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Investigating Non-Linear Exchange Rate Pass-Through in Sweden: Estimates from a Logistic Smooth Transition Vector Autoregressive Model

Gabriella Linderoth (42423) and Malte Meuller (42431)

Abstract: This paper provides novel estimations of a non-linear exchange rate pass-through dependent on inflation for Sweden using a logistic smooth transition vector autoregressive model. The model enables smooth transitions between high and low inflation regimes, mirroring the dynamics of the economy and capturing regime-specific effects. The results show that the pass-through from an exchange rate depreciation shock to consumer prices depends on the level of inflation, reaching 17.4% in the high inflation regime and 6.9% in the low inflation regime. The estimations utilize data from the period 1995Q1 to 2023Q2, covering periods of both low and high inflation, as well as substantial exchange rate depreciations. The pass-through is also estimated for producer and import prices, establishing a decreasing pass-through along the pricing chain. We find limited evidence of a regime-dependent pass-through to producer prices and no evidence for import prices. The findings suggest stronger monetary policy reactions following a depreciation of the exchange rate in high inflation environments to limit the pass-through and, by extension, the impact on consumer prices.

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1 Introduction

The Exchange Rate Pass-Through (ERPT) investigates how fluctuations in the exchange rate affect consumer prices. Various channels contribute to the impact, but the effect is primarily driven by increases in import prices that are subsequently transmitted to consumer prices (Ortega & Osbat, 2020). Exchange rate movements impact the overall economy, but its effect on inflation become of importance for central banks when conducting monetary policy (Forbes et al., 2018). A flawed comprehension of the ERPT may result in inadequate inflation prevention or overly contractionary policies, damaging the economy. The importance of understanding the dynamics and magnitude of the ERPT could also be extended to governments, businesses, and economic agents relying on correct information about price fluctuations (Rincon & Rodríguez, 2016). In the context of a small open economy with a floating currency, such as Sweden, the relevance of the ERPT is amplified for two main reasons. First, the exchange rate tends to be more volatile, leading to more frequent depreciations. Second, small open economies tend to have characteristics suitable for greater impact of depreciation shocks, such as a higher share of imported goods in the final consumer basket (Khan & Savoie-Chabot, 2015).

For Sweden, periods of significant depreciation of the Swedish Krona can be observed around 2002, 2008, 2017, and 2022. In close proximity, increases in import prices and consumer prices are also observed, see Figure 1. Particular attention is given to the depreciation of the Swedish Krona in 2022/2023, as it coincided with inflation rising to the highest levels in over 30 years. This development heightened the Riksbank's awareness of the ERPT in Sweden, as evident from their statements and public speeches (Sveriges Riksbank, 2023a). Sweden has also experienced more volatility in the exchange rate and higher persistence in inflation compared to other small open economies such as Canada, Norway, and Denmark (World Bank, 2023), drawing additional attention to the topic.[1] However, the most recent in-depth analysis of the ERPT for Sweden includes data until 2017 (Corbo & Di Casola, 2022), which underscores the importance of updated estimates.[2] Corbo & Di Casola (2022) find that following an exogenous depreciation shock, the pass-through to consumer prices is 5% and has fully fed through after 2 years.[3] Updated estimations of the ERPT could enhance the understanding of the high inflation period in 2022/2023, as well as of the low inflation period predominant between 2009-2021.

The impact of the ERPT is primarily attributed to three channels (Colavecchio & Rubene, 2020). First, the price of imported goods rises, establishing a direct link between the exchange rate and inflation. Second, the prices of domestically produced goods, using imported inputs, increase, creating an indirect channel to inflation. Third, the exchange rate depreciations indirectly make domestically produced goods relatively less expensive than imported goods, thus exerting upward pressure on domestic demand and inflation.

The majority of the ERPT literature focuses on explaining the magnitude of the ERPT by emphasizing country-specific characteristics, such as the share of imported goods in the consumption basket (Khan & Savoie-Chabot, 2015), trade openness, invoice currency, and market power (Ortega & Osbat, 2020).

[1] See Holmgren (2023), Isaksson (2023), and Krusell (2023) for discussions about the exchange rate's effect on inflation.

[2] Other studies provide estimates for Sweden using data up to 2021, see Anderl & Caparole (2023), or Ortega & Osbat (2020) using data up to 2019. However, these studies use cross country panel data and does not put emphasis on Sweden.

[3] For a discussion about different measures used in the literature *See 5.5 Exchange Rate Pass-Through*.

Another field of research finds that the ERPT can be non-linearly dependent on dynamic characteristics in the economy, such as economic activity (Campa & Goldman, 1999), or monetary policy credibility (Kwon & Shin, 2023). The seminal paper by Taylor (2000) suggests that the ERPT is non-linear with respect to the level of inflation. Taylor (2000) states that low inflation causes low ERPT due to lower persistence in cost changes, and that high inflation makes firms more likely to pass on depreciation shocks.

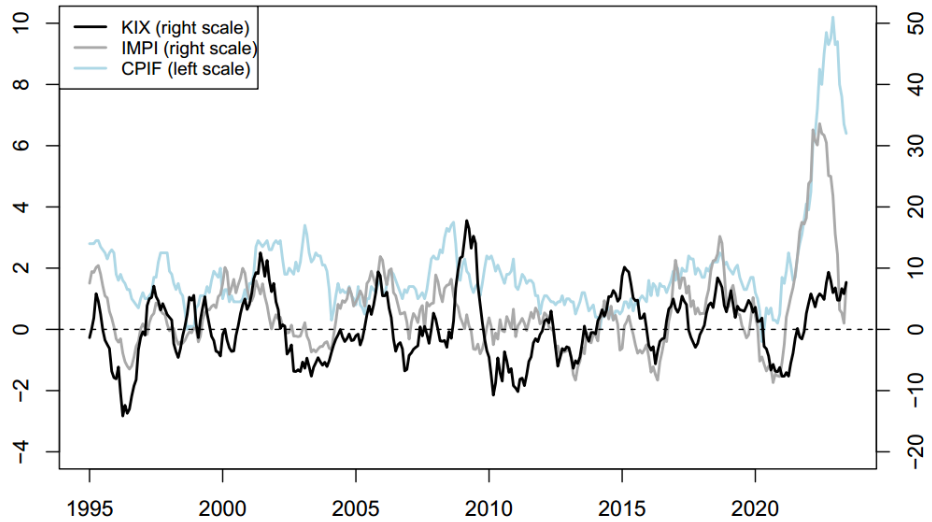

Figure 1: Inflation and the Krona Index (KIX)

Note: The figure displays the change in import prices (IMPI) and the Swedish nominal effective exchange rate index (KIX), plotted against the right axis, and consumer prices (CPIF), plotted against the left axis. The variables are on a monthly frequency and computed as the annual rate of change.

A common practice in the literature involves establishing a "rule of thumb" for the magnitude of the ERPT, providing a reference point for policymakers of how much inflation is expected to increase in response to a depreciation in the exchange rate (Forbes et al., 2018). These guideline are derived from models making linear assumptions about exchange rates and price movements (Borio et al., 2023). In the Riksbank's Monetary Policy Report published in June 2023, scepticism about the accuracy of the ERPT guidelines for Sweden is expressed. Notably, the Riksbank (2023b) suggests that the ERPT may be higher during periods of high inflation, proposing a non-linear relationship, similar to Taylor (2000).

This paper will investigate to what extent the ERPT depends on the level of inflation in Sweden for the period of 1995Q1-2023Q2. To capture potential non-linear dynamics, we employ a Logistic Smooth Transition Vector Autoregressive model (LST-VAR) with a Cholesky decomposition. This modeling approach facilitates meaningful economic interpretation of the estimates and allows for regime-specific dynamics in a more coherent fashion than comparable models. We will measure the ERPT for consumer prices (CPIF), producer prices (PPI), and import prices (IMPI) to analyze how the ERPT is transmitted along the pricing chain. In addition, our findings will be complemented with qualitative evidence from The Riksbank's Business Surveys to highlight the individual pricing decision behind the aggregate measures analysed.

The results of our paper provide novel evidence of a non-linear ERPT to consumer prices in Sweden, reaching 17.4% in the high inflation regime and 6.9% in the low inflation regime. In addition, we estimate a linear ERPT of 92% to import prices, 57% to producer prices, and 11% to consumer prices. We find indications of a regime-dependent ERPT to producer prices and no evidence for a regime-dependent ERPT to import prices. In accordance to previous research, the ERPT is found to be declining along the pricing chain, but the relative divergence between the regimes is found to be increasing along the pricing chain. Our findings suggest stronger contractionary monetary policy following a depreciation of the exchange rate in a high inflation regime to limit the pass-through and the impact on inflation.

This paper contributes to the literature in several ways. First, we expand the knowledge about how exchange rate depreciations impact inflation by providing novel evidence of a non-linear ERPT for Sweden. Second, by estimating the ERPT with the latest data available, we provide insights of the driving forces of the 2022/2023 inflation period. Last, we contribute to the non-linear literature by further developing the usage of quasi-Bayesian estimations for LST-VAR models. These contributions could be useful for central banks and government, not only for ERPT estimations, but also for analysing other non-linear relationships in the economy.

The paper is structured as follows: Chapter 2, 3 and 4 provides a literature review, description of the data and background information on the Swedish case. Chapter 5 elaborates on the methodology, while Chapter 6 presents the results. Lastly, Chapter 7 and 8 includes a discussion and the conclusions.

2 Literature Review

This section summarizes the traditional ERPT literature and the research on ERPT along the pricing chain. Furthermore, we present theoretical frameworks for non-linear studies of the ERPT as well as literature on inflation regime dependent ERPT.

2.1 ERPT and the Pricing Chain

The ERPT literature has established multiple factors impacting the size of the pass-through. Predominant country-specific factors include the share of imported goods in the consumption basket (Khan & Savoie-Chabot, 2015), trade openness, invoicing currency, market power (Ortega & Osbat, 2020) and the frequency of price adjustments (Gopinath & Itskhoki, 2010). Studies using disaggregated data reveal a divergence in the ERPT between goods, where homogeneous goods, such as oil and raw materials, have a higher ERPT (Ben Cheikh & Rault, 2017). The ERPT is also found to be asymmetric, where greater exchange rate shocks have a disproportional effect on prices (Colavecchio & Rubene, 2020). The degree of pass-through has also shown to be time-variant, with a declining trend in the ERPT over the last 20 years (Campa & Goldberg, 2008). Another strand of literature finds that the origin of the underlying shock that impacts the exchange rate determines the size of the ERPT (Shambaugh, 2008; Forbes et al., 2018; Corbo & Di Casola, 2022). Notably, the ERPT literature offers multifaceted insights, contributing to the understanding of the pass-through dynamics. However, in this paper, the focus will be on the literature concerning ERPT along the pricing chain and non-linear ERPT dependent on inflation.

Previous research has established that the ERPT decreases along the pricing chain, resulting in a higher pass-through for import prices compared to producer and consumer prices (see McCarthy, 2000; Ito & Sato, 2006; Ben Cheikh & Louhichi, 2015). While Ito & Sato (2006) find these results for the East Asian countries, the estimates for the UK and the U.S are more ambiguous (McCarthy, 2000). McCarthy (2000) also states that higher persistence in exchange rate shocks leads to greater ERPT. Ben Cheikh & Louhichi (2015) extends McCarthy's (2000) approach, assuming a cointegrating relationships between the variables. Their findings, covering 12 euro area countries between 1980-2010, provide evidence of a decreasing ERPT along the pricing chain. The estimated ERPT (accumulated over 8 quarters) spans from 69-137% for import prices, from 3-111% for producer prices, and from 7-28% for consumer prices. The variation is explained by differences in inflation levels, persistence in the exchange rate shock, and inflation volatility.

Ortega & Osbat (2020) provide a summary of estimated ERPT to import and consumer prices in the euro area, obtained from VAR-models. For consumer prices the estimates range from 4-10% and to import prices between 30-70%. For EU countries that are not members of the euro area, ERPT to import prices is generally higher, ranging from 40-80%.

2.2 ERPT and Inflation

Non-linear ERPT dependent on inflation, was first suggested in the seminal paper by Taylor (2000). Taylor (2000) constructs a micro model where firms set prices for several time periods ahead to derive a relationship between low inflation, low persistence in cost shocks, and low pass-through. For example, if firms believe that cost increases are occasional, such as temporary exchange rate depreciations, they are less likely to adjust their prices to compensate for increased costs. Furthermore, Taylor argues that low inflation causes lower markups, as firms refrain from increasing prices to avoid losing market shares. Taylor (2000) therefore states a direct linkage between inflation and pass-through.

In light of the rise in inflation in 2022/2023, new perspectives on pass-through and inflation have emerged. Borio et al. (2023) provide a "two-regime view" for understanding price dynamics in high and low inflation. First, the cost shocks related to low inflation are more sector-specific and do not correspond to movements in aggregate inflation. In contrast, cost shocks related to the high inflation regime tend to have a broader impact, affecting aggregate price levels, for example, energy or exchange rate shocks. Second, the cost shocks are amplified or reduced as the difference in spillover effects, i.e., that prices in one sector affects the prices of other sectors, is regime-dependent. In the high regime, spillovers between sectors are more pronounced, while in the low regime, spillover effects decrease, making inflation self-stabilizing and less sensitive to cost shocks. Borio et al. (2023) also state that firm markups increase with the level of inflation as firms try to protect the current, but more importantly, future markups, as they anticipate future cost increases. Similar to Taylor (2000), Borio et al. (2023) argue for the existence of self-stabilizing forces maintaining the current inflation regime.

