STOCKHOLM SCHOOL OF ECONOMICS
Department of Economics
BE551 - Degree Project in Economics
Spring 2024

Quantitative Easing's Effect on Inflation in the Swedish Economy

Rasmus Bjersing (25393) and Arian Hanifi (25540)

The Swedish Riksbank is facing scrutiny because of billions of dollars in deficits incurred due to its quantitative easing (QE) program during the COVID-19 pandemic. Quantitative easing programs have now been run in Sweden for 8 years (2015-2023), but its full effects are not yet fully understood. This SVAR/VECM analysis sets out to measure the short term effect of asset purchases on inflation in the Swedish economy. Due to instability in our data, the interpretation of effects were limited to the acceleration rates of asset purchases and inflation. As the SVAR model produced inconclusive results, the final estimations were made using a VECM model. The acceleration rate of asset purchases had a precisely estimated zero effect on the acceleration rate of inflation. This conclusion is limited by the potential of omitted variable bias and the challenges in performing the VAR models with multiple differencing. The potential policy implications are restricted by the acceleration rate of inflation being less relevant for the central bank than the levels of inflation itself. Furthermore, our thesis highlights that analyzing monetary policy effects using VAR models can be challenging during times of financial instability.

Keywords: Monetary Policy, Quantitative Easing (QE), Vector Auto Regression (VAR), Structural Vector Auto Regression (SVAR), Vector Error Correction Model (VECM), Inflation, Central Banking

JEL: E52, E58, E31, C32

Supervisor: Sofia Hernnäs
Date Submitted: Maj 13, 2024
Date Examined: Maj 29, 2024
Discussants: Emma S. Johnson, Filip Nyman
Examiner Johanna Wallenius

Contents

1 Introduction **3**

2 Literature Review **4**
2.1 Previous studies 4

3 Transmission channels **5**

4 Methodology **7**
4.1 Macroeconomic framework 7
4.2 Methodology 8

5 Data **9**

6 Empirical Analysis & Result **10**
6.1 Stationary Variables 10
6.2 Cointegration 12
6.3 Lag Length 13
6.4 Normality of errors 14
6.5 Multicollinearity 14
6.6 SVAR model 15
6.7 VECM Model 15
6.8 Lag Length 15
6.9 Control Variables 15
6.10 Coefficients 16
6.11 Autocorrelation in Residuals 17
6.12 Normality of Residuals 18
6.13 Bootstrapped Confidence Intervals 18
6.14 Impulse Response Functions 20

7 Discussion **21**

8 Conclusion **23**

9 AI-Appendix **26**

1 Introduction

The Swedish Riksbank, the central bank in charge of Sweden's monetary policy, requested over 7 billion dollars from the Swedish Parliament in October 2023 to cover losses primarily associated with its quantitative easing(QE) programme (Rolander, 2023). The last few years has seen the reemergence of high inflation throughout western economies. In December 2022, the Swedish annual inflation rate peaked at 12.39% and stayed above 8% from June 2022 to July 2023. The last time the Swedish inflation rate was above 8% was in September 1991, during the bank, finance and property crisis in Sweden of the early 1990s (OECD, 2024).

The combination of unprecedented use of QE by the Swedish Riksbank along with the peak in inflation in the following years provides ample opportunity to estimate a potential relation between the use of QE and inflation. Sweden's position as a small open economy, not part of the eurozone, is a setting in need of further study regarding the effects of QE, as is the need in general for QE. As a novel tool in the monetary policy toolbox for central banks, the full consequences of QE are yet to be discovered, and opinions differ regarding the efficacy and the full impact of it.

Our objective with this study is to measure the magnitudes of the transmission channels through which QE could affect inflation. Especially in the context of financial turmoil with regards to the COVID-19 pandemic and a small open economy such as Sweden.

The analysis is performed through a Structural Vector Autoregression (SVAR) that evaluates the potential relations between the variables over several time periods, limiting the estimated relations to those constrained by previous economic knowledge. Using Impulse Response Functions (IRFs), the shocks between variables can be estimated over time and capture the dynamics of the transmission channels. This was the original methodology, which over the course of the analysis was performed to the extent it was possible but also complemented with a Vector Error Correction Model (VECM). Since QE was first used in 2015 in Sweden, the studied period is limited to 2015-2023, which covers all available data in Sweden.

Our analysis cannot confirm that QE has any effect on inflation in the short-term. Due to the non-stationarity of the variables of interest, the interpretation of our results is limited to the acceleration rate of asset purchases on the acceleration rate of inflation. For these accelerations rates, the result we received was precisely estimated zeros indicating no relationship between the acceleration rates.

Quantitative Easing (QE) is a monetary policy tool to mitigate distressed financial markets through large-scale asset purchases and boost inflation. By expanding the central bank balance sheet, assets can be purchased from financial institutions in uncertain financial markets. The overall effect on the institution is increased liquidity and an increased ability to meet capital reserve requirements. This effect occurs both through the reduction of held assets, leading to lower capital reserve requirements and the proceeds from the asset sale, increasing liquidity and the size of the capital reserve (Bank of England, 2024). The measure has primarily been used as a next resort when adjusting nominal interest rates has been insufficient to combat deflation and when lack of liquidity threatens the functioning of financial markets. The zero lower bound is one such phenomenon, which is the limited effect of lowering nominal interest rates when they get close to zero. Due to practical constraints, financial institutions and lenders tend to not lend or borrow at negative interest rates and the effect on lending of nominal interest rate cuts have a smaller effect than at a higher interest rate level (European Central Bank., 2019).

First implemented by Japan in the early 2000s, it has since been used by central banks all over the world, primarily in the most serious financial crises of the 21st century, namely the 2008 Great Recession and the economic downturn due to the COVID-19 pandemic. Apart from extensive usage

in the event of crises, it has been used at a smaller scale to reach the inflation target when inflation is below the target.

Such was the case for the Swedish Riksbank when it began its first quantitative easing programme in 2015 to combat an inflation on the slightly negative (annual inflation rate of -0.3% in January 2015). Along with QE, the Swedish Riksbank notably lowered the nominal interest rate to -0.1%, a prime example of QE's role in supporting expansionary monetary policy when nominal interest rates near or exceed zero. The Riksbank's asset purchases consisted of government bonds up until the COVID-19 pandemic when securities such as covered bonds, municipal bonds and corporate bonds were also included (Swedish Riksbank, 2022). During the COVID-19 Pandemic the scale of purchases also reached unprecedented levels (Flodén, 2022) which raised the question of the impact of the policy on the overall economy. The Swedish Riksbank purchases assets by expanding the Riksbank's balance sheet. The assets and debts increase by the equivalent amount to the price of the purchased securities and is transferred directly to the counter part's deposits in RIX from the Swedish Riksbank. RIX is the Swedish Riksbank's system to facilitate payments between banks and the Swedish Riksbank (Swedish Riksbank, 2022). The Riksbank then either holds the securities throughout their maturity, or sells the assets, thereby performing Quantitative Tightening. Hence, the holdings will decrease over time unless new assets are acquired. When the Riksbank holds securities, they are subject to the same risks any holder of the asset would be and risk making financial losses.

2 Literature Review

2.1 Previous studies

The literature on assessing the effects of QE on financial markets is vast, however the research on the effect on inflation and GDP is much more limited, partly due to the increased difficulty. In general there are three ways of assessing the macroeconomic impact which can be seen as three steps on a spectrum ranging from data-centric to theory-based (Borio & Zabai, 2018). From the data-centric perspective, the changes in the balance sheet from the asset purchase programs are used to analyse the effect on inflation and GDP. Commonly used models here are different forms of Vector Autoregressions. On the other side of the spectrum, the theory-based approaches construct an equilibrium model for how the asset purchases are expected to work in the economy and from this the effects are identified in the system. These studies are more suitable for understanding the transmission mechanism than the absolute effect of the policies. In between these two approaches is a two-step process. The data is first transformed into variables and shocks that are commonly used in traditional economic models. The constructed variables are then used to identify the effect of QE on inflation and GDP (Borio & Zabai, 2018).

Studies on the effect of QE have returned inconclusive results. Some studies have shown positive effects on GDP and inflation (Di Casola & Stockhammar, 2022; Jomaa, 2022; Kim et al., 2023). Haldane et al. (2016) expand the work of Weale and Wieladek (2016) and estimate the effects of QE for a selection of countries. Based on the findings they identify two forms of QE with differing levels of effect. The asset purchases that were conducted for liquidity purposes appear to have minimal effect. In comparison the asset purchases that were part of a loosening of monetary policies had a significant impact on activity and prices. Furthermore, the size of the impact of QE is generally hard to estimate. Williams (2014) suggests that the uncertainty regarding the the effects of QE is twice as high in comparison with the effect of conventional monetary policy. Analyses of large-scale asset purchase programs are often conducted under the order of central banks, which is a potential source of bias; Fabo et al.'s (2021) show that central bank research generally shows a greater effect of QE on the

economy than studies conducted by academia.

