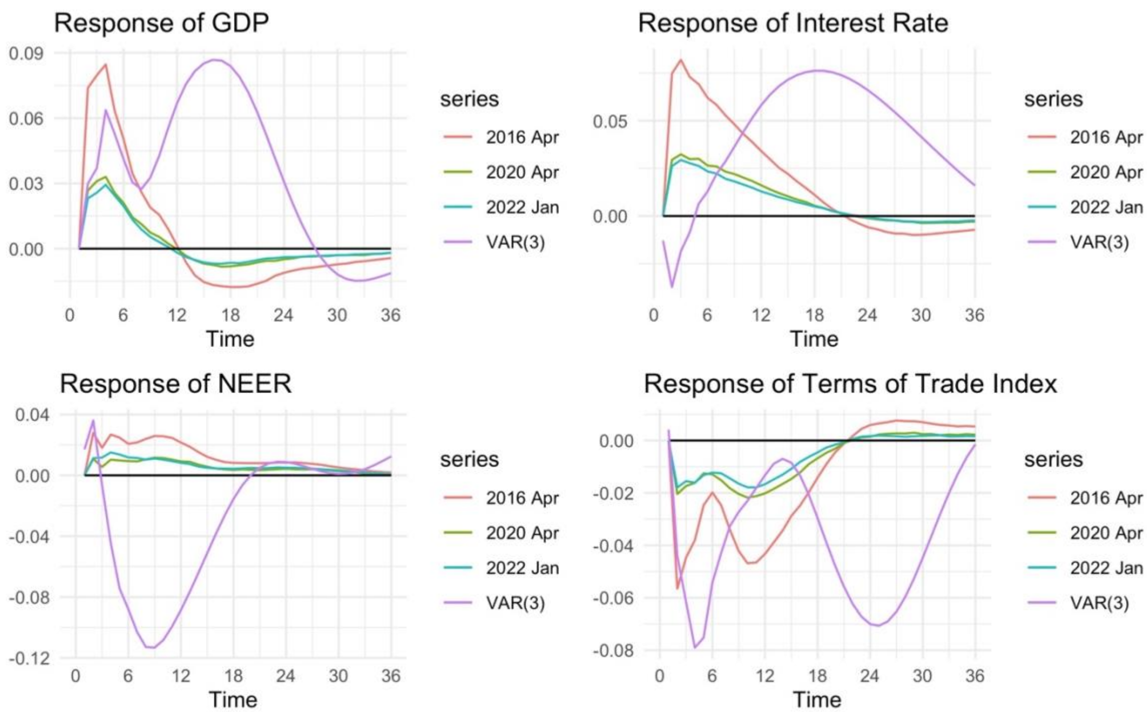

Figure 9. Median impulse responses to one standard deviation of the consumer price index shock at 2016M4, 2020M4 and 2022M1 versus the benchmark; self-response excluded.

APPENDIX B

MEDIAN IMPULSE RESPONSES TO A TERMS OF TRADE INDEX SHOCK AT 2014M4, 2020M4, 2022M1

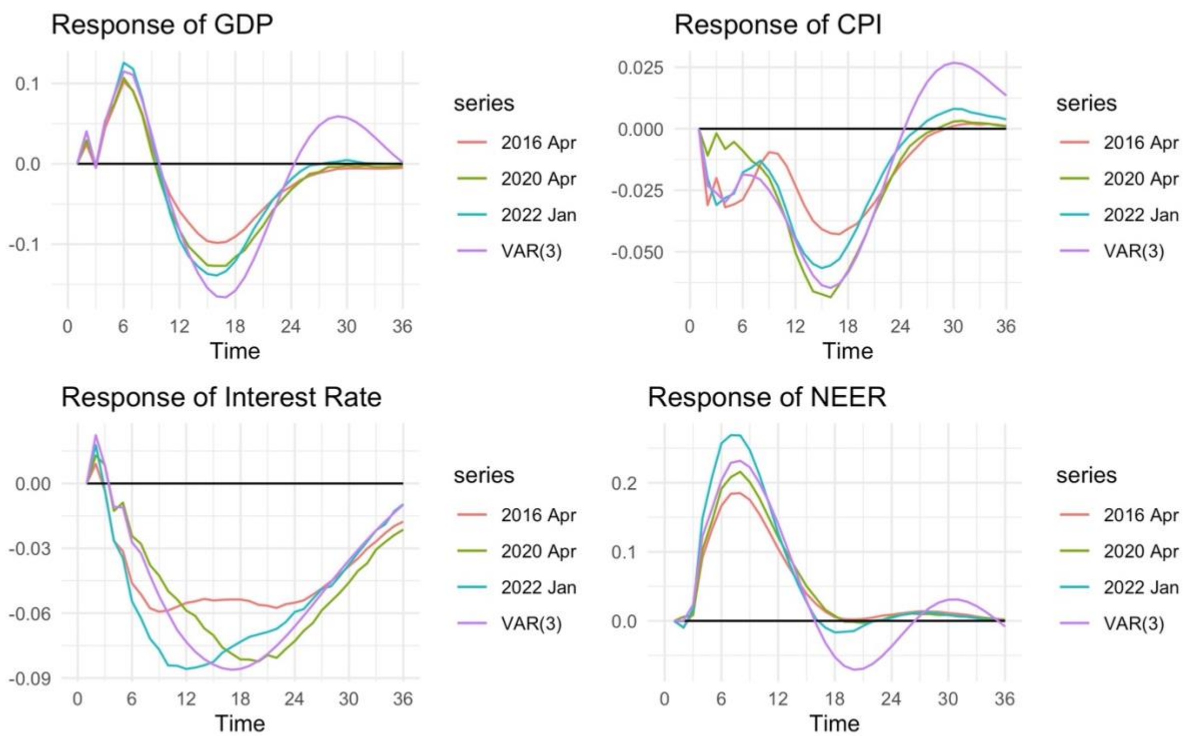

Figure 10. Median impulse responses to one standard deviation of terms of trade index shock at 2016M4, 2020M4 and 2022M1 versus the benchmark; self-response excluded.

