**ÓBUDA UNIVERSITY**

**Keleti Károly Faculty of Economics**
**Institute of Enterprise Management**

# SELECTING RECESSION-FORECASTING INDICATORS FOR THE HUNGARIAN ECONOMY WITH THE APPLICATION OF DYNAMIC FACTOR MODELLING AND THE MARKOW-SWITCH METHOD

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**Keleti Károly Gazdasági Kar**
Vállalkozásfejlesztés és Infokommunikációs Intézet

# DIPLOMAMUNKA FELADATLAP

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**Specializáció:**

**A dolgozat címe:** Selecting recession-forecasting indicators for the Hungarian economy with the application of dynamic factor modelling and the Markow-switch method
**A dolgozat címe angolul:** Selecting recession-forecasting indicators for the Hungarian economy with the application of dynamic factor modelling and the Markow-switch method
**A feladat részletezése:**
1. Collect and analyze the literature on composite leading indicators and the application of Markov regime switching modes for developing economies!
2. Give a brief historical overview of business cycle forecasting in Hungary and give reasoning on the selection of economic indicators used by the MNB to identify macroeconomic imbalances!
3. Collect a set of financial and macro indicators to perform the Markov regime switching method and build the spillover table as in Diebold and Yilmaz's 2012 work! Connect the results using economic theory of recessions!
4. Determine the best leading indicators for the Hungarian economy through the proposed Markov regime switching and spillover table method!

**Intézményi konzulens neve:** Dr. Csiszárik-Kocsir Ágnes Teréz

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P.H.

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Intézetigazgató dh.

A dolgozatot beadásra alkalmasnak találom:

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belső konzulens

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külső konzulens

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# STUDENT'S DECLARATION

I the undersigned student named Molnár Albert (Neptun code: [redacted]) hereby declare that the degree project is the result of my own work; I referred to the special literature and the means used in an identifiable manner. The results included in the degree project completed are allowed to be used by the university and the institution announcing the task for their own purposes free of charge, subject to any restrictions on classification as confidential.

Budapest, 11 day 12 month 2023 year

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student's signature

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## 1. INTRODUCTION

The interest in business cycle forecasting usually wanes during prosperity and surges during depressions (Zarnowitz, 1992, chapter 2, p.20). The current recession is a compound result of monetary and fiscal measures undertaken by central banks to stabilize markets (specifically, keeping down interest rates) and keep businesses solvent as a response to the Covid-19 lockdowns. While leading indicators have a long history of successfully predicting recessions and the field has a large body of literature with empirical support, often the time series are unobtainable, the models are too abstract or simply inapplicable in case of the Hungarian economy. For instance, the time series used by Wharton and Brookings institution, such as unfilled durable goods orders, active working hours and private employee compensation might not be suitable variables in a model that would adequately represent business cycle dynamics. As a result, we opt for a more transparent simpler model with time series that are easily obtainable and provide a deep understanding of economic conditions. Given the fact that U.S recessions tend to last shorter than European ones (Moore, Zarnowitz, 1986), many western empirical studies containing data sets might not suffer from class imbalances (due to recession comprising a significantly smaller portion of time periods than expansions) simplifying the algorithms for some of the machine learning techniques introduced in this studyThe authors of this research believe that a combination of indicators from capital markets and the real economy obtained from Hungarian central bank's (MNB) database have the advantage of immediate availability and contain valuable information of forward looking expectations of economic participants. We provide a brief historical overview of business cycles and discuss how academics of economic philosophies describe business cycles. Afterwards, we utilize the Markov Switching model for regime changes in the economy and finally, employ a VAR to analyze spillover effects of the European Central Bank's ECB's surprise interest rate decisions on Hungarian economic time series.

To capture the full spectrum of an economic indicator's dynamics inherent to its non-stationary nature, the research employs a regime switching methodology known as the Markov switching model. In Section 3 the Markov Switching dynamic regression model is specified. In section 4, the VAR model is explained, and Sections 5-6 present the results.

Evidence on the successful application of stochastic models for time series forecasting, such as the ones developed in the 70's by Box and Jenkins (1970) – Auto regressive moving average (ARMA), and later, Seasonal Autoregressive integrated moving average (SARIMAX) models. The aim of this research is to determine whether conventional VAR models are useful for forecasting economic downturns.

In the Spillover research, 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 2012 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.

In the Markov chain research, we apply the hidden Markov switching dynamic regression (MSDR) model to estimate transition probabilities of the Hungarian GDP between recessionary and expansionary periods. The transition probabilities are then compared to the OECD Hungarian binary business cycle indicator to assess the predictive power of the model. The paper proposes a linear model with a mean and a homoscedastic component. The level of symmetry between the GDP and business cycles is explained by the panel data variables (Unemployment rate, IPI index, Inflation, BUX year-on-year change, and 10-3 Year sovereign bond yield spreads). It is assumed in this paper that by extending the model to encompass an exogenous variable listed in the panel data, essentially making the model bivariate, the maximum likelihood function would capture the business cycle more accurately. The results show that by plugging the unemployment rate as the exogenous variable in the regression, our model's accuracy is 70%.

### 1.1. A short overview of the theory of business cycles and economic forecasting

According to the Austrian school of economics, theory comes before perception, therefore it renders the empirical testing useless. Is that so? In his book, "On Globalization" the prominent hedge fund manager and intellectual, George Soros, argues that economics are inherently amoral (Soros, 2002, p.104). A new concept of "good" and "bad" must be invented to circumvent the issue of amorality, according to him. Yet, in another book, "The New Paradigm for Financial Markets", he argues that economists observe the economy in a way which is similar to the parable of the 5 blindfolded men who had never seen an elephant, and trying to imagine or tell what it is by touching it (Soros, 2008). Our works' suppositions are very much in line with this argument, but not with the former argument of amorality. Morality is a necessary component of business. Once a party behaves immorally, for example, a debt is not repaid, fraud or robbery is committed, it is impossible to restore trade relations. Trade is no longer feasible from that point. In any market, morality comes before business. When a third party tries to impose limits and define what good is, one must inevitably ask oneself the question, *cui bono*?

Markets are inefficient. If one were to suppose any kind of efficiency, the counterargument in this study is: why do spreads exist? Why is there an unequal distribution of information between institutional and retail investors? Why are stocks so far from their P/E ratios?

We don't argue that a democratization of trading brings markets nearer to a more efficient state. Instead, we believe that the removal of barriers of information flow and distortions by government actions enhances the efficiency of markets.

Boom-and-bust cycles in the economy have been well-known since Hayek's (1934) article on Carl Menger. Business cycles were initially thought to be a result of interest rate dynamics, an idea first incorporated in the Austrian and later revised in the Chicago economic schools. It was only in the 1940's, in a period in the United States when post-war Keynesian economics began to gain popularity thanks to the novelty offered by embracing exogenous random shocks (nonseasonal fluctuations) and incorporating stochastic economic models, that recessionary and expansionary periods of an economy were put within an empirical framework by former Fed chairman and NBER director Arthur Burns and Wesley Mitchell (Burns and Mitchell, 1946). A dynamically stable linear model of a business cycles consists of endogenous and exogenous factors that tend to persist over time (expansions tend to last longer than recessions) and a disturbance component (white noise) that allows for random shocks to alter the amplitude and the oscillation of business cycles as in Samuelson's equilibrium theory (1947) More modern interpretations reconcile the New Keynesianism and the new synthesis. The effects of the boom or bust are then dispersed across the economy through propagation mechanisms. A reevaluation of the Austrian theory of economics came with the stagflation of the 70's brought by the exogenous oil shocks and the subsequent 'Volckerian' monetary tightening policy. In this neoclassical interpretation, deflationary periods have vanished from the business cycle (this of course had been refuted by Japan's central bank's experience in dealing with a nearly 3 decade long deflation, which between 1991 and 2001 came to be known as the "lost decade").

The Keynesian school of economics is based on the assumption that demand drives supply. A market economy is incapable of regulating itself in times of depressions, and therefore government intervention is necessary. To maintain a certain level of aggregate demand, measures must be taken by a centralized monetary authority to stimulate demand with a set of monetary transmission mechanisms such as interest rates, currency devaluations, asset purchasing programs. Roosevelt's "New Deal" is a classic example of policy measures taken to counteract the effects of the great depression by initiating infrastructure projects, subsidization of housing and the creation of the FDIC[1] to make sure that banks have liquidity to cover periods of heightened deposit outflows. This, of course, follows the Keynesian model.

Fluctuation of investment is the key driver in business cycles and profits. Savings adjust to investment, which is the driving variable. Savings, therefore, fluctuate as a response to investment demand. The Keynesians assume a feedback loop of investment and consumption that underlies every business cycle. Investment has a multiplier effect on income, which accelerates investment (Keynes, 1936). The effect on the business cycle is magnified through the acceleration principle. In growth cycles companies overinvest, while in recessions they underinvest. The role of the government is to stabilize the economy by closing the gap. According to classical theory, the investment variable is substituted by interest rates. The substitution is a subject of research of Friedman's "A monetary History of the United States" (Friedman, 1963).

A counter to the Keynesians came with Friedman's monetary theory which argues that increases in the money supply cause fluctuations of aggregate demand from its natural rate – this is the driving force of booms and busts. Following the low inflation and low unemployment policy, central banks can control interest rates and initiate asset purchasing programs with the objective of stimulating demand in the economy. The artificially induced credit flow causes malinvestment and misallocation of capital, whereby consumers shift demand forward in time, allocating capital to immediate consumption in favor of saving. Firms, in response to favorable rates invest in production and bet on the materialization of larger consumer demand in the future. Because the immediate aggregate supply is unable to meet the increased demand from consumers, the result is a change in the price of goods and services. An increase in consumer spending leads to increases in income (a positive reinforcement loop called the wage price spiral) and hence there exists a lag between the rate of change of the quantity of money and economic output. Compared to earlier theories, Friedman's model suggests that credit fluctuations arise outside the business sector and are the main drivers of booms and busts

[1] Federal Depository Insurance corporation

(Montgomery, et al, 1998. p-48). Proponents of the Monetarist theory of the business cycle suggest the separation of the central monetary authority (the central bank) from government. An autonomous central bank has long been the key focus of monetarists. However, given the interdependence of modern central banks with the European monetary institutions and the role the US Dollar and Euro play as world reserve currencies, a centralized decision making entity and the reliance on exchange rate mechanisms inevitably links government and central banks. The increase in the output of the economy, in defiance of classical Austrian economics, recessions have become shorter and more frequent, therefore their timely prediction is a matter of urgency. The theory of efficient markets is a contra to New-Keynesianism, which assumes markets are imperfect and therefore are inefficient – that is how sticky wages are explained and the slow adjustment mechanism.

It is important to distinguish economic deceleration from recessions. Decelerations are regarded as below average growth rates of the economy – an anticipated occurrence indicated by above average unemployment, inflation and interest rates. The effects of slow growth are primarily reflected in the housing and equity markets, where, as a result of increasing interest rates a rotation occurs from stocks into safe haven high-yield securities, such as corporate and government bonds (particularly short-term bonds), and home sales decline due to mortgages becoming more expensive. But it is also possible for slow growth rates to be a part of an upswing, which is the result of pent up demand slowly soaking up liquidity. Modern central banks use Keynesian and new monetary principles, that even include environmental consciousness to address the gap between the government's output and the private industry's output.

While the individual explanatory effect of Keynesian or monetarist schools on business cycles diminishes, Mitchell also settled debate on the extent of the influence of exogenous (natural cataclysms, political crises, wars) and endogenous factors (interest rates, unemployment, expenditures, productivity) on the business cycles.

Economic indicator dynamics follow a well-recognized pattern in business cycles. Cycle peaks can be characterized, for instance, by the convergence of short and long-term interest rates, the rise in labor costs relative to output. At cycle peaks the labor force is usually near or at total employment (conversely, unemployment is very low). Prior to busts corporate profits after taxes decline, and consumer sentiment (also regarded as the consumer confidence index) - a concept introduced by Friedman's (1957) permanent income hypothesis and later verified in Mueller's (1963) research – declines as well, indicating a recession in the future. On modern markets obvious changes can be noticed as well, for example a steepening, and eventually, an inverted yield curve (on government bonds), rise of non-performing-loans, currency devaluations.

The GDP and GNP coincident indicator time series have long been prominent measures of the performance of the economy. While lagging indicators such as inflation and the unemployment are monitored closely together with the GNP, the calculation methods and measurements of these economic time series have changed over the years – this aspect is rarely considered in modern works about business cycle forecasting. Modern researchers are therefore not only faced with the problem of the credibility of current government data, but also with the reliability of past data. By imposing current volatilities on historic data, (Kuznets, 1961) was able to determine that in fact the claim that post-war expansionary periods last longer, while recessions are shorter but deeper. NBER[2] research points out that while the total duration of business cycles hadn't changed over time, their phases have. According to measurements by Balke and Gordon (1986), the proportion of time a business cycle is in a state of contraction averages only 20%, compared to 40% between 1850-1940. By 2006 the consensus remained the same with Zarnowitz's and Ozyildirim's business cycle phase average trend analysis (2006). However, the attention had shifted from business cycles to growth cycle analysis. Provided that not all slowdowns end in recessions, it follows that growth cycles outweigh business cycles both in frequency and potential severity. Arguably a long economic slowdown (below-trend growth) might result in greater collateral damage than a short recession. Economic slowdowns happen prior to and after recessions, but a slowdown of economic growth might not necessarily lead to a recession. Using a set of simple time series decomposition

[2] National Bureau of Economic Research

models Zarnowitz extracts the growth component of the business cycle and proves quantitatively that there is a difference between a recession and an economic slowdown.

It is true that information gathering techniques have changed over time. The value of an indicator calculated nowadays would likely differ from the value of the same indicator calculated twenty or thirty years ago. A limit on the availability of data is also imposed by the fact that economic measurement in Hungary is a relatively new science, since the market economy is barely 30 years old.

The current work is based on neo-Keynesian principles augmented with the rational expectation hypothesis. We believe that whilst a case can be made for the convergence of neo-Keynesian and neo-classical principals into a “new synthesis” school of economics in modern governing monetary institutions, it is certainly advantageous to discuss the potential of forecasting business cycles within a neo-Keynesian framework. It is employed by the National bank of Hungary as stated by Lentner (2017). Lentner further highlights that what was a nearly two-decade experiment in Hungarian neo-liberal economics under loose private bank regulations, removal of exchange rate restrictions, and austerity packages such as the “Bokros package” had ultimately failed with the onset of the 2008 GFC[3]. Deemed to be unfit to the social construct of Hungary, neo-liberalism had faded from Hungarian economic thinking in favor of a shift of banking and finances from the private to the government sector. Therefore, given that under government supervision and regulation the negative effects of financial crises can be dampened through a coordinated monetary and fiscal policy, it follows that it lies within the responsibilities of the central bank to estimate probabilities of future recessions using a wide spectrum of methodologies. Pursuing these goals this research aims to provide a quantitative estimation of recessions for the Hungarian economy backed by economic theory and statistical evidence.

The rest of the work is structured in the following way: Section 2 provides a literature review of the forecasting methodologies (further details are in Section 3) employed in this

[3] Great Financial Crisis 2008-2009

study, together with recent evidence in the application of these methodologies by the central bank of Hungary. In section 3 we introduce and compare VAR, regime switching and Bayesian models. Section 4 and 5 provide a platform for discussion and summary.

### 1.2. Current dynamics of Hungarian economic indicators. How the MNB's neo-liberal policy promotes secular growth.

The reasoning for the inclusion of unemployment as a determinant coincident indicator in the panel data is primarily based on the role it plays in every central bank's agenda (usually it includes price stability and maximum employment) and its connection with inflation, which was originally defined through the Phillips curve (Phillips, 1958). Given a predictable inflation target (globally it is established at 2%, the Hungarian central bank establishes it at 3% (MNB, 2023)) that grows at a stable rate of $\pi^e$, wages adjust gradually with the labor market reaching the unemployment rate that approaches $U^N$(long-run Philips curve). However, if there is an unanticipated rise in aggregate demand (as a result of a low-interest rate policy for example), the inflation rate rises above the $\pi^e$ target. With the additional revenue firms realize from the sale of goods and services they are able to hire more employees resulting in a reduction of the unemployment rate (short-run Phillips curve). Friedman and Phelps argue that in the long run the Phillips curve represents economic realities. Recent works in the Philips curve theory suggests that modern inflation expectations are anchored around the targets set by central banks $\pi = \pi^e$ , in other words, in the long term the deviations of the observed inflation converge to the expectations set by the market and monetary authorities. This implies that the modern Phillips curve is more accurate if the rate of change of inflation is considered instead of its level (Gordon, 2018; Blanchard, 2016). The unemployment rate is therefore not dependent on inflation in the long run.

In Hungary independent IMF-led studies point to systemic risks in the Alert Mechanism report. Strategic insights are provided by central decision makers, but often, they don't include sentiments of the public. The target policy rate is part of the monetary transmission mechanism employed by the MNB to achieve its stated goals of price stability and full employment. The rate is announced on an MNB decree upon on a monthly meeting of the Monetary council. There is a vast set of instruments the MNB utilizes to maintain liquidity and confidence in markets (further mentioned below), however the key policy rate only serves as the bottom of the interest rate corridor, and since it is updated only on a monthly or bi-monthly basis, usually the 3-month treasury bill (sometimes referred to as the Hungarian T-Bill) is used as a substitute, which according to Vonnák (2007) provides a broader picture of interest rate as well as inflation expectations. Interest rates convey little information on the probability of a recession because they are determined by the central bank as a reaction to unfavorable economic conditions. However, the speed at which interest rates change conveys a greater deal of information about the central banks' reaction to its previous attempts to stimulate or suppress aggregate demand. We are in search of anomalies – inconsistencies in monetary policy rates and short-term interest rate expectations of the market. For example, how can a risk premium on a 3 month BUBOR be lower than an overnight lending rate? At that pace, ceteris paribus, a consecutive reinvestment of the funds in an overnight instrument would yield higher returns than investing in an instrument with a 3-month maturity. This phenomenon is not explained by the expectation hypothesis[4] and can instead only characterized by the word "anomaly". Current trends suggest interbank interest rate volatility had stabilized with the increase of the frequency of issuance of quick tenders by the MNB, such as the 1 week discount bills Figure 1. Frequent issuance of one-week Discount T-bills drains reserves from commercial banks. The blue point indicates a year-on-year change of reserve requirements by the MNB. Figure 1.

[4] The Expectation hypothesis assumes that the shape of the yield curve depends on future short-term interest rate expectations. Long-term bond rates are a product of a consecutive acquisition of the short-term bonds. The MNB adopts this framework within its monetary transmission mechanism, therefore it is mentioned in this study. In a 2016 study the New York fed criticized the shortcomings of the hypothesis.

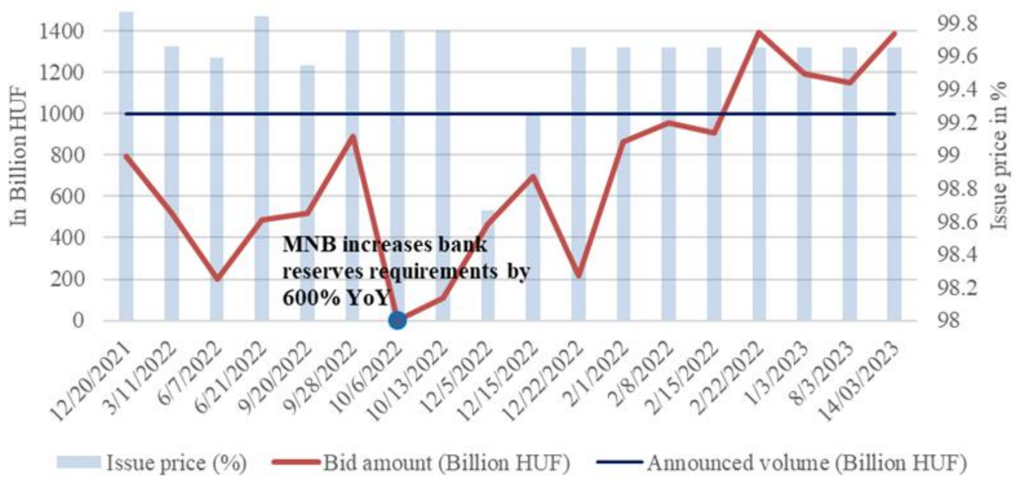



Figure 1. Frequent issuance of one-week Discount T-bills drains reserves from commercial banks. The blue point indicates a year-on-year change of reserve requirements by the MNB.

