SCHOOL OF
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Decomposing Import Price Inflation in the EU

The Role of Demand and Supply

by

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Abstract

This thesis examines what drives import price inflation in the EU by decomposing it into supply and demand driven inflation. The decomposition is done by using product level import data retrieved from Eurostat. The paper examines the period from 2019-01 to 2023-01 which captures events such as the Covid-19 and the war in Ukraine. To classify the product as demand or supply driven, two methods are used, one static as well as one dynamic. The dynamic model sometimes show equivocal results due to its volatility, though it captures events such as the outbreak of the Covid-19. The static model indicates a negative demand-driven inflation during 2020 which then shifts to being to being the main component of the soaring import price inflation. This thesis is a part of project together with Denmarks Nationalbank which also included a creation of a dashboard, the link can be found in the conclusion.

Contents

List of Abbreviations

BEA – Bureau of Economic Analysis

BIC – Bayesian Information Criterion

CPI – Consumer Price Index

ECB – European Central Bank

HICP – Harmonized Index of Consumer Prices

HSX – Harmonized System X

IMF – International Monetary Fund

MPI – Import Price Index

PI – Price Index

PPI – Producer Price Index

UVI – Unit Value Index

VAR – Vector Autoregression

XPI – Export Price Index

1 Introduction

The Covid-19 as well as the war in Ukraine has led to an economic crisis around the globe. These events have given rise to a multitude of challenges, where the massive increase in inflation is one of the major challenges. Consequently, inflation has become a central focus of discussion and analysis within the field of macroeconomics. Economists and policymakers are required to make numerous critical judgments under these circumstances. Hence, it is important to understand the underlying components impacting inflation when making decisions in the field of fiscal and monetary policy. One part of understanding inflation is to examine if the movements in price are driven by supply or demand. Shapiro (2022) has created a method to decompose the inflation into these components which has been extensively used. Demand driven inflation is when the prices rise together with the quantities, whereas supply driven inflation is instead when prices and quantities move in separate directions. Freund (2022) explains the importance of classifying if the inflation is driven by demand or supply by an example, if a product market has a vertical supply curve (or close to it), higher demand only drives prices without increasing supply. In this case the central bank can raise the interest rate to decrease demand and therefore the price without affecting the output. Thus, one can not only take the inflation rate into account within monetary policy but also its sources of the inflation.

This paper will focus on the import price inflation since the import sector has been largely impacted during the last years. Import prices has skyrocketed in Europe since the pandemic broke out and escalated after the war started. The effects of these events led to large supply constraints which some argue is one of the reasons for the merging prices (Comin, Johnson & Jones, 2023; Attins, Balatti, Mancini & Metelli, 2021). The import price index (MPI) is one the most impactful macroeconomic performance measurements (IMF, 2009). Import prices have a significant effect on countries' economies, for instance due to "imported inflation", which is a term used when international trade and import prices has the power to drive the domestic inflation rate. It is therefore critical for the central banks to understand the effects from import prices when they e.g. forecast inflation (Ahn, Park & Park, 2021). Furthermore, Freund (2022) also mentions that knowing what drives import price inflation is beneficial when making decisions regarding tariffs. While lowering tariffs normally promotes competition and limits price inflation, the reduction may not be as impactful during times of shortages. Thus, the goal of affecting the end consumers may not be reached due to the lack of response by the suppliers. Though, over time supply is expected to be more elastic when production improves but the instant effect might be limited in these situations (Freund, 2022). Freund (2022) argues that breaking down the inflation to supply and demand using Shapiro's (2022) method also can be applied to the import sector. Lowering demand should move import price inflation downwards and if import supply is restricted, then low demand should not affect differences in importation.

In previous research, studies have predominantly focused on either the United States or the EU as a whole (See Shapiro (2022), Freund (2022) and Gonçalves & Koester (2022)). However, this thesis will concentrate specifically on the countries in the European Union (EU). Similarly to Freund (2022) we use import data on a product level to examine how different goods have changed in price and in quantities. The period between 2019 to 2023-01 will mainly be used to determine how and if import prices inflation shifted during the years of the Covid-19 pandemic and the war in Ukraine. To determine if the import price inflation was driven by demand or supply, both static and dynamic methods inspired by Shapiro (2022) are used.

By examining all the EU countries this thesis will provide an extensive picture on how the region has been affected by the economic crisis. As already mentioned, this paper aims to decompose the import price inflation between supply and demand driven for the EU countries around the time period of Covid-19. The reason for this is to be able to answer questions such as if the import price inflation has been influenced by the large supply constraints due to the pandemic and the war in Ukraine, or if the constraints in supply in some products were matched with higher demand in other goods. Further, by using product-level data it will be possible to track down the inflation to specific goods, because of this one can answer which has been influenced to import price inflation the most. Also, if there are certain products which drive the inflation by demand or supply.

This paper is a part of a project together with Danmarks Nationalbank which has expressed interest in analyzing the sources of import price inflation on a product level. Furthermore, as part of the project a dashboard in Streamlit is also being created which has the purpose of making it easier to interpret the results from the models. Beyond the models being displayed, descriptive statistics will also be included in the dashboard to give the reader a general picture of the data. **A link to the dashboard will be provided in the concluding part of the thesis.**

The remainder of the thesis is structured as follows. The second part is the literature review where general inflation literature is discussed as well as the framework used to divide the inflation into demand-driven and supply-driven components. Under the third part, readers can find information about the data used, including its sources and the scale of the data. The fourth part outlines our methodology, which follows Shapiro's (2022) approach, and provides insights into our perspective on unit values and more general econometric theory, such as VAR models. Section 5 presents the results and analysis from our dynamic and static models. Additionally, we compare our data with official statistics to visualize its representativeness. In Section 6, we discuss our findings in comparison to previous research. The thesis concludes with a summary of findings, contributions, address the limitations of our study and outline potential areas for future research. Additionally, the appendix contains graphs and tables referred to in the thesis.

2 Literature Review

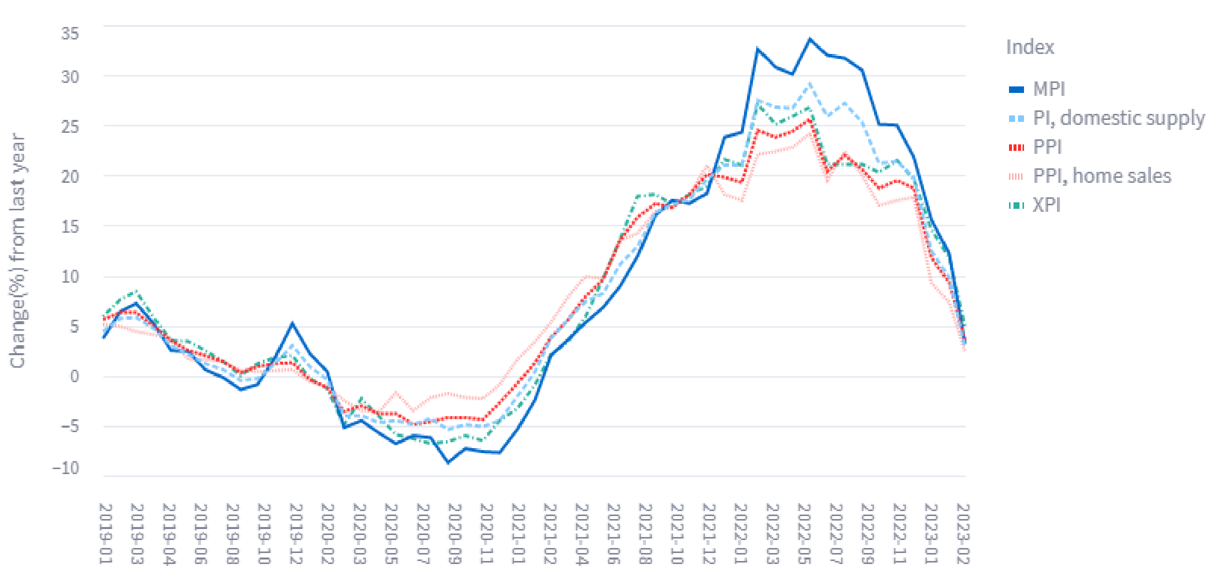
2.1 Inflation and Import Price Inflation

The inflation literature is extensive and has been a focal point in macroeconomics research for long. The influential work of Phillips (1958) exemplifies the inflation's impact on the economy and society in general. William Phillips pioneered the Phillips curve, which has greatly shaped and influenced research in this area with the help of Samuelson & Solow (1960) who made the finding explicit. Their findings highlighted the significance of inflation and discovered the negative relationship with unemployment rate. Though, the concept faced challenges due to times with stagflation when both the inflation and unemployment rate rose (Gordon, 2018). Nevertheless, there have been new discoveries and the Phillips curve continues to be widely utilized in various forms of analysis (Gordon, 2018).

Inflation and the import sector are connected since imported goods have the power to influence the domestic inflation, the phenomenon is called "imported inflation" (Ahn, Park & Park, 2021). It can both affect the consumer price index (CPI) through imported goods included in the index, and also the producer price index (PPI) through imported raw and intermediate goods, which in addition may affect the CPI as well. Thus, understanding how international trade and their prices affect the domestic market is crucial for central banks. Furthermore, trade between countries with different currencies also affect the exchange rates, examining the pass-through effect to domestic goods is therefore important for exchange rate policies. (Ahn et al., 2021)

IMF (2009) mentions that there are four essential indices when it comes to economic statistics, consumer price index (CPI), producer price index (PPI), export price index (XPI) and import price index (MPI). The indices are all indicators of macroeconomic performance and are constantly being used for various purposes. IMF (2009) argues similarly to Ahn et al. (2021) that MPIs provide an understanding of how inflation transmit through the procedure from the domestic producers to end consumers, governmental organizations, and other institutions. In figure 1, different indices for Sweden are visualized and one can observe the relationship between macroeconomic indicators. A shift in the PPI can indicate similar movements in the e.g MPI or the opposite.

Figure 1: Indices, Sweden



Source: SCB

2.2 Decomposing Inflation into Supply and Demand

Shapiro (2022) presents a framework to decompose the inflation into demand and supply driven which has been extensively used since it was introduced. The paper also decomposes core and non-core inflation, cyclical and acyclical inflation, persistent and non-persistent inflation, on the consumer price index (CPI) in the United States.

Shapiro (2022) proposes two different methods for decomposing inflation into supply and demand-driven, static and dynamic labeling. In the static method, inflation is divided into four different labels, supply, demand, insensitive and ambiguous. The four components make up the total inflation and are derived from two least squares regressions. The two regressions are based on quantities and prices for a 10-year window with a dummy variable for the event window. Depending on the t-values of the dummy variables, each product is classified into one of the four labels. Evidence from the method on the US-inflation displayes a great shift in demand-driven inflation before and after the onset of the Covid-19 pandemic.

For the case of the dynamic labeling, the labels are able to switch monthly as opposed to the static labeling. The labels for the dynamic case are based on the residuals from a one-month forecast using a Vector Autoregression-model (VAR). Depending on the results of the residuals, it gets either labeled as demand-driven, supply-driven or ambiguously-driven. The results from dynamic labeling on the US consumer price index, show that the proportions between the labels remain unchanged.

Goncalves and Koester (2022) applies Shapiro's (2022) framework on the euro area by decomposing the HICPX index into supply- and demand-driven inflation (ECB, 2022) framework. HICP is the Harmonised Index of Consumer Prices (ECB, n.d.). The authors use disaggregated and seasonally adjusted, turnover indices as proxy for different HICP categories and matched them against the HICP. In total, 72 categories were matched against 45 turnover indices. The results display mostly demand driven effects for the year 2017. The following years a varying shift between supply- and demand-driven is evident up until the beginning of 2020 were a mainly supply-driven effect is prominent. From Q3 2021, the inflation is mostly driven by supply but with a gradual increase of demand as well.

Caroline Freund (2022) instead applies Shapiro's framework on import data from the United States with the use of HS10 codes. She did this during the event period 2019-2022 to examine the effects of the pandemic. She uses in total 15 000 HS-10 codes to get as detailed data as possible. Freund benchmarks her index against the Bureau of Economic Analysis (BEA), Import Price index (MPI) using both Fixed- and Variable-weighted index. The Fixed index was based on the 2018-2022 aggregated turnover for each product and the variable-weighted was based on monthly turnover for all products. Empirical evidence showed strong correlation between MPI and both fixed- and variable-weighted indices using HS10 codes.

In line with her indices, Freund (2022) concludes that import price inflation has risen substantially since the start of the pandemic. She continues by arguing that the inflation rate is not a result of global constrained or declining import quantities during Covid-19. If that would be the case, then global constraint and import quantities would have been flat or falling. According to Freund that is not the case, the average growth of import quantities has increased even during times of Covid-19. When Covid-19 starts the indices with fixed and variable-weight performs very differently, when the fixed-weight index increases, the variable-weight index decreases. The contrast in movements can be explained by the exceptional demand for specific commodities and a collapse in demand for others.

Freund (2022) concludes that the import price inflation during Covid is driven by demand to the same extent or even more compared to supply constraints. As discussed in the introduction, such results are important for decision making in policy analysis to reduce the disparity between supply and demand, and hence stabilize the inflation. The results are also relevant for understanding the effects of tariffs. Since there were supply constraints for a large portion of the total import at certain time points, reducing tariffs might not give the instant wanted effect. Freund (2022) argues that import quantities need to have the potential to increase for tariff reduction to give immediate consequences.

