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**Research Report**

## Asset price shocks and inflation in the Finnish economy

BoF Economics Review, No. 6/2024

**Provided in Cooperation with:**

Bank of Finland, Helsinki

*Suggested Citation:* Koivisto, Tero (2024) : Asset price shocks and inflation in the Finnish economy, BoF Economics Review, No. 6/2024, Bank of Finland, Helsinki, <https://nbn-resolving.de/urn:nbn:fi-fe2024061955575>

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## Asset price shocks and inflation in the Finnish economy

\*Tero Koivisto

### Abstract

This study aims to explore the extent to which changes in wealth contributes to inflation utilizing a highly flexible non-Gaussian SVAR framework which minimizes the risk of distributional misspecification. We employ narrative sign restrictions to label the asset price shock and leverage the property of the Bayesian approach to compute the posterior probability of each shock satisfying these proposed restrictions. The structural shock associated with wealth has a positive impact on private consumption and GDP. The asset price shock is also positively related on consumer prices. Therefore, variations in wealth appear to stimulate the real economy.

**Keywords:** Asset price shocks, wealth effect, inflation, structural vector autoregression, non-Gaussianity

**JEL codes:** E31, E44

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*Footnote: \*Tero Koivisto was working as an Economist Trainee at the Bank of Finland from May 2023 until Sep 2023.*

*I thank two anonymous referees, Juha Kilponen, Aino Silvo and especially Petteri Juvonen for useful comments and discussions. I would also want to show gratitude for Jetro Anttonen for sharing some code. All remaining errors are of the authors alone. The views expressed in the paper are those of the authors and do not necessarily represent the views of Bank of Finland*

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# 1 Introduction

Financial and uncertainty shocks have been studied extensively in the past literature (see e.g., Ajello, 2016; Bloom, 2009; Brunnermeier et al., 2021; Caldara et al., 2016; Carriero et al., 2021; Christiano et al., 2015; Smets & Wouters, 2007). Essentially, these shocks manifest themselves as changes in wealth. The wealth effect is the phenomenon where changes in individuals' wealth impact their spending habits. An increase in wealth tends to boost consumer spending, while a decrease leads to reduced spending. This concept highlights the influence of perceived wealth on economic activity (see e.g., Boeckx et al., 2017; Chodorow-Reich et al., 2021; Schaffer & Segev, 2023). In this paper we are interested in a structural shock that is characterized by abrupt change in wealth that can be caused by many factors. We are going to refer to these shocks as asset price shocks.

We estimate a non-Gaussian SVAR model in Finland, a small open economy part of a large monetary union. We identify a shock that causes immediate changes in wealth measured by the stock price index and study the impulse response functions. The Bayesian estimation is done by using a Hamiltonian NUTS-algorithm. The identified structural shock related to wealth and uncertainty is labelled using narrative sign restrictions and further strengthened by analysing Bayes factors. This paper builds on the methodology of Lanne & Luoto (2017) and further extended by Anttonen et al. (2022, 2023) and uses the latest data and methods in the Finnish context. Our paper contributes to the extensive body of work exploring the connection between stock market wealth, consumption patterns, and the real economy and is closely related to Brunnermeier et al. (2021).

One strategy to attain better results and identification in SVAR model is to allow the error terms to follow a non-Gaussian and highly flexible distribution. Our approach exploits the skewness of structural errors for identification which makes the identification stronger and avoids distributional misspecification compared to majority of previous SVAR literature (see e.g., Valcarcel, 2012). We also try to label the shock using narrative sign restrictions that have been widely adopted in the past few years (see e.g., Caggiano et al., 2021; De Santis & Van der Veken, 2022). Traditional sign restrictions truncate the prior distribution which can cause misspecification of the model. They are used to constrain the impulse response functions (IRFs) or the structural parame-

ters themselves within a BSVAR model, and thus exclude parameter values that could have been compatible with the data. Our approach does not require such restrictions since the model and related impulse response functions are identified solely by non-Gaussianity.

It is common knowledge that wealth distribution within an economy is often characterized by significant asymmetry and is not evenly distributed. The distribution is skewed, and thus wealth effect as a monetary policy transmission channel has been criticized for potentially widening wealth gaps, since not everyone owns assets. Adam & Tzamourani (2016) argued that price increases in equity, bond, and housing markets have varying distributional effects, highlighting that changes in bond prices do not alter the wealth distribution. Specifically, changes in equity prices primarily benefit the higher end of the net worth distribution, while housing market price changes impact a larger proportion of households, which also imposes difficulties on the transmission of higher wealth into increased consumption. This gives further evidence to high skewness in the data making our approach even more desirable.

The results of the empirical analysis produced findings that are consistent with the economic theory. The structural shock associated to wealth influences positively consumer prices, private consumption and GDP. This underscores that changes in wealth indeed foster activity in the real economy, though the mechanisms of transmission are intricate. Thus, we can argue that periods of downturns on the equity market can have significant adverse effects on the real economy. In the bulk of majority literature with various different models, a negative relationship was found (see e.g., Adams et al., 2004; Eldomiaty et al., 2020; Fama, 1981; Li et al., 2010; Valcarcel, 2012). A minority of papers has also found a positive relationship (see e.g., Luintel & Paudyal, 2006). Economic theory suggests that the relationship should indeed be positive as found in our paper. None of the previous models have been based on the strong identification via non-Gaussianity.

This paper is structured as follows. The data is presented in section 2. In section 3, we introduce a statistically identified SVAR model with non-Gaussian errors. The analysis, labelling and the results are presented in section 4. Finally, section 6 concludes the paper.

## 2 Data

Our baseline model consists of five variables. Most of them are retrieved from the Statistics Finland and Nasdaq Data Link. The dataset and variables are described in Table [1](#).

We use the trend indicator of output by Statistics Finland as a proxy for monthly real GDP. However, the real private expenditures data series is transformed into monthly series using the method introduced by Chow & Lin (1971). All variables, except for the 10-year Finnish government bond, are presented in logarithmic form.

Table 1

| Data period 01/2000-09/2023 |                    |           |   |
|-----------------------------|--------------------|-----------|---|
| Variable                    | Source             | Frequency | Description                             |
| <i>cpi</i>                  | Statistics Finland | monthly   | Finland, Consumer Price Index, 2015=100 |
| <i>omx</i>                  | Nasdaq             | monthly   | Nasdaq OMX Helsinki                     |
| <i>i<sub>10</sub></i>       | Bank of Finland    | monthly   | Government Bond, 10 Year, Yield         |
| <i>gdp</i>                  | Statistics Finland | monthly   | Trend indicator of output               |
| <i>consumption</i>          | Statistics Finland | quarterly | Private consumption expenditure         |

### 3 Econometric methods

To study the wealth effect related to asset price shocks, we make use of a SVAR model and especially the methodology of Anttonen et al. (2021). In this section, the econometric framework and the estimation of the model will be presented.

