

OTDK - DOLGOZAT

2025

Óbudai Egyetem

Keleti Károly Gazdasági Kar



**AZ EURÓPAI KÖZPONTI BANK KAMATEMELÉSI SPILLOVER
HATÁSAI AZ EURÓ FORINT ÁRFOLYAMRA ÉS A 3 HÓNAPOS
BUBOR-RA. EGY VAR MEGKÖZELÍTÉS A DIEBOLD-YILMAZ
MÓDSZER SEGÍTSÉGÉVEL**

**ANALYZING SPILLOVER EFFECTS OF ECB RATE HIKE ON
THE EURO FORINT EXCHANGE RATE AND THE 3-MONTH
BUBOR. A VAR APPROACH USING THE DIEBOLD-YILMAZ
METHOD**

Molnár Albert

Konzulens: Dr. habil. Csiszár-Kocsir Ágnes

Kézirat lezárásának dátuma: 2023.11.11

Contents

Abstract	1
1. Introduction.....	2
2. The Hungarian interbank rate	5
3. Literature review and characterization of distinctions between Lütkepohl's and Diebold-Yilmaz's (2009) and (2012) methods	10
4. Methodology	13
5. Data, descriptive statistics and commentary	20
6. Results how inefficiencies in the IRF lead to the utilization of the FEVD, and can a simpler model capture volatility spillovers better	25
7. Discussion	42
8. Conclusions.....	43
References	44
Appendix A: Control VAR model.....	46
Appendix B: Consequences of correlated shocks and the Cholesky decomposition	47
Appendix C: Source code in R	48

Table of Figures

Figure 1. The interest rate corridor of the Hungarian central bank. Compiled by author. Source: MNB	5
Figure 2. Rate of change of MNB the policy rate (Y -axis = current value/previous*100%). Compiled by Author. Source: MNB	6
Figure 3. Rate of change of the ECB policy rate (Y-axis = current value/previous*100%). Compiled by Author. Source: ECB	6
Figure 4. The ECB interest rate corridor. Compiled by author. Source: ECB	7
Figure 5. (a) Percentage of Hungarian variable rate mortgage loan from total mortgage loans. Compiled by author. Source: MNB. (b) Value of variable rate consumer loans issued each month (L-HS), interest rate on those loans (R-HS). Compiled by author. Source: MNB	8
Figure 6. Value of monthly loan contracts originated for non-banking business sector (L-HS) and the interest rate (R-HS). Compiled by author. Source: MNB	9
Figure 7. (a) 3-month BUBOR time series. Compiled by author. Source: BÉT. (b) I(1) difference of 3-month BUBOR time series (value at t – value at $t - 1$) Compiled by author. Source: BÉT.	20
Figure 8. (a) 3-month EURIBOR time series. Compiled by author. Source: ECB. (b) I(1) difference of 3-month EURIBOR time series (value at t – value at $t - 1$) Compiled by author. Source: ECB.	21
Figure 9. (a) EUR/HUF time series. Compiled by author. Source: MNB. (b) I(1) difference of EUR/HUF time series (value at t – value at $t - 1$) Compiled by author. Source: MNB.	21
Figure 10. (a) 50%RMAX+50%ZMAX benchmark time series for OTP prémium pénzpiaci alap BBG ISIN code: HU0000712161. Compiled by author. Source: ÁKK. (b) I(1) difference of 50%RMAX+50%ZMAX time series (value at t – value at $t - 1$) Compiled by author. Source: ÁKK.	22
Figure 11. . (a) Euro Short term rate (ESTER) time series. Compiled by author. Source: ECB. (b) I(1) difference of ESTER time series (value at t – value at $t - 1$) Compiled by author. Source: ECB	23
Figure 12 (a) Impulse response function for BUBOR (impulse), and EUR/HUF (response). (b) IRF for EUR (impulse), and BUBOR (response). Y-axis = standard deviations, X-axis, Periods = trading days.	28

Figure 13 (a) Impulse response function for MAX (impulse), and BUBOR (response). (b) IRF for BUBOR (impulse), and MAX (response). Y-axis = standard deviations, X-axis, Periods = trading days.	29
Figure 14 (a) Impulse response function for MAX (impulse), and exchange rate (response). (b) IRF for exchange rate (impulse), and MAX (response). Y-axis = standard deviations, X-axis, Periods = trading days.	30
Figure 16. Total volatility spillover plot. K=5, VAR(4) model. Compiled by author. Source code attached in appendix.	35
Figure 17. Directional spillover plot, From the K=5 variables in VAR (4). Compiled by author. Source code attached in appendix. Source: MNB, ÁKK, ECB	37
Figure 18. Directional spillover plot, To the K=5 variables in VAR (4). Compiled by author. Source code attached in appendix. Source: MNB, ÁKK, ECB	38
Figure 19. Net spillover plot, K=5 variables in VAR (4). Compiled by author. Source code attached in appendix. Source: MNB, ÁKK, ECB	39
Figure 20. Net pairwise volatility spillovers. K=5 variables in VAR (4). Compiled by author. Source code attached in appendix. Source: MNB, ÁKK, ECB	40
Figure 21. From/To pairwise. K=5 variables in VAR (4). Compiled by author. Source code attached in appendix. Source: MNB, ÁKK, ECB	41

Tables

Table 1. Descriptive statistics of the panel VAR. Compiled by author. Source: MNB, ECB, ÁKK. Note that the order of the variables in the VAR model is from left to right.	23
Table 2. Results for the ADF test of the panel data variables.....	24
Table 3. Summary of VAR(4) K=3, Model 1. Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1	25
Table 4. Summary of VAR(4) K=3, Model 2. Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1	26
Table 5. Summary of VAR(4) K=3, Model 3. Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1	26
Table 6. Orthogonalized FEVD. (a) EUR/HUF, (b)BUBOR, (c) EURIBOR , (d) RMAX+ZMAX	31
Table 7. The 10-step ahead Generalized Forecast error variance decomposition for the EUR.HUF exchange rate variable. Compiled by author. Source code attached in appendix.	31
Table 8. The 10-step ahead Generalized Forecast error variance decomposition for the 3-month BUBOR variable. Compiled by author. Source code attached in appendix.	31
Table 9. The 10-step ahead Generalized Forecast error variance decomposition for the RMAX+ZMAX variable. Compiled by author. Source code attached in appendix.	32
Table 10. Generalized spillover table, Hungarian interbank rate volatility, 10/1/2019-07/01/2023. Values in percentage.....	33
Table 11. Residuals of the VAR(4) K=5 covariance matrix. Compiled by author. Source code attached in the appendix.	47
Table 12. Correlation of residuals of the VAR(4) K=5. Compiled by author. Source code attached in the appendix.	47
Table 13. Correlation of residuals after the Cholesky decomposition. VAR(4) K=5. Compiled by author. Source code attached in the appendix.	48

Abstract

We intend to show the directional volatility spillovers between the short term interbank lending rates in EU and in Hungary. We employ the Diebold and Yilmaz methodology of dealing with non-orthogonal innovations through a Generalized forecast error variance decomposition framework and we also highlight the issues with the impulse response functions when it comes to ordering the variables that arise from the Cholesky decomposition, which solves the contemporaneous correlation problem of residuals. In case of the 3-month BUBOR rate, the Euro/Hungarian Forint exchange rate and for the MAX government benchmark variable we are able to identify three episodes of increased volatility: Q3-Q4 of 2019, the 2020 lockdown recession and the October 2022 rate hikes of the MNB. These volatility increases correspond with volatility spikes in EU markets that had to some extent a measurable spillover effect on Hungarian interbank rates.

We find that on average, across the entire sample of over 957 observations of 5 variables, about 6.3% of the volatility forecast error variance in all 5 variables comes from spillovers. The total and directional spillovers over the sample are extremely low.

In light of these findings, we conclude that the ECB's surprise policy decisions have a marginal impact on Hungarian financial time series.

From the 300-day rolling sample plot we observed that the BUBOR is a net receiver of spillovers from the MAX short term government bond benchmark rather than the EURIBOR – this disproved our initial considerations.

Keywords: Bubor, Economic crisis, Euribor, Generalized Forecast variance error decomposition, Spillover, Recession.

1. Introduction

The short end of the yield curve usually conveys the markets' expectations of the central banks' interest rate policy. The yield of any short-term liquid non-collateralized debt instrument in question will be closely correlated to the overnight lending rate of the central bank. Short-term debt instruments such as overnight deposits, notes, commercial papers (their yield is often tied to an index) create the plumbing of the modern financial system (Karpoff, 1988). Fluctuations in short-term interest rates can also affect commercial loans, structured securities such as Mortgage backed securities, Collateralized loan obligations and even derivative instruments (Black and Scholes, 1974, Black et al., 1972). These securities are often found on the books of large asset managers, pension funds, insurance companies and hedge funds¹. They often pay on a semi-annual or quarterly basis and the payout depends on the value of the reference index at the given date (since the interest rate is determined as the value of an index plus a pre-determined spread with the specification of a floor). Therefore, the effect of short-term interest rates on securities and money markets is clearly immense. Fama and French argue for three separate forms of efficient markets, frequently it is the case that releases of economic data do not significantly alter prices of securities proving the theorem. However, it is clear that unexpected interest rate hikes or cuts can trigger significant asset dislocations across markets and increase volatility in the financial system. Fat tails are also a major issue contradicting the existence of efficient markets. Assuming a normal distribution of returns and a volatility which is constant, an erroneous assumption is usually made that the likelihood of three or even ten sigma events is so small, that their occurrence is inconceivable and therefore should be disregarded. In volatile markets asset correlations tend to 1, the flight to quality (usually USTs) ensues and spreads between high quality and high risk assets widen. This in turn creates inefficiencies (opportunities) for arbitrage, however, it is important to understand the source of the volatility. With the availability of high-frequency data the plumbing of the economy can be analyzed from the perspective of reference rate volatilities.

The long end of the yield curve conveys information about expectations of future inflation, unemployment, and general economic activity. It is also the target of quantitative easing programs. The demand across the supply of maturities reflected in the price of the asset is inversely related to their yields. Widening spreads correspond to an increase in

¹ In 2022, Hungarian banks were exposed to more than 1 Trillion HUF in inflows of capital to money market funds

volatility. Spreads reflect the expectations of markets; they are not governed by realized volatilities. Spreads tell you what premium the market is willing to pay for a higher quality asset (Lowenstein, 2001).

Currently, the European economy is forecasting a GDP growth of below 1%, there is a significant loss of productivity due to lack of investment and interest rates are increasing making businesses finance growth more difficult, crediting standards are tightening and the retail base eligible for borrowing is shrinking (Papi, 2023). Many early warning systems are reaching their signaling thresholds pointing to an inverted yield curve, decrease in investment, total Eurozone PMI and PPI dipping below 50 etc. (PMI, 2023). China's slow reopening and property crisis, the German recession, uncertainties on the prospects of repeating the March banking crisis are only some of the factors weighing down on the global economy. At the same time, unemployment throughout Europe and the U.S is historically low, consumer spending is still high, and the global economy is going through a de-inflationary² correction. With the conflicting data it becomes difficult to estimate if the European Union in its entirety is in a recession or not, we can only say for certain that Hungary is eagerly trying to escape from its grips.

We assess the spread of interest rate volatility from European markets to Hungarian markets by creating a spillover index table proposed by Diebold-Yilmaz (henceforth DY) in their seminal work (2012). We also create an intuitive mathematical framework for analysis. Our work focuses on the application of generalized forecast error variance decompositions, generalized spillover indexes and generalized impulse response functions to measure the contribution of one endogenous variable to a shock in the panel data. We realize that there are issues in DY's (2009) study, where the ordering of variables limits the analysis of potential effects of cross spillovers from variables. This is circumvented later in DY's (2012) work. We follow the same logic.

However, in their latest work DY lack a framework for understanding why the order of the variables in the VAR model leads to spurious results. Which is why we intend to provide the mathematical and theoretical framework for this.

The motivation of this work, on one hand, is to provide an alternative in light of the limitations of the methodology applied in the latest MNB study (Antal and Kaszab, 2021),

² De-inflationary, not deflationary, as only the speed of the price increases has dropped. Prices are still continuing to rise. In a deflationary environment we refer to the speed at which prices are falling.

and on the other hand, to estimate the total rolling window, and thereby visualize the to/from and net pairwise spillover effects. In addition, we estimate the impulse response functions of the realized variance on their own.

The paper is structured as follows. Part 1 will reflect on the case of the Hungarian economy, that is, we will give an explanation, why the BUBOR index is of a particular interest to us. In Part 2, avoiding unnecessary notational clutter, and avoiding delving unnecessarily deep into VAR models we compare the forecast error variance proposed by Lütkepohl (1996, 2007), and how the DY method is both similar and different. Part 3 presents the results, and in part 4 we provide a critical assessment of the results and of the methodology in the discussion section and summarize.

We do not aim to replicate the work of DY 2009 or DY 2012 for Hungarian time series, instead, we aim to highlight the inefficiencies of ordering of variables and the SVAR approach towards the resolution of the problem.

2. The Hungarian interbank rate

Let's first examine the Hungarian market for loans. The Hungarian interbank offering rate known as the BUBOR is an index that is used primarily for adjustable loans, which may include mortgages, car loans, personal loans and business loans. Banks usually add a spread on top of these indexes. In other words, BUBOR represents the price at which banks acquire the funds to originate loans and mortgages, and the loan that banks issue is what generates their income. The interest rate corridor is determined by the central bank and the market rate (BUBOR) usually moves between the overnight central bank deposit rate and the overnight loan rate, rarely diving below the deposit rate, except in times of significant volatility as shown in Figure 1.

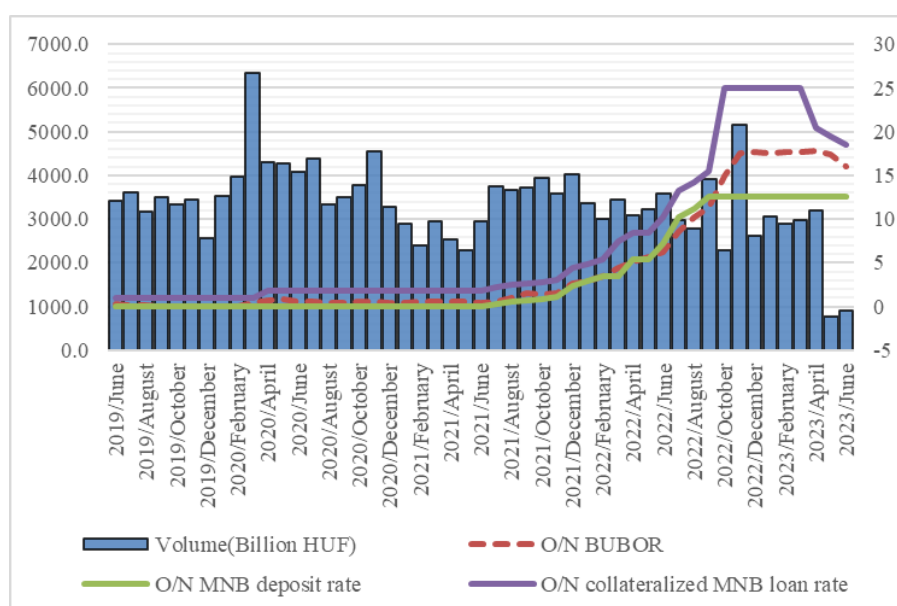


Figure 1. The interest rate corridor of the Hungarian central bank. Compiled by author. Source: MNB

In the past 18 months the MNB increased interest rates at the fastest pace on record. Such a drastic tightening cycle is likely to have caused an inefficient allocation of assets, the only cure to which is liquidation at strict market prices (Figure 2). Such an increase in the interest rate was the only solution to tame rising inflation as a result of large influxes of cash and low interest rates in the past decade.

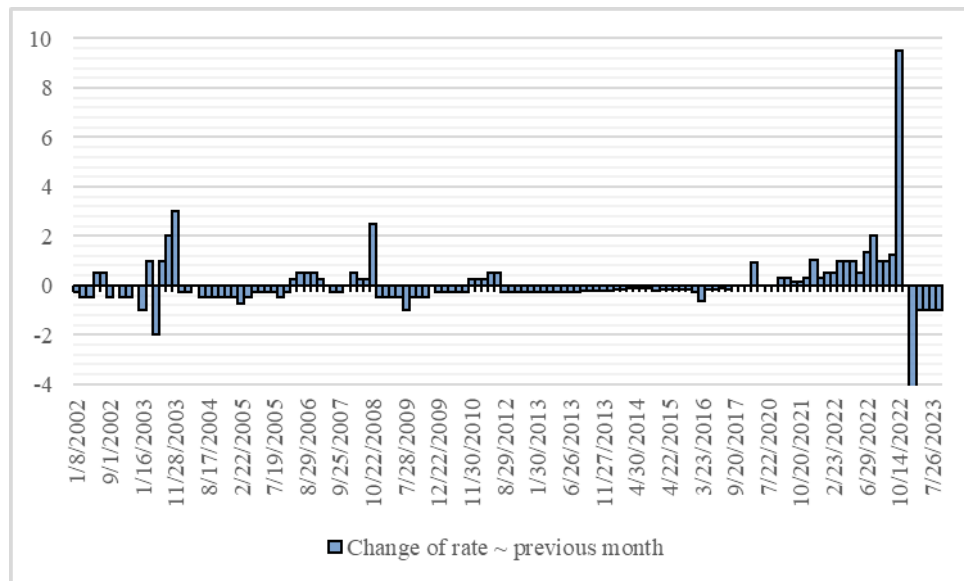


Figure 2. Rate of change of MNB the policy rate (Y -axis = current value/previous*100%). Compiled by Author. Source: MNB

The Hungarian National bank has never raised rates so fast. This precedent creates opportunities for structural and macroprudential risks to surface, as the banking system adjusts to higher global rates. Each bar in Figure 2 shows the decision of the meeting of the Hungarian Monetary Council within the MNB a to change the policy rate. The number of decisions to change the policy rate amounts to almost 100.

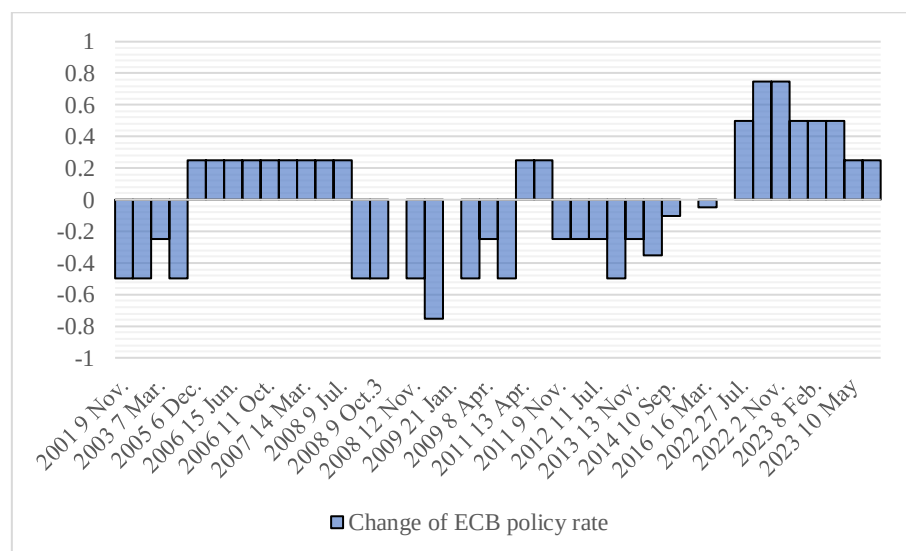


Figure 3. Rate of change of the ECB policy rate (Y-axis = current value/previous*100%). Compiled by Author. Source: ECB

Consider, in comparison, the rate at which the ECB has been increasing its policy interest rate. On the one hand, notice the number of times the rate has changed in the last 20 years – barely 40 decisions. On average- two decisions per year. In Hungary, the decisions per

year average 5. On the other hand, there is a significant difference between the speed at which rates were increased in Hungary versus in the Eurozone.

The MNB's decision to raise interest rates to such a dramatic level coupled with the inherent structural risks in Hungarian capital markets is a recipe for trouble. The spillover effects from ECB decisions on their own are enough to trigger systemic shocks in the Hungarian banking system. As shown in Figure 4, the ECB started the rate hiking cycle at a later time than Hungary.

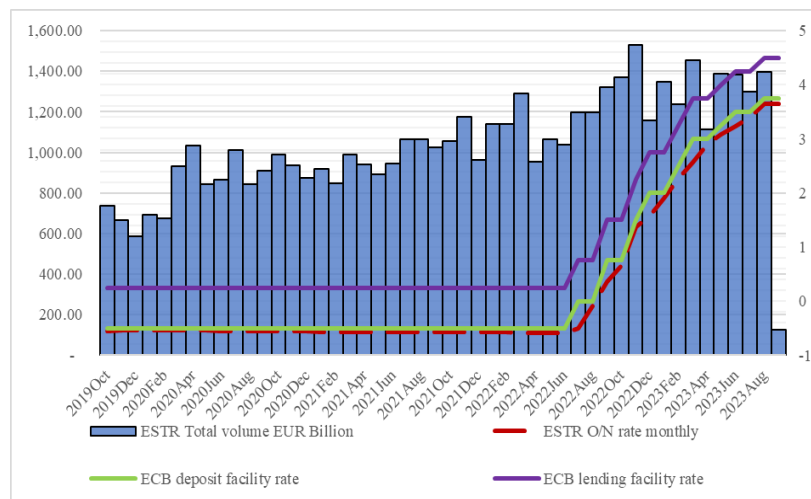


Figure 4. The ECB interest rate corridor. Compiled by author. Source: ECB

Because the subject of our study is the BUBOR index and the spillover effects that other indexes cause to BUBOR, we examine the primary component in the variable rate loan market (variable mortgages, variable-rate consumer loans, variable rate business loans) – the reference index. Any exogenous shock to the BUBOR is likely to have an immediate impact on the size of the periodic payments on the loans.