3 Data

This study is based on import data from the countries in the European Union. Import data are commonly categorized based on the Harmonized system developed by the World Customs Organization (ITA, n.d.). The Harmonized system is a classification system used for different commodity groups, where each commodity has its unique code. The codes are commonly referred to HSX, where X represents the level of classification specificity for the commodity. The system is based on chapters between 01 and 99, which represent the first two digits of the code (WCO, n.d.). The next two digits represent different categories within each chapter (WCO, n.d.). The last two digits represent the product within each category. Further subdivisions differ between regions and countries, but at an international level the 6-digit code is the most common (WCO, n.d.).

The data are retrieved from Eurostat with the use of their API. Eurostat is the official office of the European Union statistics (Eurostat, n.d.a). The data are collected from the dataset, DS-045409, "EU trade since 1988 by HS2-4-6 and CN8" (Eurostat, n.d.b). The dataset contains all Harmonized system codes up to 6-digits and the Combined Nomenclature system of 8-digits. The Combined Nomenclature system is similar to the Harmonized system but with adjustments specific for the European Union and at a higher level of disaggregation (European Union, n.d.).

All HS6 codes are collected except codes with letters such as '1019XX' since they do not contain any information regarding the product. Data are collected for each month for the period 2002 to 2023-01 for all countries in the European Union. The data from Eurostat is available and collected in two measurements, quantity per 100kg and total turnover in Euros. 8084 HS6 codes for all countries are collected which corresponds to 218 268 products in total and 56 million unique observations. For the HS6 codes, 73.4% of products contain missing values or have zero in quantity in their time series. Furthermore, all CN8 codes from 10 HS chapters were collected from the country Sweden, to test at an even more disaggregated level. However, this diluted all quantities to zero which is incompatible with Shapiro's (2022) framework. Therefore, this thesis limits itself to the HS6 codes. The collected data are thereafter stored in a light-weight database (Duckdb) as separate tables for each country.

4 Method

4.1 Missing Values

Due to the scope of this thesis, a unified framework for handling missing values needs to be implemented. Implementation of Shapiro's (2022) framework on the European Union require complete time series for the whole period with non-zero quantities. As mentioned in section 3, most HS6 codes contain an extensive amount of zeroes and missing quantities, this is due to the high reporting threshold of 100kg. This is especially evident for smaller countries such as Malta since they frequently do not reach the threshold weight due to the product specificity of the HS6. Furthermore, most products with incomplete time series, regardless of country, in either value or quantity also exhibit missing values for an extended period of time. This hinders reliable estimation of the data. Regular interpolation techniques such as linear interpolation would therefore provide heavily biased estimates. As a consequence, we remove all HS6 codes with incomplete time series. Moreover, similarly to Fontagné, Freundenberg & Gaulier (2006), we remove all products in category 7102 (diamonds) which are known for their volatility. In total 73.4% of the products are removed, from 218 268 to 58 112 products across all countries. For detailed removal information for each country, see Appendix A.1.

4.2 Unit Values and Outlier Detection

A key component in estimating supply- and demand-driven import inflation is estimating unit values (UV) which is used as a proxy for prices. The most common way of computing unit values is using turnover and quantity as measurement. In this study, prices are estimated with the following equation:

$$p_t = \frac{V_t}{Q_t} \tag{1}$$

V_t = Import value in Euros at time t
Q_t = Quantity per 100kg at time t

How good of a proxy the unit-values are for product prices is mainly influenced by the homogeneity of the product that is measured. The homogeneity refers to the level of price dispersion within each product. In the manual Export and Import Price Index from IMF (2009), IMF emphasizes the weight of unit values and its biases. According to IMF (2009) unit value bias is apparent in all levels of HS-codes, even in HS10. Furthermore, Fu, Xu, & Sheng (2023) found that while the number of HS6 codes are decreasing, the number of imported varieties have increased with 58.3% between 1995 and 2010. This likely increases the heterogeneity in each HS6 code. There also exist other sources of bias. Jiang et al. (2022) found reporting errors at the HS6 level in most countries of the world in the UN Comtrade database. Evidence of this can also be found in the Eurostat database. An example of this is product 610711 "Men's or boys' underpants and briefs of cotton, knitted or crocheted" (Eurostat, n.d.b) for Belgium. Reported quantity for the period 2018-02 exceeded 22 million which gives a unit value of 0.18 Euros. The average unit value for the year, excluding 2018-02, is 1 409 Euros. Furthermore, the month to month inflation for the period 2018-02 to 2018-03 for product 610711 is 901 943%, which is highly unlikely.

Researchers have invented methods to identify heterogeneous products and reduce sources of bias. Fontagné, Freundenberg & Gaulier (2006) used cross-country import data of HS6 codes to identify heterogeneous products. The researchers applied a method which removed outliers depending on the standard deviation and kurtosis of a HS6 product for different countries, depending on the cross country product distributions. Gaulier et al. (2008) also used cross country data to detect outliers. They employed cross country median for a specific product at time $\tilde{p}_t$ and removed the product for a specific country if $p_{t+1} > 5\tilde{p}_t$ or $p_{t+1} < 0.2\tilde{p}_t$. Miao & Wegner (2022) combined Gauiler et al.'s (2008) framework with earlier OECD papers, using a three-step approach. The researchers pooled HS6 codes into HS4 stratum's across countries. The first step applied the Asymmetric Fence Method (AFM) and the revised Mean Absolute Deviation (MAD) (Miao & Wegner, 2022). The methods rely on the distribution of cross-product and cross-country data in different stratum's for detection of outliers. In the second step they applied Gaulier et al.'s (2008) method for outlier detection with threshold levels $p_{t+1} > 10\tilde{p}_t$ or $p_{t+1} < 0.2\tilde{p}_t$ and only removed outliers with a value less than 10% of the stratum. In the third step the researchers re-applied the first step on products that were larger than 10% in each stratum for the HS4 codes.

As a large portion of the products were removed due to missing quantities, product commonality between countries is modest. This makes methods that rely on stratum techniques and cross-country distributions unfeasible. Therefore, our choice of method draws inspiration from Gaulier et al. (2008). We remove a product if unit value exceeds a certain threshold compared to a specific period. If the product exceeds this threshold once, the product is removed. The main purpose of this is to identify heterogeneous HS6 codes and reduce bias. To find a representative threshold level, tests were conducted. The tests showed that the products were very sensitive against certain threshold levels, e.g was threshold value of a 200% increase in month-to-month inflation tested, this resulted in a clear majority being removed.

Based on the results from our tests and threshold values influenced by Gaulier et al. (2008) a two-step process was conducted which balances both product homogeneity and small sample-bias. In the first step all products which exceed the threshold value of 5 times or 0.2 times the unit value from the month before are removed. This captures products with irregular month to month behavior, stemming from different types of biases. In total this reduces the number of products for all countries with 49,7% from 58 112 to 29 204 products. This results in equation:

$$\text{product}_i = \begin{cases} 1 & \text{if } p_t > 5p_{t-1} \text{ or } p_t < 0.2p_{t-1} \ \forall t \\ 0 & \text{otherwise } \forall t \end{cases} \tag{2}$$

p_t = unit value at month t

In the second step, the methodology from the first step is re-applied with adjustment to the time period. Instead of monthly changes, the second step uses the change in unit value from the same month the year before, similarly to the computation of CPI-inflation. This reduces the number of remaining products by 0.5% from 29204 to 29038. This gives equation:

$$\text{product}_i = \begin{cases} 1 & \text{if } p_t > 5p_{t-12} \text{ or } p_t < 0.2p_{t-12} \ \forall t \\ 0 & \text{otherwise } \forall t \end{cases} \tag{3}$$

p_t = unit value at month t

Thereafter an index is created for quantity and unit value for each product, with base 2002-01. For detailed removal of country specific outliers and their sustained import value, see appendix A.4.

4.3 Currency Adjustments

The main currency in the European Union is the Euro, however not all countries have implemented the currency. To be able benchmark our Unit value index (UVI) for all countries in the EU, currency adjustments need to be made. Out of 27 countries in the EU, eight countries have their own national currency during the investigated period. Croatia is one of the eight countries but changed from their national currency to the Euro-currency on 1st of January 2023. During January of 2023, Croatia have a fixed rate between their national currency and the euro (ECB, 2022). The monthly unit values are adjusted with ECB monthly average exchange rate (ECB, n.d.). In table 1 the eight countries with their respective currency-adjustments are presented.

Table 1: Adjusted Currencies

Country	Currency
Bulgaria	BGN
Czech Republic	CZK
Denmark	DKK
Croatia	KN
Hungary	HUF
Poland	PLN
Sweden	SEK

4.4 Dynamic Labeling

A common method to analyze the factors which drive the inflation is to use what Shapiro (2022) calls dynamic labeling (See Shapiro (2022), Freund (2022) and Gonçalves & Koester (2022)). The methodology origins from Shapiro (2022) and uses fundamental microeconomics theory to explain how movements in supply and demand should be interpreted. When both quantities and prices move in the same direction, it suggest a shift in demand. If the change is driven by supply, then the quantities and prices move in the opposite directions (Shapiro, 2022). This intuition also holds for the static model in section 4.5. Dynamic labeling creates one label for each month per product and uses the residuals from VAR models to classify the products as either demand, supply or ambiguous.

4.4.1 VAR Model

The VAR model was introduced by Sims (1980) and has been influential within forecasting especially in econometrics and finance. The method is an extension on the univariate autoregressive model which also takes the lags of other variables into account (Leutkepohl, 2011). The regular VAR model assumes stationarity and examines if a variable is exogenous or depends on other variables current and lagged values.

VAR models are traditionally used for stationary variables (Leutkepohl, 2011). To test for stationary, an augmented Dickey-Fuller test (ADF) is conducted. The ADF-test, tests the null hypothesis that there exists a unit root in a time-series sample (Dickey & Fuller, 1979). If there is a unit root present then the time-series is not stationary. Tests on products from Spain were conducted. The results from 10 different products all showed non-stationarity in either quantity, unit-value or both, see appendix A.3. This suggests that most products are non-stationary in either quantity or unit value. To ensure stationarity in all products, we take the first difference of all product quantities and unit values. The equation is given by:

$$\Delta y_t = y_t - y_{t-1} \tag{4}$$

The optimal number of lags is determined by using the Bayesian information criterion (BIC), the lag order which minimizes the selection criteria is ideally chosen (Enders, 2014). Shapiro (2022) proposes a lag structure of 6-24 lags and use 12 lags in his own VAR models. According to the BIC values in our tests, lag order one minimizes the information criteria, however since this paper follows Shapiro's (2022) methodology, a conservative decision is made and therefore six lags in our VAR model is used. This results in the final model:

$$\Delta p_{i,t} = \beta_{xi} \Delta P_i + \alpha_{xi} Q_i + \epsilon^p_{i,t} \tag{5}$$

$$\Delta q_{i,t} = \beta_{xi} \Delta Q_i + \alpha_{xi} P_i + \epsilon^q_{i,t} \tag{6}$$

$p_{i,t}$ = The log of the unit value index of product i and month t
$q_{i,t}$ = The log of quantity index of product i and month t
$\beta_x i$ = A vector of estimated parameters for product i for the months *t-1* to *t-6*
$\alpha_x i$ = A vector of estimated parameters for product i for the months *t-1* to *t-6*
P_i = A vector of the log lagged unit value index for product i from *t-1* to *t-6*
Q_i = A vector of the log lagged quantity index for product i from *t-1* to *t-6*
ϵ^p_x = The residual from the forecast in the unit value index for product i and month t
ϵ^q_x = The residual from the forecast in the quantity index for product i and month t

4.4.2 The Labeling

The VAR model in the dynamic labeling method is used for one-month forecasts for each product's unit value and quantity. Similarly to Shapiro (2022) our model is based on a 120 month rolling window, the rolling window starts from 2002-01 to 2011-12 and rolls up until 2022-12. For each step of the rolling window a one-month forecast is conducted. This results in monthly forecasts for the period 2012-01 to 2023-01. The values from the forecast are thereafter subtracted from the observed values to retrieve the residuals. The residuals are then grouped in two different periods, control- and test-period. The control period spans from 2012-01 to 2018-12, while the test period reaches from 2019-01 to 2023-01. The product is then assigned its label depending on the sign of the residuals and the distributions of the residuals from the control period. If the residuals for both quantity and the prices are of the same sign, product at time t is labeled as demand. If the residuals are of different signs at time t they are labeled as supply. This gives the following equations:

$$\mathbb{1}_{i\in\text{Demand}} = \begin{cases} 1 & \text{if } \epsilon^p_{i,T} < 0 \; and \; \epsilon^q_{i,T} < 0 \; or \; \epsilon^p_{i,T} > 0 \; and \; \epsilon^q_{i,T} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

$$\mathbb{1}_{i\in\text{Supply}} = \begin{cases} 1 & \text{if } \epsilon^p_{i,T} < 0 \; and \; \epsilon^q_{i,T} > 0 \; or \; \epsilon^p_{i,T} > 0 \; and \; \epsilon^q_{i,T} < 0 \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

Similarly to Shapiro (2022), we adopt a strategy to relabel products at time t to reduce the level of noise. Specifically, if the residuals from either quantity or unit value in the test period are in the middle 20% from their corresponding control period distributions, the product is labeled as ambiguous.