#### 3.1 Framework

Let  $\mathbf{y}$  be an  $n \times 1$  vector containing the variables of the model.  $\mathbf{A}_1, \dots, \mathbf{A}_p$  refer to  $n \times n$  matrices that contain the coefficients. Here,  $p$  represents the lag length. Additionally,  $\mathbf{c}$  is a vector of constants. The matrix  $\mathbf{B}$  encompasses the contemporaneous structural relations of the components of the error vector  $\epsilon_t$ . The error vector  $\epsilon_t$  is assumed to comprise independent and non-Gaussian components. We further assume that the components of  $\epsilon_t$  are mutually independent. At most one of these components follows a Gaussian marginal distribution with a mean of zero and an unit scale of  $\sigma_i$ .

Lanne et al. (2017) showed that if the assumptions hold (related to  $\sigma_i$ ), it becomes evident that the identification of  $\mathbf{B}$  is unique, except for permutations and signs of its columns. Essentially, there are  $n!$  observationally equivalent  $\mathbf{B}$  matrices, disregarding sign reversals. Successful identification of the model only requires independence and sufficient non-Gaussianity (see the proof of Proposition 1 in Lanne et al., 2017). This result also yields unique and statistically identified impulse response functions. However, they do not carry any economic meaning without labelling.

A general Vector Autoregression (VAR) model of order  $p$  takes the form:

$$\mathbf{y}_t = \mathbf{c} + \mathbf{A}_1 \mathbf{y}_{t-1} + \mathbf{A}_2 \mathbf{y}_{t-2} + \dots + \mathbf{A}_p \mathbf{y}_{t-p} + \mathbf{B} \epsilon_t \quad (1)$$

In previous research, it is commonly assumed that the error terms follow a Gaussian distribution, which poses issues for the identification of the SVAR model. Therefore, this study adopts a methodology inspired by Anttonen et al. (2021), wherein a highly flexible skewed generalized t-distribution is employed to account for the skewness and kurtosis of the shocks. This distribution is not common in the previous literature. This choice also forms the basis for the identification based on non-Gaussianity.

The highly flexible distribution fits data well when it is characterized by randomness.

Economic variables, especially those associated with the stock market, often exhibit "fat tails," indicating a higher likelihood of extreme events (negative ones) than it would be assumed under Gaussianity. The information pertaining to these fat tails is captured by the third and fourth moments of the distribution. Consequently, a model relying on the normal distribution might be too inadequate for our purposes since it is defined solely by its mean (the first moment) and its variance (the second moment). In this paper, the estimation of the Structural Vector Autoregressive (SVAR) model is performed using Bayesian inference. This approach is preferred because it offers distinct advantages when dealing with short time series data. More information about the Bayesian estimation and the algorithm can be found in Appendix B.

### 3.2 Estimation of the model

We will adopt<sup>1</sup> a lag length of 12, which is standard practice in previous studies (see e.g., Anttonen et al., 2021).

We utilize the algorithm outlined in Appendix B to estimate the parameters of the SVAR(12) model mentioned in equation (1). Specifically, we employ the HMC algorithm, executing it with four chains (N=4) to ensure reliable results each consisting of two thousand draws. Half of the each chain was used to tune the algorithm. Thus, 4000 draws describe the final posterior sample.

An improper prior for the matrix  $\mathbf{B}$  is chosen. More information on the priors for the parameters can be found in Appendix.

To assess the convergence of the chains and validate the accuracy of our estimates, we use the  $\hat{R}^2$  statistic, commonly known as the "Gelman-Rubin statistic" (Gelman et al., 2013) in Figure 1. The established threshold is 1.1, and a value below it signifies the convergence of the chains. Based on the results of this analysis, the chains were deemed to have converged, indicating that our estimation process was successful, posterior sample sufficiently large and the obtained parameter estimates can be considered reliable.

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<sup>1</sup>Chodorow-Reich et al. (2021) found a delay of 1-2 quarters, indicating a minimum lag length of 6. However, due to the dynamic nature of the stock markets and inflation observed over the past two years, it is preferable to use a longer lag length.

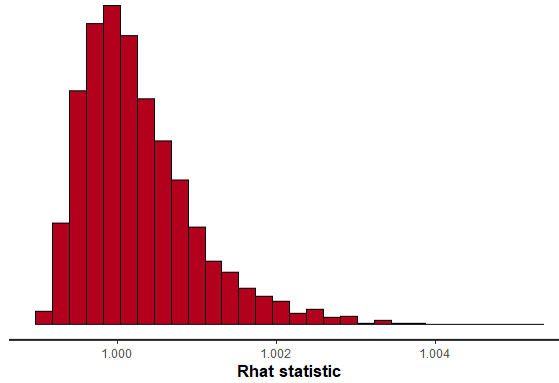


Figure 1: The histogram of  $\hat{R}^2$  statistic for the base model. Gelman et al (2013) stated that the value of 1.1 can serve as a treshold value.

In our analysis, we have made an initial assumption that the error terms follow a non-Gaussian distribution. To confirm this assumption, we examine the posterior distribution of the parameters that define the distribution of these error terms. We want to see skewness in Figure 2 for successful identification, and this indeed happens.

Anttonen et al. (2021) highlighted that weak identification of the parameters would result in posterior marginal densities that appear justifiable but excessively wide. Consequently, the confidence intervals derived from such distributions would be unsuitable for drawing meaningful conclusions. Therefore, if the impulse response functions derived from the model are well-behaved, it provides evidence supporting our assumption of non-Gaussian errors and the convergence of the algorithm.

So far our statistical identification of the SVAR model has been successful: however, at this point we have just five random structural shocks from our model. In essence, we have not yet labelled the shocks. For meaningful economic interpretation, it is crucial to label the specific shock that is related to wealth changes.



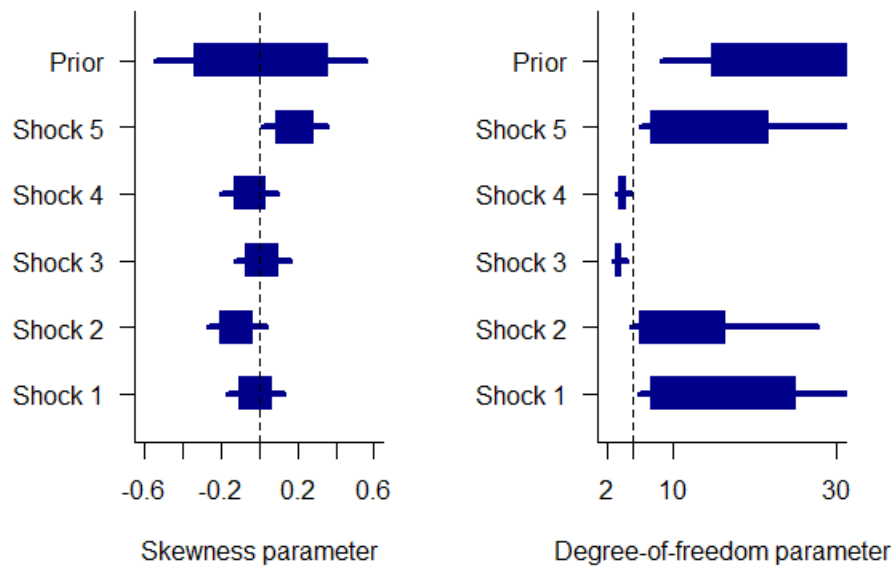


Figure 2: 68% and 90% posterior and prior confidence intervals for the parameters of the model controlling for skewness and kurtosis (tails) of the sgt-distributed shocks. High levels kurtosis or skewness imply non-Gaussianity which improves the statistical identification of our model.  $\alpha \approx p_i q_i$  can be viewed as roughly the degree-of-freedom parameter that summarizes the tail behaviour.

