DEMAND DRIVERS' ANALYSIS AND FORECASTING FOR PRODUCTION PLANNING

Lappeenranta–Lahti University of Technology LUT

Master's in Business Analytics, Master Thesis

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Examiners: Professor Pasi Luukka

Professor Jan Stoklasa

ABSTRACT

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LUT Business School

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93 pages, 23 figures, 15 tables and 16 appendices

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The purpose of this study is to examine macroeconomic indicators and their ability to explain demand relationships for Stora Enso as well as forecasting future values. Indicators examined were Wholesale Trade, Industrial Production, Harmonized Index of Consumer Prices (HICP), and Retail Trade. We studied if commonly used macroeconomic indicators can be utilized to determine a linear relationship. The hypothesis is that there exists a linear relationship with some of the indicators. The data is collected from the European Commission's database from the years 2010-2023. Empirical studies show that macroeconomic indicators have been able to explain Stora Enso's production and Wholesale Trade is statistically significant. Vector Auto Regression (VAR) and Impulse response plots were utilized to study the short-term impact on Y_1 (target variable) and the results show that HICP and industrial production have the most volatile impact on Y_1. Future forecasts of both VAR and ARIMA show stagnating production in the short-medium term.

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SYMBOLS AND ABBREVIATIONS

ARIMA – Autoregressive Integrated Moving Average

VAR – Vector Auto Regression

OLS – Ordinary Least Squares

TRAMO- Time series Regression with ARIMA noise, Missing values, and Outliers

SEATS- Signal Extraction in ARIMA Time Series

AR – Auto Regression

MA – Moving Average

IP – Industrial Production

MAE – Mean Absolute Error

MSE – Mean Squared Error

IR – Interest Rate

BI – Business Intelligen

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1 Introduction

In a global context of economic environments that are inclined to quick changes with unpredictability, the ability of an organization to foresee and adjust to those changes becomes not only useful but rather necessary for survival and development. This thesis emerges at the intersection of predictive analysis and production planning, an area that, while not new, has taken on renewed significance due to recent global challenges. In essence, the insights that the present study seeks to draw is one that tries to look at how macroeconomic indicators can essentially become a guiding tool into the complexity of market demands, thus enabling businesses to plan, produce, and prosper with greater accuracy and foresight.

Analysis of production planning is a relatively unknown task at Stora Enso, especially using macroeconomic indicators. It may provide a systematic way of predicting the future conditions of the market and the impact it could have on production needs. This implies that through our analysis of production trends, there would be an early warning not only on market falls in the future but also an opportunity in the market that is timely enough so that resources can be channeled effectively in optimization of profitability and sustainability.

Macro-economic indicators have historically been important to economists and business leaders as they offer them insights into the broader economic health and consumer behavior. These indicators, from the rate of inflation to patterns of consumer spending are analyzed with the best follow-through on some market situations. It is not only academic and theoretical; it has practical value. In fact, these indicators are pragmatic tools in the pursuit of strategic decision-making, from the fiscal policies of governments down to investment plans of corporations. With the rise of machine learning methods and data analytics for the implementation of advanced statistical methods, their practical use has shifted, mainly in the field of production planning.

This study aims to utilize linear regression methods to assess the significance and impact of the macroeconomic indicators thereby helping us understand the nuances of market conditions and the variables that may have an impact on our production. Following the regression analysis, we aim to forecast future values using Vector Auto Regression and Autoregressive Integrated Moving Average.

1.1 Research Questions

The core focus of this study is to develop an understanding of macroeconomic activity and its implications for production for Stora Enso. The analysis of this study will be based on a theoretical sound approach of regression analysis. Furthermore, the existing production data will be put under scrutiny for forecasting purposes using well established methods such as Autoregressive Integrated Moving Average and Vector Auto Regression. The study will lean on preliminary data analysis that will pave the way to establish the use of regression analysis and model assumptions.

The research problems this paper addresses can be formulated as the following questions:

1. Is Linear Regression Analysis applicable to investigate the macroeconomic environment and market dependencies?

2. Have Macroeconomic indicators been able to explain the future development of Stora Enso’s production and is the explanation power significant?

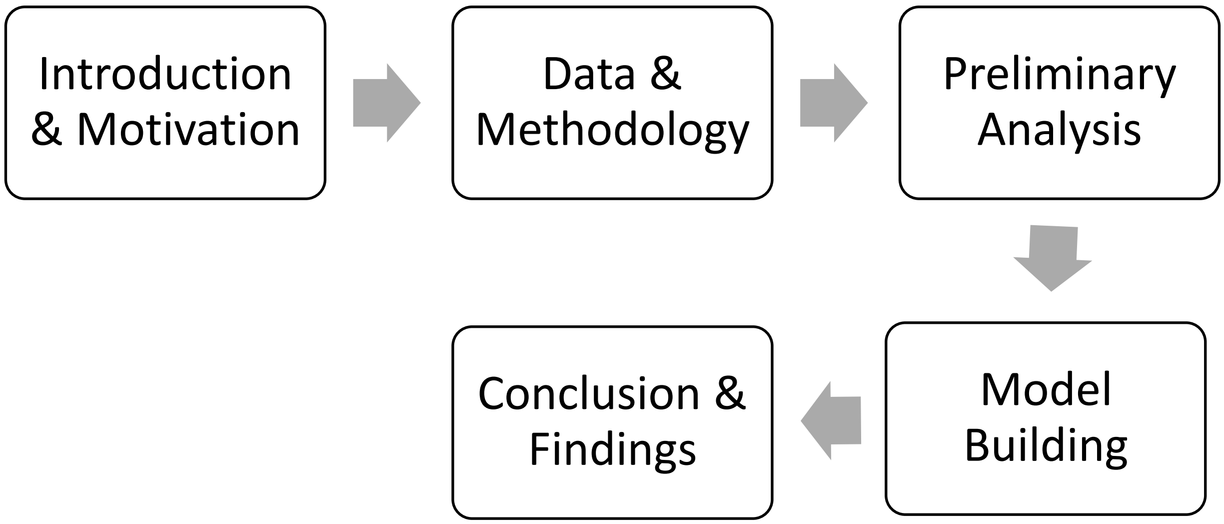
3. How do forecasted production outlook differ when comparing ARIMA and VAR models?

4. What do the impulse response plots tell us about the dynamic relationship of macroeconomic variables.

1.2 Structure of Study

Figure 1 Structure of Study

An outline of the study structure followed and implemented in this study is displayed in Figure 1. The introduction, motivation, and literature review culminate the first chapter of this study, aiding in laying the foundation for the study. It also presents a detailed overview of the macroeconomic indicators chosen to drive the analysis. The second chapter introduces the data and methodology used to conduct the study, outlining the tools and techniques that complete a holistic approach. The third chapter dives into the preliminary data analysis that is crucial to inspect whether our chosen tools are viable to implement. Where necessary, it conducts data transformations to ensure appropriate application. The fourth chapter delves into building and executing regression models and forecasting analysis.



1.3 Motivation & Related Background

Previously, Stora Enso has focused their research on Wholesale Trade, one of the indicators considered in our aggregate analysis under the consensus that sales is the leading indicator for the development of production. Previous research carried out by the department focused on simple linear regression utilizing R^2 as the evaluating metric. The research concluded with a finding that Wholesale Trade was responsible for explaining roughly 80% of the production patterns and trends.

However, the research did not consider regression diagnostics, or a validation method such as train and test split. Furthermore, to account for wholesale trade explaining such a large percentage of production prompted a curiosity for further investigation. It is also important to point out that previous examination of production only considered the largest aggregate of production. The approach of utilizing a singular indicator in macroeconomic analysis is an simplified approach that is prone to over-reliance and errors. Economic analysis is a complex environment where interactions of several economic variables are in play. It is, however, a good starting point for predictive analysis. This study builds upon the initial research conducted by Stora Enso, by re-investigating Wholesale Trade as an indicator alongside more economic indicators that are closely aligned with consumer demand.

As a result, potential macroeconomic indicators of interest were identified within the context of Stora Enso's interests and consensus from the BI department. Therefore, the following 4 indicators are initially introduced and thoroughly investigated in this paper:

1. Harmonized Index of Consumer Prices (an Inflation Indicator).
2. Industrial Production
3. Retail Trade
4. Wholesale Trade

2 Literature Review

Numerous studies have looked at how businesses in a variety of industries predict demand for their products using economic indicators. These studies frequently show how these indicators and industry-specific demand are correlated, enabling businesses to modify their production plans and stock levels in advance of changes in the economy. This chapter looks at the literature that exists on the use of macroeconomic indicators for demand forecasting and production planning. The rapid change in the global economic environment points up the importance of being able to assess and predict market conditions so that production may be appropriately and strategically adjusted for organizational resilience and growth. The literature review analyses predictive models using Macroeconomic indicators and focuses on the manner of their application, methodologies, and the synergies from other industrial applications.

2.1 The Role of Macroeconomics in Production Planning

Macroeconomic indicators are vital for demand forecasting and are critical in adjusting the production planning. Traditionally, Inflation and industrial growth indicators have been a guide for assessing market conditions (Akhtar & Javed, 2012). The Harmonized Index of Consumer Prices (an inflation indicator) has been a guide for strategic decision-making on the state of economic health and consumer behavior. These developments in statistical methods and data analytics have shifted their application toward the use of more sophisticated forecasting models that promise accuracy in strategic foresight for production planning.

Amisano and Geweke (2013) studied prediction using macroeconomic models. The macroeconomic indicators they used were log growth of real consumption, investment, income (GDP), and inflation as measured by the growth rate of GDP deflator. They conducted a comprehensive comparative analysis of three forecasting models: Dynamic Factor Models (DFM), Dynamis Stochastic General Equilibrium (DSGE), and Vector Auto Regression (VAR).

DFM models excel at handling large datasets, extracting common trends from several indicators. They are suitable for capturing a broader economic picture affecting production. DSGE models can incorporate microeconomic principles and thus are useful for tailoring to specific industries(Amisano & Geweke, 2013).

VAR, a popular forecasting model investigates the dynamic interactions between time series (in this case different indicators) and how they affect each other. In the case of VAR models, Amisano and Geweke (2013) found that the consumption growth series the VAR model forecasts performed poorly and did not anticipate sharp drops accurately. Inversely, the inflation series performed well and more accurately predicted drops. The use of VAR models to predict future conditions is a strong approach particularly in the case of an indicator as responsive as inflation. In our study, the Harmonized Index of Consumer Prices is an inflation indicator that tracks the growth of consumer goods over time. Thus, a VAR model analysis of its impact on our production as well as other macroeconomic variables would prove fruitful.

Amisano and Geweke (2013) conclude that predictive modeling is useful using macroeconomic indicators, but their accuracy is subjective. They suggest that the combination of multiple models can rectify accuracy concerns.

Broadly, the methodological approach of our study is informed, by the method and empirical findings from Amisano and Geweke. Their recommendation of using multiple models to compare accuracy is well founded. As a result, we will use other forecasting models such as ARIMA to compare forecasting accuracy across methods.

2.2 Robustness of Macroeconomic Indicators

Macroeconomic variables have a long-standing history in forecasting analysis. They have frequently been used to predict economic recession periods and stock market performance. The vast number of studies highlighting this indicates the robustness and utility of macroeconomic indicators in prediction analysis.

The work of Sirucek (2012) and Humpe & Macmillan (2009) cover the predictive ability of macroeconomic indicators by examining the relationship with stock market movements in the US and Japan. Sirucek (2012) explored the impact of several economic factors including interest rate, inflation & money supply on the S&P 500 index and Dow Jones Industrial Average indices. He found that, there exists a strong correlation between the chosen indicators and the movement of stock market indices. Similarly, Humpe & Macmillan (2009) investigated the longstanding relationship between industrial production, consumer price index, money supply and stock prices. They conducted a cointegration analysis which revealed a strong impact of these macroeconomic variables on stock markets in Japan and the US. Furthermore, the impact of these variables mirrors the potential influence on the production behavior of firms.

Both studies made use statistical analysis methods such as OLS regression and cointegration analysis to investigate the relationships between stock market indices and macroeconomic variables. This approach is relevant to our study as it provides a tested framework for analyzing the impact of macroeconomic variables on production planning. These findings highlight the ability of macroeconomic variables in economic analysis, indicating their robustness and effectiveness for predictive analysis. Their analysis offers compelling evidence of the predictive capabilities of macroeconomic indicators to assess broader market conditions. While they focus on stock market indices, the economic principles and method of evaluation can be adjusted for our production planning analysis. By utilizing this approach this study aims to assess the link between economic forecasting and its practical applications in production strategy.

The utilization of VAR models for understanding the underlying relationships between macroeconomic variables is vastly implemented. Another instance of this is the work by Mohan et al. (2019) where they utilized Vector Auto Regression to study the impact of crude oil price, 30-year mortgage interest rate (IR), Consumer Price Index (CPI), Dow Jones Industrial Average (DJIA), and unemployment rate (UR), on housing prices over time. The fact that all the variables are of macroeconomic nature bodes well for the application of our study. In particular, Mohan et al. (2019) fitted impulse response plots and studied the effect of shocks applied to macroeconomic indicators on housing prices over a period of 1-12 months. The methodology applied by Mohan et al. (2019) helps lay the structure for this study. Testing for unit root and converting for stationarity and then applying Vector Auto Regression is the basic required for a valid analysis. Mohan et al. (2019) did not in-fact use Vector Auto Regression to estimate parameters of the regression equation but rather, to observe the influence other predictors have on housing prices.

2.3 Autoregressive Integrated Moving Average (ARIMA) and Demand Forecasting

The use of ARIMA forecasting has longstanding validity in the world of macroeconomics and demand forecasting. ARIMA is particularly useful, when forecasting a time series over a long time period. The approach and methodology utilized in this paper stems from the work of Fattah et al. (2018). Their work focuses on ARIMA demand model forecasting of a food company citing the importance of inventory management over rapidly changing customer environments. Fattah et al. (2018) argue that while there exist other methods for forecasting demand, taking into account historical data is important as, historical data provides insights during different economic time frames. As with VAR in the previous section, the methodology utilized by Fattah et al. (2018) is applied to this study in ARIMA model building, going through all of the pre-requisite testing and troubleshooting needed to build a reliable model. Fattah et al. (2018) made use of the Box-Jenkins approach, which is popular and widely used in ARIMA modeling. Fattah et al. (2018) concluded that ARIMA modeling and forecasting was successfully implemented to forecast demand for a food company. Drawing synergies from the study, this paper aims to implement ARIMA modeling for Stora Enso and their packaging materials function. While packaging may not seem to be directly related to customer purchases. It is, invariable linked to the other companies that sell the products that Stora Enso packages. Therefore, parallels can be drawn in this study to analyze possible demand outcomes in the near future.

2.4 Industrial Production and Macroeconomics

The financial crisis that first erupted in the year 2007 in the United States and its consequent worldwide impact underlies importantly the necessity of understanding the nuances of the links between various macroeconomic variables with that of industrial production. The study by Gutu et al. (2015) identifies a strongly tested relationship between the Romanian industrial sector and how economic shocks affect the ability of businesses to remain operationally efficient. Their study finds that industrial production is significantly affected by variables such as interest rates, and inflation.

Gutu et al.(2015) studied the systemic risks of the financial crisis and the effects on the level of industrial production. Making up an elaborate framework based on which a better understanding can be developed for the broad repercussions related with macroeconomic fluctuations in relation to production planning. The results of this study are relevant to the main hypothesis of this thesis, which focuses on the use of macroeconomic indicators, for reliable forecasting, intending to adjust productions and planning strategically.

A key finding by Gutu et.al (2015) is that holding financial equilibrium at the firm level is key to withstanding macroeconomic shocks. The thorough analysis of the movements of macro indicators may provide an early warning-signal for potential production changes.

Stora Enso is a leader in sustainable packaging and contributes significantly to the overall production in the industry. As a result, it is relevant to understand that such a large player in the industry would be affected by market changes. Gutu et al. (2015) uncovers the factors that impact the industry as a whole and this allows us to tailor this approach specifically for Stora Enso.

The study by Gutu et al. (2015) rectifies the choice of Industrial Production as an important variable in production planning. The accounted impact of macroeconomic variables on industrial production during financial crises highlights a pattern for companies to follow. By incorporating these insights, our study addresses the literature gap concerning predictive analysis and production planning and sets the stage for future research in this domain. Future studies could explore different methods of application and different macroeconomic indicators that remain uninvestigated in this scope.

3 Macroeconomic Indicators

3.1 Industrial Production (IP)

The Industrial Production (IP) indicator is a key economic metric that measures the output of the industrial sector of an economy. It encompasses the production activities of manufacturing, mining, and utilities. The indicator is often presented as an index, based on a baseline year, allowing for the analysis of changes in industrial output over time. Generally, it consists of 3 components:

Manufacturing: This is typically the largest component and includes the production of goods ranging from consumer goods, such as clothing and electronics, to industrial goods like machinery and equipment.

Mining: This includes the extraction of minerals, oil, coal, and gas. The volatility in mining output can significantly affect the IP due to changes in commodity prices and demand.

Utilities: This covers the production of electricity, water, and gas for distribution to businesses and consumers. It's often influenced by seasonal factors, such as weather conditions affecting heating or cooling demand.

The IP index is calculated relative to a base year, which allows for the comparison of production levels over time. The formula generally involves summing the production quantities of various industries, weighting them by their importance to the economy, and then standardizing the total against a base year. The weights can be adjusted periodically to reflect structural changes in the economy.

Industrial production is a leading indicator of the economic health of the industrial sector, which is a critical component of Gross Domestic Product (GDP). An increase in industrial production suggests economic growth, while a decrease may indicate economic downturns (Ejaz & Iqbal, 2021)

Investors and analysts monitor changes in industrial production to make decisions about investing in industrial stocks or sectors. A rising IP index could signal growing demand for industrial goods, potentially leading to higher corporate profits and stock prices in the sector (Silva et al., 2018).

Industrial Production allows for the analysis of specific industrial sectors, providing insights into which sectors are expanding or contracting. This can be useful for businesses and investors looking to diversify or target specific markets (Foerster et al., 2008).

3.2 Harmonized Index of Consumer Prices - HICP

Among the macroeconomic indicators is the Harmonized Index of Consumer Prices (HICP), which allows the European Union to estimate inflation on a community basis. In simple terms, the HICP is a tool that can measure the change in prices over time of the goods and services purchased by household consumers. From the European standpoint, it provides a very reliable base for international comparison in the field of consumer price inflation. Some major data types included in the HICP are the indices for the Euro Area, the European Union, and individual member states. It also provides data for the European Economic Area (EEA), individual countries of the EEA, Switzerland, and even proxy HICP data for the United States. Our research geography is focused on Europe, specifically the 27 EU member countries.

The HICP is compared significantly with the conceptual pure price indexes, which exclude non-consumption expenditures, such as financial transactions. It covers a wide range of goods and services but includes certain exclusions if for operational or methodological reasons, such as imputed rentals for housing or services of financial intermediation indirectly measured. Both geographical and population coverage aim at reflecting consumption duly within the Economic Territories of Member States, including the spending by foreign visitors and institutional households but excluding that of the residents abroad.

The HICP is a price index that includes the money expenditure on final consumption and is formulated in the Laspeyres-type index, covering both prices and weights changes. This ensures that methods in computing the indices applied reflect truly the average price change in the EU, while considering the widely different consumption patterns and weights in the population of consumers.

The HICP contains a lot of special aggregates, such as "all-items excluding energy" or "processed food, alcohol, and tobacco." Hence, the exclusion can be very interesting for the basic consumer demand developments, as mentioned above, for it excludes volatile elements since prices for energy can be from external influence and are not demanded by consumers alone.

The Harmonized Index of Consumer Prices (HICP) is an important tool for macroeconomic analysis and forecasting consumer demand for the whole European Union. It is important for many reasons due to its wide coverage and methodology.

Consumer Spending Trends: HICP can allow following the increase and decrease of consumer spending over time in sectors. If an increased HICP shows up for a specific category, this would mean that consumers are demanding more of this product, while constant or decreased HICP numbers would certainly indicate that there is probably lower demand for the product or changes in consumers' preferences.

3.3 Wholesale Trade & Retail Trade

Wholesale Trade is characterized by the sale of goods to retailers and to industrial, commercial, institutional, or professional users. It includes agents dealing for others and own-account wholesalers, which are dealers who buy and sell merchandise for their account and profit. The same is further subdivided into five categories: agricultural products, consumer goods, intermediate goods, and machinery and equipment, respectively. Such classification points out that there are diversified tasks to be executed by wholesalers in relation to varying market segments.

Besides distribution, it provides a range of value-added services, including those related to storage, sorting, grading, logistics, and increasingly, pre-, and post-production operations. From this, we find that planning for efficiency and sophistication in the supply chain should include how the wholesalers can function.

Further analyzing the breakdown of the wholesale trade into more detailed product categories gives some idea about the changing dynamics in demand, because the economic contributions will be different across different segments. This is useful information when assessing how the macro indicators may affect various market segments. Similarly, Retail trade is defined as the sale of goods exclusively to retailers and has identical segments to wholesale (Consumer goods, intermediate goods, machinery, and equipment).

4 Data & Methodology

4.1 Data

This chapter contains the description of the data utilized for the basis of the quantitative analysis, formal definitions and descriptions of the methods undertaken to pre-process, shape, and analyze the data.

The data considered for this research is twofold and separated in the form of independent explanatory variables and dependent target variables. The dependent target variable extracted from Stora Enso database, granted permission by the BI & Modeling department to use anonymized historical production data in the research to investigate the relationship between macroeconomic indicators and Production.