Hungary faces a fourth quarter of contraction of the GDP, which means technically the country is in a recession. High short term interest rates have attracted significant investment into money market funds in 2022. By the first quarter of 2023, however, foreign direct investment had turned negative. Figure 5a shows the percentage of variable rate loans from the total number of mortgage loans originated in a given month. If we take into account the average amount of loans originated monthly since December 2022, which approximates to 42-45 Billion HUF/month, the share of variable rate loans, that is loans that's interest rates are fixed for up to 1 year and then are floating, would only amount to a size of 400 million

HUF in a month or 4.8 billion HUF annually. Evidently, any endogenous shock originating from outside the country, for example the ECB's decision to hike rates would not have a significant impact on the mortgage market.

Figure 5b illustrates the amount of variable consumer loans issued each month and the interest rate on those loans. The trough in the interest rate between March 2020 and January 2021 is due to the government enactment of loan repayment moratorium. This corresponds to a spike in the number of issued variable rate loans. Both variable rate house loans, (with issuance of less than 0.4 billion HUF a month) and variable rate personal loans constitute a very small percentage of total retail loans in a given month. Therefore, unlike in the late 2000's when most of the borrowers took out CHF denominated house loans that were exposed to currency and interest rate fluctuations, in the current economic environment borrowers have much lower exposure to variable rate loans overall.

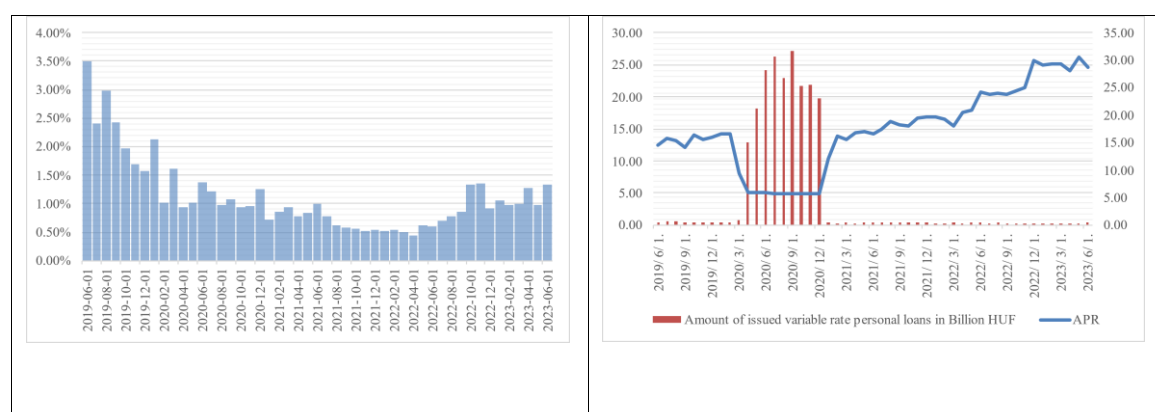


Figure 5. (a) Percentage of Hungarian variable rate mortgage loan from total mortgage loans. Compiled by author. Source: MNB. (b) Value of variable rate consumer loans issued each month (L-HS), interest rate on those loans (R-HS). Compiled by author. Source: MNB

The business sector has the greatest exposure to variable rate loans. On average between 2019 and 2023, banks originated 120 billion HUF in variable rate loans to the non-bank business sector. Figure 6 shows the monthly value of new variable rate loan contracts and the average annual percentage rate. Despite the increase of the variable interest rate by four times in a matter of 1 year, the appetite for business loans didn't decrease as drastically as expected. Therefore, non-financial firms and small businesses are at a greater risk of rate swings (volatility) in the BUBOR. The monthly size of loans originated for the business sector indicates an inverse relationship although with some seasonality present.

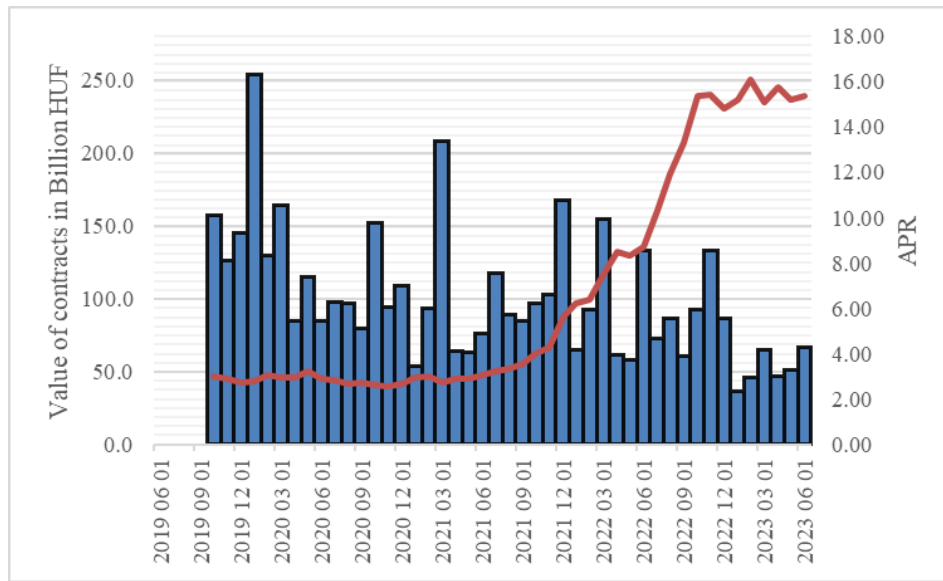


Figure 6. Value of monthly loan contracts originated for non-banking business sector (L-HS) and the interest rate (R-HS). Compiled by author. Source: MNB

In the next section, we consider a Vector Autoregressive (VAR) model proposed first by (Sims, 1980) will be utilized to analyze the spillover effects of a surprise rate hike from the ECB on Hungarian interest rates.

Two-thirds of the Hungarian GDP is consumer spending, which means that a resilient consumer, although, economic textbooks hypothesize of such, in reality, the consumer is rarely resilient, can drive prosperity without producing much, just spending. This is, of course, debt financing, and its perpetuation does not result in technological improvements or higher efficiency in the long run.

3. Literature review and characterization of distinctions between Lütkepohl's and Diebold-Yilmaz's (2009) and (2012) methods

This research gravitates toward a solution to a problem that plagued the research methodologies of economists for more than 3 decades. Bernanke (1986), Blanchard and Watson (1986), Sims (1986) all found an elegant SVAR solution to the problem of the variable ordering as a result of the Cholesky decomposition. As it will be discussed in the Methodological section, as a solution to identifying contemporaneous correlations of the innovations in a VAR model, Σ is decomposed into a lower triangular Cholesky matrix with nonnegative diagonal coefficients.

Liquidity shocks happen due to a sharp loss of confidence in the operability of credit facilities. Market panics, speculation, political instability (for example the 2023 debt ceiling debate) hinders the confidence of market participants of the soundness of financial institutions. The provision of liquidity in times of stress is one of the main tasks of the central bank. However, using the central banks discount window as a way to obtain liquidity remains a last resort for any depository institution, as this means that all attempts to find a market solution to the problem have been exhausted. Market participants (like pension funds and asset managers) might want to obtain liquidity, like short term loans, or invest their excess cash. To do this, they make use of SIVs (special investment vehicles), commercial paper, money market funds, reverse repo facilities. Money market funds often invest in short term government debt. Because the annual GDP of some countries often dwells compared to the size of money market funds, in this study we will also consider their impact on the Hungarian interbank lending market. To measure market stress overseas traders often look at the VIX (it measures the 1-month implied variance of the S&P 500 index) and the Move index (it measures the implied variance of treasuries). Domestic investors view the RMAX and CMAX as a measure of sovereign bond rate volatility and BUX for equity volatility.

In case of severe market stress, to raise cash, market participants often rely on short-term borrowing facilities that operate through SIVs (special investment vehicles). Other liquidity sources can be the central banks discount window or special liquidity injection programs, like the BTFP³ (Bank Term funding program). As of writing this paper, liquidity

³ In need of raising cash distressed banks use the BTFP facility and swap hold-to-maturity securities that have dropped in value with cash from the FED. BTFP participants send the eligible securities (United States Treasuries, Agency Mortgage-Backed Securities, Agency Securities, Merchant Marine Bonds) via

in the markets is abundant, although the investors' risk appetite dwindled as a result of fears of an imminent recession across the US and Europe.

While a significant portion literature on liquidity focuses on stocks, bonds, commodities, we limit the scope of this study to the spillover effects between reference rates in Europe and Hungary.

The two primary sources of literature we use to devise the methodology in the subsequent chapter is Lütkepohl's seminal (2007) work on VARs, Watsons (1994) work and Diebold Yilmaz's (2009) and (2012) works.

We start with some notations: A' - transpose matrix, A^{-1} - inverse matrix, $tr(A)$ - trace matrix, $rk(A)$ - rank of a matrix. Lütkepohl breaks down the Vector Autoregression analysis into the below concepts:

1. Differencing. To obtain stationarity, or to remove the unit root, the time series can be differenced at most once: $I(1)$, $I(0)$
2. The Unrestricted VAR. We have a set of K time series variables. The basic VAR model without deterministic components is:

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + u_t = AY_{t-1}^{t-p} + u_t$$

$A = [A_1 : \dots : A_p]$ - these are $K * K$ coefficient matrices, $Y_{t-1}^{t-p} = (y'_{t-1}, \dots, y'_{t-p})'$ and $u_t = (u_{1t}, \dots, u_{Kt})'$ is an unobservable zero mean white noise process with a time invariant positive covariance matrix.

Using the lag operator, the stochastic process can be represented as $A(L)y_t = u_t$, where $A(L) = I_K - A_1 L - \dots - A_p L^p$ is a matrix polynomial in the lag operator of order p . In terms of the lag operator: $(1 - A_1 L - A_2 L^2 - \dots - A_p L^p) y_t = u_t$. Using the moving average representation $y_t = \sum_{i=0}^{\infty} A^i L^i u_t$

3. The stability principle. The VAR process is stable if the eigenvalues of the A_1 companion matrix $Z_t = A_0 + A_1 Z_{t-1} + \phi_t$ (this is a VAR(1) representation of a VAR(p)), an alternative method to test for non-explosivity is to compute the roots of the $A(L)$ determinantal polynomial - if they are outside the complex unit circle expressed as

FedWire, which custodies the collateral . The BTFP participant pays the ongoing overnight interest rate plus a 0.10% spread – and the participant receives the loan at par value (usually a “haircut” is applied, where the value of the collateral is smaller than the pledged cash). The banks don't need to sell their distressed assets.

$\det(I_K - A_1 z - \dots - A_p z^p) \neq 0$ for $|z| \leq 1$, the process is stable. if there are variables on the unit circle, then some variables are $I(1)$ and cointegrated. The stability of the model implies that the stochastic process has time invariant means, variance and covariance structure. The Vector error correction model is used to verify the stability of the model. Here $\delta y_t = \Pi y_{t-1} + \Gamma_1 \delta y_{t-1} + \dots + \Gamma_{p-1} \delta y_{t-p+1} + u_t = \Pi y_{t-1} + \Gamma \Delta Y_{t-1}^{t-p+1} + u_t$.

$\Pi = -(I_K - A_1 - \dots - A_p)$, $\Gamma_i = -(A_i + 1 + \dots + A_p)$ ($i = 1, \dots, p-1$), $\Gamma = [\Gamma_1 : \dots : \Gamma_{p-1}]$, $\Delta Y_{t-1}^{t-p+1} = Y_{t-1}^{t-p+1} - Y_{t-2}^{t-p+1}$. Because ΔY doesn't contain a stochastic trend, we assume all variables are at most $I(1)$

4. Restrictions. We add an intercept, a linear trend term and seasonal dummy variables to properly represent data. This is the “levels form” of the VAR process representation.

$y_t = \mu_t + x_t$, μ is a deterministic term (for example it can be a linear trend term $\mu_t = \mu_0 + \mu_{1t}$) and x_t is a stochastic process ($x_t = A_1 x_{t-1} + \dots + A_p x_{t-p} + u_t$) which can be represented as a $VAR(p)$ or a VECM. Deterministic terms are omitted from papers, since the area of interest is usually the stochastic process.

5. The non-orthogonal nature of errors. For Impulse response analysis Lütkepohl uses the levels MA representation of VAR without deterministic terms. $y_t = \sum_{j=0}^{\infty} \phi_j u_{t-j}$. Here $\phi_0 = I_K$ and ϕ_j 's ($j = 1, 2, \dots$) are $K * K$ coefficient matrices. The elements of ϕ_j represent responses to u_t forecast errors. For Stationary processes $\phi_j \rightarrow 0$ as $j \rightarrow \infty$, therefore the impulse is transitory. Because Σ_u can be represented as a product of two nonsingular matrices satisfying the property $PP' = \Sigma_u$, we can rewrite $y_t = \sum_{j=0}^{\infty} \phi_j u_{t-j}$ as $y_t = \sum_{j=0}^{\infty} \phi_j PP^{-1} u_{t-j}$.

To deal with non-orthogonality, Lütkepohl mentions Giannini's (1992) AB-model, Amisano and Gianninni (1997) model used in (Bernanke, 1986). The most important way DY differ from this, is that they use the Generalized impulse response function devised by (Koop et al., 1996) and (Pesaran & Shin 1998).

The original VAR model used in DY's (2009) work utilizes the Cholesky factor of the covariance matrix of e_t . Using their notation $x_t = \theta(L)e_t$; $A(L) = \theta(L)Q_t^{-1}$; $\theta(L) = (I - \phi L)^{-1}$; $u_t = Q_i e_t$, where Q^{-1} is the unique lower triangular cholesky factor of covariance matrix of e_t . Calculating variance decompositions requires orthogonal errors,

however, in VAR models the errors are contemporaneously correlated. The Cholesky transformation circumvents this, however it introduces another problem. The ordering of the variables, that is allowing the shock from one variable to spread on the other but not vica versa, is based on economic theory. Reliance on such theoretical framework has disadvantages when it comes to relationship between variables with no proven causal relationship. That's why the impulse response function is useful for SVAR models, but to allow for correlation of errors, we utilize the generalized impulse response function and the generalized forecast error variance decomposition in our VAR.

To measure the impact of shocks of one time series on another, DY further introduce the Variance decomposition associated with an N-variable generalized VAR. Consider $y_t = \Phi_t X_{t-1} + e_t$, where e_t has a distribution with a vector mean μ and covariance matrix Σ . The assumption is that the error terms are iid (independent identically distributed) - meaning their μ is 0 and covariance matrix is positive. The variance decomposition allows us to assess the proportion of the T-step ahead error variance in forecasting y_1 that is due to shocks to y_2 . DY's proposition is related to the works of Koop, Pesaran and Potter (1996) and Pesaran and SHin (1998) which allows correlated shocks.

According to DY, a spillover is a cross variance share, which is the level of the fraction of the T-step-ahead error variance in forecasting y_i that are due to shocks to y_j , for $i, j = 1, 2, N$ such that $i \neq j$. They implement the KPPS T-step-ahead forecast error variance decomposition. DY further operate with a MA representation of the VAR model, unlike in Lütkepohl's mainstream work, where the Vector Error Correction Model (VECM) is applied.

4. Methodology

We employ a restricted VAR model, as it is popular in literature and its representation in a moving average form allows us to compute the non-directional spillover effects. Some of the literature including Lütkepohl and DY hastily skip the intricacies of the Lag representation of the y_t VAR (p) polynomial, but we will start with the basics. The VAR model is an n-equation, n-variable linear model in which each variable is explained by its own lagged values plus current and past values. Following Lütkepohl, we consider the time series are of integrated order $I(1)$, meaning to obtain stationarity, it is sufficient to difference the times series once.

Given a $K = (n \times 1)$ vector of time series variables $y_t = (y_{1t}, \dots, y_{Kt})'$, consider a simple restricted VAR process without a deterministic trend, which has the form

$$y_t = \Phi_1 y_{t-1} + \dots + \Phi_p y_{t-p} + \varepsilon_t = \sum_{i=1}^p \Phi_i y_{t-i} + \varepsilon_t \quad (1.1)$$

where $\Phi_i = (K \times K)$ coefficient matrix and the error process $\varepsilon_t = (\varepsilon_{1t}, \dots, \varepsilon_{Kt})'$ is a K dimensional zero mean white noise with covariance matrix $E(\varepsilon_t \varepsilon_t') = \Sigma$. In short $\varepsilon_t \sim iid(0, \Sigma)$.

Of course, the general VAR (p) process in 1.1 can also be rewritten using the summation operator.

VAR models assume linearity, stationarity and invertibility of the resulting moving average representation. All VAR variables are assumed to be endogenous and interdependent.

We introduce the lag operator to minimize notational clutter in deriving the moving average representation of the VAR model that will be used later for the variance decomposition.

Based on the definition that $L^0 = 1$ let's apply the recursive property $L^k y_t = y_{t-k}$. We rewrite the first-order difference equation (which a one dimensional VAR(1) essentially is), in terms of a lag operator $y_t = \phi(L)y_t + \varepsilon_t$ and rearranging in terms of the error component we get $\phi(L)y_t = \varepsilon_t$, where $\phi(L) = (I - \phi L)$, and I is an identity matrix (in a single variable VAR(1) model this is just 1). Let's generalize, so it applies to 1.1 as well. Given a p -th order difference equation, which 1.1 obviously is, the lag operator representation is $(I - \phi_1 L - \phi_2 L^2 - \dots - \phi_p L^p)y_t = \varepsilon_t$. Again, we can rewrite this as $\phi(L)y_t = \varepsilon_t$, where $\phi(L) = (I - \phi_1 L - \phi_2 L^2 - \dots - \phi_p L^p)$.

Alternatively, if we consider an inverse of the $\phi(L)$ operator $\phi(L)^{-1}$, that we denote as $\theta(L) = \phi(L)^{-1}$, we can finally rewrite 1.1 as such.

$$y_t = \theta(L)\varepsilon_t \quad (1.2)$$

For clarification, $\theta(L) = (I - \phi_1 L - \phi_2 L^2 - \dots - \phi_p L^p)^{-1} = (I - \theta_1 L - \theta_2 L^2 - \dots - \theta_p L^p)$

What happens when the time series are not stationary, (I.e they contain a unit root⁴) and a two sigma shock is applied to it? Most literature commonly refers to such an occurrence as an explosive time series, meaning that the effect of the shocks does not die out. However, the non-trivial explanation to the explosivity is that the mean and variance of the variables changes. Determining if the effect of the shocks dissipates over time involves a companion form matrix Φ , that allows us to reduce the dimensionality of a VAR(p) model into a VAR(1) model.

It is often useful to represent a higher order VAR model as a VAR(1) model by stacking $y_t, y_{t-1}, \dots, y_{t-p+1}$ on a larger vector:

$$\begin{bmatrix} y_t \\ y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p+1} \end{bmatrix} = \begin{bmatrix} \Phi_1 & \Phi_2 & \dots & \Phi_{p-1} & \Phi_p \\ I_q & 0 & \dots & 0 & 0 \\ 0 & I_q & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & I_q & 0 \end{bmatrix} \begin{bmatrix} y_{t-1} \\ y_{t-2} \\ y_{t-3} \\ \vdots \\ y_{t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad (2.1)$$

Let's set $Y_t = [y_t, \dots, y_{t-p}]'$, $\xi_t = [\varepsilon_t, \dots, 0]'$ the dimensions of which are $Kp \times 1$, and the companion matrix $\Phi = [\Phi_1, \dots, \Phi_p]'$ of dimensions $Kp \times Kp$, to obtain

$$Y_t = \Phi Y_{t-1} + \xi_t \quad (2.2)$$

For the model to be stable the eigenvalues λ of the companion matrix Φ must be less than one in absolute value $|\lambda_i| \leq 1$ for $i = 1, \dots, p$. The eigenvalues are the solutions of $\det|\Phi - \lambda I_K| = 0$.

Lütkepohl and DY define the stability of a higher order VAR(p) process by using the characteristic roots of

$$\det(I_K - \Phi_1 z - \Phi_2 z^2 - \dots - \Phi_p z^p) \neq 0 \text{ for } |z| \leq 1 \quad (3.1)$$

If the roots of the determinantal polynomial are outside the complex unit circle, then the model is covariance stationary.

Given the state space representation, the original VAR(p) is contained in the first block of K rows of Φ , so the stability condition in 3.1 can be rewritten as

$$\det(I_{Kp} - \Phi z) \neq 0 \text{ for } |z| \leq 1 \quad (3.2)$$

⁴ The process is invertible, following the Wold decomposition theorem, it can be rewritten as an MA infinite process. Conversely an MA(q) process would be represented as an AR infinite process.

If the determinantal polynomial has a unit root for $z = 1$, then some of the variables are $I(1)$, and may be cointegrated.

Obviously, the condition on the eigenvalues is equivalent to the characteristic roots condition.

Let's return to (2.2). Notice, that following the Wold decomposition theorem a covariance stationary $VAR(p)$ can be represented as $MA(\infty)$ by either the backshift operator in (1.2) or by recursive substitution, such as

$$\begin{aligned} Y_t &= \Phi Y_{t-1} + \xi_t \\ &= \Phi(\Phi Y_{t-2} + \xi_{t-1}) + \xi_t \\ &= \Phi^2(\Phi Y_{t-3} + \xi_{t-2}) + \Phi \xi_{t-1} + \xi_t \\ &\quad \vdots \\ &= \Phi^{j+1} Y_{t-(j+1)} + \Phi^j \xi_{t-j} + \cdots + \Phi \xi_{t-1} + \xi_t \end{aligned}$$

As $j \rightarrow \infty$, and as long as $|\Phi| < 1$,⁵ $\Phi^{j+1} Y_{t-(j+1)}$ reduces to 0, so it can be ignored, and the above can be written succinctly as

$$Y_t = \sum_{i=0}^{\infty} \Phi_i \xi_{t-i} \quad (4.1)$$

Of course, the representation in (4.1) holds if the eigenvalues of Φ_i have a modulus of less than 1.