An article that is often referenced in the literature is Weale and Wieladek's (2016) study on the effect of large-scale asset purchases in the UK and US between 2009 to 2014 using a Bayesian VAR (BVAR) model. Instead of using actual asset purchases, announcements about the purchases by the central banks are used as a proxy. Four identification schemes are constructed for disentangling the orthogonal and structural shocks in the residuals. They find that an asset purchase announcement of 1% of nominal GDP leads to a maximum impact of 0.62% (0.25%) on real GDP and 0.58% (0.32%) on CPI in the US (UK).

The role of QE and its effect on the economy in Sweden have only been analysed in a few studies. This could partly be accredited to it being a new field of study as the Riksbank's first large-scale asset purchase program was put in effect in 2015 (Riksbank, 2024). Jomaa (2022) looked at the asset purchase program of the Riksbank between 2015 and 2018 and estimated the effects on inflation using a Structural Vector Autoregressive (SVAR) model. The result of her study showed that an asset purchase the size of 1% of GDP had a maximum effect of 0.3923 %. The study also identifies the signalling channels as the main mediator of the effect of QE on the economy.

Di Casola and Stockhammar (2022) argue that as Sweden is a small economy it is affected by shocks in its main trading partners based on a study by Corbo and Strid (2020). Thus they analyse the effect of large-asset purchases by both the Riksbank and the European Central Bank (ECB) on output and inflation in Sweden from 2015 to 2018 with a Bayesian Vector Autoregressive (BVAR) model. In terms of the effect of Domestic QE ,i.e. the Riksbank, on inflation, the results are not clear as the 68% confidence interval includes zero. However, the simultaneous QE program of the ECB had large positive spillover effects on both output and inflation. A share of the positive effect was mediated through the response of domestic QE to the foreign QE.

A study on the Swedish QE using a small open economy two-region dynamic stochastic general equilibrium model (DSGE) suggested that the purchases increased GDP by 0.2% and inflation by 0.25 percentage points on average in 2020-2023. Of the total effect, circa half could be accredited to the purchases of municipal and covered bonds half. They also argue that the estimates are likely a lower bound as they do not capture that the asset purchases reduced the risk of a financial crisis happening (Akkaya et al., 2023).

Kim et al. (2023) analyse the effect of the Federal Reserve's large-scale asset purchases (LSAPs) with a SVAR model. Instead of using the size of the central bank's balance sheet or the announced asset purchases they utilise a survey-based approach to capture the expectation of the public. The analysis shows that a surprise $500 billion asset purchase had a peak effect on the level of industrial production by about 2% and on the level of the CPI by about 0.8%, while reducing the unemployment rate by about 0.5 percentage points. However there are uncertainties on the accuracy of the estimates as the 68% confidence intervals of the impulse response functions, although zero-excluded, are quite wide.

3 Transmission channels

Understanding through what mechanisms large-scale asset purchases affect the economy is of great importance for central banks, in particular when there are multiple monetary policies in place. There is no clear answer to this from either a theoretical or practical perspective. The nature of the transmission is still a subject of debate in the literature. However, a transmission scheme commonly referred to is the one Haldane et al. (2016) proposes as seen in Figure 2.

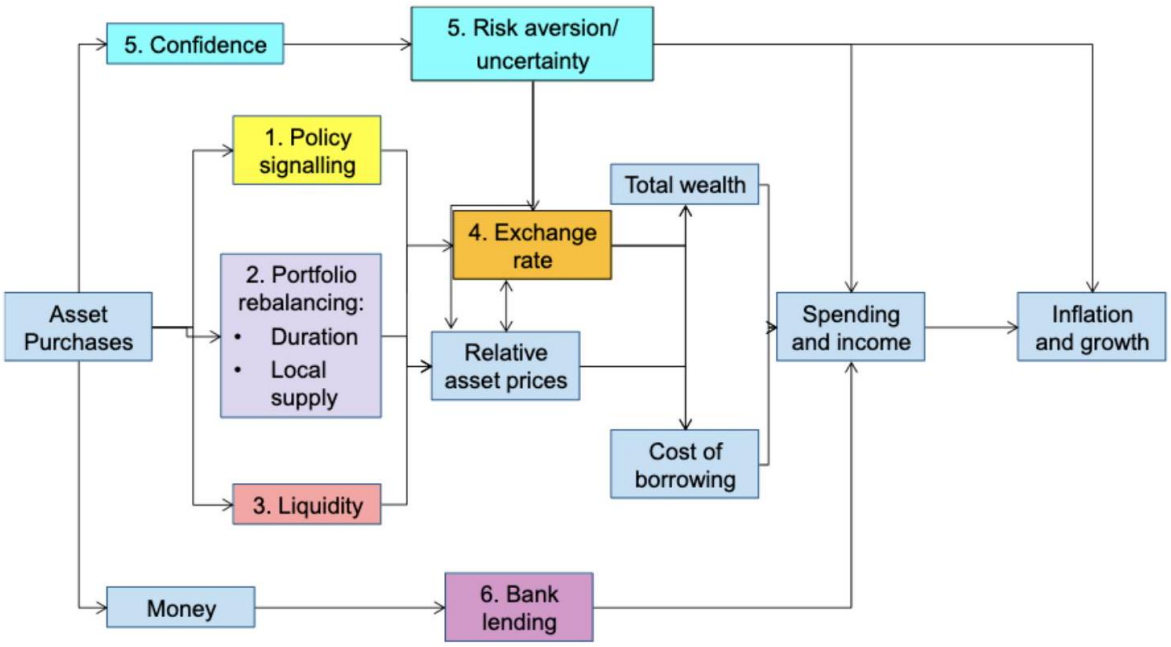


Figure 1: Transmission Channels Flow Chart

The main paths for the transmission can be narrowed down to:

- monetary policy signalling channel
- portfolio balance channel
- exchange rate channel

The monetary policy signalling channel is based on the idea that QE can convey information about how the short-term interest rates might develop. The view is that the purchases signal that the central banks will hold the policy interest rate at its lower rate for longer (Weale & Wieladek, 2016). Since the asset purchases happen under a longer period, often several years, it is the announcement of them that give rise to the signalling effect. The longer time span is also a part of why it signals how the future short-term rates are going to develop.

The portfolio balance channel functions through market frictions due to imperfect asset substitutability. The large-scale purchases of long-term bonds by the central bank push up the price of assets bought and thus reduce the yield of them. Due to investors having a preferred-habitat demand, that is to say a preference for bonds of specific maturities, they do not see bonds of different maturities as perfect substitutes. Thus some investors rebalance their allocation of different assets and money. This leads to an increased demand for long-term bonds which drives up the prices and in turn lowers the yields (Bernanke et al., 2004; Jomaa, 2022).

The idea behind the exchange rate channel is that QE lowers the price of domestic assets compared to foreign assets (Di Casola & Stockhammar, 2022). The asset purchases increase the price of domestic bonds which in turn reduces the bond yield of the bonds making them less attractive for foreign investors. Lower demand for domestic bonds leads to a depreciation of the currency (Neely & Fawley, 2013). A depreciation in the domestic currency makes domestic goods and services cheaper relative to foreign alternatives which increases demand and leads to an increased inflation (Glick & Leduc, 2013).

For each of the transmission channels to be effective they are dependent on the assumption that there are certain frictions in the financial market. Without these frictions the effect of asset purchases on asset pricing would be near non-existent (Haldane et al., 2016; Wallace, 1979).

Studies on the effect of quantitative easing in Sweden have suggested that the announcements by the Riksbank have had effects through the above mentioned channels. The announcements lead to lower long-term government, corporate, mortgage bond yields. The mediation through the exchange rate channel could be seen via the weakened exchange rate. For the signalling channel the lower interest rate expectations at different horizons indicate that it also had a role in the transmission (De Rezende, 2017).

4 Methodology

4.1 Macroeconomic framework

The macroeconomic framework we use to analyse the effect of QE on inflation are Vector Autoregressions (VARs) as introduced by Sims (1980). A VAR is an n-equation, n-variable linear model where each variable is modelled by its own lagged values and the current and past values of the remaining variables (J. H. Stock & Watson, 2001). This framework allows for a systematic approach of examining the dynamic relationships that exist between variables that interact with each other and as such are often used as a credible method for data description, forecasting, structural inference and policy analysis (J. H. Stock & Watson, 2001). VARs can generally be found in three different forms: reduced, recursive, and structural form. We will describe the structural form, also known as Structural Vector Autoregression SVAR, as that model is used in our analysis. For readers interested in learning more about the other models we refer to Vector Autoregressions (J. H. Stock & Watson, 2001) and the article by Kotzé (n.d.).

Structural Vector Autoregressions
Structural Vector Autoregressions are a form of VAR models in which there are identifying assumptions that allow correlations across contemporaneous variables to be interpreted casually (J. H. Stock & Watson, 2001). The assumptions should be based on theory and it is up to the researcher to choose a suitable schema for this. In comparison with a VAR the SVAR, instead of identifying the coefficients of the variables, the identification is imposed on the errors of the system which can be interpreted as exogenous shocks (Lütkepohl & Krätzig, 2004). Framing it differently, SVAR models decompose the effects of each variable into an expected and an unexpected part, and then impose the identifying restrictions on only the unexpected parts (Gottschalk, 2001). To estimate a SVAR model, a reduced form VAR model is first estimated by using OLS per equation. Thereafter, the identifying scheme is applied to the coefficients and residuals from the equation above. This results in orthogonal residuals or error shocks as they are also referenced to as (Gottschalk, 2001). For the OLS estimators to be consistent the following assumptions have to be fulfilled; No perfect multicollinearity, the error term has a conditional mean of zero given all regressors and their lags, the variables follow a stationary distribution, and large outliers are unlikely (J. Stock & Watson, 2015).