Source: Compiled by author (MNB, 2022)

Inflation is regarded as the general increase in the price of goods; however, it is also the increase in the broad money supply through the introduction of more fiat currency into the system. Inflation can also be expressed through the availability of credit, and therefore it is possible to establish a connection between interest rates and inflation. From a modern monetary theory perspective, inflation is a supply side problem. The MNB heavily stresses that Hungary is a small, open, export-oriented economy, and its central bank is in the Euro bank system. Therefore, the Hungarian economy is greatly affected by the adverse movements of the nominal effective exchange rate.

Repo markets like BIRS, BUBOR and HUFONIA are a measure of liquidity and speed of monetary transmission. The MNB absorbs and emits liquidity through controlling the short end of the yield curve. Repo markets, such as the HUFONIA allow commercial banks to borrow against collateral (usually long-term government bonds. Figure 2 shows the dynamics of the yield curve of financial instruments on the balance sheets of Hungarian commercial banks.

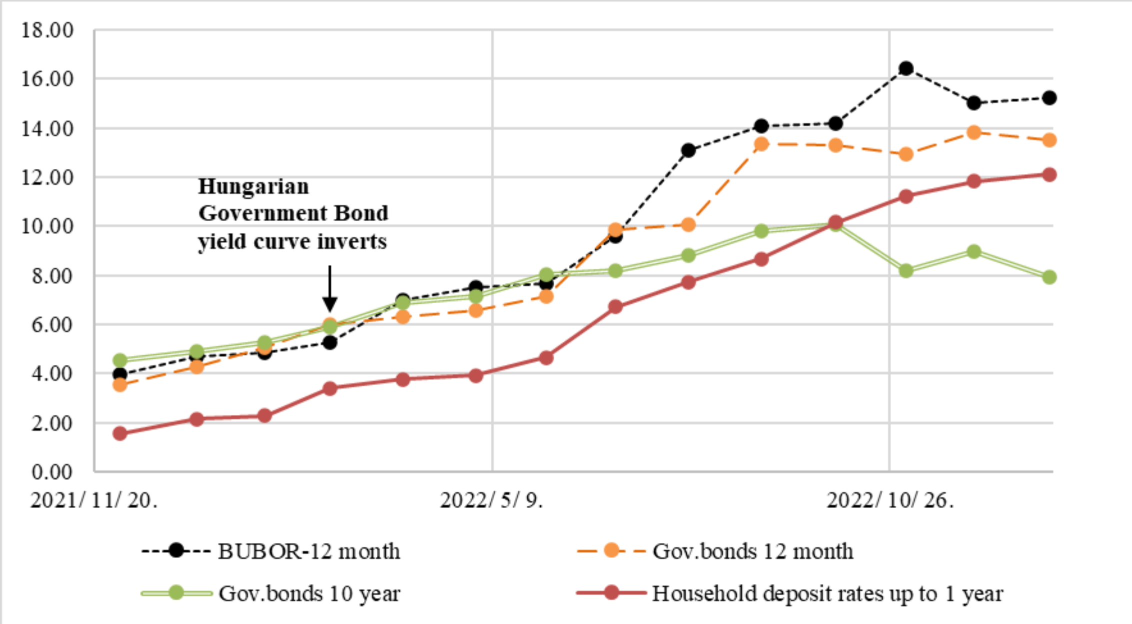



Figure 2. Hungarian financial market yields.

Source: MNB

The breach of the 10% minimum reserve requirement incurs a penalty equal to an interest payment of double the actual key policy rate. To further support liquidity in the markets and to ease the effects of sudden exchange rate spikes, the MNB issues one week discount bills paid par value at maturity. The non-interest bearing bonds allow excess reserves to earn interest and limit the amount of money available for lending pursuant to the MNB monetary policy. Non-interest bonds one-week discount bills accrue 18% at maturity.

More advanced financial derivatives such as credit default swaps that are traded on the open market provide a measure of investors' confidence in a firm or a country. Since investor confidence is inversely correlated to the premium paid on the swap (the higher the risk of default, the higher the interest rate of the swap), the rate of change of the swap's valuation would provide a useful insight in how default risk dynamics (it quantifies consumer sentiment in the framework of a security other than a stock market index) through a hedging instrument.

Short term T-bill and long term bond interest rates as a measure of policy rate expectations and future economic conditions according to Rezessy (2005). What are the implications of a widening yield gap between short and long term bonds? In the literature review section, we provide an answer to this question. The argument can be made that the government competes with the commercial banks for funds and outbids it on the short end of the curve by at least 150 basis points, attracting more funds from credit institutions.

To counteract the effects of heteroskedasticity, and to limit the extreme fluctuations of data, instead of a classical percentage change, we employ a log change method as a part of data normalization.

### 1.3. The BUBOR and EURIBOR interbank rates. Does the MNB harmonize its policy with the ECB?

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 3.

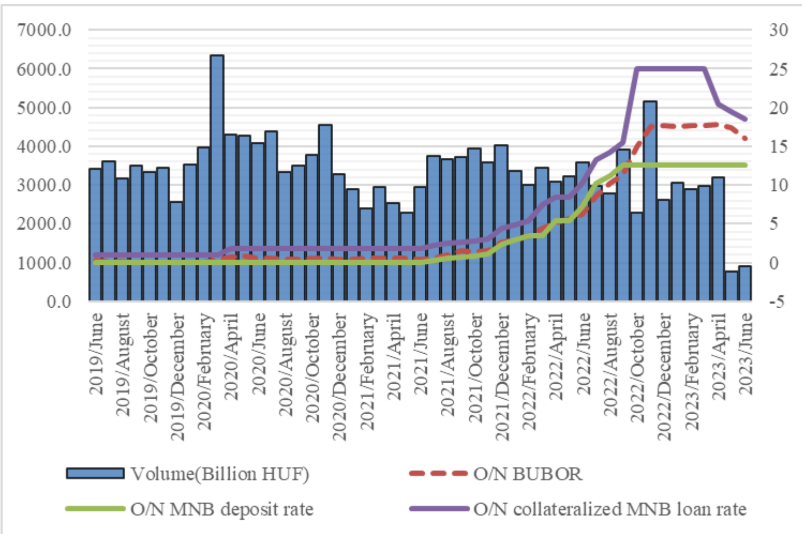



Figure 3. The interest rate corridor of the MNB (2019-2023). Compiled by author.

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 4). 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.

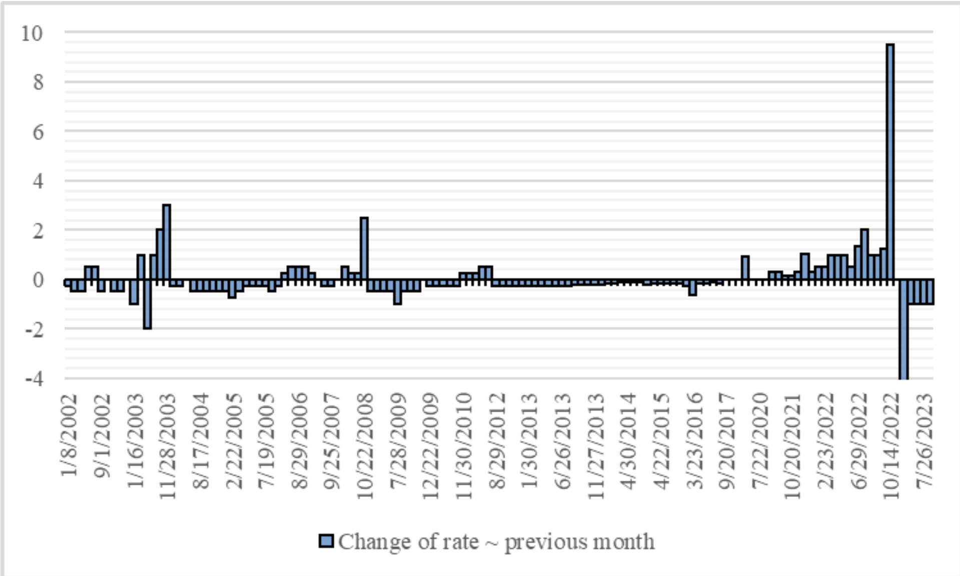



Figure 4. Rate of change of MNB the policy rate (Y -axis = current value/previous*100%). Compiled by Author.

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 4 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.

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 the number of 5. On the other hand, there is a significant difference between the speed at which rates were increased in Hungary versus in the Eurozone (Figure 5).

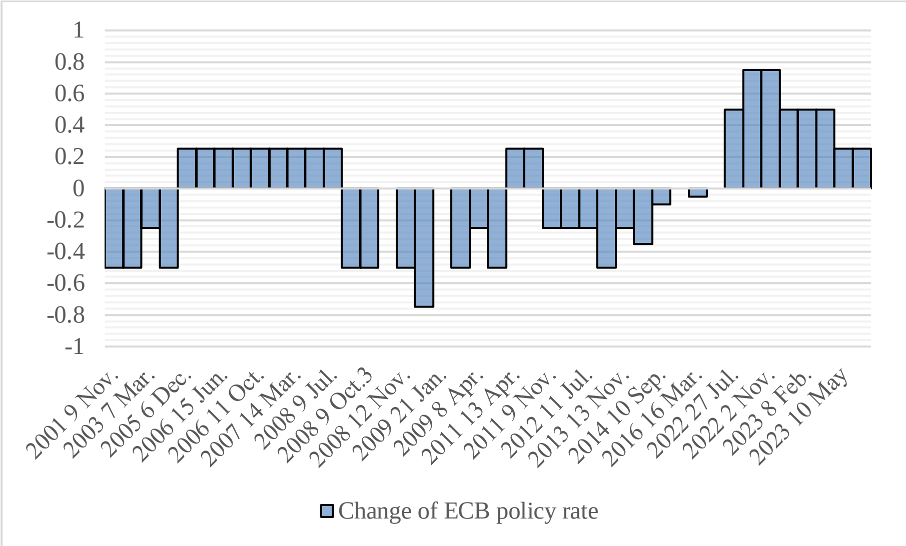



Figure 5. Rate of change of the ECB policy rate (Y-axis = current value/previous*100%). Compiled by Author.

Source: ECB

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 6, the ECB started the rate hiking cycle at a later time than Hungary.

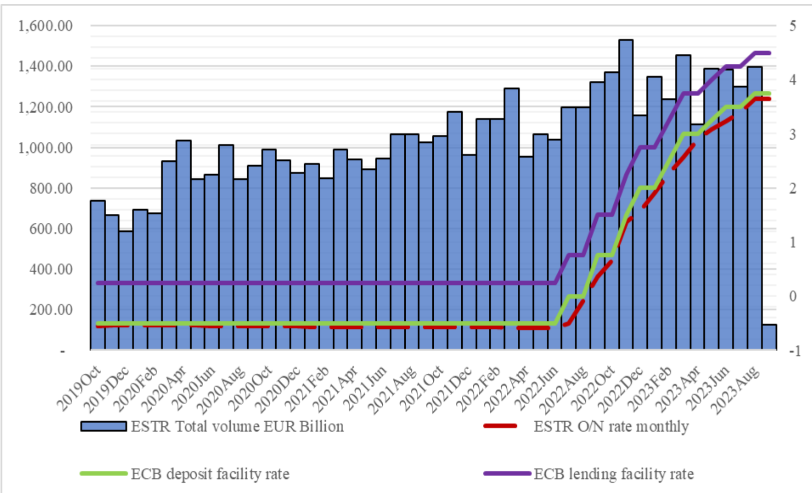



Figure 6. The ECB interest rate corridor. Compiled by author.

Source: ECB

### 1.4. Borrowing conditions in times of market stress

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 7 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 7 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.

(a) (b)

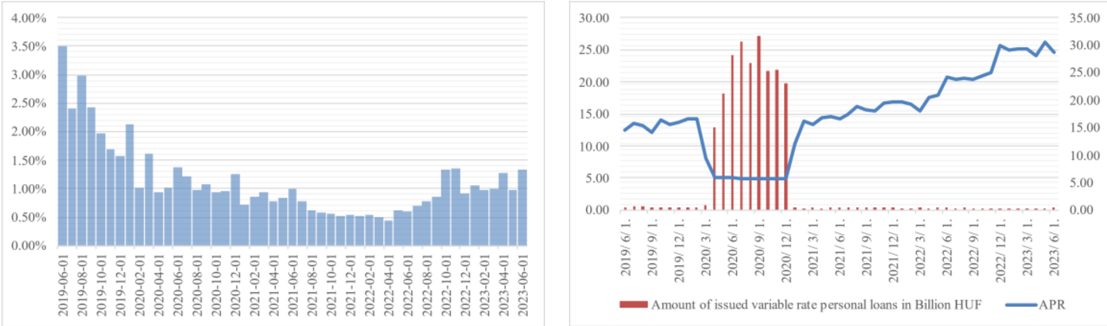



Figure 7. (a) Percentage of Hungarian variable rate mortgage loan from total mortgage loans. Compiled by author. Source: MNB. (b) Value of variable rate consumer loans issued each month (L-HS), interest rate on those loans (R-HS). Compiled by author.

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. 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.

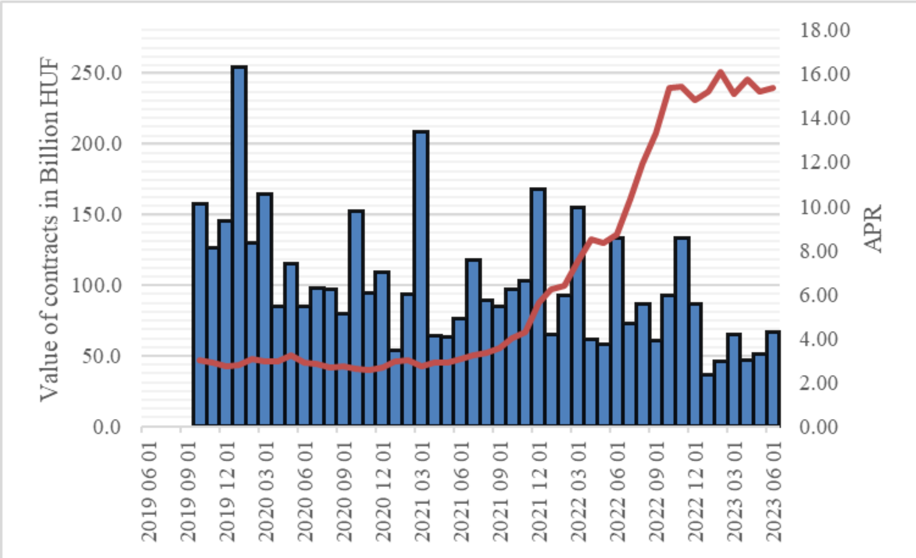



Figure 8. Value of monthly loan contracts originated for non-banking business sector (L-HS) and the interest rate (R-HS). Compiled by author. Source: MNB

## 2. THE LITERATURE REVIEW OF FORECASTING METHODOLOGIES

### 2.1. A brief review of Dynamic Stochastic General Equilibrium models and the MAPE metric to estimate forecasting performance

The MNB has limited capability and expertise when it comes to forecasting Hungarian business cycles. The monetary transmission mechanisms prior to a recession communicate a low incentive for banks to fund lending in the interbank market from deposit proceeds.

A recent study by the Hungarian central statistical agency employs the dynamic stochastic general equilibrium model (DSGE) to forecast the movement of economic variables in the near future. The performance of the model is estimated by comparing it to conventional ARIMA and VAR forecasts. The Hungarian economic research community had turned its attention to the application of the DSGE model following the New York Fed’s 7 year log experience (since 2011) in forecasting economic time series using the DSGE. By measuring the Mean Average Percentage Error (MAPE) between the actual time series and the forecasts (using the DSGE, ARIMA and VAR techniques), Mellár

(2005) concludes that while there are some larger MAPE deviations between the models at greater forecast horizons, in general, the DSGE model is more accurate specifically for short term forecasts (up to 1-2 quarters) due to a comparatively low MAPE. The novelty of the approach is threefold. First, instead of using existing models and testing them on Hungarian data and then trying to predict them using vector autoregressive processes, Mellár proposes building a linear regression within the Hodrick-Prescott filter using multiple specifications (for example the Cobb-Douglas specification for the supply block) adjusted to Hungarian economic realities. This approach allows us to eliminate any methodological constraints inherent to each one of the specifications. The second novelty lies within the methodology itself. Dynamic stochastic general equilibrium models often yield more accurate forecasts than Bayesian vector autoregressive models. Since Mellár's model isn't limited to one single specification, it can gain advantages of its building block (the error correction model, for instance, doesn't require the underlying time series to be stationary, and it captures long run autocorrelations between lagged components of the time series). Thirdly, there are very few studies that start investigations by first stating axioms. It is a most appropriate and a welcoming approach, the advantages of which materialize in a transparent model and a straightforward interpretation of results together with the possibility of tweaking the components of the model. While some of the axioms presented in the introduction are still a subject of research and economic debate, such as the idea of representing the relationship between prices and wages through the short-run Phillips curve, they provide adequate theoretical constraints. The MAPE metric might not be a suitable estimate of the accuracy of the model due to some of its limitations revealed through the comparison of forecasts versus actual time series values, namely: 1) when values are close to zero, for example in demand forecasting, the output of MAPE is undefined; 2) MAPE overweighs negative errors (modified APE is asymmetric compared to APE); and 3) obscures results in case of a small sample. Alternatively, data scientists commonly utilize weighted MAPE, Scaled MAPE Mean Absolute Scaled Errors, a log accuracy ratio (ratio of forecasted to actual values), Root Mean Square Error (RMSE). The RMSE metric is in fact the industry standard for ARIMA forecasting performance measurement. It is also worth pointing out the inadequacy of using outdated forecasting techniques, such as ARIMA and VAR. SARIMAX specifications add seasonality and exogenous components into the model, thereby capturing the seasonal effects that might occur in demand or consumption. Contemporary studies employ more advanced estimation techniques such as a maximum likelihood function (Szilágyi, et al., 2013), machine learning algorithms such as the Long-term, short-term (LTST) memory technique.

### 2.2. Experience in the application of Markov regime switching models.

Nelson and Plosser (1982) and Campbell and Mankiw (1987) dtudied ARMA models, which have been used as tine series forecasting tools – with the Hodirck-Prescott filter, it was possible to give an estimation of possible innovations of the GDP. Simultaneously, a cointegration approach of Granger (1969, 1987) developed a cointegration method to see if the lagged values of a time series are useful in predicting the future values of the reference series.

Goldfeld and Quandt (1973) first applied the regime witching model, as they saw that the time series behavior depends on the changes in the economy's business cycle. Hamilton (1989) used Neftçi's (1984) model, where the two regimes are charataraized by a two-state first-order Markov model. Since the model is first – order, this means that the switch is dependent on previous state. This is a short memory model.

Markov models have been applied to German, American and Polish time series so far. There is little evidence of their application for Hungarian economic time series. Bandholz (2005), Siničáková (2017), are some of the papers where the Markov model was applied for time series of developing countries. Artis (2004) and Darvas and Szapáry (2008) measure synchronization by applying the Hodrick-Prescott filter. Developing countries have regimes switches at different times. This is obvious, since the economies of the European Union are heterogeneous. In CEEC the Markov switch was also used to analyze the regime switches in stock markets, like in Moore and Wang (2007), Linne (2002) and Krolzig's (1999). What determined the switch was the volatility in the indexes. Higher volatility meant crisis, and low volatility meant growh and stability. More recent works include Balcilar et. al (2015) and Bilgili et. al (2020). In these works the authors analyzed the impacts of globalization. Some other notable applications of Markov regime switching models can be found in Hoque et. al (2019), where the authors investigated how a change in economic policy drives regime changes in the stock market. The GDP of the countries often doesn't follow the Euro area secular growth cycle. Moore and Wang (2007) found that in Hungary there was a long period of high volatility in the stock market (interpreted as secular decline), and when Hungary joined in the European Union, the volatility decreased – a hallmark of growth and stability. There is no clear observable simoultaneous growth both in EU and periphery countries.

Petreski's (2011) studies inflation policies Hungary and the Czech Republic and how they impact exchange rates. Kuan (2002) and Balanchard and Quah (2002) use a bivariate regression in the Markov model to estimate supply and demand shocks. As for Asian countries, for example Taiwan Chen et. al. (2000) used consumption expenditure, gross capital formation and real exports to estimate the regime changes and the inflection points. A powerful indicator is the sovereign government bond yield curve. Dueker (1997) argued that if the slope of the curve is positive – a stability and prosperity ensues, when the curve inverts, that is the short duration bonds yield more than long duration bonds, a crisis ensues. The inflection point is therefore the slope of the cure. Historically yueld curve inversions predicted all of the recessions in the US. Economic decline is characterized by smaller returns after a significant bull market, low sales, high employment, a period of very low interest rates. Estrella and Hardouvelis (1991) fuse the yield curve inversion as a result of monetary policy.