Weber & Wasner (2023) further expand on why markups are able to increase despite higher inflation. They argue that industry-wide upstream cost shocks, for example increases in energy prices or exchange rate depreciations, could effectively function as tacit collusion by creating a signal for firms within an industry to raise prices at the same time. This in turn reduce the competitiveness and increase the markups. Additionally, Weber & Wasner (2023) state that the public knowledge about the shocks play an important role in shaping consumer perceptions of the legitimacy of price increases by firms.

Even if Taylor's (2000) analysis focuses on the relationship between low inflation and low pass-through, the framework has been frequently used, and further developed, for example by Borio et al. (2023), to understand the exchange rate pass-through in high and low inflation environments. In addition, the research by Weber & Wasner (2023) could be used to complement the understanding of the specific dynamics in the high regime.

2.3 Non-Linear Literature

Estimations of non-linear relationships could be conducted with various methods and help to uncover complex and more realistic dynamics of the economy that linear models fail to capture (Albu, 2006). Bacon & Watts (1971) first argued for estimations incorporating smooth transitions between different states of the economy to capture the sluggish movements of macro variables. Chan & Tong (1986) extended this to an autoregressive smoothing transition model which was later developed in the seminal paper by Teräsvirta (1994) by incorporating a logistic and a exponential smoothing function as well as providing a general specification procedure. In the ERPT literature, non-linear models have enhanced the understanding of the ERPT dynamics. Common approaches include Threshold-autoregressive models (Aleem & Lahiani, 2014) and Smoothing autoregressive models (Kwon & Shin, 2023), with both single and vector equation specifications, as well as local projection models (Colavecchio & Rubene, 2020; Carrière-Swallow et al., 2023).

2.4 Non-Linear ERPT Dependent on Inflation

Ben Cheikh (2012) estimate a non-linear ERPT to consumer prices in the euro area using a logistic smoothing autoregressive model with lagged inflation as the transition variable and finds evidence of regime dependent ERPT for 8 of 12 countries during the sample period of 1975-2010. Aleem & Lahiani (2014) expand the autoregressive ERPT equation to a vector model by using a Threshold-VAR to analyze the regime-dependent ERPT in Mexico and conclude that the ERPT is higher for high inflation environments. Aleem & Lahiani (2014) also state that the depreciation shocks are more persistent in periods of high inflation which tends to incentivize firms to increase prices, similar to the findings by Taylor (2000) and Borio et al. (2023).

Kwon & Shin (2023) provide additional perspectives by analyzing non-linear ERPT dependent on the central bank's credibility in South Korea, using an LST-VAR model. By incorporating import, producer, and consumer prices, Kwon & Shin (2023) find evidence of regime-dependent ERPT for consumer prices but not for producer or import prices. They state that following a depreciation shock, higher credibility will limit the size of the ERPT as the central bank will achieve its policy objectives faster. In contrast, lower credibility implies that firms believe inflation to become more persistent and therefore push over a larger share of the cost increases, resulting in a higher ERPT. Anderl & Caporale (2023) reach the same conclusions regarding consumer prices but with more ambiguous evidence for all three price measures.

Carrière-Swallow et al. (2023) estimate non-linear ERPT dependent on the inflation level using local projections. The paper studies 46 countries for the period of 1990-2022 and finds insignificant ERPT to consumer prices in the low regime and up to a 40% impact in the high regime. The ERPT to import prices is not dependent on regime and is estimated to be around 40-60%. Additionally, they observe an immediate impact for import prices, while the impact on consumer prices is more moderate in the first periods.

3 The Swedish Case

This section further motivates the analysis of non-linear ERPT in Sweden and provides additional information relevant for Sweden as a subject of study. As stated by Apel et al. (2004), inflation is the aggregate outcome of individual companies pricing decisions and by utilizing theoretical and empirical research, along with qualitative evidence from the Riksbank's Business Surveys[4], we provide insights about the pricing behavior of firms to complement the macroeconomic analysis.

There are several compelling reasons to examine the ERPT in Sweden. Notably, in 2022/2023, Sweden witnessed its highest inflation rate in three decades, a trend that has persisted beyond initial forecasts (Sveriges Riksbank, 2023c). During the same period, the Swedish Krona (SEK) depreciated, as indicated by the KIX index (see Figure 1). The Riksbank (2022a) predicts ongoing exchange rate volatility, with the possibility of further depreciations as long as uncertainty prevails in the international financial markets. As suggested by Taylor (2000) and Borio et al. (2023) persistent inflation and cost shocks amplifies the ERPT, making updated studies on Swedish ERPT interesting. It should also be noted that during the sample period, Sweden has also experienced periods of notorious low inflation (Andersson et al., 2015) which could lead to a lower ERPT (Taylor, 2000).

Research on markup and sector characteristics in Sweden provides information relevant for the magnitude and regime-specific dynamics of the ERPT. For instance, estimates from Bukeviciute et al. (2009) suggest that Sweden exhibits a higher ERPT in the retail sector compared to the average European country. The authors observe that currency depreciations in other countries are, to a greater extent, absorbed by reduced markups among firms, while in Sweden, a larger share is passed on to the final consumer. A Riksbank Business Survey states that the pass-through following the depreciations of 2017/2018 had a greater impact on prices in the retail sector compared to other sectors (Sveriges Riksbank, 2018). In addition to this, recent estimates suggest that profit shares have increased following the inflation period of 2022/2023 (NIER, 2022). In the Riksbank's Business Survey, a manager explains that customers are less price-sensitive and states that "after eight years of low-interest rates, consumers have gotten used to not caring about prices" (Sveriges Riksbank, 2023d, p.5). On the contrary, a survey conducted in a low inflation regime observed that firms are unable to pass along depreciation shocks due to increased competition and would rather decrease their markups than risk losing market shares (Sveriges Riksbank, 2015).

As mentioned in *2. Literature Review*, Weber & Wasner (2023) argue that cost shocks could function as tacit collusions, allowing firms to raise prices simultaneously. We observe indications of this in the Riksbank's Business Survey where a company manager states, "Price increases are a daily occurrence for most; everyone does it at the same time" (Sveriges Riksbank, 2022b, p.6), which could increase the ERPT as firms disregard competitive pressure and pass along their cost increases. Additionally, Weber & Wasner (2023) assert that knowledge about disruptions could increase consumer perceptions of the legitimacy of price increases. In the Riksbank's Business Survey, firms testify that consumers are willing to pay a higher price since they understand the cost shocks facing the Swedish economy, for example: currency depreciation, higher energy cost, and input prices. During the high inflation period of 2022/2023, a company manager exemplifies this by expressing that "I have never experienced

[4]The survey is conducted on a regular basis by the Riksbank and interviews firms in the largest sectors on how they view economic development and their pricing plans ahead.

customers accepting price increases so easily" (Sveriges Riksbank, 2022b, p.5).

The frequency of price adjustments has also shown to impact the Swedish inflation (Ewertzh et al., 2022) and in comparison to other European countries, Swedish firms adjust prices more frequent (Bukeviciute et al., 2009). Gopinath & Itskhoki (2010) argues that the possibility for small, but many, price increases leads to a higher ERPT as larger share of the cost increase could be pushed over, little a time, to consumer prices. Borio et al. (2023) states that during high inflation firms tend to adjust prices more frequently as it becomes relatively more costly to keep prices constant. The Riksbank's Business Survey from a high inflation period states that prices were adjusted on daily basis (Sveriges Riksbank, 2022b). In addition to this, the Riksbank Business Survey state that firms plan to increase prices in line with inflation, or even more, which could be seen in the comment from a company manager "Since we haven't had inflation for a long time, there is a pent-up need to compensate with increased prices" (Sveriges Riksbank, 2022b, p.6). This indicates that companies are eager, and able, to increase prices by effectively pushing over the cost increases to customers.

4 Data

The LST-VAR model is estimated using quarterly observations for the period 1995Q1-2023Q2, encompassing the entire Swedish inflation-targeting period, officially started in 1995 (Sveriges Riksbank, 2023e). The model includes four domestic variables to capture the structure of the Swedish economy, along with three global variables to control for international economic activity. Due to the limited number of observations (113), we restrict the specification to these variables to keep the model parsimonious (Enders, 2014).

The national variables consist of Gross Domestic Product (*GDP*), Consumer Price Index with a Fixed interest rate (*CPIF*)[5], Swedish Nominal Effective Exchange rate Index (*NEER*), and the Policy rate. *NEER* is constructed using the weighted average of Sweden's exchange rate against the currencies of 32 major trading partners. The weights are based on bilateral trade flows and reflect the importance of each country for Sweden (Alsterlind, 2006). We will also consider two alternative measures of prices: Producer Price Index (*PPI*) and Import Price Index (*IMPI*) to investigate how ERPT transmits along the pricing chain as in Ito & Sato (2006). *PPI* measures the prices of goods from all producing firms in Sweden, and *IMPI* measures the prices (in SEK) that Swedish firms import for.

The global variables consist of KIX-weighted CPI, GDP, and Policy rate. These measures are created by multiplying country-specific quarterly data (GDP, CPI, and Policy rate) with the KIX-weights for the respective country.[6] Following Corbo & Di Casola (2022), we use *KIX-CPI* as a proxy for global export prices.[7] Therefore, we are able to separate the impact of the exchange rate on domestic prices from the influence of changes in international prices, addressing a point of criticism in the ERPT literature (Shambaugh, 2008). *KIX-GDP* and *KIX-Policy Rate* capture global economic trends influencing Swedish variables. Assuming that the Small Open Economy condition holds, i.e., that Sweden cannot influence foreign variables, allows us to treat the variables as exogenous in the model. This approach also mitigates the impact of global shocks on Sweden, as their effects are captured in the global variables, thus minimizing bias in the specification.

All series, except for the policy rates (both domestic and global), are specified in their natural logarithm first-difference form, representing quarterly percentage changes. This procedure ensures that the time series follow a stationary process while retaining sufficient variation for our study. *CPIF* would then be formally described as quarterly inflation, but for interpretability, we will refer to it as "inflation". Following Corbo & Di Casola (2022), we assume that the negative and later positive trends observed in policy rates across many countries are exogenous. Therefore, the policy rates are detrended using an HP-filter to better capture the effect of monetary policy. The quarterly data is presented in Figure 2. Notably, the series appear to exhibit weak stationarity.

[5] The CPIF is the official inflation measure in Sweden (Sveriges Riksbank, 2023e).

[6] *KIX-GDP, KIX-CPI, and KIX-Policy Rate* consist of the Euro-Zone plus the US (in total 20 countries) and are created at the Riksbank for internal use. We are grateful for their generosity in sharing this data with us.

[7] Corbo & Di Casola (2022) argue that other measures, such as the Global Export Price Index for Sweden, are suboptimal proxies for measuring global price pressure since many imported goods to domestic firms are directly exported again, never influencing domestic prices.

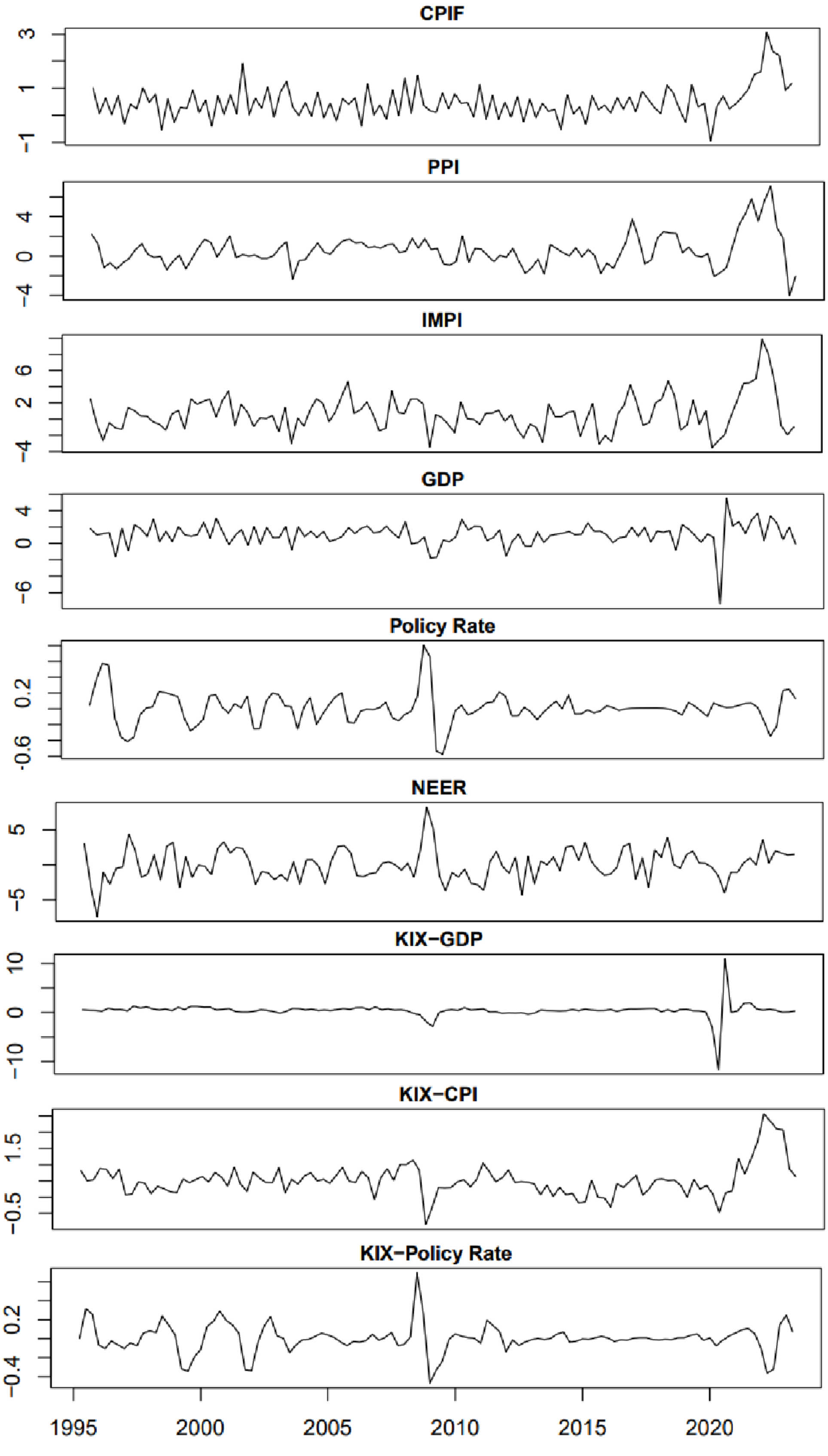

Figure 2: National and global KIX-weighted variables

Note: The figure plots the endogenous domestic variables and exogenous global variables used in the model specification. The endogenous variables are: gross domestic product (GDP), policy rate, the nominal exchange rate (NEER) and three measures for price: consumer prices (CPIF), producer prices (PPI) and import prices (IMPI). The global variables constructed using KIX-weights are: gross domestic product (KIX-GDP), consumer prices (KIX-CPI) and policy rate (KIX-Policy rate). All variables are on quarterly frequency and in natural logarithm first difference form except for the policy rates which have been HP-filtered.