APPENDIX C

IMPULSE RESPONSES TO A MONETARY POLICY SHOCK AT 6^{TH}, 12^{TH}, AND 24^{TH} MONTH

C.1. IMPULSE RESPONSES TO A MONETARY POLICY SHOCK AT 6^{TH} MONTH

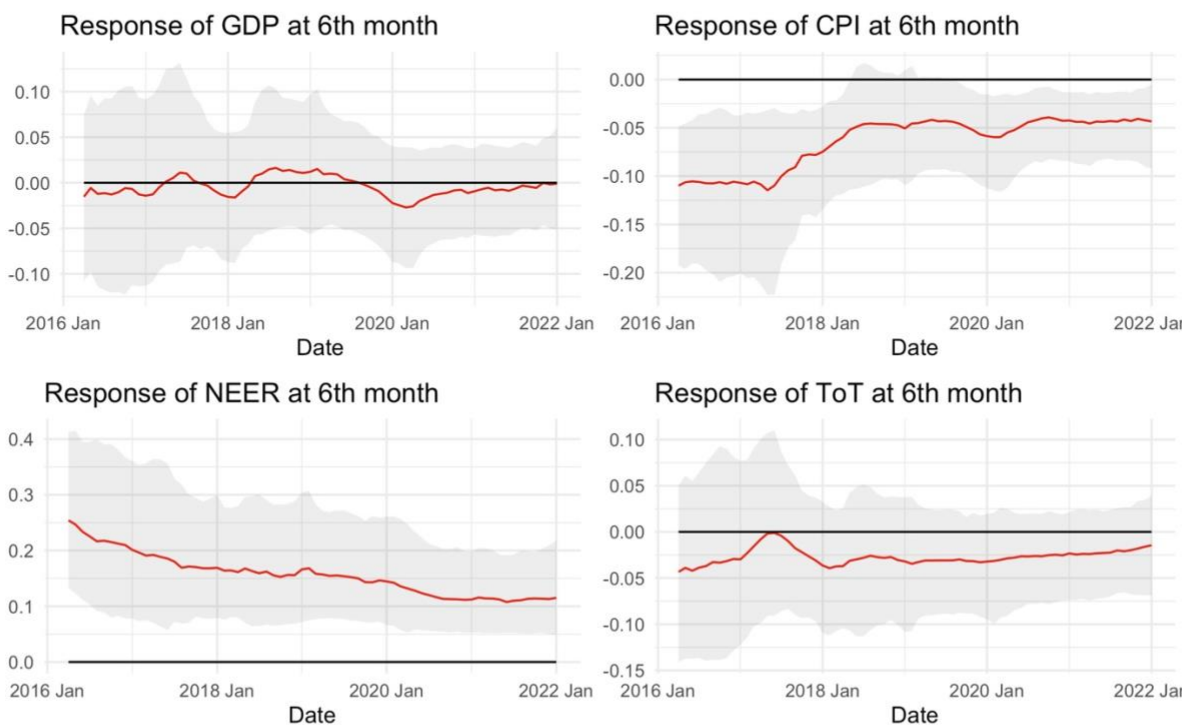

Figure 11. Median impulse responses to one standard deviation of the contractionary monetary policy shock with 16th and 84th percentiles of the posterior distribution of the responses at 6th month since the initial shock.

C.2. IMPULSE RESPONSES TO A MONETARY POLICY SHOCK AT 12TH MONTH

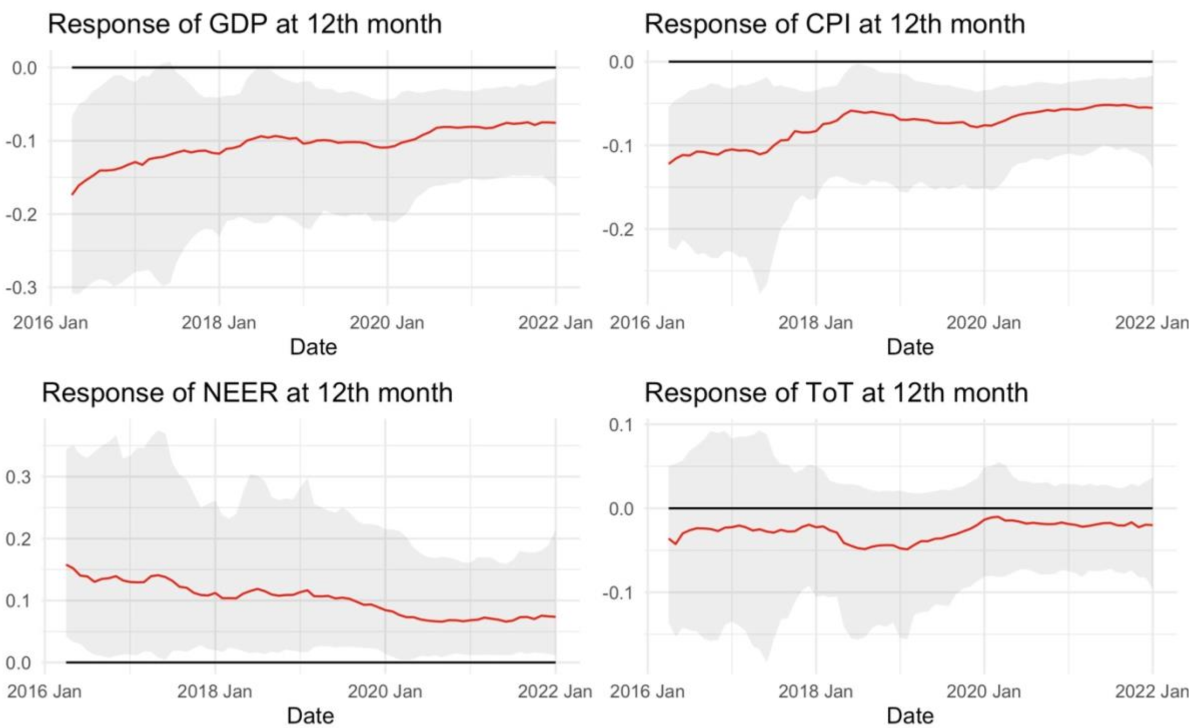

Figure 12. Median impulse responses to one standard deviation of the contractionary monetary policy shock with 16th and 84th percentiles of the posterior distribution of the responses at 12th month since the initial shock.

C.3. IMPULSE RESPONSES TO THE MONETARY POLICY SHOCK AT 24^{TH} MONTH

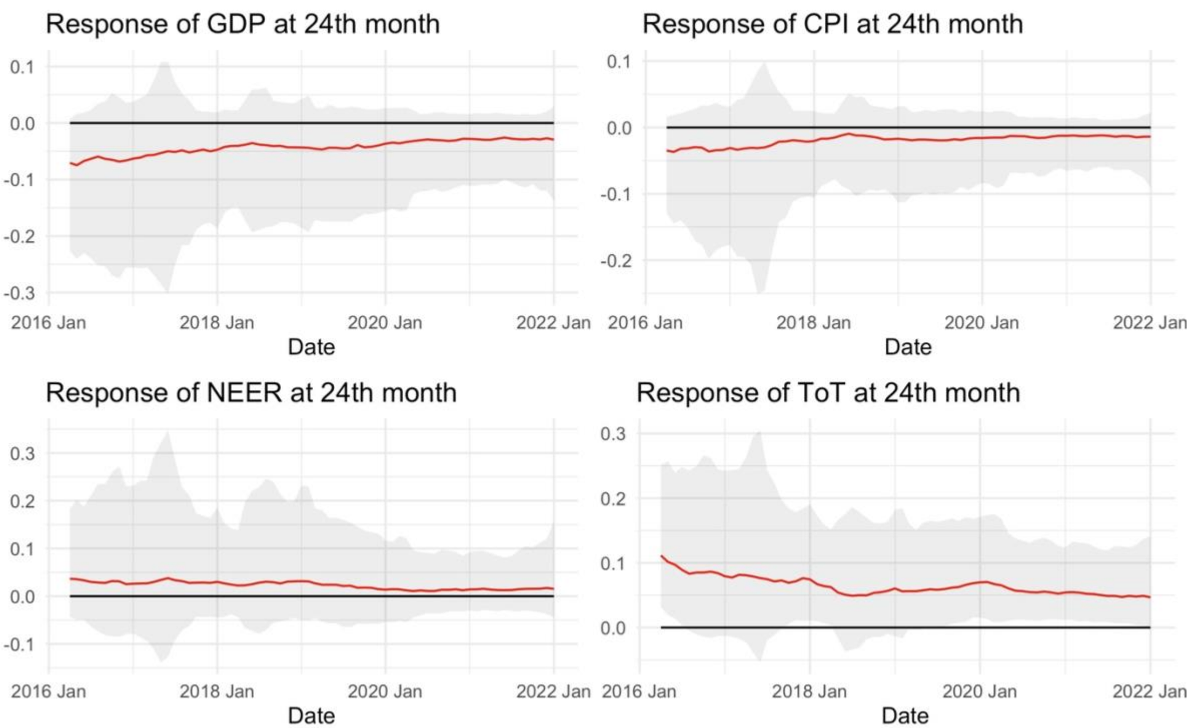

Figure 13. Median impulse responses to one standard deviation of the contractionary monetary policy shock with 16th and 84th percentiles of the posterior distribution of the responses at 24th month since the initial shock.