In the study of Hamilton and Kim (2002), the yield curve is a strong predictor of GDP. We therefore included it in our model as will be outlined by the subsequent chapters. Plosser and Rouwenhorst (1994) studied german time series and found that arbitrage and spreads are powerful predictors of the Gross Domestic Product. We follow Diebold and Rudebusch (1996) and Chauvet's (1998) methodology.

### 2.3. Spillover analysis with a VAR model

Part of 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) hinder 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 bank's 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 BTFP[5] (Bank Term funding program). As of writing this paper,

[5] 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 s, Agency Securities, Merchant Marine Bonds) via 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.

liquidity 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 determenistic components is:

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t = A Y_{t-1}^{t-p} + u_t$$

$A = [A_1 : \ldots : A_p]$ - these are $K * K$ coefficient matrices, $Y_{t-1}^{t-p} = (y'_{t-1}, \ldots, y'_{t-p})'$ and $u\_t = (u_1 t, \ldots, y_{Kt})'$ 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 $A(L) = I_K - A_1 L - \ldots - A_p L^p$ is a matrix polynomial in the lag operator of order $p$. In terms of the lag operator: $1 - A_1 L - A_2 L^2 - \ldots - A_p L^p)\, y_p = u_t$. Using the moving average representation $y_t = \infty \sum_{i=0}^{\infty} A^i L^i u_t$

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 $\det(I_K - A_1 z - \cdots - A_p z^p) \neq 0$ 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 $\delta y_t = \Pi y_{t-1} + \Gamma_1 \delta y_{t-1} + \cdots + \Gamma_{p-1} \delta y_{t-p+1} + u_t = \Pi y_{t-1} + \Gamma \Delta Y_{t-1}^{t-p+1} + u_T$.

$\Pi = -(I_K - A_1 - \ldots - A_p), \Gamma_i = -(A_i + 1 + \ldots + A_p)(i = 1, \ldots, p-1), \Gamma = [\Gamma_1 : \ldots : \Gamma_{p-1}], \Delta Y_{t-1}^{t-p+1} = Y_{t-1}^{t-p+1} - Y_{t-2}^{t-p+1}$. Because $\Delta Y$ 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 $\mu_t = \mu_0 + \mu_1 t$) and $x_t$ is a stochastic process ($x_t = A_1 x_{t-1} + \ldots + A_p x_{t-p} + u_t$) 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 $\phi_o = I_K$ and $\phi_j's = 1,2,..)$ are $K * K$ coefficient matrices. The elements of $\phi_j$ represent responses to $u_t$ forecast errors. For Stationary processes $\phi_j \to 0$ as $j \to \infty$ , therefore the impulse is transitory. Because $\Sigma_u$ 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 $y_t = \sum_{j=0}^{\infty} \phi_j P P^{-1} u_{t-j}$ .

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 erros, 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 $y_t = \Phi_i X_{t-1} + e_t$ , 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.

# 3. THE TWO-PART METHODOLOGICAL FRAMEWORK

We divide the methodology into two parts: the first part concerns the mathematics behind regime changes of a Markov process, and the second part concerns the measurement of spillover effects with a VAR model. To unify the very different outcomes of the two methodological frameworks, we propose an economic theory on macroeconomic imbalances.

Univariate ARIMA models don't take into account regime switches of the endogenous variable, so they likely produce incorrect results. We opt of a bivariate model to determine if Hungarian macro time series predict the GDP growth. The indicators in question are 1. unemployment rate, 2. inflation, 3. industrial production index, 4. BUX composite stock market quarterly returns and 5. 10-3-year yield spreads of Hungarian sovereign bonds. If we estimate the hidden Markov model, it would be possible to explain the changes in the GDP with the dynamics of the underlying indicators. We built the model in Python and the code source will be provided in the subsequent chapters.

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 lacks 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. 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. We built the model in R.

### 3.1. Multivariate Markov regime-switching model

The works of Hamilton (1994), Kim and Nelson (1999) provide a comptrehensive algorithm for building the Markov model. Perlin (2015) created a MATLAB package so we can actually implement it without indulging into the inticacies of the model. We used Hamilton's (1989) notation further on.

How can a Markov model be applied to a real-life data set?

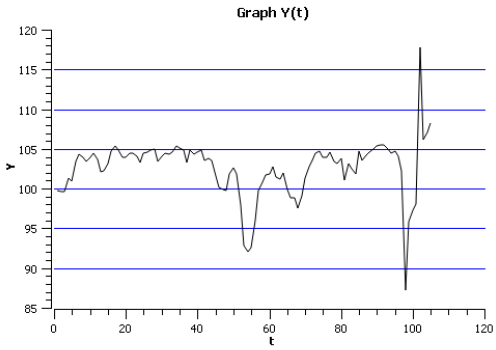



Figure 9. Hungarian GDP rate of growth – same period of last year in % - y(t), instead of dates in t I used just an arbitrary serial number. Source: compiled by author

First of all, consider the above graph shows. It shows times of positive and negative growth – recessions and expansions.

Our postulates are the following:

(i) an unknown process affects the behavior of an underlying indicator, so the time series moves between two regimes, and it is impossible to model the entire time series without considering the regimes.

(ii) (ii) Suppose there are two regimes in the Hungarian economy, 1 and 2, growth and decline.

(iii) Each indicator is shown in a two-state model with a maximum likelihood estimation function.

(iv) We can increase the accuracy of the maximum likelihood function if we include exogenous variables.

(v) We suppose that when there is a regime change in the GDP explanatory variable, simultaneously, there is a regime change in OECD countries.

If we find the turning points, we ewill have found the moments where recessions occur. There is the random variable y(t), which we observe (GDP), and a hidden random variable m(t) (IPI, U, Inflation, BUX) that changes the regime of the GDP. A change in *m(t)* impacts the mean and variance of *y(t)*. Hence, a hidden Markov model.

Consider that *m(t)* switches between states 1 and 2. *m(t)* is the hidden part of the model, because we do not know what state the system is in at time t. This is a generalization of the Bernouilli scheme.

The state transition probability matrix is of form:

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}, \tag{1}$$

where $p_{11}$ – is the probability of transition from state *1* to the same state *1*. $p_{11}$ equals to the conditional probability that event $m(t+1)=1$ will occur at $t+1$ if at the moment $t$ event $m(t)=1$ has occurred. This doesn't depend on past events.: $p_{11}=P(m(t+1)=1|m(t)=1)$. For other probabilities: $p_{12}=P(m(t+1)=1|m(t)=2)$, $p_{21}=P(m(t+1)=2|m(t)=1)$, $p_{22}=P(m(t+1)=2|m(t)=2)$. The following unity is always in effect: $p_{11}+p_{12}=1$, and $p_{21}+p_{22}=1$. In other terms expressed as:

$$P = \begin{bmatrix} p_{11} & 1-p_{11} \\ 1-p_{22} & p_{22} \end{bmatrix}, \tag{2}$$

We just need to know $p_{11}$ and $p_{22}$. The random variable *m(t)* depends on 1 or 2. The probability distribution at time t is a two-component vector *D(t)* with components: $d_1(t)$ – probability of state *1*, and $d_2(t)$ – the probability of state 2. We can express it as such.

$$D(t) = \begin{bmatrix} d_1(t) \\ d_2(t) \end{bmatrix} = \begin{bmatrix} P(m(t)=1) \\ P(m(t)=2) \end{bmatrix}. \tag{3}$$

Let's start with a prior probability distribution m(0), D(0). To calculate D(t) we multiply *P* with itself *t* number of times:

$$D(t) = D(0) \cdot P^t. \tag{4}$$

Let *y(t)* be an economic time series such that $x_i(t)$, $i=1,2,\ldots n$, it explains the variability of *y(t)*. The general linear regression model is such:

$$Y = X\theta + \varepsilon, \tag{5}$$

where $Y = \begin{bmatrix} y_1 \\ \vdots \\ y_p \end{bmatrix}$ is a vector of y(t) values at different time, so that $y_1=y(t_1),\dots,y_p=y(t_p)$, $X = \begin{bmatrix} 1\ x_{11} \dots x_{1n} \\ 1\ x_{21} \dots x_{2n} \\ \dots\ \dots\ \dots\ \dots \\ 1\ x_{p1} \dots x_{pn} \end{bmatrix}$ is matrix that contains the explanatory variables. For every $x_{ij}$ $i$ means the value of the point, while index $j$ is the value of the explanatory variable ($x_{11}=x_1(t_1)$, $x_{21}=x_1(t_2),\dots,x_{pn}=x_n(t_p)$), $\theta = \begin{bmatrix} \theta_0 \\ \vdots \\ \theta_n \end{bmatrix}$ the vector $\theta$ contains the coefficients of the linear model. We need to determine $\theta$. $\varepsilon = \begin{bmatrix} \varepsilon_0 \\ \vdots \\ \varepsilon_p \end{bmatrix}$ is the vector innovations with $\varepsilon \sim N(0, \sigma^2)$. $\varepsilon$ is homoscedastic.

The model is of the following form:

$$\begin{cases} Y = X\theta^1 + \varepsilon_1, when\ m = 1, \\ Y = X\theta^2 + \varepsilon_2, when\ m = 2. \end{cases} \tag{6}$$

Here $Y$ – is the vector of explanatory variables, $X$ – $n \times p$ matrix of explained variables, $\theta^m$ – is a vector of linear regression coefficients which corresponds to regime $m$ (here $m$ – is the index), and the random variables $\varepsilon_m \sim N(0, \sigma_m^2)$. For $t_i$ we can write

$$[1\ x_{i1} \dots x_{in}] \cdot \begin{bmatrix} \theta_0^1 & \theta_0^2 \\ \vdots & \vdots \\ \theta_n^1 & \theta_n^2 \end{bmatrix} = [y_i^1\ y_i^2],$$

$$\overline{y_i} = y_i^1 \cdot P(m = 1) + y_i^2 \cdot P(m = 2) \text{ or } \overline{y_i} = [y_i^1\ y_i^2] \cdot D(t_i), \text{where} \tag{7}$$

$$D(t_i) = \begin{bmatrix} P(m(t_i) = 1) \\ P(m(t_i) = 2) \end{bmatrix}.$$

The $\hat{\theta} = \begin{bmatrix} \theta_0^1 & \theta_0^2 \\ \vdots & \vdots \\ \theta_n^1 & \theta_n^2 \end{bmatrix}$ matrix of regression coefficients is estimated using the maximum likelihood function or Maximum Likelihood Estimation (MLE) method. MLE maximizes the joint probability density of observing the entire data set of y.

$$L = \prod_{i=1}^{p} f\big(y(t_i)\big).$$

Since $\varepsilon_m \sim N(0, \sigma_m^2)$ it is obvious and convenient to assume that

$$f\big(y(t_i)\big) = \frac{1}{\sigma\sqrt{2\pi}} \cdot e^{-\frac{1}{2}\left(\frac{y_i - \overline{y_i}}{\sigma}\right)^2}.$$

So, we get:

$$L\left(\sigma, \theta_l^k, P(m=1), P(m=2)\right) = \prod_{i=1}^{p} \frac{1}{\sigma\sqrt{2\pi}} \cdot e^{-\frac{1}{2}\left(\frac{y_i - \overline{y_i}}{\sigma}\right)^2}, \tag{8}$$

$$\overline{y_i} = y_i^1 \cdot P(m=1) + y_i^2 \cdot P(m=2), \tag{9}$$

$$y_i^1 = [1\ x_{i1} \dots x_{in}\ ] \cdot \begin{bmatrix} {\theta_0}^1 \\ \vdots \\ {\theta_n}^1 \end{bmatrix}, y_i^2 = [1\ x_{i1} \dots x_{in}\ ] \cdot \begin{bmatrix} {\theta_0}^2 \\ \vdots \\ {\theta_n}^2 \end{bmatrix}. \tag{10}$$

To obtain the estimated parameters we need to solve the below differential equations:

$$\begin{cases} \frac{\partial L}{\partial \sigma} = 0 \\ \frac{\partial L}{\partial \theta_l^1} = 0, l = 1, \dots, n \\ \frac{\partial L}{\partial \theta_l^2} = 0, l = 1, \dots, n \\ \frac{\partial L}{\partial P(m=1)} = 0 \\ \frac{\partial L}{\partial P(m=2)} = 0 \end{cases}. \tag{11}$$

To avoid notational clutter, we used the python library to get the results.

### 3.2. The DY 2012 spillover table

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

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

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 $\left(I - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p\right)y_t = \varepsilon_t$. Again, we can rewrite this as $\phi(L)y_t = \varepsilon_t$, where $\phi(L) = \left(I - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p\right)$.

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.

$$y_t = \theta(L)\varepsilon_t \tag{1.2}$$

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

What happens when the time series are not stationary, (I.e they contain a unit root[6]) 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 $\boldsymbol{\Phi}$, 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 $y_t, y_{t-1}, \ldots, y_{t-p+1}$ on a larger vector:

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

[6] 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.

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

$$\boldsymbol{Y_t} = \boldsymbol{\Phi Y_{t-1}} + \boldsymbol{\xi_t} \tag{2.2}$$

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

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

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

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 $\boldsymbol{\Phi}$, so the stability condition in 3.1 can be rewritten as

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

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

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

As $\boldsymbol{j} \to \infty$ , and as long as $|\boldsymbol{\Phi}| < 1$,[7] $\boldsymbol{\Phi}^{\boldsymbol{j+1}}\boldsymbol{Y}_{\boldsymbol{t}-(\boldsymbol{j}+\boldsymbol{1})}$ reduces to 0, so it can be ignored, and the above can be written succinctly as

$$\boldsymbol{Y_t} = \sum_{i=0}^{\infty} \boldsymbol{\Phi}_i \, \boldsymbol{\xi}_{t-i} \qquad (4.1)$$

Of course, the representation in (4.1) holds if the eigenvalues of $\boldsymbol{\Phi}_i$ have a modulus of less than 1.

In this representation $\boldsymbol{Y_t}$ is expressed in terms of past and present error or innovation vectors $\boldsymbol{\xi_t}$. This representation is more useful in determining the autocovariances of $\boldsymbol{Y_t}$. $\boldsymbol{\Phi}_0 = I_K$, and $\boldsymbol{\Phi}_i$ is obtained by making use of the relationship defined in (1.2),

$$I_K = \left(\phi_0 + \phi_1 L + \cdots + \phi_p L^p\right)(I_K - \Theta_1 L - \cdots - \Theta_p L^p) \qquad (5.1)$$

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

Expanding the brackets in (5.1) we obtain

$$I_K = \phi_0$$

$$0 = \phi_1 - \phi_0 \Theta_1$$

$$0 = \phi_2 - \phi_1 \Theta_1 - \phi_1 \Theta_2$$

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

Hence, $\phi_i$ are obtained recursively by

---

[7] If $|\boldsymbol{\Phi}| > 1$, as $j \to \infty$, so does $\boldsymbol{\Phi}^j \to \infty$, therefore it is not infinitely summable.

$$\phi_i = \sum_{j=1}^{i} \phi_{i-j}\theta_j \tag{5.2}$$

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 $t = i$, $y_i = (y_{1,i}, y_{2,i})' = \Phi_1^i y_0$. $\Phi_1^i$ 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 system[8]. 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 $\boldsymbol{Y_i} = \boldsymbol{\Phi^i Y_0}$. Let's turn to a two-dimensional VAR(1) form of (1.1). In a $MA(\infty)$ representation, the jk-th element of the system that is, $\Theta_i = J\,\Phi^i J'$, where $J = [I_K : 0 : \cdots : 0]$ is a $(K \times Kp)$ matrix. In

[8] If we assume stationarity and invertibility, any $VAR\ (p)$ can be represented as a $VAR(1)$ given by (2.2)

other words, $\Theta_{jk,i}$, the $jk$-th element of $\Theta_i$ 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 $\Sigma_\varepsilon$can be rewritten as a product of $\Sigma_\varepsilon = PP'$, where $P$ is a lower triangular nonsingular Cholesky matrix.

In any VAR model, $\phi_i$, $\Theta_j$ and $\Sigma$ 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.

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

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

$$y_t = \sum_{s=0}^{\infty} \Psi_s \, PP^{-1} \epsilon_{t-s} \tag{5.3}$$

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

The response to an orthogonalized shock is given by"

$$y_t = \sum_{s=0}^{\infty} \Psi_s \mathrm{PP}^{-1} \epsilon_{t-s} \tag{5.3}$$

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:

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

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 $\Sigma$ is the variance matrix for the vector of innovations $e$, $\sigma_{jj}$ 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:

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

The generalized total spillover index is of form

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

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.

# 4. DATA, DESCRIPTIVE STATISTICS AND COMMENTARY

## 4.1. Macroeconomic time series

To satisfy the objective of the first part of the research of estimating the business cycle, we collected the data from OECD quarterly national accounts, the IMF International Financial statistics database, the central statistical office of Hungary (KSH) as well as the Budapest stock exchange (BÉT) data warehouse. We used a binary 1,0 recession indicator calculated by the OECD web data warehouse. The data now has been discontinued. We follow Estrella and Mishkin’s (1998) indicators of economic activity and add unemployment, industrial production index, inflation rate and the Hungarian composite stock index. We also add the 10 year and 3 year government bond yield spreads. Table 1 provides the descriptive statistics.

Table 1. Descriptive statistics of selected Hungarian economic time series. Source: Own calculation. U- Unemployment rate (KSH), IPI – Industrial Production index(KSH), $\pi$- inflation (KSH), N.S BUX –

Non stationary BUX time series (BÉT), S.BUX – Stationary BUX (BÉT), 10Y-3M yield – difference between 10 year and three month government bonds (BÉT). Own compilation

| | GDP % | U | IPI | $\pi$ | N.S BUX | S. BUX | 10Y-3M yield |
|---|---|---|---|---|---|---|---|
| obs | 105 | 105 | 105 | 105 | 105 | 105 | 93 |
| mean | 2.60 | 7.02 | 5.10 | 6.21 | 20575.3 | 0.03 | 0.10 |
| std | 3.58 | 2.33 | 7.71 | 5.50 | 12523.2 | 0.07 | 1.42 |
| min | -12.8 | 3.3 | -22.9 | -1 | 2635.0 | -0.28 | -3.6 |
| max | 17.8 | 11.1 | 21.1 | 27.9 | 54197.7 | 0.32 | 2.3 |

The sample is between Q1-1996 and Q1-2022. The number of observations is 105. The 10-year and 3-year yield time series are slightly shorter from Q1-1999 to Q1-2022. McGrane (2022) argued that there exists a disconnect between unemployment cycles and cycles of credit in the economy. Unemployment is sticky, under Keynesian assumptions. However, for the sake of the research we disregard wage stickiness. Krolzig et. al (2000) used industrial production as an endogenous variable, which inspired us to include it in our model as well. Inflation is a direct result of money printing. To keep credit available in the economy, the monetary policy of Hungary engaged into a direction of easing interest rates and printing money. Because Bandholz (2005) used the composite stock market indicator, we included it in our model as well. Additionally, since more time has passed since his research, we think that the conclusions will be more relevant. The 10-year and 3-year Hungarian sovereign bond yield spreads converge just before a recession. We think it's an important indicator, so it is included in the model as well. The explained variable is the GDP. Figure 10 illustrates recessions in Hungary with grey bars.


Figure 10. GDP quarterly growth rate superimposed on OECD recession periods. Source: Own calculations (OECD)

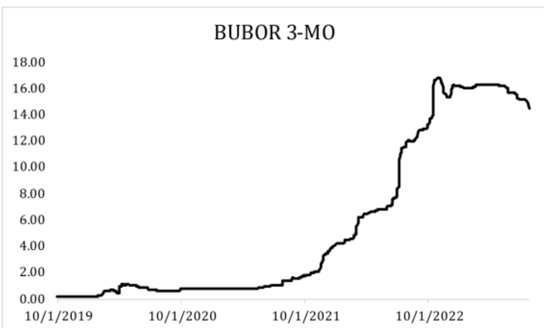
Further is a brief overview of the Hungarian economy between 1996 and 2022, as illustrated in Figure 10. From 1996 to 2022 there were 7 recessions in Hungary. The fiscal policy and the “Bokros” package allowed the MNB to avoid a default, but it did not help in avoiding a recession. In 1998 as sa result of a twin crisis coming from Asia and Russia, Hungary experienced a sharp decline in demand Foreign direct investment led to a boom, and a subsequent bust in 2001. The 2008 GFC was triggered by the collapse of the US housing market and a decline in the value of financial products. Hungary later received significant influxes of cash from the IMF and the EU. From 2012 until 2013 the eurozone experienced a debt crisis with PIGS countries unable to repay borrowed funds. This resulted in another round of bailouts. The mild recession of 2016 was attributable to low demand. The short sharp recession of 2020 was due to the Covid crisis and the lockdowns which followed.