## 4 Analysis

### 4.1 Labelling the asset price shock

We have successfully estimated and identified the model, the structural shocks and the related impulse response functions, but we still need to label the structural shock related to wealth. However, we can not rely on short-run sign restrictions approach since it is hard to credibly impose such restrictions in the case of stock markets. Labelling the asset price shock is a complex task, primarily because of the forward-looking nature of asset prices. This characteristic makes it extremely difficult to apply traditional short- or long-term constraints. This challenge is also better known as the foresight problem (Elbourne and Ji, 2019). This dynamic results in the exogenous shock altering prior to its manifestation in the data - posing a substantial obstacle to different identification schemes.

We opted for a method known as "uncontroversial sign restrictions" based on the methodology of Antolín-Díaz and Rubio-Ramírez (2018) and Anttonen et al. (2021). We use this approach to calculate the posterior distribution of individual shocks while taking into account predefined sign constraints that are based on their narrative interpretations: meaning that we compute the probability of the shock being positive or negative at given point of time.

Unlike Antolín-Díaz & Rubio-Ramírez (2018), we do not impose these restrictions during the estimation of the model. Instead, we leverage the property of the Bayesian approach, which allows us to compute the posterior probability of each shock satisfying these proposed restrictions after the estimation. This is more convenient since we will not impose any prior restrictions on the model.

With the estimated model, we compute the posterior probability of each of the five shocks being positive or negative depending on the narrative restrictions. For any shock to be the asset price shock, it has to fulfil all the narrative restrictions with high posterior probabilities and especially the joint posterior probability has to be relatively high. Note that occasionally multiple shocks can satisfy the restrictions on a given date with a high probability and this is why we need multiple restrictions so that we can compute a joint posterior probability. The outcome of this analysis is presented in

Table 2 and the marginal posterior distributions can be found in Figure 3.

### **Narrative sign restrictions:**

**Narrative sign restriction 1:** *In September 2001, the shock must take negative value. September 11 attacks increased uncertainty and plummeted asset prices (Bloom, 2009).*

**Narrative sign restriction 2:** *In October 2008, the asset price shock must take negative value. The negative asset price shock is the most important driving force in the stock market due to the start of the financial crisis and bankruptcy of Lehman Brothers. (De Santis & Van der Veken, 2022)*

**Narrative sign restriction 3:** *In July 2012, the asset price shock must take a positive value. The famous speech "Whatever it takes" by Mario Draghi. See Alcaraz et al. (2019). The speech has been cited to restore trust within the Eurosystem and thus increase asset prices.*

**Narrative sign restriction 4:** *In April 2020, the asset price shock must take a positive value. The stock market recovered rapidly after the COVID-19 crash partly due to the actions of the government (stimulus checks) and the Fed inserting liquidity into the financial system. Karavias et al. (2022) argued that the negative effect of the negative COVID-19 asset price shock stopped dead in April 2020 and attribute to the massive amount of quantitative easing. The effect of the negative COVID shock seemed to have disappeared suddenly which also might imply that the original response was overexaggerated. This would suggest that a positive asset price shock was present after April 2020 and it was exogenous to some extent.*

**Narrative sign restriction 5:** *In March 2022, the asset price shock must take a negative value. The Russian invasion<sup>2</sup>. This caused the asset prices to drop more in Finland than e.g., in US due to geography.*

In our case, the second shock satisfies all the necessary criteria, boasting a relatively high probability of 0.85%. However, to ensure accuracy, we need to verify the opposite scenario by multiplying the signs by -1. This step becomes necessary since we did not impose any restrictions on the signs of the elements in the matrix B. We find that

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<sup>2</sup><https://www.imf.org/en/Publications/fandd/issues/2022/03/the-long-lasting-economic-shock-of-war>

none of the shocks had a high a probability. Based on these results, we can confidently conclude that the second shock is the one we are interested in, representing the asset price shock.

To further strengthen our labelling, we consider medium term sign restrictions. We restrict the asset price shock to have a positive impact on itself. Chodorow-Reich et al. (2021) suggested that the stock wealth has a positive effect on consumption with a delay of 1-2 quarters. Thus, we are going to use timespan of 6 months and restrict the effect to be positive. We evaluate the feasibility of these constraints by employing Bayes factors<sup>3</sup>. Consistent with Lanne & Luoto (2020), we determine that a Bayes factor exceeding 3.2 indicates significant evidence in favor of the restrictions. The shock number 2 had a Bayes factor of 3.98 and for the rest it was below the value of 3.2.

Figure 4 shows the posterior distribution of the identified shocks over time. The shocks seem to exhibit heteroskedasticity, with periods of higher volatility evident. Specifically, the asset price shock appears to exhibit heightened volatility following the 2000 dot-com bubble and the 2008 financial crisis. This observation further strengthens the labeling of the shock since it can be verified by looking at the historical data.

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<sup>3</sup>To do this, we need to set a proper prior for the matrix  $\mathbf{B}$ . We set the diagonal mean to 4 and non-diagonal mean to 0 and prior standard deviation on all components to 100.

| <b>Probabilities</b> |         |         |         |         |         |
|----------------------|---------|---------|---------|---------|---------|
|                      | Shock 1 | Shock 2 | Shock 3 | Shock 4 | Shock 5 |
| 09/2001 (-)          | 0.01    | 1.00    | 0.42    | 0.39    | 0.96    |
| 10/2008 (-)          | 1.00    | 1.00    | 0.00    | 0.61    | 0.68    |
| 7/2012 (+)           | 0.06    | 0.98    | 0.13    | 0.34    | 0.95    |
| 4/2020 (+)           | 0.90    | 0.96    | 0.34    | 1.00    | 0.10    |
| 3/2022 (-)           | 0.37    | 0.92    | 0.58    | 0.55    | 0.43    |
| Total                | 0.00    | 0.86    | 0.00    | 0.04    | 0.03    |