4.1.1 Target Y variable

The monthly historical data ranges from the years (2010 - 2023). In total the target variable data consists of one aggregate Y variable. This study will discuss the target variable based on its relative importance to Stora Enso, focusing on the aggregate. Table 1 shows summary statistics for the Y_1 variable:

Table 1 Summary Statistics Target Variables

Unit (Tons)	Y_1 (tons)
Mean	214415
Standard Error	1474
Median	207410
Standard Deviation	18938
Sample Variance	358629475
Kurtosis	-0.70

Skewness	0.56
Range	71528
Minimum	184598
Maximum	256126

4.1.2 Explanatory Variables

The explanatory variables, in this case the macroeconomic indicators discussed previously are extracted from the European commission's Eurostat database. The time frame chosen for these variables (2010-2023) is identical to our target variables. The macroeconomic indicators (HICP, Industrial Production, Wholesale Trade, Retail Trade) were chosen in consensus with the BI department. Previous research on Wholesale Trade led the basis of identifying indicators related to end use consumption by consumers and subsequently fit to represent consumer demand. Table 2 shows the summary statistics of the Macroeconomic Indicators:

Table 2 Summary Statistics Explanatory Variables

Statistics	All-items HICP (index 2015 =100)	Industrial Production(index 2015 =100)	Wholesale Trade(index 2015 =100)	Retail Trade(index 2015 =100)
Mean	103.6172727	102.1460606	111.8248485	108.0157576
Standard Error	0.641091724	0.529295853	1.307025874	1.049342155
Median	100.7	101.8	102.9	102.7
Mode	93.06	96.3	101.1	100.4
Standard Deviation	8.234972297	6.798928332	16.78905133	13.47904404
Sample Variance	67.81476874	46.22542646	281.8722446	181.6846282
Kurtosis	1.624746477	0.04493812	0.766003208	0.045247457
Skewness	1.416137666	-0.229724538	1.354342239	1.074779359
Range	36.06	39.4	65	47.6
Minimum	91.51	76	89.9	92.8
Maximum	127.57	115.4	154.9	140.4
Count	165	165	165	165

4.2 Methodology

4.2.1 Seasonal Adjustment

Before investigating and identifying drivers of production, it is important to pre-process and transform the data to extract the data required by this specific analysis. Seasonal Adjustment and trend extraction is an important step in that regard. Seasonal adjustment is the removal of systematic calendar related variation in time series data. It captures the trend component otherwise missed from seasonal sales and moving holidays. Brooks (2008, pg.156) highlights that seasonal effects can cause autocorrelation in data and in turn cause an inflated model fit. To establish general pattern of data and identify long term movements it is important to remove seasonal short-term effects in the data. Furthermore, macroeconomic indicators extracted from Eurostat database are already seasonally adjusted. To maintain the consistency of data through both our response and predictive variables we carried out seasonal adjustment to our response Y_1 variable. To do so, we utilized JDemetra+, a software utilized by the European Commission and standard practice at Stora Enso. Figure 2 outlines the before and after of the subsequent seasonal adjustment.

Seasonal adjustment in JDemetra+ was carried out using the TRAMO SEATS Method. TRAMO (Time series Regression with ARIMA noise, Missing values, and Outliers) and SEATS (Signal Extraction in ARIMA Time Series) are two-step approach methods, used in conducting seasonal adjustment in time series data. Designed by Victor Gomez and Agustin Maravall (1994) , this method is used to help in economic and financial data adjustment to eliminate seasonality impacts. TRAMO has been designed with various goals: the modeling and correction of a great variety of components that might corrupt the series signal, such as outliers, missing values, complex seasonal patterns, and the like. Maravall (2016) details the mathematical operations of the TRAMO seats method, but in general can be expressed as a combination of a regression term and an ARIMA model.

Maravall (2016) outlines the general level equation of the method that the statistical software JDemetra+ utilizes:

$$z_t = y'_t \beta + x_t ; \quad (1)$$

Where:

1) y'_t is the regression term.

2) β is the coefficient term of the time series.

3) x_t follows an ARIMA model.

4) t is the observation number.

5) z_t is the resulting seasonally adjusted time series.

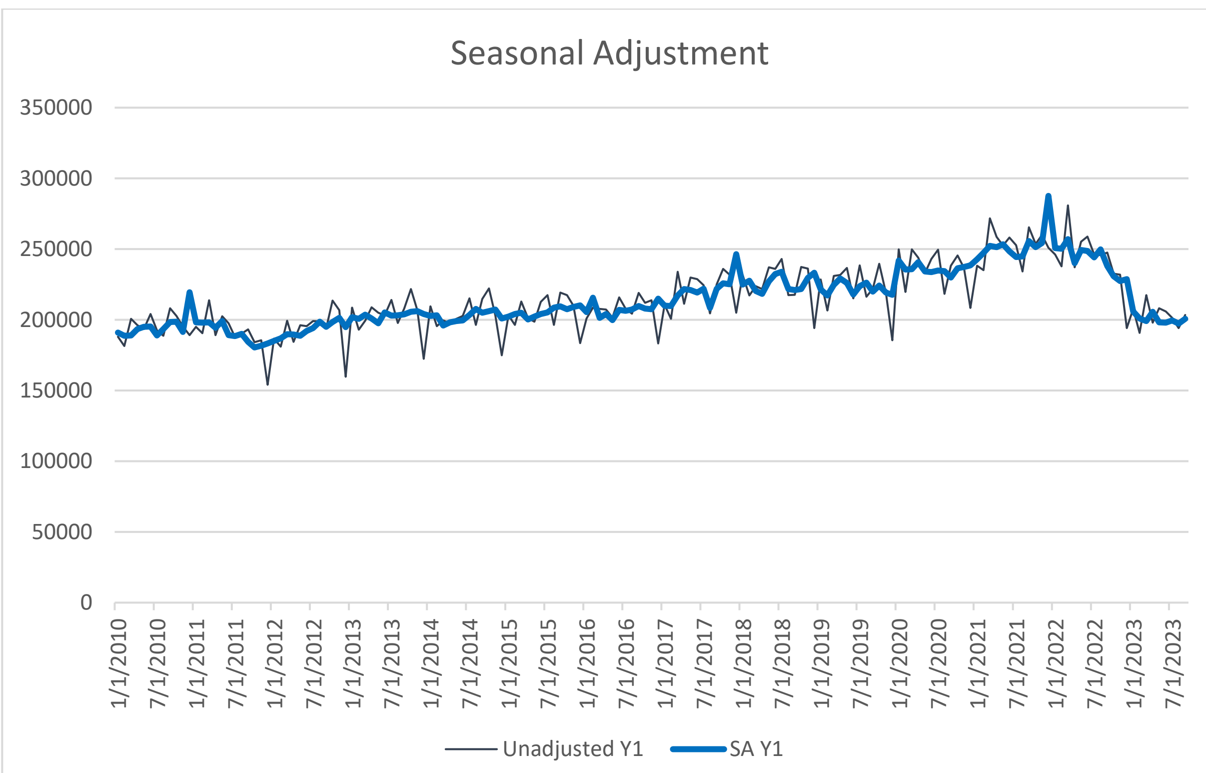


Figure 2 Seasonal Adjustment

The TRAMO module remains by providing the initial pre-adjustment through introducing a regression model with atypical observations, calendar effects, and missing values(Maravall, 2016). In effect, the model prepares the data by removing these by-deviations that may introduce bias into the analysis, and hence the following steps are carried out based on a purer and more accurate series of data. The adjusted data in the presence of the exogenous variables, the regression coefficient describing the so-adjustment due to these variables, and is modeled through the ARIMA process and, hence, can be inferred to describe the underlying stochastic processes of the data.

SEATS takes over the process followed in working toward extracting the signal, or the true and underlying pattern, from the ARIMA-modeled time series through the TRAMO process. It uses spectral decomposition techniques, where it extracts the seasonal component and the series thus produced is reflective of the genuine trend and cyclical components without the distortions emanating from the season. One of the most important capabilities of SEATS is effective decomposition of the series into its seasonal and irregular components for clearly showing the underlying trends and cycles, which are very critical in making accurate forecasts and strategic decisions.

Framework:

Gomez & Maravall (1997) provide a detailed description through a user manual about the TRAMO SEATS process of seasonal adjustment.

The dataset consists of monthly economic indicators from January 2010 to September 2023 with a total of 165 observations. Appendix 1 highlights the summary of the seasonality decomposition. It indicates that:

1) The series has been log transformed to stabilize variance and minimize heteroscedasticity.
2) Adjustments were made for trading days (1 day), Easter (6 detected) and Outliers (5 detected).

The TRAMO process then selected the best fit ARIMA model for the x_t term through minimizing AIC and BIC criterion. It successfully chose the final model parameters ARIMA(0,1,1) for handling the non-stationarity and seasonal patterns. The estimation of the model output:

1) Log Likelihood: 330.475
2) AIC and BIC: 991.706 and -6.591
3) The standard error of regression: 0.02669, measuring the average distance values fall from regression line.

The equations for the ARIMA model:

$$D: 1 - B - B^{12} + B^{13} \tag{2}$$

$$MA: 1 - 0.438921B - 0.733157\,B^{12} + 0.321798\,B^{13} \qquad (3)$$

B represents the time series lagged by one period (Y_{t-1})

B^{12} introduces the seasonal differencing component, that lags the series by 12 periods to consider annual seasonality due to the monthly data.

B^{13} then re-adjusts the seasonal differencing by adding the time series by 13 lags.

The moving average part of the ARIMA model is used to model the error term as a combination of the error terms at various lags.

4.2.2 Regression – Removal of Extreme Scenario

Figure 3 shows the development of the indicators over time. A common occurrence between of them is the sharp decline during the years of COVID-19 (2020). The presence of extreme dips or scenarios can be classified as outliers or anomalies. Such events in time series analysis can distort long term trends and subsequently affect forecasts. It is important to diagnose this hindrance to maintain long term trends. It is common practice to exclude these periods when conducting time series analysis to maintain long term trend components for accurate forecasts. The practical implication of this study allows us to remove extreme scenarios altogether as the linear regression part of our analysis is to discern whether it is an appropriate approach to find linear dependencies with macroeconomic indicators.

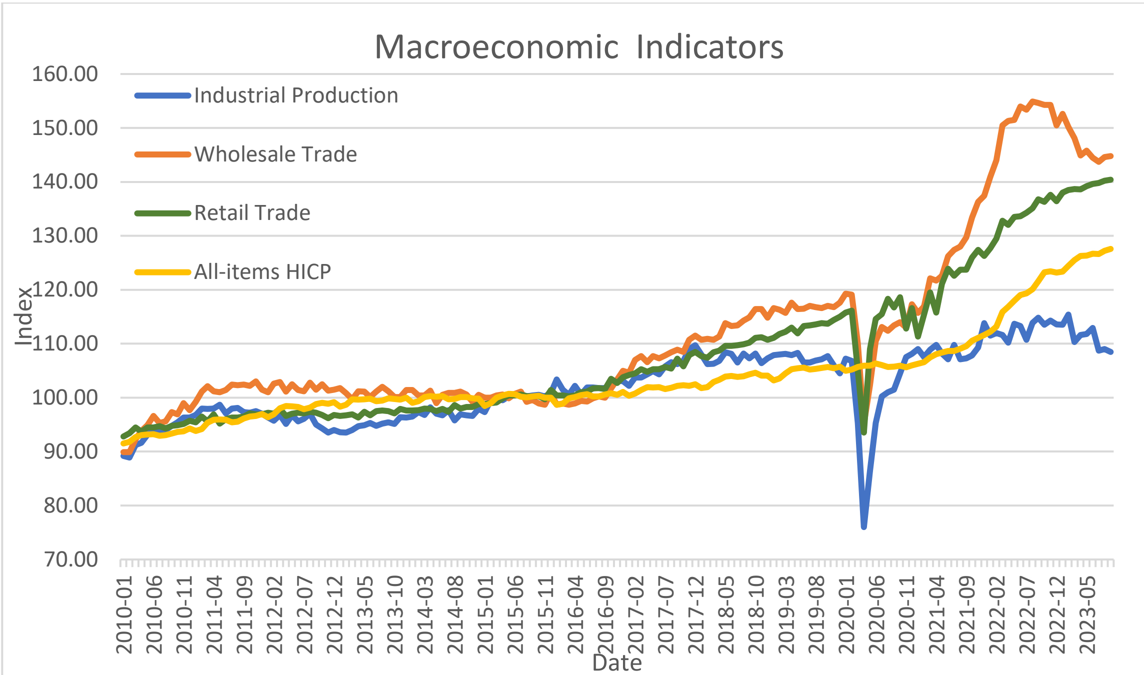


Figure 3 Macroeconomic Indicators Over Time

COVID-19 is an ordinary extreme event, as its impacts are still felt today in the industry. Therefore, we have chosen to assess the market before the impact of this event with the use of segmented regression analysis. This is because the core focus of this study is to investigate the long-term impact of macroeconomic variables subject to long term trends. Simply, we have decided to cutoff the time series before the period 2020 (up to 2019-12), and after 2020 (including 2020-01). Linear regression will be examined if it is a viable approach to study this approach. Alternatively, we will use Vector Auto Regression (detailed in the next chapter) and ARIMA to study the time series in its full capacity (up to 2023) as well. This allows us to exhaustively study our time series, taking into account the nuances of linear regression. This approach enables us to independently analyze an important factor for this study. The effect of macroeconomic indicators on our production without the presence of COVID-19 disruption. This will help us to understand long-term trends. First, we will assess the nature of the data to determine if linear regression is an applicable approach in both scenarios. If it is not applicable, particularly in the case of post 2020 analysis we will implement time series modeling techniques to assess impacts of macroeconomic factors and take a look at future forecasts.

4.3 Linear Regression analysis

Linear regression is a classical predictive analysis approach used to establish statistical relation between two variables. According to Kutner (2005, pg.375) a regression model is a means to establish a predictive relation between a response variable Y and a predictor variable X such that there is a probability distribution of Y for each level of X. Simply, a linear regression model helps establish that there exists a linear relation in which the movements of response variable Y and predictor variable X are related. Linear Regression models are used to explain the extent to which other variables can explain the movements of response variable Y.

The general form of a linear regression model is expressed in the following equation:

$$y = \alpha + \beta x_t + u_t \qquad (4)$$

Where:
- y is the value of the response variable
- β is the estimated coefficient
- x denotes the explanatory variable
- t denotes the observation number
- u is the error term which can be used to assess the overall accuracy of the model and

The validity of a linear regression model and the resulting coefficients of predictor variables depends upon several assumptions that the model should fulfill. Brooks (2008,pg.292) highlights the assumptions of an OLS regression model. For a model to be considered BLUE (Best Linear Unbiased Estimator) 4 assumptions must hold:

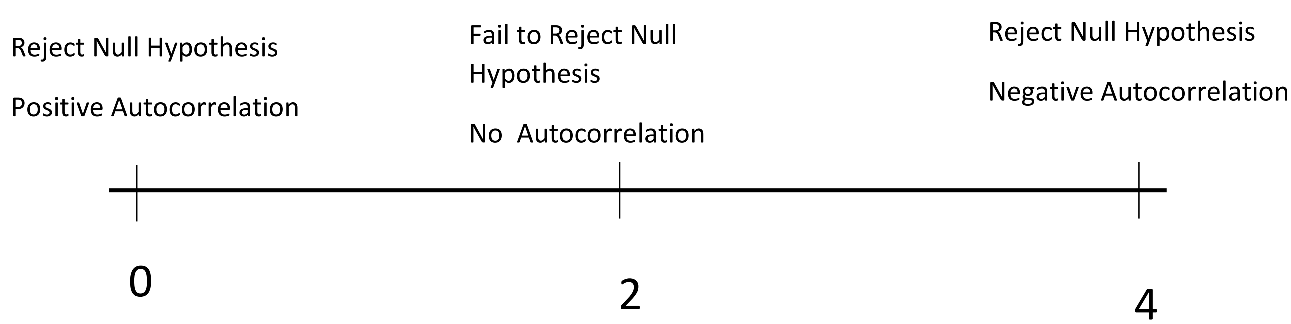
1) The errors/residuals must have a mean of zero.
2) The variance of the error terms must be constant.
3) The errors must be linearly independent from each other.
4) There should be no relation between the error terms and the corresponding X variable.

4.3.1 Autocorrelation

Autocorrelation is a major issue in regression analysis, as it violates a basic OLS assumption concerning error terms. According to Brooks (2008, p264), autocorrelation is a phenomenon where future values of a time series are affected by its previous values. Simply, the error of one observation is in correlation with its previous value. Autocorrelation does not directly affect the estimates of coefficients; however, it does make the standard errors unreliable making it difficult to assess the importance of predictor variables.

To detect autocorrelation the Durbin Watson (DW) test is commonly used. The DW test was first introduced in 1951 to test autocorrelation of one lagged value, hence it is a first order detection method. Figure 4 from Brooks (2008, pg147) describes the test and its score range:

Figure 4 Durbin Watson Test



A score of 2 indicates that the variable is free from autocorrelation, while values below 2 indicate positive autocorrelation and values above 2 indicate negative autocorrelation.

4.3.2 Heteroscedasticity

Assumption 2 in linear regression mentioned previously, variance of error terms being constant is also known as heteroscedasticity. Brooks (2008, pg132) explains that if the variance of errors is changing then it is said to be heteroscedastic. He further explains that Its effects are somewhat mixed, if this error is ignored the OLS regression would still output consistent and unbiased coefficient estimates but they would not be BLUE. Like autocorrelation, it affects the standard errors and inflates them leading to more difficulty in interpretation and reliability of estimates.

The White's test developed by Halbert White (1980) is a versatile tool for testing the presence of heteroskedasticity. It involves regressing squared residuals from the original regression model on the predictor variables. A test result indicating an insignificant p-value (> 0.05) would indicate the presence of heteroscedasticity and the rejection of null hypothesis.

4.4 Multicollinearity

One of the assumptions that is made during multiple linear regression is that explanatory variables are not correlated among themselves. Brooks (2005, P292) explains that when variables are not correlated to one another they are said to be orthogonal. Meaning the removal or addition of other variables would not affect the coefficients of the regression model. This may be simple in theory, but in a practical context multicollinearity always exists to some degree.

Multicollinearity occurs when two or more predictor variables are highly correlated with each other. Essentially, the high correlation indicates that the predictor variables are providing similar information, and the addition of these highly correlated variables does not bring new information.

The case of Multicollinearity

Multicollinearity can cause problems in the accuracy and validity of regression models. According to Brooks (2005, p294), the effect of multicollinearity can be masked by R^2 as it might be high indicating that the model is good. However, the standard errors of the individual coefficients would be very high. Pointing out that the model becomes highly sensitive to changes. The addition of removal of explanatory variables results in a significant impact on the model. Brooks (2005, p294) implies that multicollinearity affects the precision and accuracy of the model due to wide confidence intervals.

However, Multicollinearity is not always directly due to high correlation among predictor variables. According to Kutner (2005, p279) a high correlation among predictor variables does not inhibit the ability to obtain a good fit or predictions in the model. Brooks (2005, p295) further demonstrates that the existence of multicollinearity may not reduce t-ratios and does not violate the BLUE properties of a regression model. It does, however, inflate the regression coefficients and the standard deviations. Therefore, the confidence interval of the regression widens and provides a less accurate model.

The importance of multicollinearity comes down to the purpose of the regression. If the regression is used for producing predictions or forecasts then, multicollinearity is not highly significant. On the other hand, if it is necessary to assess the impact of explanatory variables on the response variable, dealing with multicollinearity is important.

Detection of Multicollinearity

Detecting Multicollinearity is the first step to dealing with multicollinearity. According to Brooks (2005, p293) there exist two types of multicollinearities: near multicollinearity and perfect multicollinearity. The former is detected rather simply through a matrix of correlations or a Pearson correlation plot. Perfect multicollinearity is more difficult to test. It is important to remember that simply correlation between variables does not directly point to multicollinearity as mentioned by Kutner in the previous section. To better detect multicollinearity a widely accepted method is the use of Variance Inflation Factor.

Variance Inflation Factor (VIF)

Both Kutner and Brooks present VIF as a better approach to detecting multicollinearity. The variance inflation factor is a calculation which involves regressing explanatory variables among themselves and utilizing the R^2 values of the regressions in the following equation:

$$\text{VIF} = \frac{1}{(1-R_i^2)} \quad (5)$$

Usually, the values of the VIF hover from 1 through 10. Generally, the higher the value the more there is the presence of multicollinearity among explanatory variables. Brooks (2005, p294) indicates that values below 5 are negligible and multicollinearity is not an issue, while values above 5 are problematic and should be troubleshooted.

Dealing with Multicollinearity

There are two popular methods to deal with multicollinearity both of which are employed in this study.

Dropping a Variable

A relatively simple approach is to drop highly correlated variables. As mentioned previously (Case of Multicollinearity), doing so does not simply mean dropping variables that show high correlation. Rather, an inspection of VIF scores is a more measured approach. Variables displaying a high VIF score (> 5) should be considered for elimination.

4.5 Model Validation and Evaluation

Testing the validity and evaluation of the model are an essential part of ensuring the reliability of the results obtained. Prior to this, model assumption checks This section outlines the steps and metrics utilized to evaluate our regression models.