APPENDIX D

IMPULSE RESPONSES TO THE EXCHANGE RATE SHOCK AT 6^{TH}, 12^{TH}, AND 24^{TH} MONTH

D.1. IMPULSE RESPONSES TO THE EXCHANGE RATE SHOCK AT 6^{TH} MONTH

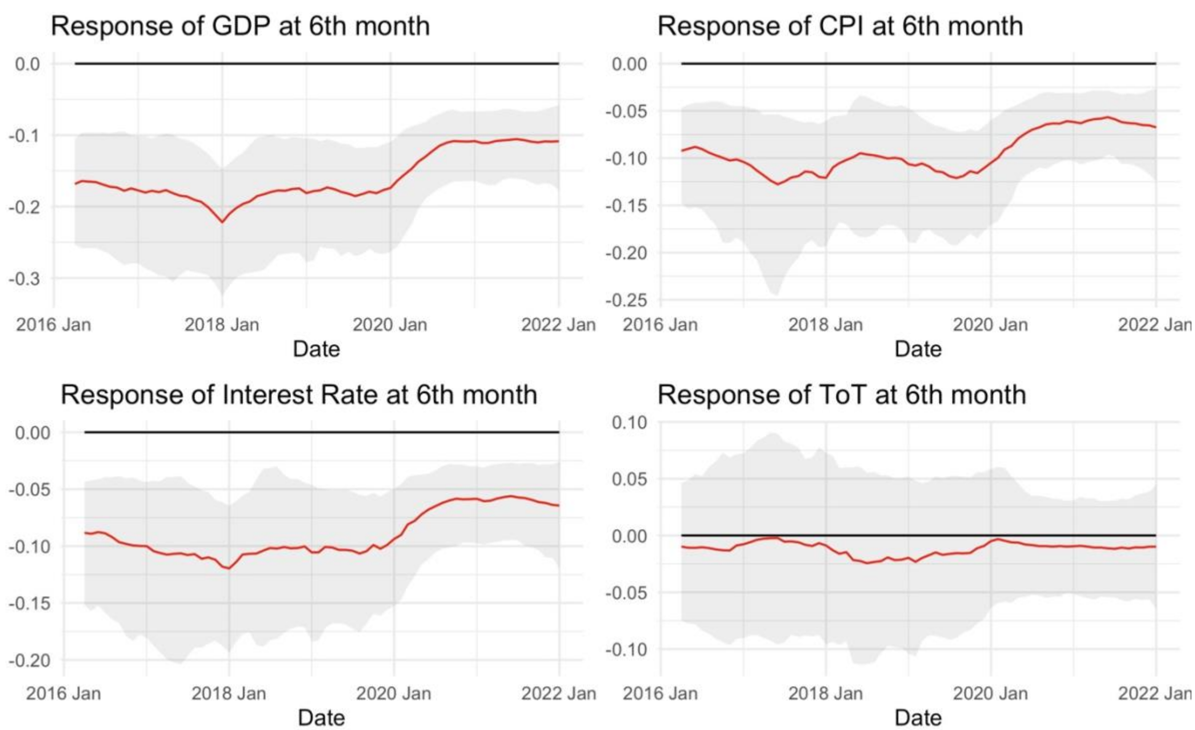

Figure 14. Median impulse responses to one standard deviation of the nominal effective exchange rate shock with 16th and 84th percentiles of the posterior distribution of the responses at 6th month since the initial shock.

D.2. IMPULSE RESPONSES TO THE EXCHANGE RATE SHOCK AT 12TH MONTH

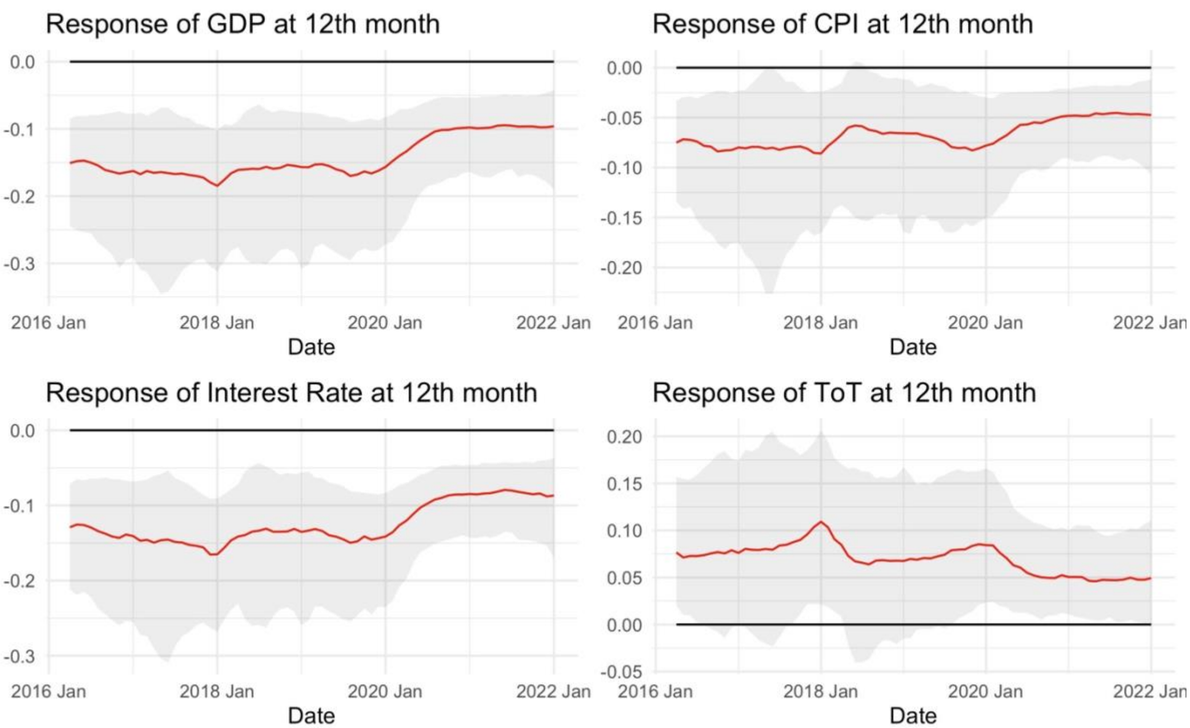

Figure 15. Median impulse responses to one standard deviation of the nominal effective exchange rate shock with 16th and 84th percentiles of the posterior distribution of the responses at 12th month since the initial shock.