We think that the indicators are selected objectively enough to test the methodology.

### 4.2. Financial time series

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 $t_1 - t_2$. Figure 11 - Figure 15 illustrate the time series together with the stationary counterparts.

(a)




(b)

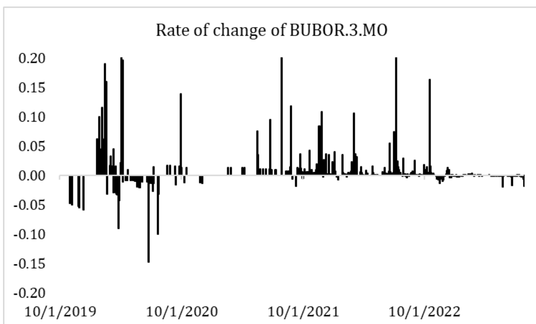
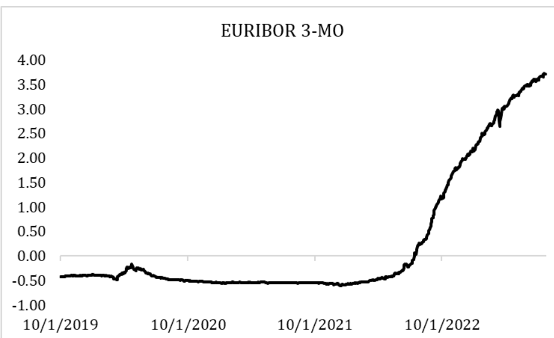


Figure 11. (a) 3-month BUBOR time series. Compiled by author. Source: BÉT. (b) I(1) difference of 3-month BUBOR time series (value at t – value at t_(-1)) Compiled by author. Source: BÉT.

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 were 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.

(a)




(b)

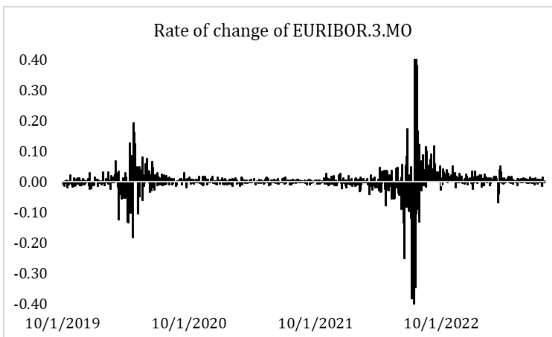


Figure 12. (a) 3-month EURIBOR time series. Compiled by author. Source: ECB. (b) I(1) difference of 3-month EURIBOR time series (value at t – value at t_(-1)) Compiled by author. Source: ECB.

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%.

(a) (b)

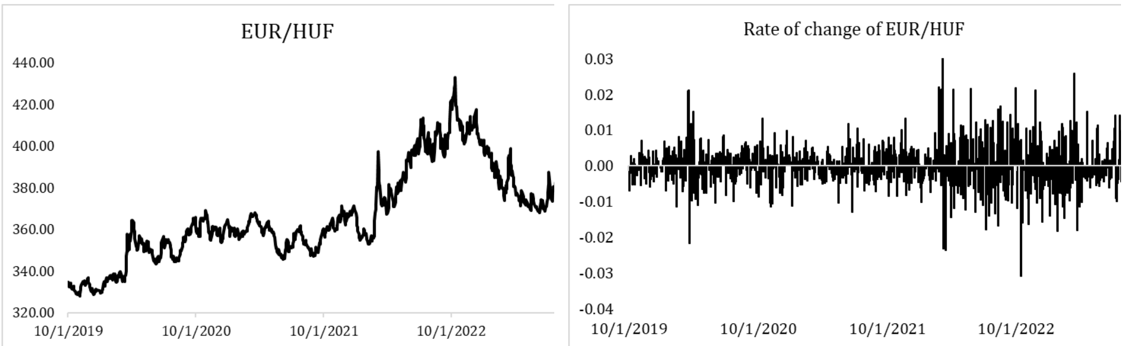
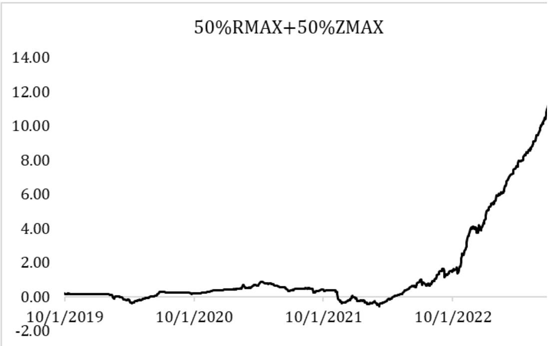



Figure 13. (a) EUR/HUF time series. Compiled by author. Source: MNB. (b) I(1) difference of EUR/HUF time series (value at t – value at $\boldsymbol{t_{-1}}$ ) Compiled by author. Source: MNB.

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.

(a)




(b)

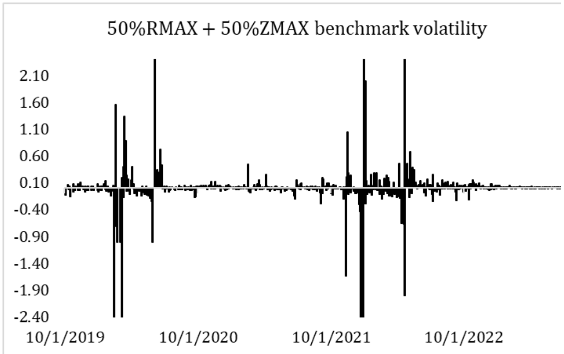
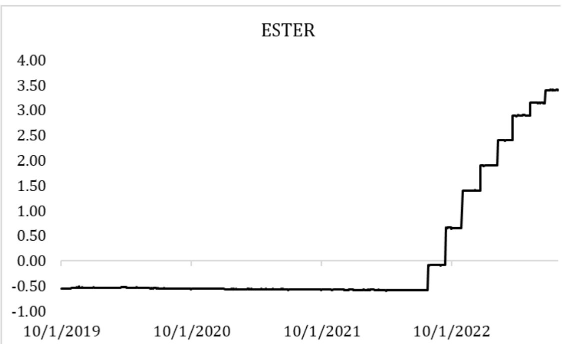



Figure 14. (a) 50%RMAX+50%ZMAX benchmark time series for OTP prémium pénzpiaci alap BBG ISIN code: HU0000712161. Compiled by author. Source: ÁKK. (b) I(1) difference of 50%RMAX+50%ZMAX time series (value at t – value at $t_{-1}$)) Compiled by author. Source: ÁKK

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)

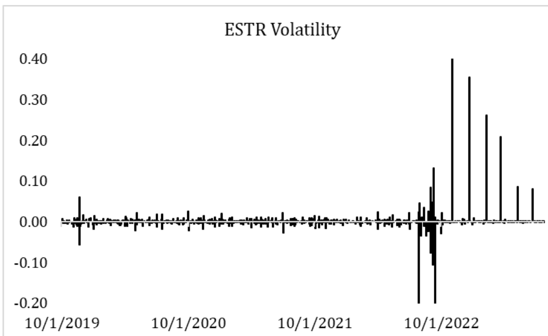


Figure 15. (a) Euro Short term rate (ESTER) time series. Compiled by author. Source: ECB. (b) I(1) difference of ESTER time series (value at t – value at $t_{-1}$)) Compiled by author. Source: ECB

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 2 summarizes the time series.

Table 2. 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.

| | *EUR/HUF* | *BUBOR 3-MO* | *EURIBOR 3-MO* | *50%RMAX+50%ZMAX* | *ESTER* |
|---|---|---|---|---|---|
| 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 the case of the EURIBOR rate, two major volatility periods are identifiable. First, like 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 3

Table 3. 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 |
| I(1) | Lag Order | 9 | 9 | 9 | 9 | 9 |

| | | | | | |
|---|---|---|---|---|---|
| P-value | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |

# 5. EVALUATION OF RESULTS

## 5.1. Comparison of the Hungarian business cycle determined by the OECD and our Markov regime switching model

Consider first the regime switches of the unemployment rate on its own. The statistics are in Table 4.

Table 4. Estimation of the Markov regime switching model. y(t) is the GDP variable, while m(t) is the unemployment rate. Source: Own calculations based on FRED and OECD data

| U | $\theta_0$ | $\theta_1$ | $\sigma^2$ | P>\|z\|$\theta_0$ | P>\|z\|$\theta_1$ | P>\|z\| $\sigma^2$ | $p_{11}$ | $p_{21}$ | AIC |
|---|---|---|---|---|---|---|---|---|---|
| Regime 1 | 6.24 | -0.33 | 0.58 | 0.00 | 0.00 | 0.00 | 0.926 | 0.098 | 441 |
| Regime 2 | 5.33 | -0.67 | 20.49 | 0.017 | 0.019 | 0.00 | | | |

Regime 1 and 2 models of the GDP as y(t) and the Unemployment rate m(t):

Regime 1: GDP %Change $= \ 6.24 - 0.33 Unemployment\ rate + 0.58$ ;

Regime 2: GDP %Change $= \ 5.33 - 0.67 Unemployment\ rate + 20.49$

The probability matrix is: $P = \begin{bmatrix} 0.9267 & 0.0733 \\ 0.0983 & 0.9017 \end{bmatrix}$, where the expected duration for regime 1 is 13.63 quarters, while the expected duration of regime 2 is 10.17 quarters.

The state probabilities D(t) at time t are below. Figure 3 illustrates a side by side comparison of the smoothed probability of recessions compared to actual recessions and The GDP %change in Figure 16 is superimposed to compare how the indicator we created performs.

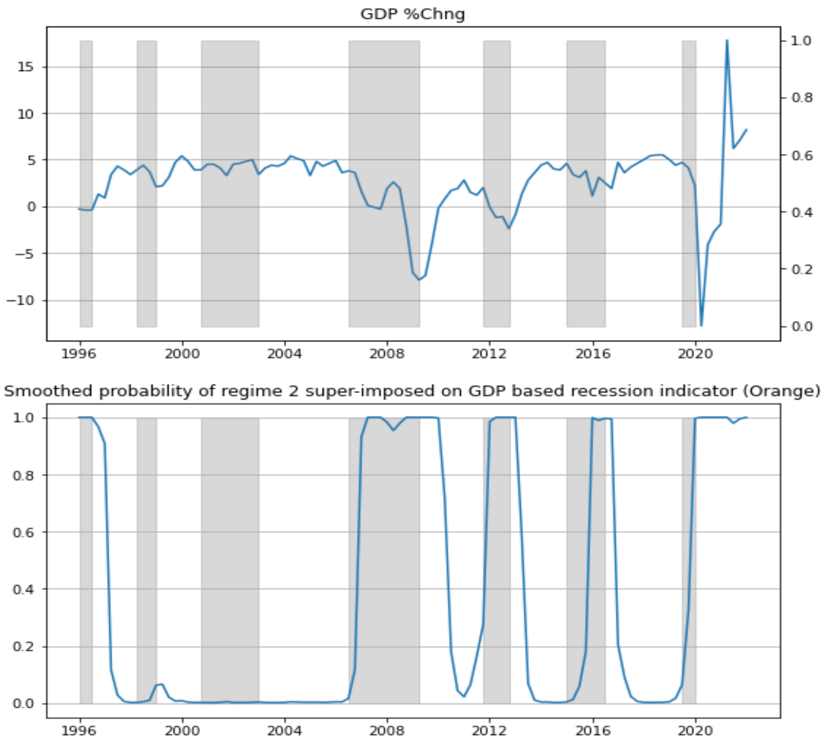



Figure 16. Smoothed probabilities of being in a recession superimposed on actual recessions determined by the OECD composite indicator obtained from FRED. Source: Own calculations

Let's substitute the consumer price index for the unemployment rate and see what the results will be.

Table 5. Estimation of the Markov regime switching model. y(t) is the GDP variable, while m(t) is the inflation rate time series. Source: Own calculations based on FRED and OECD data

| Inflation | $\theta_0$ | $\theta_1$ | $\sigma^2$ | P>\|z\|$\theta_0$ | P>\|z\|$\theta_1$ | P>\|z\| $\sigma^2$ | $p_{11}$ | $p_{21}$ | AIC |
|---|---|---|---|---|---|---|---|---|---|
| Regime 1 | 4.41 | -0.017 | 0.407 | 0.00 | 0.35 | 0.00 | 0.921 | 0.074 | 453.4 |
| Regime 2 | 0.40 | 0.031 | 19.60 | 0.67 | 0.767 | 0.00 | | | |

Below are the regression models for the two regimes:

Regime 1: GDP %Change $= \ 4.41 - 0.017 Inflation\ rate + 0.407$ ;

Regime 2: GDP %Change $= \ 0.40 + 0.031 Inflation\ rate + 19.60$

The P-matrix is: $P = \begin{bmatrix} 0.9206 & 0.0794 \\ 0.0748 & 0.9252 \end{bmatrix}$, We expect expansions to last 12.60 quarters, and expect that an average recession lasts 13.36 quarters.

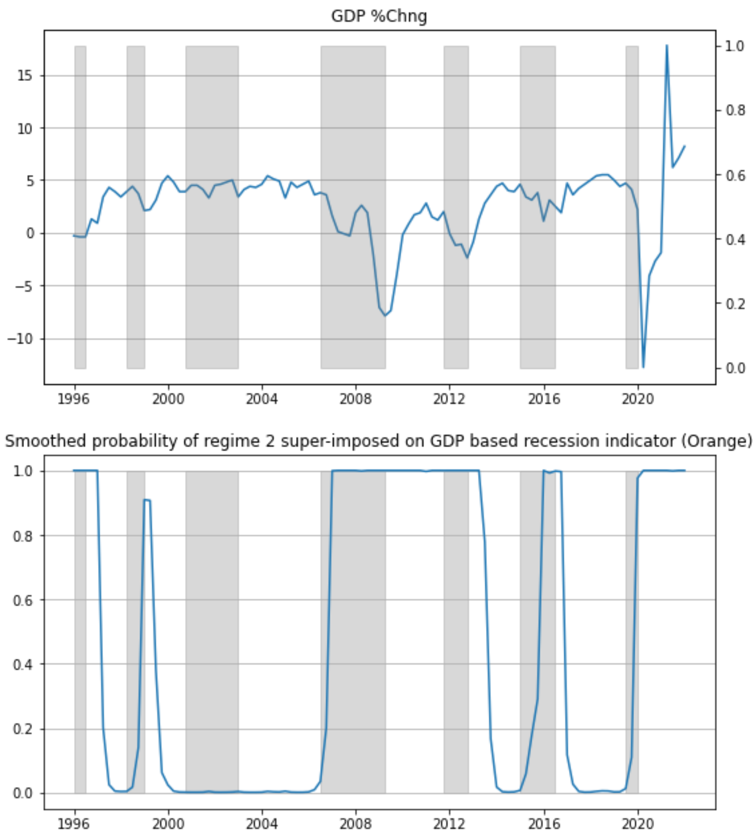



Figure 17. Smoothed probabilities of a recession, with inflation rate as the exogenous variable superimposed on actual recessions determined by the OECD composite indicator obtained from FRED. Source: Own calculations

The industrial production index is a useful measure of credit cycles, as when companies order and produce durable goods, they inevitably export it. As international trade balances tilt in favor of Hungary, more money flows in, which enhances credit creation.

Table 6. Estimation of the Markov regime switching model. y(t) is the GDP variable, while m(t) is the Industrial Production Index (IPI) time series. Source: Own calculations based on FRED and OECD data

| IPI | $\theta_0$ | $\theta_1$ | $\sigma^2$ | P>\|z\|$\theta_0$ | P>\|z\|$\theta_1$ | P>\|z\| $\sigma^2$ | $p_{11}$ | $p_{21}$ | AIC |
|---|---|---|---|---|---|---|---|---|---|
| Regime 1 | -0.44 | 0.286 | 1.159 | 0.309 | 0.00 | 0.00 | 0.936 | 0.042 | 495 |
| Regime 2 | 1.90 | 0.356 | 9.81 | 0.00 | 0.00 | 0.00 | | | |

Regime 1 and 2 models of the GDP as y(t) and the Industrial production index m(t): Regime 1: $\text{GDP \%Change} = -0.44 + 0.286IPI + 1.159$; Regime 2: $\text{GDP \%Change} = 1.90 + 0.356IPI + 9.81$

The P-matrix is: $P = \begin{bmatrix} 0.9359 & 0.0641 \\ 0.0421 & 0.9579 \end{bmatrix}$, in this model from 1996 to 2022, an average expansion lasts 15.61 quarters, and an average contraction is 23.73 quarters.

Figure 18 illustrates the smoothed recession probabilities with the industrial production index being the explaining variable m(t) of the GDP %Change.

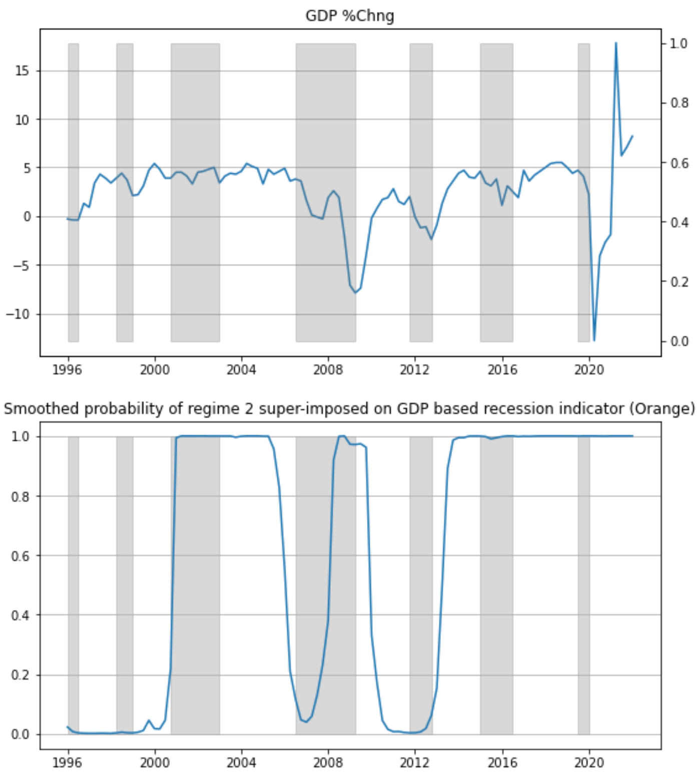



Figure 18. Smoothed probabilities of a recession, with Industrial production index (IPI) as the exogenous variable superimposed on actual recessions determined by the OECD composite indicator obtained from FRED. Source: Own calculations

A drop in the stock market often precedes a recession. Let's see how closely the regime changes of the BUX follow the OECD baseline credit cycle history of Hungary.

Table 7. Table 8 Estimation of the Markov regime switching model. y(t) is the GDP variable, while m(t) is the BUX year-on-year percentage change time series. Source: Own calculations based on FRED and OECD data

| BUX YoY% | $\theta_0$ | $\theta_1$ | $\sigma^2$ | P>\|z\|$\theta_0$ | P>\|z\|$\theta_1$ | P>\|z\| $\sigma^2$ | $p_{11}$ | $p_{21}$ | AIC |
|---|---|---|---|---|---|---|---|---|---|
| Regime 1 | 0.79 | -0.42 | 1.99 | 0.097 | 0.55 | 0.07 | 0.894 | 0.035 | 567 |
| Regime 2 | 2.732 | 2.415 | 13.744 | 0.00 | 0.10 | 0.00 | | | |

Regime 1: GDP %Change $= 0.79 - 0.42BUXYoY + 1.99;$

Regime 2: GDP %Change $= 2.732 + 2.415BUXYoY + 13.74$

The P-matrix is: $P = \begin{bmatrix} 0.8945 & 0.1055 \\ 0.0351 & 0.9649 \end{bmatrix}$, expansions last on average 9.48 quarters according to this model, while recessions last 28.51 quarters – an imprecise result.