Vector Error Correction Model
When the variables are co-integrated the resulting values from a VAR model will not be precise as there is a long-run trend that is not taken into consideration. To solve this a Vector error correction model (VECM) can be used. The difference compared to a VAR model is that an error correcting term is added which represents the long-term relationship between the variables (Ren et al., 2020).

4.2 Methodology

Following the approach of Jomaa (2022) and Weale and Wieladek (2016) we construct our VAR as follows:

$$Y_t = \alpha_x + \sum_{k=1}^{L} A_k Y_{t-k} + e_t, \quad e_t \sim N(0, \Sigma)$$

Y_t is a vector containing our endogenous variables: GDP Indicator, Consumer Price Index, Swedish Krona real effective exchange rate, and the term spread between 10-year and 3-month government bond yields. A_k is the vector of coefficients for the corresponding lagged variables for lag k. e_t is the vector of residuals at time t. L is the lag length.

Determining the optimal lag can be done based on economic theory and previous studies, or different forms of information criteria such as Akaike Information Criterion (AIC) and Bayesian Information Criterion(BIC) (Jomaa, 2022; Lütkepohl, 1991). The number of lags affects the performance of the model: too many lags lead to forecasting errors and omitting lags can lead to estimation bias (Jomaa, 2022). For this study we evaluate several information criteria for optimal lag length selection including those Jomaa (2022) or Weale and Wieladek (2016) resulting in running the following tests: Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), Hannan-Quinn Criterion (HQ). Finally, the HQ Criterion is selected for determining the lag length.

Identification Scheme

Table 1: Identifying restrictions for the baseline model. Cholesky Decomposition Scheme

	Log CPI	GDP-indicator	Asset Purchases	Term Spread	Log Exchange Rates	STIBOR
Log CPI	1	0	0	0	0	0
GDP-indicator		1	0	0	0	0
Asset Purchases			1	0	0	0
Term Spread				1	0	0
Log Exchange Rates					1	0
STIBOR						1

Inspired by earlier studies (Jomaa, 2022; Weale & Wieladek, 2016) the identification scheme utilised in the analysis is based on the Cholesky Decomposition Scheme. As seen in Table 1 the scheme uses a lower-triangular scheme, with log CPI appearing first, followed by real GDP, asset purchases, and then the remaining variables. This implies that the identifying assumptions are that real GDP and CPI react with a lag and that aside from responding to these two, asset purchases do not react to any other variable (Weale & Wieladek, 2016). According to Weale and Wieladek's (2016), identification schemes that are constructed using timing exclusion restrictions have been criticised because similar restrictions are not found when employing DSGE models. Therefore, to include such restrictions there has to be strong theoretic support. To justify the scheme, Weale and Wieladek (2016) present earlier studies showing that an increase in asset purchases will lead to lower interest rates on long term bonds. Similarly Jomaa (2022) argues that the term spread, exchange rates and the 1-month STIBOR rate respond immediately when the announcement of asset purchases is made public. It is worth mentioning that designing an identification scheme that can identify asset purchase announcements perfectly is challenging as the economic theory underlying the mechanism of asset purchases is not understood very well currently (Weale & Wieladek, 2016).

5 Data

Table 2: Description and Source of Variables used in the Analysis of QE Effects

Variable	**Description**	**Source**
GDP Indicator	Serves as a proxy for economic activity. Used to estimate impact on the economy.	Statistics Sweden
Log(Consumer Price Index)	Used to estimate the impact on inflation.	Statistics Sweden
1-month STIBOR Rate	Used to examine the signalling effect of QE on interest rate expectations.	Riksbank
Term Spread	Difference between the 10-year and the 3-month government bond yields. Measures the portfolio balance channel	Riksbank
Log(Real Effective Exchange Rate)	Measures the exchange rate transmission mechanism.	Bank for International Settlements (BIS)
Cumulative Asset Purchases	The ratio of cumulative announced purchases by the Riksbank to the annualised nominal GDP as of December 2014 is measured.	Riksbank

The data used in the model is aggregated at a monthly level for the time period ranging from 2015 up until and including 2023. An overview of the variables can be seen in Table 2. This period includes all asset purchase announcements by the Riksbank up until the moment of the writing of this article.

For the variable of most interest in the report, the measure of QE, we follow the approach of the articles by Jomaa (2022), and Di Casola and Stockhammar (2022) which in turn are inspired by Weale and Wieladek (2016). The measure is defined as the cumulative amount of announced asset purchases divided by the annualised nominal GDP of December 2014, the last period before the start of the QE program. This is done to eliminate endogeneity effects coming from effects of QE on contemporaneous GDP levels (Di Casola & Stockhammar, 2022; Jomaa, 2022). We use announcements as a proxy since our model assumes that changes in the macroeconomic variables are responses to the announcements rather than actual asset purchases. As Laséen (2023) mentions, analysing the assets purchases of central banks rather than the announcements is a complex task due to the built in endogenous nature of central bank purchase operation.

The term spread variable is the difference between the 10-year and 3-month government bond yields. Previous studies argue that the existence of the portfolio balance channel can be seen from a reduced or negative term spread. The rationale is that the portfolio rebalancing leads to a large impact on the long-term bonds and reduces the term premia (Jomaa, 2022; Weale & Wieladek, 2016). The data is acquired from the Riksbank.

The real effective exchange rate is acquired from the Bank for International Settlements (BIS) and is calculated with regard to a basket of 27 countries. The weights for calculating the effective exchange rate come from the manufacturing trade flows amongst the countries (Bank for International Settlements, 2023). This variable is used to capture the exchange rate transmission channel. As mentioned in the description of the transmission mechanism the hypothesis is that if QE is mediated through this channel then the domestic currency should depreciate and the exchange rate decrease.

The 1-month STIBOR rate is included to examine the portfolio signalling effect. The role of swap rates for this purpose has appeared in several previous studies (Weale & Wieladek, 2016). EONIA swap rates and the London Interbank Offered Rate, LIBOR, have been used when analysing the asset purchases of the European Central bank and the United Kingdom central bank respectively (Haldane et al., 2016). As the corresponding instrument in Sweden is the Stockholm Interbank Offered Rate, STIBOR, we select it as the proxy for the signalling effect (Jomaa, 2022). The role of the variable is to capture how the expectations of economic agents shift after an asset purchase announcement. Since QE informs that the policy rates will remain low in the short-term this should be reflected in changes in the rate of the STIBOR instrument.

The GDP-indicator is used as a proxy for economic activity and inflation is the change in CPI. Both variables are acquired from the Statistical Database which is maintained by Statistics Sweden.

6 Empirical Analysis & Result

6.1 Stationary Variables

When performing a Vector Auto Regression model, the included variables need to be stationary for the model's assumption to hold. A stationary variable is one for which the mean, variance and co-variance are constant over time. If the sample variable is not shown to be stationary through an Augmented Dickey-Fuller (ADF) test, it needs to be differenced, i.e. each data point is obtained by subtracting one years observation with the previous year's. A variable's integration order is determined as the number of differencings needed to be performed for the resulting variable to become stationary. Note that for each differencing one degree of freedom is lost and it is generally recommended not to difference to higher than the second order, to prevent losing to much information in the variable from the differencing.

Table 3: ADF Test

Variable	Integration Order	p-value
GDP	1	0.4406
Log (Consumer Price Index (Log(CPI))	3	0.9478
1-month STIBOR Rate	1	0.7578
Term Spread	1	0.9883
Log (Real Effective Exchange Rate)	1	0.3385
Cumulative Asset Purchases Ratio	3	0.8617

Notes:

Table 3 shows the integration order of each variable and p-values for the original variable, obtained from the ADF-test. A p-value lower than 5% means we can reject the null hypothesis of non-stationarity at a 95% confidence level.