4.5 Static Labeling

The static labeling model serves as an alternative approach used to test for sensitivity in inflation to specific events, in this case the Covid-19 and the war in Ukraine. Moreover, in contrast to dynamic labeling, which gives labels once per month, static only assigns labels once per included dummy variable.

The model relies on two distinct linear regressions, one focusing on quantities and the other on unit values. Each regression consists of a constant and several dummy variables for different time periods to capture shifting dynamics. Our regression runs over the period 2010 to 2023-01, whereas 2010 to 2018-12 serves as a control period. The model includes four dummy variables ranging between 2019-01 to 2019-12, 2020-01 to 2020-12, 2021-01 to 2021-12 and 2022-01 to 2023-01. The first dummy, 2019-01 to 2019-12 act as a benchmark period for the other dummies since it is the period before the examined events. The regressions for quantity and unit value are performed on each product individually. This gives the equations:

$$\Delta\pi_{i,t} = \boldsymbol{\beta}_{\pi i}\mathbf{I}_{\pi i} + \alpha_{\pi i} + \epsilon_{\pi i,t} \tag{9}$$

$$\Delta x_{it} = \boldsymbol{\beta}_{xi}\mathbf{I}_{xi} + \alpha_{xi} + \epsilon_{xi,t} \tag{10}$$

$\pi_{i,t}$ = Unit value index compared to the same month the year before for product i at month t
$x_{i,t}$ = Quantity index compared to the same month the year before for product i at month t
$\mathbf{I}_{\pi,i}$ = Vector of dummy variables for unit value index π, for product i.
$\mathbf{I}_{x,i}$ = Vector of dummy variables for quantity index x for product i.
$\boldsymbol{\beta}_i$ = Vector of parameter estimates of dummy variables for product i
α_i = Estimated constant for product i

In total, 58 408 regressions are computed. The period for each pair of dummy variables is then classified based on the estimated parameters t-value. The classification system is outlined as a set of four equations. Every product for each country gets one classification for the matching period between the two regressions. The static model either labels a product as insensitive, demand sensitive, supply sensitive or ambiguously sensitive. The product's label depends on the t-value from the parameters. Products labeled as insensitive for a given period, does not meet the t-value threshold in either quantity or unit value. Meaning that the difference against the control period is not significant. If a product is labeled as ambiguously sensitive the t-value threshold is exceeded by one of the regressions, but not both. Meaning that the product was sensitive to the Covid-shock in either change in unit value or quantity. If a product is labeled as demand or supply for a certain period, the t-value threshold is exceeded by both regressions. t-values of the same sign means that the product for the time period is predominantly driven by demand effects, opposite signs indicates that the product is instead driven by supply. Shapiro (2022) points out that products can of course be both demand and supply sensitive but this method allows us to see which effect is dominating. In this thesis the t-value threshold is set to 1.64. Moreover, the equation system below explains the labeling process as described above:

$$\mathbb{1}_{i\in\text{insens}} = \begin{cases} 1 & \text{if } |t(\beta_{\pi,1i})| < t_k \text{ and } |t(\beta_{x,1i})| < t_k \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

$$\mathbb{1}_{i\in\text{sens}(d)} = \begin{cases} 1 & \text{if } [t(\beta_{\pi,1i}) < -t_k \text{ and } t(\beta_{x,1i}) < -t_k] \text{ or } [t(\beta_{\pi,1i}) > t_k \text{ and } t(\beta_{x,1i}) > t_k] \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

$$\mathbb{1}_{i\in\text{sens}(s)} = \begin{cases} 1 & \text{if } [t(\beta_{\pi,1i}) < -t_k \text{ and } t(\beta_{x,1i}) > t_k] \text{ or } [t(\beta_{\pi,1i}) > t_k \text{ and } t(\beta_{x,1i}) < -t_k] \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

$$\mathbb{1}_{i\in\text{sens}(a)} = \begin{cases} 1 & \text{if } 1_{i\in\text{sens}(d)} = 0 \text{ and } 1_{i\in\text{sens}(s)} = 0 \text{ and } 1_{i\in\text{insens}} = 0 \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

t_k = t-value threshold

4.6 Computation of Weights

To be able to determine the main influences of the import price inflation, all products need to be aggregated. In this thesis, Freund's (2022) methodology for product weights is applied since it provided accurate results when compared to the Import price index in the United States. The product's weights are summed up using what Freund (2022) calls fixed and variable weights. The fixed weights are calculated by summing the import value for each product from 2018-01 to 2023-01. The sum is then divided by the total sum of all products for the same period for each respective country. This is given by equation:

$$w_i = \frac{\sum_{t=2018m1}^{2023m1} V_{it}}{\sum_i^I \sum_{t=2018m1}^{2023m1} V_{it}} \tag{15}$$

V_{it} = Import value in period t, for product i

The variable weights are based on the monthly import value relative to the total import value for a given month. This gives larger weights to products that are prominent in a given month. This is given by equation:

$$w_{it} = \frac{V_{it}}{\sum_i^I V_{it}} \tag{16}$$

Then, the weights for the product are multiplied with the product's inflation for the given month. The inflation is calculated as the year on year inflation, meaning the difference between unit value p_t and p_{t-12}.

5 Results and Analysis

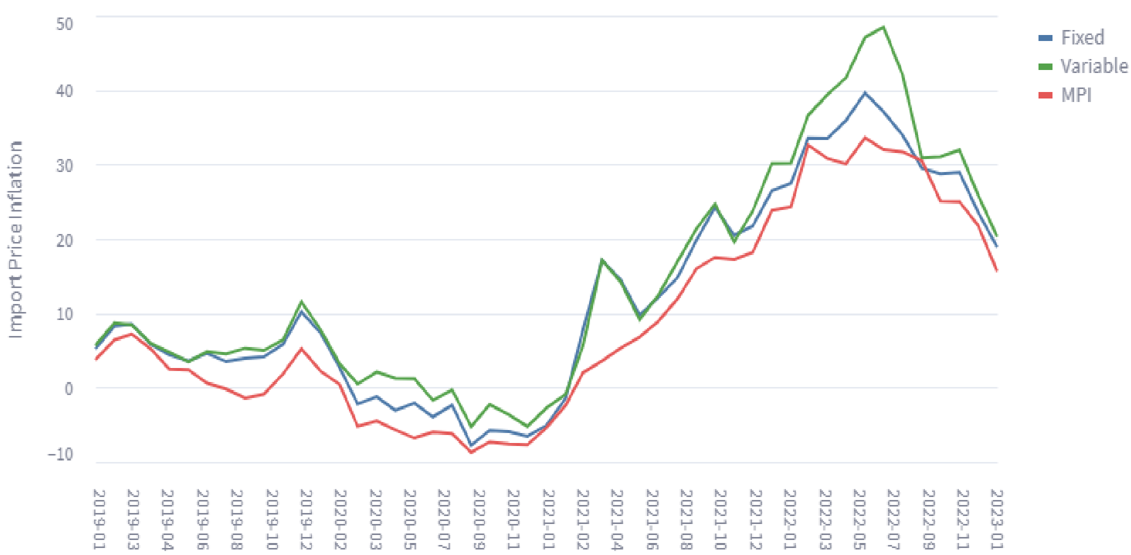
Due to the scope of the thesis a small selection of the EU countries will be analyzed. The selection is based on the country's total imports and interest of Denmarks Nationalbank. Only figures from Sweden and Denmark are displayed in the result section, while the EU's largest importers are found in appendix B. When interpreting the figures, one should keep in mind that the countries are not fully comparable. They include different products because of missing values as well as exclusion of outliers. Though, overall this should give a general picture on the import price patterns among the different countries. The results for all other EU countries can be found in the Streamlit dashboard.

5.1 Benchmarking

To provide the reader with an understanding of the representativeness of the data, the national import price index (MPI) is compared with our unit value index (UVI). The red line in the figures is the MPI based on data from the country's respective national statistics office. The green and blue line is our own UVI based on variable and fixed weights.

In figure 2, Sweden is represented. As one can observe, the UVI overestimates MPI both for fixed and variable weight. However, the indices mostly follow similar dynamics except for 2021-03. In this period both fixed and variable weight display a notable spike, which is not observable in the MPI. During the peak in the midst of 2022, notable differences between all indices are observable. Variable weight is far from the MPI, while fixed weights display dynamics more comparable to MPI. Furthermore, a similar descent in late 2022 is observable for both UVI's and MPI.

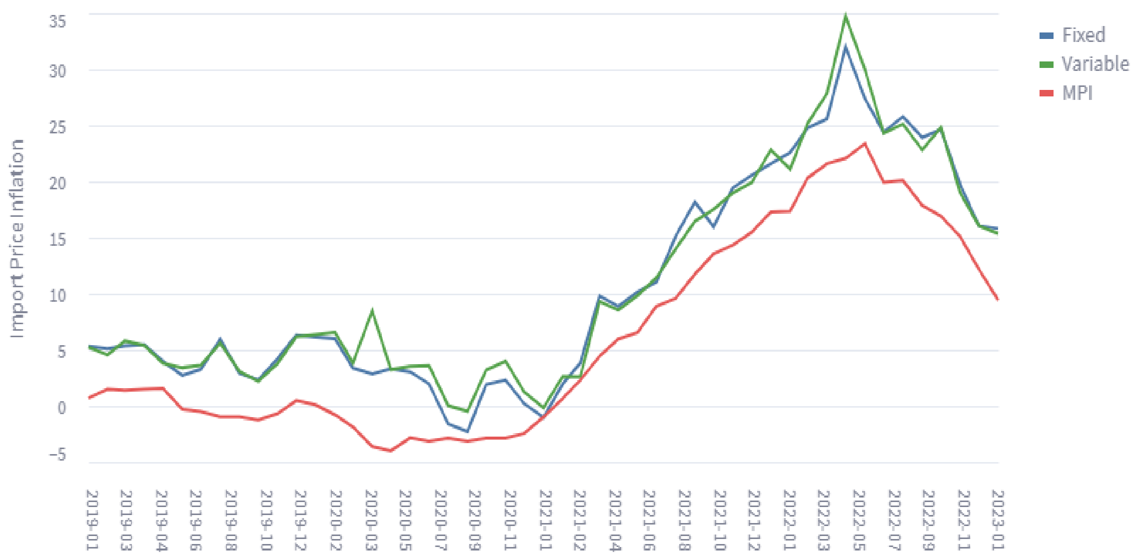
Figure 2: UVI vs MPI, Sweden.



Note: The data for the MPI is collected from SCB (n.d).

For Denmark (figure 3), both fixed and variable weight have a notably higher inflation compared to the MPI during the whole period. Nevertheless, they display similar trends but with larger variation compared to Sweden. Especially prominent differences are observable in 2022-05 for both fixed and variable weight during its peak. For this period, both fixed and variable weights exceed the benchmark with 10%.

Figure 3: UVI vs MPI, Denmark.



Note: The data for the MPI is collected from Statistics Denmark (DST) (n.d).

Both countries display mostly similar dynamics compared to their corresponding benchmarks. The discrepancies are larger for Denmark. Reasons for this can be attributed to both methodological differences as well as different sources of biases. First of all, the removal of missing values weigh the data differently compared to national MPI's. Secondly, statistical offices commonly use surveys to determine price of commodities, which is the case for both DST and SCB (SCB, n.d; DST, n.d.b).

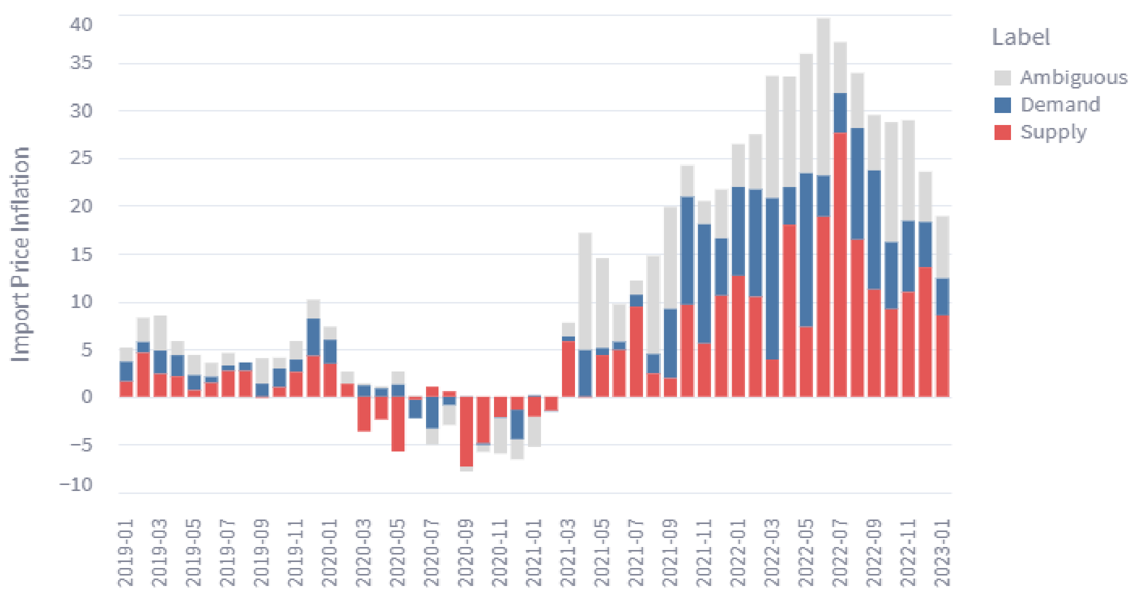
Furthermore, similar results can be observed for the largest importers in the EU (appendix B.1). The UVI follows the same trend to their corresponding national MPI's with varying differences. For most countries, the UVI's perform in line with Freund (2022) which provides a basis for the applied methodology. Also, since the fixed weight generally perform better this is used in the following sections.