R-squared

R^2 is a popular and widely used metric to assess the performance of regression models. Categorized under the goodness of fit statistics, it helps explain how well the predictor variables are at explaining the response variable. According to Brooks (2008, pg.109) it represents how well the regression line fits the data points. However, R^2 on its own is not enough to warrant the performance of the regression model. For that reason, we have implemented further model validation methods.

$$R^2 = 1 - \frac{RSS}{TSS} \qquad (6)$$

Adjusted r squared

The adjusted r-squared is an extension of the R^2. The difference between them is that traditional R^2 does not account for the degrees of freedom or number of variables added. Brooks (2005, pg110) outlines that adjusted R^2 introduces a penalty when more variables are added balancing the behavior of R^2 increasing when variables are added. Therefore, we can use R^2 to observe if additional variables should be added to a model.

$$Adj\ R^2 = \quad 1 - \left(\frac{(1-R^2)(n-1)}{n-p-1}\right) \qquad (7)$$

Where:

1) n is the number of observations in the dataset
2) p is the number of predicting variables

Mean Squared Error MSE

MSE is a useful metric when assessing the accuracy of a regression model. It measures the mean squared difference between actual values and predicted values. Brooks (2008, pg.252) highlights that it is rather useful when large forecast errors are a serious concern. This is handy especially in the regression analysis we will implement later on in this study.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2 \qquad (8)$$

Mean Absolute Error MAE

MAE is a more direct approach, as it practically measures the difference between the predicted and actual value. Showing how far in absolute magnitude is the value predicted by the model to the actual value of the response variables.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{9}$$

Both MAE and MSE are more well used when comparing with their values with other models, with the best model minimizing the value of the two metrics.

4.6 Time Series Cross Validation

Another robust and practical application for model evaluation is creating training and testing splits. Kutner (2005, pg.372) highlights the use of this practical method also known as data splitting. Particularly useful with large datasets in involves dividing the dataset into a model building set and a prediction set. The model building data set is then used to train or run the regression model on and estimate regression coefficients. It is then utilized to make predictions in the validation data set. The purpose of this is to observe how well we can make predictions about the prediction dataset. Kutner (2005, pg.372) explains it simply as how close the predictions are we made to the actual prediction dataset. The closer the predictions, the more accurate our model is.

An important factor in using this method is to make sure that there occurs no data leakage Data leakage may occur when information from prediction set may leak into the model building dataset and result in inflated results commonly known as overfitting. Dealing with data leakage is crucial for the reliability of model evaluation.

Time series cross-validation is an important procedure that assesses accuracy of predictive models. Unlike traditional cross-validation where the data is split up at random, time series cross-validation keeps its natural order. This is critical to ensure that there is no form of information leakage so that the future data is not a factor in the model training and overfitting occurs.

A widely used approach to time series cross-validation is the rolling window. It is defined as a movement of the training and testing dataset along the time series (Hyndman et al. 2018). The training set and testing set have a certain number of observations, at each step, the model is trained with the current training set and then tested with the following observations across the time series. The process stops when each model has been tested with all the data. The approach is suitable for use with time-series data, as this is in-line with real sequential data . The model is trained on a specific dataset and resets the learning process at certain intervals to adjust for the possible fluctuations of the underlying data pattern over time, which is very helpful for a non-stationary series (Bregmeir et al .2018).

5 Forecasting

Once we have established and explained the relationships between our independent variables and dependent variables using regression analysis mentioned above. We move on to the second phase of our analysis. We will produce forecasts of our dependent and independent variables using forecasting techniques (ARIMA, VAR). Furthermore, we will utilize Vector Auto Regression and Impulse Response Plots to examine the effect of giving a shock to our macroeconomic variables and observing the resulting impact on our response variable.

5.1 Autoregressive Integrated Moving Average (ARIMA):

ARIMA is a key method in time series forecasting, characterized by flexibility and efficiency to model different ranges of time series data. Popularized by Box and Jenkins (1976) ARIMA forecasting is used to model a time series and find significant lags that help predict the future values of the time series. There are three crucial components that are weaved into an ARIMA model include Autoregression (AR), Differencing (I) for stationarity, and Moving Average

(MA). This combination allows capturing various temporal structures in the data, hence proving very effective in many applications for univariate time series where data points are expected to follow certain trends and seasonality.

The difference between AR, MA models and ARIMA models is the addition of the Differencing (I) term. ARIMA does not require the time series to be transformed into stationary prior to fitting the model. Rather it does so in the model itself. When executing in the python environment, there exists an auto arima function that identifies the best fitting model based on the AIC and BIC criterion. These criteria are key in identifying a good fit model and are explained in the next section.

We will, however, apply ARIMA in this study focusing on forecasting Y_1. We start by making sure the data is in the right shape and format to fit an ARIMA model.

Information Criteria AIC and BIC:

According to Brooks the information criteria works by two distinct factors. First a function of the residual sum of squares and second, a penalty applied for the loss of degrees of freedom as a consequence of adding extra parameters. In this study we will use Akaeke's Information Criteria (1974) and Schwarz's Bayesian Information Criteria (BIC).

The AIC and BIC criterion displayed algebraically:

$$AIC = ln(\hat{\sigma}^2) + \frac{2k}{T} \qquad (10)$$

$$BIC = ln(\hat{\sigma}^2) + \frac{k}{T} + ln\,T \qquad (11)$$

Where:

1) $\hat{\sigma}^2$ is the estimated variance of the residuals from the fitted model.
2) k is the number of parameters in the model
3) T is the total number of observations in the dataset

In general, AIC focuses on finding the best fitting model regardless of how complex the model can become. While this may sound good, a complex model is also difficult to interpret and run on large datasets. BIC, on the other hand, looks for more simpler models by penalizing the addition of more parameters.

5.2 VECTOR AUTO REGRESSION

Vector Auto Regression (VAR) is a popular forecasting tool, more specifically renowned for its ability to be fitted in multivariate time series data where the interdependency between many variables is present. It was first introduced by Sims (1980) and is widely used due to its simplicity and effective practical application. Brooks (2008, pg.290) summarizes the value of VAR models stating that it can capture the linear interdependencies each variable shares with its own lags and with the lags from all other remaining variables in the system, unlike the univariate forecasting model. This is what makes VAR very appropriate for the understanding and prediction of systems where the variables influence one another over time.

In this regard, VAR is used in the definition and prediction of the dynamic interrelatedness between the chosen macroeconomic indicators and Y aggregate volumes. In other words, a VAR model helps to figure out how a shock to one of its variables, say Wholesale Trade, propagates through the system in such a way that it affects the future values not only of this variable but also of other variables' future values, such as production in Industry. Furthermore, Kutner explains (2008, pg291) that a VAR model makes it possible for the system to forecast the future values of all the variables within the system from their past values, thereby summarizing the expected market conditions and production requirements under one horizon in the system.

The equation of a vector auto regression model can be expressed as:

$$Y_t = \beta_0 + \beta_{11}\, y_{t-1} + \alpha 11\, X_{t-1} + u_t \qquad (12)$$

Where:

1) Y_t is the current value of the time series.
2) Y_{t-1} is the previous lagged value of time series Y_t.
3) X_t is the second time series.
4) X_{t-1} is the previous value of time series X_t
5) β_0 is the constant term.
6) β_{11} is the coefficient of the Y_{t-1}.
7) a_{11} is the coefficient of X_{t-1}

GRANGER CAUSALITY TEST

The Granger Causality test, first introduced by Engle and Granger (1987) is a statistical test that allows us to determine if one time series has any predicting power over another. Engle and Granger stated that if the past lagged values of one time series help improve prediction of another time series, then the time series are 'granger-caused'. This test is the foundation for our Vector Auto Regression analysis, as it gives us insight whether one time series causes movements in another time series.

Framework:

Essentially it works by setting up two regression models. The first model predicts Y_t based on its own lagged values and the second model predicts Y_t based on the lagged values of X_t and Y_t.

The base of the Granger test relies upon the calculation of the F-test that compares the two regression models.

The F-test is calculated as: $F = \frac{(RSS_1 - RSS_2)/q}{RSS_2/(n-p-q-1)}$ *(13)*

Where:

1) RSS_1 and RSS_2 are the residuals sum of squares of the two regression models.

2) p represents the number of lagged Y_t terms
3) q represents the number of lagged X_t terms
4) n represents the number of observations in the dataset.

Like other regression models, p-values of the lagged observations of the variables are derived from the calculated F-statistic from the F-distribution. Based on the significance level, commonly 0.05, we can determine whether we can reject the null hypothesis of the test.

The Null hypothesis states: H_0: Past values of time series X_t do not granger cause time series Y_t A p-value less than the significance level 0.05 would reject the null hypothesis and confirm that time series X_t does granger cause time series Y_t. We implement this test on our four-time series drafting a granger causality matrix that is introduced in the forecasting chapter of this study.

Johansen Cointegration Test

Cointegration, first introduced by Johanssen (1991) is a tool that allows us to investigate whether time series exhibit a long run significant relationship between them. To properly understand cointegration we should revisit the order of integration, commonly known as differencing. Later in this study we implement differencing to convert time series into stationary for analysis. According to Johanssen (1991) if the order of differencing required for a combination of two or more time series to be stationary is less than the order of differencing required for the time series individually. Then, we can say that the time series are cointegrated. That is, we can confidently state that the time series display a long standing statistically significant relationship amongst them. The test itself uses eigenvalues and eigenvectors from a matrix of the time series in question. It uses two tests, trace, and maximum eigenvalue to determine if there are cointegrating relationships between the time series data.

Brooks(2008,pg.351) highlights the equations:

$$\lambda_{\{\{trace\}(r)\}} = -T \sum_{\{i=r+1\}}^{g} ln\left(1 - \hat{\lambda}_i\right) \quad (14)$$

$$\lambda_{max}(r, r+1) = -T \, ln\left(1 - \hat{\lambda}_{r+1}\right) \quad (15)$$

Where:

1) r is the number of cointegrating vectors
2) $\hat{\lambda}_i$ is the estimated value for ith eigenvalue derived from the matrix.
3) T is the number of observations in the time series data

The eigenvalues themselves detect the overall strength of long run relationships between chosen time series. Intuitively, the larger $\hat{\lambda}_i$ is the larger the test statistic will be. A non-zero eigenvalue would suggest cointegrating vectors.

Impulse Response Plots

Besides the above forecasting models, we use the Impulse Response Plots necessary for the analysis of the dynamic impact of shocks from one variable onto the others in a VAR framework. According to Kutner (2008, pg.299) impulse responses are plots of the reaction of the dependent variable (in our case, the reaction of our Y aggregate variables) to one-time shocks in independent variables (for example, an unexpected jump in Wholesale Trade) with some time lag. The Impulse Response Plots are needed to assess the restoring ability of production in response to the external economic jolts and prove very useful to determine the lagged impact from the macroeconomic changes on production-related activities. Kutner (2008, pg299) further explains that impulse responses can also map out the effects of the dependent variable on each of the other variables. This is quantified and visualized with the aid of the Impulse Response Plot, giving the duration of its effects on the level of production when there is a shock to any of the macroeconomic indicators. This would allow us to examine the relationships between our variables and it would help develop stronger models for forecasting or strategic planning frameworks which could anticipate or adapt to market volatilities.

6 Preliminary Exploratory Analysis

Before diving into implementing models and extracting insights, it is crucial to conduct a preliminary analysis to understand the shape and characteristics of our variables. Given the unique context of our study regarding splitting the time series mentioned previously due to

COVID-19 it is imperative to study these changes. Therefore, we will implement a two-pronged approach to the initial analysis. First, we will conduct a preliminary analysis before the split, and then once again after the split.

The initial analysis will aid our understanding of the general distribution and identifying global issues in our data. While the second analysis will enable us to conduct targeted exploration of how distributions, trends and statistical properties might change due to the pandemic. Furthermore, this approach can provide insights on the adjustments that might be needed to our regression models.

The initial exploratory analysis acts as a fitness test of our variables for model implementation in the next sections. The process allows us to make sure we are in a state of BLUE assumptions for our linear regressions. Multicollinearity is one of the major issues in regression analysis as highlighted previously. By dealing with it early on we can ensure the robustness of our models. However, examination of residuals and can only be done after a model is implemented and thus is carried out after initial model implementation to further improve on our models.

Overall Distribution of Indicators:

The macroeconomic indicators show different distributional characteristics to each other. Table 3 and Figure 5 show the distribution plot and statistics of the macroeconomic variables in question. Both figures point to the existence of positive skewness in 3 of the 4 indicators (All-items HICP, Wholesale Trade, Retail Trade) while Industrial production is only slightly negatively skewed and is closer to a normal distribution. These findings signal that appropriate data transformations are potentially needed to achieve normality which is essential for regression analysis. Logarithmic transformation is a common tool to reduce the impact of outliers and output a more symmetrical distribution of data. However, before acting on these initial findings, segmenting the distribution analysis to consider pre and post 2020 would bring more detailed insights into the necessary transformations required.

Table 3 Distribution Statistics Explanatory Variables

Statistics	All-items HICP	Industrial Production	Wholesale Trade	Retail Trade
Kurtosis	1.624746477	0.04493812	0.766003208	0.045247457
Skewness	1.416137666	-0.229724538	1.354342239	1.074779359

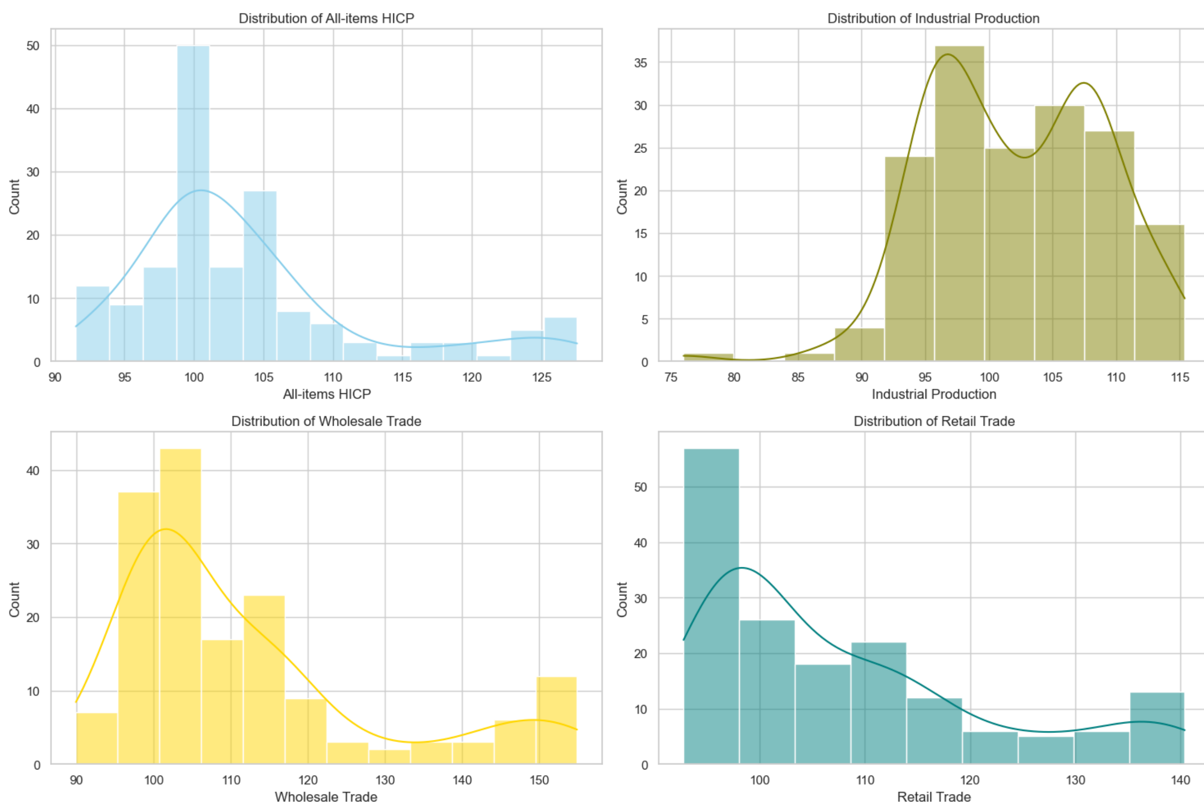


Figure 5 Distribution Plot Explanatory Variables

Distribution Before 2020

Figure 6 highlights the distributions before 2020. HICP shows a slightly negative skew but is roughly normally distributed, while Industrial Production shows an only slight right skew, which bodes well for our regression analysis. Retail Trade shows a slight positive skew that might hint marginal volatility in the retail sector prior to the pandemic. Wholesale Trade also shows a slight right skew but most of the distribution is roughly normal. Indicating that a logarithmic transformation may not be required in the analysis before 2020.

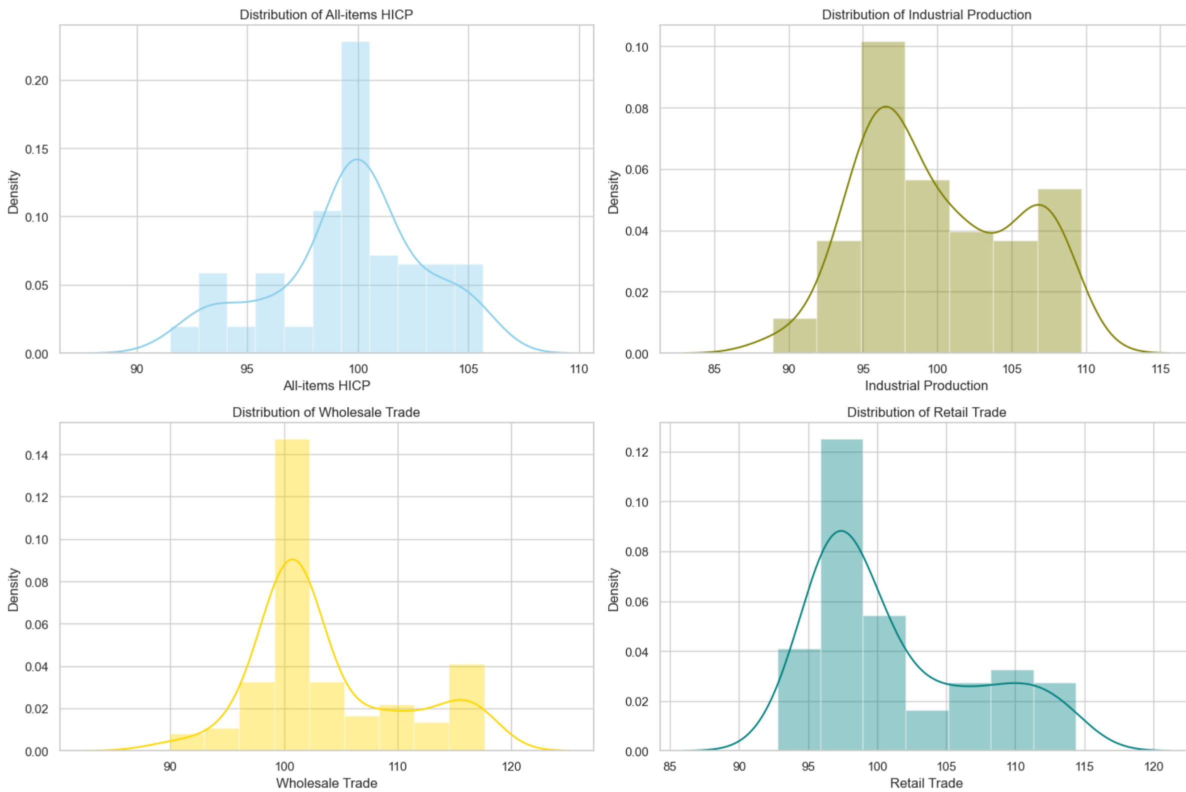


Figure 6 Distribution Before 2020 Explanatory Variables

Distribution After 2020

The time period after 2020 which marked the beginning of the pandemic shows a significant shift in the distributions of macroeconomic indicators signifying the major economic impact of the pandemic (Figure 7). HICP experienced an increase in both mean and standard deviation which shows heightened inflation during that time, with peaks on either side of the mean. Industrial Production outlines a heavy negative skew, while wholesale trade is a bit more stable albeit shows signs of volatility. Retail trade, on the other hand, shows a slight rise in negative skewness. This may indicate signs of changing consumer spending patterns.