As a robustness test, we will consider a specification using monthly data. However, since monthly data on GDP (both for Sweden and other countries) is unavailable, we will follow Balcilar et al. (2021) and use the Swedish Industrial Production Index and the World Industrial Productions Index as proxies for economic activity.[8] The variables are suboptimal proxies for economic activity, as it excludes the service sector, which constitutes a substantial share of the economy. Furthermore, the World Industrial Production Index is considered a noisy measure since it lacks weighting to reflect the relative importance of countries for Sweden. Furthermore, the remaining variables are originally at daily or monthly frequencies, and the same transformations are applied as in the quarterly specification. For a more detailed description of the data, see Appendix A13.

[8] The Swedish IPI is available from January 2000 but has been linked with earlier data by the Riksbank for internal use.

5 Methodology

This section outlines the methodology used to specify and estimate the LST-VAR model by following the specification procedure developed by Teräsvirta (1994) and (Teräsvirta & Yang, 2014) and the estimation procedure outlined in Auerbach & Gorodnichenko (2012). Initially, a linear SVAR is specified with an appropriate lag order and identifying restrictions. Subsequently, tests for non-linearity in the structural model are conducted, and a case is made for the use of a logistic smoothing function. The model is then expanded to a logistic smooth transition VAR (LST-VAR). Lastly, the quasi-Bayesian estimation method and the calculations of Exchange Rate Pass-Through (ERPT) are described.

5.1 SVAR

The underlying model in our paper is the Vector Autoregressive model (VAR), which allows for simultaneous effects among the variables of interest (Lütkepohl, 2005).[9] To derive meaningful economic interpretations from the estimations, we extend the model to a structural VAR, i.e., a SVAR model (Sims, 1980).

In the interest of readability, we streamline the notation by excluding constants and rewrite to matrix formation. The SVAR is constructed as:

$$\mathbf{A}_0\mathbf{Y}_t = \mathbf{B}(L)\mathbf{X}_t + \boldsymbol{\epsilon}_t \tag{1}$$

where $\mathbf{Y}_t$ is the vector of endogenous variables at time t with coefficients $\mathbf{A}_0$. $\mathbf{X}_t$ is the combined vector of lagged endogenous and exogenous variables with the following coefficients matrix $\mathbf{B}(L)$ and $\boldsymbol{\epsilon}_t$ is the vector of shocks with the variance-covariance matrix $\sum_{\boldsymbol{\epsilon}} = E[\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t']$. The structural shocks are assumed to follow a white noise process with $\epsilon_t^i \sim N(0,\sigma^2)$ where $i = GDP, POLICY\ RATE, NEER, PRICE$ and PRICE is consumer prices (CPIF), producer prices (PPI), or import prices (IMPI).

While the economic analysis is conducted for the SVAR model, the parameters can not be directly estimated due to feedback effects from contemporaneous variables (Gottschalk, 2001). However, the reduced form parameters can be estimated using standard estimation procedure. We therefore multiply through with $\mathbf{A}_0^{-1}$ and rewrite as the reduced form VAR:

$$\mathbf{Y}_t = \mathbf{A}_0^{-1}\mathbf{B}(L)\mathbf{X}_t + \mathbf{A}_0^{-1}\boldsymbol{\epsilon}_t \tag{2}$$

$$\mathbf{Y}_t = \boldsymbol{\Pi}(L)\mathbf{X}_t + \mathbf{u}_t \tag{3}$$

where $\boldsymbol{\Pi}(L) = \mathbf{A}_0^{-1}\boldsymbol{B}(L)$ and $\mathbf{u}_t = \mathbf{A}_0^{-1}\boldsymbol{\epsilon}_t$ with the variance covariance matrix $\sum_{\boldsymbol{u}} = \mathbf{u}_t\mathbf{u}_t'$.

5.1.1 Identification Restrictions

As mentioned, we estimate the reduced form model. However, the reduced form variance-covariance matrix is underdetermined which makes it impossible to disentangle the structural shocks of interest from the estimated reduced form shocks. In order to retrieve the structural model for meaningful

[9]This would otherwise be problematic in the case of inflation and exchange rates, where causality is bidirectional. Inflation can influence exchange rates, and vice versa.

economic interpretation we therefore need to impose 6 restrictions (Lütkepohl, 2005).[10] This is conducted by imposing assumptions about no contemporaneous effects between selected variables, i.e., zero short run restrictions. The identifying restrictions will be implemented through a Choleksy decomposition which orthogonalize the reduced form error.[11]

The identification restrictions imposed make causal claims about the contemporaneous impact between certain variables and are often based on economic theory and timing assumptions (Stock & Watson, 2001). The justification of a particular ordering is crucial for a credible identification strategy as the results could be sensitive to how the variables are ordered. However, Stock & Watson (2001) criticize that the choice of the "justifying" economic theory might be altered to favor certain orderings, which other economic theories might reject, in order to achieve desirable results. For transparency and comparability we will instead rely on the ordering used in previous ERPT research.

GDP is uncontroversially placed first in the system, assuming that changes to the policy rate, inflation, or exchange rate do not affect economic activity in the same period due to frictions in the economy. Next, we allow the policy rate to have a contemporaneous effect on the exchange rate, following Ito & Sato (2006), Jiang & Kim (2013) and Sims & Zha (2006), which recognizes the movements seen in the exchange rate after changes in the monetary policy. In addition, the mentioned papers allow the policy rate to have a direct effect on inflation which assumes that the monetary policy affects prices within one quarter, and that the central banks does not react to inflation within one quarter, but rather react when changes occur over longer time periods. This ordering is opposed by McCarthy (2000) and Kwon & Shin (2023) who places the policy rate last to acknowledge that central banks react to all information available and that the monetary policy has a delayed effect on inflation. A drawback of the ordering of McCarthy (2000) and Kwon & Shin (2023) is that the policy rate is not allowed to have a contemporaneous effect on the exchange rate. We will consider the ordering of the policy rate of Ito & Sato (2006), Jiang & Kim (2013) and Sims & Zha (2006) as our main specification and the ordering of McCarthy (2000) and Kwon & Shin (2023) as a robustness test to examine if the results are sensitive to this alternation.

Next, we order NEER as the third variable and the price measure (CPIF, PPI or IMPI) as the fourth variable. This is commonly done in the ERPT literature to allow the exchange rate shock to have a direct effect on prices (for example: McCarthy, 2000; Ito & Sato, 2006; Rincon & Rodríguez, 2016; Kwon & Shin, 2023). This assumption holds the strongest for the price measure of IMPI as changes in the exchange rate will have a contemporaneous effect on import prices. For consumer prices the effect of a depreciation would require longer time to transmit along the pricing chain. However, the Riksbank's Business Survey states that for firms within the retail sector the effect of an depreciation has contemporaneous effect on consumer prices (Sveriges Riksbank, 2009). Since the purpose of this paper is to analyse the effect of exchange rate shocks to prices, we rather allow for the data to speak for itself then to restrict potential effects. If the data reveals no contemporaneous effects, then the estimates will adjust to fit the data, but if we restrict this direct channel we force the coefficient to be zero which could be a stronger limitation.

[10] Follows from the equation $\frac{K(K-1)}{2} = \frac{4(4-1)}{2} = 6$ where k is the number of endogenous variables.

[11] Sometimes this is refereed to as a recursive/triangular VAR and SVAR is reserved for identification by using long run restriction (Blanchard & Quah, 1989) or sign restriction (Faust, 1998; Uhlig, 1997) (see Stock & Watson, 2001). However, we will use the term SVAR following the majority of the literature.

The mentioned ordering follows the structure imposed in the majority of the ERPT literature (see McCarthy, 2000; Ito & Sato, 2006; Jiang & Kim, 2013; Rincon & Rodríguez, 2016; Leigh & Rossi, 2002; Faruqee, 2006). However, the literature diverge on the ordering of the policy rate and is therefore tested as a robustness test.[12]The main specification is ordered as:

$$\mathbf{Y}_t = [GDP \quad POLICY\,RATE \quad NEER \quad PRICE]'$$

where PRICE is consumer prices (CPIF), producer prices (PPI), or import prices (IMPI).

5.1.2 Lag Selection and Model Diagnostics

Next, we specify the appropriate lag structure. Additional lags tend to improve the model fit but, at the same time, reduce the ability to draw general conclusions (Enders, 2014). We will follow the suggestions for lag selection for impulse responses by Ivanov & Kilian (2005). For quarterly data with more than 120 observations, the HQ criteria (Hannan & Quinn, 1979) is the most appropriate criterion, and with fewer than 120 observations, the Bayesian Information Criteria is recommended.

Following Teräsvirta & Yang (2014), we perform model diagnostics on the residuals to evaluate the specification. We test for remaining autocorrelation in the residuals using the Ljung-Box test for 2, 4, 6, and 8 lags, as well as the Jarque-Bera test to evaluate if the residuals are normally distributed (Enders, 2014). We conduct the tests for each of the endogenous variables and perform joint tests for all four residual series by utilizing the additive property of the Chi-square distribution (Lancaster, 1969).

5.2 LST-VAR

In order to capture the regime dependent dynamics of the ERPT, we extend the model to the Logistic Smooth Transition Vector Autoregressive model (LST-VAR) following Teräsvirta & Yang (2014).

5.2.1 The Logistic Transition Function

To allow the estimates to depend on the level of inflation, we incorporate the logistic transition function, defined as:

$$F(z_t) = \frac{1}{1+e^{-\gamma z_t}}, \quad where \quad \gamma \in [0, \infty) \tag{4}$$

where z_t represents the transition variable that separates the two inflation regimes, with c as the threshold. The threshold value is set to $c = 0$ by subtracting the threshold value from the transition variable.[13] The parameter γ measures the speed of adjustments between the regimes. When $\gamma \to \infty$, there is an instant shift between regimes after the threshold value is passed, equivalent to a Threshold-VAR. When $\gamma \to 0$, the model becomes a linear VAR since $F(z_t) = 0.5$, thus the average of both regimes. For γ between 0 and ∞, the transition function becomes smooth, allowing for non-linear estimations with regime switches coherent to the dynamics of the economy (Granger & Teräsvirta, 1993).

[12]Robustness specification : $\mathbf{Y_t} = [GDP \quad NEER \quad PRICE \quad POLICY\,RATE]'$.

[13]This transformation facilitates the use of the Matlab function $Sign(z_t)$ as a splitting decision and simplifies the logistic function to its current representation: $z = z_{org} - c \longrightarrow \quad F(z_t) = \frac{1}{1+e^{-\gamma(z_{org}-c)}} = \frac{1}{1+e^{-\gamma z_t}}$.

The logistic smooth transition function is preferred over the exponential smooth transition function used by Auerbach and Gorodnichenko (2012), since it is more compatible with our hypothesis of separate dynamics for the high and low inflation regime.[14] To intuitively map the regime-dependent dynamics to the level of inflation the same specification of the logistic function will be used for all variables, allowing the entire economy to switch regimes simultaneously, as suggested by Tsay (1998).[15]

5.2.2 LST-VAR Model

Extending the model with the logistic function yields the LST-VAR:

$$\mathbf{Y}_t = [1 - F(z_t)]\,\mathbf{\Pi}_{Low}(L)\mathbf{X}_t + F(z_t)\,\mathbf{\Pi}_{High}(L)\mathbf{X}_t + \mathbf{u}_t \tag{5}$$

$$\mathbf{u}_t \sim N(0, \mathbf{\Omega}_t) \tag{6}$$

$$\mathbf{\Omega}_t = [1 - F(z_t)]\,\mathbf{\Omega}_{Low} + F(z_t)\,\mathbf{\Omega}_{High} \tag{7}$$

$$F(z_t) = \frac{1}{1 + e^{-\gamma z_t}}, \quad \gamma \in [0, \infty) \tag{8}$$

$$F(z_t) \in [0, 1] \tag{9}$$

where $\mathbf{Y}_t$ represents the vector of endogenous variables, $\mathbf{X}_t$ is the vector of lagged endogenous variables and exogenous variables with coefficients given by $\mathbf{\Pi}(L)$. $\mathbf{u}_t$ represents the shock vector with the weighted variance-covariance matrix $\mathbf{\Omega}_t$ and $F(z_t)$ represents the transition function, putting weights on the coefficients for the regimes, represented by the subscript $High$ or Low.