D.3. IMPULSE RESPONSES TO THE EXCHANGE RATE SHOCK AT 24TH MONTH

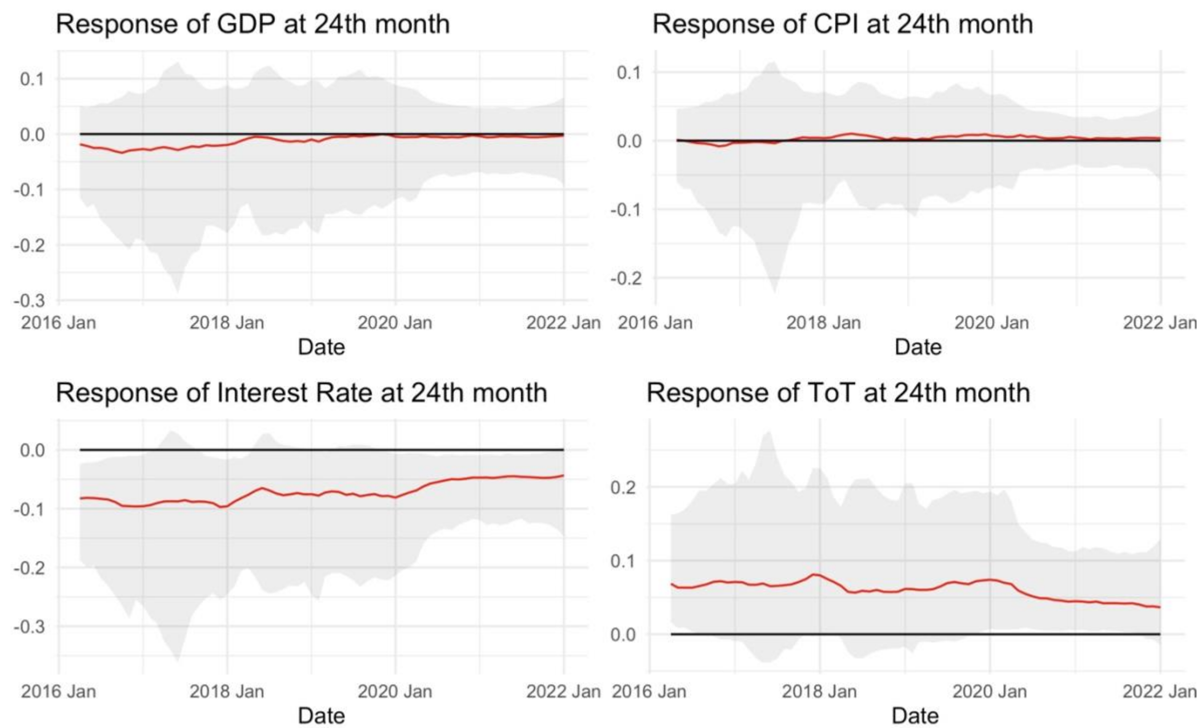

Figure 16. Median impulse responses to one standard deviation of the nominal effective exchange rate shock with 16th and 84th percentiles of the posterior distribution of the responses at 24th month since the initial shock.

APPENDIX E

IMPULSE RESPONSES TO THE DEMAND SHOCK AT 6TH, 12TH, AND 24TH MONTH

E.1. IMPULSE RESPONSES OF CPI TO DEMAND SHOCK AT 6TH MONTH

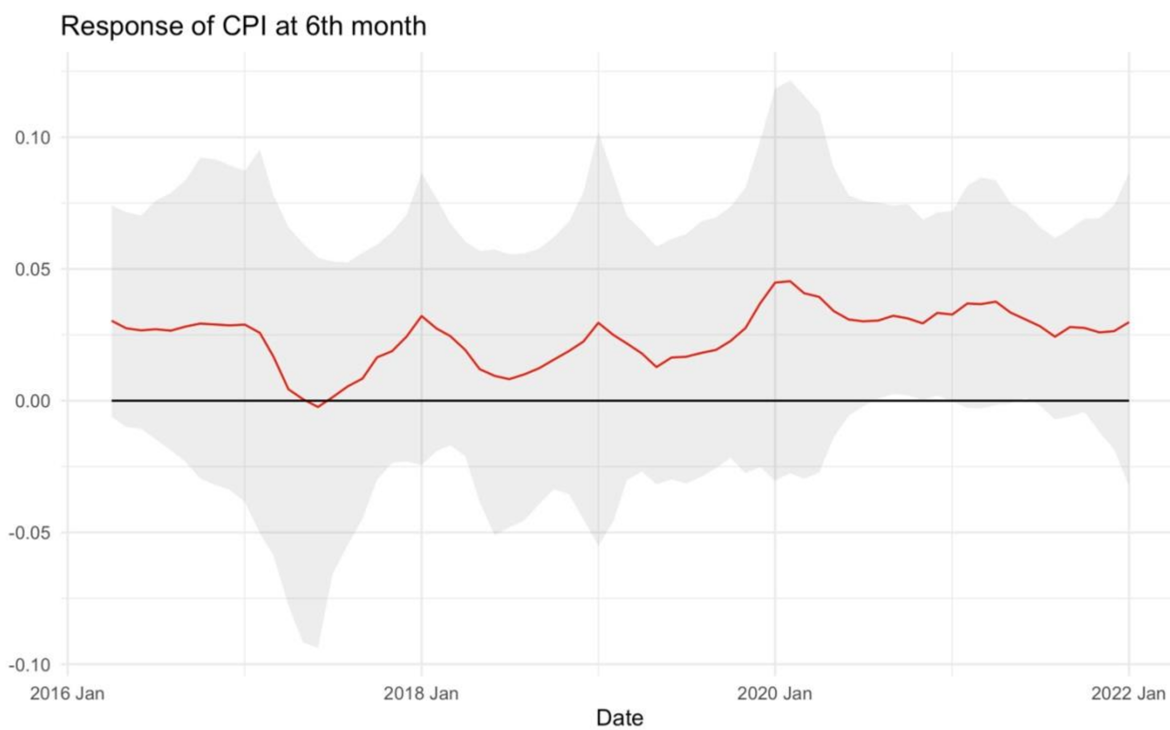

Figure 17. Median impulse responses to one standard deviation of the demand shock with 16th and 84th percentiles of the posterior distribution of the responses of CPI at 6th month since the initial shock.