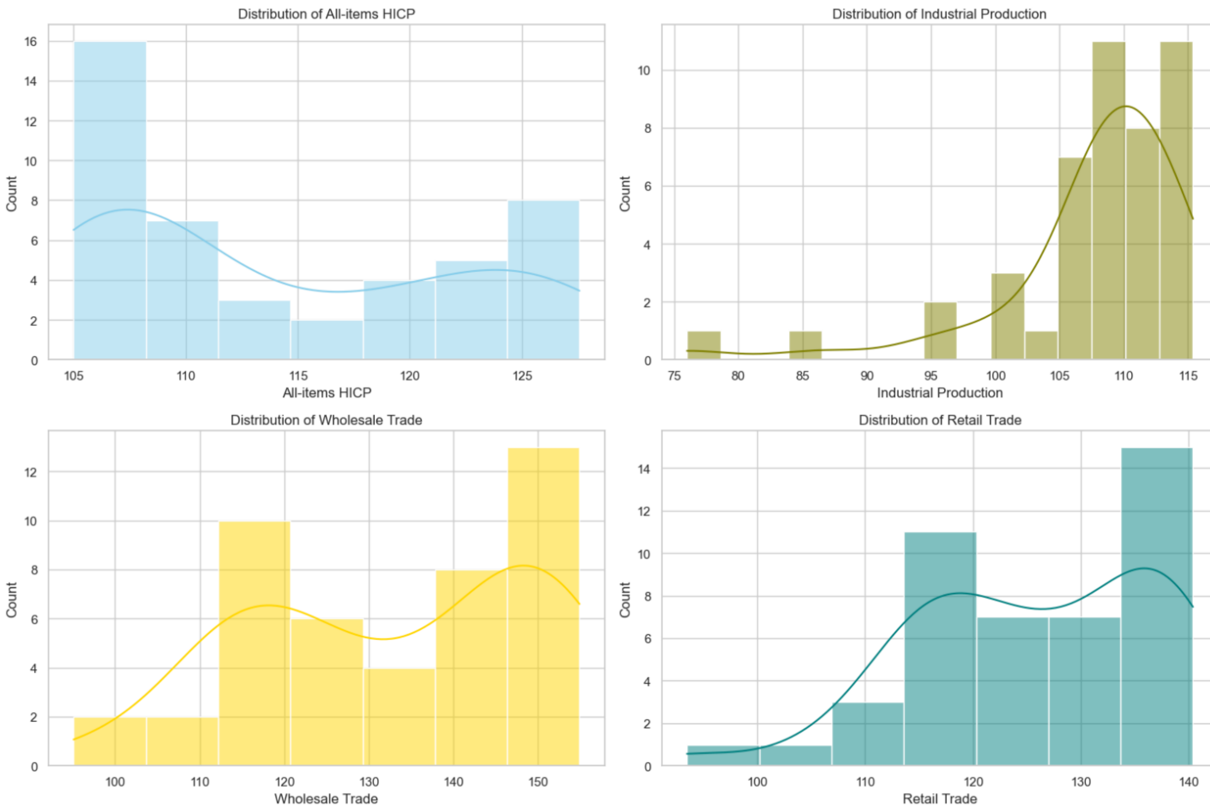


Figure 7 Distribution After 2020 Explanatory Variables

Distribution of Dependent variable

Figure 8 displays the distribution plot of our dependent variable Y_1. Based on the plot the distribution appears to be only slightly right skewed and shows one peak to the right which does not represent a large disruption to our analysis. As such, logarithmic transformation of our dependent variable may not be strongly required. Recall that a transformation of the dependent variable is not strictly required as Brooks explains (2008, pg.216). Transformations are more critical for explanatory variables.

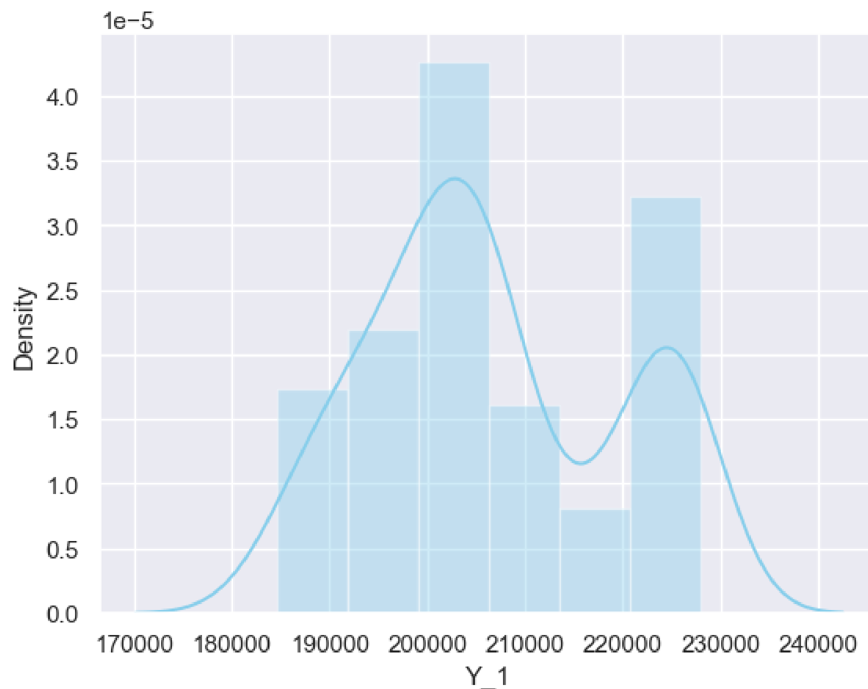


Figure 8 Distribution of Y_1

Recommendations for Analysis

The distributions of macroeconomic indicators presented in figures 5, 6, 7, and 8 give us insight on the macroeconomic environment. The evidence of skewness in the distribution of the indictors suggests that transformations such as logarithmic transformations may be needed to stabilize and normalize the distribution of the indicators. Figures 5 is heavily influenced by the changes due to the pandemic. This is evidenced by figures 6, and 7 which show the distributions of the macroeconomic indicators before and after 2020. At this stage, we can adopt the following two insights:

1) Analysis Before 2020 does not necessarily require data transformation.
2) Analysis both before and after 2020 requires linearity analysis to assess if linear regression is an acceptable approach.

Furthermore, the apparent large difference in the distributions of indicators before and after 2020 indicate that segmenting the time series and conducting separate analysis in two different timeframes is the correct approach. This will allow us to conduct a thorough analysis of the market dynamics before the pandemic where long-term trends are strong, and post pandemic where short-term chaos disrupts long-term trends. This preliminary analysis strengthens the importance of a pre-study due to the complex nature of the macroeconomic environment amid a global crisis.

6.1 Linearity

The next step in assessing the fitness of our variables is the assumption of linearity required for linear regression analysis. Recall as Brooks (2008, pg292) highlighted that for a linear regression model to be BLUE the target variable and predictor variables must exhibit some sort of linear relationship. Therefore, to assess the viability of our models we utilize scatter plots between our target variable Y_1 and explanatory variables (macroeconomic indicators). Since we will be splitting the time series due to the pandemic, we investigate the relationship between the indicators and Y_1 in separate plots. This will enable us to understand how COVID-19 has impacted trends.

Industrial Production

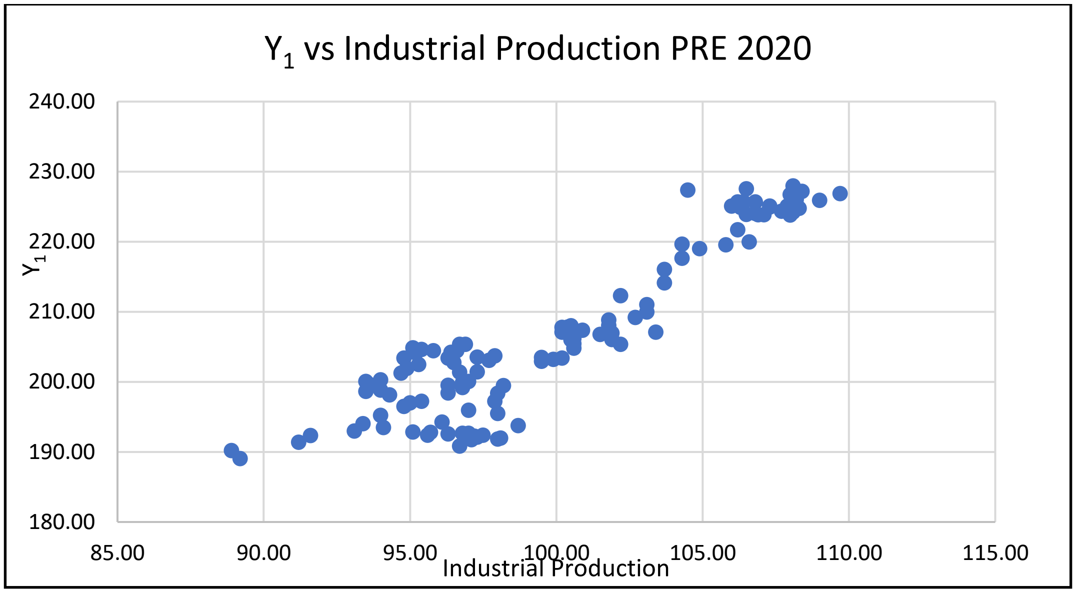


Figure 9 Scatter Plot IP vs Y_1 Pre 2020

Figure 9 & Appendix 3 display the relationship between Industrial Production and Y_1 using scatterplots. As observed, Figure 9 shows the presence of a relatively strong positive linear relationship between them. That is, generally, as the production in industry increases Y_1 also tends to increase. Recall that Y_1 is a production metric for Stora Enso, therefore this relationship is largely expected as Stora Enso is a major player in their respective industry. Appendix 3, on the other hand, displays an erratic scatter plot indicating very little to no relationship between the two variables. The stark difference between the two time periods highlights the adverse and unpredictable effects of the COVID-19 pandemic on the industry making it difficult to discern any insights particularly in the short-term.

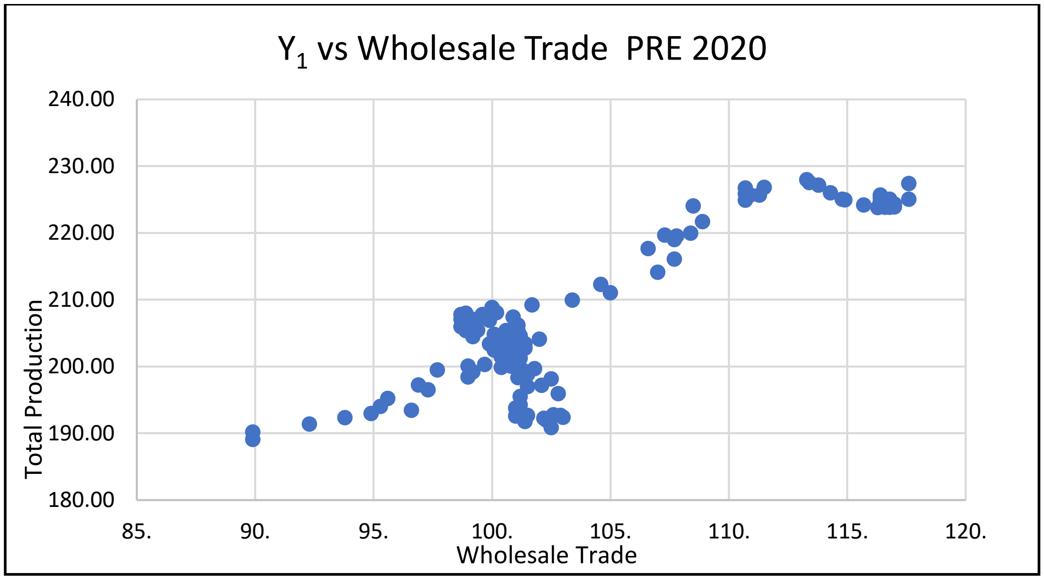


Figure 10 Scatter Plot Wholesale Trade vs Y_1 Pre 2020

Figures 10 & Appendix 4 display the relationship between Wholesale Trade and Y_1. Similar to industrial production, we observe two strongly different scenarios before and after Jan-2020. Figure 9 illustrates a visible linear relationship between our target and predictor variables, indicating that a linear regression model may be useful in explaining their relationship. Figure 10 on the other hand, exhibits a curved pattern between the two variables. While this is not suitable to be captured using Simple Linear Regression, a polynomial regression model could be useful in explaining their relationship.

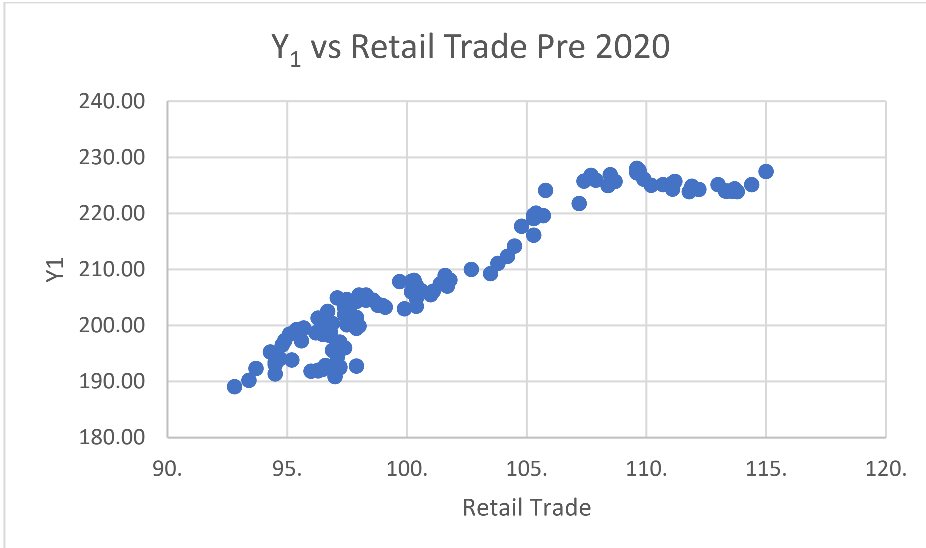


Figure 11 Scatterplot Retail Trade vs Y_1.

Along the lines of Wholesale Trade is the presence of Retail Trade. Recall that the 2 indicators originate from the same dataset and exhibit similar movement patterns. Figure 11 & Appendix 5 display the scatterplots between Y_1 and Retail Trade. Like wholesale trade, retail trade also shows a positive linear relationship with Y_1 Pre 2020 and a decreasing curved plot after 2020 (Appendix 5) Post 2020, the relationship is clearer when compared to wholesale trade.

Harmonized Index of Consumer Prices

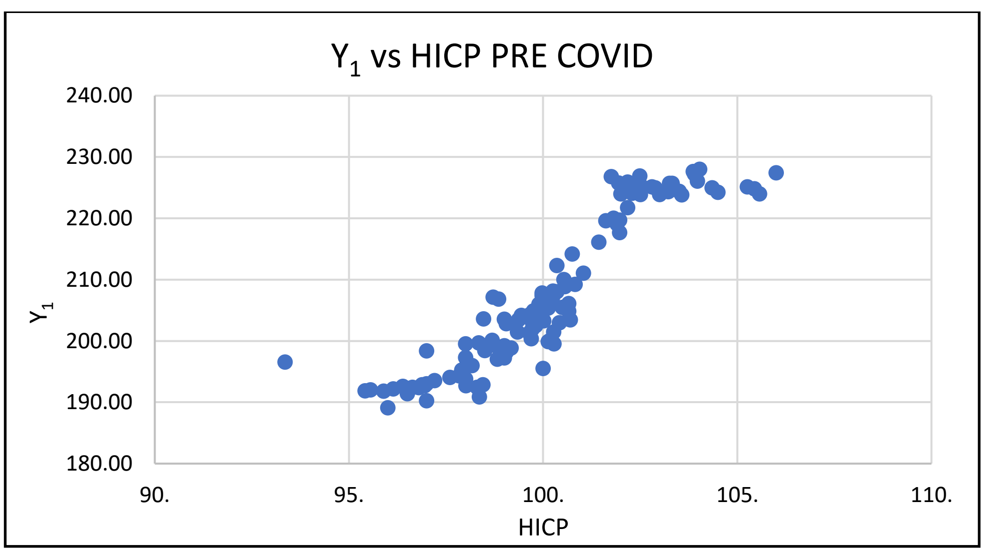


Figure 12 Scatter plot HICP vs Y_1.

The last of our indicators assessed via scatter plot is the harmonized index of consumer prices. Figure 12 and Appendix 6 detail its relationship with Y_1 before and after 2020. The two scatter plots display a stark difference in the relationship with Y_1. Figure 12 shows the presence of a positive linear relationship albeit with a little curve stabilizing at the latter stage. Appendix 6 interestingly displays an initial positive relationship, which later shifts to a negative decreasing relationship. The curved non-linear relationship shows that a linear regression would not be beneficial post 2020 to capture the relationship.

6.2 Multicollinearity

Multicollinearity will be assessed in two stages, first through a correlation matrix, then through variance inflation factoring as outlined in the methodology section. Figure 13 shows the correlation heatmap for the explanatory variables. At first glance, it may seem that the correlations of all variables are on the higher end. However, a closer look and context of the indicators can give us insights as to why that is. The indicator with the highest overall correlations is Retail Trade holding correlations of 0.96, 0.84, 0.97 followed by Wholesale Trade. The correlation of 0.97 between wholesale trade and retail trade may be due to the source of the data. Recall that these two indicators are found in the same dataset. Furthermore, their purpose (measuring sales) to different level of distributors in the same value chain may cause overlapping information.

A high score of correlation can be a problem as Brooks mentions (2008, pg.266) and can cause R^2 to give an inflated value indicating a too good fit of a model usually known as overfitting. Therefore, it is important to consider and deal with multicollinearity. An alternate school of thought presented by Kutner (2005, pg.380) states that high correlation does not necessarily mean a lack of information in the model and that in practical contexts such as this study it can be taken into consideration. However, Kutner does acknowledge that multicollinearity can be a problem and should be minimized if possible. Initial inspection of the correlation plot shows that retail trade is an indicator that seems to provide almost the same information as wholesale trade. Recall that wholesale trade is an important indicator for Stora Enso and has been verified as significant in previous studies. At this stage, the importance of retail trade is to be questioned and justifiably so. Kutner's suggested method of Variance Inflation factoring is implemented in the next section and acts as a litmus test for our indicators. In particular, the performance of retail trade is put under the microscope.

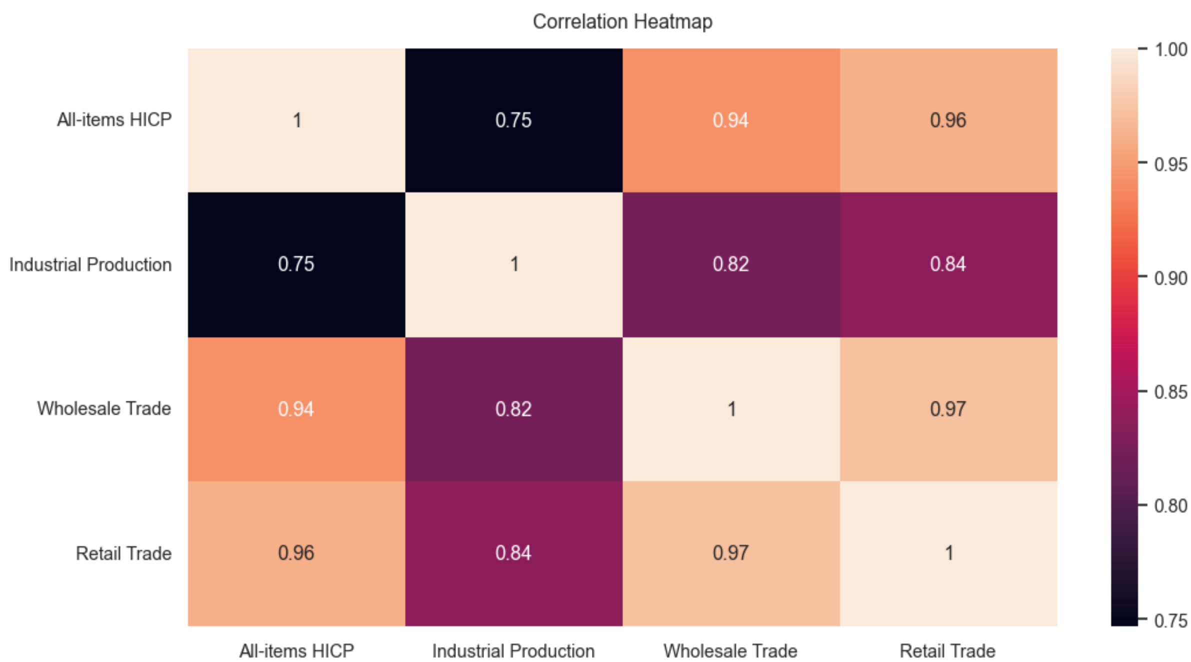


Figure 13 Correlation Heat Map Explanatory Variables

Variance Inflation Factoring (VIF)

Remember that VIF regresses the indicators amongst themselves to assess their impact on each other. The VIF was calculated in the Python environment and is appended in Appendix 3. Table 4 presents the VIF scores of our indicators. As mentioned by Kutner (2005, pg.) VIF scores can take a range of values, but typical values range from 1 through 10. The most notable value presented by table 4 is the VIF score of retail trade. A score 19.5 shows an extreme presence of multicollinearity. Other indicators also display a high score and are cause for concern for our analysis. A look at figure 13 which displayed the Pearson correlation plot reaffirms the presence of multicollinearity. The consensus of both approaches that retail trade exhibits the largest multicollinearity among indicators is telling that a remedy is required.

Table 4 VIF scores I

Indicator	**VIF Score**
Harmonized Index of Consumer Prices	4.662861
Industrial Production	8.075710
Wholesale Trade	7.940766
Retail Trade	19.537963

Dropping a Variable

The first approach highlighted to deal with multicollinearity was that of dropping the highest correlating factor. Therefore, logically, the removal of retail trade appears to be the first step in addressing the issue of multicollinearity. From a theoretical standpoint, it is important to minimize the loss of information and potential insights we may gain from investigating the indicators. The fact that retail trade stems from the same dataset as wholesale trade provided us initial reason for concern. The subsequent Pearson correlation plot and variance inflation factoring further strengthens the approach of the removal of the variable. The next step was to reassess the variance inflation factors after the removal of retail trade. Table 5 displays the new VIF scores of the remaining macroeconomic indicators.

Table 5 VIF Scores II

Indicator	**VIF Score**
Harmonized Index of Consumer Prices	3.861067
Industrial Production	4.523379
Wholesale Trade	4.867961

6.3 Stationarity

The last step before building our regression models is the issue of stationarity. Brooks discusses the nuances of stationarity (2008, pg.280) stating that a stationary time series can be defined as:

"Having a constant mean, variance and autocovariances for each lag."