In this representation Y_t is expressed in terms of past and present error or innovation vectors ξ_t . This representation is more useful in determining the autocovariances of Y_t . $\Phi_0 = I_K$, and Φ_i is obtained by making use of the relationship defined in (1.2),

$$I_K = (\phi_0 + \phi_1 L + \cdots + \phi_p L^p)(I_K - \theta_1 L - \cdots - \theta_p L^p) \quad (5.1)$$

Where $\theta(L) = \frac{\phi(L)^{adj}}{\det(\phi(L))}$

Expanding the brackets in (5.1) we obtain

$$I_K = \phi_0$$

$$0 = \phi_1 - \phi_0 \theta_1$$

⁵ If $|\Phi| > 1$, as $j \rightarrow \infty$, so does $\Phi^j \rightarrow \infty$, therefore it is not infinitely summable.

$$0 = \phi_2 - \phi_1\theta_1 - \phi_1\theta_2$$

$$0 = \phi_i - \sum_{j=1}^i \phi_{i-j}\theta_j$$

Hence, ϕ_i are obtained recursively by

$$\phi_i = \sum_{j=1}^i \phi_{i-j}\theta_j \quad (5.2)$$

The autocovariances of the VAR system can be estimated with the Yule-Walker equations. The reader can refer to the following literature: Lütkepohl (1997), Kunst (2009), Sims (1980).

Testing the variables for Granger causality is important, because if one time series does not Granger-cause another time series, the impulse response, which will be detailed further down is expected to be 0.

To isolate the effect of an innovation in a reference rate (let's say the 3 month EURIBOR) in a $p = 1$ system containing the European reference rate (y_1) and the Hungarian reference rate (y_2), we assume that for $t < 0$, $y_t = \mu = 0$ and at time $t = 0$, a unit shock (as it will be demonstrated later, an innovation of one standard deviation is used instead for scaling purposes) is applied to (y_1), that is $\varepsilon_{1,0} = 1$. If we further assume that no further shocks occur, that is $\varepsilon_{2,0} = 0$, $\varepsilon_2 = 0$, $\varepsilon_3 = 0$, $\varepsilon_i = 0$, we find that at $t = 0$ in a system like (1.1), $y_0 = (y_{1,0}, y_{2,0})' = (\varepsilon_{1,0}, \varepsilon_{2,0})' = (1, 0)$, at $t = 1$, $y_1 = (y_{1,1}, y_{2,1})' = \Phi_1 y_0$, at $t = 2$, $y_1 = (y_{1,2}, y_{2,2})' = \Phi_1 y_1 = \Phi_1^2 y_0$, and at $t = i$, $y_i = (y_{1,i}, y_{2,i})' = \Phi_1^i y_0$. Φ_1^i show the effects of unit shocks in the variables of a system after i periods.

Let's generalize the above thought chain. Consider the VAR(1) representation of a VAR (p) process (2.2) in a K variable system⁶. Under the assumptions in the previous example, that is at $t < 0$, $y_t = \mu = 0$, for $t > 0$, $y_0 = \varepsilon_0$, it follows that $Y_t = \Phi^t Y_0$. Let's turn to a two-dimensional VAR(1) form of (1.1). In a $MA(\infty)$ representation, the j k-th element of the system that is, $\theta_i = J \Phi^i J'$, where $J = [I_K : 0 : \dots : 0]$ is a $(K \times Kp)$ matrix.

⁶ If we assume stationarity and invertibility, any VAR (p) can be represented as a VAR(1) given by (2.2)

In other words, $\theta_{jk,i}$, the jk -th element of θ_i is the reaction of the j -th variable of the system to a unit shock in variable k , i periods ago.

Measuring the accumulated effect of a shock in one variable over time involves summing up the MA coefficient matrices. $\psi_\infty := \sum_{i=0}^{\infty} \phi_i$. Having derived the $MA(\infty)$ representation of our $VAR(p)$, we can confront the next problem. The error terms are correlated, because an innovation to variable i is correlated with the innovation to variable j . The Choleski decomposition orthogonalizes the shocks.

Any positive definite matrix Σ_ε can be rewritten as a product of $\Sigma_\varepsilon = PP'$, where P is a lower triangular nonsingular Cholesky matrix.

In any VAR model, ϕ_i , θ_j and Σ are unknown parameters that are estimated using an Optimal least squares regression.

The non-orthogonalized impulse response is the partial derivative with respect to the error term of the VAR model. Using the companion form, we can represent $VAR(p)$ as a $VAR(1)$ like in 2.2.

$$\frac{\partial y_{t+h}}{\partial \xi_{j,t}} = \frac{\partial}{\partial \xi_{j,t}} \Phi Y_{t+h-1} + \xi_{t+h-1}$$

The problem of contemporaneous correlation among innovations has been solved by performing the Cholesky decomposition and then ordering the variables (placing the variables in decreasing order of exogeneity) according to economic theory. Pearsan and Shin (1998) propose the following solution to bypass the problem of ordering dependence of the impulse response function.

$$\psi_j^0(n) = \Phi_n P e_j$$

Where Φ_n is the n th coefficient matrix from the $MA(q)$ representation of (1), P is the lower-triangular Cholesky matrix $n = 0, 1, 2 \dots N$,

$$y_t = \sum_{s=0}^{\infty} \Psi_s P P^{-1} \epsilon_{t-s} \quad (5.3)$$

In 5.3, the Cholesky decomposition is used to orthogonalize the shocks. If the covariance matrix of the individual e 's is Ω , then we can decompose it as $\Omega = PP'$, and $u_t = P^{-1}e_t$.

The response to an orthogonalized shock is given by”

$$y_t = \sum_{s=0}^{\infty} \Psi_s PP^{-1} \epsilon_{t-s} \quad (5.3)$$

The generalized impulse response function averages out future shocks by using the expectation operator conditioned on history and the shock.

We follow Koop, Pesaran and Potter's (1996) and Pesaran and Shin (1998) generalized VAR framework to come to the generalized forecast error variance decomposition equation. We use the notation as in DY (2012) to streamline the interpretation of the spillover table:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \phi_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' \phi_h \Sigma \phi_h' e_j)^2} \quad (6.1)$$

In 6.1, the own variance share, is the fraction of the H-step-ahead error in forecasting y_i , for $i = 0, 1, 2, \dots, N$. As defined by the forecast error variance decomposition (DY. 2012, p.2). Here Σ is the variance matrix for the vector of innovations e , σ_{jj} is the standard deviation of e for the j -th equation and e_i is the selection vector. To make the sum of the elements in each row equal 1, $\theta_{ij}^g(H)$ has to be normalized as such:

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)} \quad (6.2)$$

The generalized total spillover index is of form

$$S^g(H) = \frac{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)}{N} \cdot 100 \quad (6.3)$$

The directional spillover received by variable i from all other variables j is expressed as

$$S_{i\cdot}^g(H) = \frac{\sum_{j=1}^N \tilde{\theta}_{ij}^g(H)}{N} \cdot 100 \quad (6.4)$$

The directional spillovers that come from variable i to all other markets j is

$$S_{\cdot i}^g(H) = \frac{\sum_{j=1}^N \tilde{\theta}_{ji}^g(H)}{N} \cdot 100 \quad (6.5)$$

The net pairwise spillovers are expressed as

$$S_{ij}^g(H) = \frac{\tilde{\theta}_{ji}^g(H) - \tilde{\theta}_{ij}^g(H)}{N} \cdot 100 \quad (6.6)$$

To put it in other words, (6.3) measures the total spillover index. Equations (6.4) and (6.5) measure the directional spillovers from other variables and to other variables. And (6.6) shows how much each variable contributes to the volatility in other variables.

5. Data, descriptive statistics and commentary

We retrieved the daily interbank offering rates (BUBOR and EURIBOR) from the official data warehouses of the MNB (Hungarian central bank) and the European central bank. In order not to lose any pieces of information hidden in the time series, we opted not to do any data wrangling, except to ensure that the data are stationary by differencing, that is $t_1 - t_2$. Figures 7-11 illustrate the time series together with the stationary counterparts.

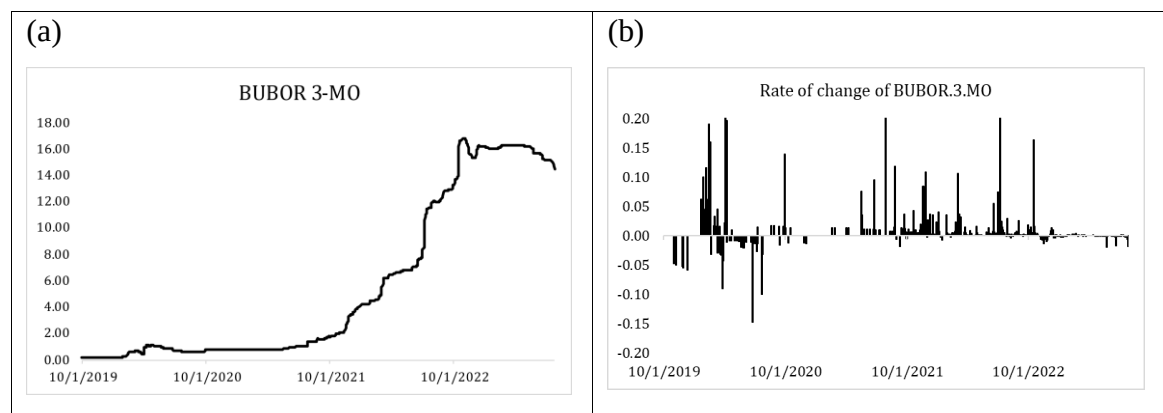


Figure 7. (a) 3-month BUBOR time series. Compiled by author. Source: BÉT. (b) I(1) difference of 3-month BUBOR time series (value at t – value at t_{-1}) Compiled by author. Source: BÉT.

The MNB's interest hiking cycle had reached its peak sometime in 2023. Issues arising from significant interest payment costs, rising trade and budget deficits, as well as a significant reduction in real wages forced the MNB to start lowering rates. Although, quite obviously, it is unlikely, that the Hungarian economy will return to a near-zero interest rate environment any time soon. Additionally, raising debt (which the government needs to cover expenditures) at rates near 20 year highs could create greater deficits, which could further destabilize the economy. Therefore, high rates, in this context are a double edged sword: they tame inflation, but cause budget imbalances.

Another interesting observation is that when we consider the 3-month Bubor rate, it is noticeably in line with the 3-month Euribor rate. That is, the difference between the BUBOR and the EURIBOR is to the score of less than 100 basis points. However, as of now, the difference between the two rates is substantial. As of writing this paper, the 3-month EURIBOR is at 3.5%, while the 3-month BUBOR is at 14%, exactly 4 times higher. Has the Hungarian central bank raised the rate to a higher level than necessary, given the

low rate in Europe? Or perhaps the European central bank's approach for determining the policy rate insofar as considering the European economies as homogenous is incorrect? Clearly, the extent where rate hikes in Hungary was so great because something drastic needed to be done to tame a rapidly deteriorating consumer purchasing power due to rising inflation.

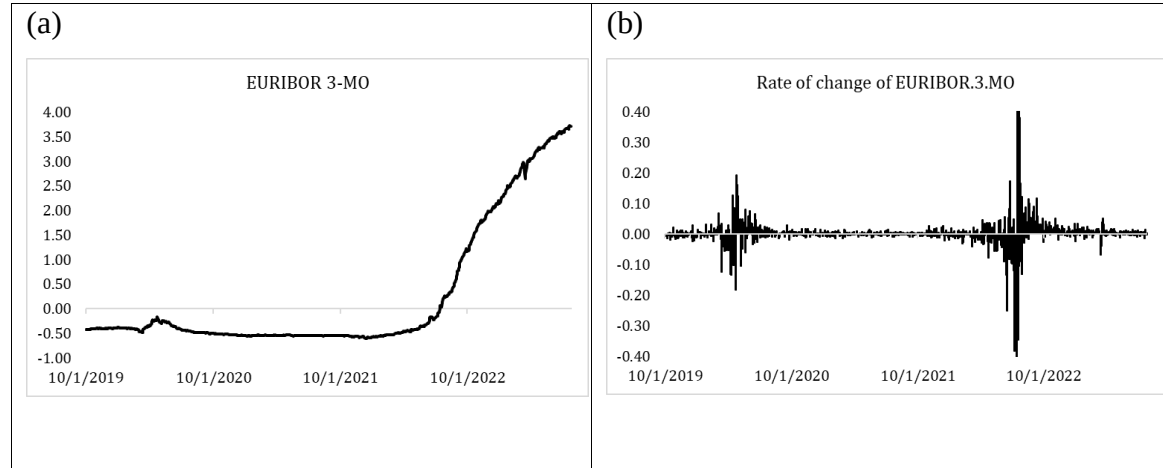


Figure 8. (a) 3-month EURIBOR time series. Compiled by author. Source: ECB. (b) I(1) difference of 3-month EURIBOR time series (value at t – value at t_{-1}) Compiled by author. Source: ECB.

Consider the EUR/HUF exchange rate between the third quarter of 2019 and the middle of 2023. There is clearly an upward trend in this time series, and as evident from Figure 9b. Volatility (number of outliers) increased in the last 18 months, as the crisis intensified, and we can see the point in Figure 9a, at around October of 2022, when the MNB increased the policy rate to 13%, the EUR/HUF exchange rate turned downward in favor of the Hungarian Forint, making it less attractive for exports. The strength of the Hungarian Forint in the last 18 months can therefore directly be attributed to the decision of the MNB to raise and keep the policy rate at 13%.

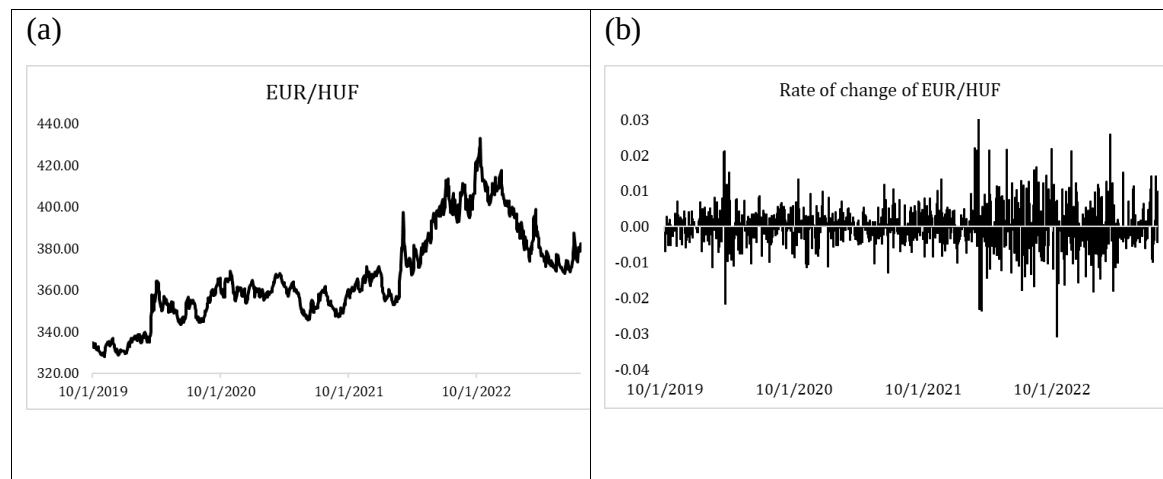


Figure 9. (a) EUR/HUF time series. Compiled by author. Source: MNB. (b) I(1) difference of EUR/HUF time series (value at t – value at t_{-1}) Compiled by author. Source: MNB.

Many short-term OTP money market funds (for example OTP Prémium Pénzpiaci Alap) measure their performance relative to a Hungarian national benchmark, rather than one of the many MSCI (Morgan Stanley Capital international) – computed benchmarks (OTP, 2023). This benchmark is a 50-50 composite of the RMAX and the ZMAX indices published on a daily basis by the Hungarian Government Debt Management Agency (Government, 2023). The ZMAX index measures the performance of those Hungarian treasury notes that have a maturity less than 3 months, according to the definition. The RMAX index measures the performance of government debt instruments with a maturity of up to 6 months. Obviously, both the RMAX and the ZMAX represent the short and the ultra-short ends of the yield curve, which is why they are a subject of interest in this study. Consider Figure 10a, and Figure 10b. The short end of the yield curve is heavily influenced by the decisions of the central bank on the overnight policy rate. That’s why the upswing in the composite index correlates to the increase in the policy rate, albeit with a lag. Because the name of this time series is lengthy, sometimes we will use the words like “MAX” and “government benchmark” instead.

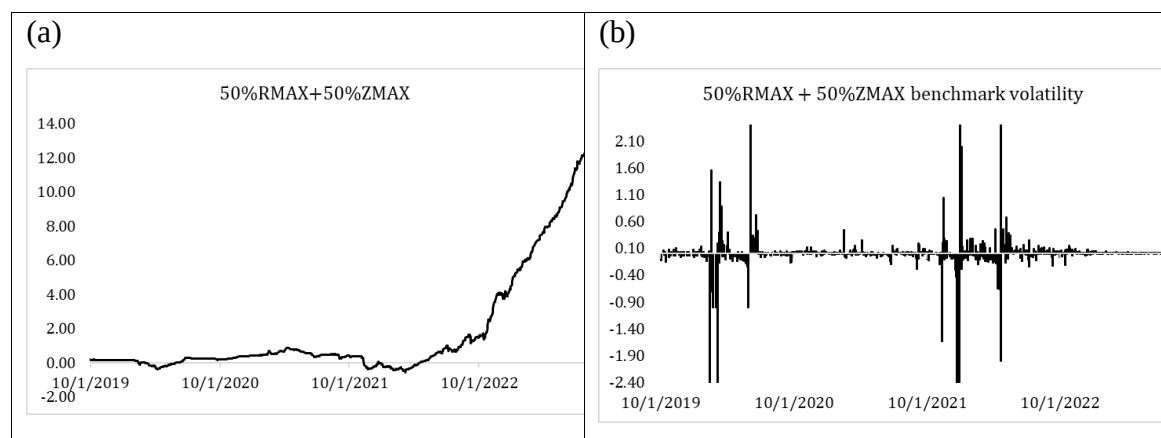


Figure 10. (a) 50%RMAX+50%ZMAX benchmark time series for OTP prémium pénzpiaci alap BBG ISIN code: HU0000712161. Compiled by author. Source: ÁKK. (b) I(1) difference of 50%RMAX+50%ZMAX time series (value at t – value at t_{-1}) Compiled by author. Source: ÁKK

The European-Short-Term-Rate, commonly referred to as ESTER, or ESTR replaced EONIA in 2019, as a benchmark for overnight money market lending in light of the LIBOR manipulation scandal in 2012. The ESTR benchmark is the initial stage in monetary policy transmission mechanism of the ECB, which is why it was included in this study. ESTR is also the benchmark for the BlackRock money market fund.

(a)	(b)
-----	-----

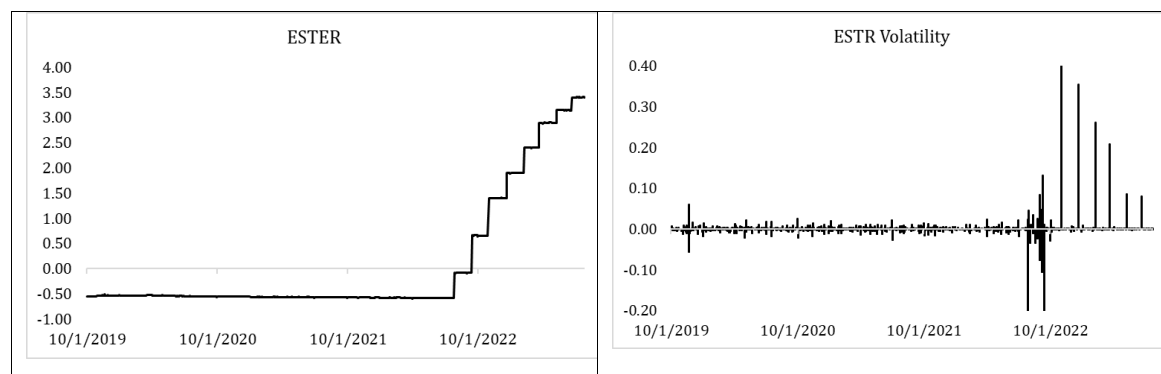


Figure 11. . (a) Euro Short term rate (ESTER) time series. Compiled by author. Source: ECB. (b) I(1) difference of ESTER time series (value at t – value at t_{-1}) Compiled by author. Source: ECB

The time series were carefully selected to represent the dynamics of the short end of the yield curve in Hungary and in the Eurozone. Table 1 summarizes the time series.

Table 1. Descriptive statistics of the panel VAR. Compiled by author. Source: MNB, ECB, ÁKK. Note that the order of the variables in the VAR model is from left to right.

	<i>EUR/HU F</i>	<i>BUBOR 3- MO</i>	<i>EURIBOR 3- MO</i>	<i>50%RMAX+50%ZM AX</i>	<i>ESTE R</i>
Mean	331.08	2.94	-0.02	1.42	0.08
Standard Error	0.60	0.09	0.02	0.08	0.04
Median	316.12	1.20	-0.33	0.34	-0.55
Mode	310.45	1.35	-0.33	0.14	-0.56
Standard Deviation	30.93	4.40	0.95	2.77	1.23
Sample Variance	956.76	19.32	0.91	7.66	1.51
Kurtosis	0.03	3.45	6.23	4.49	1.21
Skewness	1.01	2.14	2.72	2.34	1.67
Range	144.79	16.74	4.33	12.81	4.00
Minimum	288.15	0.02	-0.61	-0.57	-0.59
Maximum	432.94	16.76	3.72	12.24	3.41
Observations	2639	2639	2049	1144	958

Over the sample, the 3-month BUBOR index went through three major periods of market volatility. In late 2019, as a result of the FED's rate hike, there has been a minor increase in BUBOR as well up until the COVID lockdowns forced the global economy into a recession, where rates dropped to zero. A slowing global economic growth also contributed to this rise in volatility. The second biggest shock in the BUBOR appeared in the end of 2021, as inflation in Hungary surpassed 6.5% (Hungary inflation, 2021). The Monetary council of the central bank of Hungary raised the policy rate by 15 basis points, and later in November by another 30 basis points to 2.1%. Following a cluster of rate hikes throughout 2022, the last two big shocks happened in June of 2022 and later in October,

when the Monetary council hiked the policy rate to 13%. Over 2022, the rate has increased by 1240 basis points, from 2.4% to 13%. Such a significant increase resulted in the strengthening Forint, and a decrease in inflation.