*Table 2: Posterior probabilities and joint posterior probabilities of each shock in the base model satisfying the narrative sign restrictions 1-5. The table presents probabilities of shocks having a positive or negative impact on a given date, based on specified signs. Rows represent different dates, and columns correspond to distinct shock components. The “Total” row provides the joint probability of consistent shock signs across all dates, while individual rows show date-specific probabilities. Note that the probabilities in each column or row do not sum to 1, and the ‘Total’ row is derived from the column-wise multiplication of probabilities for each date since we can assume that the dates and shocks are independent. For example, we can see that for the date 10/2008 (the financial crisis), it yields probability 1 for shocks 1 and 2. Thus, we need more narrative restrictions to achieve successful labelling.*

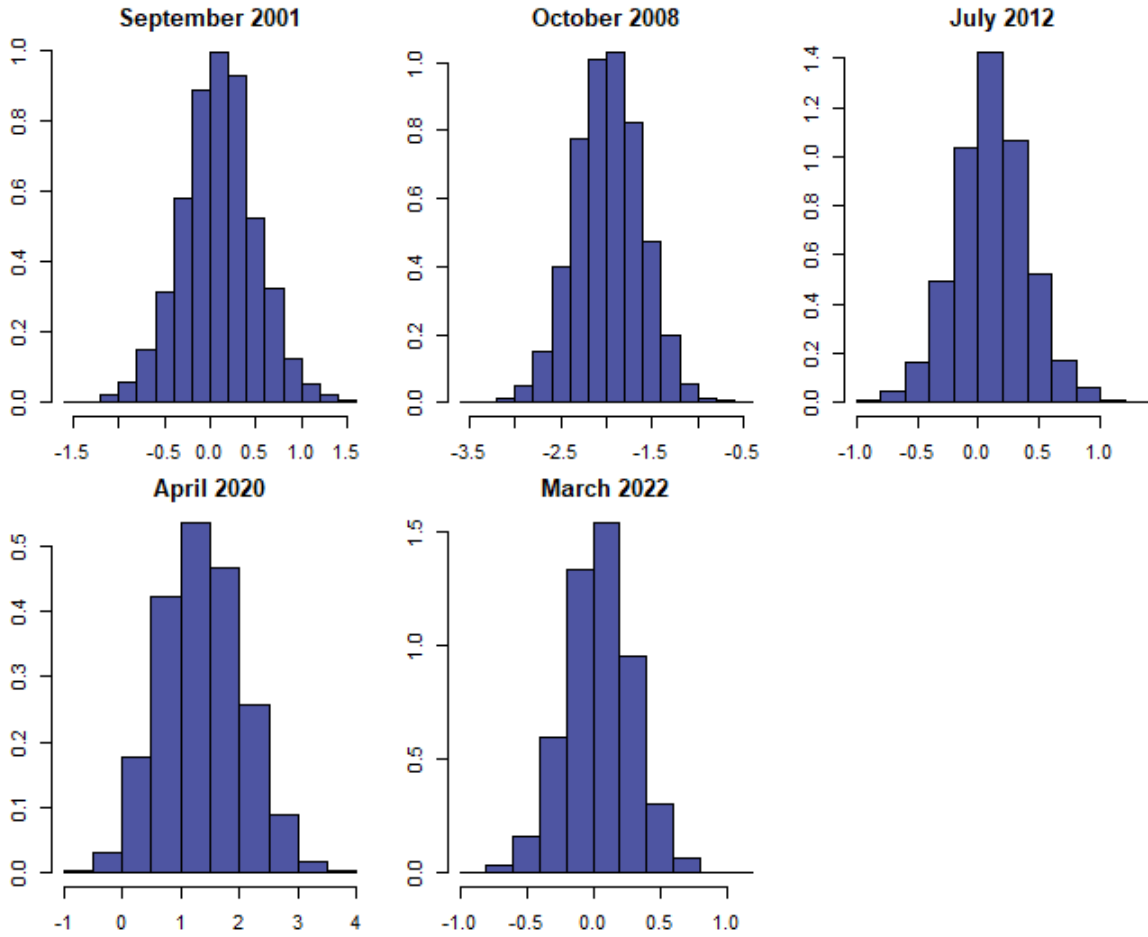


Figure 3: The marginal posterior distribution of the asset price shock corresponding to the narrative sign restriction dates.

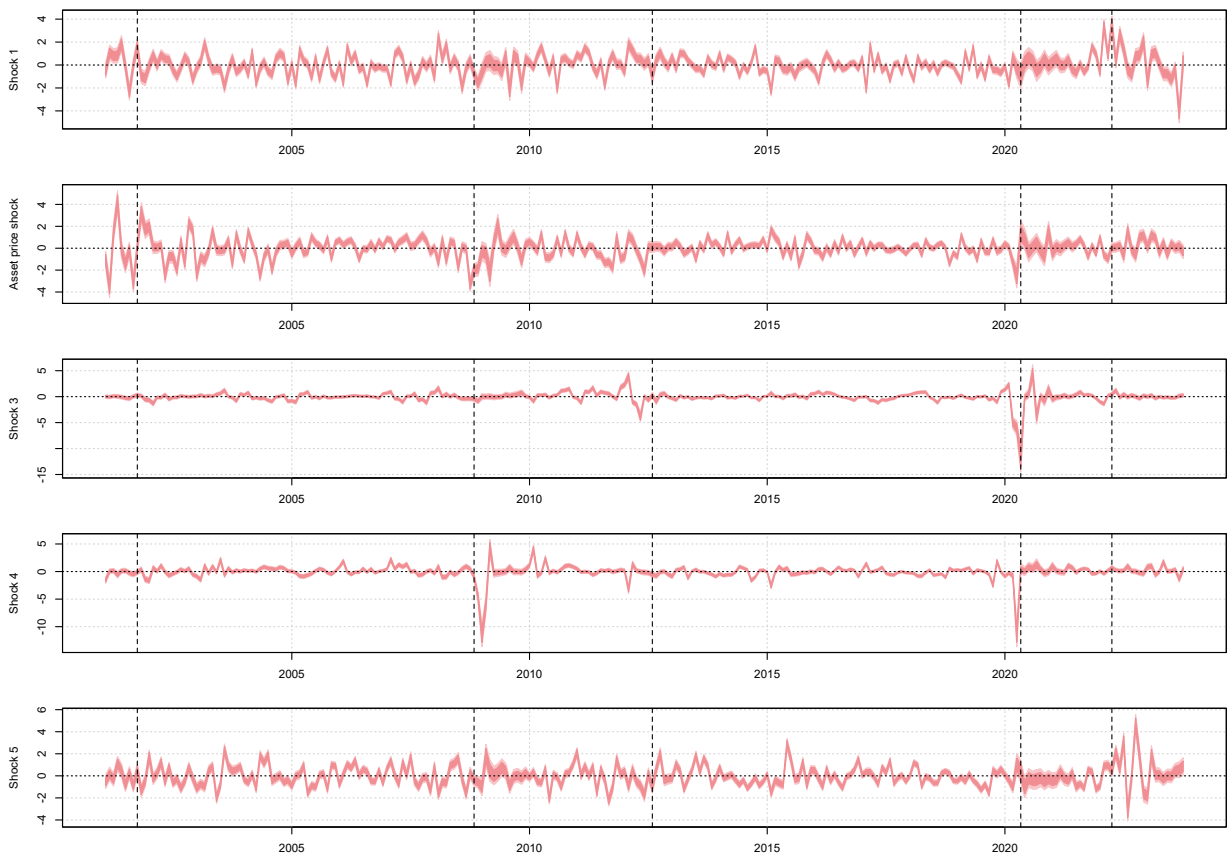


Figure 4: 68% and 90% point-wise credible sets of all the shocks over time for the baseline specification. The vertical dashed lines correspond to the dates of the narrative records.