Why is stationarity important?

Brooks (2008, pg.281) continues to state that non-stationarity can cause problems when regressing time series known as spurious regression. Spurious regression occurs when the regression model generated is actually misleading and portrays a good model fit. Brooks evidenced this case by regressing two random generated time series 1000 times and observing the R^2 obtained. The results of this experiment showed that the regression model showed a good fit 16% of the time. This inaccuracy is particularly sensitive when practical applications are concerned. Since this study focuses on macroeconomic variables and their impact on Stora Enso, high correlation does not directly imply causation. To make sense of our regression model it is essential to deal with non-stationary time series and transform them into stationary ones.

Detecting and Dealing with Non-stationarity

The work Dickey and Fuller (1976; Dickey and Fuller, 1979) is instrumental in detecting non-stationarity. Known as the Augmented Dickey Fuller test (ADF) is a popular statistical method to detect non-stationarity. The test detects the presence of a unit root in the time series and presents the following null and alternative hypotheses:

H_0: The distribution of the series is non-stationary
H_1: The distribution of the series is stationary, and not time dependent.

The test statistic is evaluated with a threshold of the p-value set at 0.05, a p-value less than this significance value would lead us to reject the null hypothesis and conclude that the time series is stationary.

If the ADF test detects non-stationarity in the time series the next step is to remedy this issue. Shumway and Stoffer (2006, pg.61) highlight that differencing is a crucial tool in making a time series stationary. Differencing involves subtracting the mean value of the time series from each of its observations. Shumway and Stoffer (2006, pg.61) iterate that a first order differencing removes a linear trend, a second order differencing (differencing of the first order) removes a quadratic trend. The equation for a first order differencing is highlighted:

$$\Delta xt = x_t - x_{t-1} \quad (16)$$

Recall that the macroeconomic indicators extracted from the Eurostat database are already seasonally and calendar adjusted data, therefore a seasonal component is not of particular concern. Furthermore, our target variable $Y_1$was also seasonally adjusted and detrended using JDemetra+ previously in the methodology section. Testing for stationarity of our time series models is the next step before finally building our models. This is highlighted in the next section.

Table 6 ADF Test Stationarity I

Variable	**ADF Test Statistic**	**p-value**	**Stationarity**
Y_1	0.409	0.982	Non-Stationary
All-items HICP	-0.514	0.889	Non-Stationary
Industrial Production	-1.043	0.737	Non-Stationary
Wholesale Trade	-0.034	0.956	Non-Stationary

Table 6 outlines the results of the ADF test. As evidenced, all of our variables suffer from non-stationarity. The p-values of all-time series are above the 0.05 significance level. As a result, we will move to utilize differencing to transform the time series into stationary.

Table 7 ADF Test Stationarity II

Variable	ADF Test Statistic	p-value	Stationarity
Y_1	-3.616	0.005	Stationary

All-items HICP	-1.33	0.614	Non-Stationary
Industrial Production	-8.931	0.000	Stationary
Wholesale Trade	-3.267	0.016	Stationary

The results of the first order differencing are displayed in table 7. Three of our four time series are now stationary with the exception of All-items HICP. Thus, we apply second order differencing to convert the time series into stationary. We will difference all-time series a second time due to issues with data consistency and model coherence. Because our end goal is to implement a regression model, time series differenced at different lags can cause issues of interpretation and coherence in our model. The results of second order differencing are displayed in table 8.

Table 8 ADF Test Stationarity III

Variable	ADF Test Statistic	p-value	Stationarity
Y_1	-3.464	0.009	Stationary
All-items HICP	-15.820	0.000	Stationary
Industrial Production	-6.612	0.000	Stationary
Wholesale Trade	-10.187	0.000	Stationary

Appendix 10 shows the plot of our time series data after second order differencing. As such, we are now ready to implement regression models to depict relationships between the variables.

7 Model Building

7.1 Building Multiple Linear Model

We utilized the rolling window cross validation method to iterate multiple models while holding the time structure of the data as the data is a time series in nature. Selecting the optimal window size for rolling window cross validation is an important step. According to Seyedan & Mafakheri (2020, pg.53) there is not an exact one size fits all approach to selecting the optimal window size. Instead, it depends on the nature of data, and use case of the analysis. Since the nature of our data is monthly and the packaging industry typically utilizing 6-to-12-month forecasts, the window size utilized is 6 months. Using MSE and MAE scores we evaluate the split and re-train the final model on the whole dataset using the best performing window. Appendix 8 displays the graphical representation of the rolling window method with the train and test sets moving across the time series. The average MSE across all windows 116.86 and the average MAE across all windows was 7.70. Table 9 iterates the final model output fitting the best performing window to the dataset.

Table 9 Multiple Linear Regression Model

Regression	Coefficient Values	
Num of Obs.	90	
R-squared	0.12	
Adj. R-squared	0.050	
F-stat	2.869	
Intercept	0.0529	**p-value**
HICP	5.0144	0.484

Industrial Production	7.3267	0.106
Wholesale Trade	0.1189	0.012

At first look, the regression model shows a very limited r-squared, and adjusted r-squared, but first it is important to test the model to fulfill regression model assumptions.

Table 10 Regression Assumption Statistics

Statistic	Value
Mean of Residuals	5.368E-14
Durbin Watson Test	1.93
Whites Test Chi2	4.868
Whites Test P value	0.845

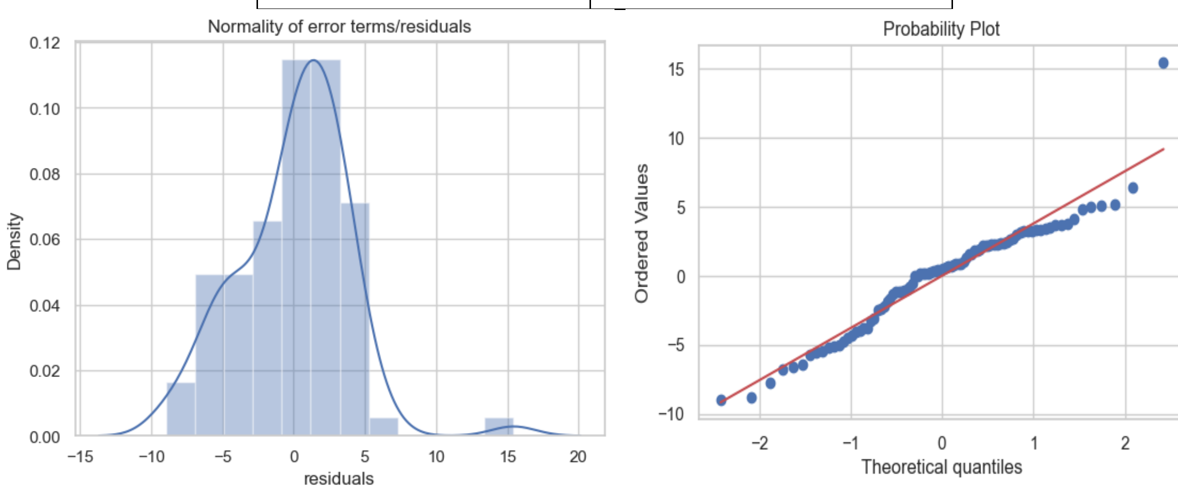


Figure 14 Normality of Residuals

Table 10 underlines the diagnostic tests and statistics required to assess the linear regression model assumptions. The mean of residuals is almost zero (power -17), therefore, it satisfies the condition that the mean of residuals is zero. The Durbin Watson test statistic of 1.93 signifies that there is not substantial autocorrelation present as it is lower than the critical value of dU of 1.85 as Brooks outlines (2008, pg.). Figure 14 displays the distribution plot and QQ plot used to assess the normality of residuals. As evidenced, the residuals follow a normal distribution with minor deviances.

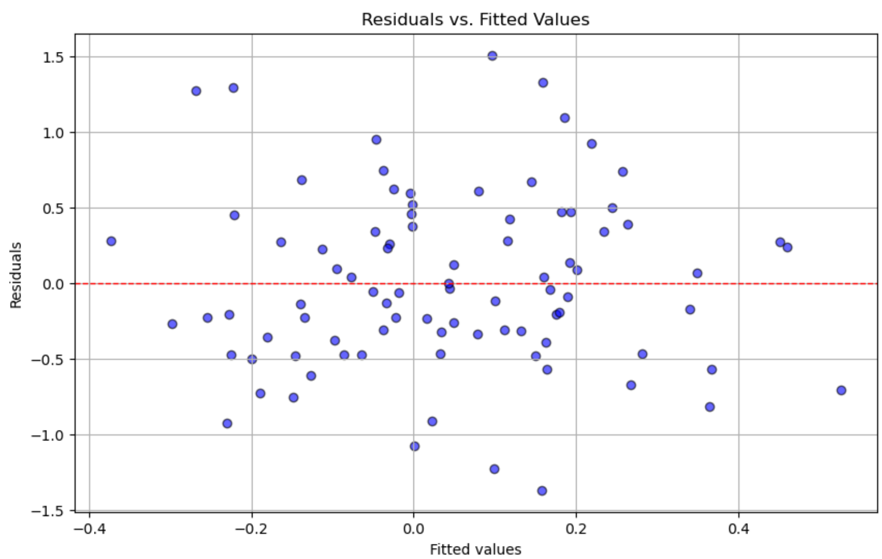


Figure 15 Residuals and Fitted Values

The Whites test shown in Table 10 is used to detect heteroskedasticity in our model. As mentioned previously in the methodology section, heteroskedasticity can affect the coefficients of our explanatory variables. Making them unreliable and thus affecting the inference of our model. The p-value of the white's test which is above the significance level of 0.05 suggests that there is not enough evidence to reject null hypothesis that our model is not homoscedastic. Meaning heteroskedasticity is not present in our model.

Furthermore, heteroskedasticity can also be detected graphically using a plot of residuals vs fitted values. Figure 15 displays the plot of residuals vs fitted values. The graph shows that the residuals do not show any significant heteroskedasticity and are roughly distributed with similar variance.

Interpreting the Linear Model

Now that we have completed diagnostic checks to fulfil our regression assumptions, we move to interpret the model itself. Table 10 highlights a very limited R^2 of 0.12. This means that our explanatory variables explain roughly 12% of the variance in our dependent variable Y_1. Furthermore, additional clues about the performance of our explanatory variables are present through p-values. HICP and Industrial Production both exhibit high p-values which are above the threshold of 0.05. meaning they are rather insignificant and do not improve our model. Wholesale trade is the only explanatory variable that exhibits a significant p-value (0.012) indicating its importance. This sparks, whether we need HICP and Industrial Production in the model at all, and if their correlation is affecting the model. Thus, the next natural step is to implement single parameter linear regression and interpret the results.

Table 11 Single Parameter Regression

Single Parameter Regression	Wholesale Trade	HICP	Industrial Production
R^2	0.063	0.016	0.008
Adj R^2	0.040	-0.001	-0.017
P-value	0.018	0.334	0.570

Table (11) highlights the results of the single parameter regression models. The models move to confirm the findings from the multiple linear regression model in Table 10, as HICP and industrial production are not significant and do not improve the model. Subsequently, linear regression with just HICP is highly significant and explains roughly 6% of the variance, while improving the adjusted R^2 from 0.044 to 0.047. Therefore, we can conclude that HICP is the only statistically significant indicator that impacts Y_1.

8 Forecasting Models

Now that we have conducted linear regression analysis with macroeconomic indicators. The next step involves forecasting for future predicted values. For this we are interested in two different types of forecasting. ARIMA of Y_1 and VAR alongside the macroeconomic indicators. The reason to pursue two different forecasting methods is to observe forecasts of Y_1 on its own compared to VAR regression model. Furthermore, we will investigate the VAR model further by utilizing impulse response plots to observe the impact on macroeconomic indicators on one another as well as our target variable Y_1.

The first step in defining an ARIMA forecasting is to identify the order of the Autoregressive (AR) and Moving Average (MA) processes. This can be achieved using autocorrelation function plot and partial autocorrelation function plot.

Remember that the stationarity process we managed earlier was for the segmented dataset before 2020. For forecasting purposes, we will use the full dataset without segmentation. We will re-test for stationarity and implement differencing where necessary.

8.1 ARIMA Modelling – The Box-Jenkins approach

To build an effective ARIMA model, it is important to do so in a systematic and repeatable manner. Box and Jenkins (1976) were the first to approach building ARMA models in this way. They iterated a 3-step process which we will follow here. Brooks (2005, pg.231) details these as Identification, Estimation and Diagnostics. Step 1 involves using graphical procedures to identify the Autoregressive and Moving Average terms of the model (detailed in the next section). Step 2 involves estimating the model itself and step 3 involves doing tests to figure out if the model is adequate and reliable for interpretation of results. It is important to mention that in practical cases ACF and PACF plots may be hard to interpret and thus the use of information criteria is essential.

Autoregressive Process (AR)

The autoregressive process is well known and is one that enables us to forecast future values based on past observations of a time series. Brooks (2008, pg.215) explains that in an AR process the current value of a time series is dependent on the previous value of the same time series. A simple AR model equation with one lagged observation is detailed:

$$y_t = \mu + \varphi_1 y_{t-1} + u_t \qquad (17)$$

Where :
1) ut is the error term
2) yt is the current observation of a time series
3) yt-1 is the previous lagged observation of a time series
4) μ is the constant term

Moving Average (MA) Process

Contrastingly, the moving average process is not related to the past observation of a time series. Instead, an MA process is simply known as a white noise process. Brooks explains it as a linear combination of a white noise terms current and previous values. The general equation of an MA model is detailed:

$$y_t = \mu + u_t + \theta 1 u_{t-1} \qquad (18)$$

Where:
1) yt is the current observation of a time series
2) ut is the white noise error term
3) ut-1 is the previous lagged value of the white noise error term
4) μ is the constant term

The partial autocorrelation function (PACF) , used to determine the order of an AR process is a plot that measure correlations between previous observations of a time series and current observations (Brooks, 2008). While the autocorrelation function (ACF) is used to is to determine the order of the MA part of the model. Let's remember that in an ARIMA model the (I) integrated part is for differencing as mentioned previously in the methodology section. However, to determine the ordering of the AR and MA parts of the model we differenced the series, in the ARIMA model we will input the original undifferenced series.

8.2 Building Forecasting Models

In this section we will build an ARIMA model on the full time series, meaning it is not cutoff before 2020 as done in linear regression analysis previously. The reason for this is because ARIMA will allow us to look at future forecasted values based on the current conditions of Stora Enso. The same will be carried out with Vector Auto Regression. Furthermore, our analysis will include an examination of impulse response plots, these will give us insights on how market dynamics work in a complex economic environment.

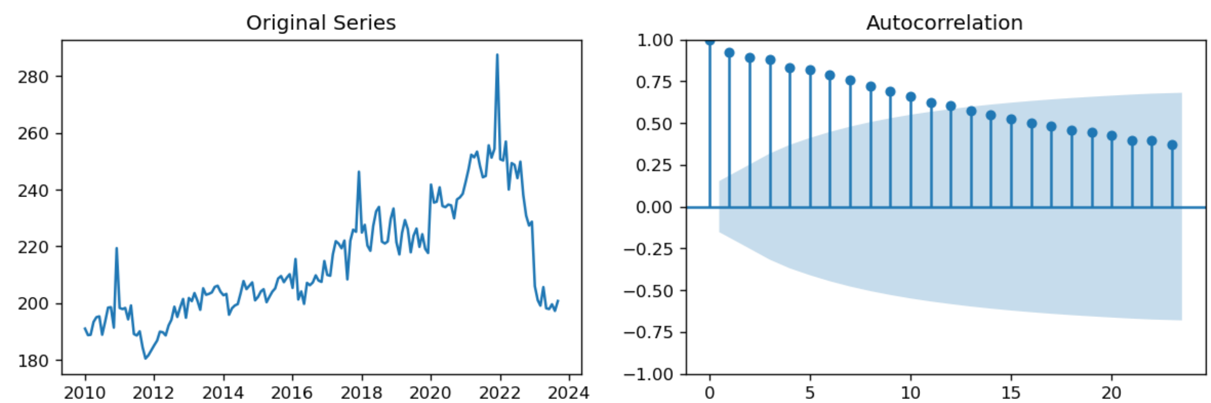


Figure 16 Original Time Series & ACF Plot

Figure 16 displays the original time series and its autocorrelation plot. Evidently, there appears a high degree of autocorrelation and the time series is not stationary. Figure 17 displays the 1^{st} and 2^{nd} order differencing of the time series. From the plots it is clear that a 1^{st} order differencing is enough to convert the time series into a stationary one.

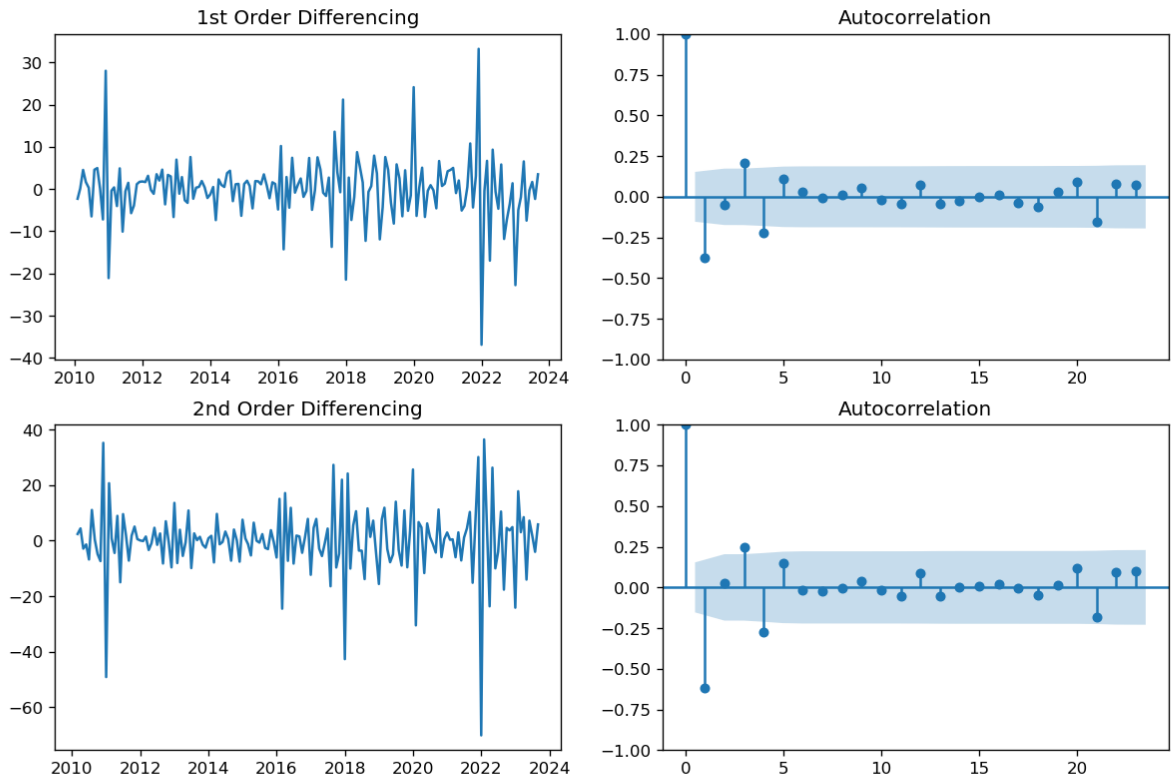


Figure 17 1st and 2nd Order Differencing of Time Series

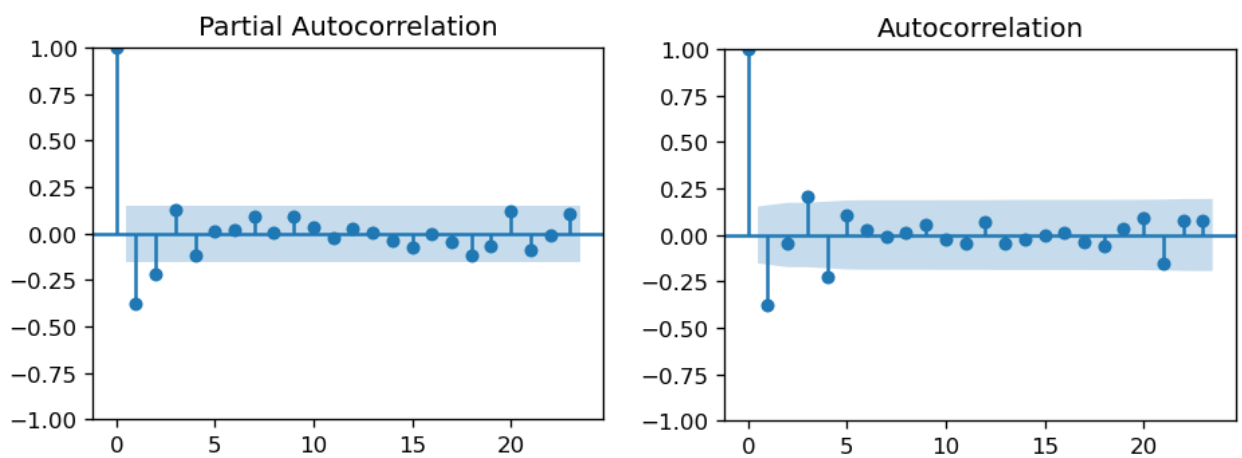


Figure 18 ACF & PACF Plots of Differenced Series

Figure 18 shows the ACF plot, we observe significant spikes at lags 1 and 4. Since the last significant spike is at lag 4, we will initially specify the MA term having an order of 4. Figure 18 also displays the PACF plot which is used to determine the order of the auto regressive part of the ARIMA model. The PACF plot shows significant spikes at lags 1 & 2. The last spike is observed at lag 2 with the next spikes very close to the confidence intervals, therefore, we would initially specify the AR term having an order of 2. However, it is worth nothing that the more complex a model that harder it is to interpret and run. The question is can we achieve a better model by choosing fewer lags?