The LST-VAR models capture the regime-specific dynamics in two ways. First, contemporaneously through the differences in the variance-covariance matrices of the shocks, changing the size of the shock and response of the contemporaneously affected variables. Second, dynamically through the coefficients determining the effect of the lagged and exogenous variables, altering the transmission of the shock. For clarification, $F(z_t)$ could more precisely be described as the probability that the economy behaves as in high inflation, given the level of the inflation. Therefore, the threshold c, does not per definition separate the regimes but rather categorises the data into the "more probable" regime. It follows then, if $F(z_t) \approx 1$, the coefficients will shift to $\{\mathbf{\Pi}_{High}(L),\ \mathbf{\Omega}_{High}\}$ reflecting the dynamics of the economy in a sufficient high inflation, and vice verse if $F(z_t) \approx 0$, the coefficients will shift to $\{\mathbf{\Pi}_{Low}(L),\ \mathbf{\Omega}_{Low}\}$. In the model the coefficients are estimated by utilizing the full sample

[14] The exponential smoothing function $F(z_t) = \frac{e^{-\gamma z_t}}{1+e^{-\gamma z_t}}$ indicates that low and high values of z_t correspond to similar impacts on ERPT, which is not compatible with our hypothesis.

[15] Another variant, used by Rincón and Rodríguez (2016), is to let every variable have its unique threshold to reflect that some variables react non-linearly at different levels of inflation. This might provide a better fit for the model but reduce the intuition of the model, as some variables will be in the high regime at the same time as others will be in the low regime.

but for simplification the sets of coefficients belonging to a specific regime, could be attributed to the outer values in each regime.

In addition, the LST-VAR is a preferable model since it mimics the slow paced dynamics observed in the economy. Since the structural framework of the model (*see 5.1.1 Identification Restrictions*) assumes that some variables have a delayed reaction to changes in other variables, we believe that a smooth transition links the structural VAR to the regimes switches in a more coherent fashion then comparable models. For example, the more commonly used T-VAR model (see Aleem & Lahiani, 2014; Tica & Posedel, 2009) forces the coefficients to abruptly change once the transition variable surpasses the threshold c.[16]

5.2.3 Linearity Test and Transition Variable

To justify the use of the LST-VAR model, the existence of non-linear dynamics amongst the variables needs to be established. Following Teräsvirta & Yang (2014), we test the linearity of the reduced form VAR model for all endogenous variables with the Lagrange multiplier test (LM-test) and CPIF as our price measure (For details, see Appendix A2). Under the null hypothesis, $H_0 : \gamma = 0$, the model is correctly specified as a linear model. If the null if rejected, the LST-VAR is preferred.[17]

Moreover, the linearity test is commonly consulted when determining which variable to use for transition (Aleem & Lahiani, 2014; Tica & Posedel, 2009). This involves testing various variables and lags, selecting the specification with the strongest rejection of linearity, i.e., the highest LM-value (Yang, 2012). However, Yang (2012) underscores that the choice of the transition variable could be based on economic intuition aligned with the research purpose, which in this paper refers to inflation. Therefore, we adopt a hybrid approach, combining statistical testing to determine the most suitable lag of CPIF as the transition variable. The chosen transition variable will be consistently employed in all specifications (using CPIF, PPI, and IMPI as the pricing variable) for comparability.

Following Aleem & Lahiani (2014) and Tica & Posedel (2009) we include up to five lags in our search. In contrast to Auerbach & Gorodnichenkos (2012) we will not consider alternative transition variables, such as moving averages or volatility measures, since they reduce the intuition of the model or include unrealized values making the probability of transition determined by future values (Alloza, 2022).[18] However, using lagged variables could also reduce the intuition as past values are used to explain dynamics in the current state. Although, as the non-linearities in the data could be driven by firm behavior, with a potential lagged perception of price movements, the usage of lags for transition variables is reasonable.

5.2.4 Estimating the Parameters of the Transition Function

The estimations of the LST-VAR model depend on the parameters in the transition function. Recall that γ determines the speed of transition, and c is the threshold value separating the two regimes.

[16] For a given threshold value c, then the coefficients will be $\mathbf{\Psi}(\min(z)) = \lim_{z\to\ c^-} \mathbf{\Psi}(\boldsymbol{z}) \neq \lim_{z\to\ c^+} \mathbf{\Psi}(\boldsymbol{z}) = \mathbf{\Psi}(\max(z))$. For example, if $c = 2$, the dynamics of the economy is the same for an inflation rate of 2.01% and 10%, while different for 1.99%.

[17] For the linearity test we use the VLSTARjoint function in the R-package *starvars* version 0.1.8 (Bucci et al., 2022).

[18] For example, Auerbach & Gorodnichenkos (2012) uses a centered moving average as transition variable including three quarters of unrealized values for every t, which Alloza (2022) states introduces bias to the estimates.

Auerbach & Gorodnichenkos (2012) suggest that γ and c are determined outside the model for estimation purposes.[19]

Following Enders (2014), we estimate the model for different values of γ. We start at $\gamma = 0$ and increment up to 500, selecting the model with the highest likelihood. For estimation precision, Teräsvirta & Yang (2014) suggest setting the threshold value c, to allow for numerous observations in both regimes. Carrière-Swallow et al. (2023) divide the data set along the median value to create equally sized regime groups. In contrast, Auerbach & Gorodnichenkos (2012) set c to represent the share of observations that historically belong to recessions or expansions as calculated by the National Bureau of Economic Research.[20] Hence, we set c to reflect the historical share of observations spent in high and low inflation environments (*see 6.2 Linearity Tests and Specification of the Transition Function*).

5.3 Estimation Method

The estimation procedure involves a multiple step approach outlined in Auerbach & Gorodnichenko (2012). The LST-VAR model (Equation 5-9) is estimated using maximum likelihood and maximizes:

$$\log L = \text{const} - \frac{1}{2}\sum_{t=1}^{T} \log|\mathbf{\Omega}_t| - \frac{1}{2}\sum_{t=1}^{T} \mathbf{u}_t'\mathbf{\Omega}_t^{-1}\mathbf{u}_t \tag{10}$$

Where $\mathbf{u}_t$ is the residuals from Equation (5) and $\mathbf{\Omega}_t = [1 - F(z_t)]\,\mathbf{\Omega}_{Low} + F(z_t)\,\mathbf{\Omega}_{High}$. However, the total set of parameters, $\mathbf{\Psi} = \{\mathbf{\Omega}_{Low}, \mathbf{\Omega}_{High}, \mathbf{\Pi}_{Low}(L), \mathbf{\Pi}_{High}(L)\}$ are non-linear and problematic to estimate with normal optimization routines. We therefore use the following procedure outlined in Auerbach & Gorodnichenkos (2012).

First, we estimate Equation (3) with a linear OLS to retrieve the residuals. With the residuals we can estimate the covariance matrix $\mathbf{\Omega}_t = [1 - F(z_t)]\,\mathbf{\Omega}_{Low} + F(z_t)\,\mathbf{\Omega}_{High}$ for the high and the low regime using MLE [21].

Next, we utilize that conditional on $\{\mathbf{\Omega}_{Low}, \mathbf{\Omega}_{High}\}$, the model is linear in the lag polynomials $\{\mathbf{\Pi}_{Low}(L), \mathbf{\Pi}_{High}(L)\}$. This implies that, for every given guess of $\{\mathbf{\Omega}_{Low}, \mathbf{\Omega}_{High}\}$ we can estimate $\{\mathbf{\Pi}_{Low}(L), \mathbf{\Pi}_{High}(L)\}$ by using weighted least squares (for more details, see Appendix A1). This yields the initial set of parameters $\mathbf{\Psi}^{(0)}$.

When the initial set of parameters is obtained the quasi-Bayesian Markov Chain Monte Carlo (MCMC) method, developed by Chernozhukov & Hong (2003), is employed.[22]. The algorithm allows the parameters to explore the parameter space and converge to a stationary distribution from which samples are drawn. The stationary distribution represents the global optimum in terms of model fit, and the drawn samples are used to create confidence intervals. In contrast to a normal MCMC used

[19] According to Auerbach & Gorodnichenkos (2012), including γ and c in the optimization routine leads to poor estimates as the model becomes sensitive to outliers.

[20] The National Bureau of Economic Research calculates the share of time spent in recession versus expansion which Auerbach & Gorodnichenkos (2012) use to calculate the threshold value.

[21] Note that this estimation is different from Equation (10).

[22] Chernozhukov & Hong (2003) refer to it as Laplace type estimator or quasi-Bayesian estimations.

in Bayesian analysis, the algorithm allows for the use of weighted least squares, necessary for the non-linear estimations, as part of the estimation routine.[23]

To implement the MCMC method we use the Metropolis-Hasting algorithm (Metropolis et al., 1953). To avoid convergence to a local optimum the algorithm allows for random disturbances drawn from $N(0,\mathbf{\Omega})$ for every iteration, which enables further exploration of the parameter space. The number of draws is set to 100 000 with an initial burn in period of 20 000 draws.[24] We check the properties of the simulated chains to ensure that they converge to stationary distributions (see Appendices A6-A7).

The quasi-Bayesian MCMC algorithm could be summarized as:

<u>1:</u>
Draw $\boldsymbol{\omega}^{(n+1)} = \left\{\mathbf{\Omega}_{Low}^{(n+1)}, \mathbf{\Omega}_{High}^{(n+1)}\right\}$, a candidate variance-covariance matrix for the state $n+1$, as $\boldsymbol{\omega}^{(n+1)} = \mathbf{\Omega}^{(n)} + \boldsymbol{\zeta}^{(n+1)}$ where $\mathbf{\Omega}^{(n)}$ is the current state n variance-covariance matrix and $\boldsymbol{\zeta}^{(n+1)}$ is a vector of random disturbances from $N(0,\mathbf{\Omega})$.

<u>2:</u>
Next, we utilize $\boldsymbol{\omega}^{(n+1)}$ to estimate the lag polynomials, $\left\{\mathbf{\Pi}_{Low}^{(n+1)}, \mathbf{\Pi}_{High}^{(n+1)}\right\}$, by using weighted least squares. Together this constitutes the full set of proposed parameters $\mathbf{\Theta}^{(n+1)}$.

<u>3:</u>
Accept the $n+1$ state of the chain as:

$$\mathbf{\Psi}^{(n+1)} = \begin{cases} \mathbf{\Theta}^{(n+1)} \text{ with probability } \min\left\{1, e^{\log L\left(\mathbf{\Theta}^{(n+1)}\right) - \log L\left(\mathbf{\Psi}^{(n)}\right)}\right\} \\ \mathbf{\Psi}^{(n)} \text{ otherwise} \end{cases}$$

where $L\left(\mathbf{\Psi}^{(n)}\right)$ is the value of the objective function at the current state of the chain and $L\left(\mathbf{\Theta}^{(n+1)}\right)$ is the value of the objective function using the candidate vector of parameter values.

<u>4:</u>
Separate and save the corresponding parameter values to $\{\mathbf{\Psi}_{Low}\} = \{\mathbf{\Omega}_{Low}, \mathbf{\Pi}_{Low}(L)\}$ and $\{\mathbf{\Psi}_{High}\} = \{\mathbf{\Omega}_{High}, \mathbf{\Pi}_{High}(L)\}$

<u>5:</u>
Repeat MCMC for 100 000 draws and discard the first 20 000 iterations.

5.4 Impulse Response Function

Sims (1980) states that the most effective approach for deriving insightful economic analysis in an SVAR is to examine how a system reacts to exogenous shocks, which is done through an Impulse Response Function (IRF).

The IRFs are constructed by sampling 1000 sets of parameters from the generated chains. To separate the two regimes, we independently sample from $\left\{\mathbf{\Psi}_{High}^{(n)}\right\}_{n=1}^{N}$ and $\left\{\mathbf{\Psi}_{Low}^{(n)}\right\}_{n=1}^{N}$ where N is 80 000.[25] Each sample contains unique parameter values that create unique shocks and responses for each draw (Koop et al., 1996). The shocks are normalized to a 1% depreciation and the estimates from the IRFs

[23] The stationary distribution represents the quasi-posterior distribution in this case, in contrast to the posterior distribution when using MCMC in a Bayesian setting.

[24] The burn in period allows the estimates to converge before sampling. 20 000 burn ins are also used by Auerbach & Gorodnichenkos (2012) and compatible with our specification (see Appendices A6-A7)

[25] N=80,000 represents the number of draws, 100 000, minus the first 20 000 burn-ins.

are saved. From the collection of 1000 IRFs, the median value is used as the point estimate. For the confidence interval, the top 5% and bottom 5% of the responses are excluded, creating a confidence interval of 90%.