5.2 Dynamic Labeling

Dynamic labeling displays month to month changes in the labels, meaning that a product can get a different label for each month. Thus, one can expect larger discrepancies in the results from dynamic labeling compared to the static labeling.

The evolution of the effects on the inflation in Sweden (figure 4), displays an oscillating effect for the whole time period, with substantial month-to-month changes. The period prior to the Covid pandemic displays a mixed effect where both supply and demand effects are equally prominent. However, after the onset of the pandemic in 2020-03, a shift is noticeable. During this period, supply is mainly the negative effect on inflation. For the subsequent years, 2021 to 2023-01, both demand and supply effects display a strong fluctuating behavior. Especially prominent is the period 2022-03, the onset of the war in Ukraine, whereas demand makes up a much larger portion relative to supply. The subsequent month this supply effect is reversed, where the opposite behavior is evident relative to demand.

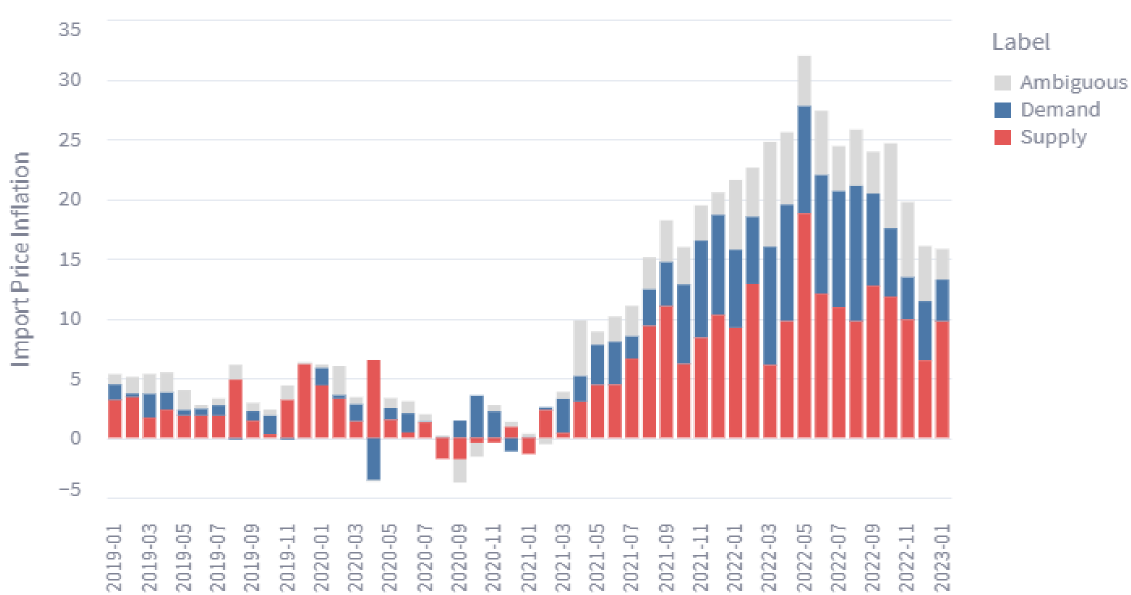
Figure 4: Dynamic labeling, Sweden



Note: The contribution of each label to inflation is based on the fixed weight UVI.

Denmark, figure 5, displays less proportions for ambiguous effect, indicating that inflation is driven by supply and demand effects to a greater extent than in Sweden. Furthermore, there's also less month-to-month oscillation in comparison to Sweden. During the whole period, the proportions of the different effects remain somewhat constant in relation to each other. However, there are brief periods, such as 2020-11 and 2021-03, where inflation is predominantly categorized as demand driven.

Figure 5: Dynamic labeling, Denmark



Note: The contribution of each label to inflation is based on the fixed weight UVI.

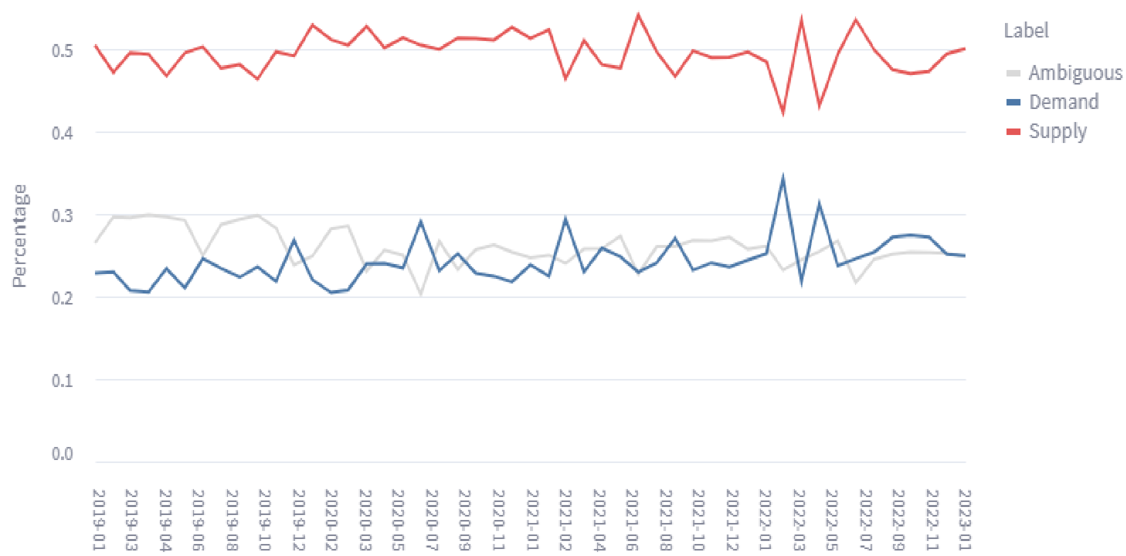
For the largest importers in the European union (Appendix B.2, figure 15-17), varied behavior is observable. Germany, figure 15, displays similar dynamics as Denmark. Whereas France and Netherlands display a volatile month to month behavior with their corresponding labels after 2020-03. Common for the three largest importers is the negative demand driven inflation throughout the initialization of the Covid-pandemic, 2020-03. Furthermore, both France (figure 17) and Netherlands (figure 16) exhibit volatile effects during the investigate period, while Germany (figure 15) demonstrates a more even pattern.

5.2.1 Evolution of Proportions

The labeled proportions (figure 6-7) represents the number of products with a certain label relative to all products at time t. The proportions should not be confused with figure 4-5 as they represent the effects corresponding to the total inflation at time, t. All selected countries display stationary behavior with their corresponding label proportions during the time period, but with clear signs of volatility. In figure 7 and 9 one can observe the actual effect from supply and demand side by side, compared to the proportions between the numbers of products getting labeled.

For Sweden (figure 6), most products display a supply effect. There are several notable peaks for demand effects during this time period. Most prominent are the peaks in the midst of 2020, the beginning of 2021 and at the beginning of 2022. For the peaks in 2021 and the peak in 2022, corresponding downward peaks are observable for the products with supply effects. This effect is reverted for both peaks in the following periods. this indicates that products formerly labeled as supply are relabeled as demand during these periods, but thereafter relabeled in the following period once again.

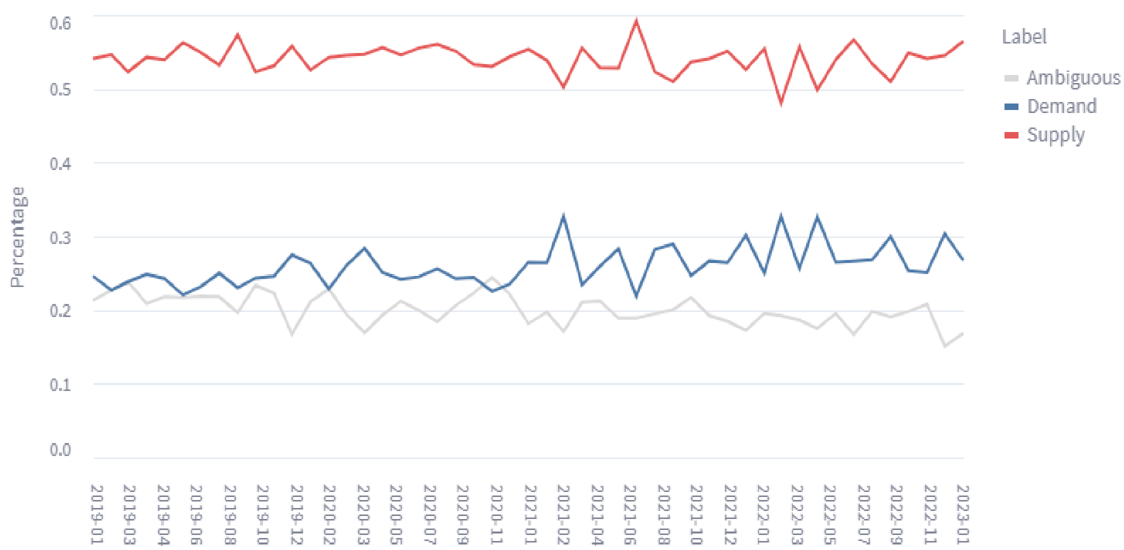
Figure 6: Proportion of labels, Sweden



Note: The proportions are calculated as the total number of products with a certain label relative to other labels

Denmark (figure 7) displays similar results as Sweden. Supply effect is most prominent among all products similar to Sweden. A noticeable effect is observed at the onset of the Covid-19 in the beginning of 2020. For the rest of the period, two periods with prominent peaks are noticeable. A strong surge in demand effect is noticeable in the beginning of 2021. In this period, products with demand effects are more than 30% of all products. The corresponding effect is most notable in supply, which means that most products with supply effect, are relabeled as demand at this period. At the onset of the war in Ukraine. Similar surges are noticeable as in the beginning of 2021, however this effect is immediately reverted in the following period by a supply effect. Once again for the following period, the effect is once again reverted, displaying a surge in demand.

Figure 7: Proportion of labels, Denmark



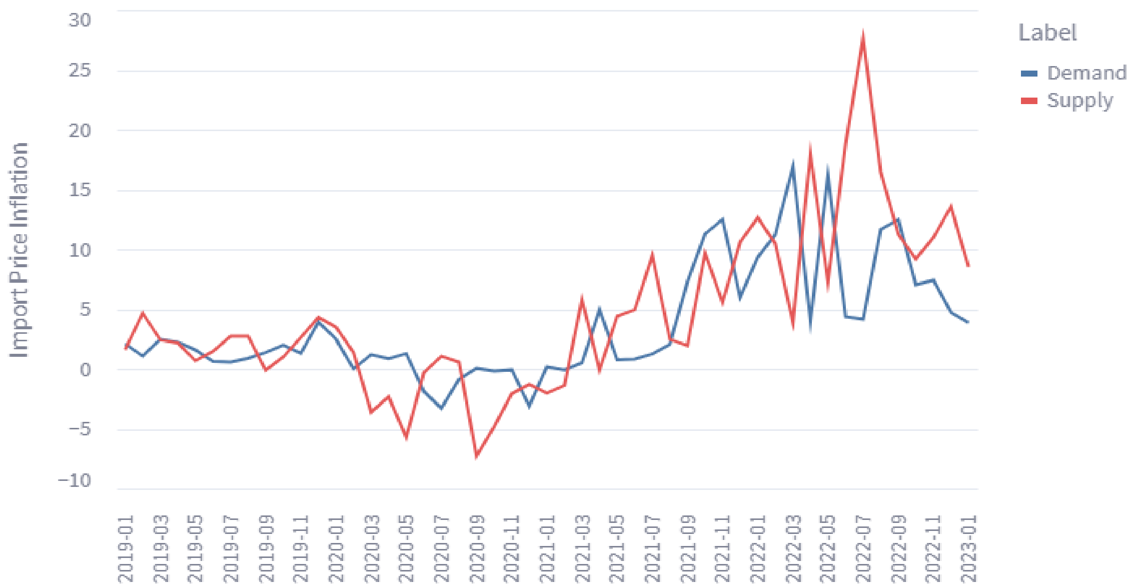
Note: The proportions are calculated as the total number of products with a certain label relative to other labels

For the largest importers in the EU (appendix B.2.1, figure 18-20). Most products are labeled as supply, except for France which has an equal proportion of ambiguous products. Surges in demand are prominent for both Germany and France at the onset of the Covid pandemic but not for Netherlands. For France, the number of products with a surge in is doubled than in comparison to months before. This effect is mostly from product with labeled as ambiguous. Interestingly, all countries display peaks in demand at the beginning of 2021, similarly to Sweden and Denmark. Furthermore, surges in demand are also notable at the initialization of the Ukrainian war.