In case of the EURIBOR rate, two major volatility periods are identifiable. First, similar to the BUBOR, the European interbank rate increased slightly, following the FED's policy hike in late 2019 as a response to slower economic growth. After came the relative calmness as a result of the ECB slashing interest rates to 0% during the lockdowns. The second volatility cluster emerged when inflation across Europe skyrocketed to 5% in December of 2021 (Annual, 2023), at which point, interest rates were still at 0%. Eight consecutive rate hikes increased volatility, and therefore made a precedent for spillovers, which is what we will see in the subsequent section.

The same two big clusters of volatility, one in late 2019, and the other in late 2021 - early 2022 can be identified in the case of the Euro-Hungarian Forint exchange rate. There is a clear uptrend in the exchange rate, in favor of the appreciation of the Euro between 2019-2022. However, since October 2022, that trend halted, as the interest rates rose, and news on a potential release of funds from the European Union raised investors' hopes, as the influx of Euros would strengthen the economy.

As the policy rate increased, so did the interest rate on newly issued government bonds. A higher interest rate on bonds means a higher interest expense for the government, which is a bigger drag on the budget. Therefore, financing government spending in a hiking cycle is a double-edged sword. On one hand, the government can provide the necessary liquidity to the segments of the economy where it is needed the most, but the high interest rates will need to be paid through imposing austerity measures, like higher taxing. The aforementioned volatility clusters are well identifiable and will be further detailed in the subsequent section.

The data were tested for stationarity by using the Augmented Dickey-Fuller test, the results of which are presented in Table 2.

Table 2. Results for the ADF test of the panel data variables

Diff.	Desc.	EUR.HUF	BUBOR.3.MO	EURIBOR.3.MO	RMAX+ZMAX	ESTER
	ADF	-2.13	-1.62	0.83	2.89	0.39
	Lag Order	9.00	9.00	9.00	9.00	9.00
I(0)	P-value	0.52	0.74	0.99	0.99	0.99

	ADF	-10.79	-6.64	-7.58	2.89	0.39
	Lag Order	9	9	9	9	9
I(1)	P-value	0.01	0.01	0.01	0.01	0.01

6. Results how inefficiencies in the IRF lead to the utilization of the FEVD, and can a simpler model capture volatility spillovers better

We estimate the reaction of our complete VAR model that contains all the variables to a shock visually with the help of an impulse response function, following Lütkepohl (2007), and then we use the forecast error variance decomposition, and the spillover tables proposed in DY (2009), (2012), the mathematics of which were introduced in the methodological section of this study.

Because primarily we are interested in the reaction of the BUBOR 3 month index, the Euro/Hungarian Forint exchange rate and the short term bond benchmark on a surprise rate change in the European bank's interest rate, we proposed the below VAR (4) models:

Model 1:

$$\begin{aligned}
 EUR.HUF = & EUR.HUF.l1 + BUBOR.3.MO.l1 + EURIBOR.3.MO.l1 \\
 & + EUR.HUF.l2 + BUBOR.3.MO.l2 + EURIBOR.3.MO.l2 \\
 & + EUR.HUF.l3 + BUBOR.3.MO.l3 + EURIBOR.3.MO.l3 \\
 & + EUR.HUF.l4 + BUBOR.3.MO.l4 + EURIBOR.3.MO.l4 + const
 \end{aligned}$$

Table 3. Summary of VAR(4) K=3, Model 1. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

	Variable		
Lag	EUR.HUF	BUBOR.3.MO	EURIBOR.3.MO
1	0.03	-0.84	-8.29*
2	-0.04	1.28.	0.16
3	-0.02	-1.65*	-2.94

4	0.04	-0.07.	6.78
---	------	--------	------

Model 2:

BUBOR.3.MO

$$\begin{aligned}
&= EUR.HUF.l1 + BUBOR.3.MO.l1 + EURIBOR.3.MO.l1 \\
&+ EUR.HUF.l2 + BUBOR.3.MO.l2 + EURIBOR.3.MO.l2 \\
&+ EUR.HUF.l3 + BUBOR.3.MO.l3 + EURIBOR.3.MO.l3 \\
&+ EUR.HUF.l4 + BUBOR.3.MO.l4 + EURIBOR.3.MO.l4 + const
\end{aligned}$$

Table 4. Summary of VAR(4) K=3, Model 2. Signif. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Lag	Variable		
	EUR.HUF	BUBOR.3.MO	EURIBOR.3.MO
1	0.00*	0.15***	0.13
2	0.01***	0.08**	0.13
3	0.01***	0.08*	0.19
4	0.00	0.04	0.07

Model 3:

X50.RMAX.50.ZMAX

$$\begin{aligned}
&= EUR.HUF.l1 + BUBOR.3.MO.l1 + X50.RMAX.50.ZMAX.l1 \\
&+ EUR.HUF.l2 + BUBOR.3.MO.l2 + X50.RMAX.50.ZMAX.l2 \\
&+ EUR.HUF.l3 + BUBOR.3.MO.l3 + X50.RMAX.50.ZMAX.l3 \\
&+ EUR.HUF.l4 + BUBOR.3.MO.l4 + X50.RMAX.50.ZMAX.l4 \\
&+ const
\end{aligned}$$

Table 5. Summary of VAR(4) K=3, Model 3. Signif. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Lag	Variable		
	EUR.HUF	BUBOR.3.MO	EURIBOR.3.MO
1	0.00**	-0.02	0.12***
2	0.00	0.03	0.11
3	0.00*	0.01*	0.10
4	0.00*	0.00**	0.09

Model 1 shows the dependency of the Euro/Forint exchange rate on the lagged changes of the 3-month BUBOR, EURIBOR and its own lagged past values. Model 2 shows how the 3-month BUBOR depends on the lagged past values of the Euro-Forint exchange rate, the 3-month EURIBOR and the past values of the 3-month BUBOR. And finally, in model 3 we estimate how the short-term bond benchmark is affected by shocks in the 3-month

BUBOR, the Euro/Forint exchange rate and the lagged values of itself. As a countercheck, we also construct a VAR(4) control model that contains all 5 variables, specified in the appendix, to see if including two extra variables in the system improves the identification of shocks. We shall consider the results of the control model first, and compare with the simpler VAR(3), K=3 variable model. The reduced VAR(4) control model contains 5 endogenous variables with no contemporaneous effects – it was shown in the methodological section how this issue is fixed with the Cholesky decomposition, albeit by introducing a number of other issues.

Consider first the impulse response functions (IRFs) presented in _____. The fact that the shocks die out is consistent with the theory that the roots of the characteristic equation are within the unit circle, that is, the time series is not explosive. The model is stable. While the AIC criterion indicates that the number of lags should be 10 in our VAR model, we opt for a smaller number, as we are aware of the consequences of overfitting, which we try to avoid. We therefore choose a lag number as in DY 2012, which is 4. Before we commence with a further description of the IRFs, let's list the short-run restrictions of the VAR model:

1. The order of variables in case of Model 1- 2 is thus: 1) Euro/Hungarian Forint exchange rate, 2) 3-month BUBOR interest rate, 3) 3-month EURIBOR interest rate.

In case of Model 3: 1) Euro/Hungarian Forint exchange rate, 2) 3-month BUBOR interest rate, 3) Short-term bond benchmark of the MAX family

In case of the control Model: 1) Euro/Hungarian Forint exchange rate, 2) 3-month BUBOR interest rate, 3) 3-month EURIBOR interest rate, 4) Short-term bond benchmark of the MAX family, 5) Euro short term rate.

2. The sequence proposed in 1. Is useful in the IRF functions in terms of revealing why DY in their 2012 work opt for a generalized approach, as the ordering of variables becomes too obscure of a question to tackle even with the help a more complex SVAR or even a TVP-FAVAR model.
3. Because the ordering of the variables becomes an issue so early in the analysis, and to facilitate the explanation of the limitation of the impulse response function, we further illustrate the inefficiencies of the IRF:
 - a. Based on the ordering in 1, we assume that BUBOR can't have any effect on EURIBOR or ESTER.

- b. Because the relation is not contemporaneous, (which, is almost never the case in VAR models) in case of the non-orthogonalized IRF, at period 0, the IRF is 0.

A non-orthogonalized version of the impulse response function fails to catch the contemporaneous correlation between the variables in our VAR(4) model. This is fixed with the Choleski decomposition, detailed in Appendix 2. For the sake of the argument, let's disregard for the time being that the ordering of the variables is an issue. The upper and lower confidence intervals depicted as the red dotted lines show the range in which the IRF varies. As the shock dissipates, and the effects of the shock become less significant. Because we chose a 4-lag VAR model, we naturally can't forecast more than 15-20 periods (trading days, in our case) into the future. The shock dissipates, which proves that the time series is stable and the bounds show the theoretical outbursts of the impulse response line.

For further comparisons and specifications of the orthogonal IRF (presented below) and the generalized IRF (proposed by Koopman and Shin), the reader should consider the works of (Kim, 2013)

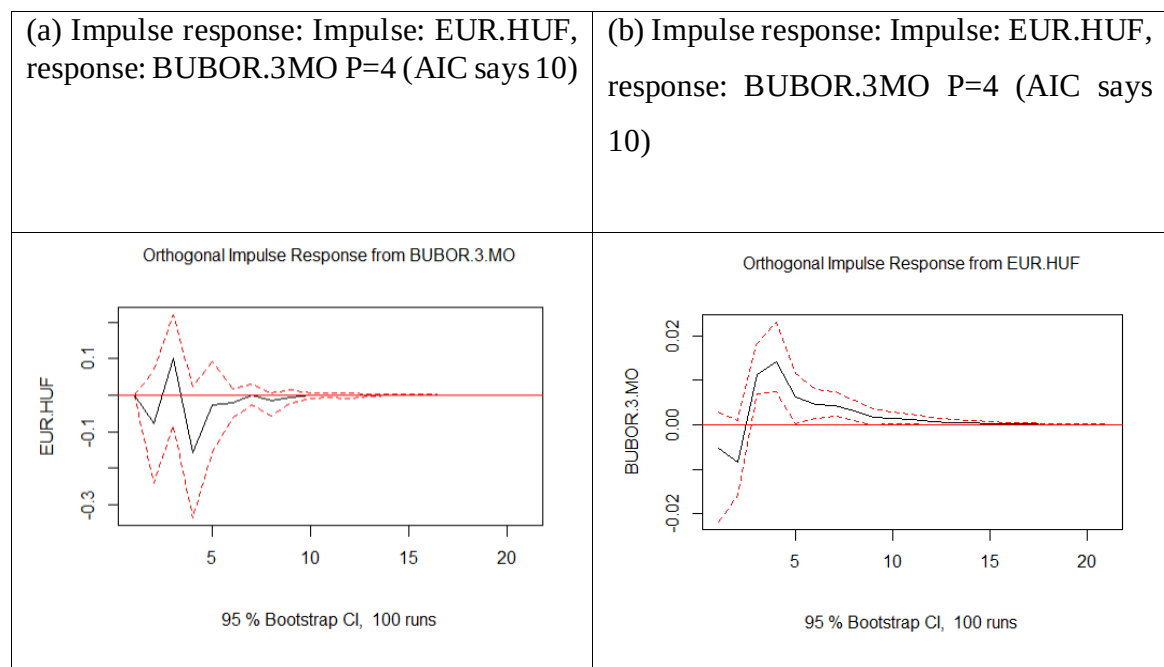


Figure 12 (a) Impulse response function for BUBOR (impulse), and EUR/HUF (response). (b) IRF for EUR (impulse), and BUBOR (response). Y-axis = standard deviations, X-axis, Periods = trading days.

Notice that the (a) graph shows that the Euro/Hungarian Forint exchange rate does not respond to a shock in the 3-month BUBOR, which would be in the case of a surprise rate hike by the MNB. A one- σ positive shock leads to a -0.1σ decrease in the exchange rate. We can't decisively conclude that in (a) there is a positive or negative relationship

between the 3-month BUBOR and the exchange rate. In case of the reverse impulse response, we can conclude that there is a positive relationship, that is, a one-standard deviation shock in the exchange rate results in an up-to 0.02 standard deviation change in the 3-month BUBOR.

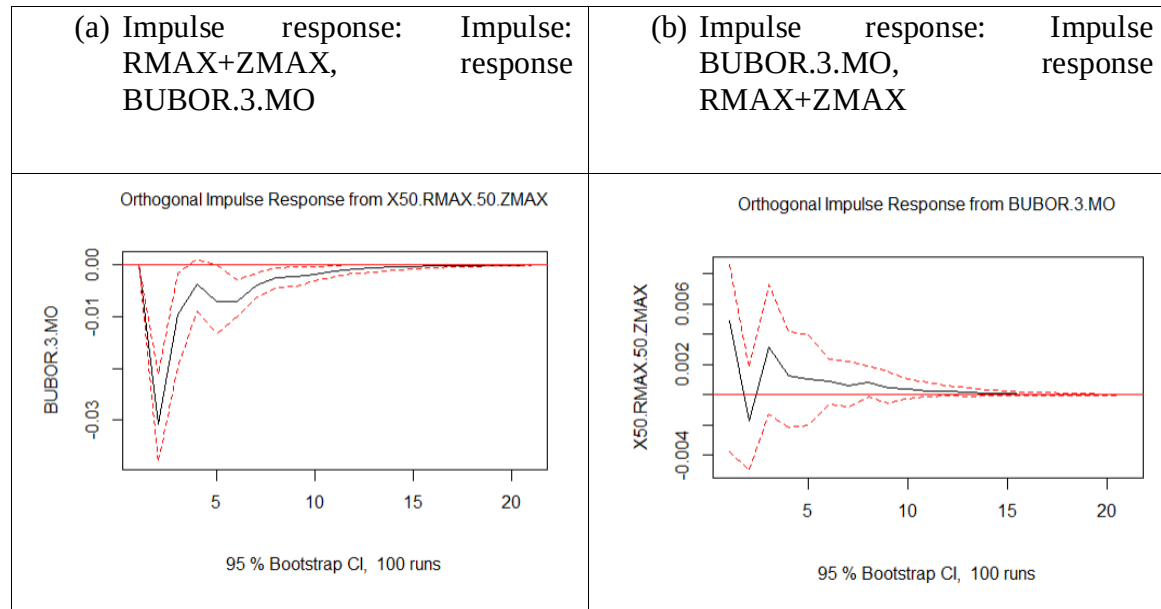


Figure 13 (a) Impulse response function for MAX (impulse), and BUBOR (response). (b) IRF for BUBOR (impulse), and MAX (response). Y-axis = standard deviations, X-axis, Periods = trading days.

Let's see if a shock in the short-term government bond benchmark measured by the RMAX and ZMAX has any effect on the BUBOR. In (a) no contemporaneous correlations are present, and we observe that the relationship is negative. A positive one-standard deviation shock from the MAX benchmark results in a 0.03 standard deviation negative shock in the BUBOR. This is hardly the case even when we consider the monetary policy of the central bank and the treasury government bond emission strategy. While it is true to some extent that low government rates crowd out private lending and high government saving rates crowd out private investing, we understand that the rate of a government bond depends on the interest rate that the central bank of Hungary (MNB) sets through the independent monetary commission. As we understand that BUBOR comes before the MAX variable in the VAR model, we can surely discard the (a) graph as spurious. Since BUBOR comes before the MAX benchmark in our VAR(4) model, the contemporaneous error correlation can only occur if the source of the shock is the BUBOR. Which in practice is exactly the case.

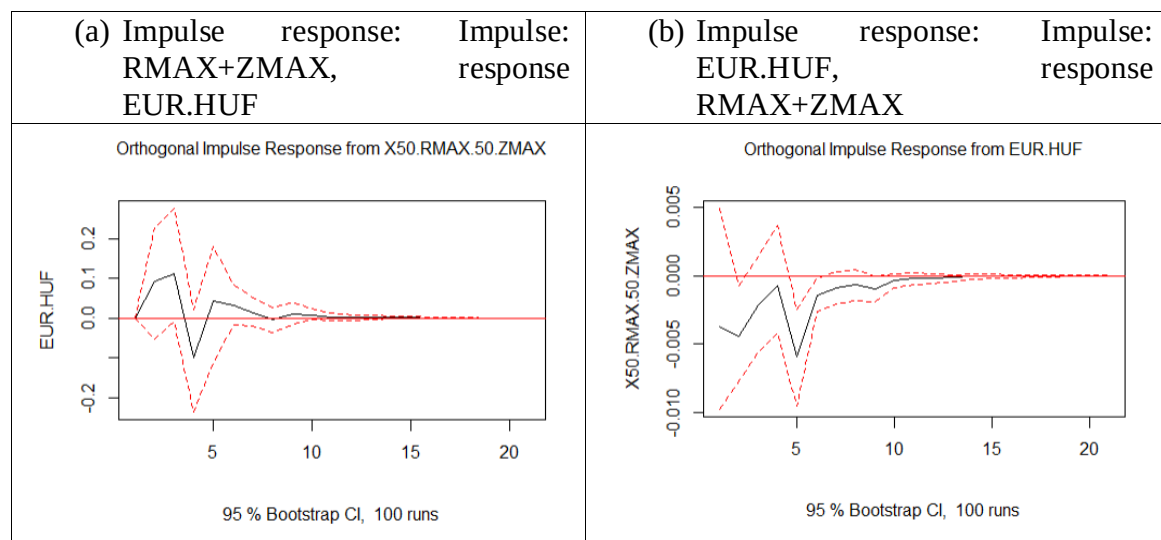


Figure 14 (a) Impulse response function for MAX (impulse), and exchange rate (response). (b) IRF for exchange rate (impulse), and MAX (response). Y-axis = standard deviations, X-axis, Periods = trading days.

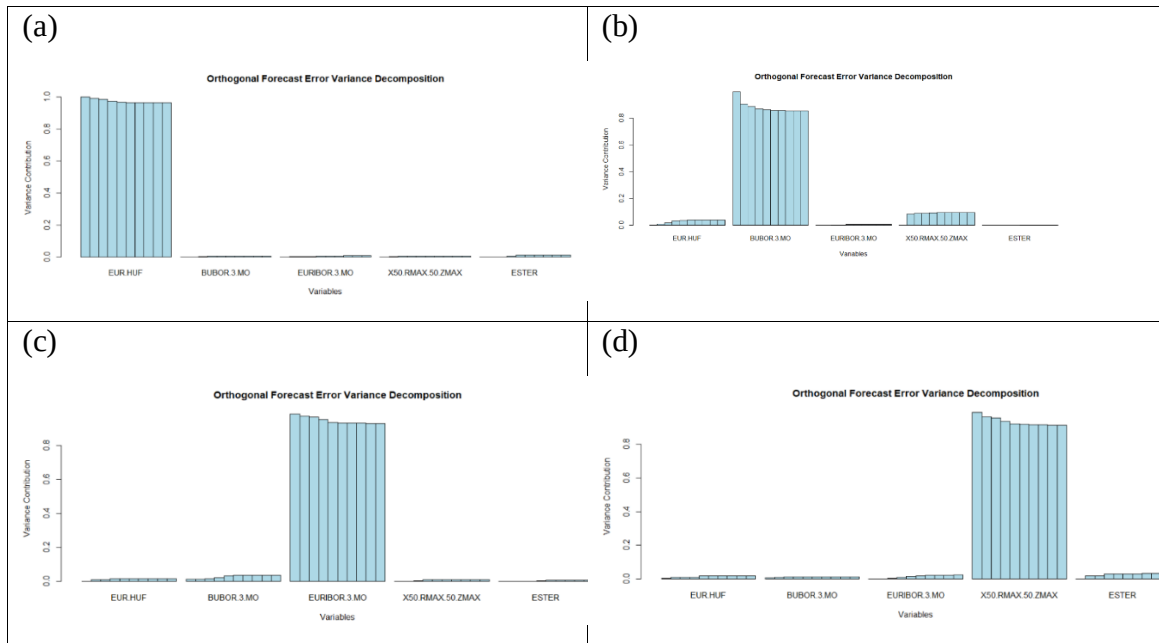
Of course, the rules of the ordering of variables apply in the MAX ~ exchange rate IRFs as well. If we consider the control VAR(4) model with 5 variables, where the MAX is the second to last variable, it is hardly any surprise that the (a) graph shows no contemporaneous correlations in case of the orthogonalized IRF. Graph (b), however, adheres to the ordering rule and shows a negative relationship between a positive one-standard deviation shock from the exchange rate to the MAX benchmark. For now, the following explanation will suffice. As the Euro appreciates and the Hungarian Forint depreciates simultaneously, government borrowing becomes cheaper thanks to the weakening currency, which means that the benchmark rate decreases.

In short, the above cases demonstrate the major flaws inherent to the Cholesky decomposition for VAR models of financial time series.

As mentioned in the Methodological section in more detail, the forecast error variance decomposition (FEVD) function returns the share of the shocks of each variable in the VAR(p) model attributable shocks in the response variables. The below graphs show the orthogonalized FEVDs. Each bar in the subsequent graphs is an h-step ahead decomposition of the contributions of each shock to the variables in order from left to right. It is possible to visualize the FEVD as a total stacked bar plot or an impulse response -like plot, but we opted to use a simpler representation.

Consider the orthogonal forecast error variance decomposition graphs shown in Table 6

Table 6. Orthogonalized FEVD. (a) EUR/HUF, (b)BUBOR, (c) EURIBOR , (d) RMAX+ZMAX



The below tables show the generalized Forecast error variance decomposition.