The IRF could be described as:

$$IRF_{t+n}^{R}\left(n, v_t, \chi_{t-1}^{R}\right) = \mathrm{E}\left[Y_{t+n} \mid v_t, \chi_{t-1}^{R}\right] - \mathrm{E}\left[Y_{t+n} \mid \chi_{t-1}^{R}\right] \tag{11}$$

where n is the number of horizons and v is the exchange rate shock. R denotes the regimes $(High, Low)$ and χ^R represent the regime specific parameters. The IRF calculates the differences in how the system reacts with and without a shock for the low and high inflation regimes separately.

However, the IRF ignores feedback to the transition variable. Once the shock occurs, the economy will stay in the same regime during the estimated IRF horizon. The same specification is used in Auerbach & Gorodnichenko (2012), and allows for linear estimations of the impulse responses. In addition, Borio et al. (2023), identifies self-stabilizing effects in the low inflation regime and significant spill-over effects between prices in a high inflation regime, suggesting regime constancy over a specific time period. Additionally, Corbo & Di Casola (2022) find that the exchange rate shock dies out in two years for Sweden, which we believe as a reasonable timeframe for being in the same regime.

5.5 Exchange Rate Pass-Through

Following Ortega & Osbat (2020), Aleem & Lahiani (2014), and Faruqee (2006), the ERPT is estimated from the impulse response function of the price measure from the exchange rate depreciation shock. Given that the transmission of the shock impacts over several periods, the cumulative effect is estimates as:

$$ERPT_t^R = \sum_{t=0}^{T} \Delta Price_t \tag{12}$$

where R denotes the inflation regime $(High, Low)$, $\Delta Price_t$ denotes the change in the price measure (CPIF, PPI, IMPI) for time t.

However, as noted by Kwon & Shin (2023), the regimes could exhibit different levels of persistence of the exchange shock on itself. For example, high inflation could itself trigger additional depreciation (Baele et al., 2020) which in turn affect the ERPT (*see 7. Discussion*). To nuance the results, the alternative measure of the Price-to-Exchange Rate Ratio (PERR) will be considered to account for this effect. The PERR measure stems from the shock-dependent literature (Corbo & Di Casola, 2022; Forbes et al., 2018; Shambaugh, 2008) and could be specified as:

$$PERR_t^R = \frac{\sum_{t=0}^{T} \Delta Price_t}{\sum_{t=0}^{T} \Delta NEER_t} \tag{13}$$

where R denotes the inflation regime $(High, Low)$, $\Delta Price_t$ denotes the change in the price measure (CPIF, PPI, IMPI) at time t and $\Delta NEER_t$ denotes the change in the exchange rate at time t.

We will refer to the first measure as ERPT and the second as PERR, following Ortega & Osbat (2020). The PERR measure could be seen as a complement to ERPT, enabling a more nuanced analysis.[26] The measures are calculated over a 20 quarter horizon for consumer prices (CPIF), producer prices (PPI) and import prices (IMPI). We define two horizons: short and long run as 2 quarters and 20 quarters. [27]

[26]The reader should note that Shambaugh (2008), Corbo & Di Casola (2022) refers to $PERR$ as $ERPT$.
[27]This definition is similar to Corbo & Di Casola (2022) and enables us to compare our results with their estimations.

6 Results

This section presents the results obtained from the LST-VAR model. First, we present the lag order test and the linearity test for the underlying model, followed by the parameter specification for the logistic function. Next, we provide the main results including the impulse response function and the ERPT measures. Last, the results from the robustness tests are presented.

6.1 Lag Order

First, the AIC, BIC, HQ, and FPE tests are conducted to decide the underlying model's appropriate lag structure. Table 1 shows that HQ and BIC propose a parsimonious model, contrary to AIC and FPE. Ivanov & Kilian (2005) recommend BIC for quarterly data with fewer than 120 observations and HQ for over 120 observations. Given our 113 observations and the poor modeling of persistence with one lag (Kilian, 2001), which is important for the ERPT analysis (*see 2.2 Inflation and ERPT*), we choose two lags as suggested by HQ. Two lags are also used by Corbo & Di Casola (2020) for similar data and sample period.

Table 1: Results from Lag selection criteria

Model	HQ	BIC	AIC	FPE
CPIF	2	1	7	7
PPI	2	1	7	7
IMPI	2	1	7	7

Note: The table contains the lag selection test for the baseline SVAR model. The test shows the suggested lag selection for the unique models with consumer prices (CPIF), producer prices (PPI), and import prices (IMPI) as the pricing variable. The lag selection tests are Hannan and Quinn Criterion (HQ), Bayes Information Criterion (BIC), Akaike's Information Criterion (AIC), and Final Prediction Error (FPE).

Next, the residuals are analysed with the Ljung-Box and Jarque–Bera tests at the 95% significance level. The results are presented in Appendices 8-9. For all residual series, except CPIF, we fail to reject the null hypothesis of no autocorrelation. Moreover, for all series, except GDP, we fail to reject the null hypothesis of normal distribution. The remaining autocorrelation for CPIF could be corrected for by using a more complex lag structure. The non normality of the residuals of GDP requires a quasi-maximum likelihood estimation, which is beyond the scope of this paper. However, for the joint test, evaluating all four residual series simultaneously, we fail to reject the null hypothesis of no autocorrelation as well as the null hypothesis of no normal distribution. This indicates of a correctly specified model and no further steps are taken despite remaining autocorrelation in CPIF.

6.2 Linearity Tests and Specification of the Transition Function

Before extending the SVAR model to the LST-VAR, the linearity test and determination of the transition variable is conducted, as described in *5.2.3 Linearity Test and Transition Variable*.[28] From the test, we conclude that the model includes non-linearities, as all variables are significant at the 95% significance level. The results for CPIF strengthens the evidence of non-linearities dependant

[28]See Appendix A2 for details on the computation of the LM-values.

on inflation. We select $CPIF_{t-2}$, which returns the second-highest LM-value overall and the highest LM-value among the relevant candidates.

Table 2: Results from the linearity test

	GDP	PR	NEER	CPIF	KIX-GDP	KIX-PR	KIX-CPI
Lag 0	109.15	148.50	86.72	113.45	122.69	126.33	102.77
Lag 1	98.72	116.99	105.89	118.63	122.98	111.51	118.86
Lag 2	102.18	111.87	109.20	**134.99**	86.35	121.01	118.570
Lag 3	90.16	126.69	109.25	125.77	93.95	118.55	90.69
Lag 4	77.02	131.19	94.33	105.83	84.19	116.86	78.00
Lag 5	91.98	111.66	119.51	102.85	87.42	114.34	107.42

Note: The table presents the LM-values from the linearity test, see Appendix A2 for calculations. All variables are in natural logarithm first difference form except for the policy rate, which has been HP-filtered. The variables included are: gross domestic product (GDP), Policy rate (PR), nominal exchange rate (NEER), consumer prices (CPIF) and the corresponding global variables constructed using KIX weights.

The chosen transition variable, $CPIF_{t-2}$, aligns with Aleem & Lahiani (2014) and Ben Cheikh (2012), who use lagged inflation as thresholds to analyse non-linear ERPT. The intuition may diminish when past observations are used to estimate dynamics in the current state. However, it is reasonable to assume that firms make decisions based on realized price movements, rather than price movements in the current state. Since the test indicates that $CPIF_{t-2}$ captures non-linearities in the data better than other lags, while also maintaining economic intuition, we will use it as the transition variable.

Next, we set the parameters of the logistic smoothing function as outlined in *5.2.4 Estimating the Parameters of the Transition Function.* Recall that the threshold value (c) divides the observations into two regimes and γ determines the speed of transition between regimes. Following Teräsvirta & Yang (2014), we aim to have a sufficient number of observations in both regimes. Instead of setting an arbitrary value for c (as in Carrière-Swallow et al., 2023), we set c to reflect the historical share of observations spent in the high and the low inflation environments, similar to Auerbach & Gorodnichenkos (2012). Given our research topic, c is set to represent the share of observations spent over the target inflation rate of 2%.[29] For our sample period, 40% of the observations are above the inflation target and 60% are below, thus resulting in the threshold value $c = 0.59$, representing a 60/40 split. Last, we evaluate the model for different values of γ and choose $\gamma = 20$ as it yields the highest log likelihood (for test statistics, see Appendix A10.)

[29] For this estimation we will consider the YoY inflation measure as the central bank does not target QoQ inflation. However, translating YoY inflation to QoQ inflation yields similar results. Since Sweden used CPI as inflation target variable from 1995 to 2017 and CPIF after 2017 we create a combined time series to classify if the inflation was above or below the target inflation rate.

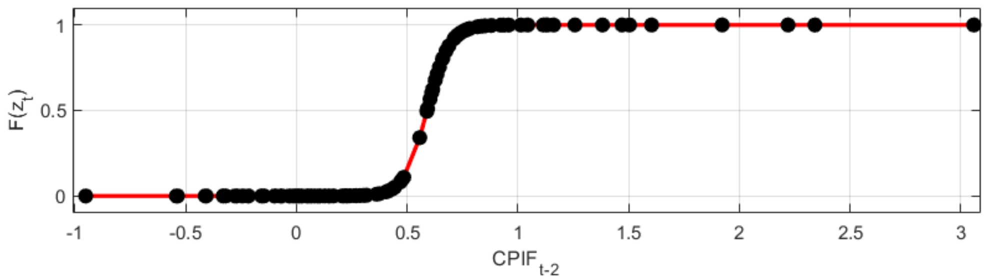

Figure 3: Logistic Smooth Transition Function

Note: The logistic smooth transition function maps the transition from high to low inflation regimes. The high inflation regime correspond to the observations where $F(z) \approx 1$, and low inflation regime $F(z) \approx 0$. The transition variable ($CPIF_{t-2}$), is the second lag order of the logarithm first difference form of consumer prices (CPIF). The black dots display the observations plotted against the transition function. The threshold value is found where $F(z) = 0.5$ and corresponds to $CPIF_{t-2} = 0.59$.

From Figure 3, we conclude that the logistic function is both smooth and well-defined for both regimes. The observations belonging to the high inflation regime satisfy $F(z_t \geq 0.82) \approx 1$, and for the low inflation regime, $F(z_t \leq 0.32) \approx 0$. This corresponds to a yearly inflation rate of a minimum of 3.3% for the high inflation regime and a maximum of 1.3% for the low inflation regime, aligning with the broader inflation target interval of 1-3% used by the Riksbank (2023e). Since the estimation procedure maximizes the total fit, the coefficients will be influenced by the full sample but are most accurately described by the observations that satisfy $z_t \geq 0.82$ and $z_t \leq 0.32$.

6.3 Impulse Response Functions

Figures 4-6 display the Impulse Response Functions (IRF), estimating how a 1% depreciation shock to the exchange rate impacts consumer prices (CPIF), producer prices (PPI), and import prices (IMPI) in the non-linear and linear estimated models.[30] The non-linear estimates of the ERPT are shown in the IRFs as "High" and "Low" corresponding to the high inflation regime and the low inflation regime. From the IRFs, we observe the estimated pass-through to inflation for 12 quarters.

In both the linear model and the high regime, the IRFs provide robust evidence of a positive ERPT for all measures of price. This also holds true for IMPI in the low regime. However, in the low regime, the evidence for a positive ERPT to PPI and CPIF is less pronounced, even though both IRFs exhibit significant (90% confidence level) ERPT for at least one period. These findings aligns with the results of Carrière-Swallow et al. (2023)

[30] For computational simplicity, we construct the linear model by assigning 50% of the weights from each regime. The linear model yields results close to identical to those obtained using a traditional linear SVAR model. The purpose of the specification is to serve as a baseline specification, facilitating a meaningful comparison with the non-linear estimations as well as with previous research.