5.2.2 Effect of Supply and Demand

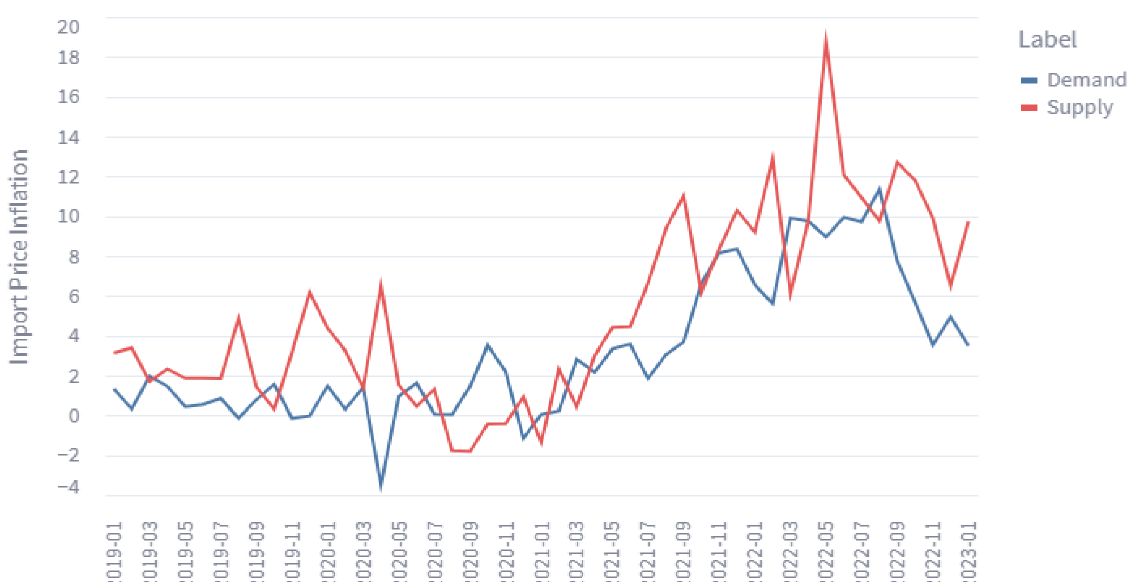
Compared to the section 5.2.1 which pictured the proportions between the number of products for each label. Figure 8 and 9 explains the impact of supply and demand on inflation. One can easily observe that demand seems to have a much larger effect in these figures compared to figure 6 and 7. This indicates that even if there are fewer products getting labeled as demand, they have in general a larger effect per product on the total import price inflation compared to the products labeled as supply. The figures also clarify the patterns in figure 4 and 5, e.g. the shift in supply and demand for Denmark 2020-03, which can be observed in figure 9.

Figure 8: Supply and demand contribution, Sweden.



Note: The contribution of each label to inflation is based on the fixed weight UVI.

Figure 9: Supply and demand contribution, Denmark.



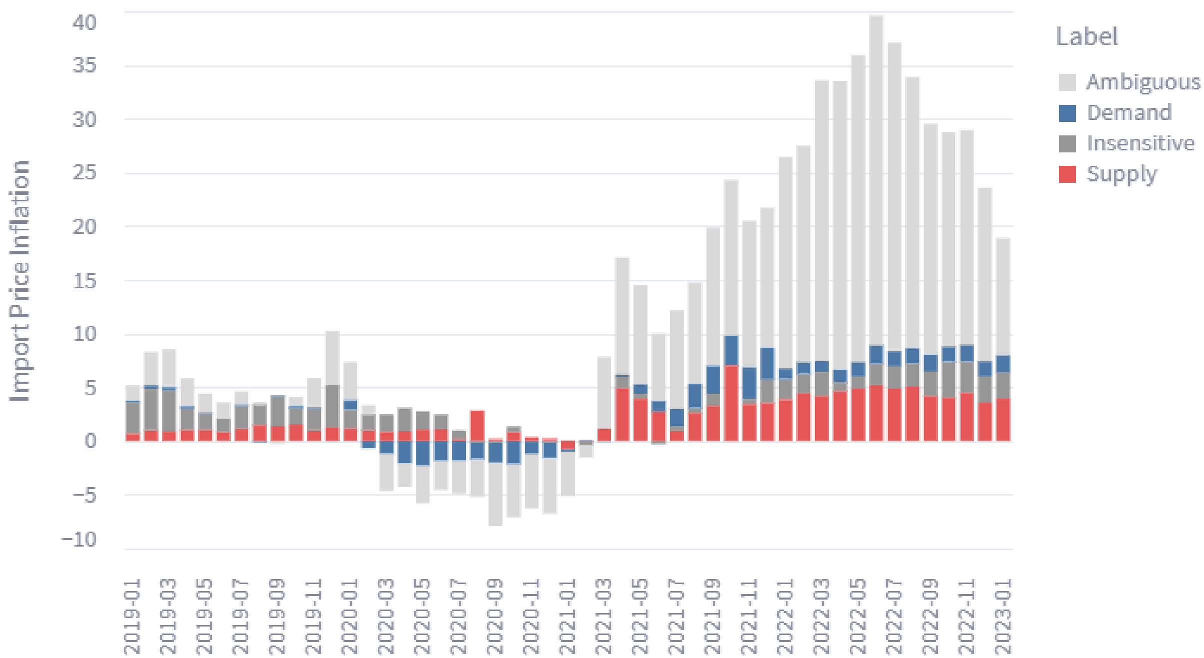
Note: The contribution of each label to inflation is based on the fixed weight UVI.

5.3 Static Labeling

Before analyzing the results from the static labeling one should keep in mind that the ambiguous label does not have the exact same meaning as in dynamic labeling. In the dynamic model ambiguously means that the residual from the VAR model of either quantity or unit value is in the 20% middle percent of the control distribution. Whereas, in the static model, the ambiguous case is when only the estimated parameter for either unit value or quantity is significantly different from the control period, but not both.

The result for Sweden (figure 10) from the static model shows that inflation prior to the Covid-19 outbreak is mainly driven by a mixed effect of ambiguous and insensitive products. Meaning that the dummy variable is insignificant for products that impacts inflation the most as well as significant in terms of either quantity or unit value. When the Covid pandemic strikes, a strong negative effect on inflation is observed, mainly driven by a combination of both demand and ambiguous effects. The following years, 2021 and onwards, is the ambiguous effect the main driving factor in the inflation. However, supply effects are also a considerable portion of the total inflation, especially relative to demand effects.

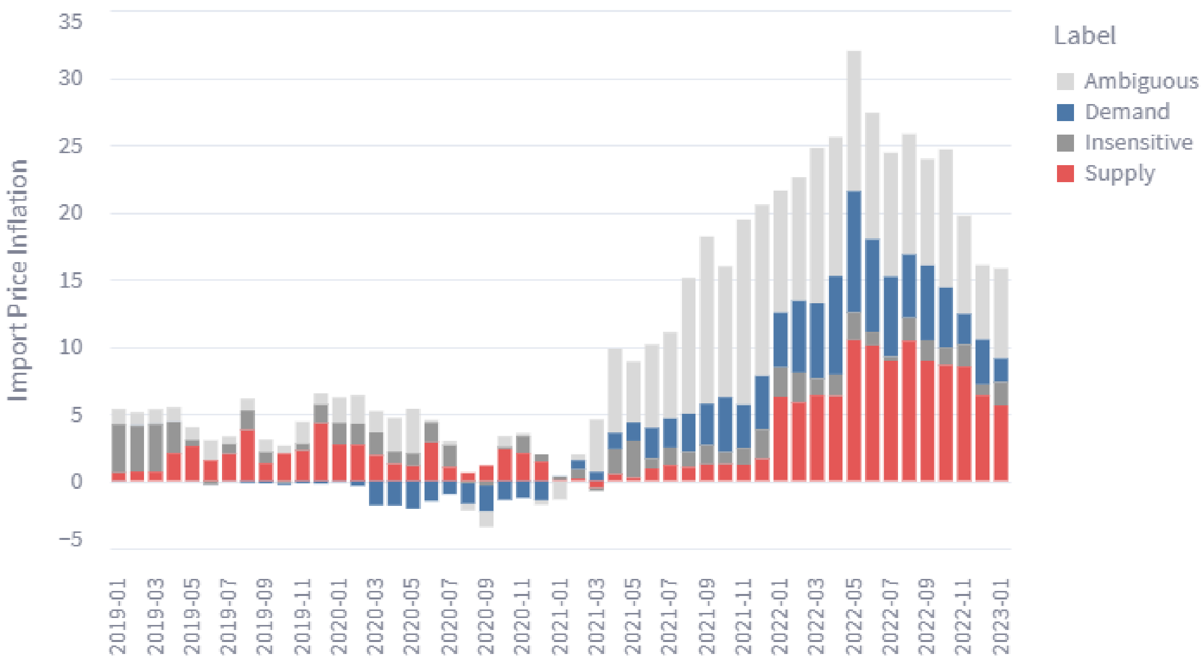
Figure 10: Static labeling, Sweden



Note: The contribution of each label to inflation is based on the fixed weight UVI.

As opposed to Sweden, inflation dynamics for Denmark (figure 11) during the pre-Covid period is mainly driven by supply effects. However, there's also notable similarities, during the initial period of the Covid pandemic the demand driven part displays a negative effect on the inflation. For the period 2021 to 2022, the demand effect is more prominent relative to the influence from supply. In the following period demand is less impactful relative to supply, yet there's a notable influence of demand on the total inflation. When comparing the inflation dynamics between Sweden and Denmark, we find that both supply and demand driven effects are more prominent in Denmark in comparison to its neighboring counterpart.

Figure 11: Static labeling, Denmark



Note: The contribution of each label to inflation is based on the fixed weight UVI.

Similar effects from demand as for Sweden and Denmark are also observable for the largest importers in the EU (appendix B.3, figure 24-26). Demand effects are the main negative effect on the import prices for the three largest importers during the onset of Covid-19. In France (figure 26), demand effect is the main contributor to the inflation effects during the period 2021-2022. For the other countries the same effect can only be said relative to supply (figure 24-25). The inflation effect in France is in large contrast to all other compared countries since it displays such a strong demand driven effect. Common for all countries, are the notable effects of demand relative to supply throughout 2021 and 2022.

6 Discussion

In previous literature both similarities and dissimilarities can be found, the methodology used in this paper is newly invented meaning that previous literature using similar methods are limited. The results will be compared to studies which either examined different countries or used consumer prices instead of import prices.

The findings from the dynamic model show in general similar patterns to previous studies. Though, both Freund (2022), Shapiro (2022) and Gonçalves & Koester (2022) display less oscillating effects between month-to-month. This disparity can be attributed to several factors. Firstly, Shapiro analysis is based on consumer data which relies on other influences compared to import prices. Secondly, data used in his study relies on surveys from BEA (BEA, n.d.). Such data are less biased in comparison to using unit values, offering a more accurate representation of true price changes (IMF, 2009). Gonçalves & Koester (2022) argues that reliability of the VAR is hard to control due to the extraordinary factors in play after the onset of the pandemic. These disruptive factors might also be a contributing factor to the oscillating results. Furthermore Gonçalves & Koester, similarly to Shapiro (2022) uses aggregated indices while also studying the effects on the CPI. In Freund (2022) the lack of details regarding modeling choice makes it harder to fully understand the discrepancies. However, one obvious reason why Freund does not experience the oscillating effects is due to the 3-month moving average used in her method. While moving averages display the general patterns in a smoother way, it would not be possible to capture instant consequences from an occurred event. Our figures picture a more volatile pattern but it also captures effects from monthly changes, such as for Denmark after the Covid-19 outbreak (see figure 9). Further, Freund (2022) uses HS10 codes which have less heterogeneity compered to HS6 codes, also while she examines the United states, this paper looks into the countries of the European Union.

Despite the observed disparities, the dynamic model also has similarities to Freund (2022). The shift in import quantities in the beginning of 2021 which Freund find, can be also be observed in figure 6, 7 & 18-20. The shift in the figures indicates that a larger portion of the products gets labeled as demand. Furthermore, noticeable peaks are displayed by most countries during significant events such as the onset of Covid-19, aligning with Freund's findings.

The results from the static model are naturally less volatile since the labeling only changes once a year. Outcomes from the models also exhibit similarities to previous research. This is especially evident during the outbreak of Covid-19 where the static models result in, for some countries, a drastic influence by demand, driving the import price inflation to negative levels (see e.g. figure 25-26). The results goes in line with Shapiro (2022) who find patterns of negative impact of demand during Covid-19, as well as Freund (2022) who also observe modest excess-demand compared to other periods during the outbreak. One could argue that these results are reasonable due to the economic shock the Covid-19 led to. During 2021, the inflation shifted to drastically increase, the surge in demand relative to supply was one of the reasons, this is especially true for the large importers (figure 24-26). Freund (2022) also finds a similar reaction to the demand-driven inflation in 2021. This contradicts the presumption that the supply constraints should be the main driver of the import price inflation during that period. Though, under 2022, the supply-part seems to substantially influence the inflation. A noticeable trend in most figures is that the supply-driven part becomes a larger share of the total inflation compared to demand when time approaches 2023. There are indications from previous studies with similar patterns but their timelines end earlier to draw such conclusions.

Results from the dynamic and static model occasionally display dissimilar behavior, which is consistent with the findings from Shapiro (2022). One explanation for this disparity is the difference in the labeling methods employed by the two models. While the dynamic labeling classifies a product as supply or demand if the residual is different from the middle 20% in the control distribution, the static model only labels products as supply or demand if the estimated parameters t-value is significant. This results in much smaller portion being labeled as supply or demand. Shapiro classifies a minor part as supply driven in the static model while it is one of the main drivers of the inflation in the dynamic model. Our study also finds discrepancies between the models, though not as noteworthy as his.