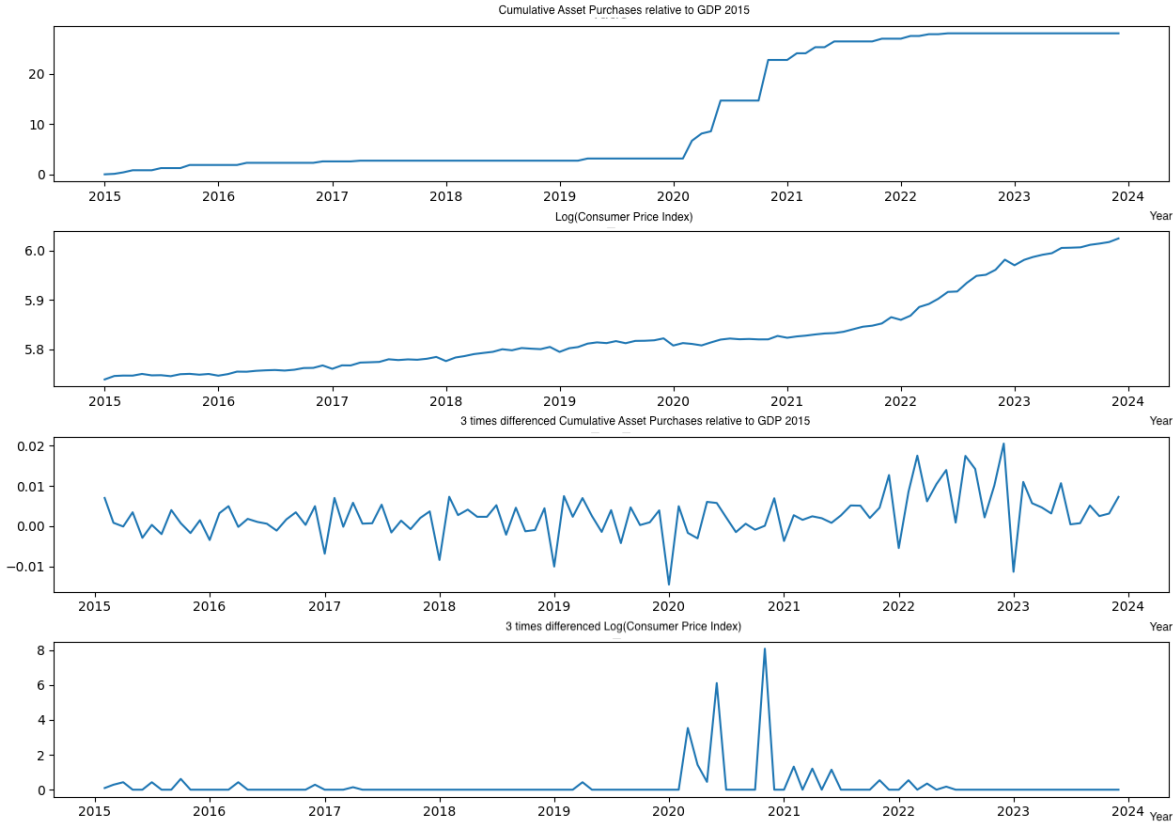


Figure 2: An overview of the variables in need of 3 levels of differencing

We observe that none of the variables are stationary (Table 3), and that the logarithmically transformed CPI variable and the Asset Purchases variable are integrated at order 3 which poses the risk of information being lost in the differencing. We can see from Figure 2 that there is a steady rise in the Log(CPI) variable, accelerating in 2022 and a sharp rise in the Cumulative Asset Purchases Ratio between 2020 and 2021, underlining the non-stationarity of those variables. The rest of the variables are integrated at order 1.

Table 4: Result from ADF test on time-range used in Jomaa (2022)

Variable	Integration Order
GDP	1
Log (Consumer Price Index (Log(CPI))	1
1-month STIBOR Rate	1
Term Spread	0
Log (Real Effective Exchange Rate)	1
Cumulative Asset Purchases Ratio	0

Notes:

Table 4 shows the integration order of each variable for the time period 2015-2018 studied by Nora Jomaa

From the results in Table 4 we can observe that the integration order of the variable is no problem for the period studied by Jomaa (2022), spanning from 2015 to 2018, which indicates that the selected period to study may have influenced the appropriateness of the SVAR model.

6.2 Cointegration

We performed an Engle-Granger Cointegration Test for each pair of variables with the same integration order. Here the non-differenced variables are used. co-integrated variables have a linear combination of them which is stationary, which implies they have a long-term relationship with each other. Performing the cointegration tests for variables of different integration order would complicate interpretation and is not in line with the assumptions of Engle-Granger Cointegration Test nor standard practice, hence only those variables of the same integration order are tested. If the model does not take account of that relationship, the short-term statistical inference is weakened as the long-term effect can influence the short-term effects estimated by the model. This long-term effect can be accounted for with an error-correction term which would extend the VAR-model into a Vector Error Correction (VECM) model.

Table 5: Engle-Granger Test

	GDP	1-month STIBOR Rate	Term Spread	Log (Real Effective Exchange Rate)
GDP	-	0.1652	0.4957	0.1033
1-month STIBOR Rate	0.1652	-	0.3173	0.3890
Term spread	0.4957	0.3173	-	0.6735
Log (Real Effective Exchange Rate)	0.1033	0.3890	0.6735	-

Notes:

Table 5 displays the calculated p-values for the Engle-Granger Test for the variables of integration order 1. A p-value lower than 0.05 leads to a rejection of the null-hypothesis of two variables not being co-integrated. Each value in the table corresponds to this p-value between the variables given by the cell's row and column indexes.

For the variables integrated at order 1, the p-values are larger than 0.05 and no significant values can be found (Table 5). Hence the null hypothesis of no co-integration can not be rejected and no co-integration is presumed.

Table 6: Engle-Granger Test

p-value	Log (CPI)
Cumulative Asset Purchases Ratio	0.0163

Notes:

Table 6 displays the calculated p-values for the Engle-Granger Test for the variables of integration order 3. A p-value lower than 0.05 leads to a rejection of the null-hypothesis of two variables not being co-integrated. Each value in the table corresponds to this p-value between the variables given by the cell's row and column indexes.

The p-value of the ADF-test on the residuals of the regression of the variables (calculated in the Engle-Granger Test, is lower than 0.05 . Hence at a 95% confidence we can conclude that log(CPI) and Asset Purchases are co-integrated at integration order 0.

6.3 Lag Length

For the lag length, a variety of optimisation criteria were attempted. The selection of lag length is a crucial step in performing a SVAR since the lag length is the amount of past observations used to predict current values. Higher lag length increases the risk of overfitting and reducing the degrees of freedom. On the other hand, a too short length may lead to missing significant important relationships. These tradeoffs are handled differently in different criteria that seek to balance these tradeoffs. In this analysis Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), Hannan-Quinn Criterion (HQ) and Final Prediction Error Criterion (FPE) are tested. Their main differences are the severity of the penalty imposed by increasing the length where their severity from conservative to less conservative (in terms of penalising higher lag length more)is BIC, HQ, AIC. In essence, BIC tends to prefer a shorter length than AIC. BIC and HQ vary with regards to sample size where large sample size leads to more conservative lag length selection, AIC and FPE are less variable with regards to the sample size. FPE is explicitly focused on prediction accuracy, whereas BIC, HQ and AIC are based on likelihood principles. These criteria were applied to a VAR model without the structural component in order to find the optimal lag length for the SVAR model.

Table 7: Different Criteria for Optimal Lag Length

Criteria	Optimal Lag Length
Bayesian Information Criterion (BIC)	0
Akaike Information Criterion (AIC)	*
Hannan-Quinn Criterion (HQ)	*
Final Prediction Error Criterion (FPE)	*

For the BIC the optimal lag length was 0 and for the other criteria the optimal length was 14 , where notably 14 was the highest lag length that could be attempted without the model malfunctioning. The process was repeated for different ranges of potential values where the other criteria were consistently the maximum value in the range. We have therefore chosen to report these lag lengths as non-conclusive, indicated with a * in Table 7. This presents an obstacle to the use of the VAR model since a lag length of 0 would mean no lags, making the VAR model obsolete. With this in consideration, we

proceeded to perform the SVAR model for all lag lengths between 0 and 14 to analyse the differences in results.

6.4 Normality of errors

To ensure that the residuals are normally distributed we performed a Jarque-Bera test for each variable in the VAR model without the structural component, used above for finding the optimal lag length.

Table 8: Jarque-Bera Test

Variable	p-value
ΔGDP	0.3157
Δ^3Log (CPI)	0.6777
Δ1-Month STIBOR Rate	0.0621
ΔTerm Spread	0.8791
ΔLog (Real Effective Exchange Rate)	0.5243
Δ^3Cumulative Asset Purchases Ratio	0.0057

Notes:

Table 8 displays the p-values for each variable with the null hypothesis that the errors are normally distributed.

As seen in Table 8 Δ^3Cumulative Asset Purchases Ratio has a p-value of 0.0057, which is significant at a 1% significance level. Moreover, the 1-month STIBOR Rate is significant at the 10% level, meaning we can reject the null hypothesis of the residuals being normally distributed at a 90% confidence level. For the other variables, normality of residuals can be presumed.

6.5 Multicollinearity

Another assumption for VAR models is that there is no multicollinearity between the variables. For this reason a Variance Inflation Factor (VIF) Test is performed.

Table 9: VIF Test

Variable	**Value**
Intercept	1.4342
ΔGDP	1.015775
Δ^3Log (CPI)	1.066763
Δ1-Month STIBOR Rate	1.1167
ΔTerm Spread	1.0964
ΔLog (Real Effective Exchange Rate)	1.0751
Δ^3Cumulative Asset Purchases Ratio	1.1168

Notes:

Table 9 displays the Variance Inflation Factors for each differenced variable

Table 9 shows the Variance Inflation Factor for each variable. A value of 1 indicates no correlation with other variables, and a value between 1 and 4 indicates moderate correlation. A value higher than 4 suggest a predictor has high correlation with the other variables and warrants further investigation (The Pennsylvania State University, 2018).

From the multicollinearity test we can see that the Variance Inflation Factor (VIF) is low, close to 1 for each variable and quite close to 1, 1.4342 for the Intercept Term. This indicates that multicollinearity issues are not present to a large extent in our model.