The Markov state probabilities D(t) at time t, where t = 1 quarter, are plotted below. The GDP %change chart is plotted alongside the dates of Hungarian recessions obtained from the OECD data warehouse:

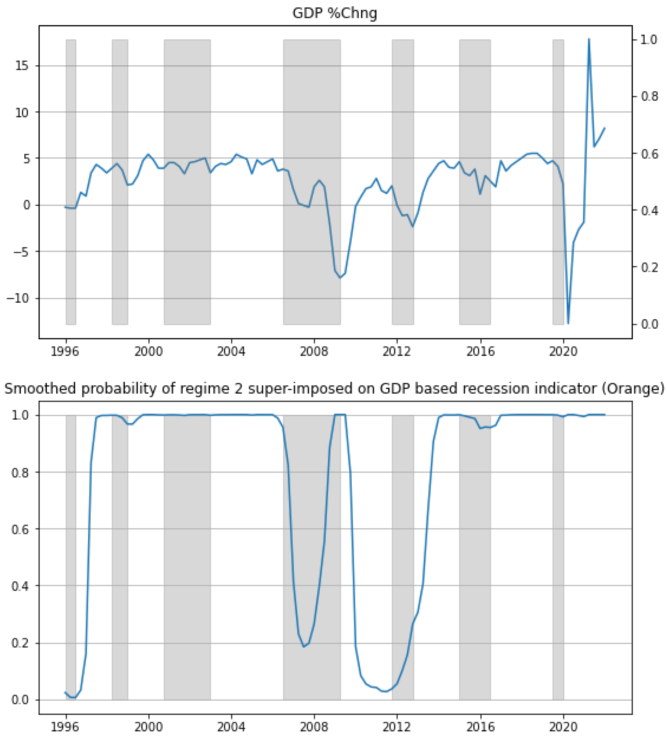



Figure 19. Smoothed probabilities of a recession, with BUX YoY% as the exogenous variable superimposed on actual recessions determined by the OECD composite indicator obtained from FRED. Source: Own calculations

Bond spreads show the risk appetite of investors.

Table 8. Estimation of the Markov regime switching model. y(t) is the GDP variable, while m(t) is the 10Year and 3Year yield spread time series. Source: Own calculations based on FRED and OECD data

| YSpread | $\theta_0$ | $\theta_1$ | $\sigma^2$ | P>\|z\|$\theta_0$ | P>\|z\|$\theta_1$ | P>\|z\| $\sigma^2$ | $p_{11}$ | $p_{21}$ | AIC |
|---|---|---|---|---|---|---|---|---|---|

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Regime 1 | 4.37 | 0.00 | 0.40 | 0.00 | 0.97 | 0.00 | 0.929 | 0.061 | 406 |
| Regime 2 | 0.62 | 0.07 | 21.80 | 0.38 | 0.89 | 0.00 | | | |

$$\text{Regime 1: GDP \%Change} = 4.37 + 0.00241 YSpread + 0.40;$$

$$\text{Regime 2: GDP \%Change} = 0.6287 + 0.07 YSpread + 21.80$$

The P-matrix is: $P = \begin{bmatrix} 0.9294 & 0.0716 \\ 0.0616 & 0.9384 \end{bmatrix}$, Economic growth lasts 14.16 quarters, according to the model, while the expected duration of a recession is 16.22 quarters.

The Markov state probabilities D(t) at time t, where t = 1 quarter, are plotted below. The GDP %change chart is plotted alongside the dates of Hungarian recessions obtained from the OECD data warehouse:

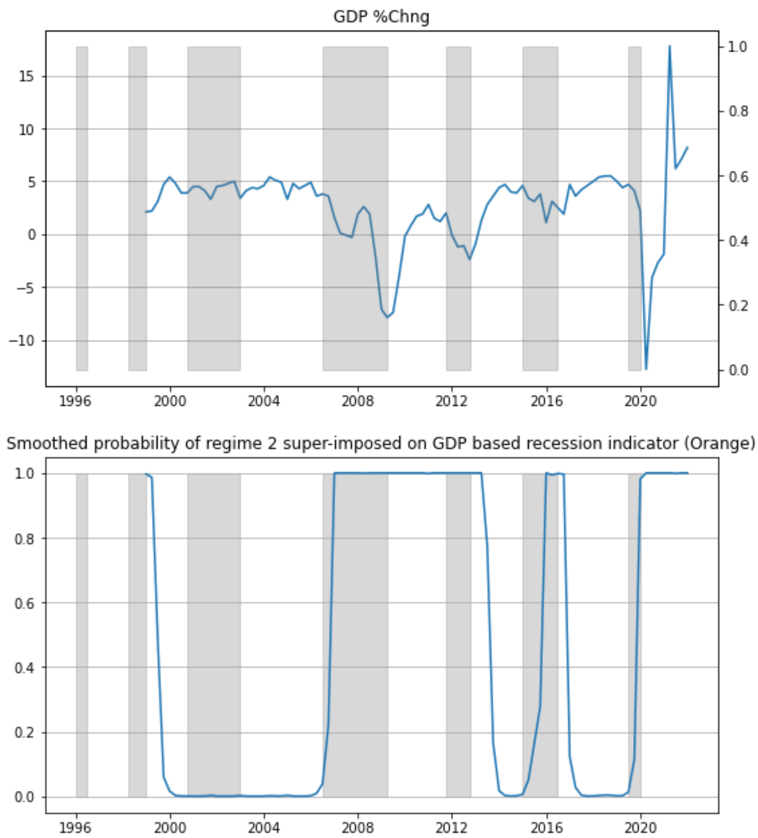



Figure 20. Smoothed probabilities of a recession, with YSpread as the exogenous variable superimposed on actual recessions determined by the OECD composite indicator obtained from FRED. Source: Own calculations

## 5.2. Estimating cross-border interbank lending index spillovers with the DY spillover table fo Hungary

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

| Lag | Variable<br>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:

$$BUBOR.3.MO = EUR.HUF.l1 + BUBOR.3.MO.l1 + EURIBOR.3.MO.l1 + EUR.HUF.l2 + BUBOR.3.MO.l2 + EURIBOR.3.MO.l2 + EUR.HUF.l3 + BUBOR.3.MO.l3 + EURIBOR.3.MO.l3 + EUR.HUF.l4 + BUBOR.3.MO.l4 + EURIBOR.3.MO.l4 + const$$

Table 10. Summary of VAR(4) K=3, Model 2. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

| | Variable | | |
|---|---|---|---|
| Lag | 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:

$$X50.RMAX.50.ZMAX = EUR.HUF.l1 + BUBOR.3.MO.l1 + X50.RMAX.50.ZMAX.l1 + EUR.HUF.l2 + BUBOR.3.MO.l2 + X50.RMAX.50.ZMAX.l2 + EUR.HUF.l3 + BUBOR.3.MO.l3 + X50.RMAX.50.ZMAX.l3 + EUR.HUF.l4 + BUBOR.3.MO.l4 + X50.RMAX.50.ZMAX.l4 + const$$

Table 11. Summary of VAR(4) K=3, Model 3. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

| | Variable | | |
|---|---|---|---|
| Lag | 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). 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 Cholseki decomposition, detailed in the appendix. 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, 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)

(a) Impulse response: Impulse: EUR.HUF, response: BUBOR.3MO P=4 (AIC says 10)

(b) Impulse response: Impulse: EUR.HUF, response: BUBOR.3MO P=4 (AIC says 10)

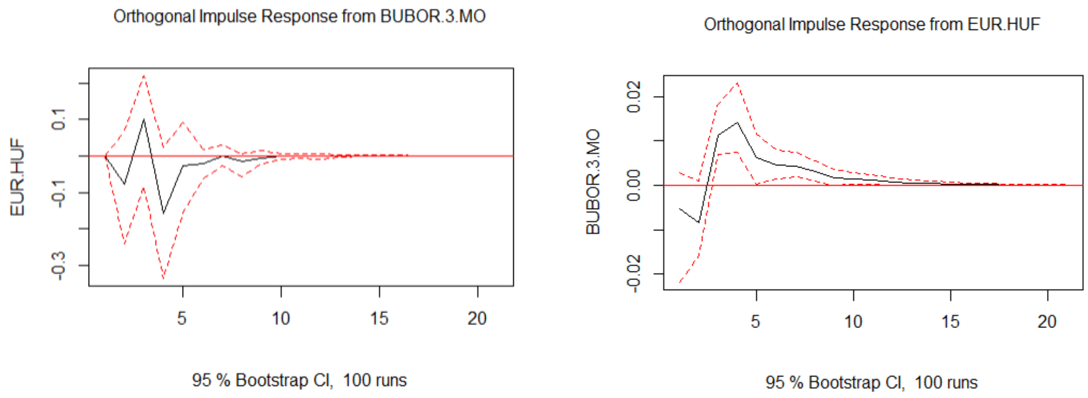



Figure 21 (a) Impulse response function for BUBOR (impulse), and EUR/HUF (response). (b) IRF for EUR (impulse), and BUBOR (response). Y-axis = standard deviations, X-axis, Periods = trading days.

Notice in Figure 21 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-$\sigma$ positive shock leads to a -0.1 $\sigma$ 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.

(a) Impulse response: RMAX+ZMAX, BUBOR.3.MO Impulse: response

(b) Impulse response: BUBOR.3.MO, RMAX+ZMAX Impulse response

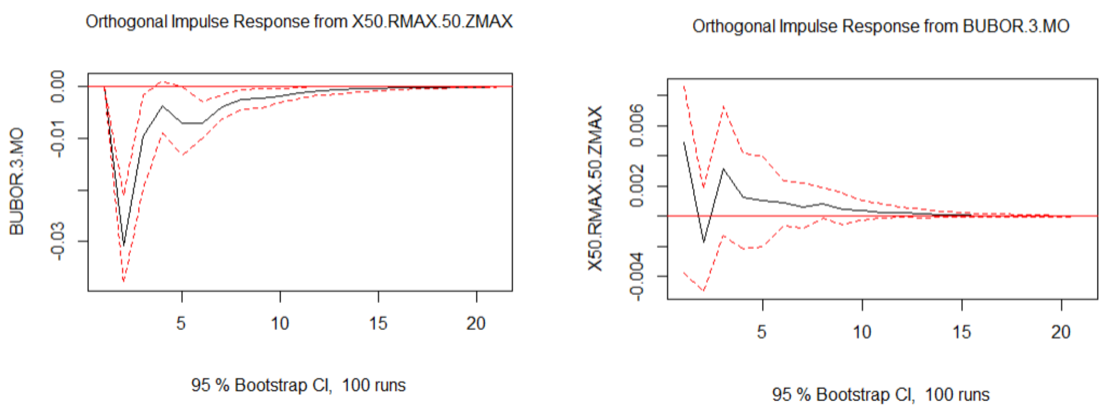
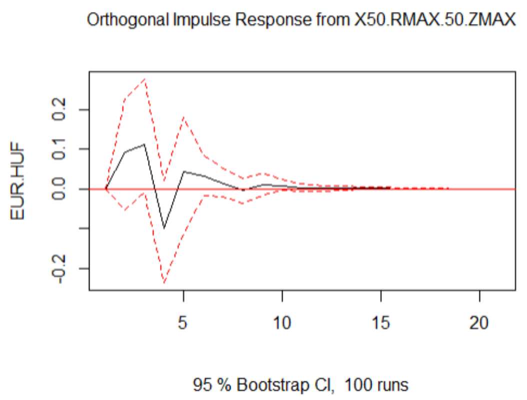



Figure 22 (a) Impulse response function for MAX (impulse), and BUBOR (response). (b) IRF for BUBOR (impulse), and MAX (response). Y-axis = standard deviations, X-axis, Periods = trading days.

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 Figure 22 (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 crow 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.

(a) Impulse response: RMAX+ZMAX, Impulse: response EUR.HUF




(b) Impulse response: EUR.HUF, Impulse: response RMAX+ZMAX

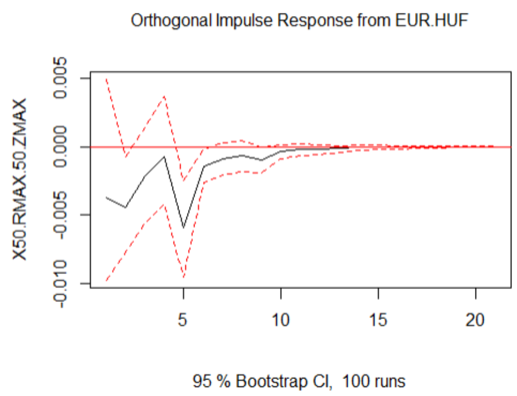



Figure 23 (a) Impulse response function for MAX (impulse), and exchange rate (response). (b) IRF for exchange rate (impulse), and MAX (response). Y-axis = standard deviations, X-axis, Periods = trading days.

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 in Figure 23 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.

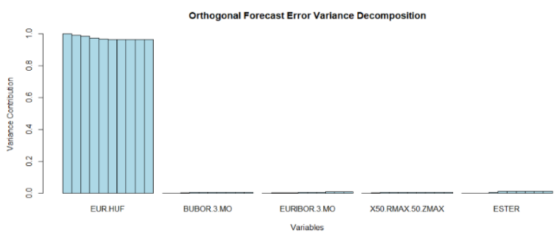
In short, the above cases demonstrate the major flaws inherent to the Cholesky decomposition for VAR models of financial time series.

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 of the 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.

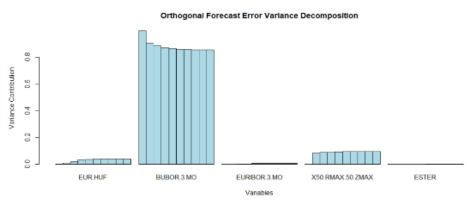
Consider the orthogonal forecast error variance decomposition graphs shown in Table 12

Table 12. Orthogonalized FEVD. (a) EUR/HUF, (b)BUBOR, (c) EURIBOR, (d) RMAX+ZMAX

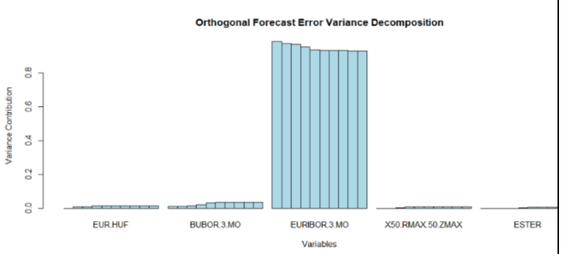
(a)




(b)




(c)




(d)

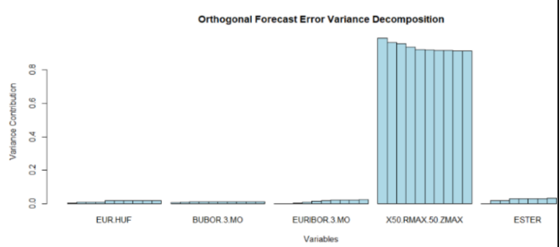


Table 13 -Table 15 show the generalized Forecast error variance decomposition tables for the three variables of interest.

Table 13. 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 14. 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 15. The 10-step ahead Generalized Forecast error variance decomposition for the RMAX+ZMAX variable. Compiled by author. Source code attached in appendix.

| | | | RMAX+ZMAX | | |
|---|---|---|---|---|---|
| h-step ahead | 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 16 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 6$^{th}$ row in the table. The off diagonal row sums are labeled "contribution *from* others". This is the 7$^{th}$ and last column in Table 16. 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*100 = 500.

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

Table 16. Generalized spillover table, Hungarian interbank rate volatility, 10/1/2019-07/01/2023. Values in percentage.

| | From |
|---|---|

| To | EUR.HUF | BUBOR | EURIBOR | X50.RMAX.50.ZMAX | ESTER | Contribution from others |
|---|---|---|---|---|---|---|
| EUR.HUF | 98.33 | 0.08 | 0.63 | 0.58 | 0.37 | 1.67 |
| BUBOR.3.MO | 1.23 | 88.35 | 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 | 92.48 | 7.52 |
| Contribution to others (spillover) | 4.23 | 1.35 | 7.15 | 10.34 | 8.02 | 6.22 |
| Contribution to others including own | 102.56 | 89.70 | 103.48 | 103.77 | 100.50 | **(31.1/500.00): 6.218%** |

Notice that from the "Contribution *to* others" row in Table 16, 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*number of variables.

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

Table 17. Orthogonalized spillover table, Hungarian interbank rate volatility, 10/1/2019-07/01/2023. Values in percentage.

| | From | | | | | |
|---|---|---|---|---|---|---|
| To | EUR.HUF | BUBOR.3.MO | EURIBOR.3.MO | X50.RMAX.50.ZMAX | ESTER | Contribution from others |
| EUR.HUF | 98.74 | 0.31 | 0.49 | 0.40 | 0.07 | 1.26 |
| BUBOR.3.MO | 1.89 | 88.00 | 0.39 | 9.70 | 0.02 | 12.00 |
| EURIBOR.3.MO | 1.27 | 2.23 | 95.48 | 0.86 | 0.16 | 4.52 |
| X50.RMAX.50.ZMAX | 1.22 | 0.88 | 1.30 | 94.59 | 2.01 | 5.41 |
| ESTER | 0.17 | 0.06 | 5.53 | 1.37 | 92.88 | 7.12 |
| Contribution to others (spillover) | 4.55 | 3.47 | 7.70 | 12.33 | 2.26 | 6.06 |
| Contribution to others including own | 103.29 | 91.47 | 103.18 | 106.92 | 95.14 | 500.00 |

For reference, Table 17 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.

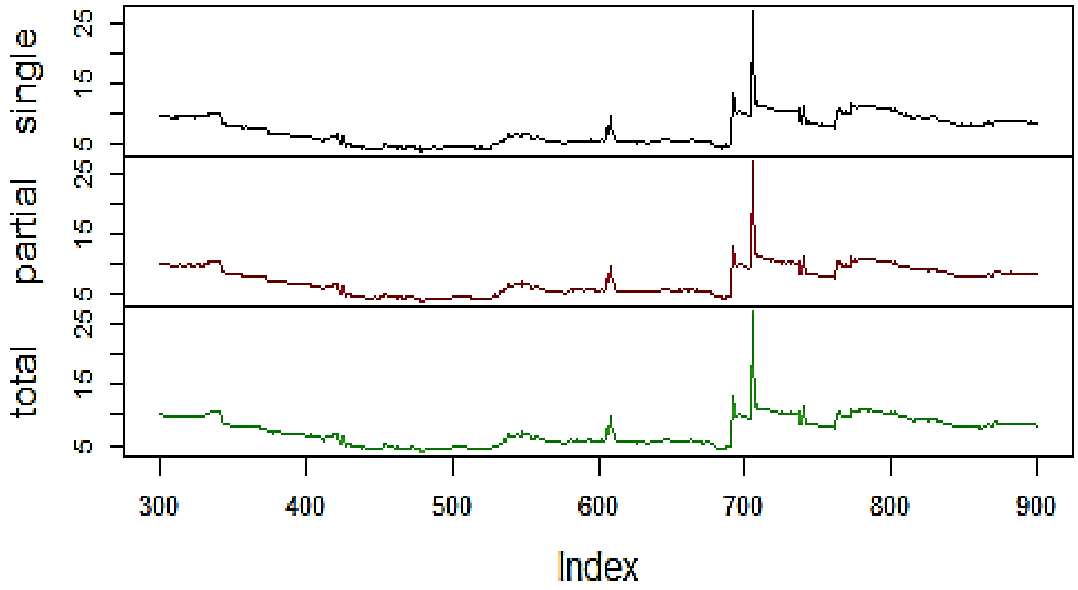



Figure 24. Total volatility spillover plot. K=5, VAR(4) model. Compiled by author. Source code attached in appendix.

From the first window up until the 600'th, we can observe a clear downtrend in the index. The total volatility spillover decreases from 15% to less than 5%. Around the $600^{th}$ 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 $600^{th}$ and the $700^{th}$ 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 16. 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 25 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.