7 Conclusion

In this thesis, we have decomposed the import price inflation for the EU countries to supply and demand driven inflation. The two major events during the examined period, Covid-19 and the war in Ukraine demonstrated vast changes in the import sector in terms of supply and demand effects. Both the static and dynamic model has provided insights into the effects on imports in EU countries during times of impactful events.

Our findings indicate that the impact from demand, particularly for certain countries, increased during the time of the Covid-19 outbreak and shortly thereafter. This effect emerged as one of the main driving factor to the negative import price inflation. Thereafter, in contrast to the outbreak of Covid-19, surging demand was instead one of the key drivers behind the increasing inflation. Insights such as this can be valuable for policy-makers and economists within monetary-policy, fiscal policy and trade-policy.

Moreover, the two methods used have been compared and evaluated, between each other as well as with previous literature. The dynamic model resulted in volatile results compared to previous research, this is due to the data and methodology used. However, our results can still provide insightful information, since they capture effects from events such as the pandemic and the war in Ukraine. The static model provides less volatile results and occasionally finds similar patterns to previous studies. Though, it should be noted that previous research using similar frameworks is limited, making the comparison challenging, also highlighting the uniqueness of this study.

Furthermore, an additional contribution of this thesis is the development of a dashboard, which was a initiated from Denmarks Nationalbank as a part of this project. In the dashboard, users can freely explore the result and the influence of each product, for all countries in the European Union. The link to the dashboard is provided below.

Link to dashboard: Dashboard

7.1 Future Research and Limitations

In this thesis we assign weight to the corresponding product based on its imported value. However, there's an extensive amount of products that could not be utilised because of the limited availability of quantities. Alternative methodologies could therefore have a notable effect on the indices. One approach for this would make use of the two classification system, The Harmonized system (HS) and Classification of Products by Activity (CPA). On Eurostat, indices using the CPA system with corresponding weights is available for some categories as well as some countries. By concatenating the HS codes to CPA and make use of the corresponding weight, could therefore have impacted the outcome. This process, however, is time consuming, which due to time constraints made it impractical for this thesis.

Furthermore, one could have used databases such as UN Comtrade to get more complete data. As mentioned in Section 3, Eurostat reporting threshold is per 100kg, this dilutes quantities to zero for most products while UN Comtrade is available in per kg. Due to restricted API availability this was not feasible for this thesis. This would result in two enhancing differences. Firstly, with more comprehensive data sets, methodologies that rely on cross-country data becomes more viable for detection of outliers. This also enhances comparability across countries. Secondly, this generates more complete data set for more products which both reduces the small sample-bias as well as enhancing the representation of the unit value indices.

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A Appendix

A.1 Country Abbreviations

Table 2: List of Countries and Country Code

Country	Country Code
Austria	AT
Belgium	BE
Bulgaria	BG
Croatia	HR
Cyprus	CY
Czech Republic	CZ
Denmark	DK
Estonia	EE
Finland	FI
France	FR
Germany	DE
Greece	GR
Hungary	HU
Ireland	IE
Italy	IT
Latvia	LV
Lithuania	LT
Luxembourg	LU
Malta	MT
Netherlands	NL
Poland	PL
Portugal	PT
Romania	RO
Slovakia	SK
Slovenia	SI
Spain	ES
Sweden	SE

A.2 Product Filtering

Table 3: Removed Products

Country code	No. Removed HS6	Percentage removed
AT	5254	0.6499
BE	5127	0.6342
BG	6477	0.8012
CY	7438	0.9201
CZ	5751	0.7114
DE	4422	0.5470
DK	5675	0.7020
EE	6822	0.8439
ES	5143	0.6362
FI	6028	0.7457
FR	4647	0.5748
GR	6262	0.7746
HR	5995	0.7416
HU	6186	0.7652
IE	6122	0.7573
IT	4738	0.5861
LT	6665	0.8245
LU	6883	0.8514
LV	6989	0.8645
MT	7888	0.9758
NL	5095	0.6303
PL	5241	0.6483
PT	5658	0.6999
RO	5743	0.7104
SE	5532	0.6843
SI	6165	0.7626
SK	6210	0.7682

A.3 Dickey Fuller Tests

Table 4: Dickey-Fullers Tests, Spain

Product	**Type**	**p-value**
020010	Quantity	0.16
020010	Price	0.09
282739	Quantity	0.29
282739	Price	0.55
292124	Quantity	> 0.01
292124	Price	0.28
390529	Quantity	0.37
390529	Price	0.58
481940	Quantity	0.21
481940	Price	0.01
700239	Quantity	0.18
700239	Price	0.07
800110	Quantity	0.05
800110	Price	0.71
821410	Quantity	0.24
821410	Price	0.94
903289	Quantity	0.73
903289	Price	0.09
940340	Quantity	0.05
940340	Price	0.24

A.4 Total Import & after Removal

Table 5: Sustained Value after Outliers

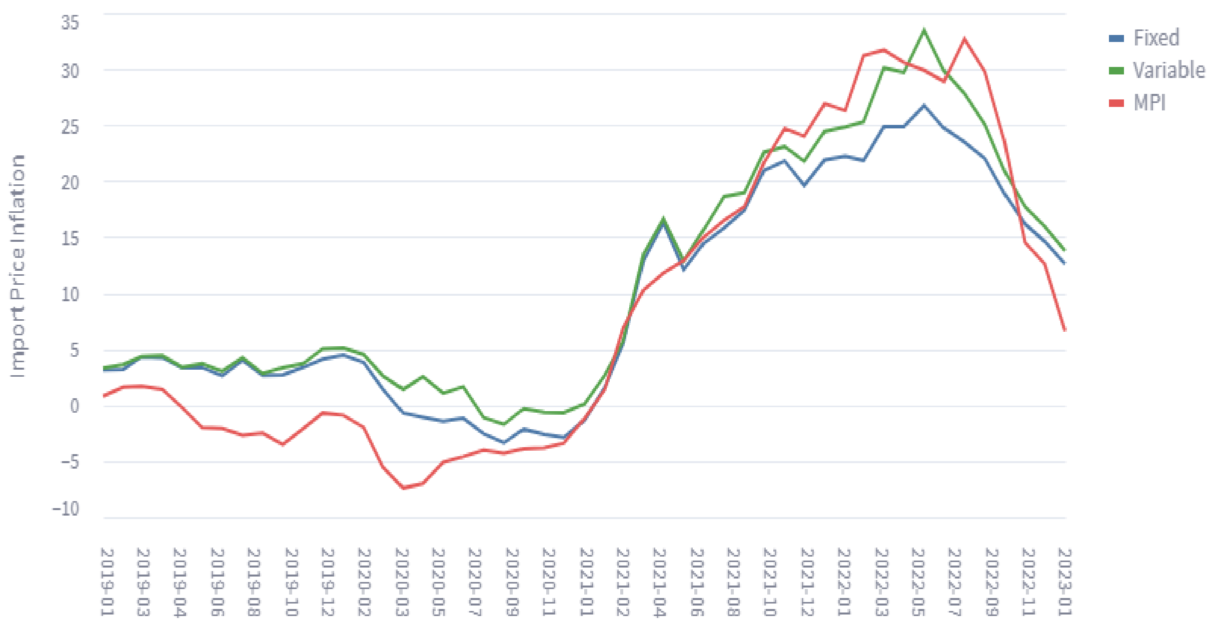
Reporter	Total import value	Imports value after removal	(%)
AT	€904,331,786,145	€560,044,971,688	61.9
BE	€2,202,987,420,878	€1,016,858,076,587	46.2
BG	€194,936,465,388	€63,567,472,272	32.6
CY	€46,833,423,492	€10,985,898,016	23.5
CZ	€887,970,902,529	€279,035,032,059	31.4
DE	€6,028,502,568,430	€3,970,682,354,056	65.9
DK	€492,065,944,119	€235,236,864,970	47.8
EE	€94,184,752,912	€26,936,112,376	28.6
ES	€1,809,090,177,050	€714,600,660,877	39.5
FI	€363,871,545,441	€202,948,876,735	55.8
FR	€3,113,447,029,857	€1,528,795,135,339	49.1
GR	€324,063,365,475	€162,383,076,899	50.1
HR	€146,990,717,004	€73,542,846,676	50.0
HU	€601,786,639,828	€262,542,396,040	43.6
IE	€521,205,607,995	€81,263,362,462	15.6
IT	€2,411,401,235,369	€1,349,070,919,018	55.9
LT	€185,878,001,622	€60,780,927,241	32.7
LU	€109,946,520,937	€32,908,279,607	29.9
LV	€100,553,925,078	€25,437,777,109	25.3
MT	€32,123,668,967	€1,175,649,990	3.7
NL	€3,203,010,170,643	€1,227,857,922,111	38.3
PL	€1,372,353,253,848	€768,565,222,232	56.0
PT	€424,418,838,909	€245,690,410,845	57.9
RO	€483,479,346,529	€242,725,833,556	50.2
SE	€782,953,230,839	€479,431,594,300	61.2
SI	€232,882,394,245	€136,760,924,426	58.7
SK	€436,159,496,003	€123,657,979,262	28.4

Source: Eurostat

B Appendix

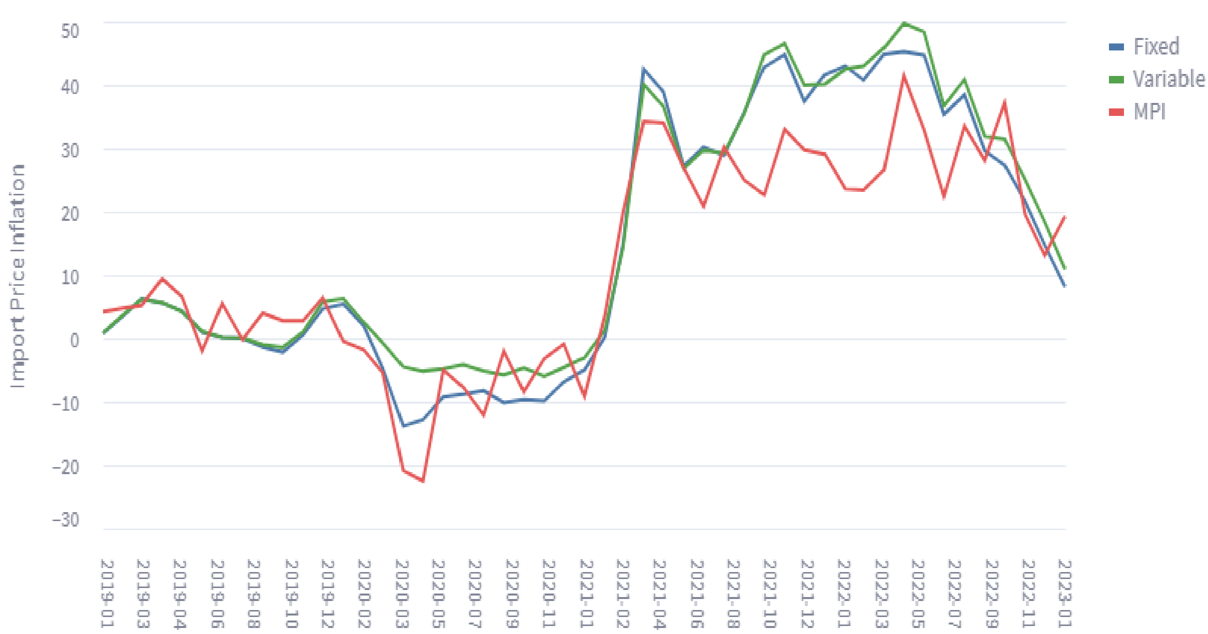
B.1 Benchmarking

Figure 12: UVI vs MPI, Germany



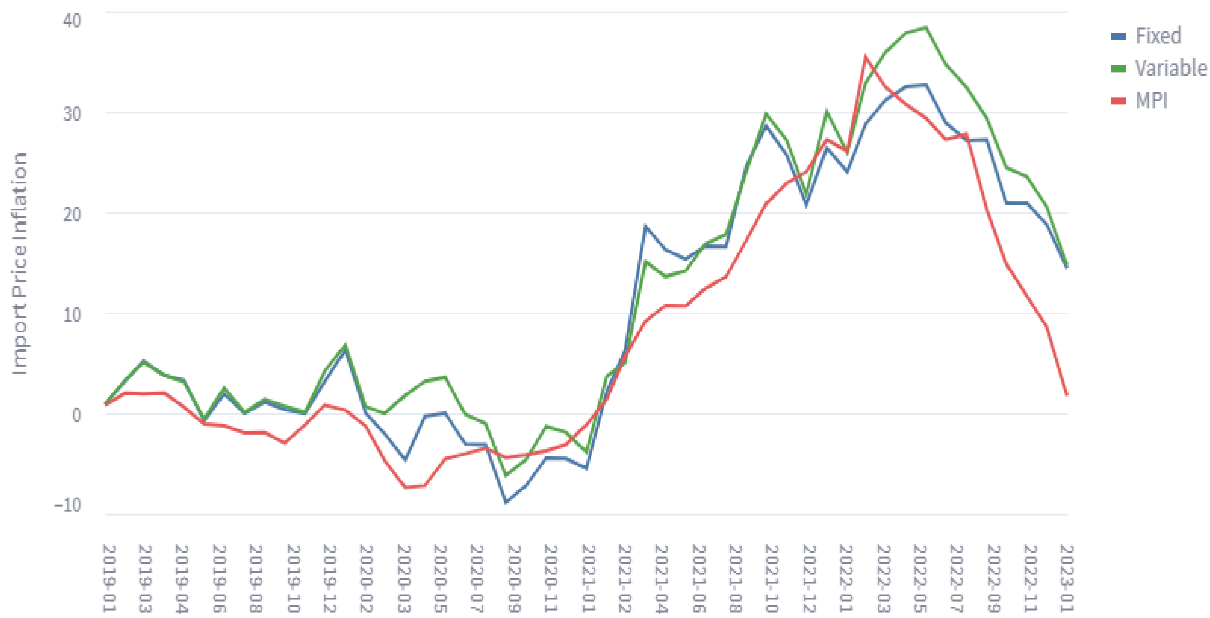
Note: The data for the MPI is collected from Federal Statistics Office of Germany (n.d).