6.6 SVAR model

Running the SVAR model, a lag length of all potential values between 0 and 14 were attempted, all rendering a warning of non-Convergence. The exact warning we received was "Convergence not achieved after 100 iterations. Convergence Value 1". The actual program was run with vars package in R but similar programs were attempted in the python statsmodels package where similar warnings were obtained. This means that the model is not finding a way to represent the data given the model design. The non-convergence means that the likelihood function being maximised by the regression model is not finding a stable global maximum that best estimates the parameters, using a scoring algorithm (R package Documentation, 2023). The resulting estimated contemporaneous relationships produced by the model cannot be trusted to reflect the actual relationships. For that reason, the estimated relationships have been excluded from this analysis.

6.7 VECM Model

Following the unsuccessful estimation of the SVAR model, a VECM model was estimated. We tested a simplified model in order to provide a rough estimate of the contemporaneous relationships between Quantitative Easing and inflation. It can be observed from the previous analysis that the variables of interest: Asset purchases and log(CPI), are both integrated at order 3 and co-integrated at order 0, indicating that there exists a long-term equilibrium relationship among them and that a linear combination of the variables can be created of integration order 0. This type of relationship could be captured by a Vector Error Correction Model where an error correction term is introduced to ensure that deviations from the long-term stability are corrected over time, allowing for interpretation of shocks at the short-term.

6.8 Lag Length

For the VECM model, the same criteria as used for the SVAR is employed.

Table 10: Different Criteria for Optimal Lag Length (VECM)

Criteria	Optimal Lag Length
Bayesian Information Criterion (BIC)	0
Akaike Information Criterion (AIC)	*
Hannan-Quinn Criterion (HQ)	5
Final Prediction Error Criterion (FPE)	*

The important differing result from the previous attempt is that HQ is now 5 instead of non-conclusive, whereas the other results are the same as for the SVAR model (Table 10). For this reason 5 is chosen as the optimal lag length.

6.9 Control Variables

To determine whether control variables from the available dataset should be included, the HQ criterion was used to evaluate the model.

Table 11: HQ-values for different combinations of Control Variables

Control Variables	**HQ Value**
None	-0.25527
ΔGDP	1.34210
ΔTerm Spread	0.16765
ΔLog (Real Effective Exchange Rate)	-0.00137
Δ1-month STIBOR Rate	0.09657
ΔGDP, ΔTerm Spread	2.08532
ΔGDP, ΔLog (Real Effective Exchange Rate)	1.96554
ΔGDP, Δ1-month STIBOR Rate	2.06036
ΔTerm Spread, ΔLog (Real Effective Exchange Rate)	0.74966
ΔTerm Spread, Δ1-month STIBOR Rate	0.87931
ΔLog (Real Effective Exchange Rate), Δ1-month STIBOR Rate	0.66704
ΔGDP, ΔTerm Spread, ΔLog (Real Effective Exchange Rate)	3.02981
ΔGDP, ΔTerm Spread, Δ1-month STIBOR Rate	3.29036
ΔGDP, ΔLog (Real Effective Exchange Rate), Δ1-month STIBOR Rate	3.02860
ΔTerm Spread, ΔLog (Real Effective Exchange Rate), Δ1-month STIBOR Rate	1.74336
All 4	4.52802

Upon testing all possible combinations of control variables, including the case of no control variables and control variables, the lowest HQ-value was obtained as the model with no control variables (Table 11). The simple model without adding the lags of other variables, was based on the HQ-criterion balancing goodness of fit with model simplicity in the best way. There is a general risk of overfitting with this approach, but given that the optimal set of variables obtained was the one containing the fewest variables, the risk of overfitting is mitigated.

6.10 Coefficients

Table 12: Lagged Endogenous Parameters for Δ^3Log(CPI)

Variable	**Coefficient**	**Std. Error**	**z-Value**	**P-value**	**95% Conf. Interval**
$\Delta^3\text{Log(CPI)}_{lag=1}$	-1.2161	0.100	-12.183	0.000	[-1.412, -1.020]
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=1}$	0.0002	0.001	0.222	0.825	[-0.001, 0.002]
$\Delta^3\text{Log(CPI)}_{lag=2}$	-1.0152	0.156	-6.497	0.000	[-1.321, -0.709]
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=2}$	0.0002	0.001	0.214	0.830	[-0.001, 0.002]
$\Delta^3\text{Log(CPI)}_{lag=3}$	-0.4801	0.180	-2.673	0.008	[-0.832, -0.128]
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=3}$	0.0003	0.001	0.421	0.674	[-0.001, 0.002]
$\Delta^3\text{Log(CPI)}_{lag=4}$	-0.2191	0.157	-1.400	0.161	[-0.526, 0.088]
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=4}$	3.823e-05	0.001	0.059	0.953	[-0.001, 0.001]
$\Delta^3\text{Log(CPI)}_{lag=5}$	-0.1240	0.097	-1.283	0.200	[-0.314, 0.065]
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=5}$	0.0001	0.000	0.207	0.836	[-0.001, 0.001]

Notes:

Δ^3Log(CPI) corresponds to the three times differenced Log(CPI) variable and Δ^3Cumulative Asset Purchases Ratio corresponds to the three times differenced variable for Cumulative Asset Purchases Ratio

Table 12 presents the coefficients for the lags of the variables where Δ^3Log(CPI) is the dependent variable. We can observe that the P-value is greater than 0.05 for all lags of Asset Purchases (Table 12). Because of the transformation and differencing of the variables, the interpretation of coefficients is nontrivial. The coefficients represents the change in (the change in (the change in the logarithmically transformed CPI)) across 4 data points as a consequence of the change in (the change in (the increase of Announced Asset Purchases))). Since $\log(\text{CPI}_t) - \log(\text{CPI}_{t-1}) \approx \frac{\text{CPI}_t - \text{CPI}_{t-1}}{\text{CPI}_{t-1}}$ = inflation rate, the change in log(CPI) can be interpreted as the inflation rate.

The interpretation of Δ^3Log(CPI) can hence be simplified into the the change in (the change in inflation) across 4 data points. This translates into the acceleration rate of inflation. For Δ^3Cumulative Asset Purchases Ratio, the change in the increase of announced Cumulative Asset Purchases Ratio is the announced Asset Purchases Ratio for a specific period, hence the change in (the change in (the increase of announced Cumulative Asset Purchases Ratio)) can be reformulated as the the change in (the change in the announced Asset Purchases). Similarly to the interpretation of Δ^3Log(CPI), it can be interpreted as the acceleration rate of Asset Purchases.

It can be observed for all the lags of Δ^3Cumulative Asset Purchases Ratio that the coefficients are precisely estimated zeros for the effect of Δ^3Cumulative Asset Purchases Ratio on Δ^3Log(CPI). This indicates that we cannot reject our null hypothesis of no short-term effect of the acceleration rate of Asset Purchases relative to GDP on the acceleration rate of inflation. Instead it indicates that the acceleration rate of Asset Purchases does not have an impact on the acceleration rate of inflation. Note that the Asset purchases is rescaled by the constant of GDP in the first period meaning the coefficients more precisely represents the acceleration rate of Asset Purchases relative to the initial GDP on the acceleration rate of inflation.

Additionally, the acceleration rate of inflation seems to be associated with a lower future acceleration rate of inflation, since the coefficients are negative and statistically significant at the 5% level, for the first three lags.

Table 13: Lagged Endogenous Parameters for Δ^3Cumulative Asset Purchases Ratio

Variable	**Coefficient**	**Std. Error**	**z-Value**	**P-value**	**95% Conf. Interval**
$\Delta^3\text{Log(CPI)}_{lag=1}$	-0.8128	19.312	-0.042	0.966	[-38.664, 37.038]
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=1}$	-0.5898	0.165	-3.570	0.000	[-0.914, -0.266]
$\Delta^3\text{Log(CPI)}_{lag=2}$	-35.9448	30.230	-1.189	0.234	[-95.195, 23.306]
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=2}$	-0.6240	0.158	-3.951	0.000	[-0.934, -0.314]
$\Delta^3\text{Log(CPI)}_{lag=3}$	-72.3645	34.746	-2.083	0.037	[-140.466, -4.263]
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=3}$	-0.3155	0.152	-2.077	0.038	[-0.613, -0.018]
$\Delta^3\text{Log(CPI)}_{lag=4}$	-70.7157	30.280	-2.335	0.020	[-130.063, -11.368]
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=4}$	-0.3317	0.125	-2.656	0.008	[-0.576, -0.087]
$\Delta^3\text{Log(CPI)}_{lag=5}$	-52.4084	18.707	-2.802	0.005	[-89.073, -15.744]
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=5}$	0.1333	0.096	1.393	0.164	[-0.054, 0.321]

Notes:
Δ^3Log(CPI) corresponds to the three times differenced Log(CPI) variable and Δ^3Cumulative Asset Purchases Ratio corresponds to the three times differenced variable for Cumulative Asset Purchases Ratio

Table 13 presents the coefficients for the equation in the system where Δ^3Cumulative Asset Purchases Ratio is the dependent variable. Looking at the effect of the lags of in the acceleration rate of inflation on the acceleration rate of asset purchases in Table 13, the P-value for Δ^3Log(CPI) as the endogenous parameter is lower than 0.05 for the lags 3-5 periods back in time, namely 0.037, 0.020 and 0.005 respectively. It is a reasonable finding that changes in the inflation rate can affect monetary policy decisions, since the central bank explicitly has an inflation target and adjusts its monetary policy to reach it. To interpret the exact magnitude and sign of these coefficients is a complicated task that is beyond the scope of this study

6.11 Autocorrelation in Residuals

An important assumption in any linear regression is that the residuals are independent and identically distributed. If residuals are autocorrelated they are not independent and this assumption would be violated. For that reason, a Durbin-Watson test is performed

Table 14: Durbin-Watson Test

Variable	Δ^3Log(CPI)	Δ^3Cumulative Asset Purchases Ratio
DW Statistic Value	2.0536	1.9547

Notes:

Table 14 contains the DW Statistic Value for two variables: the Δ^3Log(CPI) and Δ^3Cumulative Asset Purchases Ratio. A DW Statistic Value between 0 and 2 suggests positive autocorrelation, a value of 2 suggests no autocorrelation, and a value between 2 and 4 suggests negative autocorrelation.