Appendix 9 denotes the first fitted ARIMA (2,1,4) model. Taking a look at the insights provided by the p-values of the lags, it is evident that most of the lags show that they are insignificant and hence it is a poor model.

Let's remember that with the ACF and PACF plots we noticed significant lags at lag 4 and lags 2 respectively and asked the question if we could build a simpler model. Let's try to improve with a simpler model. For this we will utilize python environments auto ARIMA function that runs multiple iterations of ARIMA models and identifies the best one based on the AIC and BIC criterion. The result for the auto Arima function in the python environment is appended in Appendix 11.

The AIC criterion suggests a model ARIMA(2,1,1) while the BIC criterion suggests a model of (0,1,1).

Improving ARIMA model

Table 12 highlights the output of the improved ARIMA models.

Table 12 AIC and BIC Suggested Models

AIC Model	**ARIMA (2,1,1)**
Lags	**P-value**
AR.L1	**0.000**
AR.L2	**0.000**
MA.L1	**0.005**
Sigma	**0.000**

BIC Model	**ARIMA (0,1,1)**
Lags	**P-value**
MA.L1	**0.000**
Sigma	**0.000**

As observed from Table 12, the improved ARIMA model specifications of (2,1,1) and (0,1,1) indicate a better model due to the highly significant p-values of the lags. As mentioned earlier AIC looks for the best model fit while BIC looks for a simpler model. Since the ARIMA (2,1,1) model is not too complex and the ARIMA (0,1,1) model might suffer from being too simple we opt for the ARIMA (2,1,1) model.

Thus, the equation of the model obtained is:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \vartheta_1 \epsilon t_{-1} + \epsilon_t \quad (19)$$

Where:

1) Y_t is the current value of the time series.
2) ϕ_1 and ϕ_2 are the coefficients of the first and second autoregressive terms.
3) Θ_1 is the coefficient of the moving average term.
4) ϵ_t represents the error term.

Model Diagnostics

one of the methods that Box and Jenkins suggested is the diagnosis of residuals of the model. Brooks explains (2005, pg.231) that diagnostic testing in the Box-Jenkins approach is basically assessing the existence of autocorrelation in the model. Figure 19 denotes the plot of residuals showing that the residuals are normally distributed , have a near zero mean and are generally follow a constant variance.

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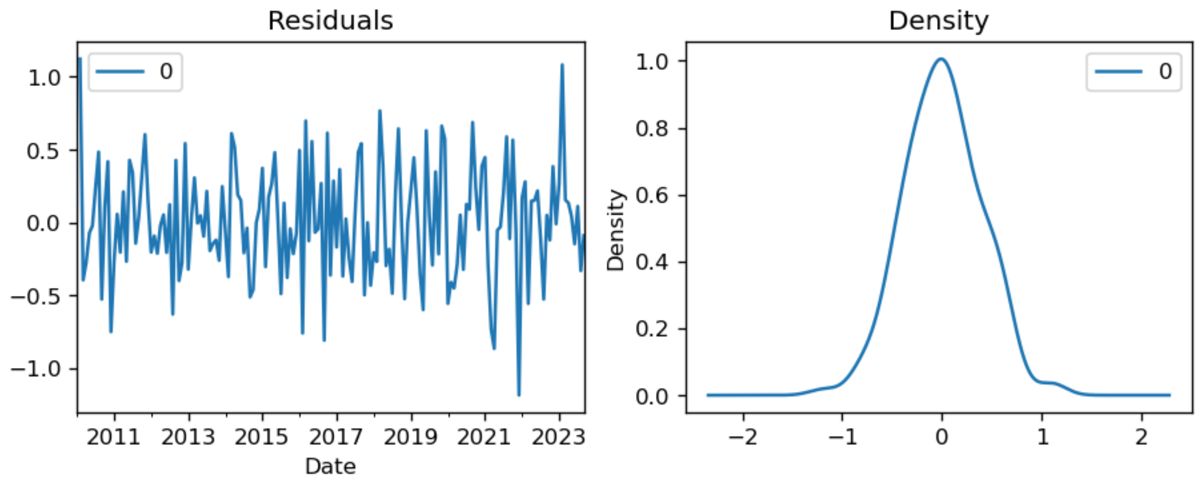

Figure 19 Plot of Residuals ARIMA Model

8.2.1 Cross Validation

The next step was to utilize rolling window cross validation on our ARIMA model to assess its performance.

Average MSE across all splits = 298.173

The average MSE score illustrates the rolling window cross validation to assess the performance of our ARIMA (2,1,1) model. Appendix (8) illustrates the rolling window movement of training and testing data with each training and testing split being the same size but moving across the time series. The window size was set at 12 as the model iterates 12 months at a time forward. This is because forecasting methods are commonly employed between 6 and 12 months forward. The model was then implemented on each split and average MSE across all splits calculated. Therefore, the best split ranged on the data trained up to the end of 2014 and shows a limited fit is illustrated in Figure 20

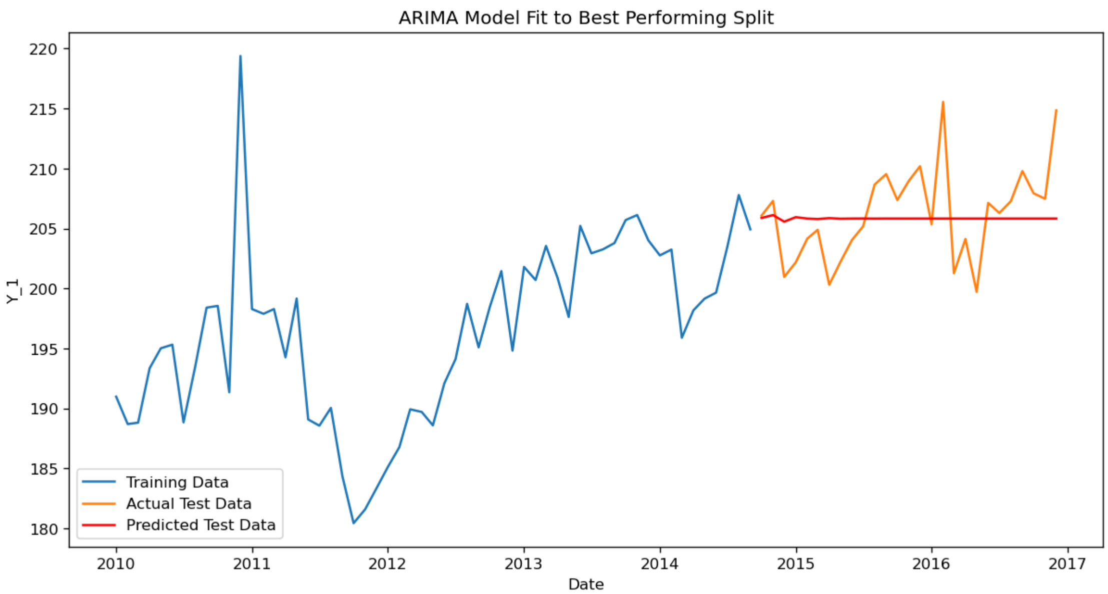

Figure 19 Best Split ARIMA model.

The next step was to implement a forecast for our ARIMA model and observe how well it can forecast future values beyond the scope of our data points that end towards 2023. Figure 21 highlights the forecast for the ARIMA (2,1,1). It can be noted that our forecast shows that Y_1 will stagnate in the next 12 months with little volatility.

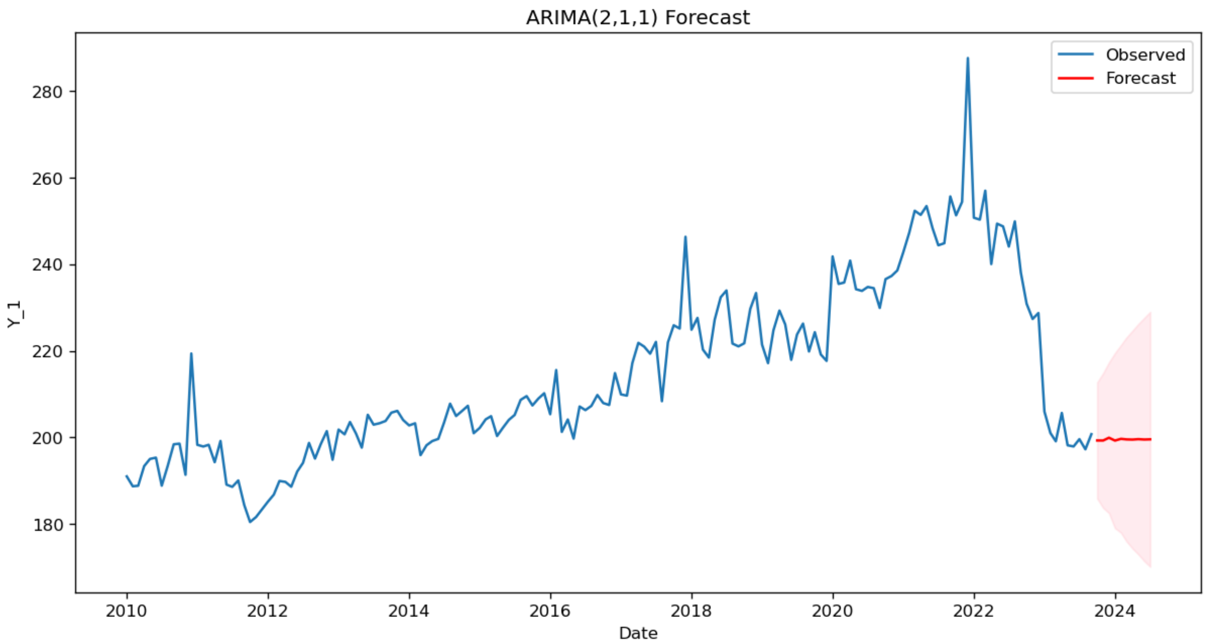

Figure 20 Forecasted Trend ARIMA Model

8.3 VECTOR AUTO REGRESSION

We now move to the last model implementation, vector auto regression. As outlined in the methodology section VAR modeling will help us understand the dynamic relationships that exist between our chosen macroeconomic indicators and Y_1. Before we implement an appropriate VAR model, we will first conduct tests of Granger Causality and Cointegration. These will help us understand whether there exists causation and relation that can be mapped out with a VAR model. Next, we will investigate impulse response plots and determine what kind of impact shocks to the variables produce. Lastly, we will look at forecasts of our VAR model and discuss the practical implications for Stora Enso.

Granger Causality Matrix

Table 13 Granger Causality

	$Y_{1\,x}$	HICP $_x$	Industrial Production $_x$	Wholesale Trade $_x$
$Y_{1\,y}$	1.0000	0.0377	0.4552	0.0016
HICP $_y$	0.0006	1.0000	0.1901	0.0000
Industrial Production $_y$	0.0002	0.0235	1.0000	0.0013
Wholesale Trade $_y$	0.0010	0.1889	0.0009	1.000

Interpreting Granger Causality Matrix

Table 13 displays the results of the granger causality test on our time series variables. Interpreting the granger causality matrix will aid in understanding the intricate relationships between time series variables. The matrix displays p-values and a p-value below the significance level of 0.05 would indicate that there is causation present. The columns represent the x variables, and the rows represent the response y variables. As observed, it is evident that HICP, and Wholesale Trade (x, columns) show a p-value below the significance level for Y_1 while Industrial Production does not. Thus, indicating that HICP and Wholesale Trade to some degree are holding causation for Y_1. Additionally, Y_{1x} also shows evidence of causality for Industrial Production_y, Wholesale Trade_y and HICP_y. These findings demonstrate that a Vector Auto Regression model would be a suitable approach to underline the dynamic relationship between the time series variables.

Cointegration Test

Table 14 Johanssen's Cointegration Test

Variable	Test Stat	C (95%)	Significance
Y_1	76.54	40.1749	True
HICP	33.04	24.2761	True
Industrial Production	11.96	12.3212	False

Wholesale Trade	0.93	4.1296	False

Table 14 shows the Cointegration test results . It is evident that Y_1 and HICP are indeed cointegrated and have long run statistically significant relationships with the other variables. Wholesale Trade Industrial Production on the other hand are below the 95% confidence interval and do no exhibit long standing relationships with other variables.

8.3.1 VAR Model

We will now implement a VAR model with the use of information criteria AIC and BIC.

Table 15 Selecting Order of Lags VAR Model

Lags	AIC	BIC
0	8.149	8.23
1	7.2	7.603
2	6.261	6.987*
3	6.176	7.225
4	5.97	7.341
5	5.558	7.251
6	5.556	7.572
7	5.593	7.931
8	5.548	8.209
9	5.582	8.566
10	5.556	8.863
11	5.065	8.694
12	5.011	8.963
13	4.934*	9.208

Table 15 displays the AIC and BIC scores of a VAR model at each lag. Evidently, the AIC score drops to its lowest at lag 13, and the BIC score drops to its lowest at lag 2 before going up again at lag 3. As such we will run VAR models with a lag order of 13 and 2 and inspect the p-values.

Appendix (13) displays the results of VAR(2) model. As observed, the VAR(2) model performs poorly, and p-values are insignificant with the exception of Y_1 lags 1 and 2. The VAR(13) model on the other hand Appendix 14 identifies significant lags from the macroeconomic indicators. Therefore, we will proceed with the VAR(13) model to forecast the future trend.

Forecast Trend

The next part is to look at potential future trends of the model. Before doing so, we will first implement an approach to forecasting through train and test split to visually evaluate how what our forecasts vs our actual values state based on the current values of the variables. Figure 21 denotes the forecasted vs actual values of the variables. Notably, Y_1 and HICP are forecasting directionally correct albeit with more volatility based on the train and test data while Wholesale Trade and Industrial Production show limited prediction power in forecasts. This is a good visual finding, as we are simply observing the visual direction of our model for strategic purposes rather than exact forecast coefficients.

Then we forecast future values beyond the scope of our data points to observe where our indicators could directionally head. Figure 22 in this context displays the forecast beyond 2023. As mentioned earlier, we are interested in the directional insights of our model. Note here we are observing the trend. From the plots we observe that Y_1 is forecasted to stagnate for the next 12 months and head marginally downwards, HICP is also forecasted to hover around the same level with minor fluctuations.

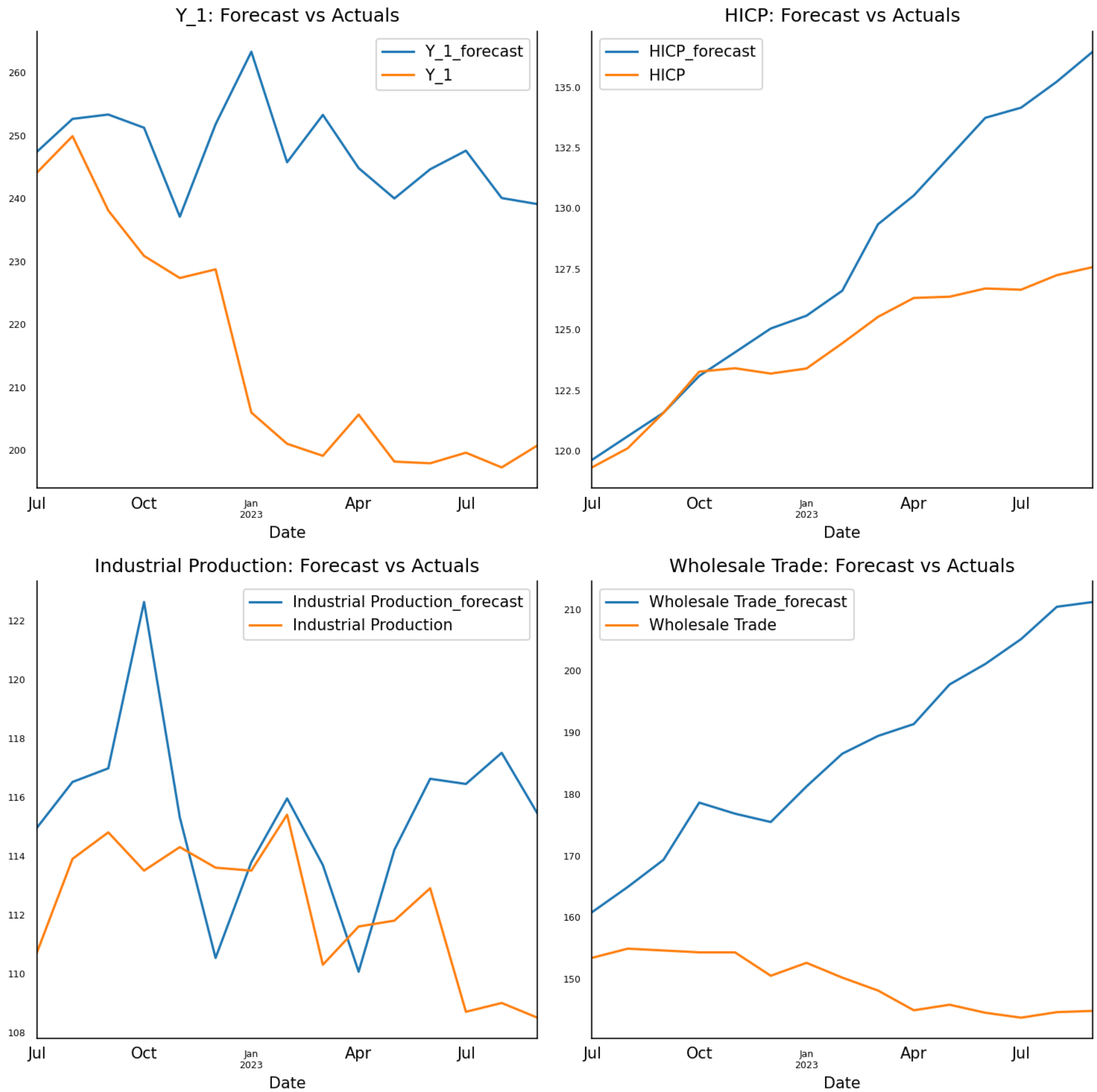

Figure 21 Actual vs Forecast VAR Model (13)

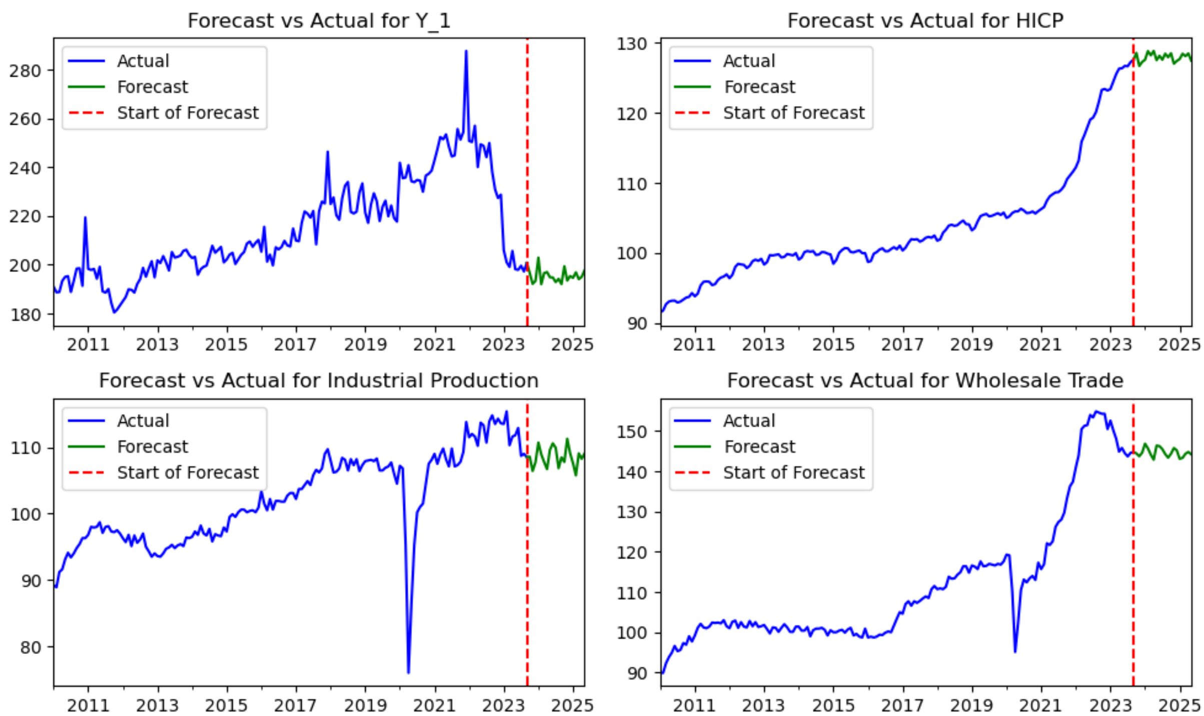

Figure 22 Projected Future Values VAR (13)

8.3.2 Impulse Response Plots

One of the key tools of VAR modeling for this study is the use of impulse response plots. Particularly in this case, impulse response plots help understand the underlying affects the changes in one time series affect another. The impulses, commonly known as shocks are sudden surges administered by the system on one variable and records the subsequent reaction on another variable. Figure 23 illustrates the impulse response of Y_1 from a shock exhibited to our macroeconomic indicators.