Table 7. The 10-step ahead Generalized Forecast error variance decomposition for the EUR.HUF exchange rate variable. Compiled by author. Source code attached in appendix.

EUR.HUF					
h-step ahead	EUR.HUF	BUBOR.3.MO	EUR-IBOR.3.MO	RMAX+ZMAX	ESTER
[1,]	0.9898	0.0036	0.0015	0.0052	0.0000
[2,]	0.9820	0.0051	0.0067	0.0062	0.0000
[3,]	0.9761	0.0068	0.0069	0.0092	0.0011
[4,]	0.9760	0.0068	0.0069	0.0092	0.0011
[5,]	0.9759	0.0068	0.0069	0.0092	0.0011
[6,]	0.9759	0.0068	0.0069	0.0092	0.0011
[7,]	0.9759	0.0068	0.0069	0.0092	0.0011
[8,]	0.9759	0.0068	0.0069	0.0092	0.0011
[9,]	0.9759	0.0068	0.0069	0.0092	0.0011
[10,]	0.9759	0.0068	0.0069	0.0092	0.0011

Notice how the row sums of the tables must add up to 1. That is how we are able to verify that the table is correct. We only decided to focus on the variables which are of interest to us, that is the forecast error variance decompositions of the BUBOR, the EUR.HUF exchange rate and the MAX benchmark.

Table 8. The 10-step ahead Generalized Forecast error variance decomposition for the 3-month BUBOR variable. Compiled by author. Source code attached in appendix.

Bubor.3.mo					
h-step ahead	EUR.HUF	BUBOR.3.MO	EURIBOR.3.MO	RMAX+ZMAX	ESTER
[1,]	0.0035	0.9708	0.0183	0.0070	0.0004
[2,]	0.0089	0.8940	0.0203	0.0756	0.0013

[3,]	0.0184	0.8743	0.0226	0.0834	0.0012
[4,]	0.0189	0.8679	0.0226	0.0893	0.0013
[5,]	0.0193	0.8668	0.0227	0.0899	0.0013
[6,]	0.0193	0.8663	0.0227	0.0904	0.0013
[7,]	0.0193	0.8661	0.0228	0.0905	0.0013
[8,]	0.0193	0.8661	0.0228	0.0905	0.0013
[9,]	0.0193	0.8661	0.0228	0.0905	0.0013
[10,]	0.0193	0.8661	0.0228	0.0905	0.0013

Table 9. The 10-step ahead Generalized Forecast error variance decomposition for the RMAX+ZMAX variable. Compiled by author. Source code attached in appendix.

h-step ahead	RMAX+ZMAX				
	EUR.HUF	BUBOR.3.MO	EURIBOR.3.MO	RMAX+ZMAX	ESTER
[1,]	0.0051	0.0071	0.0001	0.9775	0.0102
[2,]	0.0103	0.0084	0.0010	0.9532	0.0271
[3,]	0.0107	0.0083	0.0089	0.9459	0.0262
[4,]	0.0114	0.0083	0.0120	0.9419	0.0264
[5,]	0.0115	0.0083	0.0125	0.9413	0.0264
[6,]	0.0115	0.0083	0.0127	0.9412	0.0264
[7,]	0.0115	0.0083	0.0127	0.9411	0.0264
[8,]	0.0115	0.0083	0.0127	0.9411	0.0264
[9,]	0.0115	0.0083	0.0127	0.9411	0.0264
[10,]	0.0115	0.0083	0.0127	0.9411	0.0264

Starting from here we provide an analysis of volatility spillovers. The spillover index is decomposed into all of the forecast error variance components for variable i coming from shocks to j , as per the definition of DY (2009, p. 162). We use rolling window estimation, to track the variation of the From, To and Net spillovers.

Let's follow the notation and definition as in DY (2009) to streamline the interpretation of the spillover tables. The ij -th entry in Table 10 is the contribution to the forecast error variance of variable i coming from innovations to j . The off-diagonal column sums are labeled "contribution *to* others". This is the 6th row in the table. The off diagonal row sums are labeled "contribution *from* others". This is the 7th and last column in Table 10. The calculation of the net volatility spillover is as follows: subtract the total for "contribution *from* others" from the total for "contribution *to* others". The total spillover value is 100 per variable. If we have 5 variables, that means that the total volatility spillover should be $5 \times 100 = 500$.

The Generalized spillover table (Like in DY, (2012)) is as follows:

Table 10. Generalized spillover table, Hungarian interbank rate volatility, 10/1/2019-07/01/2023.
Values in percentage.

To	From					
	EUR. HUF	BUB OR	EURI BOR	X50.RMAX.5 0.ZMAX	EST ER	Contribution from others
EUR.HUF	98.33	0.08 88.3	0.63	0.58	0.37	1.67
BUBOR.3.MO	1.23	5	0.04	9.12	1.27	11.65
EURIBOR.3.MO	0.83	0.71	96.32	0.01	2.13	3.68
X50.RMAX.50.ZMAX	1.42	0.07	0.83	93.43	4.25	6.57
ESTER	0.75	0.49	5.65	0.63	92.4 8	7.52
Contribution to others (spillover)	4.23	1.35	7.15	10.34	8.02	6.22
Contribution to others including own	102.5 6	89.7 0	103.4 8	103.77	100. 50	<u>(31.1/500.00):6</u> <u>.218%</u>

Notice that from the “Contribution to others” row in Table 10, we can see that the gross directional volatility spillovers to other markets from each of the four is least significant in case of the BUBOR index. Also, we may also conclude that the gross effect of the shocks of these variables to others does not vary significantly, except perhaps for the MAX benchmark. Furthermore, from the “Contribution from others” column we learn that the gross spillover from other variables to the BUBOR rate is the largest at 11.7%, and on the second place, the ESTER, as the spillovers from other explain 7.52% of the forecast error variance.

To measure the net volatility spillover, we can follow the formula: (element in Contribution to others) – (element in Contributions from others). The results are in order of size of net spillover effect:

1. From X50.RMAX.50.MAX to others ($10.34 - 6.57 = 3.77$)
2. From EURIBOR.3.MO to others ($7.15 - 3.68 = 3.47$)
3. From EUR.HUF to others ($4.23 - 1.67 = 2.56$)
4. From ESTER to others: ($8.02 - 7.52 = 0.5$)
5. From BUBOR.3.MO to others ($1.35 - 11.65 = -10.3$)

The total volatility spillover index, or, borrowing the word from (DY, 2012, p.61), “distillation” from all other spillovers can be expressed as the sum of the “contribution to others” divided by $100 \times \text{number of variables}$.

Further below is an orthogonal spillover table (Like in DY2009) VAR (p=2).

Values in percentage.

To	From				ES	Contribution from others
	EUR. HUF	BUBOR .3.MO	EURIBO R.3.MO	X50.RMAX. 50.ZMAX	TE R	
	98.7				0.0	
EUR.HUF	4	0.31	0.49	0.40	7	1.26
					0.0	
BUBOR.3.MO	1.89	88.00	0.39	9.70	2	12.00
					0.1	
EURIBOR.3.MO	1.27	2.23	95.48	0.86	6	4.52
					2.0	
X50.RMAX.50.ZMAX	1.22	0.88	1.30	94.59	1	5.41
					92.	
ESTER	0.17	0.06	5.53	1.37	88	7.12
Contribution to					2.2	
others (spillover)	4.55	3.47	7.70	12.33	6	6.06
Contribution to	103.				95.	
others including own	29	91.47	103.18	106.92	14	500.00

For reference, Table 11 shows the orthogonalized spillover table. At the readers convenience, a comparison can be made between the generalized spillover table and the orthogonalized spillover table, however, upon closer examination, one would find that the total spillover index expressed as either “contribution to others”/100*number of variables. Is 6.062%, while in the case of the generalized on it is 6.218% – a difference of 15 basis points – not significant to further delve into. The above spillover tables only show the “average”, or in other words, past observations of volatilities, based on which conclusions are made. Let’s see the other attributes of the time series. In our example, we used a 300-day rolling sample. This is more than a year of elements of daily trading data. Let’s plot the spillover index against the time period.

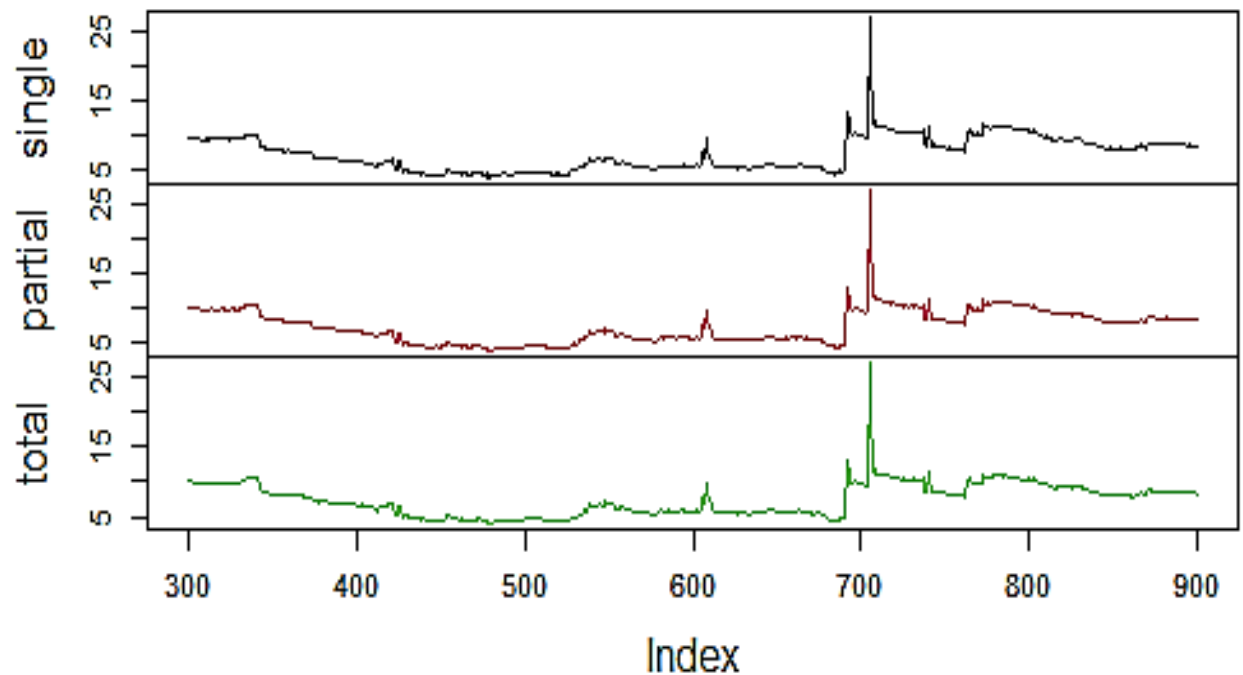


Figure 15. Total volatility spillover plot. K=5, VAR(4) model. Compiled by author. Source code attached in appendix.

From the first window up until the 600th, we can observe a clear downtrend in the index. The total volatility spillover decreases from 15% to less than 5%. Around the 600th mark, we observe a spike in the volatility. This indicates the beginning of the rate hiking cycle of the MNB in late 2021. After a period of relative stability between the 600th and the 700th periods, there is a significant jump of up to 25% and then dropping back to 10%

Unlike in DY (2009), (2012), we can't specifically identify cycles in our case. This could be because of the VAR specifications. At the same time, the time series don't show any cyclical patterns (the reason for this is likely an extremely short time frame 2019-2023, with observations amounting to less than 4 years of trading days).

Nonetheless, let's try to trace the chain of events that happened in global markets from 2019, and see if the volatility spikes correspond to those periods:

1. As a response to slowing global economic growth, the Fed's board of governors cut interest rates three times in 2019, and by November, reducing the rate to 1-1.25% (300-330). The ECB followed the FED's hiking cycle raising the rate to about 75 bps.

2. During the Covid emergency meetings in March of 2020, the board of governors of the FED cut rates to 0-0.25% - a historical minimum that resulted in asset misallocations and asset bubbles during the latter half of 2020. The ECB went on the same trajectory reducing the policy rate to 0.1% and keeping it there until December 2021, way after the MNB started raising rates. (At the same time the monetary commission of the MNB did not cut rates in 2020, as the policy rate was left in the -0.05 - 0.9% corridor). This surprise rate cut of 150bps from the FED in 2020 can be noticed as a bump in the spillover index at about the period that corresponds to March-April of 2020 (period 330)
3. In July-August of 2021 the MNB started raising the policy rate (610)
4. On the 14th of October 2022, the MNB raised interest rates by 950 bps from 15.5% to 25%. Additionally, it started to hold one-day deposit tenders and FX swap tenders. This enhanced liquidity in the market, but created spillovers across BUBOR, the Euro Forint exchange rate and the short-term government bond MAX benchmark. (710)

The rise in the spillover index can also be attributable to the US banking crisis in early 2023, where three major banks failed, scaring off investors. At that point, the BTFP (Bank term funding program) was initiated whereby the FED would purchase on the run treasury bonds at face value with high velocity money. Many considered this a pivot, a breaking point, where central banks around the world would start lowering interest rates and expanding their balance sheets.

The spillover index remains above 10% as of period 900, which corresponds to July of 2023.

The total spillover plot is unquestionably a useful tool in analyzing heightened volatility in the VAR framework. But it fails to address the directional spillover effects. For this, we must, yet again, turn our attention to Table 10. The row sum of the “Contribution to others” $S_{i\cdot}^g(H)$ and the column sum of the “Contribution from others” $S_{\cdot i}^g(H)$, to begin with, are equal, and secondly, they show, most importantly, the directional spillover effect.

Consider the spillover index graphed against periods, not unlike Figure 16 , which shows the directional (to, from and net) spillovers. Figure 17 presents the directional spillover from the 5 variables to others – this corresponds to the $S_{i\cdot}^g(H)$. When stress is absent from the system, the spillover contribution from each of the rates is under 1%.

During market stress, volatility spillover ranges between 3% to 6%. The lowest spillover effect is attributable to ESTER – under 2% throughout the rolling window. The highest spillover effect is attributable to the BUBOR interbank rate.

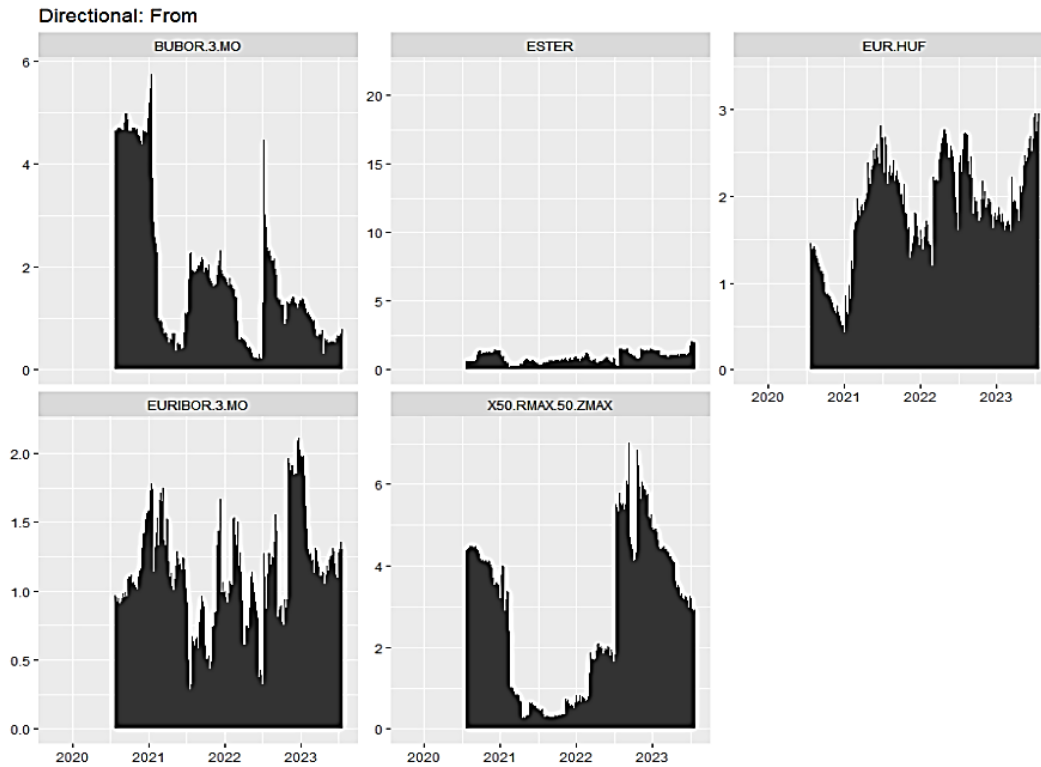


Figure 16. Directional spillover plot, From the K=5 variables in VAR (4). Compiled by author. Source code attached in appendix. Source: MNB, ÁKK, ECB

The $S_{i.}^g(H)$, which is the column sum of the “Contribution *from* others”, has the reverse properties to $S_{i.}^g(H)$, which means that it presents the directional spillovers from other variables to the individual variables in the model. The variation pattern differs only slightly.

Briefly, let’s review Figure 18. The Euro Short-Term rate, again, is the variable on which other variables in the model have the smallest effect. This is unsurprising, given the nature of the time series. If we turn our attention to Figure 11, it is noticeable that there is no cyclicity in the time series. The ESTER time series, while continuous, shows a positive step-by-step increase, like the ECB rate. The volatility in the ESTER is practically absent. The BUBOR rate is the biggest ‘victim’ of volatility spillovers in our model, with the spillover index reaching levels of almost 8%. In other words, the heightened volatility spillover effect in Q3 of 2022, when the surprise MNB 950 bps interest rate hike was

announced, produced an index that reached nearly 8%. On second place, the MAX benchmark index is also a victim of spillovers from other variables.

spillovers from other variables.

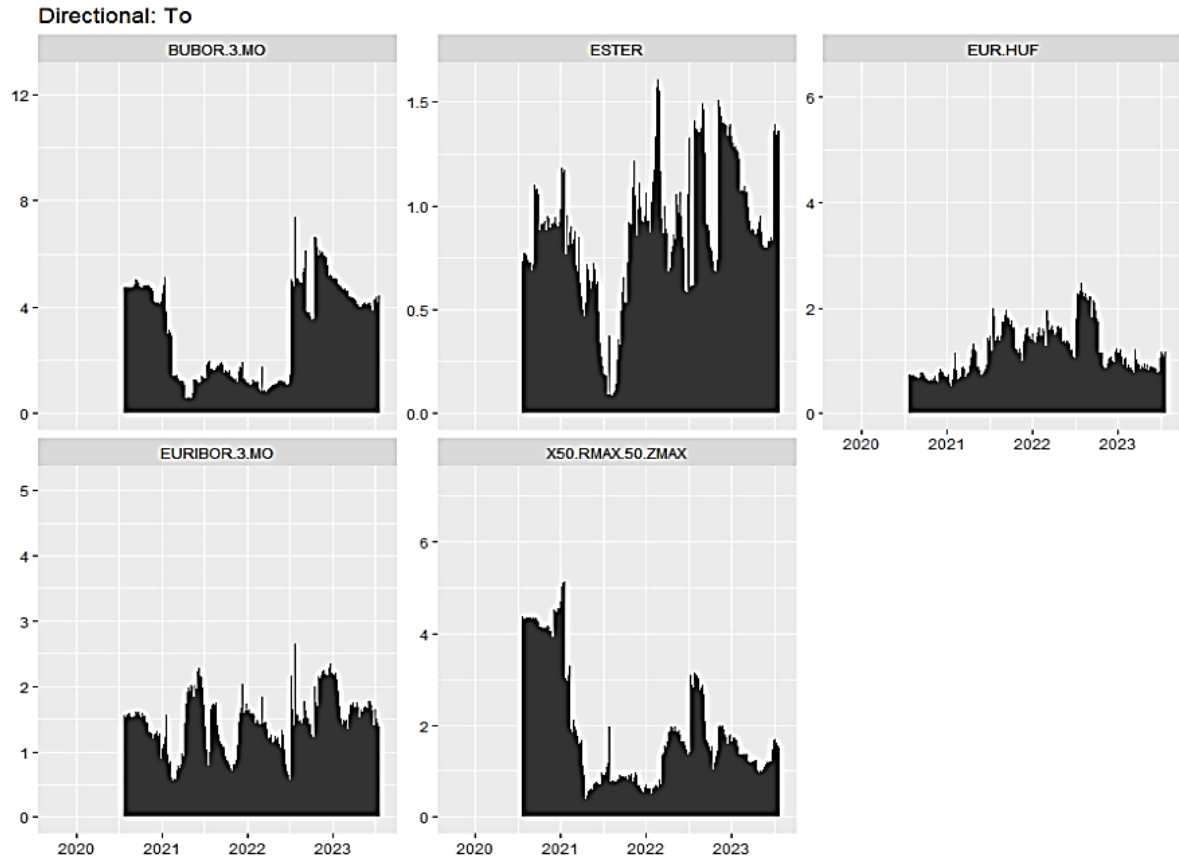


Figure 17. Directional spillover plot, To the K=5 variables in VAR (4). Compiled by author. Source code attached in appendix. Source: MNB, ÁKK, ECB

The net directional spillover is calculated as “contribution to others” – “contribution from others”. It is also plotted as a rolling window of width 300. In Figure 19, we can see that between 2020 and late 2022 the net spillover from/to each of the five variables rarely exceeded 1% in positive and negative directions. Although, if we consider Figures 7-11, we can see some heightened volatility in this period of almost all of the variables. The net spillover effect was low. Sometimes the interbank rate was a net receiver, and sometimes a net transmitter.

The situation is a bit more interesting with the Euro/Forint exchange rate. We can identify 4 cycles, where the exchange rate was a net transmitter of volatility to the other variables. In the periods when it was a net receiver of volatility: in late 2020, and early and late 2022. Consulting Figure 9a, we see three spikes at exactly those intervals. Also, notice

the abnormal 20% spillover index in the ESTER variable. Such a high spillover rate is highly unlikely, so this observation will not be detailed.