E.2. IMPULSE RESPONSES OF CPI TO DEMAND SHOCK AT 12TH MONTH

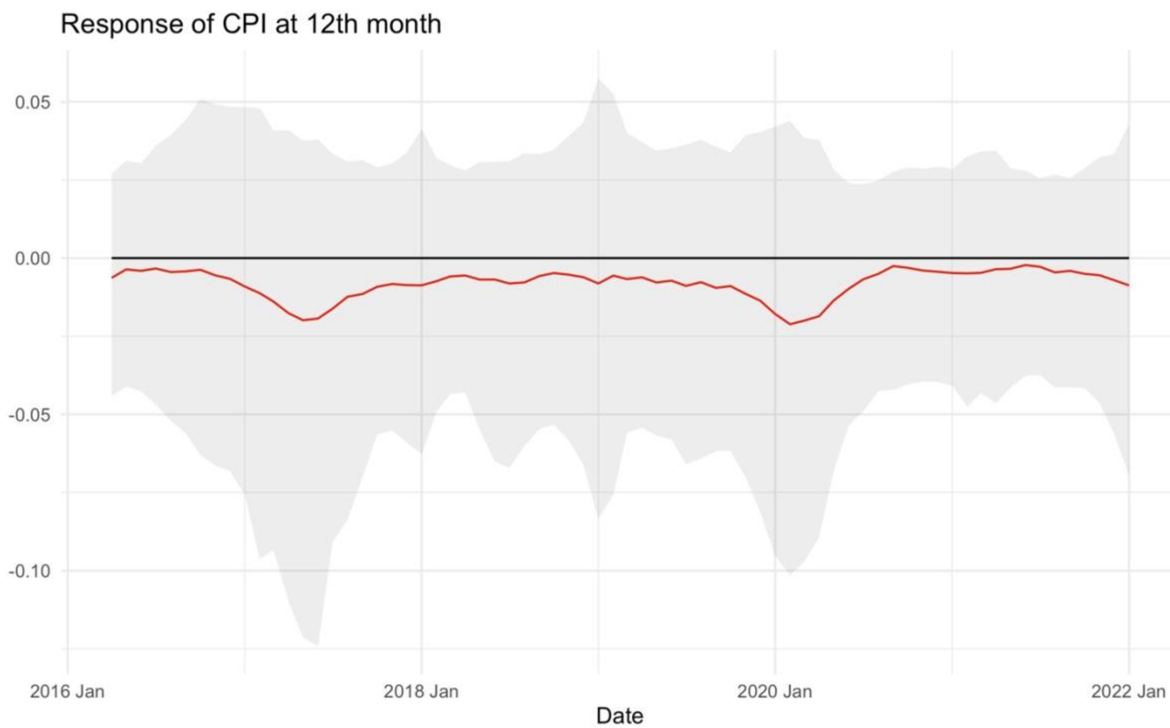

Figure 18. Median impulse responses to one standard deviation of the demand shock with 16th and 84th percentiles of the posterior distribution of the responses of CPI at 12th month since the initial shock.

E.3. IMPULSE RESPONSES OF CPI TO DEMAND SHOCK AT 24TH MONTH

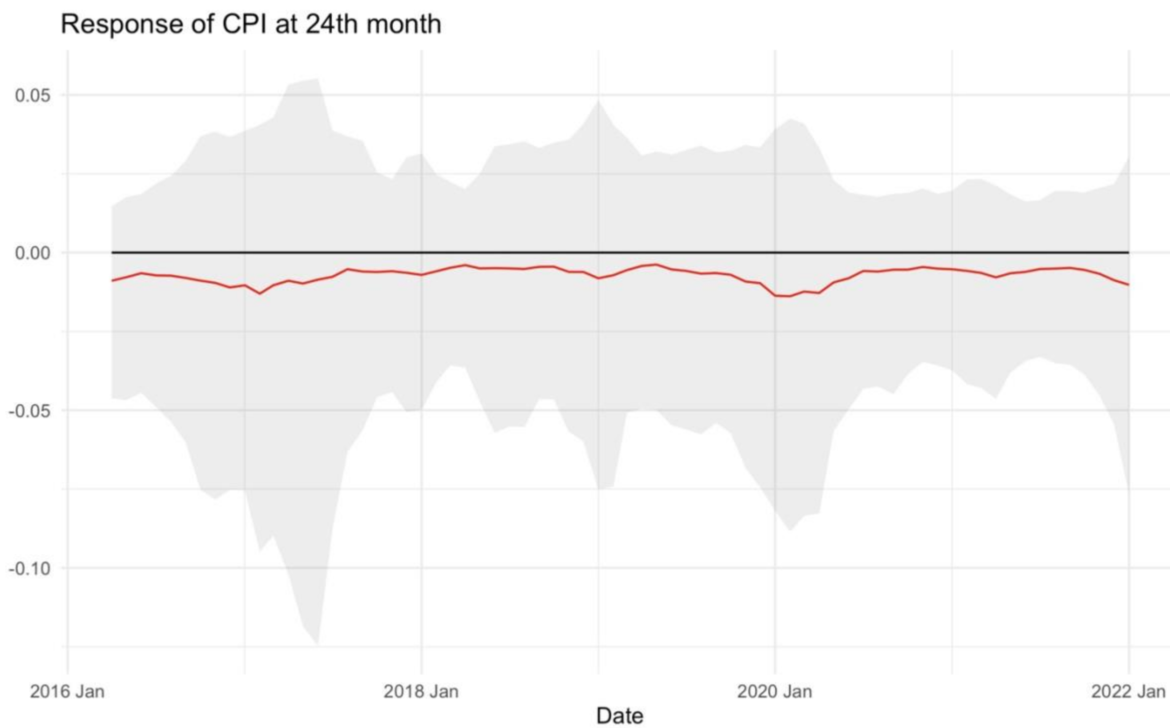

Figure 19. Median impulse responses to one standard deviation of the demand shock with 16th and 84th percentiles of the posterior distribution of the responses of CPI at 24th month since the initial shock.

APPENDIX F

WILCOXON TEST FOR THE RESPONSES TO THE SAMPLE AVERAGE MONETARY POLICY SHOCK AT DIFFERENT HORIZONS

Table 10. Wilcoxon rank sum test for equal medians of two distributions for the responses to the mean monetary policy shock at different horizons ahead after the initial shock.

Horizon	1 M	6 M	12 M	24 M	36 M
GDP					
2016/2020	≠	≠	=	≠	≠
2016/2022	≠	≠	=	≠	≠
2020/2022	≠	≠	=	=	=
CPI					
2016/2020	=	≠	≠	≠	=
2016/2022	≠	≠	=	=	=
2020/2022	≠	=	=	=	=
NEER					
2016/2020	≠	=	≠	≠	≠
2016/2022	=	=	≠	=	=
2020/2022	≠	≠	≠	≠	=
ToT					
2016/2020	=	≠	≠	=	=
2016/2022	=	≠	≠	=	≠
2020/2022	=	≠	≠	=	=