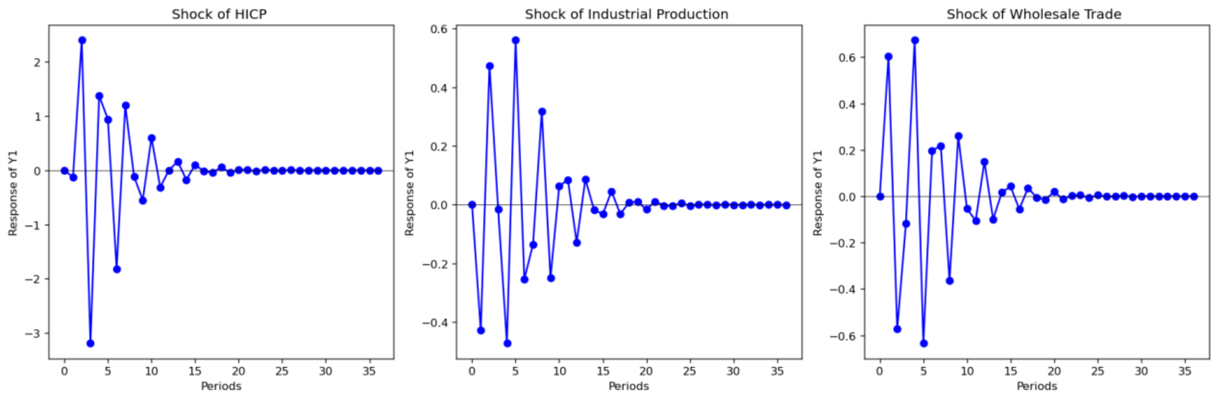

Figure 23 Impulse Response Plots

The shock administered to HICP instigates a strong response from Y_1 with the range between 2 and -3 suggesting that HICP strongly influences Y_1 in comparison to the Industrial Production and Wholesale Trade. The larger negative magnitude suggests that HICP tends to have more of a negative impact on Y_1 than a positive one. Furthermore, the response dissipates after 15 periods implicating a long-run relationship among the two variables. Industrial production instigates a response within the range of 0.6 - -0.4, considerably less than HICP, suggesting that industrial production does not have as much of an impact on Y_1. The volatility and length of the response also dissipates earlier around 15-20 months. The magnitude of response shows that industrial production tends to impact Y_1 positively more than negatively whereas HICP tends to affect Y_1 more negatively. Wholesale trade impacts Y_1 within the range 0.6 – -0.6. The impact also does not last as long dissipating around 15-20 months. Wholesale trade tends to impact Y_1 approximately both positively and negatively.

The findings coincide with the granger causality tests, which indicated that HICP does granger cause Y_1. Furthermore, the cointegration test also indicated that HICP is cointegrated with Y_1. A closer look at the impulse response plots does show that the magnitude of response from HICP significantly shrinks after 10 periods, whereas the magnitude of response from Wholesale Trade is higher at that stage. This indicates that wholesale trade has a stronger impact in the medium term as compared to HICP. A result which our linear regression analysis also supports, as wholesale trade was the only indicator that proved to be significant.

9 Conclusion

Over the last few years globalization and international trade has strengthened strongly. Europe has been a large prat of this. The European economy as a whole and its impacts are felt far in the industry. Due to this, economic indicators have gathered even more importance to give insights on the current and future conditions of the economy.

This thesis explored the specific case of economic impact on Stora Enso and their operations, particularly drivers of demand and forecasting models. This study explored linear regression, , ARIMA and VAR models in that respect. Linear regression was used to test if there exists a linear relationship between macroeconomic indicators and Y_{1}.This allowed us to examine if macroeconomic variables hold any significant explanation power over Y_1. The results of the regression indicated that with the exception of Wholesale Trade, HICP and Industrial Production were held insufficient explanation power. While Wholesale trade was statistically significant, it also was responsible for explaining roughly 4% of Y_1.

We then moved onto forecasting models ARIMA and VAR. We identified what order of the models best defined our variables. For ARIMA we established the model (7,2,0) indicating 7 AR terms and 0 MA terms are the most influential explaining the time series. Time series validation allowed us to confirm that our model gave directionally the correct forecast albeit with a wide confidence interval. The directionally correct forecast is valuable for strategic planning allowing Stora Enso to anticipate needs, optimize resources and potentially reduce costs. Following our ARIMA modeling, we moved forward with Vector Auto Regression. Similar to linear regression, the aim was to identify and measure the effects macroeconomic variables have on Y_1. Since, linear regression gave us limited information for the cause, implementing VAR was a natural step as it is better suited to understanding the dynamic relationships between time series. The study investigated causal and cointegration effects ass well implementing a VAR model to find statistically significant lags of other time series.

Granger Causality and cointegration tests preceded the VAR model to establish present relationships between variables.

The Granger Causality test gave us insights into how indicators interrelate together. The results were not so surprising as all three macroeconomic variables were significant and pointed to causation for Y_1. Furthermore, wholesale trade was also impacting HICP and Industrial production. Given Wholesale Trade is in the middle ground in the supply chain that links production in industry and consumer consumption. It is therefore unsurprising to note that Industrial Production and HICP are not granger causing each other.

The Johanssen cointegration test indicate that there exist long-term relationships on a macroeconomic level between Y_1 and HICP. This makes sense because in basic economics a rise in consumer prices deters demand which subsequently would affect supply. Notably, wholesale trade and industrial production did not exhibit long run relationships with other variables. The case of wholesale trade is particularly interesting as other factors of the supply chain such as inventory adjustment are in play to minimize long-term impacts from taking hold. At best, wholesale trade points to short- and medium-term impact on Y_1.

Following on from Granger Causality and Cointegration, a key part of our analysis was examining impulse response plots. Impulse responses of the three macroeconomic indicators on Y_1 was inspected and moved to confirm the insights extracted from Granger Causality. We observed that all 3 indicators caused substantial volatility on Y_1 in the short and medium term. Wholesale trade appeared to stabilize quickest with lower levels of volatility compared to HICP and industrial production. This finding can be confirmed through our cointegration test which outlined that wholesale trade was not exhibiting long run trends.

9.1 Answering Research Questions

1. Is Linear Regression Analysis applicable to investigate the macroeconomic environment and market dependencies?

This study, we outlined a methodology for the possibility of linear regression analysis in analyzing the impact of macroeconomic variables on Stora Enso. We can conclusively outline that linear regression in general terms is an acceptable method to find linear dependencies between variables. It is however prone to too much simplicity. In reality, macroeconomic variables are hardly ever linear and display varying relationships over time. Nevertheless, if a somewhat linear relationship can be identified prior to regression analysis, as in our preliminary analysis, it can be applied. The results, however, showed that there is a limited fit, and we cannot strongly suggest a linear relationship. For macroeconomic indicators and market dependencies other regression models may prove to be more fruitful.

2. Have Macroeconomic indicators been able to explain the future development of Stora Enso's production?

Through linear regression and vector auto regression we aimed to examine the relationship between macroeconomic indicators and Stora Enso's production. While linear regression gave a limited fit, it still pointed at wholesale trade being a significant variable. This initial finding was added to by the vector auto regression, granger causality test and cointegration test. Granger causality and cointegration confirm that macroeconomic variables are significant, display long run relationship and are granger caused. The future development of Stora Enso's production is predicted by both the ARIMA and VAR models to stagnate in the near future. Impulse response plots aid in the understanding with a more short-term outlook.

3. How do forecasted production outlook differ when comparing ARIMA and VAR models?

In the case of ARIMA (2,1,1) and VAR (13) we forecasted future developments in response variable Y_1 using the best fitted model after cross validation. In both cases the projected outlook is a stagnated steady movement in the short term.

4. What do the impulse response plots tell us about the dynamic relationship of macroeconomic variables.

Impulse response plots implemented as part of the vector auto regression, revealed several dynamic relationships between macroeconomic variables and Y_1. We observe that a shock in HICP affects Y_1 strongly, while industrial production and wholesale trade administer weaker impact, all three indicators tend to affect Y_1 until 15-20 time periods.

Appendix 16 shows the full-scale impulse responses plots between the macroeconomic indicators. Interestingly, a shock of HICP brings the strongest responses in magnitude for both wholesale trade (between 0.8- -0.8) and industrial production (1.5 - -1.0), while the opposite is not true.

This suggest that while the indicators are inter-related, the harmonized index of consumer prices is more responsible for strong reactions in other indicators. Economically this also makes sense as HICP is an inflationary indicator, a rise in the HICP index points to a rise in prices of products and services. A change in prices affects the purchasing power of consumers which directly affects volume of wholesale and manufacturing of goods.

9.2 Limitations of this study

The methods adopted by this study and the time frame analyzed point to some limitations in this study. Firstly, we implemented an ordinary least square regression after first establishing linearity among target and explanatory variables. While linear regression is a simple and easily applicable method, it leaves room for more complex understanding. Secondly, the study does not cover post 2020 analysis due to limited data points and non-linear relationships exhibited after the pandemic.

In economic analysis, it is easy to get drawn into isolating the effects of macroeconomic variables on chosen target variables. In reality, the macroeconomic environment is one where a multitude of factors are at play simultaneously, making it difficult to precisely quantify the magnitude of impact a specific test outlines. Clearly, we can predict but not guarantee future forecasted values. For example, this study does not take into account the effects of the war between Russia and Ukraine that has significantly impacted the European Economy. Liadze et al. (2023) highlight that the GDP in Europe expected to decrease by more than 1%.

Significantly, the dependence of energy imports from Russia and Ukraine further cast a dark cloud over the industries. In the case of Stora Enso, the war has caused wood costs to soar, making production expensive and thus shrink. The geo-political landscape of such an event has made long term impacts that make predictions difficult to make.

Future Research

This study encompassed identifying linear relationships and forecasting for the short-medium term. Primarily, linearity analysis drove the linear regression analysis, where we stopped the time series before the period 2020 to analyze long run relationships in the absence of COVID-19. For future research and to continue to map the relationships between macroeconomic indicators and Stora Enso's production planning, future studies investigating specifically the period impacted by the covid through other regression analysis will shed more light on the underlying nuances between their interdependencies. Furthermore, we investigated impulse response plots and how Y_1 changes due to sudden changes in economic indicators, the impulse response plots allowed us to observe the volatility that resulted in the short-term. However, it would be useful to measure and forecast this volatility for further insights into the volatility of consumer markets. For this, a method introduced by brooks to measure volatility such as Generalized Auto Regressive Conditional Heteroskedasticity could be utilized to investigate further.

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Appendices

Summary

Estimation span: [1-2010 - 9-2023]
165 observations
Series has been log-transformed
Trading days effects (1 variable)
Easter [6] detected
5 detected outliers

Decomposition (Seats)

sa. Innovation variance: 0.76712
trend. Innovation variance: 0.05975
seasonal. Innovation variance: 0.01907
transitory. Innovation variance: 0.00000
irregular. Innovation variance: 0.38873

Diagnostics

summary
Good

Basic checks
definition: Good (0.000)
annual totals: Good (0.003)

Regarima residuals
normality: Uncertain (0.081)
independence: Good (0.718)
spectral td peaks: Good (0.814)
spectral seas peaks: Bad (0.035)

Outliers
number of outliers: Uncertain (0.030)

Residual seasonality tests
Qs test on SA: Good (1.000)
F-Test on SA (seasonal dummies): Good (1.000)

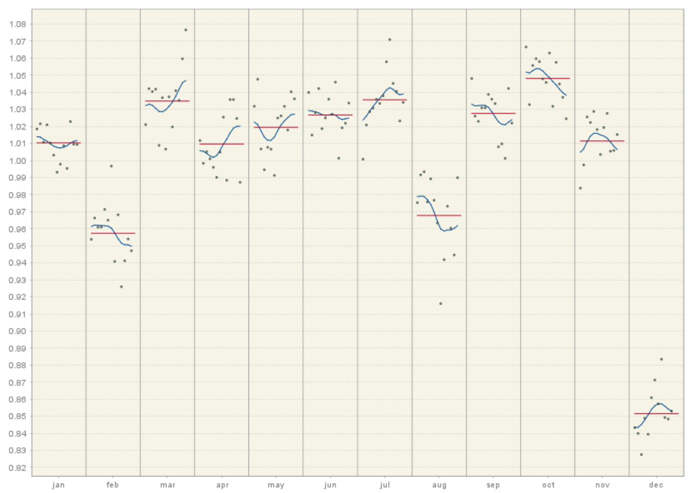
Residual trading days tests
F-Test on SA (td): Good (0.982)

Seats
seas variance: Good (0.545)
irregular variance: Good (0.367)
seas/irr cross-correlation: Good (0.888)

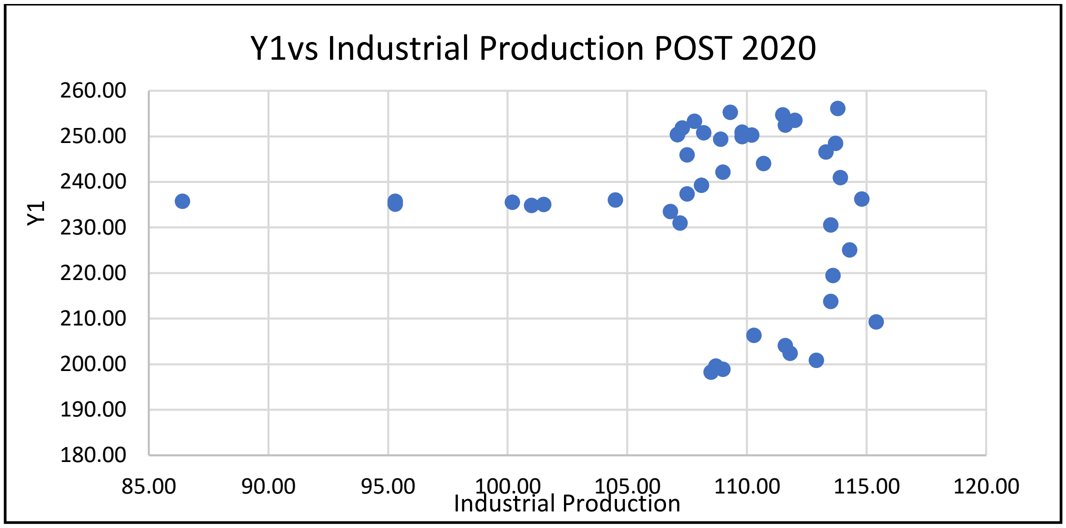
Model
D: 1.00000 - B - B^12 + B^13
MA: 1.00000 - 0.438921 B - 0.733157 B^12 + 0.321798 B^13

sa
D: 1.00000 - 2.00000 B + B^2
MA: 1.00000 - 1.41659 B + 0.430831 B^2
Innovation variance: **0.76712**
trend
D: 1.00000 - 2.00000 B + B^2
MA: 1.00000 + 0.0255203 B - 0.974480 B^2
Innovation variance: **0.05975**
seasonal
D: 1.00000 + B + B^2 + B^3 + B^4 + B^5 + B^6 + B^7 + B^8 + B^9 + B^10 + B^11
MA: 1.00000 + 1.36421 B + 1.40337 B^2 + 1.31052 B^3 + 1.10630 B^4 + 0.860450 B^5 + 0.600992 B^6 + 0.349180 B^7 + 0.139445 B^8 - 0.0545428 B^9 - 0.181476 B^10 - 0.456350 B^11
Innovation variance: **0.01907**
irregular
Innovation variance: **0.38873**

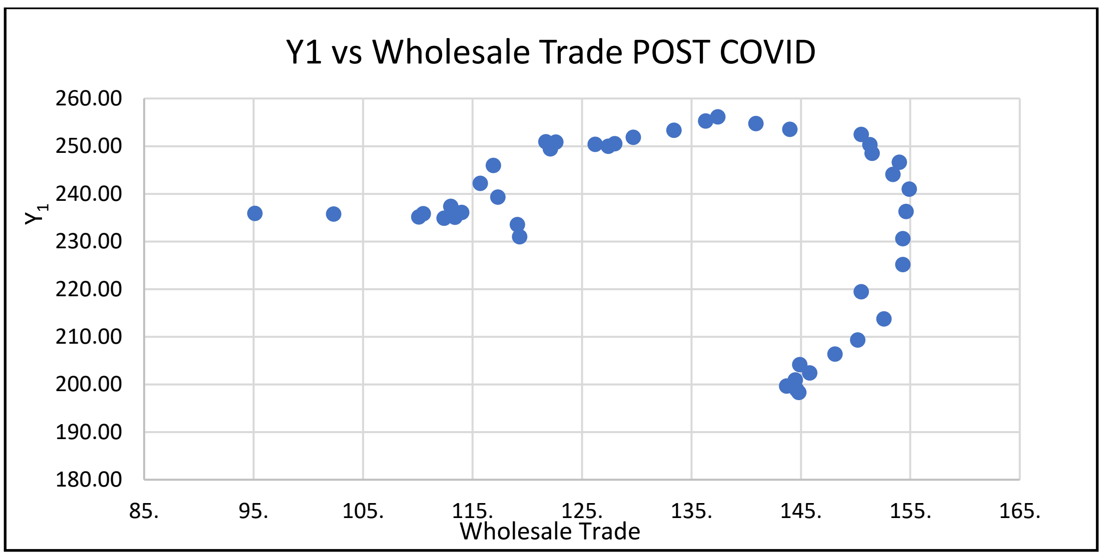
Appendix 1 Seasonal Adjustment Summary Output



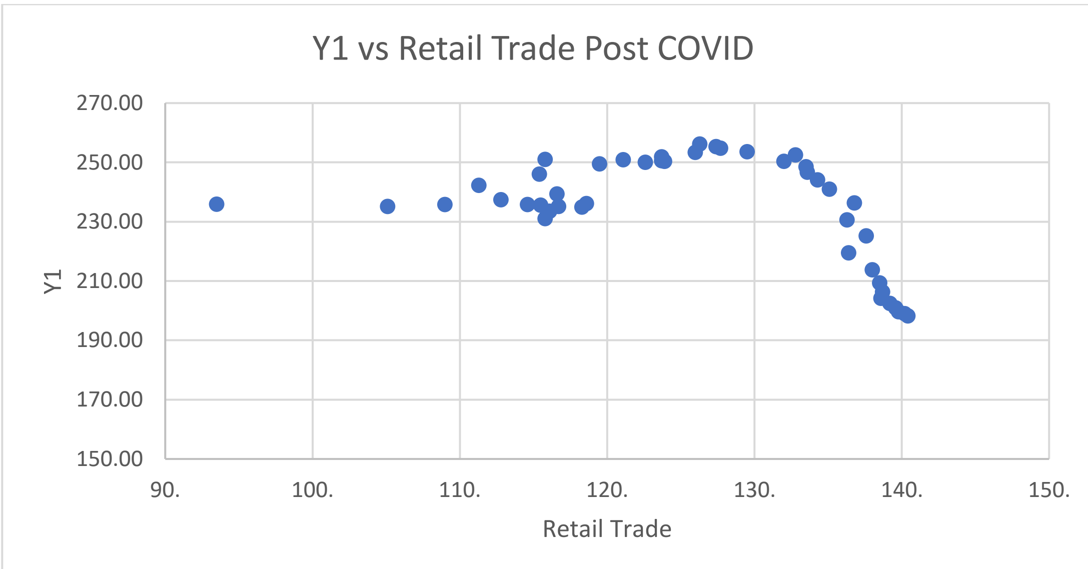
Appendix 2 Monthly Seasonality component plot