When the MNB made a surprise 950 bps interest hike in October of 2022, the net volatility spillover to the BUBOR turned negative, where it became a net receiver of volatility. Prior to that it was cyclical: once it was receiving, then in other times transmitting volatility. Coincidentally, Q3 of 2022 was also the time when the FED and the ECB engaged in a tightening cycle. At this point, it is beneficial to clarify that when the net volatility spillover is negative, that means that the variable is a net receiver of volatility, if the net volatility spillover is positive, it is a net transmitter of volatility.

From late 2022, the BUBOR is a net receiver of spillovers from other variables. Primarily from the MAX benchmark. The BUBOR became a net receiver of spillovers at the time, when the MAX benchmark became a net transmitter.

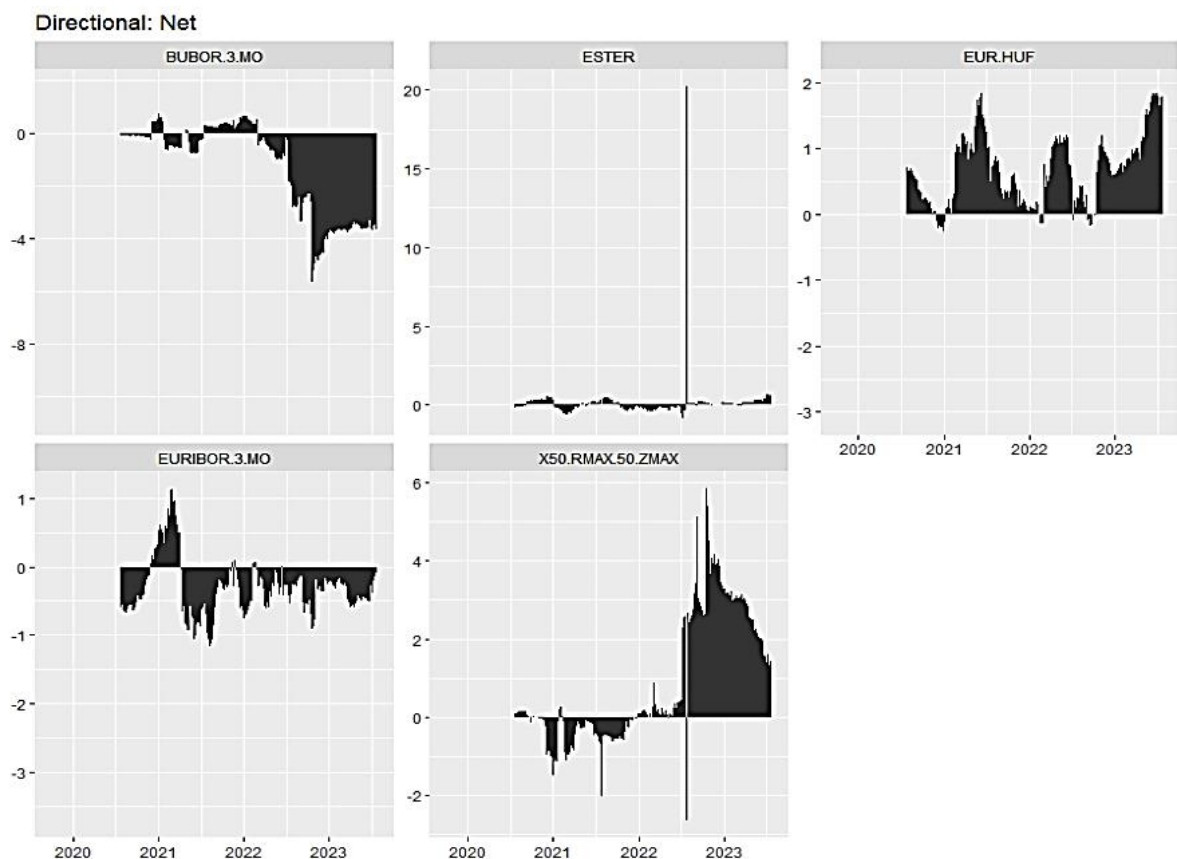


Figure 18. Net spillover plot, K=5 variables in VAR (4). Compiled by author. Source code attached in appendix. Source: MNB, ÁKK, ECB

The net volatility spillover from the BUBOR reached -4% at the end of 2022. Figure 20 illustrates the net pairwise volatility spillovers. It is clear that as the BUBOR became a net receiver of volatility from the MAX index. The strength of the spillovers between the BUBOR -MAX index is to the extent of -4%, while the pairwise spillover between the EURIBOR and the BUBOR is of magnitude less than 1% in both directions. This implies that the European interbank rate does not have a strong spillover effect on the Hungarian interbank rate.

How about the EUR/Forint exchange rate? It turns out, it is in the second place, as a net transmitter of volatility to BUBOR. The summary of Figure 20 is therefore very simple: it reveals that the BUBOR is primarily affected by the EUR/HUF exchange rate and the MAX index, and to a very limited extent – the EURIBOR. We discard the ESTER rate, as it has no predictive capability.

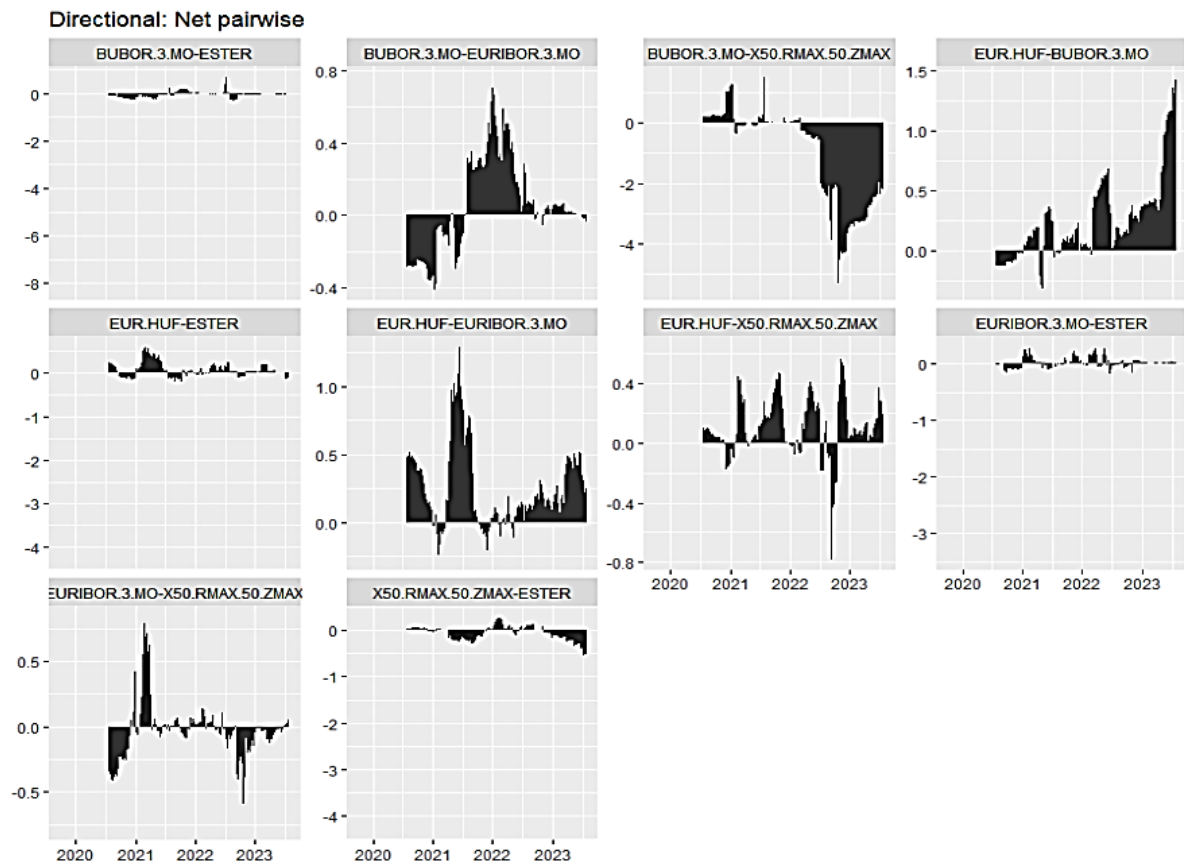


Figure 19. Net pairwise volatility spillovers. K=5 variables in VAR (4). Compiled by author. Source code attached in appendix. Source: MNB, ÁKK, ECB

Finally, the from/to pairwise Figure 21 shows how a variable transmits or receives volatility from another one. It's purpose is to supplement the Figure 20 and to provide support for the claim that the three primary volatility interactions in our control VAR(4),

happen between the BUBOR, the EUR.HUF exchange rate and the 50%RMAX+50%ZMAX benchmarks.

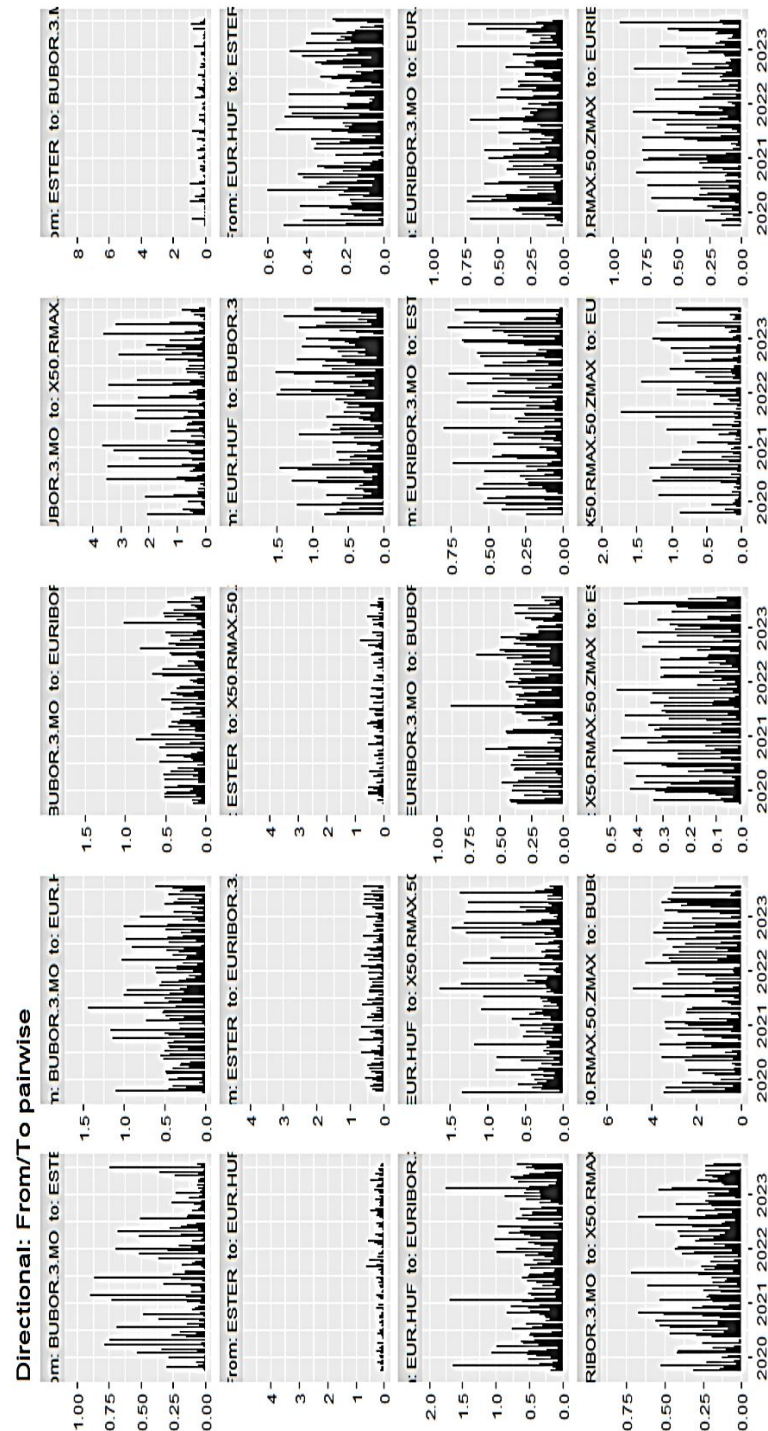


Figure 20. From/To pairwise. K=5 variables in VAR (4). Compiled by author. Source code attached in appendix. Source: MNB, ÁKK, ECB

7. Discussion

DY's 2012 work highlighted the issues of the Cholesky decomposition which manifest in the ordering of variables. In case of economic time series that relate to broad aggregates, such as "investment" and "consumption", which are computed from the flow of funds database, the argument can be made that Sims' 1980 VAR framework is suitable and the IRF is usable. This is because the ordering of the variables is simple to interpret and straightforward. Following economic theory that "before one can consume, one must produce", which dates back to the Smithean philosophy, one can conclusively state that income must drive consumption and not vica versa. This statement can easily be shown as a lower triangle matrix of error terms, with 0's as the upper triangle. However, when it comes to financial time series, which often produce signals on the well-being of the economy, the ordering is hardly based on theory. One might try and create a structural framework, but it would be too complicated to interpret as the interconnectedness in a globalized economy increases as technological progress occurs.

In case of the IRFs, we showed that the Cholesky transformation solves the problem of identifications of contemporaneous correlations via a lower triangular matrix, where one variable may affect the other but not vica versa. This becomes obvious from the (b) graphs, as based on ordering the exchange rate affects the BUBOR in the same time period, similar to the BUBOR affecting the MAX in the same period and the exchange rate effecting the MAX benchmark. We know that the decomposition works, because:

1. The response in period 0 is non-zero.
2. When we switch the variables, that is, turn the impulse variable into a response one, the ordering rule applies.

The Generalized spillover table indicates that about 6% of the volatility forecast error variance in all variables comes from spillovers. This means that the net effect of spillovers in the VAR(4) specification is low. A surprise rate hike in the ECB, therefore, is not likely to contribute much volatility to the Euro and Hungarian Forint exchange rate or the 3-month BUBOR, contrary to the hypothesis. But, at the same time over the period of the sample, the 3-month BUBOR variable displays interesting behavior, as all variables, contribute up to 11% (primarily the MAX benchmark) to its forecast error variance.

During times of heightened market volatility, in our 5-variable control VAR (4), the ESTER rate has the lowest $S_i^g(H)$, that is, the gross spillover effect from ESTER to other,

primarily Hungarian financial variables, is the lowest among the 5 variables. The greatest spillover effect is attributable to the BUBOR rate.

Finally, we've established that the BUBOR is a net receiver of volatility primarily from the EUR/HUF exchange rate and the MAX benchmark.

8. Conclusions

In this study measured the net directional spillover effect of four variables on the BUBOR rate, which was of primary interest to us given a certain degree of exposure of Hungarian consumers and businesses to variable rate loans heavily dependent on the value of the BUBOR. A surprise ECB rate hike is thought to have spillover effects on the BUBOR rate. Within DY's (2012) framework of net and gross volatility spillovers, we came to the conclusion, that while the EURIBOR's spillover effect on BUBOR is not zero, is measurable, and in the past rarely exceeded 1%, it dwells in comparison to the spillover BUBOR receives from the MAX benchmark volatility (signalizing government bond demand shifts) and the Euro-Forint exchange rate.

Having this in mind, the achievement of this paper is in the contextualization of a VAR model what's ordering is supported by economic theory contrasted against the generalized measurement techniques. In other words, by using the forecast error variance decomposition tool, we constructed the spillover index, akin to that of DY (2012) and we identified episodes of heightened volatility in the Hungarian interbank market.

What was an interesting revelation in this study is the from October 2022, when the MNB made a surprise rate hike of 950 basis points on the overnight collateralized loan side, the BUBOR became a net receiver of spillovers. Prior to that the BUBOR was fluctuating between a net transmitter and net receiver. The cyclicity disappeared. We realize that some conclusions are inappropriate to make due to the extremely short timeframe of the data, so we refrain from mentioning them. However, as for future work, an interesting direction for extension would be to compare a 5-variable VAR(4) model currently in effect with a 3-variable VAR(4) model that only contains the Hungarian variables to see if the spillovers hold. Although, predictably, the effects would likely be the exact similar as in a VAR (4) model. Secondly, the AIC criterion suggested a lag of 10. To avoid overfitting, we opted for a smaller lag, but it is nonetheless important to test it for 10 lags as well.

References

1. Amisano, G and Giannini, C. (1997). Topics in Structural VAR Econometrics, 2nd edn, Springer, Berlin
2. *Annual inflation more than tripled in the EU in 2022 (2023) Annual inflation more than tripled in the EU in 2022 - Products Eurostat News - Eurostat*. Available at: <https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20230309-2#:~:text=In%202022%2C%20EU%20annual%20inflation,2013%2D2022%20was%202.1%25>. (Accessed: 30 October 2023).
3. Antal, M., Kaszab, L. (2021). Spillover effects of the European Central Bank's expanded asset purchase program to non-eurozone countries in central and eastern Europe, MNB Occasional Paper, 140. ISSN 1585 5678 (on-line)
4. Bernanke, B. (1986). Measuring monetary policy, Quarterly Journal of Economics 113:869-902.
5. Black, F., & Scholes, M. (1974). The effects of dividend yield and dividend policy on common stock prices and returns. *Journal of financial economics*, 1(1), 1-22.
6. Black, F., Jensen, M. C., & Scholes, M. (1972). The capital asset pricing model: Some empirical tests.
7. Giannini, C. (1992). Topics in Structural VAR Econometrics, Springer, Heidelberg.
8. Government Debt Management Agency Private Company (2023) *Government Bond Indices description*, AKK. Available at: <https://akk.hu/content/path=government-bonddices-description> (Accessed: 30 October 2023).
9. Hamilton, J. D 1994. Time Series Analysis. Princeton: Princeton University Press
10. *Hungary inflation 6.5% in October (2021) Hungary Today*. Available at: <https://hungarytoday.hu/hungary-inflation-october-2021-cpi-prices/> (Accessed: 30 October 2023).
11. Karpoff, J. M., & Walkling, R. A. (1988). Short-term trading around ex-dividend days: Additional evidence. *Journal of Financial Economics*, 21(2), 291-298.
12. Kim, H. (2013). Generalized impulse response analysis: general or extreme?. *EconoQuantum*, 10(2), 136-141.
13. Koop, G., Pesaran, M. H., Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics* 74, 119-147. [doi:10.1016/0304-4076\(95\)01753-4](https://doi.org/10.1016/0304-4076(95)01753-4)

14. Kunst, R. M. (2009). Applied time series analysis-part i. *University of Vienna and Institute for Advanced Studies Vienna*.
15. Laura Papi, D.D. (2023) *The European outlook and policymaking: Seeing off inflation and pivoting to longer-term reforms*, IMF. Available at: <https://www.imf.org/en/News/Articles/2023/10/18/sp-laura-papi-remarks-at-budapest-economic-forum#:~:text=We%20expect%20that%20for%20Europe,about%201%20to%20a bout%203%20%25>. (Accessed: 29 October 2023).
16. Lowenstein, R. (2001). *When genius failed: The rise and fall of Long-Term Capital Management*. Random House trade paperbacks.
17. Lütkepohl, H. (2007). *New introduction to multiple time series analysis* (2nd ed.). Berlin: Springer.
18. Lütkepohl, H., & Saikkonen, P. (1997). Impulse response analysis in infinite order cointegrated vector autoregressive processes. *Journal of Econometrics*, 81(1), 127-157.
19. MNB (2021) *Press release on the Monetary Council meeting of 30 November 2021*. Available at: <https://www.mnb.hu/en/monetary-policy/the-monetary-council/press-releases/2021/press-release-on-the-monetary-council-meeting-of-30-november-2021> (Accessed: 30 October 2023).
20. OTP (2023) *OTP Bank Hirdetmény*. Available at: https://www.otpbank.hu/static/portal/sw/file/U_Portfoliokezelesi_strategia_20230801.pdf (Accessed: 30 October 2023).
21. Pesaran, H. H., Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters* 58(1), 17-29. [doi:10.1016/S0165-1765\(97\)00214-0](https://doi.org/10.1016/S0165-1765(97)00214-0)
22. Pfaff, B. (2008). VAR, SVAR and SVEC Models: Implementation Within R Package vars. *Journal of Statistical Software* 27(4).
23. Plosser, Charles I. and Rouwenhorst, K. Geert. "International Term Structures and Real Economic Growth." *Journal of Monetary Economics*, February 1994, 33(1), pp. 133-55.

24. PMI releases - S&P global. Available at: <https://www.pmi.spglobal.com/Public/Release/PressReleases> (Accessed: 29 October 2023).
25. Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica*, 48(1), 1–48. <https://doi.org/10.2307/1912017>
26. Stock, J. H. (1987). Measuring business cycle time. *Journal of Political Economy*, 95(6), 1240-1261.
27. Stock, J. H., & Watson, M. W. (2001). Vector autoregressions. *Journal of Economic perspectives*, 15(4), 101-115.
28. Stock, James H., and Mark W. Watson, "A Probability Model of the Coincident Economic Indicators," in K. Lahiri and G.H. Moore (eds.), *Leading Economic Indicators: New Approaches and Forecasting Records* (Cambridge: Cambridge University Press, 1991), 63-89.
29. Stock, James H., and Mark W. Watson, "A Procedure for Predicting Recessions with Leading Indicators: Econometric Issues and Recent Experience," in J.H. Stock and M.W. Watson (eds.), *Business Cycles, Indicators and Forecasting* (Chicago: University of Chicago Press for NBER, 1993), 255-284. University of Oxford. Applied Economics Discussion Paper, 194.
30. Watson, M. W. (1994). Vector autoregressions and cointegration. *Handbook of econometrics*, 4, 2843-2915.