## 4.2 Impulse response analysis

The impulse response functions for the whole model are presented in Appendix Figure 7. The impulse responses for the asset price shock is presented below in Figure 5. The shock related to asset prices has a positive effect on consumer prices (cpi) which contradicts the consensus view of the literature (see e.g., De Santis & Van der Veken, 2022; Fama, 1981; Schenkelberg & Watzka, 2013; Valcarcel, 2012). The effect of the structural shock on stock prices is positive on impact and stays positive in the long run as it was supposed to be. The effect on interest rates is positive.

In addition, it seems that the asset price shock has a positive effect on the GDP, as in Lewis (2021). When a sudden increase in wealth occurs, it presumably tends to stimulate economic activity, leading to an overall boost in the GDP. This phenomenon might be driven by increased consumer spending, investments, and business expansion, all of which contribute to the economy. Similar results was found by Chodorow-Reich et al. (2021). They also noted that it increases private consumption which is inline with our model.

Rough and simplifying calculations reveal that one percentage point change in the stock index corresponds to around 0.01, 0.01, and 0.02 percentage point changes in consumer prices, GDP and private consumption respectively within six months (2 quarters).

However, it is essential to note that the relationship between asset price shock, GDP, and private consumption is complex and multifaceted. Various economic and policy factors come into play, influencing the outcomes of such shocks. For instance, the magnitude and duration of the asset price (presumably it must last long to have any effect on e.g., demand), the country's economic structure, monetary and fiscal policies, and even public sentiment can impact the overall dynamics.



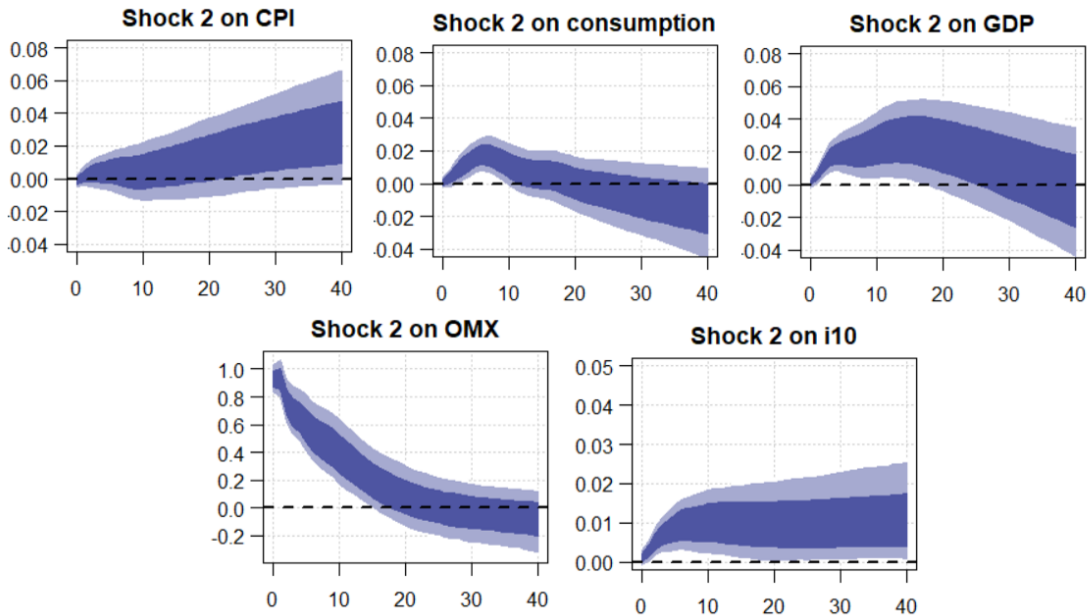


Figure 5: *BENCHMARK MODEL*. Impulse responses for the suspected asset price shock with the 68% and 90% point-wise posterior intervals. The size of the shock is scaled to unity. Y-axis is scaled to percentage points. Time period 01/2000-09/2023.

### 4.3 Robustness

Uncertainty and asset price shocks are manifested in the economy in a similar way. Thus, we must try to distinguish these two. We are going to add Chicago Board Options Exchange's CBOE Volatility Index (VIX) to control for uncertainty. Bekaert et al. (2013) argued that VIX index contains information on uncertainty and risk aversion which makes it highly attractive variable to control for uncertainty. We are going to refer this model as "VIX model". Nothing else changes compared to the base model than the number of variables.

We are going to use the same set of narrative restrictions for this model and they are presented in Table 3. Notably, the incorporation of the VIX led to a decrease in the joint probability associated with shock 2. This phenomenon is attributed to the narrative restriction linked to Mario Draghi's speech. If we omit this restriction, the joint probability would be 74%. We can see that it clearly had something to do with uncertainty since the probability of the shock 6 being positive (negative) is 0.00 (1.00). The impulse response functions for the "VIX" shock is presented in Appendix in figure 8. There are no notable differences when it comes down to shock 2.

We additionally modified the time series by taking first order difference. Furthermore, we explored models with various lag lengths, including 2 and 6 lags. Notably, the impulse response functions exhibited similar patterns across these different configurations.

We also tested for different priors on the parameters but the results remained similar.