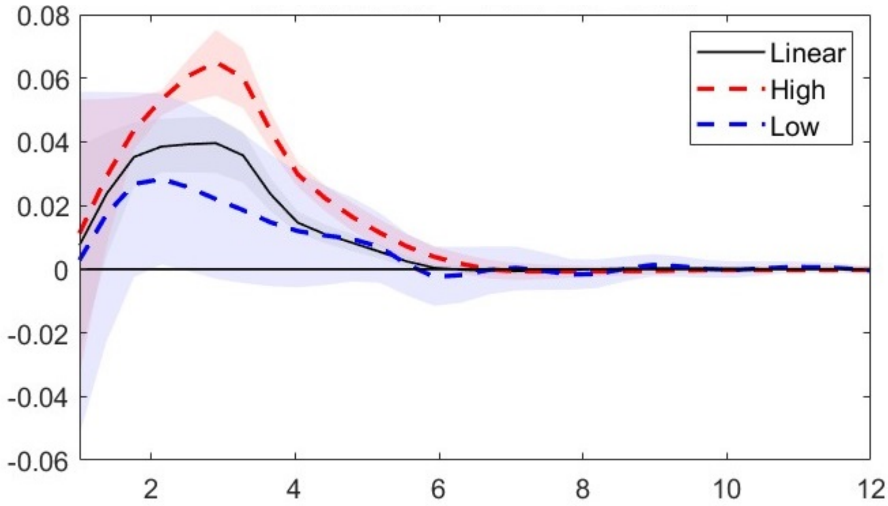

Figure 4: Impulse response functions to consumer prices

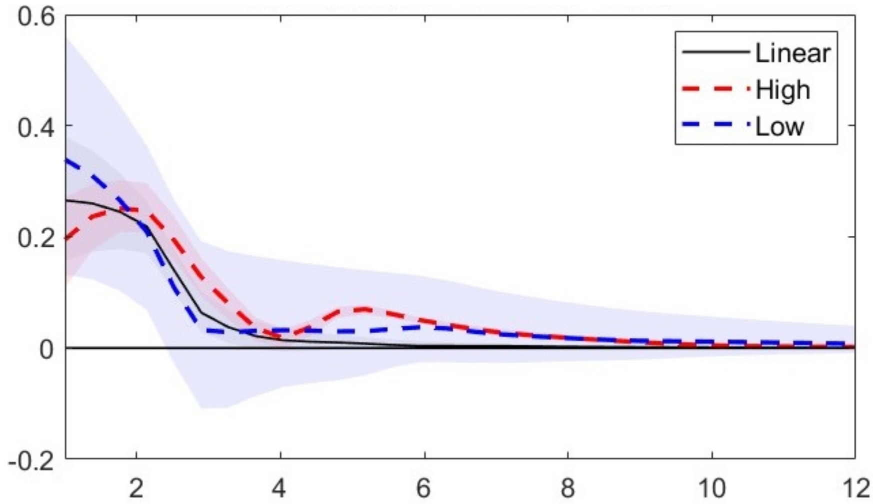

Figure 5: Impulse response functions to producer prices

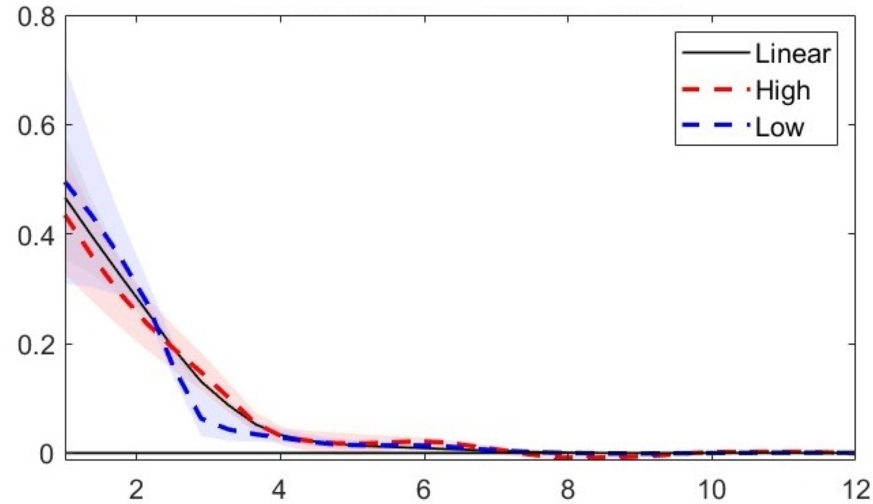

Figure 6: Impulse response functions to import prices

Note: The impulse response functions display how a 1% depreciation in the exchange rate (NEER) impacts consumer prices (CPIF), producer prices (PPI) and import prices (IMPI) over 12 quarters. The red and blue lines correspond to the impact in high and low inflation regimes and the black solid line represent the linear model. The 90% confidence intervals are shown in red, blue and grey for the corresponding regime and linear model. The y-axes shows the percentage point increase in the pricing measure for each time period. Note that the scale on the y-axes are different for the three pricing measures.

The duration of the shock varies depending on the price measure and regime. The response to CPIF persists for approximately six quarters before converging to zero. The impacts on PPI and IMPI exhibit a shorter duration of approximately four quarters. Our findings align with expectations, as the transmission of pass-through from import prices to final consumer prices involves a time delay, which is explained by the structure of the pricing channel outlined by Colavecchio & Rubene (2020). This could also be observed by analysing the shape of the IRFs. For IMPI and PPI, the maximum effect is observed in the first quarter, with a minor exception for PPI in the high regime. In contrast, CPIF shows the maximum effect in the second and third quarters. Carrière-Swallow et al. (2023) and Kwon & Shin (2023) find similar dynamics with a larger direct effect on import and producer prices and a delayed effect on consumer prices.

Furthermore, the ERPT is declining along the pricing chain with the greatest effect on IMPI, followed by PPI and then CPIF. This result is found in the majority of the ERPT research (see Carrière-Swallow et al., 2023; McCarthy's, 2000; Ben Cheikh & Louhichi, 2015: Ito & Sato, 2006). This is due to the direct impact of exchange rate changes on import prices. In contrast, CPIF and PPI is composed of both imported and domestically produced goods resulting in a smaller ERPT.

The regime dependent impact on ERPT is not statistically different for the majority of the periods when using a 90% confidence interval. For CPIF, the regime dependent impact is only statistically different between the second and fourth quarter. For IMPI and PPI we find no differences. As seen this is mostly due to high uncertainty in the low regime.[31] However, when using a 68% confidence interval, the statistical significant differences for CPIF are found for longer periods. Focusing on the point estimates, the IRF indicate greater ERPT in the high regime for CPIF and PPI. This aligns with the findings of Kwon & Shin (2023), who find regime-dependent ERPT for CPIF but not for PPI and IMPI.

6.4 Measures of Exchange Rate Pass-Through

To measure the pass-through of an exchange rate depreciation shock, we calculate the Exchange Rate Pass-Through (ERPT) and the Price to Exchange Rate Ratio (PERR), as outlined in *5.5 Exchange Rate Pass-Through*. Recall that ERPT represents the cumulative effect of the IRFs presented above, and PERR incorporates the dynamic effects that the exchange rate shock has on itself (NEER). Table 3 presents the results for ERPT, PERR, and NEER over the short run (2 quarters) and long run (20 quarters) to consumer prices (CPIF), producer prices (PPI), and import prices (IMPI). The table includes all estimations from the IRFs, even if not significant for all time periods.

[31] We check the standard deviation for the 80000 draws of regime specific parameters and conclude that the variation in $\Omega^{(n)}_{\text{Low}}$ are systematical larger than the variation in $\Omega^{(n)}_{\text{High}}$. This is likely an effect from the acceptance criteria of the MCMC algorithm:
$\Psi^{(n+1)} = \begin{cases} \Theta^{(n+1)} \text{ with probability } \min\left\{1, e^{\log L\left(\Theta^{(n+1)}\right) - \log L\left(\Psi^{(n)}\right)}\right\} \\ \Psi^{(n)} \text{ otherwise} \end{cases}$ more likely accepting variation in Ω_{Low} as the effect on log likelihood is small, due to the inactivity of economy (seen from Π_{low}) in the low regime. This results in bigger confidence intervals for the low regime as we sample from a more diverse set of parameter values and scale up the "insignificantly" sized shock to equal a unit sized shock. Whether this is an undesirable feature, or not, we leave to the reader to decide.

Table 3: Measures of exchange rate pass-through (ERPT) and price to exchange rate ratio (PERR)

		CPIF			**PPI**			**IMPI**		
Model	Horizon	NEER	ERPT	PERR	NEER	ERPT	PERR	NEER	ERPT	PERR
Linear	Short	1.353	0.046	0.034	1.361	0.484	0.356	1.353	0.740	0.547
	Long	1.524	0.108	0.071	1.570	0.573	0.365	1.542	0.915	0.594
High	Short	1.523	0.063	0.041	1.525	0.457	0.300	1.507	0.690	0.458
	Long	1.827	0.174	0.095	1.991	0.799	0.401	1.704	0.894	0.525
Low	Short	1.191	0.030	0.039	1.221	0.553	0.397	1.208	0.801	0.613
	Long	1.232	0.069	0.056	1.273	0.733	0.576	1.279	0.907	0.710

Note: The table presents the cumulative measured exchange rate pass-through (ERPT), cumulative price to exchange rate pass-through (PERR) and the cumulative responds of the exchange rate shock on itself (NEER). PERR is computed by dividing ERPT by NEER. The estimates are calculated for the three price variables: consumer prices (CPIF), producer prices (PPI) and import prices (IMPI). The table contains both the cumulative short term response (after 2 quarters) and cumulative long term response (after 20 quarters). The response to each price variable are estimated in the linear model, and non-linear model for the high and low inflation regime.

Over the long run, the ERPT to CPIF is estimated to 10.8% in the linear model, 17.4% in the high inflation regime and 6.9% in the low inflation regime. The ERPT to PPI is 80% in the high regime and 73% in the low regime. For IMPI the ERPT is approximately 90% for all regimes. The measures shows that the magnitudes of the ERPT decreases along the pricing chain, returning the highest estimates to IMPI, followed by PPI and lastly CPIF.

Few studies have conducted non-linear estimations of the ERPT with similar approaches, making comparisons challenging. Focusing on linear estimates provides a more meaningful understanding of pass-through compared to previous research. For the euro area, Ortega & Osbat (2020) report an ERPT to import prices ranging from 30-70%, and for consumer prices, the range is 4-10%. We estimate a linear ERPT of 92% to import prices, which aligns with the fact that the ERPT tends to be higher for EU countries not in the euro area as stated by Ortega & Osbat (2020). The linear ERPT to consumer prices is estimated at 11%, which is also at the upper bound of that found in Ortega & Osbat (2020). Other studies estimate ERPT to consumer prices between 5-20%, with the majority around 10% (see Hahn, 2003; Colavecchio & Rubene, 2020; Hüfner & Schröder, 2003).

The estimates of PERR and NEER allow us to analyse how the persistence of exchange rate depreciation effect the non-linearities of pass-through. Within the same regime, the cumulative effect on NEER is similar for the three price measures. However, it differs between regimes, which is most evident for the long run, where the high inflation regime experiences a higher cumulative change than the low regime. For instance, the long run change in NEER for CPIF is 83% for the high regime, and 23% for the low regime, disregarding the initial unit shock. Overall, this suggests that after a depreciation shock, additional depreciations occur, and that the effect is greater in the high inflation regime as suggested by Kwon & Shin (2023), Ben Sheik (2012) and Aleem & Lahiani (2014). Consequently, the persistent depreciations in the high inflation regime contribute to a higher pass-through.

The PERR suggest a smaller regime dependence of pass-through for CPIF. In the high regime, the

PERR measure is 9.5% (compared to 17.4% for the ERPT), and in the low regime, it is 5.6% (compared to 6.9% for the ERPT). Additionally, for PPI and IMPI, the PERR suggests higher pass-through in low inflation regimes, contrary to the ERPT. Using the PERR measure also allows us to compare with the latest pass-through estimations for Sweden measuring a long run PERR to CPIF of 5% (Corbo & Di Casola, 2022), similar to our estimated PERR in the linear model of 7%. However, a notable difference is found in PERR to import prices, with our estimates around 59%, compared to Corbo & Di Casola's (2022) 30%. One possible explanation could be that we include observations characterised by higher inflation and depreciations in contrast to Corbo & Di Casola (2022) whose sample period ends in 2017.

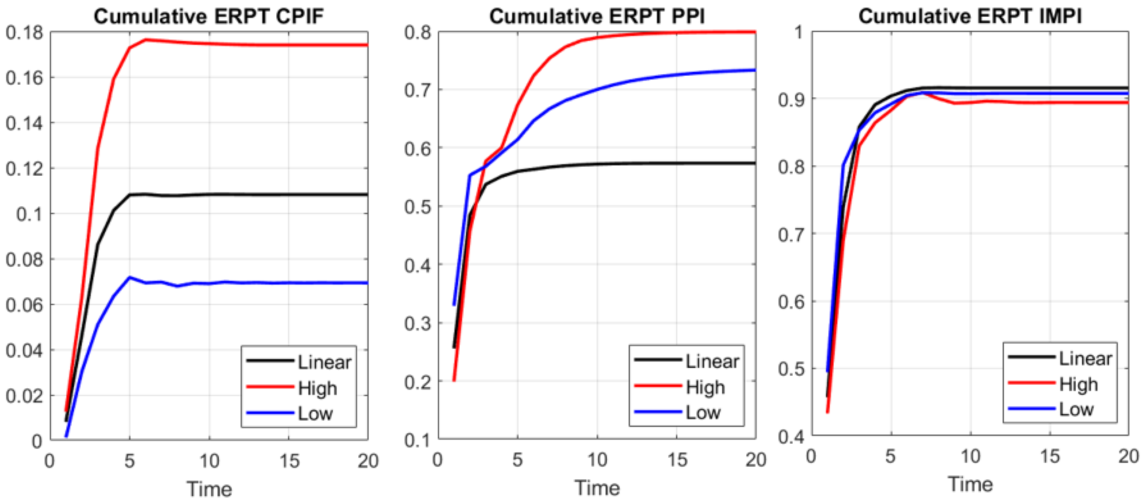

Figure 7: Cumulative exchange rate pass-through (ERPT)

Note: The cumulative ERPT are calculated by accumulating the point estimates obtained of the impulse response functions (IRF) from a 1% depreciation of the exchange rate to the three pricing measures in the linear model (black line) and non-linear model for the high (red line) and low (blue line) inflation regime. The plots are calculated over 20 quarters and returns the cumulative percentage point increase in the respective price measure. Note that the scale on the y-axes are different for the three pricing measures and that the cumulative ERPT include point estimates from the IRFs that are not statistically different from zero.

Figure 7 presents the cumulative ERPT for a better visual inspection of the pass-through. Focusing on the high and low regime we can see that the divergence, in relative terms, increases along the pricing chain.[32] For IMPI we find no divergence between regimes and therefore conclude that import prices is not regime dependent. For PPI, the second "stage" in the pricing chain, the divergence increase, with an ERPT of 73% in the low regime and 80% in the high regime. For CPIF the ERPT in the low regime is 6.9% and 17.4% in the high regime. In relative terms this is equivalent to percentage difference of 9% (PPI) and 152% (CPIF) between the high and low inflation regime. We conclude that the regime dependent ERPT is evident for CPIF, less pronounced for PPI and not found for IMPI.