Figure 13: UVI vs MPI, Netherlands



Note: The data for the MPI is collected from CBS (n.d).

Figure 14: UVI vs MPI, France.



Note: The data for the MPI is collected from Insee (n.d).

B.2 Dynamic Labeling

Figure 15: Dynamic labeling, Germany

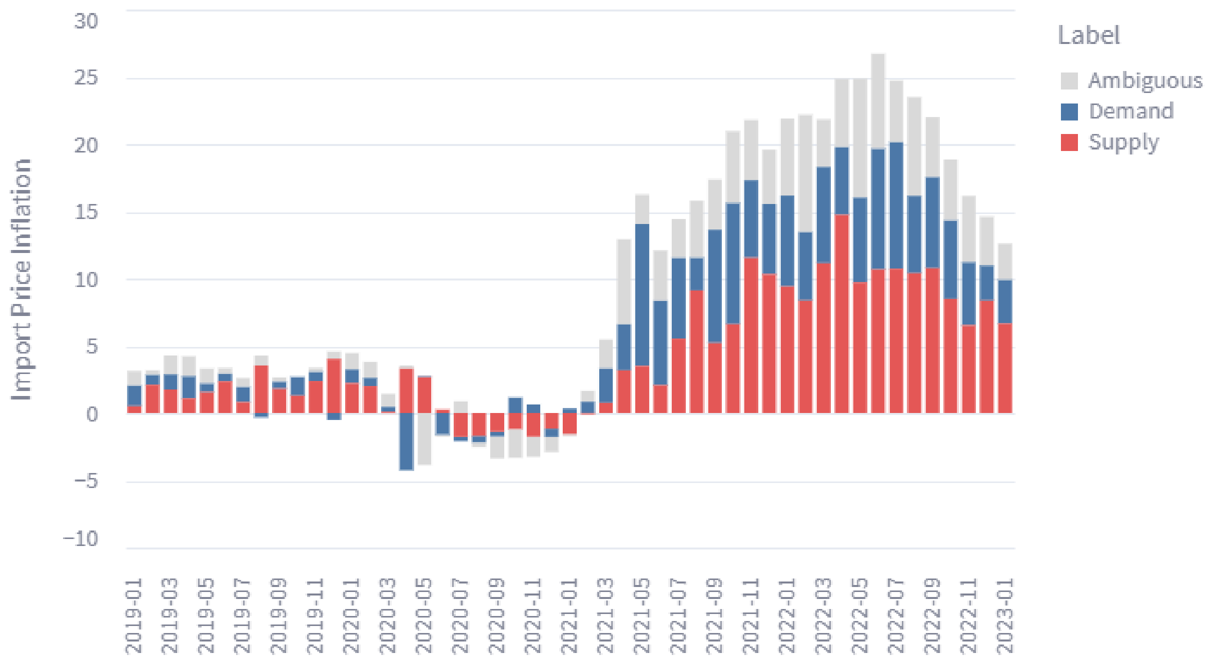


Figure 16: Dynamic labeling, Netherlands

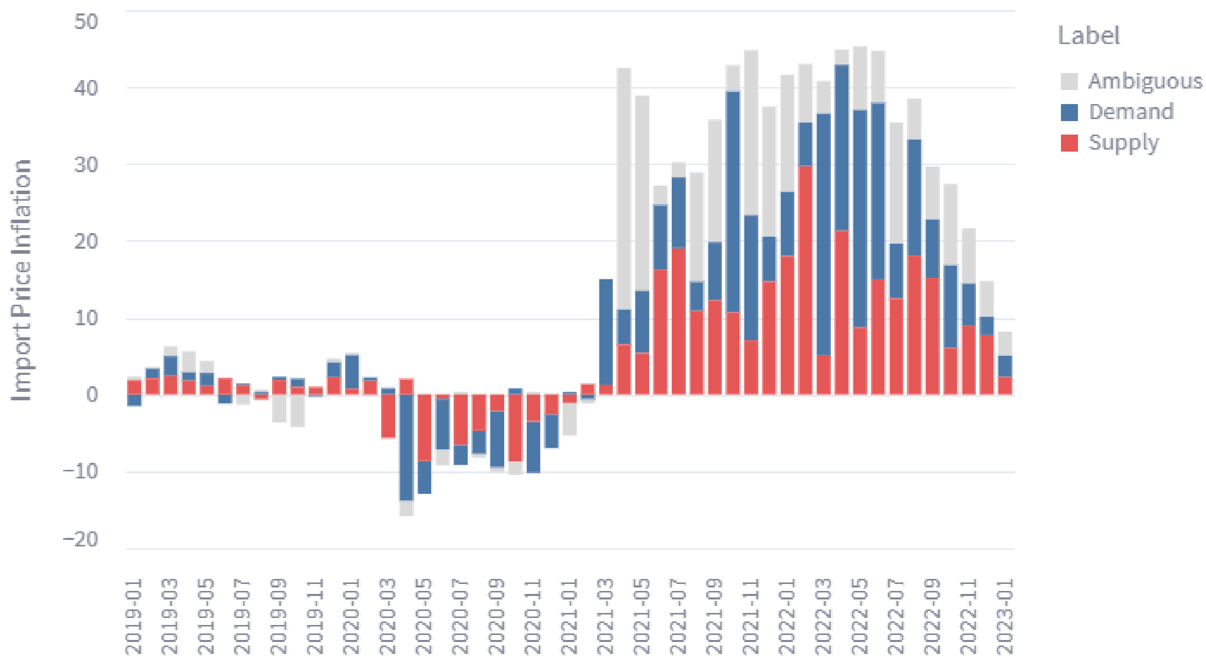
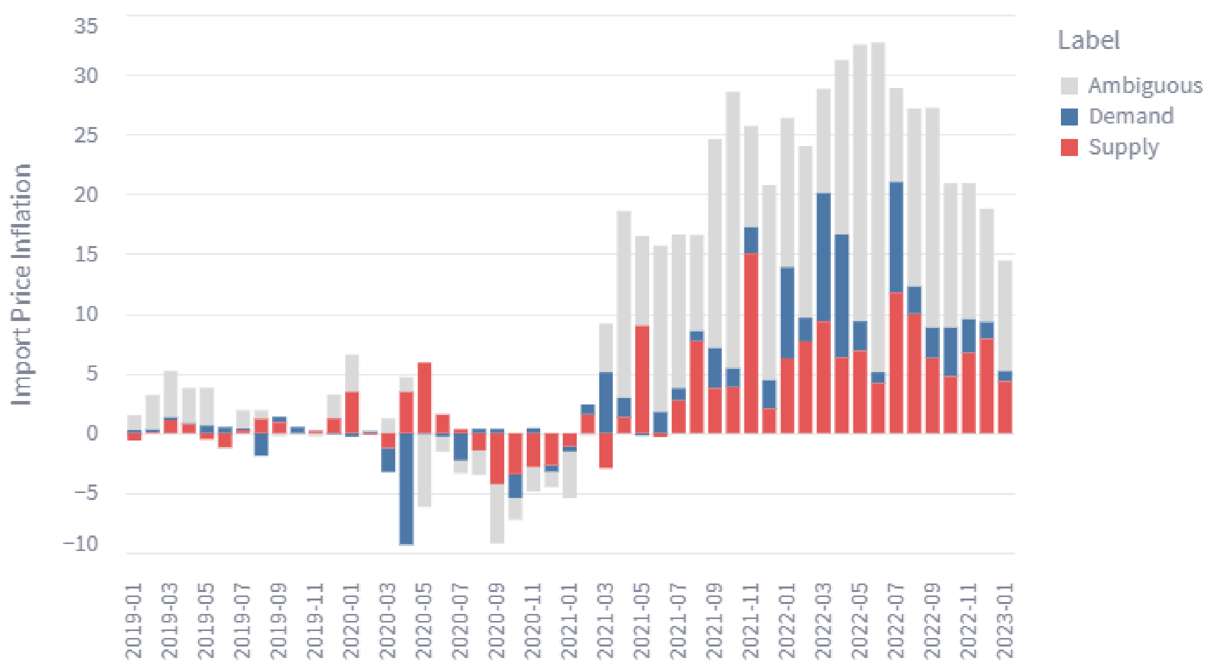


Figure 17: Dynamic labeling, France



B.2.1 Evolution of Proportions

Figure 18: Proportion of labels, Germany

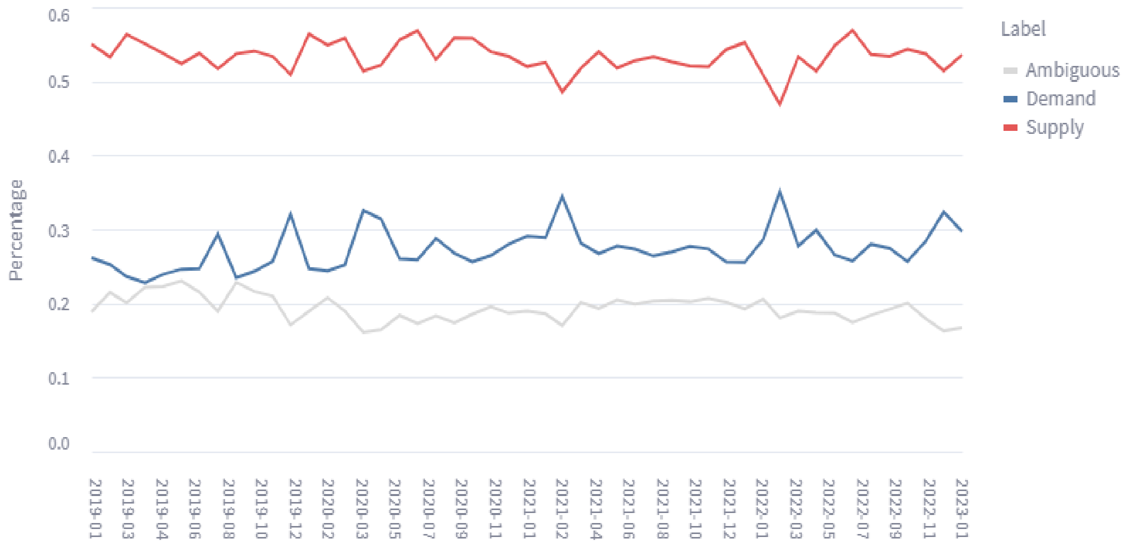


Figure 19: Proportion of labels, Netherlands

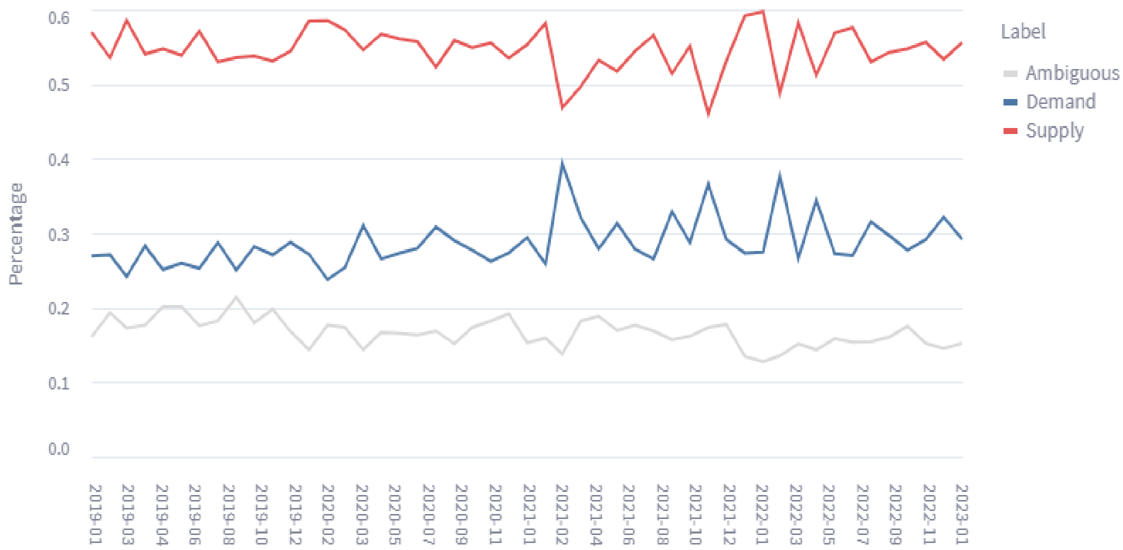
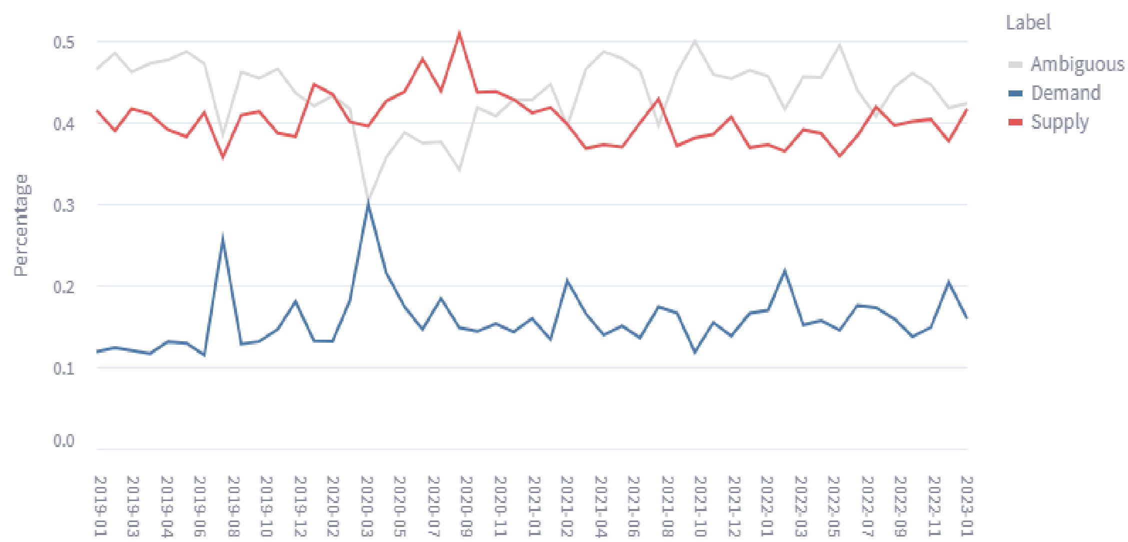