Finally, we considered model with shorter time periods starting from 2005 and 2012. The medians of the impulse response functions are presented in figure 6. The impulse response exhibit similar shape but we can see differences in scale. One possible explanation is quantitative easing. This might also explain the large difference in the interest rate. When considered the time after 2012, the effect of the identified asset price shock has larger effect on consumption and the GDP than before. The effect on price level, however, is smaller.

| <b>Probabilities</b>  |         |         |         |         |         |         |
|-----------------------|---------|---------|---------|---------|---------|---------|
|                       | Shock 1 | Shock 2 | Shock 3 | Shock 4 | Shock 5 | Shock 6 |
| 09/2001 (-)           | 0.00    | 1.00    | 0.33    | 0.33    | 0.88    | 0.00    |
| 10/2008 (-)           | 1.00    | 1.00    | 0.00    | 0.68    | 0.65    | 0.80    |
| 7/2012 (+)            | 0.27    | 0.37    | 0.44    | 0.63    | 0.91    | 0.00    |
| 4/2020 (+)            | 0.78    | 0.83    | 0.32    | 1.00    | 0.09    | 0.00    |
| 3/2022 (-)            | 0.32    | 0.89    | 0.49    | 0.41    | 0.40    | 0.14    |
| Total                 | 0.00    | 0.28    | 0.00    | 0.06    | 0.02    | 0.00    |
| Total excluded 7/2012 | 0.00    | 0.74    | 0.00    | 0.11    | 0.02    | 0.00    |

Table 3: Posterior probabilities and joint posterior probabilities of each shock in the "VIX" model satisfying the narrative sign restrictions 1-5. The table presents probabilities of shocks having a positive or negative impact on a given date, based on specified signs. Rows represent different dates, and columns correspond to distinct shock components. The "Total" row provides the joint probability of consistent shock signs across all dates, while individual rows show date-specific probabilities.

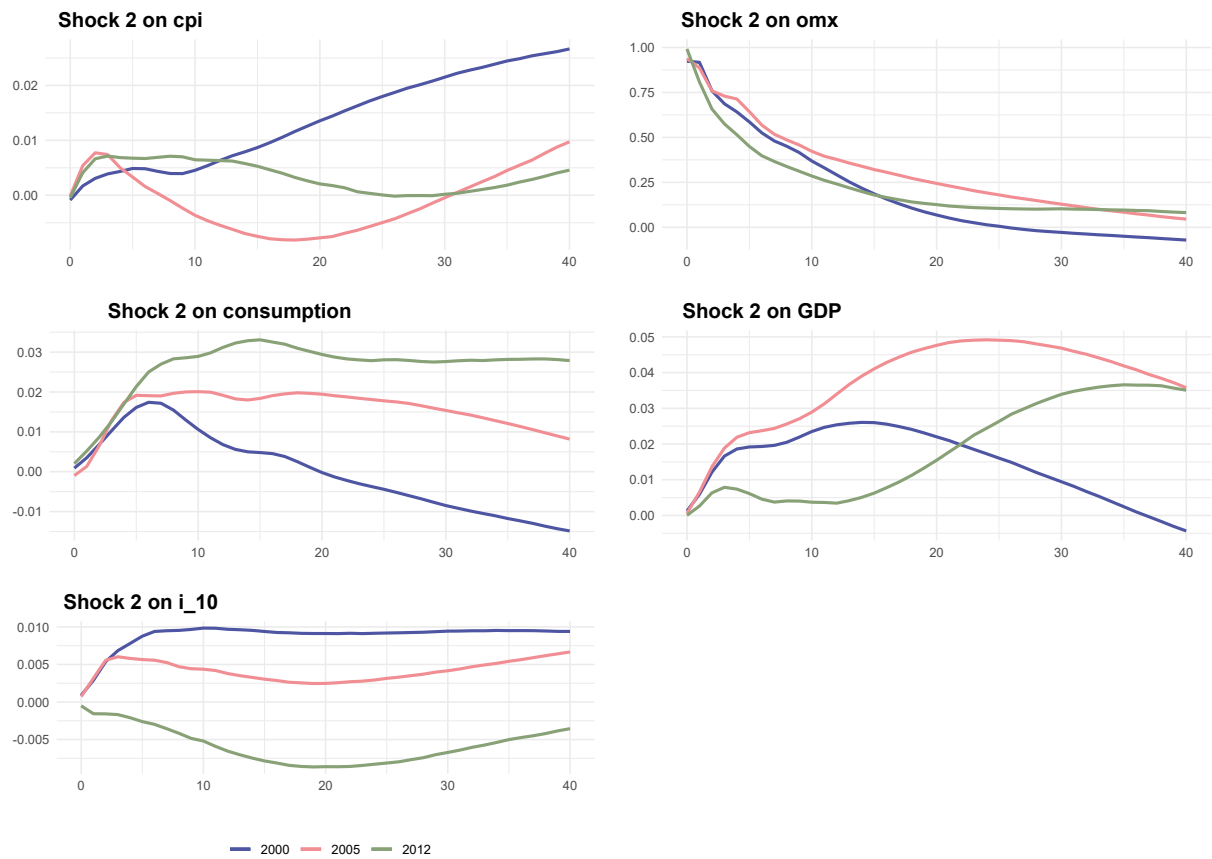


Figure 6: Median of the impulse response functions of the labelled asset price shock with different time periods. From 01/2000 (base model), 01/2005, 01/2012 to 09/2023.

## 5 Conclusion

In this paper, a statistically identified Structural Vector Autoregressive (SVAR) model was formulated to examine the role of asset price shocks in inflation. The assumption of non-Gaussian error terms was made, following a highly flexible skewed generalized t-distribution, enabling stronger identification of the SVAR model. The process of labeling this shock was carried out through the application of narrative sign restrictions and further strengthened with standard sign restrictions.

Analyzing the impulse response functions revealed that the asset price shock has a weakly positive effect on consumer prices. However, the relationship is multifaceted since the shock had positive effect on GDP and private consumption which has been found to drive up inflation. The increasing wealth seems to increase private consumption which then contributes to economic growth often measured by the GDP. Consequently, this exerts upward pressure on prices, leading to inflation. Therefore, it is reasonably safe to argue that this aligns with the wealth effect described in economic literature. Our result diverges somewhat from majority of past literature, where a (weakly) negative association between stock prices and inflation was observed (see e.g., Fama 1981, Valcarcel 2012, Eldomiaty et al. 2020).