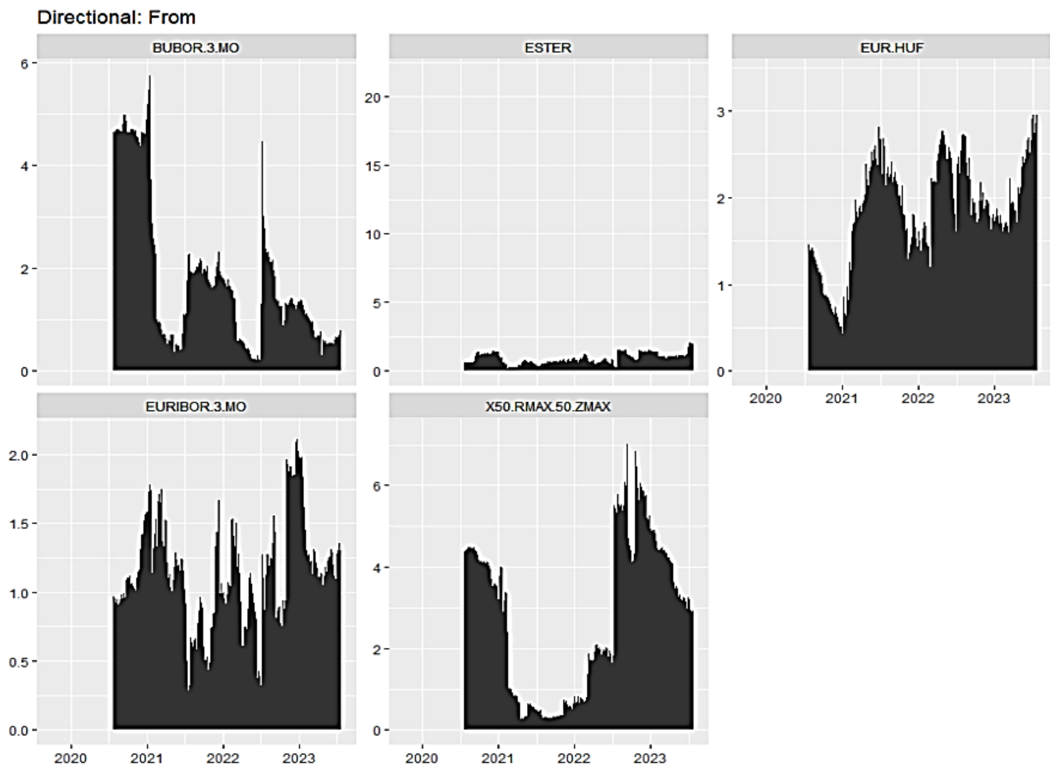



Figure 25. Directional spillover plot, From the K=5 variables in VAR (4). Compiled by author. Source code attached in appendix. Source: MNB, ÁKK, ECB

The $S_{\cdot i}^{g}(H)$, which is the column sum of the "Contribution *from* others", has the reverse properties to $S_{i\cdot}^{g}(H)$, 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 26Figure 25. 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. 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.

### *5.2.1. spillovers from other variables.*

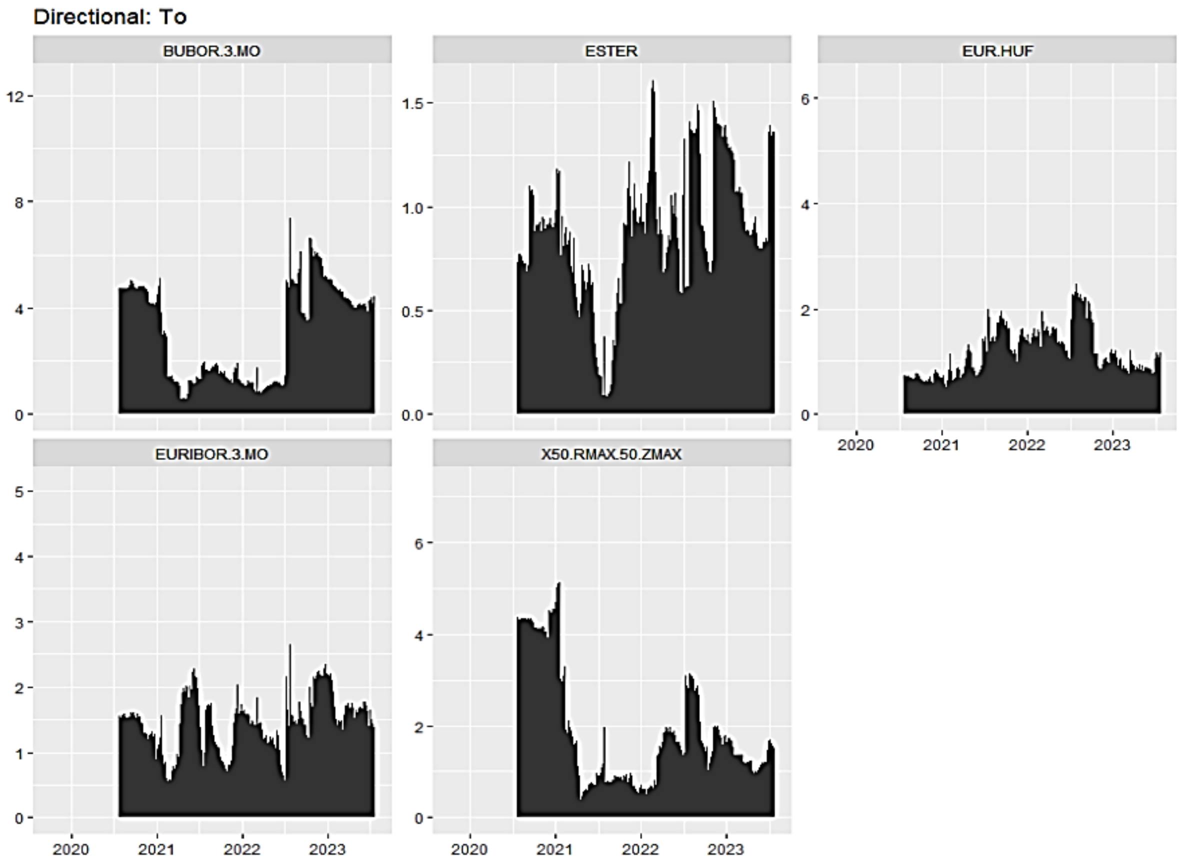



Figure 26. Directional spillover plot, To the K=5 variables in VAR (4). Compiled by author. Source code attached in appendix. Source: MNB, ÁKK, ECB

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 27, 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, 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.

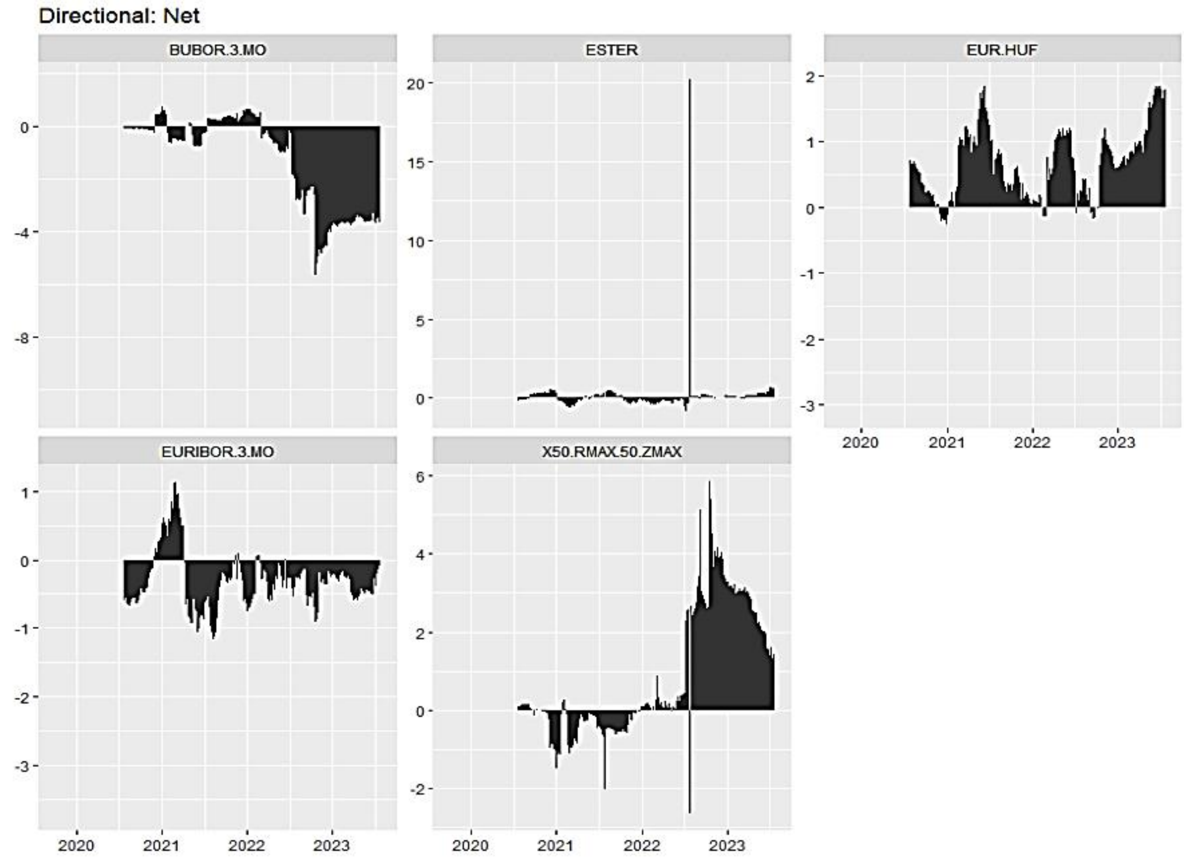



Figure 27. Net spillover plot, K=5 variables in VAR (4). Compiled by author. Source code attached in appendix. Source: MNB, ÁKK, ECB

The net volatility spillover from the BUBOR reached -4% at the end of 2022. Figure 28 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 28 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.

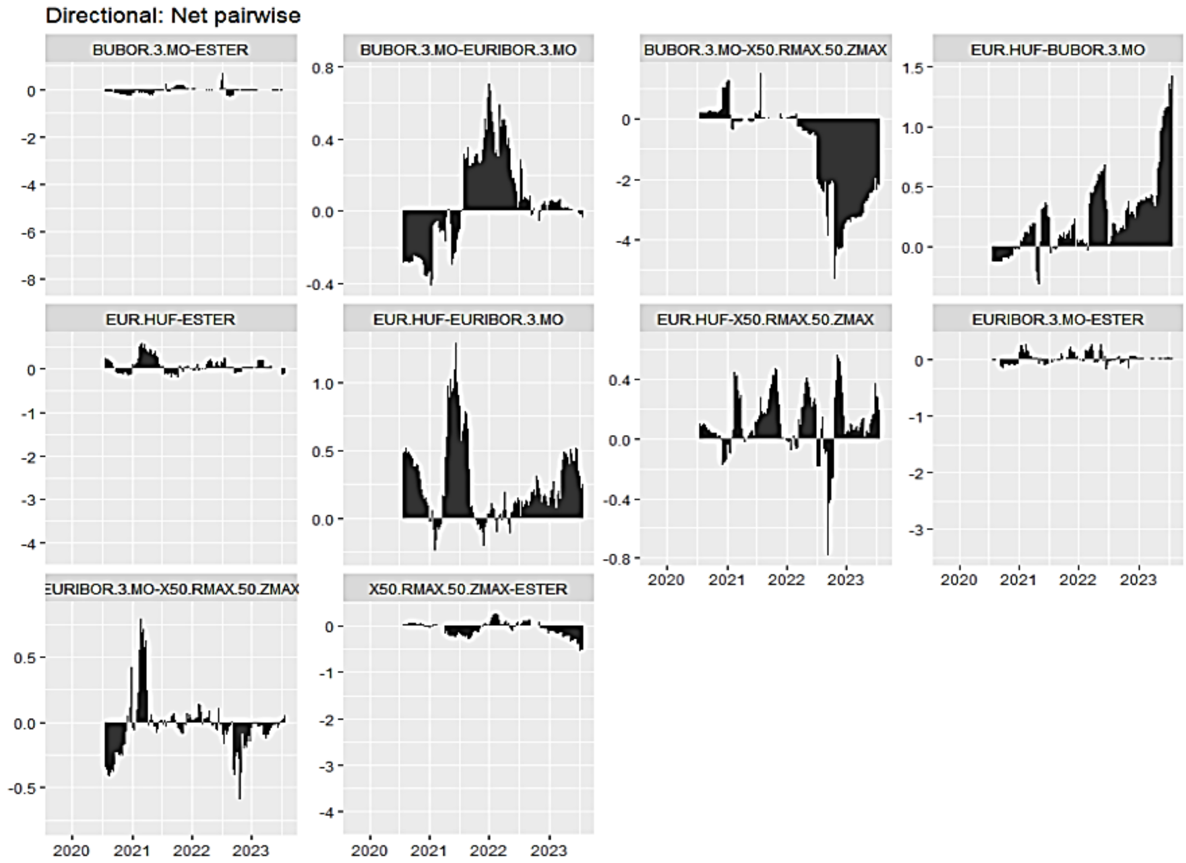



Figure 28. Net pairwise volatility spillovers. K=5 variables in VAR (4). Compiled by author. Source code attached in appendix. Source: MNB, ÁKK, ECB

Finally, the from/to pairwise Figure 29 shows how a variable transmits or receives volatility from another one. It's purpose is to supplement 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.

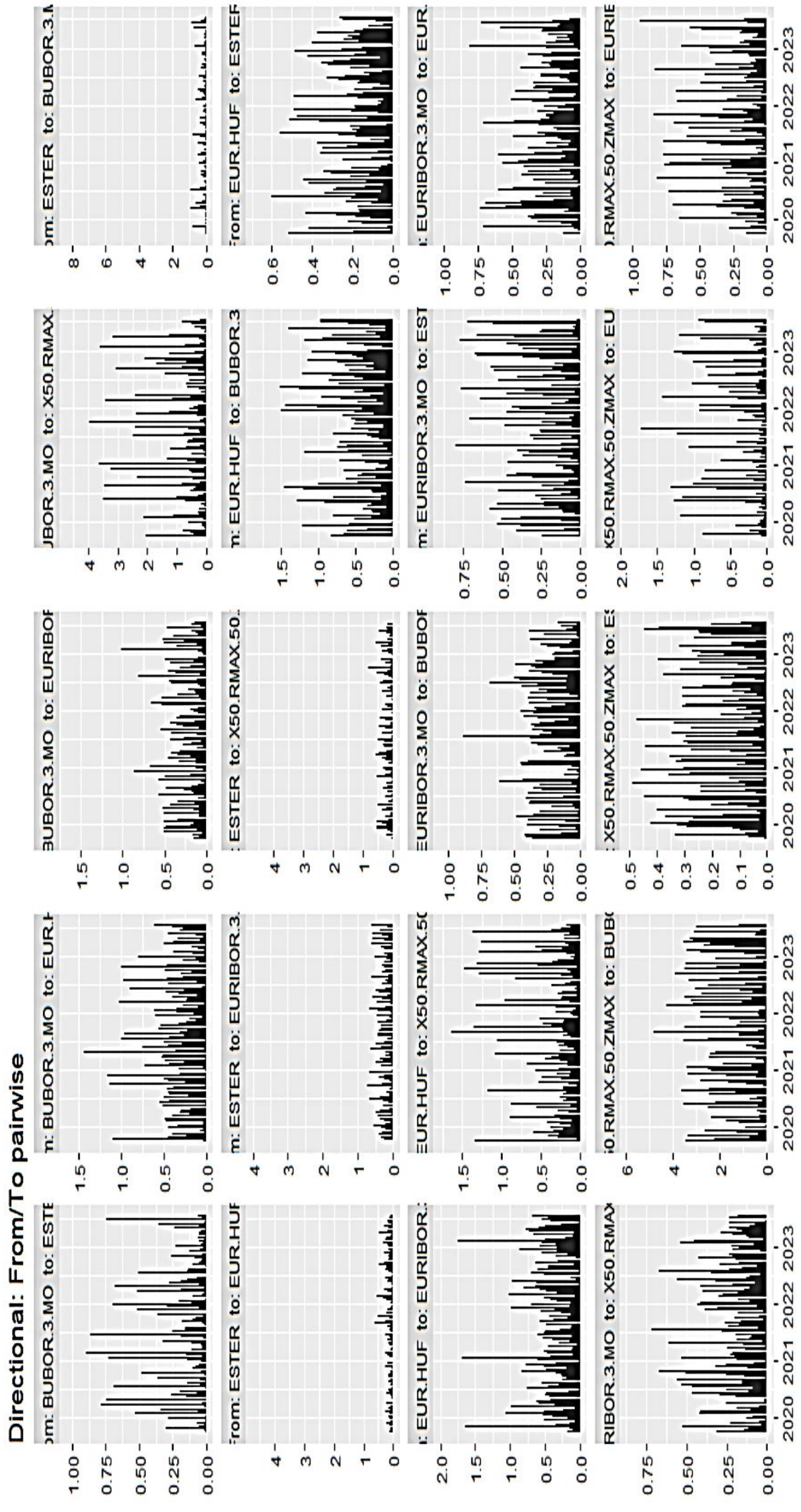



Figure 29. From/To pairwise. K=5 variables in VAR (4). Compiled by author. Source code attached in appendix. Source: MNB, ÁKK, ECB

# 6. DISCUSSION

## 6.1. What did we learn from forecasting Hungarian business cycles?

In the first part of the research we used an Markov Switching Dynamic Regression (MSDR) model to see if the dynamics of leading macroeconomic variables correspond to recession periods determined by the OECD. Table 4 through Table 8 shows the statistics of the $\theta_1$ and $\theta_2$ regression coefficients. We have justified the selection of exogenous variables in section 4 of this paper. Overall we had 105 observations spanning 26 years. In Figure 16 through Figure 20 we plotted the smoothed recession probabilities.

### *6.1.1. Unemployment:*

During expansions the $\theta_1$ coefficient is negative. It is an obvious conclusion supported by economic theory, that during expansions unemployment tends to drop. In Hungary throughout the 26 year timespan, it was confirmed to be the case. As credit is more available, companies use it to expand operations and expand the labor force. What our model shows is that the regression coefficient $\theta_1$ in recessions is also negative, furthermore its slope is steeper. This means that unemployment decreases faster during recessions in Hungary. The error term's variance in regime 2 is higher than in regime 1. is significantly higher during a recession – this points to stronger propagation of the shocks. Figure 16 captures 5 out of the 7 recessionary periods of the economy – a 71%. The regression model doesn't account for the early 2000's recession and the 1999 recession. According to the unemployment model, Hungary is currently in a recession.

### *6.1.2. Inflation:*

The coefficients we obtained for the recession state are positive. High inflation, which is a monetary phenomenon is always positive during a recession. But it must be noted that rising inflation needn't mean a certainty of recession. MMT[9] states that as long as the

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[9] Modern Monetary THeory

growth of the aggregate output of the economy exceeds that of the money supply, secular growth can be achieved. It is therefore the responsibility of central governmental organizations and institutions to monitor and adjust the M2 rate according to the principle. At the same time, rising inflation is not to be associated with the certainty of a recessionary state. The inflation regression model captures 6 of the 7 recessionary periods in Hungary. But it gave a number of false signals.

### *6.1.3. Industrial Production Index:*

The industrial production index regression variable did not yield useful results, since the slope of the variable was positive in both regimes 1 and 2. The IPI didn't react to the 2012 European crisis, but it predicted the 2016 shallow recession.

### *6.1.4. BUX YoY% change*

The coefficient for BUX during an expansion is -0.42. According to the results in Appendix F, the duration of recessions on average is 3 times longer expansions. The model captures 5 of the 7 recessions in the proposed sample. We think that the stock market is strong in predicting changes in regimes, however because of volatility, regime 2 persists longer than 1.

### *6.1.5. 10-Year and 3-Year Hungarian sovereign bond yield spreads.*

Yield curve inversions have long been known to predict recessions. In an expansion, the yield curve is positively sloped, and in regime 2, the yield curve is negatively sloped. We found that in our regression model yield spreads aren't useful in predicting the Hungarian GDP. In the early two thousands the spread has been negative in favour of short term government borrowings for years. These likely skewed results. According to Appendix F, the probability of the persistence of a low regime is nearly 95%, while the persistence of a high regime is 94%.

From the methodological standpoint, there are a few remarks to be made:

We imposed some limitations to the model. Specifically, we set the initial probability of a regime change to 0.5. This is not supported by any theoretical evidence. It is how we constructed the model. But the probability of regime change is not exactly 50%. To estimate this number more precisely, we should count how many quarters a recession or expansion last and divide it bz the total number of observations.

We assume that the P-matrix, that is the matrix of transition probabilities, is constant. Filardo (1994) challenges this assumption, and allows the probabilities to vary over time. It is worth to further indulge in the time varying transition probability (TVTP) framework, as it would yield interesting results.

## 6.2. How cross border interbank lending rate spillovers affect Hungarian banking.

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 the 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 affecting 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 $S_{i\cdot}^{g}(H)$, 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.

## 7. SUMMARY

The first part of this paper aimed to answer the question if it is possible to rethink how business cycles are determined in Hungary. We've isolated the hidden variable from the observed one as a part of our Markov switch framework. With the help of a regression with a mean, intercept and error term, we modeled the observed variable and fitted it into the hidden variable framework, which is unobserved. Having determined the transition probability matrices, the recession probabilities were graphed against recessionary periods calculated by the OECD. What we found in the testing part is that theory supports the findings. To begin with, the time series have different behaviors depending on whether there is a recession or a boom. We determined the expected durations of the recessions by substituting in the panel data variables as the exogenous term in the regression model. The highest correlation between our model and the OECD estimates was determined to be the unemployment rate.

The GDP corresponds to the business cycles the most. when the exogenous variable is the unemployment rate. To determine possible long-term correlations of the GDP with the business cycle, the exogenous variables lagged by 1 quarter. Generally, this extension did not result in a higher predictive capability, than by not lagging the variable.