Figure 20: Proportion of labels, France



B.2.2 Effect of Supply and Demand

Figure 21: Supply and demand contribution, Germany

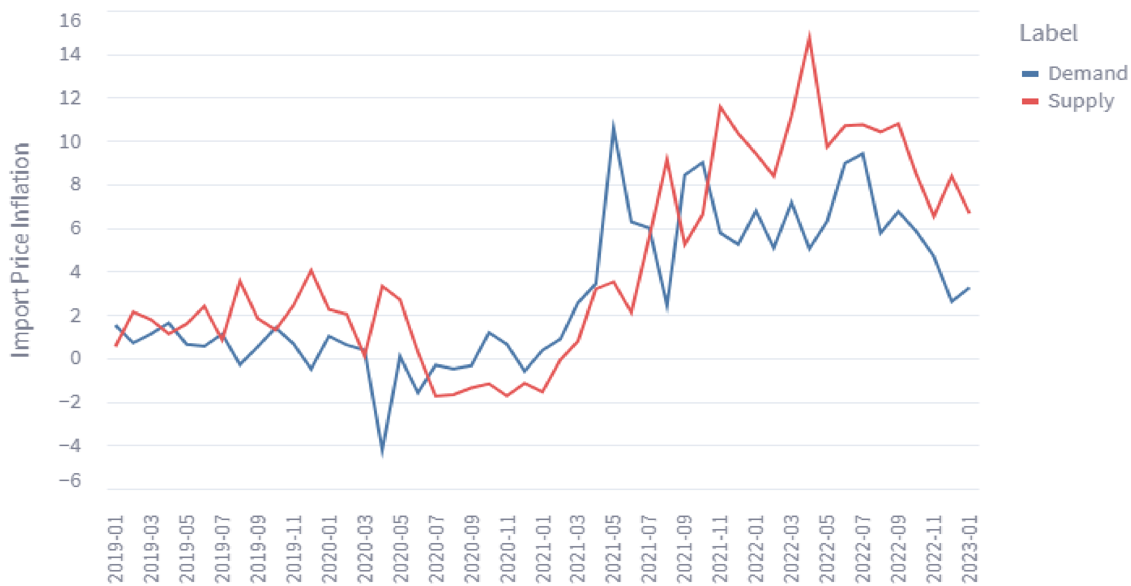


Figure 22: Supply and demand contribution, Netherlands

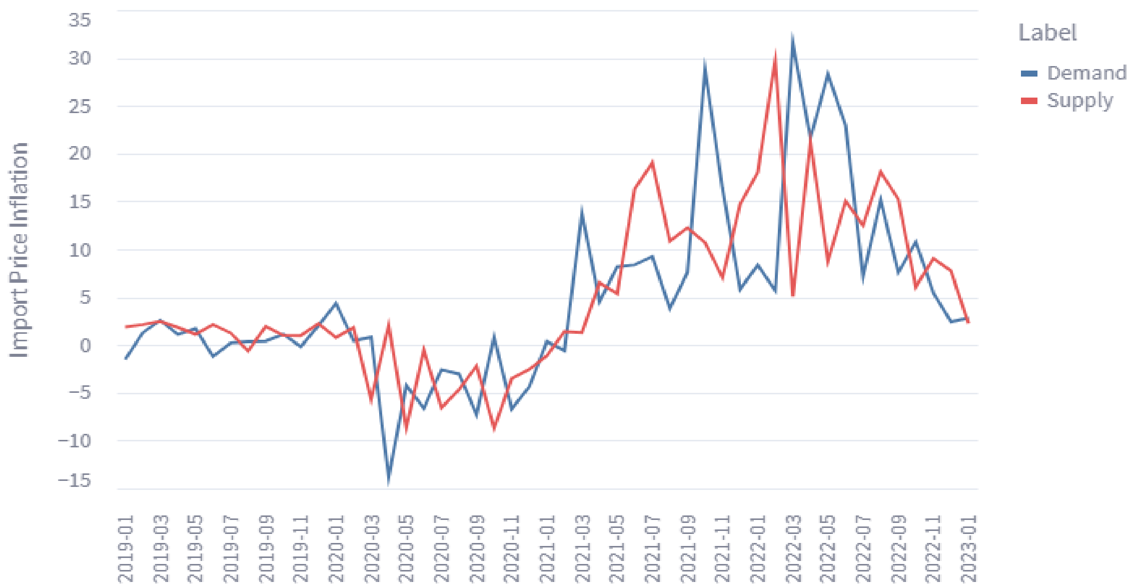
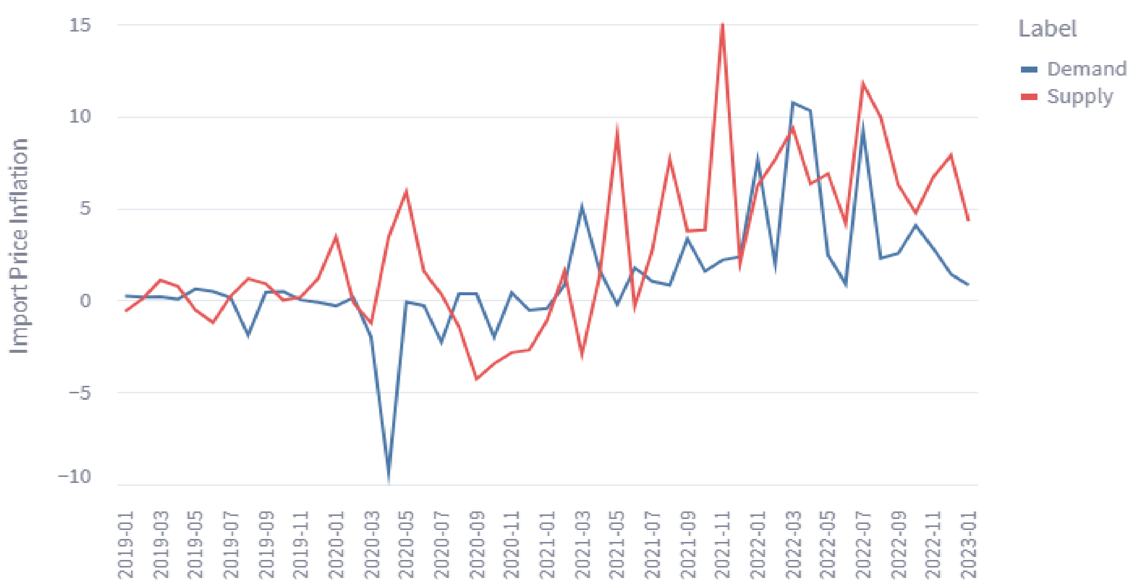


Figure 23: Supply and demand contribution, France



B.3 Static Labeling

Figure 24: Static labeling, Germany

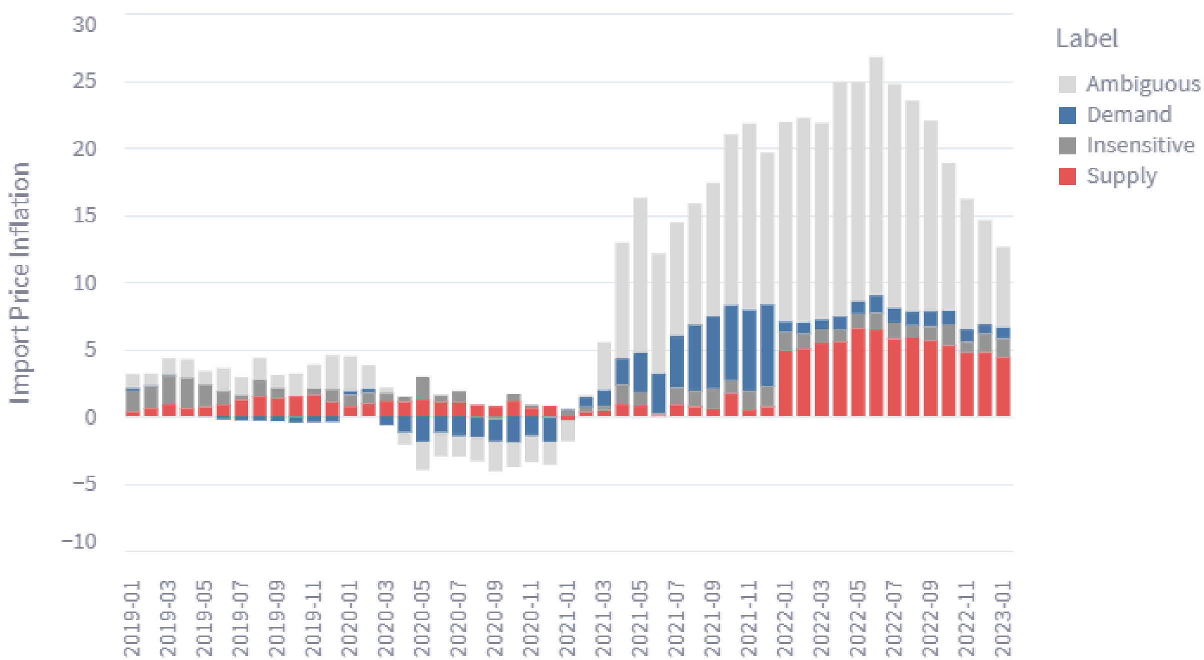


Figure 25: Static labeling, Netherlands

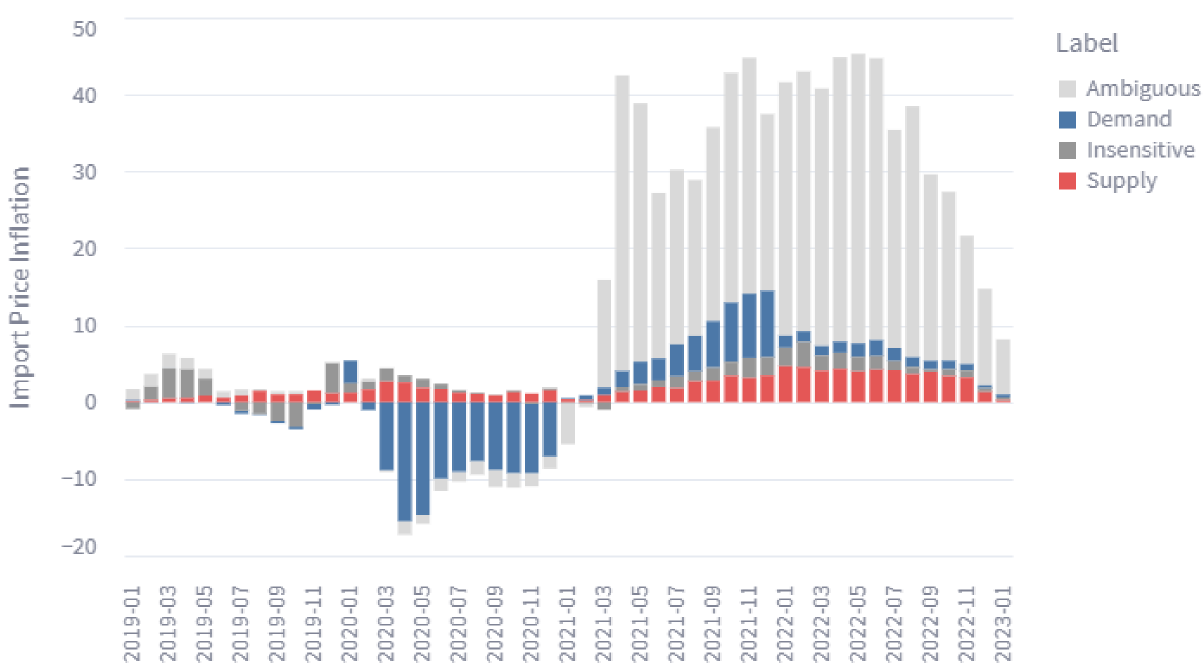


Figure 26: Static labeling, France