APPENDIX G

IMPULSE RESPONSES ANALYSIS FOR THE TVP-VAR MODEL ON A SAMPLE PERIOD FORM 2016M4 TO 2022M1

G.1. MEDIAN IMPULSE RESPONSES TO A MONETARY POLICY SHOCK AT 2014M4, 2020M4, 2022M1

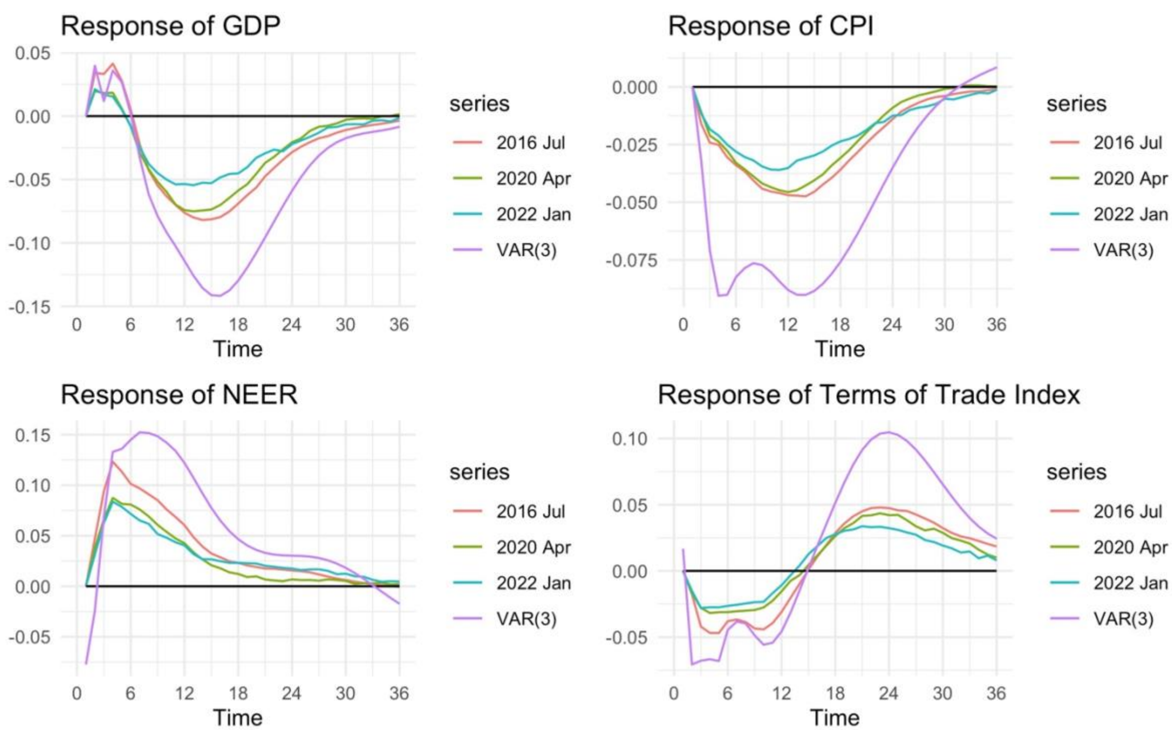

Figure 20. Median impulse responses to one standard deviation of the contractionary monetary policy shock at 2016M4, 2020M4 and 2022M1 versus the benchmark; self-response excluded.

G.2. MEDIAN IMPULSE RESPONSES TO AN EXCHANGE RATE SHOCK AT 2014M4, 2020M4, 2022M1

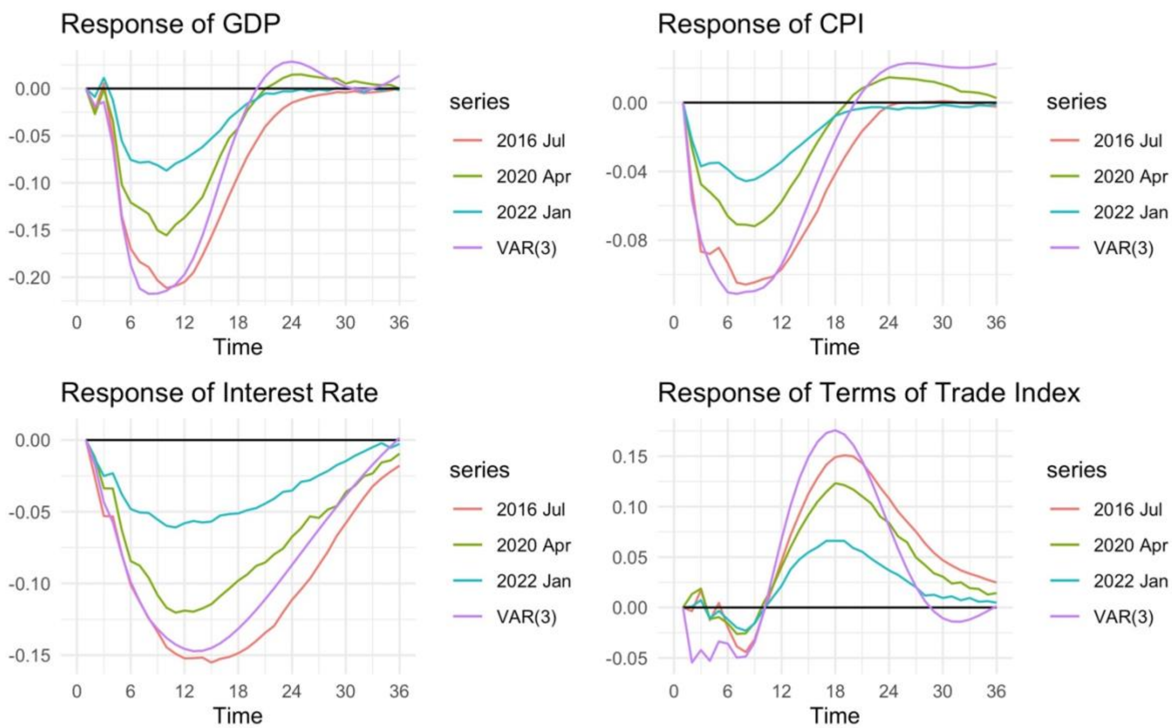

Figure 21. Median impulse responses to one standard deviation of the nominal effective exchange rate shock at 2016M4, 2020M4 and 2022M1 versus the benchmark; self-response excluded.

G.3. MEDIAN IMPULSE RESPONSE OF CPI TO A DEMAND SHOCK AT 2014M4, 2020M4, 2022M1

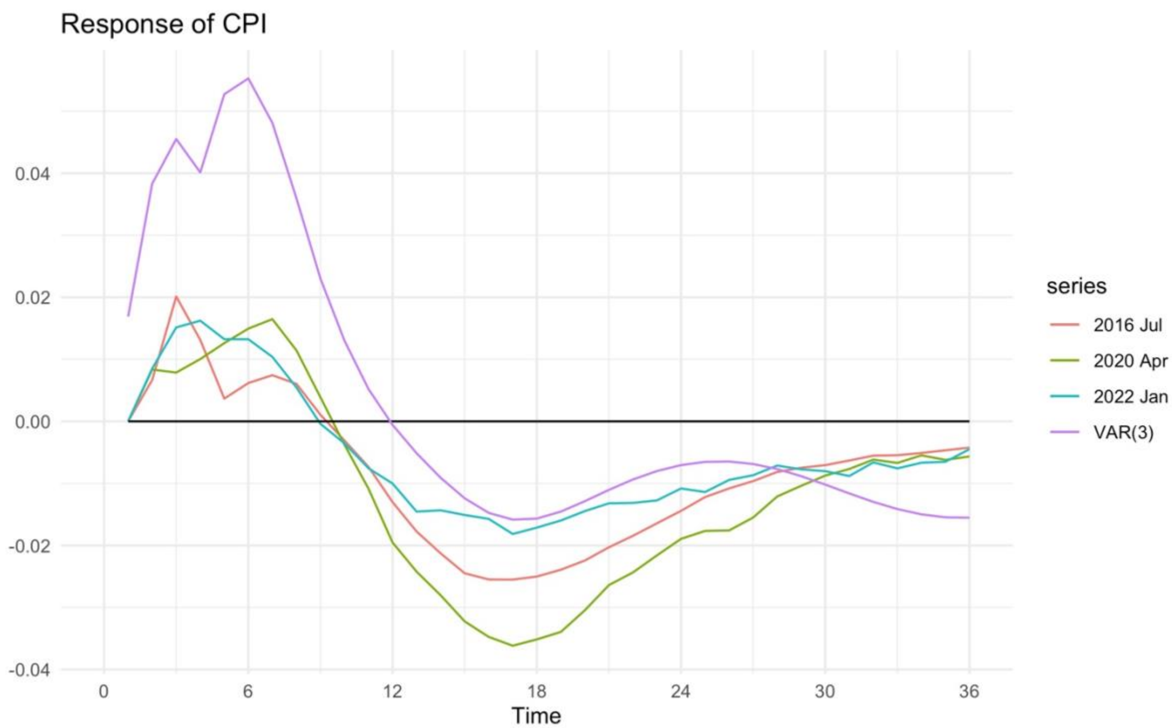

Figure 22. Median impulse responses of CPI to one standard deviation of the demand shock at 2016M4, 2020M4 and 2022M1 versus the benchmark.