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## 7 Appendix A



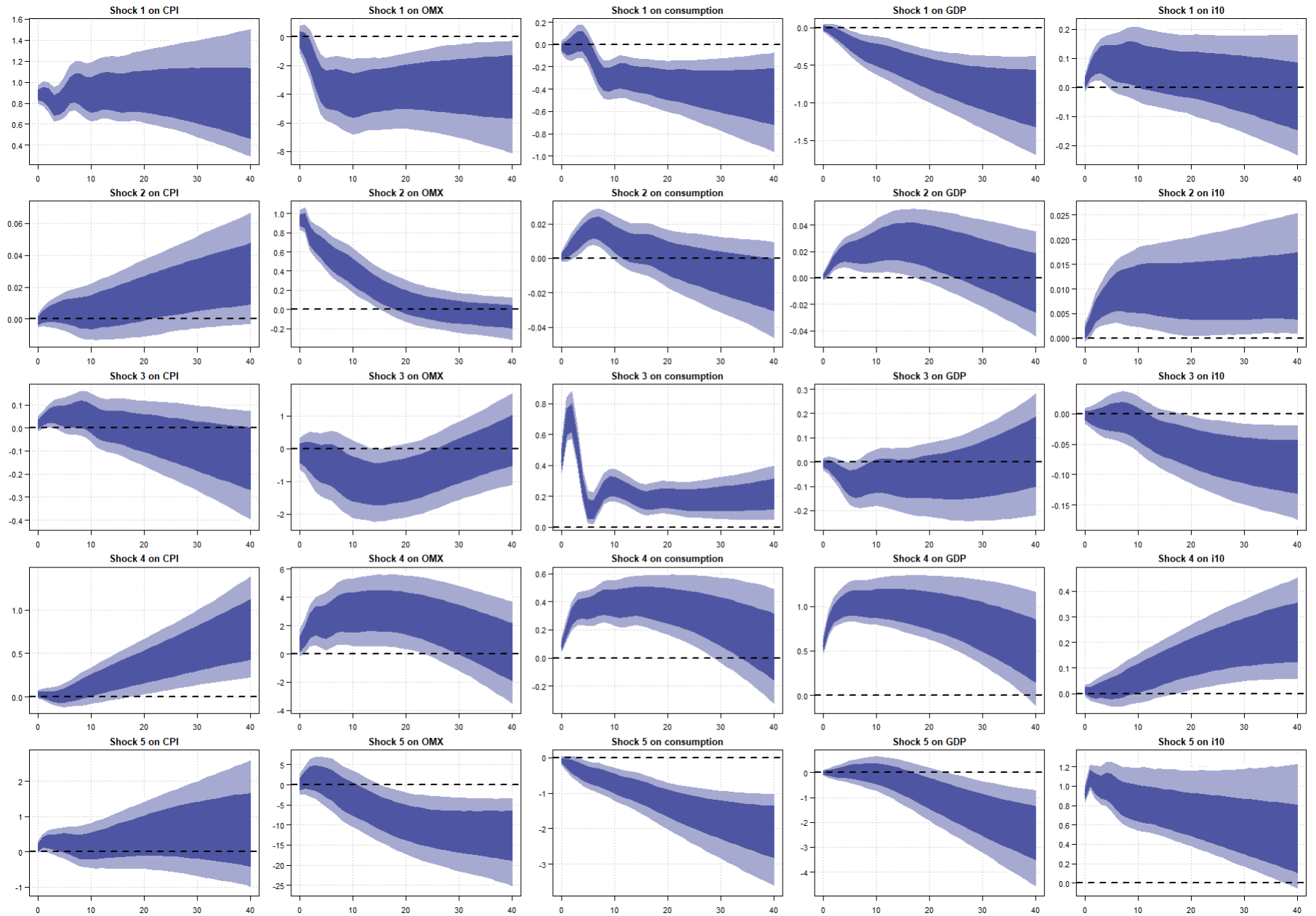


Figure 7: BENCHMARK MODEL. Impulse responses of all shocks with the 68% and 90% point-wise posterior intervals. The size of the shock is scaled to unity. Y-axis is scaled to percentage points. Time period 01/2000-09/2023.

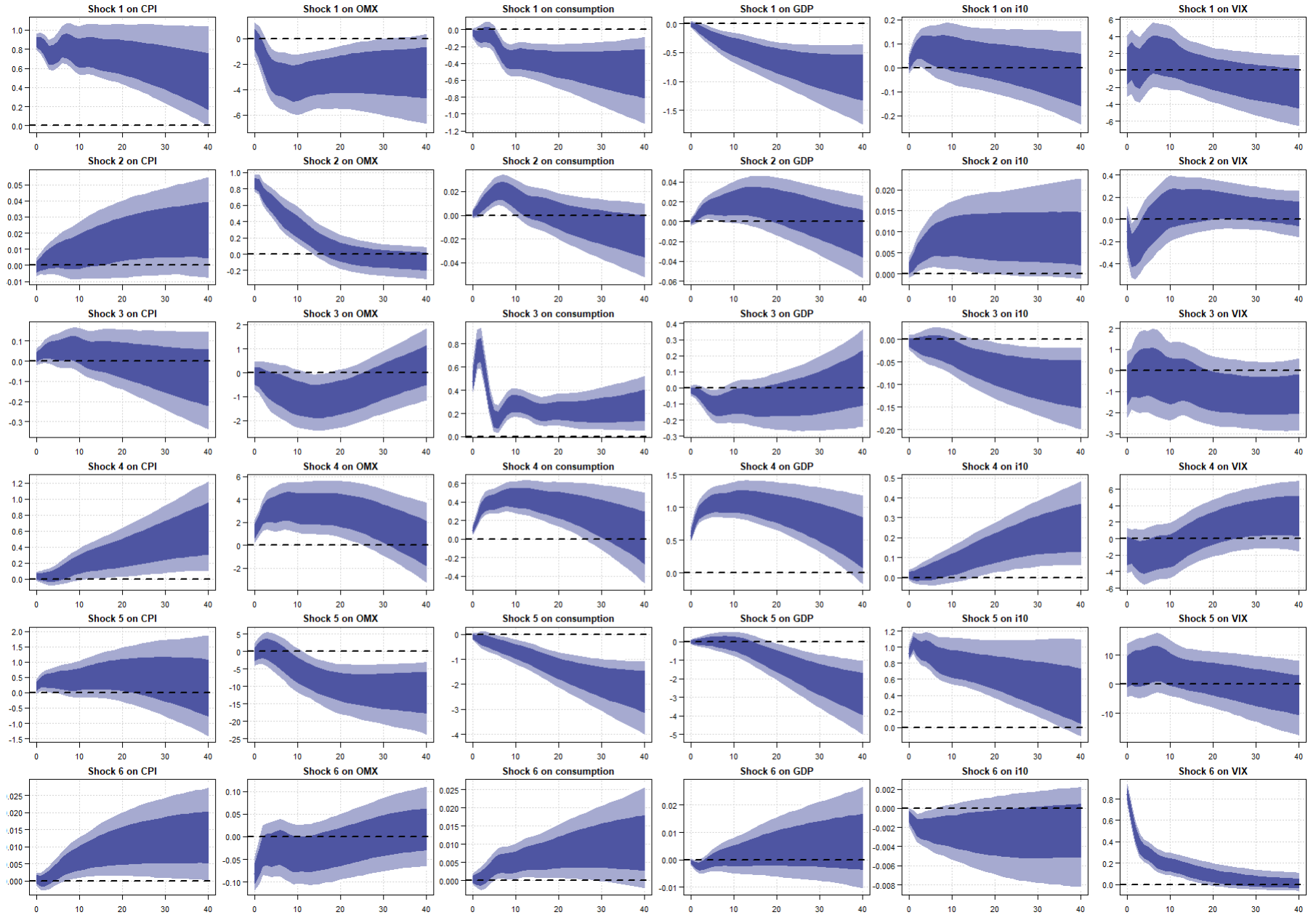


Figure 8: THE VIX MODEL. Impulse responses of all shocks with the 68% and 90% point-wise posterior intervals. The size of the shock is scaled to unity. Y-axis is scaled to percentage points. Time period 01/2000-09/2023.