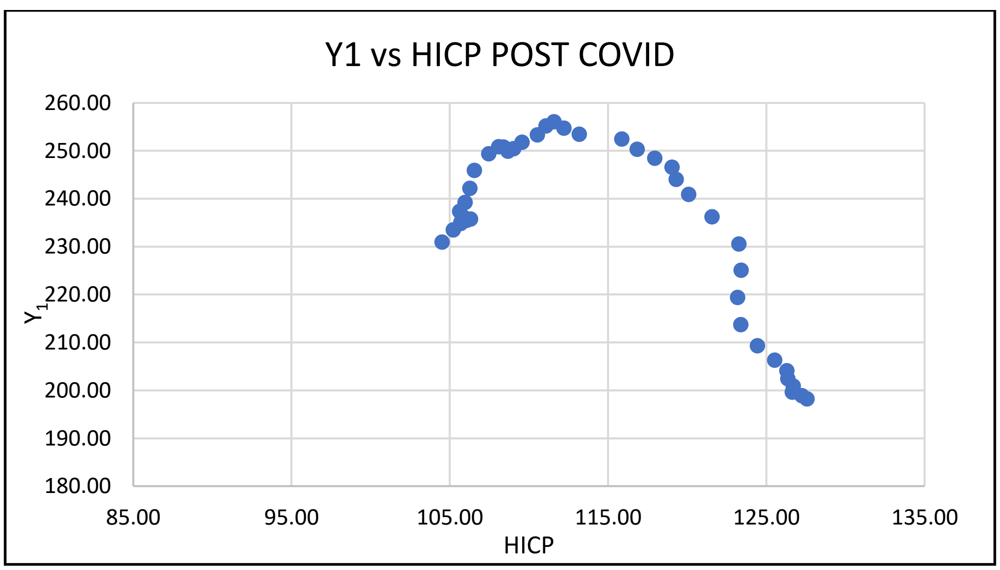
Appendix 3 Y1 vs IP Post 2020



Appendix 4 Y1 vs Wholesale Post 2020



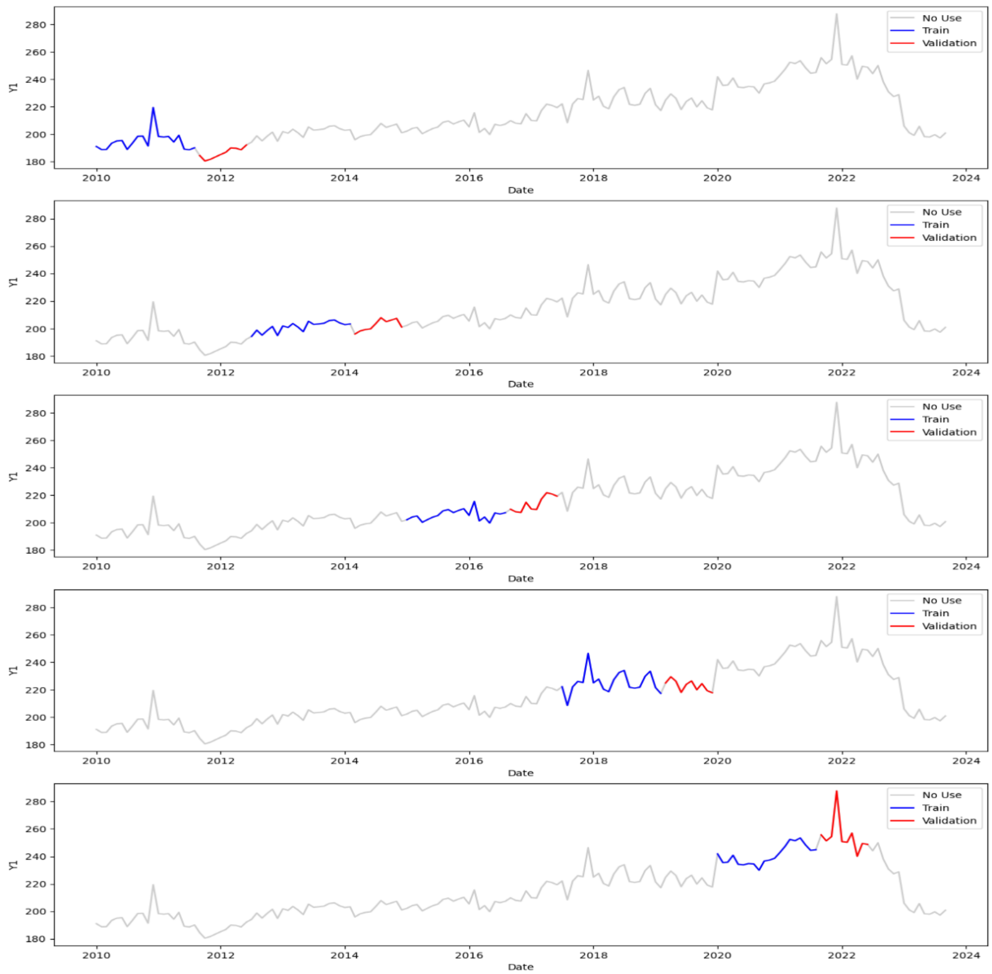
Appendix 5 Y1 vs Retail Trade Post 2020



Appendix 6 Y1 vs HICP Post 2020

```
MSE: 122.89405111850866
MAE: 8.031082514780604
R²: -0.9173353788915352
                            OLS Regression Results
==============================================================================
Dep. Variable:               Y_1_diff   R-squared:                       0.120
Model:                            OLS   Adj. R-squared:                  0.073
Method:                 Least Squares   F-statistic:                     2.580
Date:                Mon, 10 Jun 2024   Prob (F-statistic):             0.0624
Time:                        09:35:55   Log-Likelihood:                -222.63
No. Observations:                  61   AIC:                             453.3
Df Residuals:                      57   BIC:                             461.7
Df Model:                           3
Covariance Type:            nonrobust
==========================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
const                      0.0292      1.233      0.024      0.981      -2.440       2.498
All-items HICP             1.3677      1.942      0.704      0.484      -2.522       5.257
Industrial Production      1.5884      0.967      1.642      0.106      -0.349       3.525
Wholesale Trade           -2.1637      0.835     -2.592      0.012      -3.835      -0.492
```

Appendix 7 Rolling Window Cross Validation OLS regression.

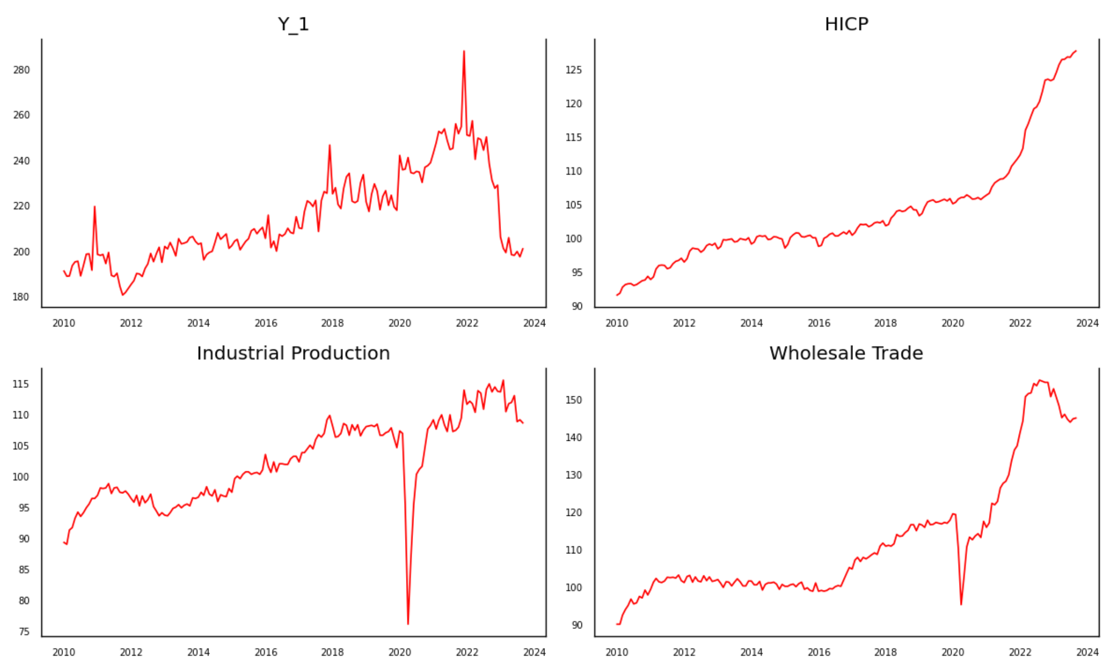


Appendix 8 Rolling Window Plots

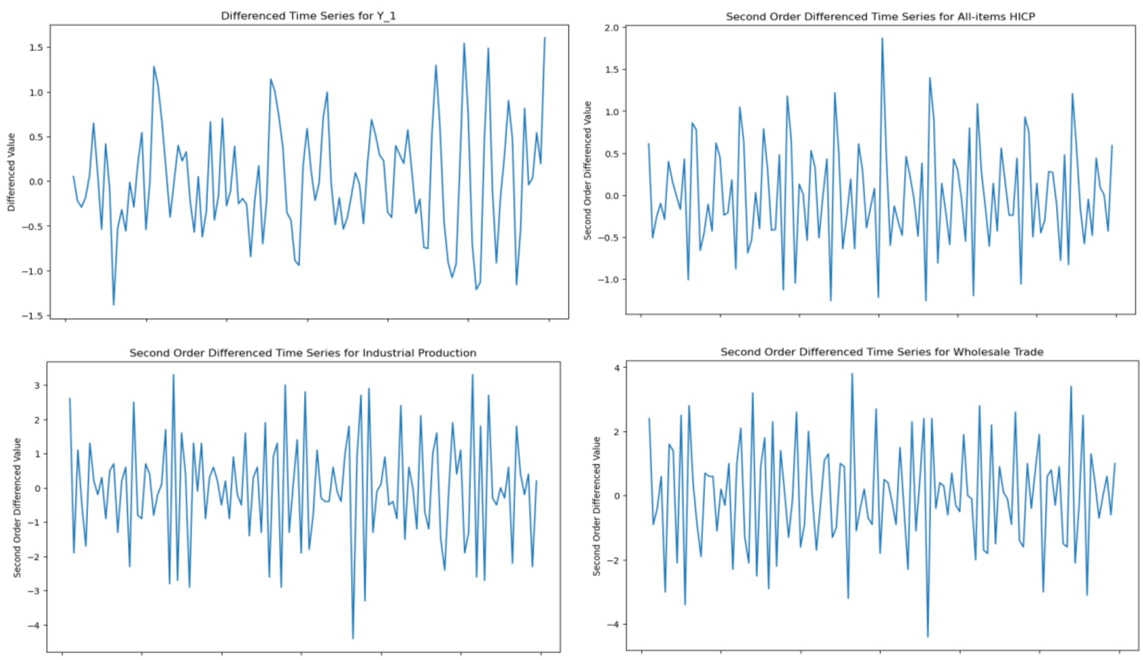
Dep. Variable:	Y_1	No. Observations:	165
Model:	ARIMA(2, 1, 4)	Log Likelihood	-547.840
Date:	Mon, 10 Jun 2024	AIC	1109.680
Time:	17:11:39	BIC	1131.379
Sample:	01-01-2010	HQIC	1118.489
	- 09-01-2023		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.8263	0.679	-1.217	0.224	-2.157	0.504
ar.L2	-0.3848	0.523	-0.735	0.462	-1.411	0.641
ma.L1	0.4205	0.677	0.622	0.534	-0.906	1.747
ma.L2	0.0397	0.316	0.126	0.900	-0.580	0.659
ma.L3	-0.0003	0.236	-0.001	0.999	-0.462	0.462
ma.L4	-0.0896	0.148	-0.606	0.545	-0.379	0.200
sigma2	46.5662	3.665	12.707	0.000	39.384	53.749

Appendix 9 ARIMA (2,1,4)



Appendix 10 Original Time Series Over Time



Appendix 11 Differenced Time Series

```
Best ARIMA model by AIC: p         2.000000
d         1.000000
q         1.000000
AIC    1104.210431
BIC    1116.609897
Name: 11, dtype: float64
__________________________________________
Best ARIMA model by BIC: p         0.000000
d         1.000000
q         1.000000
AIC    1108.241890
BIC    1114.441623
Name: 1, dtype: float64
```

Appendix 12Auto Arima Function Output

No. of Equations:	4.00000	BIC:	6.83664
Nobs:	161.000	HQIC:	6.42740
Log likelihood:	-1372.68	FPE:	467.828
AIC:	6.14763	Det(Omega_mle):	376.352

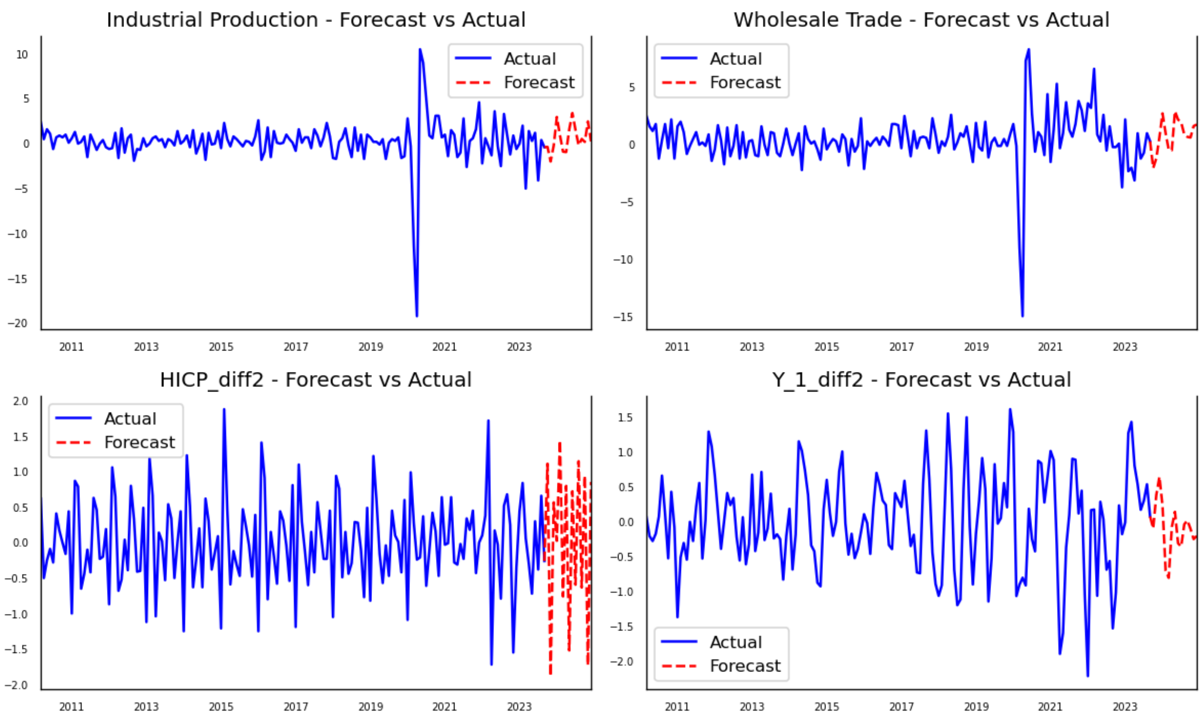
Results for equation Y_1

	coefficient	std. error	t-stat	prob
const	-0.008550	0.649405	-0.013	0.989
L1.Y_1	-0.942822	0.067764	-13.913	0.000
L1.HICP	-0.124004	1.139367	-0.109	0.913
L1.Industrial Production	-0.427105	0.319920	-1.335	0.182
L1.Wholesale Trade	0.604034	0.378802	1.595	0.111
L2.Y_1	-0.564688	0.067583	-8.356	0.000
L2.HICP	2.170247	1.150678	1.886	0.059
L2.Industrial Production	-0.371225	0.319285	-1.163	0.245
L2.Wholesale Trade	0.570436	0.381207	1.496	0.135

Appendix 13 VAR (2)

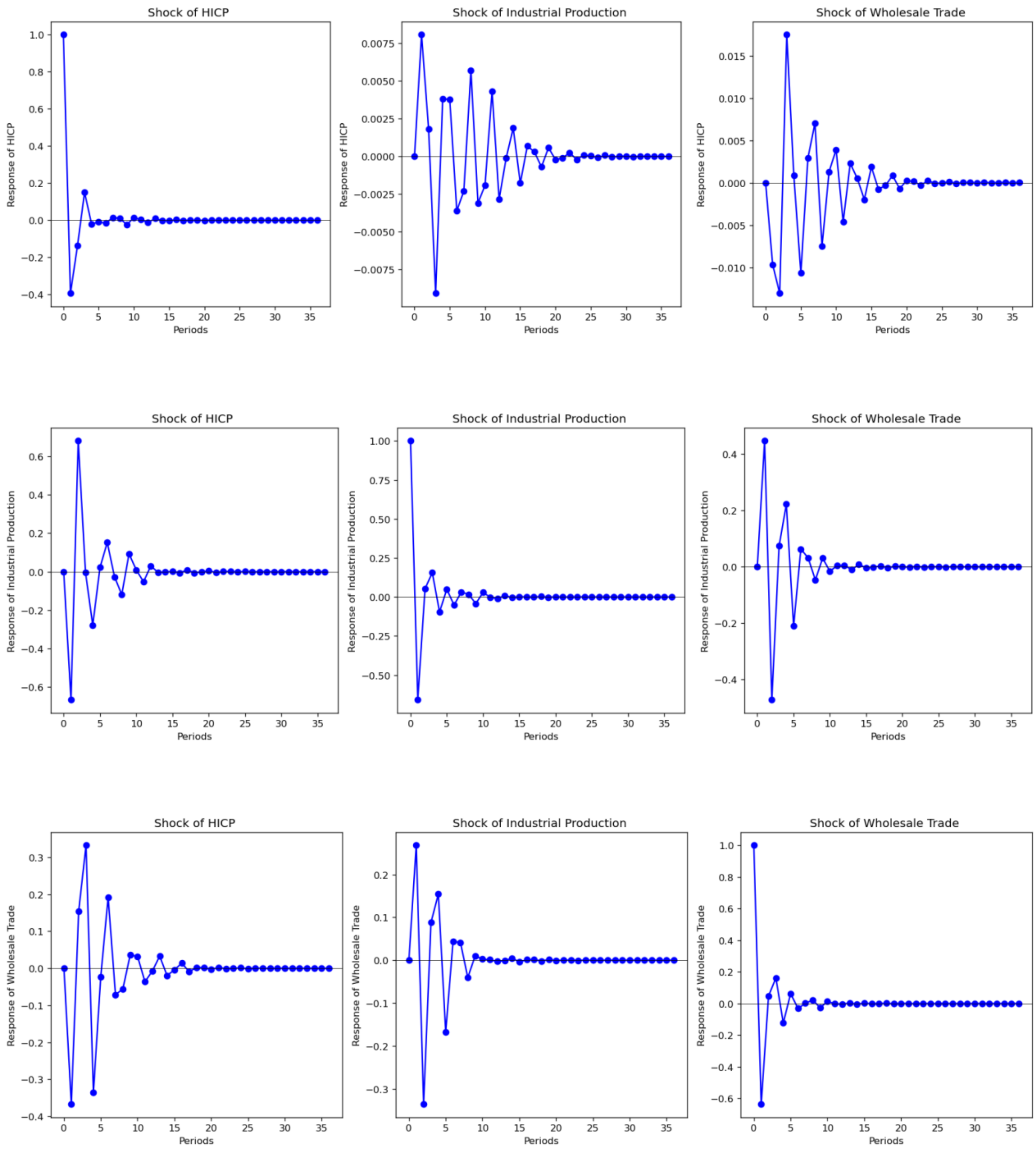
	coefficient	std. error	t-stat	prob
const	-0.108555	0.562142	-0.193	0.847
L1.Y_1	-1.213163	0.103886	-11.678	0.000
L1.HICP	-0.121482	2.391932	-0.051	0.959
L1.Industrial Production	-0.973977	0.390115	-2.497	0.013
L1.Wholesale Trade	1.254063	0.447995	2.799	0.005
L2.Y_1	-1.219214	0.165989	-7.345	0.000
L2.HICP	-1.387278	2.913140	-0.476	0.634
L2.Industrial Production	-1.692358	0.592092	-2.858	0.004
L2.Wholesale Trade	2.251721	0.676296	3.329	0.001
L3.Y_1	-1.206827	0.215727	-5.594	0.000
L3.HICP	-3.149177	3.094857	-1.018	0.309
L3.Industrial Production	-1.464007	0.729946	-2.006	0.045
L3.Wholesale Trade	2.197775	0.830157	2.647	0.008
L4.Y_1	-1.430307	0.252582	-5.663	0.000
L4.HICP	-2.049801	3.115228	-0.658	0.511
L4.Industrial Production	-1.422901	0.776495	-1.832	0.067
L4.Wholesale Trade	1.495189	0.908796	1.645	0.100
L5.Y_1	-1.339111	0.289252	-4.630	0.000
L5.HICP	-3.419965	3.126216	-1.094	0.274
L5.Industrial Production	-1.186096	0.792640	-1.496	0.135
L5.Wholesale Trade	1.772980	0.956580	1.853	0.064
L6.Y_1	-1.169769	0.315638	-3.706	0.000
L6.HICP	-4.355766	3.154114	-1.381	0.167
L6.Industrial Production	-1.433308	0.775775	-1.848	0.065
L6.Wholesale Trade	1.950738	0.978905	1.993	0.046
L7.Y_1	-1.104236	0.327662	-3.370	0.001
L7.HICP	-3.446029	3.149823	-1.094	0.274
L7.Industrial Production	-0.433916	0.746944	-0.581	0.561
L7.Wholesale Trade	0.798447	0.996697	0.801	0.423
L8.Y_1	-1.020974	0.322881	-3.162	0.002
L8.HICP	-2.179385	3.186087	-0.684	0.494
L8.Industrial Production	0.312972	0.742819	0.421	0.674
L8.Wholesale Trade	-0.194734	1.020454	-0.191	0.849
L9.Y_1	-0.691399	0.304396	-2.271	0.023
L9.HICP	-0.308640	3.135572	-0.098	0.922
L9.Industrial Production	-0.413866	0.746786	-0.554	0.579
L9.Wholesale Trade	0.721967	1.049361	0.688	0.491
L10.Y_1	-0.411327	0.272418	-1.510	0.131
L10.HICP	-1.897323	3.051410	-0.622	0.534
L10.Industrial Production	-0.453313	0.723024	-0.627	0.531
L10.Wholesale Trade	0.625027	1.003742	0.623	0.533
L11.Y_1	-0.305166	0.236909	-1.288	0.198
L11.HICP	-1.366935	3.074609	-0.445	0.657
L11.Industrial Production	0.413055	0.697012	0.593	0.553
L11.Wholesale Trade	-0.700745	0.935102	-0.749	0.454
L12.Y_1	-0.205321	0.178502	-1.150	0.250
L12.HICP	0.366173	2.928259	0.125	0.900
L12.Industrial Production	0.281001	0.595426	0.472	0.637
L12.Wholesale Trade	-0.163554	0.777783	-0.210	0.833
L13.Y_1	-0.089529	0.104570	-0.856	0.392

Appendix 14 VAR (13)



Appendix 15 VAR (13) Model Forecast

Appendix 16 Impulse Response Plots



Y1