G.4 WILCOXON TEST FOR THE RESPONSES TO A MONETARY POLICY SHOCK AT DIFFERENT HORIZONS

Table 11. Wilcoxon rank sum test for equal medians of two distributions for the responses to the monetary policy shock at different horizons ahead after the initial shock.

Horizon	1 M	6 M	12 M	24 M	36 M
GDP					
2016/2020	≠	≠	=	≠	=
2016/2022	≠	=	≠	=	=
2020/2022	=	=	≠	=	=
CPI					
2016/2020	≠	=	=	≠	=
2016/2022	≠	≠	≠	=	≠
2020/2022	=	≠	≠	≠	≠
NEER					
2016/2020	≠	≠	≠	≠	=
2016/2022	≠	≠	≠	=	=
2020/2022	≠	≠	=	≠	=
ToT					
2016/2020	=	≠	≠	=	≠
2016/2022	=	≠	≠	≠	≠
2020/2022	=	=	≠	≠	=

G.5. WILCOXON TEST FOR THE RESPONSES TO AN EXCHANGE RATE SHOCK AT DIFFERENT HORIZONS

Table 12. Wilcoxon rank sum test for equal medians of two distributions for the responses to the nominal effective exchange rate shock at different horizons ahead after the initial shock.

Horizon	1 M	6 M	12 M	24 M	36 M
GDP					
2016/2020	≠	≠	≠	≠	=
2016/2022	≠	≠	≠	=	=
2020/2022	≠	≠	≠	≠	=
CPI					
2016/2020	≠	≠	≠	≠	=
2016/2022	≠	≠	≠	=	=
2020/2022	≠	≠	≠	≠	≠
I					
2016/2020	≠	≠	≠	≠	=
2016/2022	≠	≠	≠	≠	≠
2020/2022	=	≠	≠	≠	=
ToT					
2016/2020	≠	≠	≠	≠	=
2016/2022	≠	≠	≠	≠	≠
2020/2022	≠	=	≠	≠	=

G.6. WILCOXON TEST FOR THE RESPONSE OF CPI TO A DEMAND SHOCK AT DIFFERENT HORIZONS

Table 13. Wilcoxon rank sum test for equal medians of two distributions for the response of CPI to the demand shock at different horizons ahead after the initial shock.

Horizon	1 M	6 M	12 M	24 M	36 M
CPI					
2016/2020	≠	≠	≠	=	=
2016/2022	=	=	=	=	=
2020/2022	=	=	≠	=	=

APPENDIX H

IMPULSE RESPONSES ANALYSIS FOR THE TVP-VAR MODEL WITH PRIMICERI'S PRIORS

H.1. MEDIAN IMPULSE RESPONSES TO A MONETARY POLICY SHOCK AT 2014M4, 2020M4, 2022M1

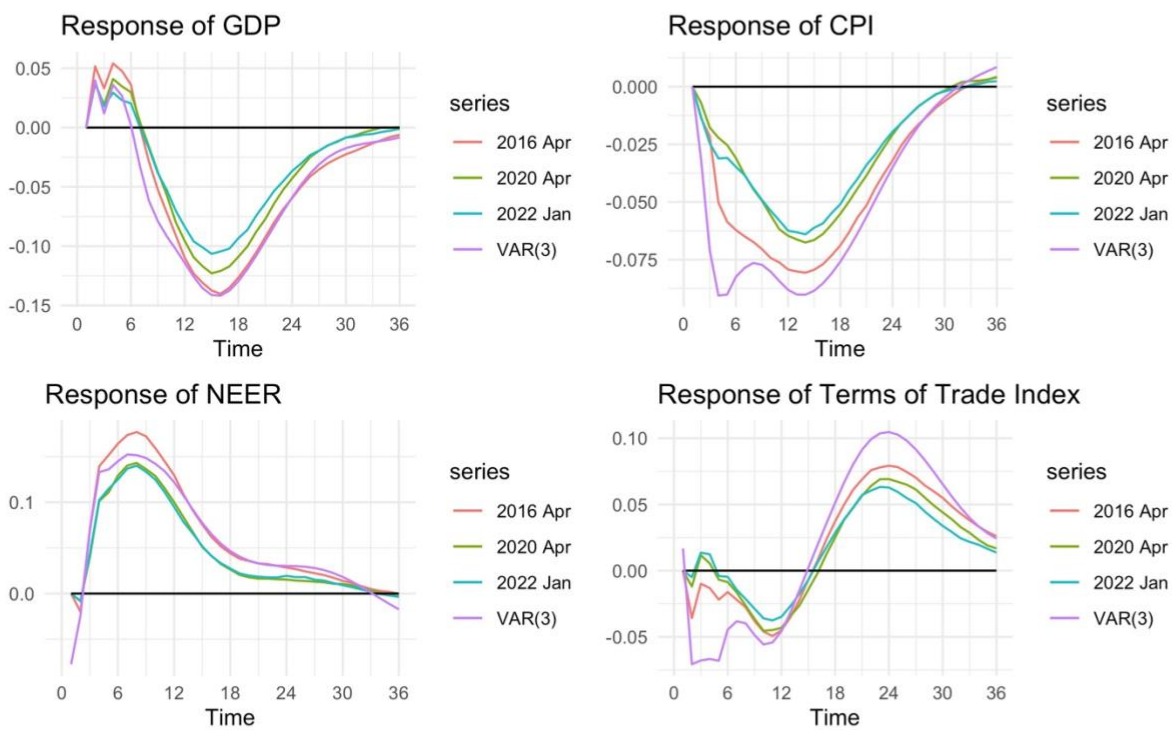

Figure 23. Median impulse responses to one standard deviation of the contractionary monetary policy shock at 2016M4, 2020M4 and 2022M1 versus the benchmark; self-response excluded.