The DW Statistic values fall within the range of 1.95-2.06, close to 2, indicating no or low autocorrelation (Table 14). Hence the issues with autocorrelation for the model performance appear to be low.

6.12 Normality of Residuals

A Jarque-Bera test is performed to test the normality of the residuals to interpret the confidence intervals for the estimated parameters. The normality assumption is crucial in the calculation and interpretation of statistics such as p-values and CI's. If the residuals are not normally distributed, it is appropriate to bootstrap the confidence intervals and interpret those, rather than the non-bootstrapped ones.

Table 15: Jarque-Bera Test

Variable	p-value
Δ^3Log(CPI)	0.0063
Δ^3Cumulative Asset Purchases Ratio	$0.0000, (3.6 \cdot 10^{-276})$

The residuals are not normally distributed since the null hypothesis of normally distributed residuals is rejected at an at least 99% confidence for both of the variables (Table 15). Consequently, the confidence intervals should be bootstrapped.

6.13 Bootstrapped Confidence Intervals

Table 16: 95% Confidence Intervals for Lagged Endogenous Parameters (Δ^3Log(CPI))

Variable	**Lower Bound**	**Upper Bound**
$\Delta^3\text{Log(CPI)}_{lag=1}$	-0.21597	0.22575
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=1}$	-0.00141	0.00123
$\Delta^3\text{Log(CPI)}_{lag=2}$	-0.23000	0.19780
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=2}$	-0.00130	0.00123
$\Delta^3\text{Log(CPI)}_{lag=3}$	-0.20725	0.21780
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=3}$	-0.00125	0.00129
$\Delta^3\text{Log(CPI)}_{lag=4}$	-0.21299	0.20893
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=4}$	-0.00114	0.00124
$\Delta^3\text{Log(CPI)}_{lag=5}$	-0.20202	0.22121
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=5}$	-0.00124	0.00142

Table 17: 95% Confidence Intervals for Lagged Endog. Param. (Δ^3Cumulative Asset Purchases Ratio)

Variable	**Lower Bound**	**Upper Bound**
$\Delta^3\text{Log(CPI)}_{lag=1}$	-0.21129	0.25474
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=1}$	-44.5254	43.7032
$\Delta^3\text{Log(CPI)}_{lag=2}$	-0.19019	0.24058
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=2}$	-41.5222	43.9989
$\Delta^3\text{Log(CPI)}_{lag=3}$	-0.18922	0.25943
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=3}$	-46.0562	44.4125
$\Delta^3\text{Log(CPI)}_{lag=4}$	-0.19635	0.22434
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=4}$	-41.6504	40.5216
$\Delta^3\text{Log(CPI)}_{lag=5}$	-0.17483	0.23498
$\Delta^3\text{Cumulative Asset Purchases Ratio}_{lag=5}$	-0.15837	0.02709

To interpret the Bootstrapped Confidence Intervals of the lagged parameters in Table 17, we observe that the lags of Δ^3Asset Purchases on Δ^3Log(CPI) are still narrow and quite similar to the ones observed in the non-bootstrapped confidence intervals. The lower bound is no lower than -0.00141 and no higher than 0.00142 for any of the lags. This strengthens the belief that the acceleration rate of Asset Purchases does not have an impact on the acceleration rate of inflation.

6.14 Impulse Response Functions

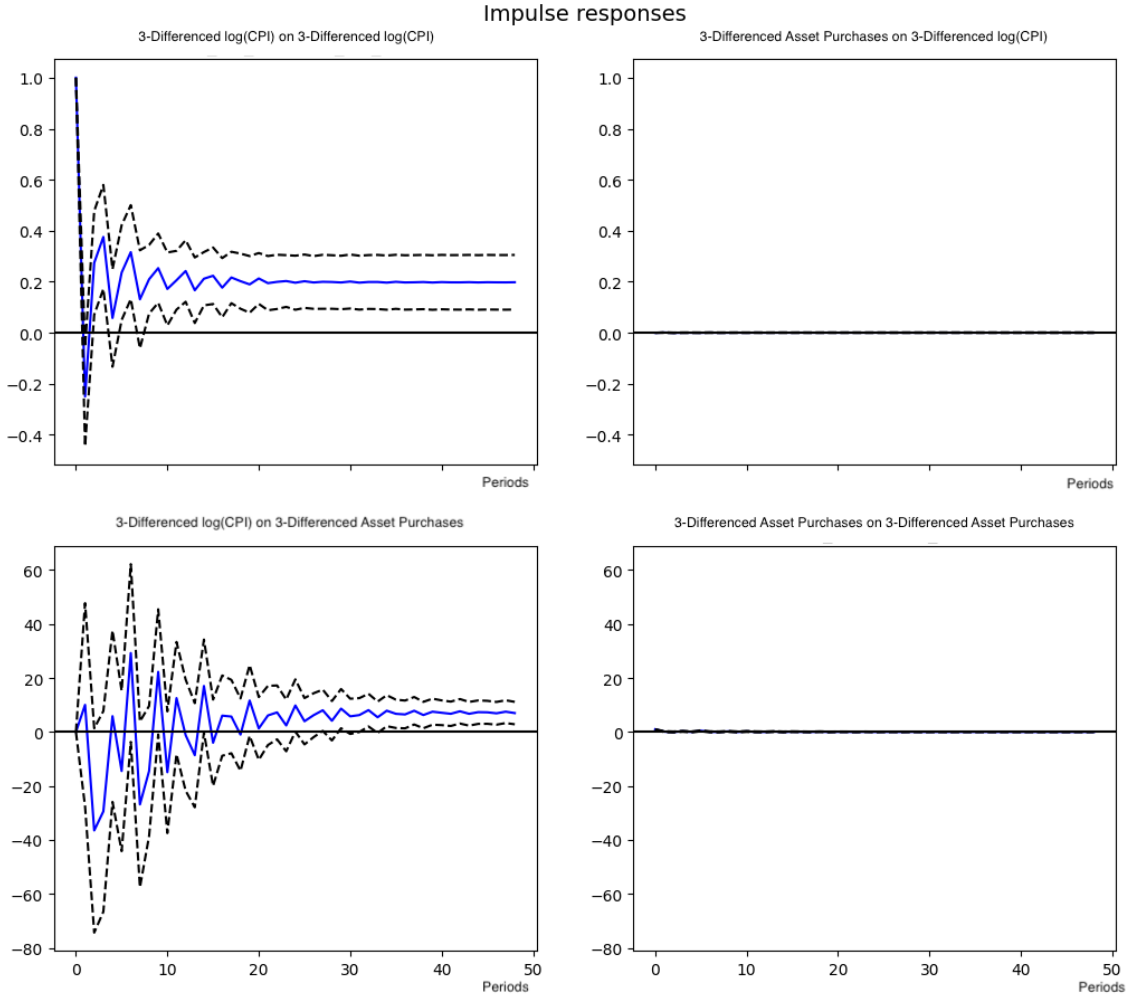


Figure 3: Impulse Response Function for the VECM

Over 48 periods, i.e. 4 years, it can be observed that the shocks in Δ^3Log(CPI) caused by shocks in Δ^3Cumulative Asset Purchases Ratio, if any, have a very small magnitude compared to that of for example Δ^3Log(CPI) on itself (Figure 3). This indicates that shocks in the change of the acceleration rate of Asset Purchases do not generate shocks in the acceleration rate of inflation. The confidence interval, the estimated shocks and the zero-line are indistinguishable on the scale used for Δ^3Log(CPI) on itself.

By analysing the IRF's we observe that the shocks in the acceleration rate of inflation are small if any and close to zero for all periods.

7 Discussion

In the following section, we will discuss potential reasons for which our attempt to estimate the SVAR model were unsuccessful.

First, we discuss the integration order and cointegration of our variables of interest. Thereafter, we discuss the COVID-19 pandemic and its multi-faceted impact on the economy. Thirdly, we discuss whether asset purchase *announcements* is the correct variable of interest, Moreover, we discuss whether Sweden's position as a small open economy and the Riksbank's other policies contributed to the difficulties in our estimation strategy. Finally, we discuss how and if we can compare our results to previous studies.