Appendix A: Control VAR(5), K=5 model

$$\begin{aligned}
 EUR.HUF = & EUR.HUF.l1 + BUBOR.3.MO.l1 + EURIBOR.3.MO.l1 \\
 & + X50.RMAX.50.ZMAX.l1 + ESTER.l1 + EUR.HUF.l2 \\
 & + BUBOR.3.MO.l2 + EURIBOR.3.MO.l2 \\
 & + X50.RMAX.50.ZMAX.l2 + ESTER.l2 + EUR.HUF.l3 \\
 & + BUBOR.3.MO.l3 + EURIBOR.3.MO.l3 \\
 & + X50.RMAX.50.ZMAX.l3 + ESTER.l3 + EUR.HUF.l4 \\
 & + BUBOR.3.MO.l4 + EURIBOR.3.MO.l4 \\
 & + X50.RMAX.50.ZMAX.l4 + ESTER.l4 + const
 \end{aligned}$$

The control model for Model 2:

BUBOR.3.MO

$$\begin{aligned}
&= EUR.HUF.l1 + BUBOR.3.MO.l1 + EURIBOR.3.MO.l1 \\
&+ X50.RMAX.50.ZMAX.l1 + ESTER.l1 + EUR.HUF.l2 \\
&+ BUBOR.3.MO.l2 + EURIBOR.3.MO.l2 \\
&+ X50.RMAX.50.ZMAX.l2 + ESTER.l2 + EUR.HUF.l3 \\
&+ BUBOR.3.MO.l3 + EURIBOR.3.MO.l3 \\
&+ X50.RMAX.50.ZMAX.l3 + ESTER.l3 + EUR.HUF.l4 \\
&+ BUBOR.3.MO.l4 + EURIBOR.3.MO.l4 \\
&+ X50.RMAX.50.ZMAX.l4 + ESTER.l4 + const
\end{aligned}$$

The control model for Model 3:

X50.RMAX.50.ZMAX

$$\begin{aligned}
&= EUR.HUF.l1 + BUBOR.3.MO.l1 + EURIBOR.3.MO.l1 \\
&+ X50.RMAX.50.ZMAX.l1 + ESTER.l1 + EUR.HUF.l2 \\
&+ BUBOR.3.MO.l2 + EURIBOR.3.MO.l2 \\
&+ X50.RMAX.50.ZMAX.l2 + ESTER.l2 + EUR.HUF.l3 \\
&+ BUBOR.3.MO.l3 + EURIBOR.3.MO.l3 \\
&+ X50.RMAX.50.ZMAX.l3 + ESTER.l3 + EUR.HUF.l4 \\
&+ BUBOR.3.MO.l4 + EURIBOR.3.MO.l4 \\
&+ X50.RMAX.50.ZMAX.l4 + ESTER.l4 + const
\end{aligned}$$

Appendix B: Consequences of correlated shocks and the Cholesky decomposition (ORTHO=FALSE)

Residuals of the covariance matrix. Because the information is contained in the off-diagonal elements of the symmetric variance matrix, some information is lost in the IRF.

Table 11. Residuals of the VAR(4) K=5 covariance matrix. Compiled by author. Source code attached in the appendix.

	EUR.HUF	BUBOR.3.MO	X50.RMAX.50.ZMAX
EUR.HUF	5.37	-0.01	-0.01
BUBOR.3.MO	-0.01	0.01	0.00
X50.RMAX.50.ZMAX	-0.01	0.00	0.00

Correlation matrix of residuals

Table 12. Correlation of residuals of the VAR(4) K=5. Compiled by author. Source code attached in the appendix.

	EUR.HUF	BUBOR.3.MO	X50.RMAX.50.ZMAX
EUR.HUF	1	-0.052	-0.068
BUBOR.3.MO	-0.052	1	0.094
X50.RMAX.50.ZMAX	-0.068	0.094	1

After Cholesky decomposition (ORTHO = TRUE)

Table 13. Correlation of residuals after the Cholesky decomposition. VAR(4) K=5. Compiled by author. Source code attached in the appendix.

	EUR.HUF	BUBOR.3.MO	X50.RMAX.50.ZMAX
EUR.HUF	2.32	0.00	0.00
BUBOR.3.MO	-0.01	0.10	0.00
X50.RMAX.50.ZMAX	0.00	0.00	0.05

Appendix C: Source code in R

Data downloaded from: <https://github.com/albertmolnar/DY2012>

1. Install required library's including the "Spillover" library the info on which is in <https://cran.r-project.org/web/packages/Spillover/Spillover.pdf>

```
library(vars)

## Loading required package: MASS
## Loading required package: strucchange
## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##   as.Date, as.Date.numeric

## Loading required package: sandwich
## Loading required package: urca
## Loading required package: lmtest

library(fastSOM)
library(Spillover)
require(tidyr)

## Loading required package: tidyr

require(dplyr)

## Loading required package: dplyr

##
## Attaching package: 'dplyr'

## The following object is masked from 'package:MASS':
##
##   select
```

```
## The following objects are masked from 'package:stats':
##
##   filter, lag

## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union

require(ggplot2)

## Loading required package: ggplot2
```

2. Load the data and summarize, date must be as factor, so use: as.factor

```
data <- read.csv("C:/Users/Albert Molnar/Desktop/MSc/Spillover research
/Bank rate2.csv")
summary(data)
```

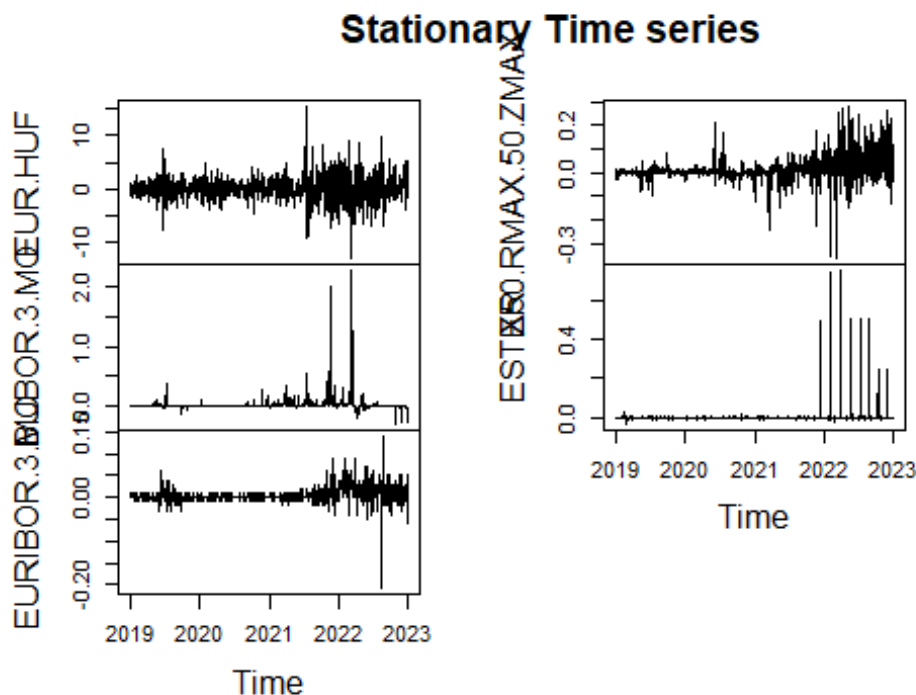
```
##      Date            EUR.HUF            BUBOR.3.MO            EURIBOR.
3.MO
## Length:957      Min.   :-13.33000   Min.   :-0.31000   Min.   :-
0.210000
## Class :character 1st Qu.: -1.16000   1st Qu.: 0.00000   1st Qu.:
0.000000
## Mode  :character Median : -0.01000   Median : 0.00000   Median :
0.000000
##                Mean  :  0.04965   Mean   : 0.01491   Mean   :
0.004326
##                3rd Qu.:  1.16000   3rd Qu.: 0.01000   3rd Qu.:
0.010000
##                Max.   : 15.60000   Max.    : 2.27000   Max.    :
0.140000
## X50.RMAX.50.ZMAX    ESTER
## Min.   :-0.3650    Min.   :-0.031000
## 1st Qu.: -0.0050    1st Qu.: -0.001000
## Median : 0.0050     Median : 0.000000
## Mean   : 0.0126     Mean   : 0.004129
## 3rd Qu.: 0.0200     3rd Qu.: 0.001000
## Max.   : 0.2800     Max.    : 0.747000
```

```
data$Date <-as.factor(data$Date)
head(data)
```

```
##      Date EUR.HUF BUBOR.3.MO EURIBOR.3.MO X50.RMAX.50.ZMAX ESTER
## 1 2019-10-02   0.04         0         0.00       -0.025 -0.002
## 2 2019-10-03  -1.49         0         0.00        0.000 -0.004
## 3 2019-10-04  -0.87         0         0.01        0.000  0.002
## 4 2019-10-07   0.60         0         0.00        0.000 -0.001
## 5 2019-10-08   0.94         0         0.00        0.000  0.002
## 6 2019-10-09   0.33         0         0.00        0.010  0.000
```

3. Turn the data into a time series object, specify start year, end year and number of observations in the year in the “frequency” variable. Plot the data

```
ts_data <- ts(data[, c("EUR.HUF", "BUBOR.3.MO", "EURIBOR.3.MO", "X50.RMA
X.50.ZMAX", "ESTER")], start = c(2019), end = c(2023), frequency = 239)
plot(ts_data, main = "Stationary Time series" )
```



4. Fit the VAR

model, p should be estimated using the AIC information criterion. Use the below code to estimate it. We use 4, because DY used 4. "lag_order <- VARselect(ts_data) selected_lag <- lag_order\$selection[1] var_model <- VAR(ts_data, p = selected_lag)"

```
var_model <- VAR(ts_data, p=4)
summary(var_model)

##
## VAR Estimation Results:
## =====
## Endogenous variables: EUR.HUF, BUBOR.3.MO, EURIBOR.3.MO, X50.RMAX.50
.ZMAX, ESTER
## Deterministic variables: const
## Sample size: 953
## Log Likelihood: 4229.939
## Roots of the characteristic polynomial:
## 0.7554 0.7554 0.6644 0.6644 0.6625 0.6625 0.6358 0.6358 0.6029 0.602
9 0.5532 0.5532 0.4875 0.4875 0.3999 0.3999 0.3625 0.3625 0.157 0.09668
## Call:
## VAR(y = ts_data, p = 4)
##
##
## Estimation results for equation EUR.HUF:
## =====
## EUR.HUF = EUR.HUF.l1 + BUBOR.3.MO.l1 + EURIBOR.3.MO.l1 + X50.RMAX.50
.ZMAX.l1 + ESTER.l1 + EUR.HUF.l2 + BUBOR.3.MO.l2 + EURIBOR.3.MO.l2 + X5
0.RMAX.50.ZMAX.l2 + ESTER.l2 + EUR.HUF.l3 + BUBOR.3.MO.l3 + EURIBOR.3.M
```

```

0.13 + X50.RMAX.50.ZMAX.13 + ESTER.13 + EUR.HUF.14 + BUBOR.3.MO.14 + EU
RIBOR.3.MO.14 + X50.RMAX.50.ZMAX.14 + ESTER.14 + const
##
##
##          Estimate Std. Error t value Pr(>|t|)
## EUR.HUF.11      0.03050    0.03269   0.933   0.3511
## BUBOR.3.MO.11   -0.80289    0.74567  -1.077   0.2819
## EURIBOR.3.MO.11 -8.53111    4.16330  -2.049   0.0407 *
## X50.RMAX.50.ZMAX.11 2.21702    1.42732   1.553   0.1207
## ESTER.11        0.23743    1.63094   0.146   0.8843
## EUR.HUF.12     -0.03227    0.03292  -0.980   0.3273
## BUBOR.3.MO.12    1.06838    0.74994   1.425   0.1546
## EURIBOR.3.MO.12   1.37500    4.20045   0.327   0.7435
## X50.RMAX.50.ZMAX.12 1.38163    1.50160   0.920   0.3578
## ESTER.12       -2.32464    1.62066  -1.434   0.1518
## EUR.HUF.13     -0.01069    0.03298  -0.324   0.7459
## BUBOR.3.MO.13   -1.51872    0.75138  -2.021   0.0435 *
## EURIBOR.3.MO.13  -2.26766    4.25890  -0.532   0.5945
## X50.RMAX.50.ZMAX.13 -1.48827    1.49440  -0.996   0.3196
## ESTER.13       -3.42047    1.59363  -2.146   0.0321 *
## EUR.HUF.14      0.05114    0.03321   1.540   0.1239
## BUBOR.3.MO.14   -0.27926    0.70693  -0.395   0.6929
## EURIBOR.3.MO.14   9.22115    4.23227   2.179   0.0296 *
## X50.RMAX.50.ZMAX.14 0.09376    1.48330   0.063   0.9496
## ESTER.14       -4.12868    1.61056  -2.564   0.0105 *
## const          0.08668    0.08586   1.010   0.3130
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 2.304 on 932 degrees of freedom
## Multiple R-Squared: 0.04016, Adjusted R-squared: 0.01956
## F-statistic: 1.95 on 20 and 932 DF, p-value: 0.007542
##
##
## Estimation results for equation BUBOR.3.MO:
## =====
## BUBOR.3.MO = EUR.HUF.11 + BUBOR.3.MO.11 + EURIBOR.3.MO.11 + X50.RMAX
.50.ZMAX.11 + ESTER.11 + EUR.HUF.12 + BUBOR.3.MO.12 + EURIBOR.3.MO.12 +
X50.RMAX.50.ZMAX.12 + ESTER.12 + EUR.HUF.13 + BUBOR.3.MO.13 + EURIBOR.3
.MO.13 + X50.RMAX.50.ZMAX.13 + ESTER.13 + EUR.HUF.14 + BUBOR.3.MO.14 +
EURIBOR.3.MO.14 + X50.RMAX.50.ZMAX.14 + ESTER.14 + const
##
##
##          Estimate Std. Error t value Pr(>|t|)
## EUR.HUF.11     -0.004108    0.001455  -2.823 0.004863 **
## BUBOR.3.MO.11   0.155950    0.033199   4.697 3.03e-06 ***
## EURIBOR.3.MO.11 0.210530    0.185361   1.136 0.256340
## X50.RMAX.50.ZMAX.11 -0.605292    0.063548  -9.525 < 2e-16 ***
## ESTER.11       -0.044436    0.072614  -0.612 0.540717
## EUR.HUF.12      0.005039    0.001466   3.438 0.000613 ***
## BUBOR.3.MO.12   0.063634    0.033389   1.906 0.056981 .
## EURIBOR.3.MO.12 0.182173    0.187015   0.974 0.330255
## X50.RMAX.50.ZMAX.12 -0.008741    0.066855  -0.131 0.896000
## ESTER.12        0.054769    0.072156   0.759 0.448019
## EUR.HUF.13      0.005271    0.001468   3.589 0.000349 ***

```

```

## BUBOR.3.MO.13      0.060182    0.033453    1.799 0.072347 .
## EURIBOR.3.MO.13    0.383879    0.189618    2.024 0.043205 *
## X50.RMAX.50.ZMAX.13 0.061867    0.066534    0.930 0.352690
## ESTER.13          -0.081861    0.070953   -1.154 0.248902
## EUR.HUF.14         0.001393    0.001479    0.942 0.346271
## BUBOR.3.MO.14      0.039691    0.031474    1.261 0.207606
## EURIBOR.3.MO.14    0.195977    0.188432    1.040 0.298591
## X50.RMAX.50.ZMAX.14 -0.067159    0.066040   -1.017 0.309444
## ESTER.14           0.024764    0.071706    0.345 0.729909
## const              0.013447    0.003823    3.518 0.000457 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.1026 on 932 degrees of freedom
## Multiple R-Squared: 0.1769, Adjusted R-squared: 0.1593
## F-statistic: 10.02 on 20 and 932 DF, p-value: < 2.2e-16
##
##
## Estimation results for equation EURIBOR.3.MO:
## =====
## EURIBOR.3.MO = EUR.HUF.11 + BUBOR.3.MO.11 + EURIBOR.3.MO.11 + X50.RM
AX.50.ZMAX.11 + ESTER.11 + EUR.HUF.12 + BUBOR.3.MO.12 + EURIBOR.3.MO.12
+ X50.RMAX.50.ZMAX.12 + ESTER.12 + EUR.HUF.13 + BUBOR.3.MO.13 + EURIBOR
.3.MO.13 + X50.RMAX.50.ZMAX.13 + ESTER.13 + EUR.HUF.14 + BUBOR.3.MO.14
+ EURIBOR.3.MO.14 + X50.RMAX.50.ZMAX.14 + ESTER.14 + const
##
##
##              Estimate Std. Error t value Pr(>|t|)
## EUR.HUF.11      -7.489e-04  2.607e-04  -2.872  0.00417 **
## BUBOR.3.MO.11     8.198e-04  5.948e-03   0.138  0.89040
## EURIBOR.3.MO.11    1.744e-01  3.321e-02   5.252 1.86e-07 ***
## X50.RMAX.50.ZMAX.11 3.747e-03  1.138e-02   0.329  0.74212
## ESTER.11         -2.796e-05  1.301e-02  -0.002  0.99829
## EUR.HUF.12        2.636e-04  2.626e-04   1.004  0.31576
## BUBOR.3.MO.12     6.409e-03  5.982e-03   1.071  0.28426
## EURIBOR.3.MO.12   -3.722e-02  3.350e-02  -1.111  0.26685
## X50.RMAX.50.ZMAX.12 2.526e-02  1.198e-02   2.109  0.03518 *
## ESTER.12         6.265e-03  1.293e-02   0.485  0.62805
## EUR.HUF.13        6.649e-04  2.631e-04   2.528  0.01165 *
## BUBOR.3.MO.13     1.336e-02  5.993e-03   2.229  0.02605 *
## EURIBOR.3.MO.13    2.307e-02  3.397e-02   0.679  0.49717
## X50.RMAX.50.ZMAX.13 2.154e-02  1.192e-02   1.807  0.07111 .
## ESTER.13         -5.880e-03  1.271e-02  -0.463  0.64375
## EUR.HUF.14        2.761e-05  2.649e-04   0.104  0.91701
## BUBOR.3.MO.14     1.280e-02  5.639e-03   2.271  0.02339 *
## EURIBOR.3.MO.14    6.793e-02  3.376e-02   2.012  0.04447 *
## X50.RMAX.50.ZMAX.14 1.373e-02  1.183e-02   1.160  0.24619
## ESTER.14         2.448e-02  1.285e-02   1.906  0.05700 .
## const            1.911e-03  6.848e-04   2.791  0.00536 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.01838 on 932 degrees of freedom

```

```

## Multiple R-Squared: 0.09619, Adjusted R-squared: 0.0768
## F-statistic: 4.96 on 20 and 932 DF, p-value: 9.154e-12
##
##
## Estimation results for equation X50.RMAX.50.ZMAX:
## =====
## X50.RMAX.50.ZMAX = EUR.HUF.11 + BUBOR.3.MO.11 + EURIBOR.3.MO.11 + X5
0.RMAX.50.ZMAX.11 + ESTER.11 + EUR.HUF.12 + BUBOR.3.MO.12 + EURIBOR.3.M
0.12 + X50.RMAX.50.ZMAX.12 + ESTER.12 + EUR.HUF.13 + BUBOR.3.MO.13 + EU
RIBOR.3.MO.13 + X50.RMAX.50.ZMAX.13 + ESTER.13 + EUR.HUF.14 + BUBOR.3.M
0.14 + EURIBOR.3.MO.14 + X50.RMAX.50.ZMAX.14 + ESTER.14 + const
##
##
## Estimate Std. Error t value Pr(>|t|)
## EUR.HUF.11 -0.0015444 0.0007524 -2.053 0.040389 *
## BUBOR.3.MO.11 -0.0310558 0.0171628 -1.809 0.070698 .
## EURIBOR.3.MO.11 -0.0047799 0.0958249 -0.050 0.960228
## X50.RMAX.50.ZMAX.11 0.1326461 0.0328521 4.038 5.84e-05 ***
## ESTER.11 0.1556153 0.0375387 4.145 3.70e-05 ***
## EUR.HUF.12 -0.0005675 0.0007578 -0.749 0.454140
## BUBOR.3.MO.12 0.0226308 0.0172611 1.311 0.190152
## EURIBOR.3.MO.12 0.1992520 0.0966799 2.061 0.039585 *
## X50.RMAX.50.ZMAX.12 0.0716312 0.0345616 2.073 0.038487 *
## ESTER.12 -0.0445388 0.0373020 -1.194 0.232780
## EUR.HUF.13 0.0005929 0.0007592 0.781 0.435006
## BUBOR.3.MO.13 0.0071442 0.0172941 0.413 0.679629
## EURIBOR.3.MO.13 0.0434334 0.0980254 0.443 0.657808
## X50.RMAX.50.ZMAX.13 0.0955430 0.0343959 2.778 0.005584 **
## ESTER.13 0.1414254 0.0366798 3.856 0.000123 ***
## EUR.HUF.14 -0.0017295 0.0007644 -2.263 0.023883 *
## BUBOR.3.MO.14 -0.0039602 0.0162711 -0.243 0.807756
## EURIBOR.3.MO.14 0.1671324 0.0974125 1.716 0.086546 .
## X50.RMAX.50.ZMAX.14 0.0946403 0.0341404 2.772 0.005681 **
## ESTER.14 -0.0162392 0.0370696 -0.438 0.661434
## const 0.0052245 0.0019762 2.644 0.008340 **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.05304 on 932 degrees of freedom
## Multiple R-Squared: 0.1312, Adjusted R-squared: 0.1126
## F-statistic: 7.04 on 20 and 932 DF, p-value: < 2.2e-16
##
##
## Estimation results for equation ESTER:
## =====
## ESTER = EUR.HUF.11 + BUBOR.3.MO.11 + EURIBOR.3.MO.11 + X50.RMAX.50.Z
MAX.11 + ESTER.11 + EUR.HUF.12 + BUBOR.3.MO.12 + EURIBOR.3.MO.12 + X50.
RMAX.50.ZMAX.12 + ESTER.12 + EUR.HUF.13 + BUBOR.3.MO.13 + EURIBOR.3.MO.
13 + X50.RMAX.50.ZMAX.13 + ESTER.13 + EUR.HUF.14 + BUBOR.3.MO.14 + EURI
BOR.3.MO.14 + X50.RMAX.50.ZMAX.14 + ESTER.14 + const
##
##
## Estimate Std. Error t value Pr(>|t|)
## EUR.HUF.11 0.0008371 0.0006606 1.267 0.205387
## BUBOR.3.MO.11 0.0019452 0.0150689 0.129 0.897315