6.5 Robustness Analysis

To further assess the reliability of the presented results, four robustness tests are considered. We will consider varying the parameter values in the logistic function, using an alternative structural

[32]The results of the linear ERPT for PPI is lower then the results for the low regime ERPT, which is not in line with our expectations. As this is not the main focus of the paper, we will not comment this further.

ordering, excluding data from the Covid-19 period and the high inflation period of 2022/2023, and conducting estimations using monthly data. This section focuses on evaluating the robustness of ERPT to consumer prices, as it represents our primary focus in this analysis. Additional robustness tests and results for IMPI and PPI are provided in Appendices A3-A5. Table 4 present a summary of three of the robustness tests in comparison to the main specification. Overall, the tests confirm our findings of a regime dependent ERPT with a higher pass-through in the high inflation regime and a lower pass-through in the low inflation regime.

Table 4: Summary table of exchange rate pass-through to consumer rices

		ERPT			
Model	Horizon	Main Specification	Alternative Ordering	Reduced Sample	Monthly Data
Linear	Short	0.046	0.040	0.038	0.069
	Long	0.108	0.101	0.095	0.069
High	Short	0.063	0.065	0.053	0.107
	Long	0.174	0.176	0.125	0.122
Low	Short	0.030	0.022	0.027	0.035
	Long	0.069	0.061	0.064	0.038

Note: The table presents a summary of the cumulative exchange rate pass-through (ERPT) to consumer prices (CPIF) for the main specification and the final three robustness tests. The robustness tests are: alternative ordering, reduced sample and monthly specification. The table contains both the cumulative short-term response (after 2 quarters) and cumulative long-term response (after 20 quarters). The response to each price variable is estimated in the linear model, and non-linear model for the high and low inflation regime.

6.5.1 Estimations using Different Parameter Values

To test the model's sensitivity to different parameter values, we evaluate it for different values of γ and c. Recall that γ determines the speed of transition, and c is the threshold value. Figure 8 presents the IRFs to CPIF for c corresponding to a 50/50, 60/40, and 70/30 split between regimes. Figure 9 presents the IRFs to CPIF for $\gamma = (10, 15, 20, 25, 50)$.

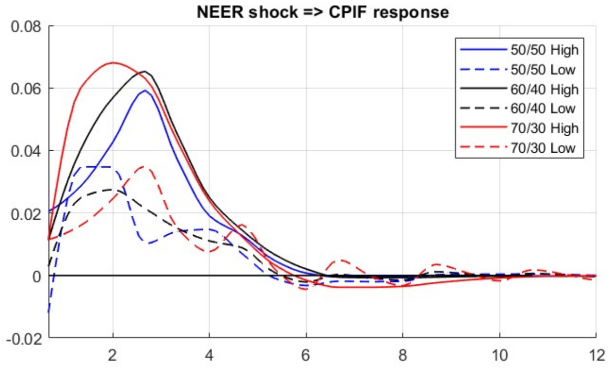

Figure 8: Sensitivity analysis for c

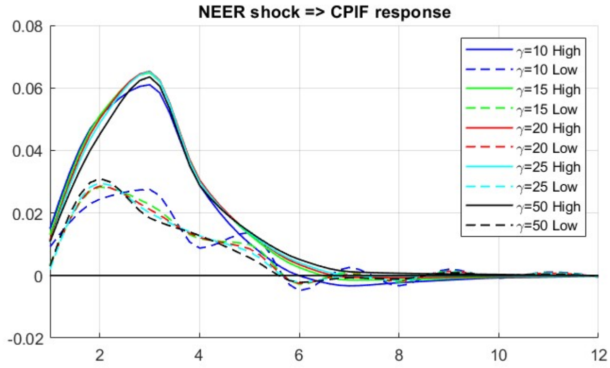

Figure 9: Sensitivity analysis for γ

Note: The figures plot the response to consumer prices (CPIF) following a 1% depreciation of the exchange rate (NEER) using different parameter values of the logistic smoothing function. The left figure shows the robustness results for different threshold values (c) and the right figure for different values of the speed of transition variable (γ). The results from the main specification corresponds to $c = 60/40$ and $\gamma = 20$. For each robustness test, the figures return the results for the high (solid line) and low (dashed line) inflation regimes.

We conclude that the model specification is stable for all tested values of c and γ. As expected, when adjusting c to include fewer observations in the high inflation regime, the high regime ERPT becomes larger, as proportionally more extreme values are included.[33] This is also anticipated when decreasing γ. However, our estimates remain stable for all tested values of γ. For $\gamma < 5$ or c corresponding to an 80/20 split, the results are not robust. This problem is addressed by Teräsvirta & Yang (2014), highlighting that too few observations in one regime make estimates less precise.

6.5.2 Estimations using Alternative Structural Order

In the second test, we estimate the model with an alternative variable ordering to assess the sensitivity of the the chosen structural order. As stated in *5.1.1 Identification Restrictions*, various orderings could be argued for. For the purpose of this paper, we will limit the test to the ordering used in McCarthy (2000) and Kwon & Shin (2023), as this is where the apparent divergence in ordering within previous literature occurs. The ordering, $\mathbf{Y}_t = [GDP \quad NEER \quad PRICE \quad POLICY\,RATE]'$, reflects that central banks react to all available information when setting the policy rate and that the policy rate has a delayed effect on the economy.

The IRFs obtained from the new ordering are presented in Appendix A3 and are close to identical to the main specification. The estimated ERPT, as shown in the second column of Table 4, is also close to identical to the main specification, returning a long-run ERPT of 17.6% (in contrast to 17.4%) for the high inflation regime and 6.1% (in contrast to 6.9%) for the low inflation regime.

6.5.3 Estimations using Reduced Sample Period

We suspect that our results could be influenced by the volatile period and disruptions in the world market from 2020 to 2023, including events such as Covid-19, the Russia-Ukraine war, and the rise in inflation in 2022/2023. These events had a significant impact on inflation and the exchange rate,

[33]Fewer observations will be categorized as $F(z_t) \approx 1$, making the parameters Π_{High} more influenced by extreme values in the sample, as they will still be $F(z_t) \approx 1$.

potentially causing endogeneity issues. Furthermore, there are indications that the ERPT increased during the inflation period of 2022/2023 (*see 2. Literature Review* and *3. The Swedish Case*). Therefore, the model is re-estimated using the sample period 1995Q1-2019Q4. To account for the reduced number of high inflation observations in the updated sample the threshold value (c) is re-balanced to correspond to a 70/30 split to resemble historical conditions.

The results are presented in Appendix A4 and in the third column of Table 4. The results remain robust when comparing to the main specification, although the IRFs exhibit more erratic behavior. There is also a noticeable reduction in the regime divergence for CPIF, where the ERPT is 6.4% (compared to 6.9%) in the low regime and 12.5% (compared to 17.4%) in the high regime. The decreased divergence is driven by lower ERPT for the high regime as the low regime, and also the linear model, is stable.

6.5.4 Estimations using Monthly Data

The fourth robustness tests estimates the LST-SVAR model with monthly data. Note that this estimation uses industrial production indices as proxy for economic activity in Sweden and the world (*see 4. Data*).[34] We follow the same estimation procedure as the quarterly specification and re-estimate the model.[35]

The results for the monthly estimations are shown in Appendix A5 and in the fourth column of Table 4. The IRF is less structured which could be a result from the noisy and unweighted proxy variables. However, the estimates confirm that the response to IMPI is the highest, followed by PPI and lastly CPIF. The regime dependency of ERPT remains evident for CPIF although returning smaller estimates, corresponding to 3.8% in the low inflation regime and 12.2% in the high inflation regime.

[34] To address the issues with poor a proxy variable, we first run the quarterly specification using the industrial production indices to ensure that the results does not deviate substantially. We find that the resulting IRFs for all measures of price return similar but more noisy measures.

[35] We will use the same specification of c and γ as in the main specification since they are invariant to frequency, but select $CPIF_{t-3}$ as the threshold variable as it returns the highest LM-value among the lags in CPIF when conducting the Linearity test.

7 Discussion

7.1 Review of Results

The main finding of this paper is that the exchange rate pass-through to consumer prices in Sweden is non-linear and dependent on inflation. Over the long run, we estimate the ERPT to CPIF to 17.4% in the high inflation regime and 6.9% in the low regime. While various factors could explain these results, our model is not designed to pin down the causal mechanisms. However, as inflation reflects the aggregate outcome of individual firms' pricing decisions (Apel et al., 2004), we can offer possible explanations for our results by drawing on theoretical and empirical research, along with qualitative evidence from the Riksbank's Business Surveys.

Inflation-dependent ERPT was first suggested by Taylor (2000), who stated that the persistence of the cost shock, in this study, the persistence of the depreciation shock, impacts the size of the pass-through. Our results align with the findings of Taylor (2000) as the exchange rate shock on itself is more persistent in the high inflation regime with an 83% additional depreciation, compared to the low inflation regime's 23%, when evaluating the model for consumer prices. This could be explained as high inflation causes elevated uncertainty among investors, making the Swedish Krona less attractive and hence vulnerable to further depreciations. The Riksbank (2022a) also states that the volatility in the financial markets following the Russia-Ukraine war, making "safe-haven currencies"[36] more attractive compared to the Swedish Krona, and the policy rate differentials between the Riksbank and other central banks (FED, ECB and BoE)[37] could partly explain the recent depreciation. To account for the effect of further depreciations, we consider the alternative measure, Price to Exchange Rate Ratio (PERR). The main results for CPIF do not change, although there is less divergence between the regimes (9.5% in the high regime and 5.6% in the low regime), but the estimates for PPI and IMPI indicate higher pass-through in the low inflation regime. The PERR measure could be seen as an approximation of the underlying pass-through, as it disregards the regime-specific dynamics. However, we argue that the ERPT measure, allowing for regime-specific dynamics by not controlling for channels through which the shock could affect, better captures the true pass-through effect.

Borio et al. (2023) develop Taylor's (2000) framework and suggest that an important transmission mechanism that differs between inflation regimes is the spillover effects between sectors. Borio et al. (2023) state that in a high inflation regime, firms pass along larger share of their cost shocks, while in a low inflation regime, firms are more hesitant to increase prices. In the Riksbank's Business Surveys from a low inflation period, firms state that since the cost increases of input goods are low, they have no need to increase their own prices (Sveriges Riksbank, 2013 & 2014). On the contrary, from a survey conducted during high inflation, firms state that despite inflation, they could, and need, to pass along cost increases to a larger extent as the input costs are rising. Some firms even state that suppliers are taking advantage of the inflation to disproportionately increase prices (Sveriges Riksbank, 2022b). The increased spillover effect in high inflation stated by Borio et al. (2023) could be exemplified with the statement from a company manager: "We barely have time to increase customer prices as quickly as the rising cost of the input goods" (Sveriges Riksbank, 2022b, p.5).

[36]Safe haven currencies are currencies that remain stable despite uncertainty in the financial markets, for example the U.S Dollar, The Japanese Yen and the Swiss Franc.

[37]FED: Federal Reserve (Central Bank of U.S), ECB: European Central Bank and BOE: Bank of England.

The ability to pass on cost shocks could also be explained by the market dynamics in each inflation regime. Taylor (2000) states that in low inflation, firms are hesitant to pass on the cost increases due to competitive pressure and the risk of losing market shares, resulting in lower markups and lower ERPT. This aligns with firm statements from the Riksbank's Business Survey during a low inflation period, where the main reason for not increasing prices is the risk of losing market share and that they rather absorb the depreciation shock by decreasing their markups (Sveriges Riksbank, 2015). In contrast, Borio et al. (2023) suggest that firm markups increase with the level of inflation, which NIER (2022) found evidence of for Swedish firms during the inflation period of 2022/2023. This could be exemplified from a company manager stating that "I have never experienced customers accepting price increases so easily" (Sveriges Riksbank, 2022b, p.5).

Weber & Wasner (2023) expand on how the markets dynamics during the high inflation period of 2022/2023 could increase the ability to pass along cost increases by stating that shocks could functions as a signal for tacit collusion allowing firms to disregard the competitive pressure. In our robustness test where observations from the inflation period of 2022/2023 are disregarded, we find that the ERPT to CPIF decreases from 17.4% to 12.5% in the high regime. The estimates for the low regime does not change, thus indicating of abnormal ERPT during the recent inflation period of 2022/2023.[38] In the Riksbank's Business Survey a company manager states "Price increases are a daily occurrence for most; everyone does it at the same time" (Sveriges Riksbank, 2022b, p.6), indicating of tacit collusion. Additionally, Weber & Wasner (2023) assert that the public's knowledge about shocks and disruptions could increase the consumers perceptions of the legitimacy of price increases. This is evident the Riksbank's Business Survey, where firms state that consumers are willing to pay higher prices since they have an understanding of the disruptions in the world and domestic markets, such as higher energy prices and currency depreciations (Sveriges Riksbank, 2022b).

From the comparison of the ERPT to consumer prices (CPIF), producer prices (PPI) and import prices (IMPI) we could conclude that the ERPT is declining along the pricing chain. For the linear model, ERPT to CPIF, PPI and IMPI is respectively 11%, 57% and 92%, which aligns with previous research (Ortega & Osbat, 2020). In contrast to the regime divergence seen for CPIF, the divergence for PPI is evident but more ambiguous, and non existing for IMPI. Similar results where found by Kwon and Shin (2023) for South Korean ERPT dependent on the credibility of the central bank. We consider these results reasonable as the ERPT to import prices should not be dependent on inflation when controlling for foreign export prices (*see 2. Data*). Consumer prices, and to less extent producer prices, are more integrated and affected by the domestic market dynamics which could drive the ERPT differently depending on the regime, for the reasons discussed above. We thus conclude that the ERPT is decreasing, and that the divergence in regime dependent ERPT is increasing, along the pricing chain.