The further development of the Markov chain method is important because this allows us to analyze the unobservable variable in greater detail. The lagged maximum likelihood function of the 10 and 3 year spreads indicates that the Hungarian economy is in a recession, which at the time of writing this paper it is in a recession. However, the unemployment rate has been determined to be the most accurate indicator, which is accurate for 8 out of the 13 cycles. From a legislative standpoint, it is worth to integrate a constantly updating maximum likelihood function that would switch if a recessionary or expansionary period is being detected. Also, it Is worth considering more frequent time series. Within the scope of this research, we have worked with quarterly time series, if for instance, we were to take the jobless claims instead of the quarterly unemployment rate, which is a monthly indicator and eliminate the noise and smooth it, we believe that it would be a much better ‘live’ version of whether the economy is bound for a recession. Further methodological developments in the case of Hungarian business cycle estimation could be in applying Filardo’s TVTP framework for the panel data.

In the second part of the study we 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 cyclicality 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.

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ANNEXES

## 8. 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:

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

The control model for Model 3:

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

## 9. 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 18. 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 19. 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 20. 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 |

## 10. 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
```

```r
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
```

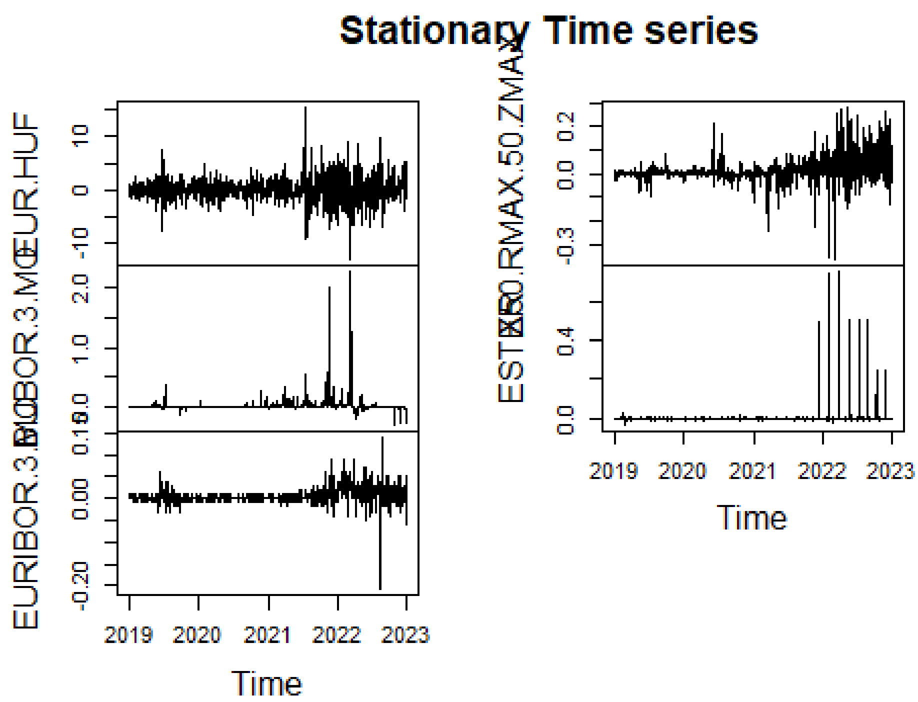
2. Load the data and summarize, date must be as factor, so use: as.factor

```r
data <- read.csv("C:/Users/Albert Molnar/Desktop/MSC/Spillover researc
h/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  ESTE
R
## 1 2019-10-02    0.04          0         0.00           -0.025 -0.00
2
## 2 2019-10-03   -1.49          0         0.00            0.000 -0.00
4
## 3 2019-10-04   -0.87          0         0.01            0.000  0.00
2
## 4 2019-10-07    0.60          0         0.00            0.000 -0.00
1
## 5 2019-10-08    0.94          0         0.00            0.000  0.00
2
## 6 2019-10-09    0.33          0         0.00            0.010  0.00
0
```

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

```r
ts_data <- ts(data[, c("EUR.HUF","BUBOR.3.MO", "EURIBOR.3.MO", "X50.RM
AX.50.ZMAX", "ESTER")], start = c(2019), end = c(2023), frequency = 23
9)
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)"

```r
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.5
0.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 0.60
29 0.5532 0.5532 0.4875 0.4875 0.3999 0.3999 0.3625 0.3625 0.157 0.096
68
## 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.5
0.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
##
##                     Estimate Std. Error t value Pr(>|t|)
## EUR.HUF.l1           0.03050    0.03269   0.933   0.3511
## BUBOR.3.MO.l1       -0.80289    0.74567  -1.077   0.2819
## EURIBOR.3.MO.l1     -8.53111    4.16330  -2.049   0.0407 *
## X50.RMAX.50.ZMAX.l1  2.21702    1.42732   1.553   0.1207
## ESTER.l1             0.23743    1.63094   0.146   0.8843
## EUR.HUF.l2          -0.03227    0.03292  -0.980   0.3273
## BUBOR.3.MO.l2        1.06838    0.74994   1.425   0.1546
## EURIBOR.3.MO.l2      1.37500    4.20045   0.327   0.7435
## X50.RMAX.50.ZMAX.l2  1.38163    1.50160   0.920   0.3578
## ESTER.l2            -2.32464    1.62066  -1.434   0.1518
## EUR.HUF.l3          -0.01069    0.03298  -0.324   0.7459
## BUBOR.3.MO.l3       -1.51872    0.75138  -2.021   0.0435 *
## EURIBOR.3.MO.l3     -2.26766    4.25890  -0.532   0.5945
## X50.RMAX.50.ZMAX.l3 -1.48827    1.49440  -0.996   0.3196
## ESTER.l3            -3.42047    1.59363  -2.146   0.0321 *
## EUR.HUF.l4           0.05114    0.03321   1.540   0.1239
## BUBOR.3.MO.l4       -0.27926    0.70693  -0.395   0.6929
## EURIBOR.3.MO.l4      9.22115    4.23227   2.179   0.0296 *
## X50.RMAX.50.ZMAX.l4  0.09376    1.48330   0.063   0.9496
## ESTER.l4            -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.l1 + BUBOR.3.MO.l1 + EURIBOR.3.MO.l1 + X50.RMA
X.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 + EURIBO
R.3.MO.l3 + X50.RMAX.50.ZMAX.l3 + ESTER.l3 + EUR.HUF.l4 + BUBOR.3.MO.l
4 + EURIBOR.3.MO.l4 + X50.RMAX.50.ZMAX.l4 + ESTER.l4 + const
##
##                      Estimate Std. Error t value Pr(>|t|)
## EUR.HUF.l1          -0.004108   0.001455  -2.823 0.004863 **
## BUBOR.3.MO.l1        0.155950   0.033199   4.697 3.03e-06 ***
## EURIBOR.3.MO.l1      0.210530   0.185361   1.136 0.256340
## X50.RMAX.50.ZMAX.l1 -0.605292   0.063548  -9.525  < 2e-16 ***
## ESTER.l1            -0.044436   0.072614  -0.612 0.540717
## EUR.HUF.l2           0.005039   0.001466   3.438 0.000613 ***
## BUBOR.3.MO.l2        0.063634   0.033389   1.906 0.056981 .
## EURIBOR.3.MO.l2      0.182173   0.187015   0.974 0.330255
## X50.RMAX.50.ZMAX.l2 -0.008741   0.066855  -0.131 0.896000
## ESTER.l2             0.054769   0.072156   0.759 0.448019
## EUR.HUF.l3           0.005271   0.001468   3.589 0.000349 ***
## BUBOR.3.MO.l3        0.060182   0.033453   1.799 0.072347 .
## EURIBOR.3.MO.l3      0.383879   0.189618   2.024 0.043205 *
## X50.RMAX.50.ZMAX.l3  0.061867   0.066534   0.930 0.352690
## ESTER.l3            -0.081861   0.070953  -1.154 0.248902
## EUR.HUF.l4           0.001393   0.001479   0.942 0.346271
## BUBOR.3.MO.l4        0.039691   0.031474   1.261 0.207606
## EURIBOR.3.MO.l4      0.195977   0.188432   1.040 0.298591
## X50.RMAX.50.ZMAX.l4 -0.067159   0.066040  -1.017 0.309444
## ESTER.l4             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.l1 + BUBOR.3.MO.l1 + EURIBOR.3.MO.l1 + X50.R
MAX.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 + EUR
IBOR.3.MO.l3 + X50.RMAX.50.ZMAX.l3 + ESTER.l3 + EUR.HUF.l4 + BUBOR.3.M
O.l4 + EURIBOR.3.MO.l4 + X50.RMAX.50.ZMAX.l4 + ESTER.l4 + const
##
##                       Estimate Std. Error t value Pr(>|t|)
## EUR.HUF.l1          -7.489e-04  2.607e-04  -2.872  0.00417 **
```

```
## BUBOR.3.MO.l1        8.198e-04  5.948e-03   0.138  0.89040
## EURIBOR.3.MO.l1      1.744e-01  3.321e-02   5.252 1.86e-07 ***
## X50.RMAX.50.ZMAX.l1  3.747e-03  1.138e-02   0.329  0.74212
## ESTER.l1            -2.796e-05  1.301e-02  -0.002  0.99829
## EUR.HUF.l2           2.636e-04  2.626e-04   1.004  0.31576
## BUBOR.3.MO.l2        6.409e-03  5.982e-03   1.071  0.28426
## EURIBOR.3.MO.l2     -3.722e-02  3.350e-02  -1.111  0.26685
## X50.RMAX.50.ZMAX.l2  2.526e-02  1.198e-02   2.109  0.03518 *
## ESTER.l2             6.265e-03  1.293e-02   0.485  0.62805
## EUR.HUF.l3           6.649e-04  2.631e-04   2.528  0.01165 *
## BUBOR.3.MO.l3        1.336e-02  5.993e-03   2.229  0.02605 *
## EURIBOR.3.MO.l3      2.307e-02  3.397e-02   0.679  0.49717
## X50.RMAX.50.ZMAX.l3  2.154e-02  1.192e-02   1.807  0.07111 .
## ESTER.l3            -5.880e-03  1.271e-02  -0.463  0.64375
## EUR.HUF.l4           2.761e-05  2.649e-04   0.104  0.91701
## BUBOR.3.MO.l4        1.280e-02  5.639e-03   2.271  0.02339 *
## EURIBOR.3.MO.l4      6.793e-02  3.376e-02   2.012  0.04447 *
## X50.RMAX.50.ZMAX.l4  1.373e-02  1.183e-02   1.160  0.24619
## ESTER.l4             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.l1 + BUBOR.3.MO.l1 + EURIBOR.3.MO.l1 + X
50.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
##
##                       Estimate Std. Error t value Pr(>|t|)
## EUR.HUF.l1          -0.0015444  0.0007524  -2.053 0.040389 *
## BUBOR.3.MO.l1       -0.0310558  0.0171628  -1.809 0.070698 .
## EURIBOR.3.MO.l1     -0.0047799  0.0958249  -0.050 0.960228
## X50.RMAX.50.ZMAX.l1  0.1326461  0.0328521   4.038 5.84e-05 ***
## ESTER.l1             0.1556153  0.0375387   4.145 3.70e-05 ***
## EUR.HUF.l2          -0.0005675  0.0007578  -0.749 0.454140
## BUBOR.3.MO.l2        0.0226308  0.0172611   1.311 0.190152
## EURIBOR.3.MO.l2      0.1992520  0.0966799   2.061 0.039585 *
## X50.RMAX.50.ZMAX.l2  0.0716312  0.0345616   2.073 0.038487 *
## ESTER.l2            -0.0445388  0.0373020  -1.194 0.232780
## EUR.HUF.l3           0.0005929  0.0007592   0.781 0.435006
## BUBOR.3.MO.l3        0.0071442  0.0172941   0.413 0.679629
## EURIBOR.3.MO.l3      0.0434334  0.0980254   0.443 0.657808
## X50.RMAX.50.ZMAX.l3  0.0955430  0.0343959   2.778 0.005584 **
```

```
## ESTER.l3             0.1414254  0.0366798   3.856 0.000123 ***
## EUR.HUF.l4          -0.0017295  0.0007644  -2.263 0.023883 *
## BUBOR.3.MO.l4       -0.0039602  0.0162711  -0.243 0.807756
## EURIBOR.3.MO.l4      0.1671324  0.0974125   1.716 0.086546 .
## X50.RMAX.50.ZMAX.l4  0.0946403  0.0341404   2.772 0.005681 **
## ESTER.l4            -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.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.
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
##
##                       Estimate Std. Error t value Pr(>|t|)
## EUR.HUF.l1           0.0008371  0.0006606   1.267 0.205387
## BUBOR.3.MO.l1        0.0019452  0.0150689   0.129 0.897315
## EURIBOR.3.MO.l1      0.0494089  0.0841341   0.587 0.557169
## X50.RMAX.50.ZMAX.l1 -0.0046725  0.0288441  -0.162 0.871348
## ESTER.l1            -0.0217206  0.0329589  -0.659 0.510045
## EUR.HUF.l2           0.0003758  0.0006653   0.565 0.572306
## BUBOR.3.MO.l2       -0.0316044  0.0151552  -2.085 0.037306 *
## EURIBOR.3.MO.l2      0.3831884  0.0848848   4.514 7.17e-06 ***
## X50.RMAX.50.ZMAX.l2  0.0392580  0.0303450   1.294 0.196082
## ESTER.l2            -0.0375425  0.0327511  -1.146 0.251966
## EUR.HUF.l3          -0.0012619  0.0006665  -1.893 0.058647 .
## BUBOR.3.MO.l3        0.0180639  0.0151842   1.190 0.234487
## EURIBOR.3.MO.l3      0.3184824  0.0860661   3.700 0.000228 ***
## X50.RMAX.50.ZMAX.l3 -0.1235655  0.0301995  -4.092 4.65e-05 ***
## ESTER.l3            -0.0516485  0.0322048  -1.604 0.109108
## EUR.HUF.l4          -0.0001191  0.0006711  -0.178 0.859121
## BUBOR.3.MO.l4       -0.0167321  0.0142860  -1.171 0.241809
## EURIBOR.3.MO.l4     -0.0552232  0.0855280  -0.646 0.518650
## X50.RMAX.50.ZMAX.l4  0.1484758  0.0299752   4.953 8.66e-07 ***
## ESTER.l4             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.ZMA
X       ESTER
## EUR.HUF             5.311e+00 -1.311e-02   -1.185e-03       -7.638e-0
3 -6.026e-06
## BUBOR.3.MO         -1.311e-02  1.053e-02    2.178e-04        4.756e-0
4 -6.564e-05
## EURIBOR.3.MO       -1.185e-03  2.178e-04    3.379e-04       -3.733e-0
6  1.456e-04
## X50.RMAX.50.ZMAX -7.638e-03  4.756e-04   -3.733e-06        2.813e-0
3 -2.776e-04
## ESTER              -6.026e-06 -6.564e-05    1.456e-04       -2.776e-0
4  2.169e-03
##
## Correlation matrix of residuals:
##                       EUR.HUF  BUBOR.3.MO EURIBOR.3.MO X50.RMAX.50.ZMA
X       ESTER
## EUR.HUF             1.000e+00   -0.05543    -0.027982        -0.06249
0 -5.615e-05
## BUBOR.3.MO         -5.543e-02    1.00000     0.115492         0.08738
4 -1.374e-02
## EURIBOR.3.MO       -2.798e-02    0.11549     1.000000        -0.00382
9  1.701e-01
## X50.RMAX.50.ZMAX -6.249e-02    0.08738    -0.003829         1.00000
0 -1.124e-01
## ESTER              -5.615e-05   -0.01374     0.170068        -0.11240
0  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 hte 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)
```

5. Find the orthogonalized and Generlaized 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.
RMAX.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.
RMAX.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
```

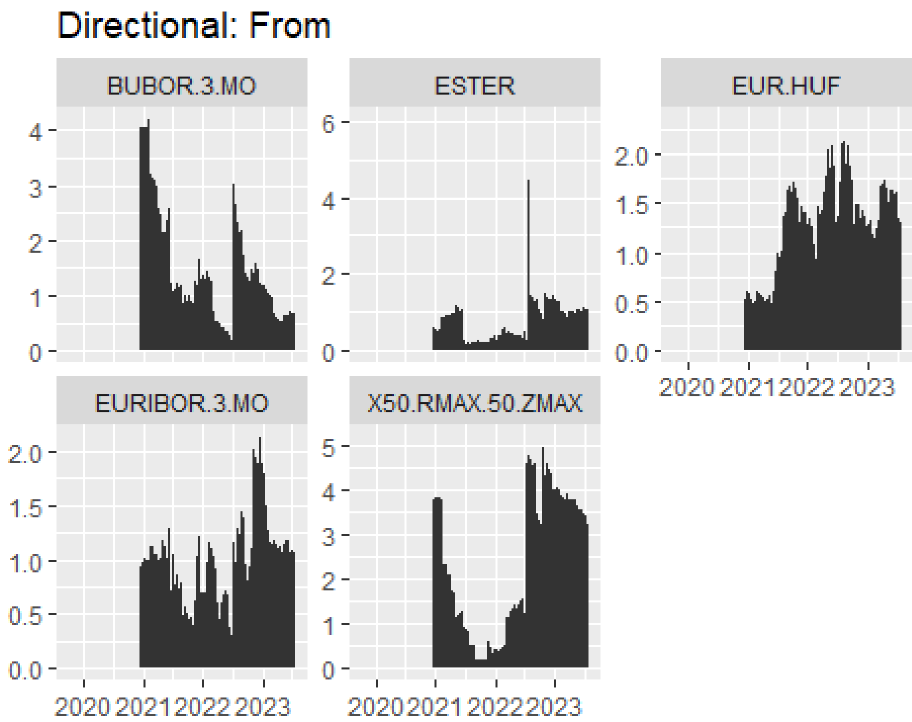
```
## ESTER                          88.0947721      11.905228
## C. to others (spillover)        8.4695882      10.104665
## C. to others including own 96.5643602     500.000000
```

6. Estimate the directional spillovers as in DY 2012

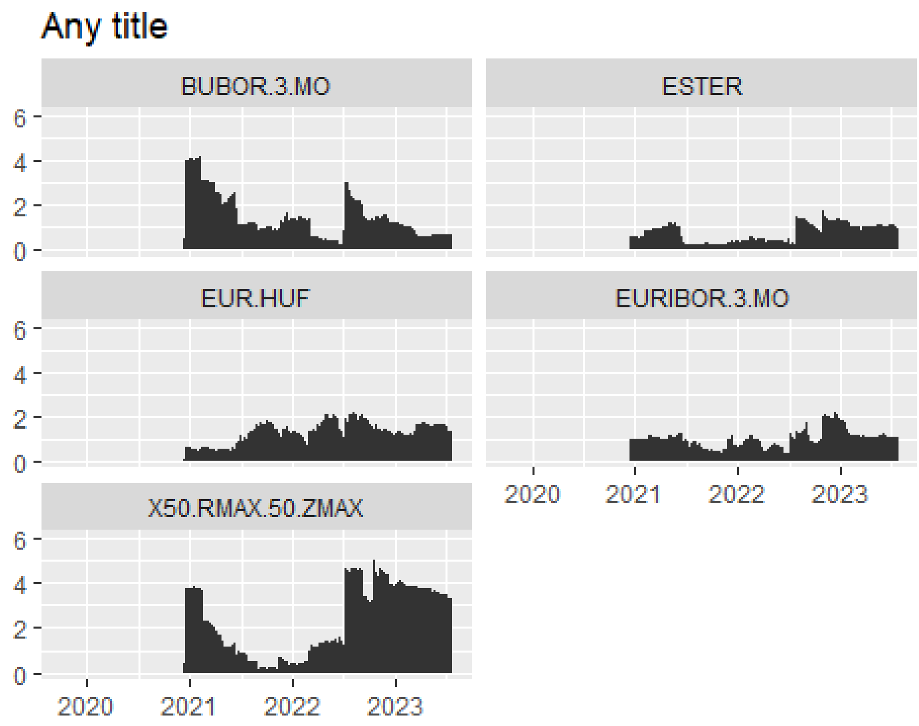
```
dy_results <- dynamic.spillover(
data,
width = 300,
n.ahead = 10,
standardized = TRUE,
na.fill = FALSE,
remove.own = TRUE)
```

7. Plot the directional spillovers as in DY 2012

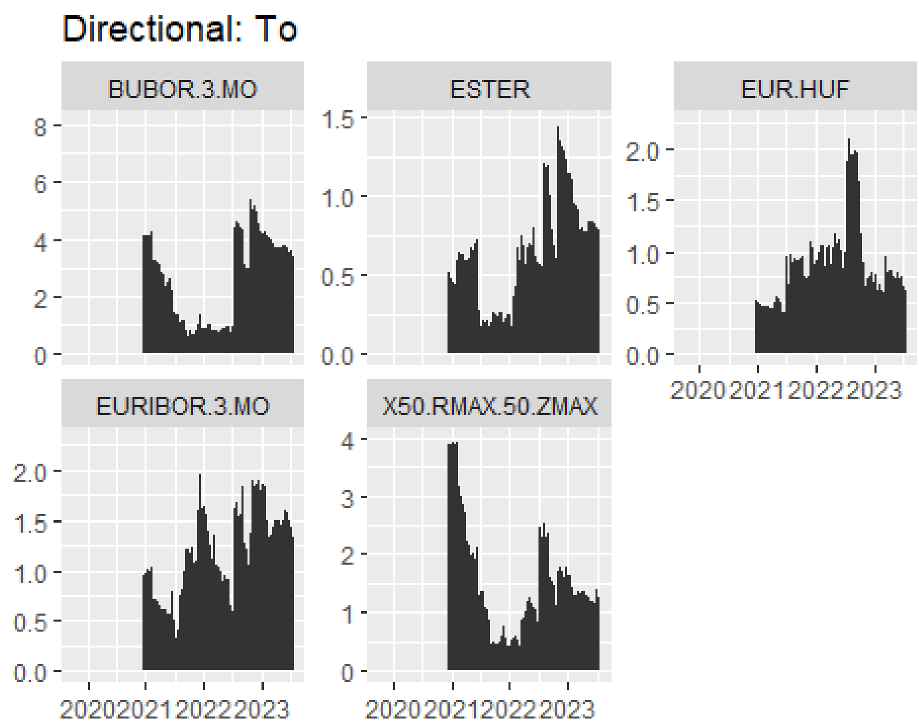
```
pp_from <- plotdy(dy_results, direction = "from")
```



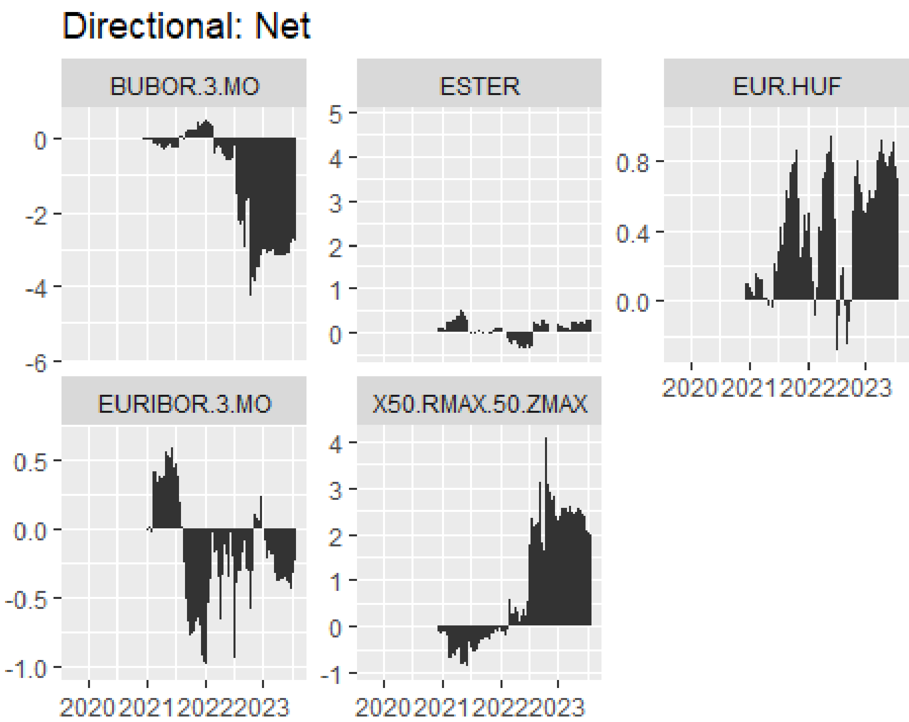