```

```

## EURIBOR.3.MO.11      0.0494089  0.0841341  0.587 0.557169
## X50.RMAX.50.ZMAX.11 -0.0046725  0.0288441 -0.162 0.871348
## ESTER.11            -0.0217206  0.0329589 -0.659 0.510045
## EUR.HUF.12          0.0003758  0.0006653  0.565 0.572306
## BUBOR.3.MO.12       -0.0316044  0.0151552 -2.085 0.037306 *
## EURIBOR.3.MO.12      0.3831884  0.0848848  4.514 7.17e-06 ***
## X50.RMAX.50.ZMAX.12  0.0392580  0.0303450  1.294 0.196082
## ESTER.12            -0.0375425  0.0327511 -1.146 0.251966
## EUR.HUF.13          -0.0012619  0.0006665 -1.893 0.058647 .
## BUBOR.3.MO.13       0.0180639  0.0151842  1.190 0.234487
## EURIBOR.3.MO.13      0.3184824  0.0860661  3.700 0.000228 ***
## X50.RMAX.50.ZMAX.13 -0.1235655  0.0301995 -4.092 4.65e-05 ***
## ESTER.13            -0.0516485  0.0322048 -1.604 0.109108
## EUR.HUF.14          -0.0001191  0.0006711 -0.178 0.859121
## BUBOR.3.MO.14       -0.0167321  0.0142860 -1.171 0.241809
## EURIBOR.3.MO.14     -0.0552232  0.0855280 -0.646 0.518650
## X50.RMAX.50.ZMAX.14  0.1484758  0.0299752  4.953 8.66e-07 ***
## ESTER.14            0.0151905  0.0325471  0.467 0.640805
## const               0.0012151  0.0017351  0.700 0.483911
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.04657 on 932 degrees of freedom
## Multiple R-Squared: 0.09267, Adjusted R-squared: 0.0732
## F-statistic: 4.759 on 20 and 932 DF, p-value: 4.051e-11
##
##
## Covariance matrix of residuals:
##
##          EUR.HUF BUBOR.3.MO EURIBOR.3.MO X50.RMAX.50.ZMAX
ESTER
## EUR.HUF          5.311e+00 -1.311e-02  -1.185e-03  -7.638e-03
-6.026e-06
## BUBOR.3.MO       -1.311e-02  1.053e-02   2.178e-04   4.756e-04
-6.564e-05
## EURIBOR.3.MO     -1.185e-03  2.178e-04   3.379e-04  -3.733e-06
1.456e-04
## X50.RMAX.50.ZMAX -7.638e-03  4.756e-04  -3.733e-06   2.813e-03
-2.776e-04
## ESTER           -6.026e-06 -6.564e-05   1.456e-04  -2.776e-04
2.169e-03
##
## Correlation matrix of residuals:
##
##          EUR.HUF BUBOR.3.MO EURIBOR.3.MO X50.RMAX.50.ZMAX
ESTER
## EUR.HUF          1.000e+00  -0.05543  -0.027982  -0.062490
-5.615e-05
## BUBOR.3.MO       -5.543e-02  1.00000   0.115492   0.087384
-1.374e-02
## EURIBOR.3.MO     -2.798e-02  0.11549   1.000000  -0.003829
1.701e-01
## X50.RMAX.50.ZMAX -6.249e-02  0.08738  -0.003829   1.000000
-1.124e-01

```

```
## ESTER          -5.615e-05   -0.01374    0.170068    -0.112400
1.000e+00
```

4.1 The forecast error variance decomposition and its plot

```
orthogonal_fevd <- fevd(var_model, n.ahead=10, normalized=TRUE)
generalized_fevd <- g.fevd(var_model, n.ahead=10, normalized=TRUE)
#the code to plot the FEVD is below. This is the orthog
#fevd_matrix <- as.matrix(orthogonal_fevd$ESTER)
#barplot(fevd_matrix, beside = TRUE, col = c("lightblue"),
#        main = "Orthogonal Forecast Error Variance Decomposition",
#        xlab = "Variables", ylab = "Variance Contribution",
#        legend.text = TRUE)
```

- Find the orthogonalized and Generalized spillover indexes which are based on the orthogonalized and generalized error variance decomposition correspondingly.

```
print("Orthogonalized spillover table")
## [1] "Orthogonalized spillover table"
O.spillover(var_model, ortho.type = "single", standardized = FALSE)
##
## EUR.HUF BUBOR.3.MO EURIBOR.3.MO X50.R
MAX.50.ZMAX
## EUR.HUF          96.4583344  0.8085934  0.8503212
0.7375069
## BUBOR.3.MO       4.0220196 85.4193431  0.6198405
9.5825750
## EURIBOR.3.MO     1.5516963  3.6450800 93.1885072
1.0803055
## X50.RMAX.50.ZMAX 1.9052233  1.2809088  2.3104251
91.2739185
## ESTER           0.7891714  0.4851697  6.4212176
4.7677933
## C. to others (spillover) 8.2681107 6.2197518 10.2018044
16.1681808
## C. to others including own 104.7264451 91.6390949 103.3903116
107.4420992
##
## ESTER C. from others
## EUR.HUF          1.1452442  3.541666
## BUBOR.3.MO       0.3562217 14.580657
## EURIBOR.3.MO     0.5344111  6.811493
## X50.RMAX.50.ZMAX 3.2295243  8.726082
## ESTER           87.5366480 12.463352
## C. to others (spillover) 5.2654012  9.224650
## C. to others including own 92.8020491 500.000000
print("Generalized spillover table")
## [1] "Generalized spillover table"
G.spillover(var_model, standardized = FALSE)
```

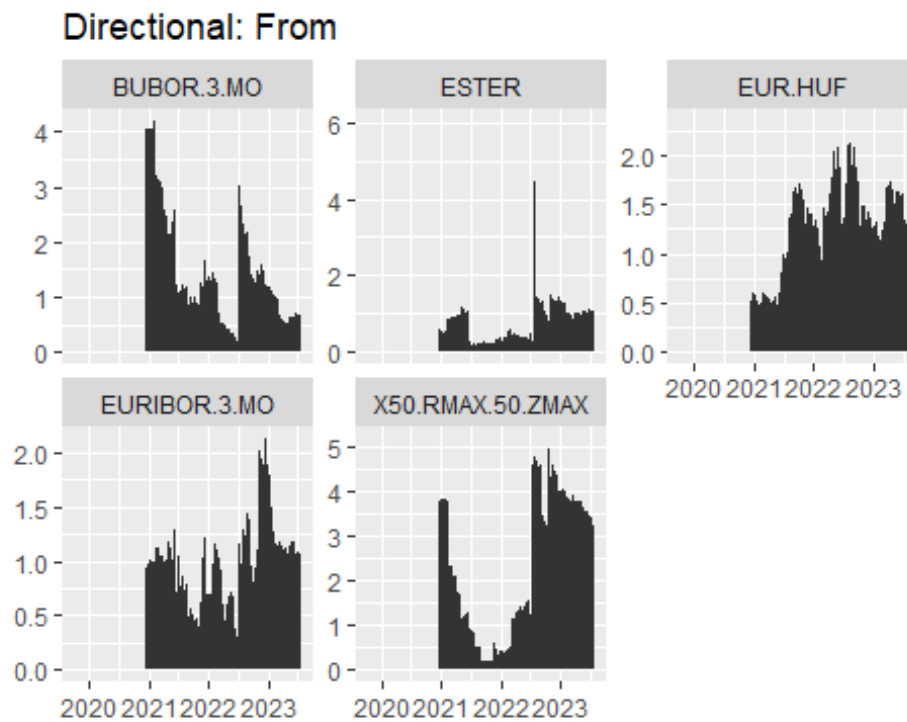
##	EUR.HUF	BUBOR.3.MO	EURIBOR.3.MO	X50.R
MAX.50.ZMAX				
## EUR.HUF	95.7202009	1.1099036	0.9813686	
1.126691				
## BUBOR.3.MO	3.9808804	84.6328132	1.9755891	
9.203403				
## EURIBOR.3.MO	1.4823047	3.4644498	90.6768578	
1.173914				
## X50.RMAX.50.ZMAX	1.8607688	1.3195552	2.4696780	
90.352033				
## ESTER	0.7632048	0.5002485	6.1118613	
4.529913				
## C. to others (spillover)	8.0871588	6.3941571	11.5384970	
16.033922				
## C. to others including own	103.8073596	91.0269703	102.2153548	
106.385955				
##	ESTER C. from others			
## EUR.HUF	1.0618359	4.279799		
## BUBOR.3.MO	0.2073138	15.367187		
## EURIBOR.3.MO	3.2024738	9.323142		
## X50.RMAX.50.ZMAX	3.9979646	9.647967		
## ESTER	88.0947721	11.905228		
## C. to others (spillover)	8.4695882	10.104665		
## C. to others including own	96.5643602	500.000000		

6. Estimate the directional spillovers as in DY 2012

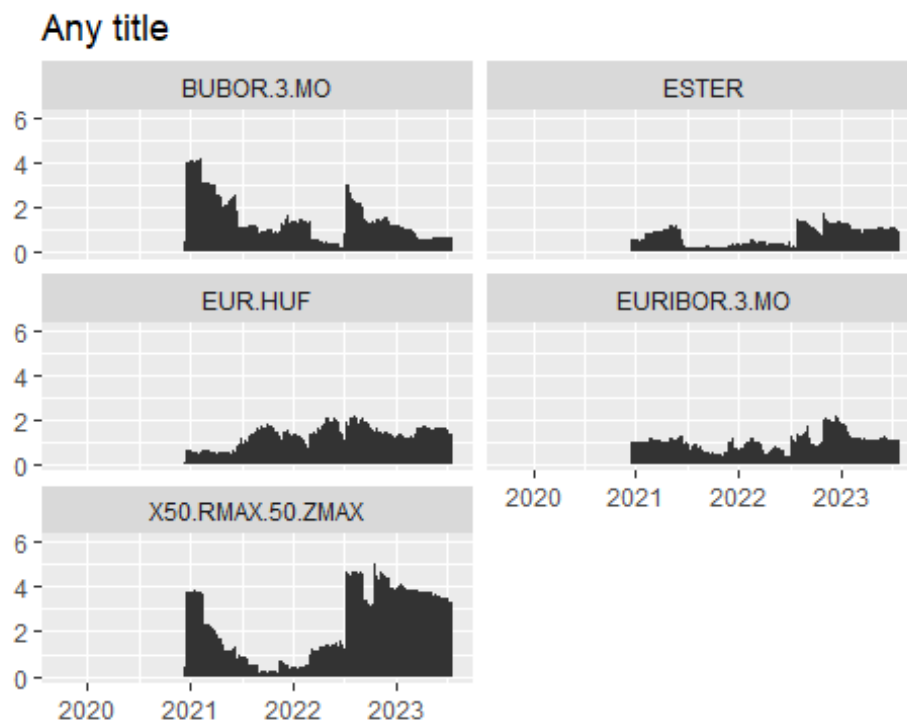
```
dy_results <- dynamic.spillover(
  data,
  width = 300,
  n.ahead = 10,
  standardized = TRUE,
  na.fill = FALSE,
  remove.own = TRUE)
```

7. Plot the directional spillovers as in DY 2012

```
pp_from <- plotdy(dy_results, direction = "from")
```

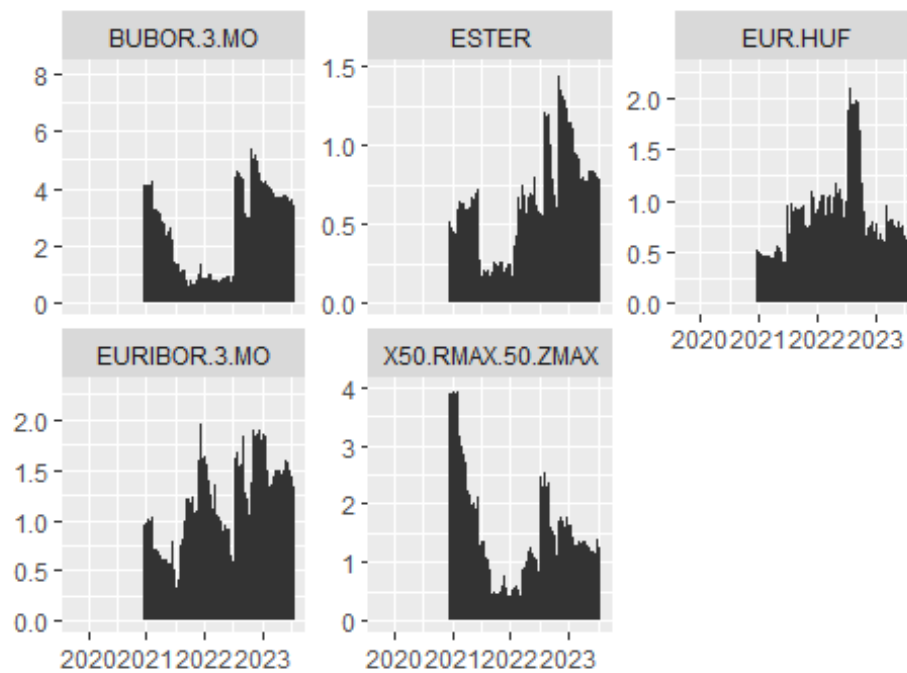


```
pp_from +
  labs(title="Any title") +
  facet_wrap(~variables, ncol = 2)
```



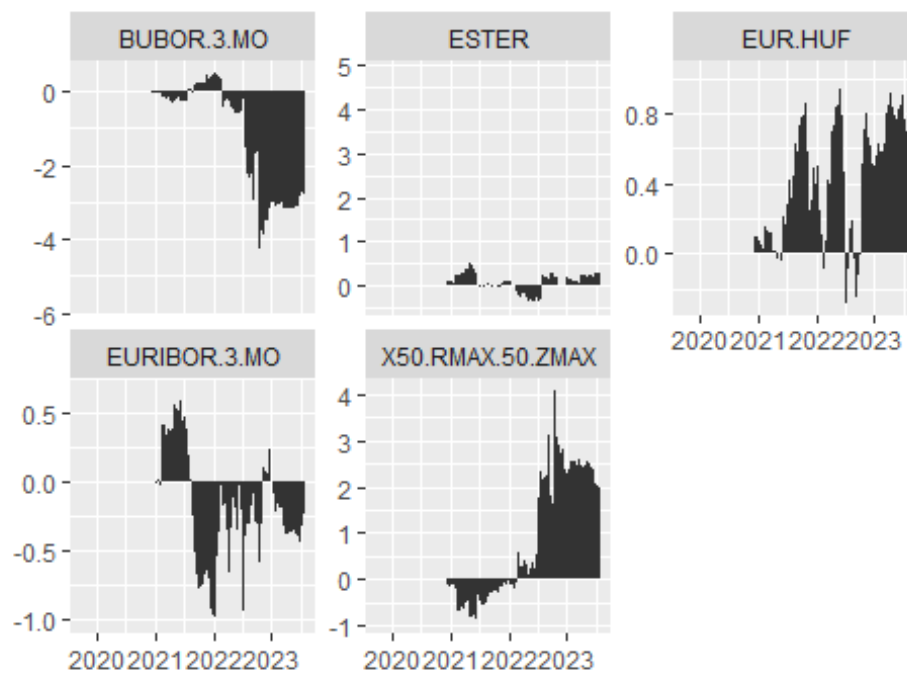
```
pp_to <- plotdy(dy_results, direction = "to")
```

Directional: To



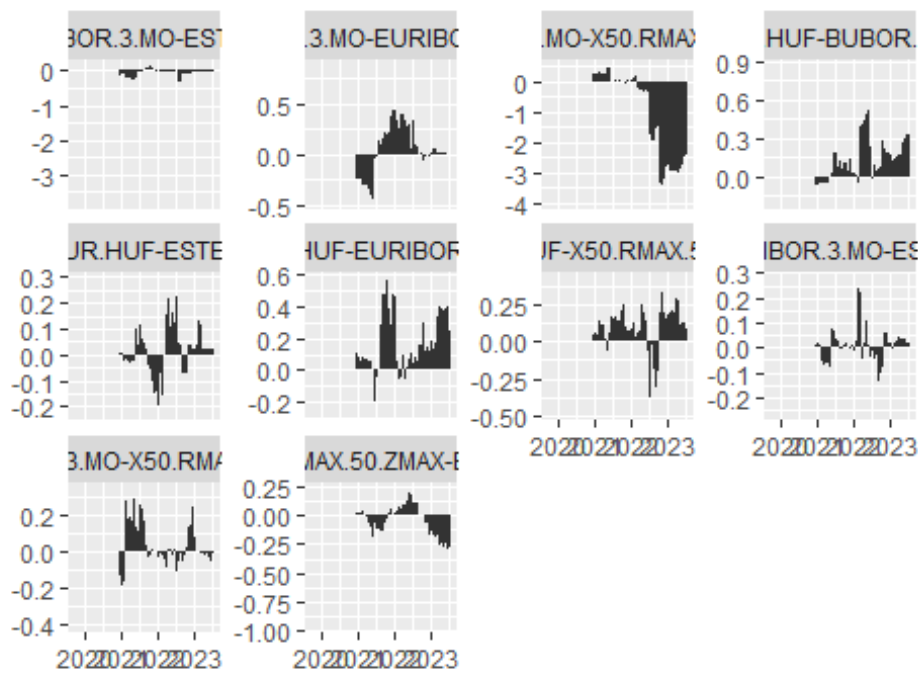
```
pp_net <- plotdy(dy_results, direction = "net")
```

Directional: Net



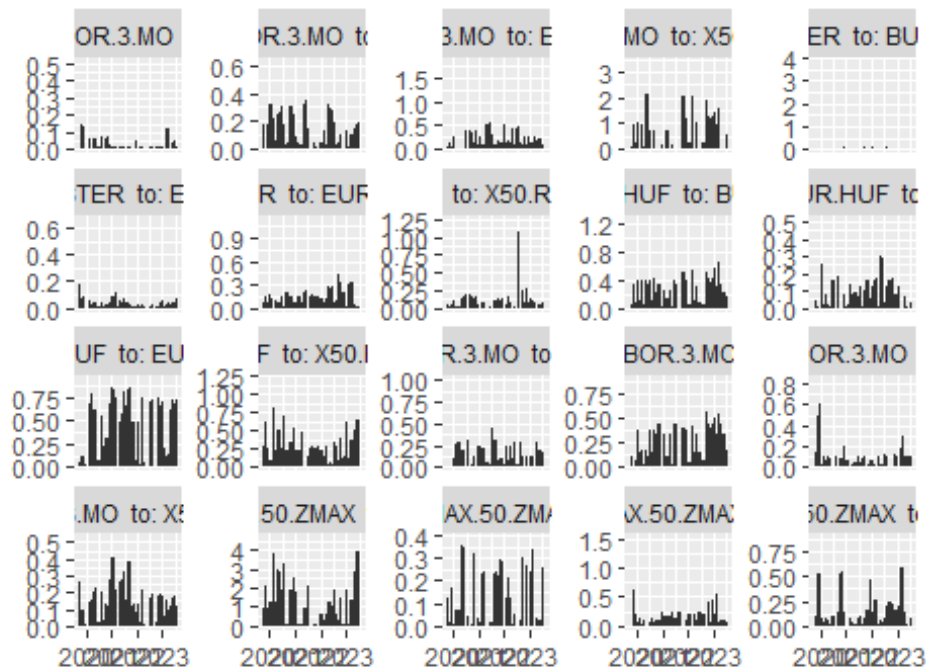
```
pp_netpairwise <- plotdy(dy_results, direction = "net_pairwise")
```

Directional: Net pairwise



```
pp_from_to_pairwise <- plotdy(dy_results, direction = "from_to_pairwise")
```

Directional: From/To pairwise



8. Estimate the dynamic spillover index given a moving window as in DY2012

```
G_net <- roll.net(as.zoo(data[1:900,c(2,3,4,5,6)]), width = 200, index=
"generalized")
# orthogonalized rolling net spillover index, based on a VAR(2)
```

```
O_net_data <- roll.net(as.zoo(data[, -1]), width = 200)
# Generalized rolling net spillover index, based on a VAR(2)
G_net_data <- roll.net(as.zoo(data[, -1]), width = 200, index="generalized")
```

9. Estimate the dynamic spillover index given a rolling window as in DY2012

```
O_index <- roll.spillover(as.zoo(data[1:900, c(2,3,4,5,6)]), width = 300, p=4)
# Orthogonalized rolling spillover index based on a VAR(4), single order
O_index <- roll.spillover(as.zoo(data[, -1]), width = 300, p=4)
# Generalized rolling spillover index based on a VAR(4)
G_index <- roll.spillover(as.zoo(data[, -1]), width = 300, index="generalized", p=4)
# A comparison: (warning: It can take several minutes.)
single <- roll.spillover(as.zoo(data[1:900, 2:6]), width = 300, p=4)
partial <- roll.spillover(as.zoo(data[1:900, 2:6]), width = 300, p=4, ortho.type = "partial")
total <- roll.spillover(as.zoo(data[1:900, 2:6]), width = 300, p=4, ortho.type = "total")
out <- cbind(single, partial, total)
head(out)

##          single  partial  total
## 300 15.16544 15.38326 15.38362
## 301 15.18790 15.39911 15.39292
## 302 15.18368 15.39600 15.39258
## 303 15.21230 15.42010 15.42211
## 304 15.24853 15.45729 15.45591
## 305 15.16984 15.39297 15.38905

plot(out, col=1:3, main="Spillover index")
```