Our variable representing Cumulative Asset Purchases was calculated cumulatively and relative to GDP in the first period. The purpose of this is rescaling the variable, capture the full effect of the asset purchases with regards to how they are aggregately affecting inflation and that spikes in a year may not be indicative of the total effect QE has had over several periods. Upon performing the ADF-test, Cumulative Asset Purchases was shown to be non-stationary up to a third level of differencing. The same integration order of 3 was found for the the logarithmically transformed Consumer Price Index variable. The Swedish inflation rate during the studied period also saw clear outliers compared to the previous years. Additionally, the usage of QE shifted more towards minimising financial turmoil during the pandemic and the range of securities was expanded, further complicating the dynamics of Asset Purchases and inflation captured by the data.

An integration order of three presents significant challenges for a VAR-model, an integration order over 2 can be seen as problematic since each level of differencing leads to a potential loss of information when constant terms are removed. The Engle-Granger Test identified a cointegrating relationship between the Cumulative Asset Purchase Ration and inflation, which indicates a significant long term relationship between our Cumulative Asset Purchases Ratio and inflation. This contravenes the VAR model assumption that variables differenced at the same order are not co-integrated. Additionally, the integration order of our Cumulative Asset Purchases Ratio and inflation is three, compared to one, for our other variables used to analyse the transmission channels. The combination of having some variables of integration order 3, co-integrated at order 0 and variables of integration order 1, not co-integrated makes a structural VECM complicated to perform. Such an analysis would be beyond the scope of our thesis and due to time constraints and lack of experience dealing with such special cases, the full SVECM is not attempted.

The unprecedented usage of QE during the COVID-19 pandemic and the high levels of inflation between 2021 and 2023 are potential reasons for the problematic features of the variables. This presents a dilemma since the usage of QE during the COVID-19 pandemic and the subsequent inflation was two events that we hoped could inform the short-term relationships between Asset Purchases and inflation. In essence, the outliers in the data contained valuable information that we did not want to lose.

During the two quantitative easing programs in Sweden there were many different shocks than just the asset purchases. The COVID-19 pandemic had a huge effect on the economy which was then followed by the Ukraine Russia war and disruptions in global supply chains. As the nature and interplay of economic entities change when the macroeconomic environment shifts the effect of QE might change. For example, an article from the UN suggests that QE might have been less effective during the COVID-19 pandemic since QE mainly relaxes financial constraints at the bank level rather than at the firm level (Rashid & Pitterle, 2022). All of which might have contributed to difficulties in assessing the casual impact of QE.

Using announcements as a proxy for the expectations of asset purchases might not give a correct estimate of the thoughts of the economic agents. Kim et al. (2023) argue that announcements fail to capture that all following announcements will be expected to some extent and thus the shock in practice will not be as large as the size of the announcement. An alternative approach would have been to follow the approach of Kim et al. (2023) and gauge the expectations by analysing survey answers.

To attempt to estimate the contemporaneous relationships, despite the limitations to the interpretation of highly differenced variables and the violation of the existence of cointegrating relationships between variables of the same order, a VAR model is fitted to apply different criteria to identify the optimal lag length for the SVAR model. Our findings are another sign of non-perfect model specification since the BIC suggests 0 lags and the other information criteria suggest the maximal amount of lags without the model crashing. We proceed with the non-conclusive lag length and decide to test all possible values without the model crashing which for all specified lag lengths lead to the same problem of non-convergence for the model. This can occur when the model specification is not appropriately in alignment with the actual structure of the data, which we have received several indications of already. We therefore label the entire SVAR model as inconclusive.

Furthermore, as Corbo and Strid (2020) present, Sweden is a small open economy that is affected by shocks in its main trading partners. This includes Quantitative Easing programs conducted by other central banks which have been shown to have an effect on the Swedish economy. Di Casola and Stockhammar (2022) found that the quantitative easing conducted by the European Central Bank, ECB, had positive spillover effects mediated partly through the response of the Swedish asset purchase programme to the actions of the ECB. Since we do not include the ECB asset purchases in our model we cannot exclude the fact that our results are biased.

Swedish monetary policy did not only consist of asset purchasing during the period. Aside from other conventional monetary policies, there were other unconventional tools used simultaneously. The Riksbank was one of the first central banks to introduce a negative exchange rate in 2015 and the first to abandon it in 2019 (Andersson & Jonung, 2020). Although some studies have tried to account for this such as Jomaa (2022) who included an additional variable for controlling for the monetary policy rate, we believe that a simple approach like this won't be able to capture the complex effect it has on the economy.

The key finding of the analysis is the precisely estimated zeros for the lags of Δ^3Cumulative Asset Purchases Ratio on Δ^3Log(CPI). The interpretation of the differenced variables was approximated to the acceleration rate of Asset Purchases on the acceleration rate of inflation. The preciseness of the zeros was supported by a closer examination of the confidence intervals of the parameter estimates. We observed from the Jarque-Bera test of the variables in our reduced VECM model that the variables are not normally distributed at a 1% significance level, and the bootstrapped confidence intervals were similar to the non-bootstrapped CI's with a range smaller than 0.003 around 0 for all lags. This could be seen as that the changes of the rate at which the announcements of QE are changed, how fast the Swedish Riksbank changes the amount of QE that is announced, appears to have no effect on how fast inflation changes. The shocks in Δ^3Log(CPI) from the shocks in Δ^3Cumulative Asset Purchases Ratio are indistinguishable from zero in the IRF's which strengthens the belief that the acceleration rate of Asset Purchases does not affect the acceleration rate of inflation.

Due to the limitations mentioned above it is difficult to compare our results with previous studies. Focusing on the studies on QE in Sweden there is no study that spans over the second QE program, ranging from 2020 and onwards. This is of interest as the problems with non-stationarity at higher integration order starts in 2019. When performing the stationarity test for the data spanning from 2015-2018 we get a maximum integration order of 1 for certain variables similar to the numbers in Jomaa's (2022) study. Di Casola and Stockhammar (2022) also note that some variables may contain

unit roots. They include the variables in levels instead of differentiating, They refer to Hamilton (1994) who suggests to run the VAR in levels as running it in first difference would take away the trends. In their study they do not present what integration order the different variables have which would have been interesting to see. Since the integration orders for our data ranged between 0 to 3 and the general assumptions of the SVAR models and the presence of cointegration relationships, we did not follow that approach. Instead we choose to use a VECM model, with the variables of integration order 3 differentiated three times.

The plan of the study was to also examine through which channels the effect of QE is transmitted. However, due to the aforementioned change of model to a VECM with a third-order differentiated version of the asset announcement variable any impulse response function derived from the model would have limited implications. Specially since the variables representing the different transmission channels would have been differentiated to different levels. This in combination with the the result from the HC criterion test for model selection lead to the exclusion of those variables.

8 Conclusion

This thesis sets out to investigate the short-term effects of Asset Purchases on inflation in Sweden. The results of the SVAR-model were inconclusive, the model did not converge. One potential explanations for this was the cointegration relationship we identified between variables differenced multiple times. We obtained another indication of the model specification being non-ideal, in the optimal lag length calculation the results were unreasonable on both the low and high end, 0 and the maximum value. Based on these findings we decided not to pursue the SVAR model further and interpret the IRF's and coefficients. Since the variables in the focus of the study, asset purchases and inflation, were non-stationary at such high levels of differencing, we had no choice but to abandon our original hypothesis of asset purchases having a short term-effect on inflation.

In the light of these findings, we performed a VECM where only the variables of interest were included. A comparison using the HQ-criterion was used to inform the selection of control variables. The coefficients of our VECM, analysed with bootstrapped confidence intervals showcased precisely estimated zeros for the effect of the acceleration rate of Asset Purchases on the acceleration rate of inflation. Similar findings were obtained when analysing the IRF plots, the confidence intervals and estimated shocks were indistinguishable from zero.

Our reduced VECM model lacks the robustness provided by the Cholesky-Decomposition scheme for the SVAR-model, incorporating previous findings in to the model. There is a risk of omitting important variables, especially as Sweden's role as an open economy in the EU means domestic economic conditions are affected by monetary policy decisions by the European Central Bank or any entity it trades significantly with. This reduces the weight that can be put to these precisely estimated zeros.

Additionally, the interpretation of the acceleration rates in the concerned variable is hard to translate into a practical implication for the monetary policy decision makers. What the analysis would suggest is that, since the effect between the acceleration rates appear to be near zero, the decision makers should perhaps not be concerned with acceleration rates of inflation and Asset Purchases and focus more on the actual effect between the variables. This was the original intention of the study. It also suggests that SVAR models can become difficult to use for analysis of the effects of a monetary policy decision if the study period contains substantial financial turmoil.

References

Akkaya, Y., Belfrage, C.-J., Casola, P. D., & Strid, I. (2023). *Staff memo: The macroeconomic effects of Riksbank asset purchases during the pandemic simulations using a DSGE model* (tech. rep.). Riksbanken.

Andersson, F. N. G., & Jonung, L. (2020). Lessons from the swedish experience with negative central bank rates. *Cato Journal*, (2020:15).