## 8 Appendix B

### Bayesian estimation

Bayesian estimation has one clear advantage in this application, it works better with many free parameters. In our model we have  $n^2p + n^2 + 4n = 345$  free parameters.  $n = 5$  is the number of variables and  $p = 12$  is the chosen lag length. If we were to use standard frequentist approach, we would end up restricting the model significantly. Bayesian estimation is based on setting prior beliefs which is then updated after observing the data which can be seen as a learning process. Selecting the prior distribution is also challenging since selecting too narrow prior makes the model to ignore the attributes of the data. Bayesian formula in general form can be expressed as:

$$p(\theta | y) \propto p(y | \theta)p(\theta) \quad (2)$$

where  $p(\theta | y)$  describes the posterior density,  $p(y | \theta)$  describes the likelihood function and  $p(\theta)$  is the prior density. One must note that the more we restrict the prior distribution, the less one can learn from data. However, sometimes you have knowledge about the prior distribution and you are able to select it accurately. One can also choose improper prior which means that the prior is selected to be 1.

To derive the likelihood function, we need to specify a probability density function for the structural shocks. In this particular model, we adopt the notation introduced by Anttonen et al. (2021), where they utilize a skewed generalized t-distribution, represented as follows:

$$f_i(\epsilon_{it}; \lambda_i, p_i, q_i) = \frac{p_i}{2v_i q_i^{1/p_i} B(\frac{1}{p_i}, q_i) [\frac{|\epsilon_{it} + m_i|^{p_i}}{q_i v_i^{p_i} (\lambda_i \text{sign}(\epsilon_{it} + m_i) + 1)^{p_i}} + 1]^{1/p_i + q_i}} \quad (3)$$

The beta function is denoted as  $B()$ . The parameters  $-1 < \lambda < 1$ ,  $p_i > 0$ , and  $q_i > 0$  play a crucial role in controlling the skewness and kurtosis of the  $i$ th shock, where  $i$  ranges from 1 to  $n$ . The tail behavior of the shock can be summarized using  $\alpha_i = p_i q_i$ , which corresponds to the degrees of freedom in a student's t-distribution. When we set  $\lambda_i = 0$  and  $p_i = 2$ , we obtain the student's t-distribution. Additionally, this distribution allows us to derive other commonly used distributions in finance and econometrics, such as the normal, skewed Cauchy and t-distribution, Laplace, and uniform distributions. This essentially means that the skewed generalized t-distribution is highly flexible. Despite the evident advantage of capturing skewness, this distribution is not commonly used in finance or econometrics. To

achieve zero mean errors, we set  $v_i = 0$  and  $m_i$  as follows:

$$m_i = \frac{2v_i^{1/p_i} B(\frac{2}{p_i}, q_i - \frac{1}{p_i})}{B(\frac{1}{p_i}, q_i)} \quad (4)$$

Drawing from equation (2), we can derive the likelihood function provided that we have knowledge of the probability function. In this paper, we adopt the approach taken by Lanne et al. (2017), and the likelihood function takes the following form:

$$p(y | \theta) = | \det(B) |^{-T} \prod_{i=1}^n \prod_{t=1}^T f_i(\iota_i' B^{-1} u_t(\pi); \lambda_i, p_i, q_i), \quad (5)$$

In which  $\theta = (\pi', \beta', \gamma')$ ,  $\pi = \text{vec}([a, A_1' : \dots : A_p']')$ ,  $\beta = \text{vec}(B)$ ,  $\iota_i$  is the  $i$ th unit vector and  $u_t(\pi) = y_t - a - A_1 y_{t-1} - \dots - A_p y_{t-p}$ .

By using the likelihood function described above, we can calculate the posterior density function by multiplying the likelihood with the prior density function.

$$p(\theta | y) = \frac{p(y | \theta)p(\theta)}{p(y)} \propto p(\theta) | \det(B) |^{-T} \prod_{i=1}^n \prod_{t=1}^T f_i(\iota_i' B^{-1} u_t(\pi); \lambda_i, p_i, q_i) \quad (6)$$

We adopt the parametrization and utilize identical prior distributions for  $\lambda$ ,  $p_i$ , and  $q_i$  as described in Anttonen et al. (2023). Specifically, informative priors are employed for  $q_i$ ,  $p_i$  and the parameter  $\lambda_i$ .

The posterior distribution has to be simulated. In this paper we are going to use Hamiltonian Monte Carlo (HMC) algorithm.

## About the prior

The parametrization of the model follows Anttonen et al. (2021, 2023).  $p_i$  is set to unity. The remaining two parameters  $(\lambda_i, q_i)$  determine the shape of the distribution.  $\lambda_i$  controls for the skewness while  $q_i$  controls for the excess kurtosis. The value for the shape parameter  $(\lambda_i)$  in the base model is set at four.

However, the prior for the parameter  $q_i$  is much more important. The prior should strike a balance by permitting an almost Gaussian distribution to avoid imposing non-Gaussian

characteristics inaccurately. Simultaneously, it should be able to effectively control the shape of the posterior distribution. The closer the posterior resembles a Gaussian distribution, the more efficient the estimation algorithm becomes in exploring it. Due to the fact that  $q_i$  is skewed, the sampling must be done in log form. Thus, a normal prior with unit mean and standard deviation of 2 is set.

The Minnesota prior is set to be in this case marginally independent and Gaussian. The prior variance for the off-diagonal elements on  $B$  is estimated from the data in a hierarchical fashion; thus, a improper prior is set. However, when we consider the Bayesian factors, the prior must be set to be informal.

## Algorithm

As one could assume, the likelihood function in (6) is very complex. The parameter space of  $\pi$  is very high dimensional and the posterior surfaces of  $\beta$  and  $\gamma$  are very complicated which easily yields to unfeasible estimation time with more standard methods. We are not able to compute or approximate the posterior with any analytical methods.

Hamiltonian Monte Carlo (HMC)<sup>4</sup> is a version of a Markov Chain Monte Carlo (MCMC) algorithm that uses Hamiltonian dynamics from classical mechanics to efficiently explore the parameter space of a probabilistic model. It employs an estimation of Hamiltonian dynamics through numerical integration, subsequently refined using a Metropolis acceptance step for corrections. Leapfrog integration is applied to approximate the continuous Hamiltonian dynamics in discrete steps, and the Metropolis-Hastings correction is used to probabilistically accept or reject proposed states. Overall, HMC provides an effective way to draw samples from complex posterior distributions, especially in high-dimensional parameter spaces such as in our case.

The practical implementation is based on the work of Jetro Anttonen (see Anttonen et al., 2023) that can be found on GitHub<sup>5</sup>.

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<sup>4</sup>[https://mc-stan.org/docs/2\\_21/reference-manual/hamiltonian-monte-carlo.html](https://mc-stan.org/docs/2_21/reference-manual/hamiltonian-monte-carlo.html)

<sup>5</sup><https://github.com/jetroant/bsvar>

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