H.2. MEDIAN IMPULSE RESPONSES TO AN EXCHANGE RATE SHOCK AT 2014M4, 2020M4, 2022M1

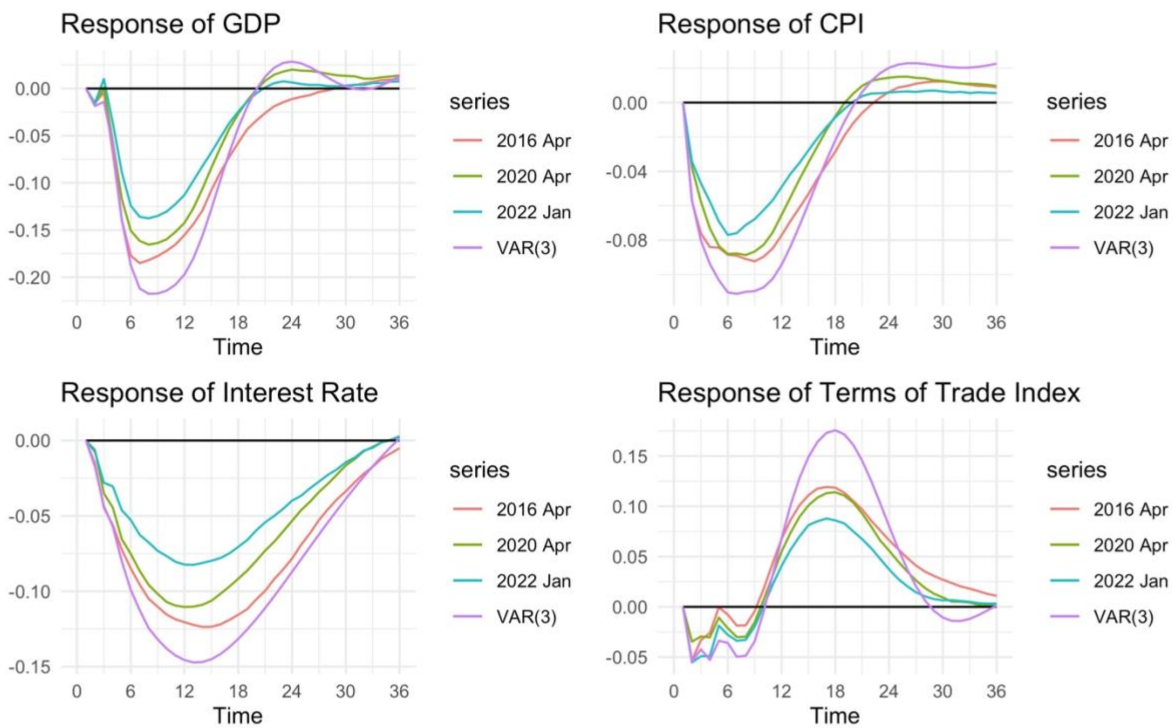

Figure 24. Median impulse responses to one standard deviation of the nominal effective exchange rate shock at 2016M4, 2020M4 and 2022M1 versus the benchmark; self-response excluded.

H.3. MEDIAN IMPULSE RESPONSE OF CPI TO A DEMAND SHOCK AT 2014M4, 2020M4, 2022M1

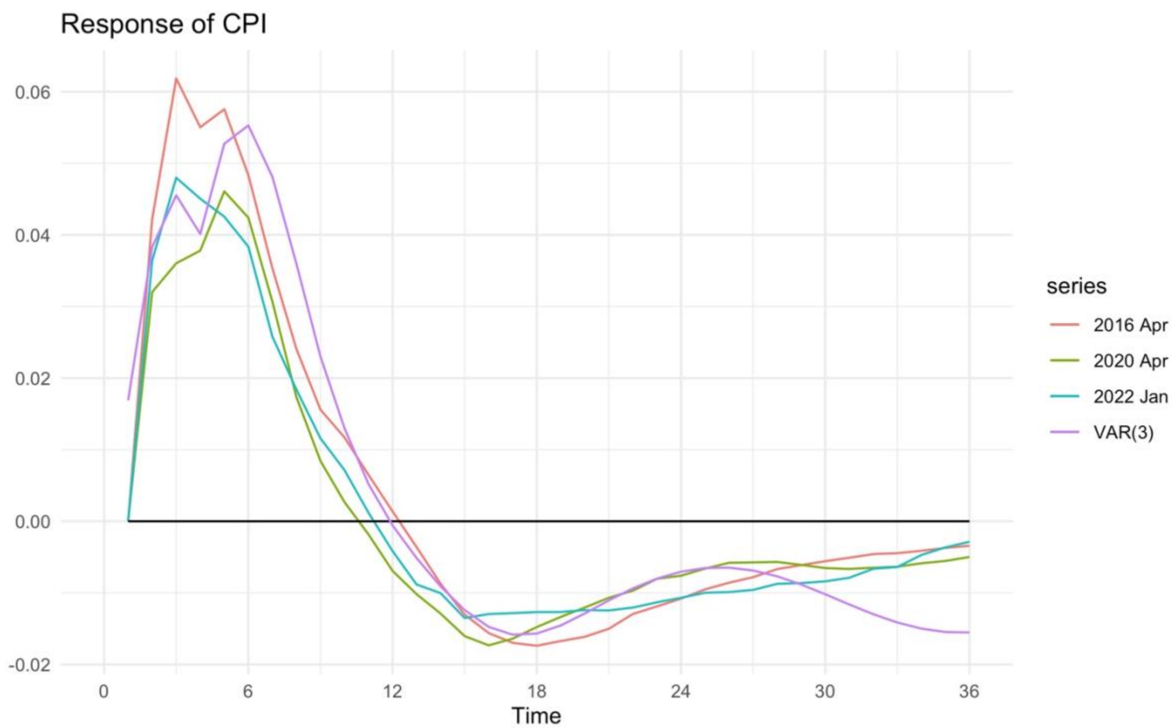

Figure 25. Median impulse responses of CPI to one standard deviation of the demand shock at 2016M4, 2020M4 and 2022M1 versus the benchmark.

H.4. WILCOXON TEST FOR THE RESPONSES TO A MONETARY POLICY SHOCK AT DIFFERENT HORIZONS

Table 14. Wilcoxon rank sum test for equal medians of two distributions for the responses to the monetary policy shock at different horizons ahead after the initial shock.

Horizon	1 M	6 M	12 M	24 M	36 M
GDP					
2016/2020	≠	=	≠	≠	≠
2016/2022	≠	=	≠	≠	=
2020/2022	=	=	≠	=	=
CPI					
2016/2020	≠	≠	≠	≠	=
2016/2022	=	≠	≠	≠	=
2020/2022	≠	=	=	=	=
NEER					
2016/2020	≠	≠	≠	≠	=
2016/2022	≠	≠	≠	≠	=
2020/2022	=	=	=	=	=
ToT					
2016/2020	≠	≠	=	≠	≠
2016/2022	≠	≠	≠	≠	≠
2020/2022	≠	=	≠	≠	=

H.5. WILCOXON TEST FOR THE RESPONSES TO AN EXCHANGE RATE SHOCK AT DIFFERENT HORIZONS

Table 15. Wilcoxon rank sum test for equal medians of two distributions for the responses to the nominal effective exchange rate shock at different horizons ahead after the initial shock.

Horizon	1 M	6 M	12 M	24 M	36 M
GDP					
2016/2020	=	≠	≠	≠	=
2016/2022	=	≠	≠	≠	=
2020/2022	=	≠	≠	≠	≠
CPI					
2016/2020	≠	=	≠	≠	=
2016/2022	≠	≠	≠	=	=
2020/2022	=	≠	≠	≠	≠
I					
2016/2020	≠	≠	≠	≠	≠
2016/2022	≠	≠	≠	≠	≠
2020/2022	≠	≠	≠	≠	=
ToT					
2016/2020	≠	≠	≠	≠	≠
2016/2022	≠	≠	≠	≠	≠
2020/2022	≠	=	≠	≠	=

H.6. WILCOXON TEST FOR THE RESPONSE OF CPI TO A DEMAND SHOCK AT DIFFERENT HORIZONS

Table 16. Wilcoxon rank sum test for equal medians of two distributions for the response of CPI to the demand shock at different horizons ahead after the initial shock.

Horizon	**1 M**	**6 M**	**12 M**	**24 M**	**36 M**
CPI					
2016/2020	≠	≠	≠	≠	=
2016/2022	≠	≠	≠	=	=
2020/2022	=	=	=	≠	=