Bank for International Settlements. (2023). Real effective exchange rates [Access to data on nominal and real effective exchange rates for 64 economies, providing measures of international competitiveness and the impact of external shocks. Updated monthly and daily, reflecting time-varying trade-based weights.]. https://data.bis.org/topics/EER

Bank of England. (2024). Quantitative easing. Retrieved April 2, 2024, from https://www.bankofengland.co.uk/monetary-policy/quantitative-easing

Bernanke, B. S., Reinhart, V. R., & Sack, B. P. (2004). *Monetary policy alternatives at the zero bound: An empirical assessment* (tech. rep. No. 2). Brookings Institution Press. http://www.jstor.org/stable/3805105

Borio, C., & Zabai, A. (2018, May). Unconventional monetary policies: A re-appraisal. In P. Conti-Brown & R. M. Lastra (Eds.), *Research Handbook on Central Banking*. Edward Elgar Publishing. https://doi.org/10.4337/9781784719227.00026

Corbo, V., & Strid, I. (2020). *Maja: A two-region dsge model for sweden and its main trading partners* (Sveriges Riksbank Working Paper Series No. 391). Sveriges Riksbank.

De Rezende, R. B. (2017). The interest rate effects of government bond purchases away from the lower bound. *Journal of International Money and Finance*, *74*, 165–186.

Di Casola, P., & Stockhammar, P. (2022). *When Domestic and Foreign QE Overlap: Evidence from Sweden* (tech. rep.). https://doi.org/10.2139/ssrn.4156196

European Central Bank. (2019). *Is there a zero lower bound?: The effects of negative policy rates on banks and firms.* Publications Office. Retrieved April 2, 2024, from https://data.europa.eu/doi/10.2866/23378

Fabo, B., Jančoková, M., Kempf, E., & Pástor, Ľ. (2021). Fifty shades of QE: Comparing findings of central bankers and academics [Publisher: Elsevier]. *Journal of Monetary Economics*, *120*(100), 1–20. Retrieved April 1, 2024, from https://ideas.repec.org//a/eee/moneco/v120y2021icp1-20.html

Flodén, M. (2022, December 14). Mina tankar kring riksbankens tillgångsköp. Retrieved April 29, 2024, from https://www.riksbank.se/globalassets/media/tal/svenska/floden/2022/floden-bilder-mina-tankar-kring-riksbankens-tillgangskop.pdf

Glick, R., & Leduc, S. (2013). *The effects of unconventional and conventional u.s. monetary policy on the dollar* (Working Paper No. 11). Federal Reserve Bank of San Francisco.

Gottschalk, J. (2001). *An introduction into the svar methodology: Identification, interpretation and limitations of svar models* (Kiel Working Papers No. 1072). Kiel Institute for the World Economy (IfW Kiel).

Haldane, A., Roberts-Sklar, M., Young, C., & Wieladek, T. (2016). QE: The Story so Far. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2858204

Hamilton, J. D. (1994). *Time series analysis*. Princeton University Press.

Jomaa, N. (2022). *The Effects of Quantitative Easing on Swedish Inflation: An empirical study of the swedish riksbank's quantitative easing programme between 2015-2019* [Master's thesis, Lund University].

Kim, K., Laubach, T., & Wei, M. (2023). Macroeconomic Effects of Large-Scale Asset Purchases: New Evidence. *Finance and Economics Discussion Series*, (2020-047r1), 1–89. https://doi.org/10.17016/feds.2020.047r1

Kotzé, b. K. (n.d.). *Vector autoregression models*. Retrieved April 28, 2024, from https://kevinkotze.github.io/ts-7-var/

Laséen, S. (2023). *Central bank asset purchases: Insights from quantitative easing auctions of government bonds* (Sveriges Riksbank Working Paper Series No. 419). Sveriges Riksbank.

Lütkepohl, H. (1991). *Introduction to multiple time series analysis* (1st ed.). Springer. https://link.springer.com/book/10.1007/978-3-662-02691-5

Lütkepohl, H., & Krätzig, M. (Eds.). (2004). *Applied time series econometrics*. Cambridge University Press.

Neely, C., & Fawley, B. (2013). Four stories of quantitative easing. *Federal Reserve Bank of St. Louis Review*, *95*, 51–88. https://doi.org/10.20955/r.95.51-88

OECD. (2024). Consumer price indices - oecd data explorer. Retrieved March 30, 2024, from https://data-explorer.oecd.org/?fs[0]=Topic%2C1%7CEconomy%23ECO%23%7CPrices%23ECO_PRI%23&pg=0&fc=Topic&bp=true&snb=30

R package Documentation. (2023). SVAR: Estimation of a SVAR in vars: VAR Modelling. Retrieved April 29, 2024, from https://rdrr.io/cran/vars/man/SVAR.html

Rashid, H., & Pitterle, I. (2022, February). UN DESA policy brief no. 129: The monetary policy response to covid-19: The role of asset purchase programmes. https://www.un.org/development/desa/dpad/publication/un-desa-policy-brief-no-129-the-monetary-policy-response-to-covid-19-the-role-of-asset-purchase-programmes/

Ren, X., Shao, Q., & Zhong, R. (2020). Nexus between green finance, non-fossil energy use, and carbon intensity: Empirical evidence from China based on a vector error correction model. *Journal of Cleaner Production*, *277*, 122844. https://doi.org/10.1016/j.jclepro.2020.122844

Riksbank, S. (2024, May 2). *Government bonds*. Retrieved May 5, 2024, from https://www.riksbank.se/en-gb/markets/the-riksbanks-securities-holdings/government-bonds/

Rolander, N. (2023, October 24). Sweden Riksbank Needs More Than $7 Billion to Cover Losses - Bloomberg. Retrieved April 1, 2024, from https://www.bloomberg.com/news/articles/2023-10-24/riksbank-says-it-will-need-more-than-7-billion-to-cover-losses

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica*, *48*(1), 1–48. http://www.jstor.org/stable/1912017

Stock, J. H., & Watson, M. W. (2001). Vector Autoregressions. *Journal of Economic Perspectives*, *15*(4), 101–115. https://doi.org/10.1257/jep.15.4.101

Stock, J., & Watson, M. (2015). *Introduction to Econometrics*. Pearson.

Swedish Riksbank. (2022). Riksbankens balansräkning har vuxit. Retrieved March 30, 2024, from https://www.riksbank.se/sv/press-och-publicerat/publikationer/ekonomiska-kommentarer/riksbankens-finansiella-resultat-och-kapital-paverkas-av-hogre-rantor/riksbankens-balansrakning-har-vuxit/

The Pennsylvania State University. (2018). 10.7 - Detecting Multicollinearity Using Variance Inflation Factors — STAT 462. Retrieved April 28, 2024, from https://online.stat.psu.edu/stat462/node/180/

Wallace, N. (1979). A Modigliani-Miller Theorem for Open-Market Operations [Publisher: Federal Reserve Bank of Minneapolis], (131). https://jstor.org/stable/community.28111527

Weale, M., & Wieladek, T. (2016). What are the macroeconomic effects of asset purchases? *Journal of Monetary Economics*, *79*, 81–93. https://doi.org/10.1016/j.jmoneco.2016.03.010

Williams, J. C. (2014). *Monetary policy at the zero lower bound: Putting theory into practice* (tech. rep.).

9 AI-Appendix

Purpose and Usage

A Generative AI tool, ChatGPT, has been used for the following purposes:

- Understand warnings and errors in code
- Receive suggestions on how to improve specific paragraphs in the text.

Specifically, the warning messages of non-convergence produced by the SVAR model was sent to ChatGPT for investigation along with a few errors in running the code, obtained when conducting the analysis. To improve the text, after a paragraph was written, it was in some cases sent in to ChatGPT with an instruction to provide suggestions on how to improve logical flow, enhance grammatical structure and point out needed clarifications. Rather than replacing text with the models suggested version, this was used to get insight into what improvements could be made and modifications were made based on the authors personal taste.

Impact

By explaining the cause of a few errors in the code, the causes of the problems were identified more quickly and thereby increased the speed at which the code could be written. The analysis of the warning message was informative although it didn't lead to any fundamental insight. With regards to improving paragraphs, it was helpful to get another perspective on the content and did lead to clearer formulations and structure of paragraphs in some cases.

Mitigation of Risks

Understanding errors and warnings was overall quite fruitful and is an example of a low risk usage. If the code is not working, an incorrect pinpoint of cause of the error will not break the code but a successful identification of the cause will considerably help the development. The main potential risk in this regard would be to rely on the model for implementing fixes of the code since the model might remove the error but change the functionality of the code. To mitigate this, the model was used exclusively to identify causes of errors.

Since the paragraphs of the text were interconnected in terms of the content, it was difficult for the model to accurately get the full context of the paragraph. Moreover, ChatGPT and Generative AI models in general are known to be uncertain in their outputs, to hallucinate. Based on these two factors, considerable precaution was taken on not relying on the model's recommendation without critical analysis.

Insights

ChatGPT and Generative AI models can be useful to understand errors in code and obtain suggestions on how to improve text. A lot of times, the outputs are helpful, but reliability is not ensured and a fair dose of caution should be taken to the outputs and critical analysis is warranted when making use of the generated suggestions.