```
pp_from +
labs(title="Any title") +
facet_wrap(~variables, ncol = 2)
```



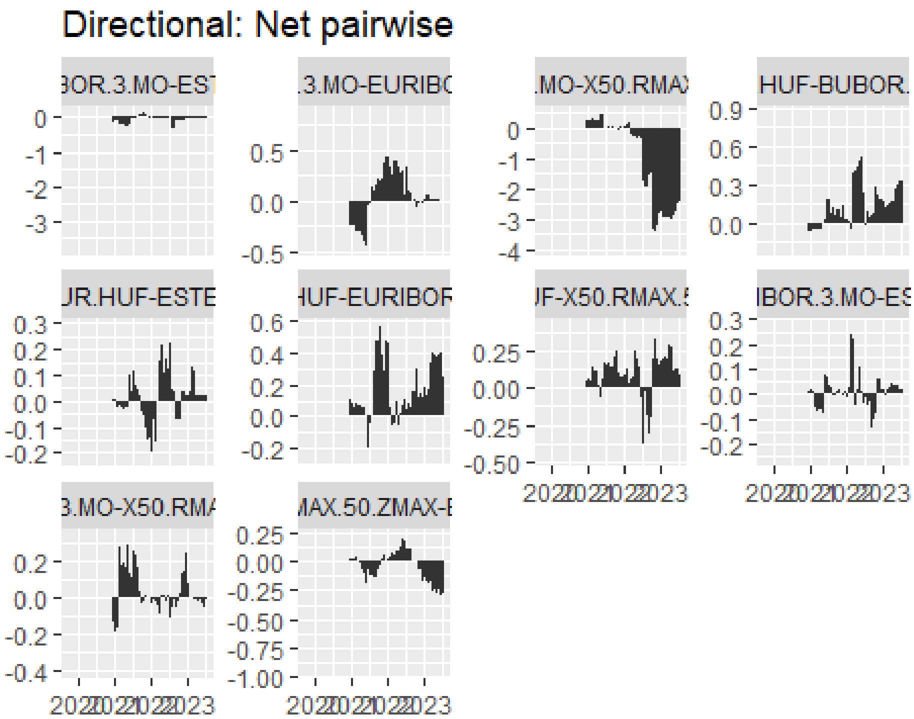

```
pp_to <- plotdy(dy_results, direction = "to")
```



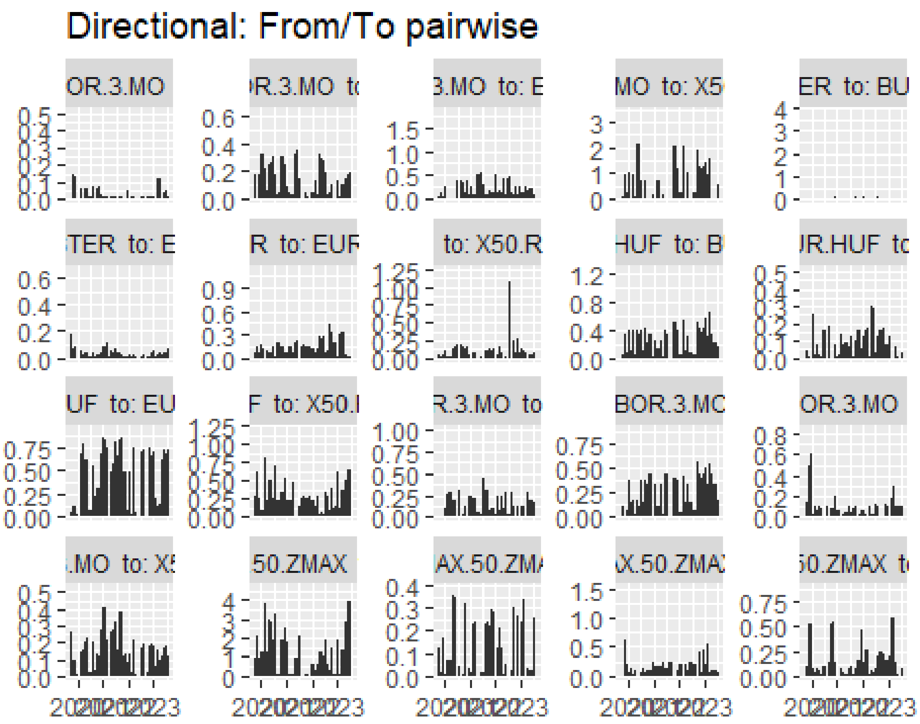

```
pp_net <- plotdy(dy_results, direction = "net")
```




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




```r
pp_from_to_pairwise <- plotdy(dy_results, direction = "from_to_pairwis
e")
```




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

```r
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

```r
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")
```

## 11. Appendix C: Additional results, calculations, and figures for the MSDR model with Unemployment as exogenous variable.

Table 21. Markov switching dynamic regression model for Unemployment model results

```
  Markov Switching Model Results
==============================================================================
Dep. Variable:                GDP %Change   No. Observations:                1
05
Model:                   MarkovRegression   Log Likelihood                -212.516
Date:                    Mon, 08 Aug 2022   AIC                            441.033
Time:                            21:41:59   BIC                            462.264
Sample:                        01-01-1996   HQIC                           449.636
                             - 01-01-2022
Covariance Type:                   approx
                             Regime 0 parameters
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          6.2440      0.406     15.369      0.000       5.448       7.040
x1            -0.3373      0.063     -5.338      0.000      -0.461      -0.213
sigma2         0.5870      0.126      4.657      0.000       0.340       0.834
                             Regime 1 parameters
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          5.3394      2.230      2.394      0.017       0.969       9.710
x1            -0.6711      0.285     -2.353      0.019      -1.230      -0.112
sigma2        20.4992      4.722      4.341      0.000      11.244      29.754
                         Regime transition parameters
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
p[0->0]        0.9267      0.033     28.268      0.000       0.862       0.991
p[1->0]        0.0983      0.050      1.963      0.050       0.000       0.196
```

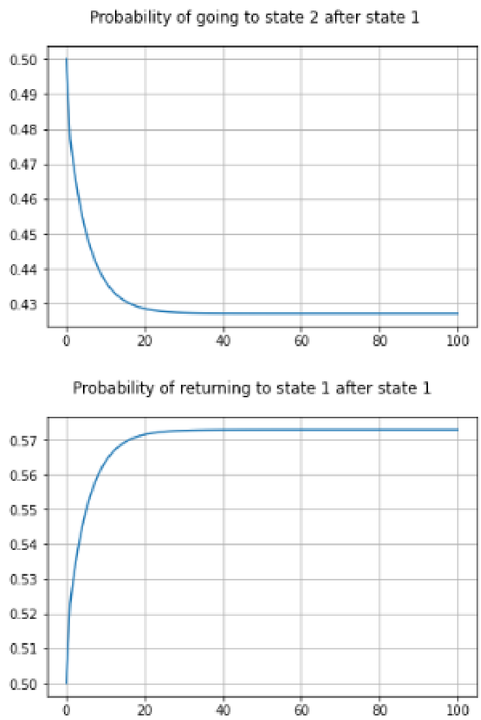



Figure 30. State probability distribution for GDP %Change & Unemployment time series.

## 12. Appendix D: Additional results, calculations, and figures for the MSDR model with Inflation rate as exogenous variable.

Table 22. Markov switching dynamic regression model for Inflation rate model results

```
                        Markov Switching Model Results
==============================================================================
Dep. Variable:                GDP %Change   No. Observations:
105
Model:                   MarkovRegression   Log Likelihood                -218.690
Date:                    Mon, 08 Aug 2022   AIC                            453.380
Time:                            23:39:30   BIC                            474.611
Sample:                        01-01-1996   HQIC                           461.983
                             - 01-01-2022
Covariance Type:                   approx
                             Regime 0 parameters
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          4.4122      0.146     30.292      0.000       4.127       4.698
x1            -0.0177      0.019     -0.929      0.353      -0.055       0.020
sigma2         0.4076      0.104      3.907      0.000       0.203       0.612
                             Regime 1 parameters
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.4096      0.964      0.425      0.671      -1.480       2.299
x1             0.0313      0.106      0.296      0.767      -0.176       0.239
sigma2        19.6046      4.017      4.881      0.000      11.732      27.477
                         Regime transition parameters
```

| | coef | std err | z | P>\|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| p[0->0] | 0.9206 | 0.037 | 25.206 | 0.000 | 0.849 | 0.992 |
| p[1->0] | 0.0748 | 0.038 | 1.962 | 0.050 | 6.88e-05 | 0.150 |

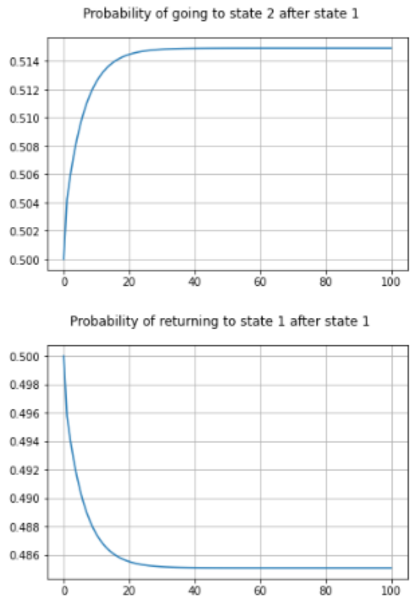



Figure 31 State probability distribution for GDP %Change & lagged Unemployment time series.

## 13. Appendix E: Additional results, calculations, and figures for the MSDR model with IPI as exogenous variable.

Table 23 Markov switching dynamic regression model for Industrial production index (IPI) results

```
Markov Switching Model Results
==============================================================================
Dep. Variable:              GDP %Change   No. Observations:                  1
05
Model:                 MarkovRegression   Log Likelihood                -239.833
Date:                  Tue, 09 Aug 2022   AIC                            495.665
Time:                          00:32:43   BIC                            516.897
Sample:                      01-01-1996   HQIC                           504.269
                           - 01-01-2022
Covariance Type:                 approx
                             Regime 0 parameters
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.4494      0.442     -1.017      0.309      -1.315       0.417
x1             0.2860      0.041      6.915      0.000       0.205       0.367
sigma2         1.1597      0.341      3.399      0.001       0.491       1.828
                             Regime 1 parameters
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          1.9046      0.446      4.273      0.000       1.031       2.778
```

```
x1              0.3561      0.055      6.481      0.000       0.248       0.464
sigma2          9.8122      1.774      5.531      0.000       6.335      13.289
                         Regime transition parameters
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
p[0->0]         0.9359      0.039     23.816      0.000       0.859       1.013
p[1->0]         0.0421      0.025      1.672      0.095      -0.007       0.092
==============================================================================
```

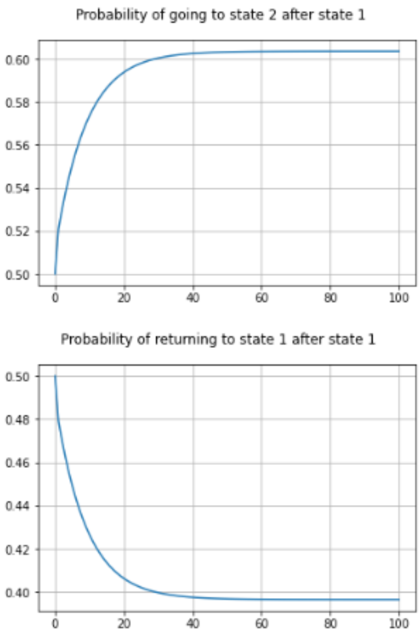



Figure 32 State probability distribution for GDP %Change & IPI time series.

## 14. Appendix F: Additional results, calculations, and figures for the MSDR model with BUX as exogenous variable.

Table 24 Markov switching dynamic regression model for BUX year-on-year percentage change results

```
                        Markov Switching Model Results
==============================================================================
Dep. Variable:                GDP %Change   No. Observations:                1
05
Model:               MarkovRegression   Log Likelihood                -275.466
Date:                Tue, 09 Aug 2022   AIC                            566.932
Time:                        01:54:52   BIC                            588.164
Sample:                    01-01-1996   HQIC                           575.536
                         - 01-01-2022
Covariance Type:               approx
                             Regime 0 parameters
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const           0.7908      0.476      1.660      0.097      -0.143       1.725
x1             -0.4256      0.720     -0.591      0.555      -1.837       0.986
sigma2          1.9972      1.111      1.797      0.072      -0.181       4.175
                             Regime 1 parameters
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          2.7321      0.486      5.627      0.000       1.780       3.684
x1             2.4154      1.491      1.620      0.105      -0.506       5.337
sigma2        13.7441      2.268      6.060      0.000       9.299      18.189
                         Regime transition parameters
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
p[0->0]        0.8945      0.071     12.591      0.000       0.755       1.034
p[1->0]        0.0351      0.022      1.576      0.115      -0.009       0.079
==============================================================================
```

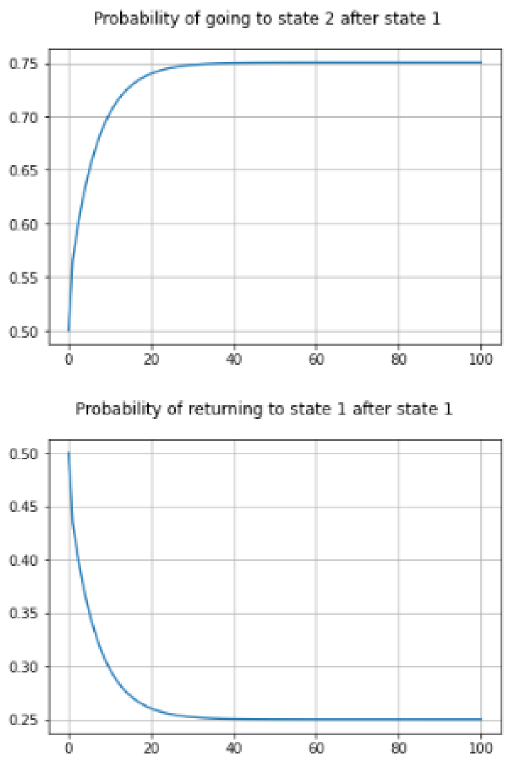



Figure 33 State probability distribution for GDP %Change & BUX YoY change time series.

## 15. Appendix G Additional results, calculations, and figures for the MSDR model with 10Year and 3Year sovereign bond yield spread as exogenous variable.

Table 25 Markov switching dynamic regression model for 10 and 3 year yield spreads results

```
Markov Switching Model Results
==============================================================================
Dep. Variable:              GDP %Change   No. Observations:
93
```

```
Model:                MarkovRegression   Log Likelihood                -195.000
Date:                 Tue, 09 Aug 2022   AIC                            406.000
Time:                         02:13:45   BIC                            426.261
Sample:                     01-01-1999   HQIC                           414.181
                          - 01-01-2022
Covariance Type:                approx
                             Regime 0 parameters
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          4.3779      0.097     45.168      0.000       4.188       4.568
x1             0.0024      0.066      0.036      0.971      -0.127       0.132
sigma2         0.4058      0.090      4.521      0.000       0.230       0.582
                             Regime 1 parameters
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.6287      0.729      0.862      0.389      -0.801       2.058
x1             0.0772      0.572      0.135      0.893      -1.044       1.199
sigma2        21.8013      4.702      4.637      0.000      12.586      31.016
                         Regime transition parameters
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
p[0->0]        0.9294      0.036     26.031      0.000       0.859       0.999
p[1->0]        0.0616      0.036      1.707      0.088      -0.009       0.132
==============================================================================
```

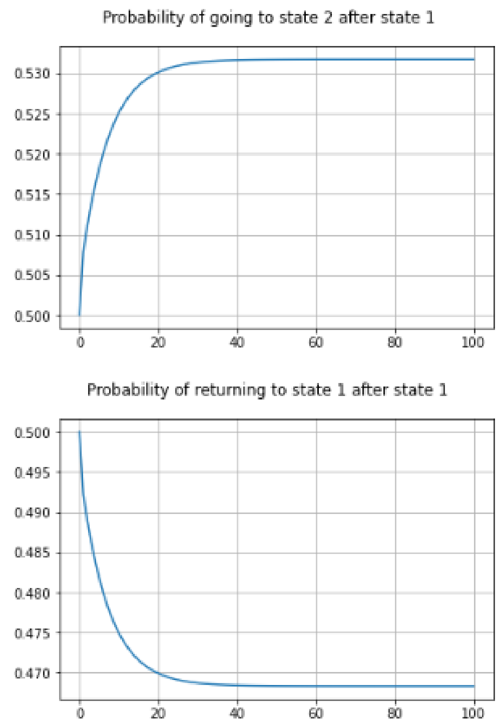



Figure 34 State probability distribution for GDP %Change & BUX YoY change time series.

**ABSTRACT**