Finally, by using the specification procedure outlined by Teräsvirta (1994) and (Teräsvirta & Yang, 2014), and estimation procedure outlined in Auerbach & Gorodnichenko (2012) we have estimated an LST-VAR model that we believe to be correctly specified for its purpose. We have established that the model is non-linear with respect to inflation and that the logistic smoothing transition function

[38] Since the robustness test uses the sample period of 1995Q1-2019Q4 we are unable to say if the increased ERPT stems from the period of Covid-19 or the inflation period of 2022/2023. Given the evidence for the later, we will simplify the discussion for clarity.

is an appropriate choice. By using the quasi-Bayesian MCMC algorithm we establish that the model fit is improved by allowing the model to explore the parameter space. Moreover, the robustness tests does not alter our conclusions and the results for IMPI provide further evidence a suitable choice of endogenous and exogenous variable.[39]

7.2 Policy Implications

The results presented in this paper raises some important implications for monetary policy. Instead of determining the optimal monetary policy using a linear understanding of the ERPT, a non-linear interpretation offers central banks the possibility to adapt the monetary policy to better address the different inflationary pressure in the two regimes.[40] Following a depreciation in a high inflationary regime, additional tightening would be necessary to successfully combat inflation. Not only would this reduce the inflationary pressure via the normal transmission channels but also limit the impact on inflation from further depreciations of the exchange rate, as evident in our results from the high inflation regime. Finally, considering including non-linear ERPT estimates could improve forecasting capabilities and provide better insights from policy evaluations.

Our findings provide support for a non-linear "rule of thumb" of the ERPT but we remain cautious to suggest a numerical rule for the ERPT in a high and low inflation regime as more research is needed to establish the accurate additional regime effect. In addition, aspects such as the origin of the shock causing the depreciation of the exchange rate has proven to also explain the size of the ERPT (Corbo & Di Casola, 2022). Hence, a "rule of thumb" needs to incorporate several aspects to be useful in policy making. However, according to our estimations, a 1% depreciation of the exchange rate causes inflation to increase by 0.174 percentage points when the quarterly inflation is above 0.82%, or equally when the yearly inflation is above 3.3%. The impact on inflation is 0.069 percentage points when the quarterly inflation is less then 0.32%, or equally when the yearly inflation is less than 1.3%.

Lastly, the non-linear model utilized in this paper could be used by governments, firms, and central banks to gain greater understanding of other non-linear relationships in the economy. The model could possibly uncover new dimensions in research that previously only have been investigated with linear approaches.

7.3 Limitation and Future Research

A limitation inherent in a significant portion of the SVAR and the ERPT literature, regards the structural order employed, which may not entirely align with real-world dynamics. In our case, assuming that the exchange rate remains unresponsive to inflation within the same period could be challenged as the exchange markets normally reacts to all information available. In the ERPT literature this assumption is often made as a trade off for estimation purposes to capture the relationship

[39] The results for import prices indicates that we effectively deal with bias from global shocks and trends by including exogenous weighted foreign variables (CPI, GDP, Policy rate). For example, if the estimated divergence in CPIF and PPI were driven by global shocks depreciating the currency and simultaneously driving up inflation through higher import prices, the divergence would also be seen for IMPI, which it does not. This is otherwise a normal pitfall in the ERPT literature raised by Shambaugh (2008).

[40] We acknowledge that the Riksbank considers other macroeconomic variables then the inflation rate when determining the policy rate. The argument made is simplified and could be seen as a "ceteris paribus" argument.

of interest, i.e., the exchange rate's effect on inflation. Another limitation of the study is that the model is not designed to pin down the causal explanations for the regime dependency. Utilizing other advanced models can potentially provide more detailed explanations by decomposing to what extent the ERPT depend on markups, persistence in cost shocks and inflation, or frequency of price adjustment.[41]

Another limitation in the analysis is that we do not allow for regime switches to occur over the 12 horizons plotted in the IRFs. This implies that the economy is forced to stay in the same regime for all 3 years and will behave accordingly. However, we believe this is of minor inconvenience in the main specification as the duration of the shocks last for 6 quarters, making a fixed regime more reasonable. Nevertheless, future research could provide additional insight by estimating how the ERPT evolves when the economy is allowed to revert back to a stable inflation. This could be combined with policy rules in the response of an exchange rate shock. For example, what would the cumulative ERPT be if the central bank determines that it would hike the interest rate more when in a high inflationary regime following an exchange rate depreciation. As impulse response functions generally provide poor evaluations of policy proposals due to the endogeneity of policy, one could instead simulate the response of a system, from an exogenous shock, with built in endogenous rules that are triggered depending on the inflation level.

For future research, we propose expanding the non-linear framework with alternative identification strategies. By employing identification by sign restrictions, one could investigate how the ERPT is influenced by the underlying shock and inflation regime, which would offer detailed insights into the ERPT dynamics. Additionally, we recommend extending the analysis in this paper to more detailed price data. Disaggregating the response to consumer prices into product categories can reveal where the highest regime dependence is found. These insights would be valuable for a more nuanced understanding of ERPT and contributions from different sectors.

[41] For example Dynamic stochastic general equilibrium (DSGE) models.

8 Conclusion

This paper investigates to what extent the ERPT depends on the level of inflation in Sweden for the period of 1995Q1-2023Q2. To capture the regime dependent dynamics we estimate a Logistic Smooth Transition Vector Autoregressive model (LST-VAR) with a Cholesky decomposition. The modeling approach contributes to the non-linear ERPT research by facilitating a meaningful economic interpretation of the estimates at the same time as allowing for regime-specific dynamics in a more coherent fashion than comparable models. Furthermore, the model could be utilized by central banks and governments for analysing other non-linear relationships in a macroeconomic setting.

We contribute to the existing literature by providing novel evidence of a non-linear ERPT to consumer prices in Sweden, reaching 17.4% in the high inflation regime and 6.9% in the low inflation regime. The estimations include the latest data available and provides insights of the driving forces of the 2022/2023 inflation period. In addition, we estimate a linear ERPT of 92% to import prices, 57% to producer prices, and 11% to consumer prices. We find indications of a regime-dependent ERPT to producer prices and no evidence for a regime-dependent ERPT to import prices. In accordance with previous research, the ERPT is found to be declining along the pricing chain, but the relative divergence between the regimes is found to be increasing along the pricing chain. By providing an extensive robustness analysis we establish that the results are stable to changes of the parameters values in the logistic function, the structural ordering of the model, the sample period and the frequency of the data.

We combine our results with theoretical and empirical research, as well as qualitative evidence from the Riksbank's Business Surveys to provide possible explanations to the causes of inflation dependent ERPT. One explanatory factor is the increased persistence in the depreciation shock, for which we find evidence for as the exchange rate continues to depreciate within the high inflation regime. Although not included in the model, domestic factors such as markups and spillover effects could provide insights into the driving factors of the regime dependent ERPT.

Our results supports a more contractionary monetary policy reaction following a currency depreciation in a high inflationary environment, compared to if the optimal policy reaction was based on a linear understanding of the ERPT. Appropriate policies could limit the exchange rate from further depreciating, prevent higher pass-through and in extension the impact on aggregate inflation.

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Appendix

A1: Estimation of $\mathbf{\Pi}_{High}$, $\mathbf{\Pi}_{Low}$

Weights are given by $\mathbf{\Omega}_t^{-1}$ and estimates of $\{\mathbf{\Pi}_{High}(L), \mathbf{\Pi}_{Low}(L)\}$ must minimize $\frac{1}{2}\sum_{t=1}^{T}\mathbf{u}_t'\mathbf{\Omega}_t^{-1}\mathbf{u}_t$.

We rewrite the RHS (excluding the the residuals) as:

$$\mathbf{W}_t = \left[\begin{array}{cccc} (1-F(z_t))\mathbf{X}_t & F(z_t)\mathbf{X}_t & \ldots & (1-F(z_{t-p}))\mathbf{X}_{t-p}F(z_t)\mathbf{X}_t \end{array}\right] \tag{14}$$

Next, let $\mathbf{\Pi} = \left[\begin{array}{cc} \mathbf{\Pi}_{High} & \mathbf{\Pi}_{Low} \end{array}\right]$ be the extended vector of regressors so that $\mathbf{u}_t = \mathbf{Y}_t - \mathbf{\Pi}\mathbf{W}_t'$ and the objective function is:

$$\frac{1}{2}\sum_{t=1}^{T}(\mathbf{Y}_t - \mathbf{\Pi}\mathbf{W}_t')'\mathbf{\Omega}_t^{-1}(\mathbf{Y}_t - \mathbf{\Pi}\mathbf{W}_t'). \tag{15}$$

Note that we can rewrite Equation (16) as:

$$\begin{aligned}
&\frac{1}{2}\sum_{t=1}^{T}(\mathbf{Y}_t - \mathbf{\Pi}\mathbf{W}_t')'\mathbf{\Omega}_t^{-1}(\mathbf{Y}_t - \mathbf{\Pi}\mathbf{W}_t') \\
&\qquad = \text{trace}\left[\frac{1}{2}\sum_{t=1}^{T}(\mathbf{Y}_t - \mathbf{\Pi}\mathbf{W}_t')'\mathbf{\Omega}_t^{-1}(\mathbf{Y}_t - \mathbf{\Pi}\mathbf{W}_t')\right] \\
&\qquad = \frac{1}{2}\sum_{t=1}^{T}\text{trace}\left[(\mathbf{Y}_t - \mathbf{\Pi}\mathbf{W}_t')'(\mathbf{Y}_t - \mathbf{\Pi}\mathbf{W}_t')\mathbf{\Omega}_t^{-1}\right].
\end{aligned}$$

The first order condition with respect to $\mathbf{\Pi}$ is $\sum_{t=1}^{T}\left(\mathbf{W}_t'\mathbf{Y}_t\mathbf{\Omega}_t^{-1} - \mathbf{W}_t'\mathbf{W}_t\mathbf{\Pi}'\mathbf{\Omega}_t^{-1}\right) = 0$. Now using the *vec* operator, we get:

$$\begin{aligned}
\text{vec}\left(\sum_{t=1}^{T}\mathbf{W}_t'\mathbf{Y}_t\mathbf{\Omega}_t^{-1}\right) &= \text{vec}\left[\sum_{t=1}^{T}\mathbf{W}_t'\mathbf{W}_t\mathbf{\Pi}'\mathbf{\Omega}_t^{-1}\right] = \sum_{t=1}^{T}\text{vec}\left[\mathbf{W}_t'\mathbf{W}_t\mathbf{\Pi}'\mathbf{\Omega}_t^{-1}\right] \\
&= \sum_{t=1}^{T}[\text{vec}\,\mathbf{\Pi}']\left[\mathbf{\Omega}_t^{-1}\otimes\mathbf{W}_t'\mathbf{W}_t\right] = \text{vec}\,\mathbf{\Pi}'\sum_{t=1}^{T}\left[\mathbf{\Omega}_t^{-1}\otimes\mathbf{W}_t'\mathbf{W}_t\right],
\end{aligned}$$

which gives:

$$\text{vec}\,\mathbf{\Pi}' = \left(\sum_{t=1}^{T}\left[\mathbf{\Omega}_t^{-1}\otimes\mathbf{W}_t'\mathbf{W}_t\right]\right)^{-1}\text{vec}\left(\sum_{t=1}^{T}\mathbf{W}_t'\mathbf{Y}_t\mathbf{\Omega}_t^{-1}\right)$$

From which we retrieve the lag polynomials $\mathbf{\Pi}$ by reshaping the vector into a matrix.

A2: Linearity Test

The linearity test for a single transition variable is carried out using the approach suggested by Luukkonen & Saikkonen (1988) and Luukkonen et al. (1988). The test is constructed by replacing the transition function in the LST-VAR with a Taylor series approximation appropriate for the system. The approach was constructed to handle the identification issue in the parameters under the assumption of non-linearity. The Taylor series approximations use polynomials to make it possible to approximate values that are otherwise difficult to evaluate. We follow the outline by Teräsvirta & Yang (2014) and use the n-order Taylor approximation suggested by Luukkonen[42] (1988) where $\gamma_j = 0$ is specified as:

$$g(z_t \mid \gamma_j, c_j) = \sum_{i=0}^{n} a_{j,n-i} z_t^{n-i} + r_{jt} \tag{16}$$

Where $a_{j,0}, ..., a_{j,n}$ represents the coefficients, r_{jt} the remainder Taylor expansion term and z_t the transition variable. The Taylor approximation used for the linearity test is specified as:

$$\mathbf{G}_t = diag\left\{\sum_{i=0}^{n} a_{1,n-i} z_t^{n-i} + r_{1t} ..., \sum_{i=0}^{n} a_{p,n-i} z_t^{n-i} + r_{pt}\right\} = \sum_{i=0}^{n} \mathbf{A}_{n-i} z_t^{n-i} + \mathbf{R_t} \tag{17}$$

$\mathbf{A}_{n-i}$ and $\mathbf{R_t}$ are diagonal matrices of the coefficients and Taylor expansion terms.

We simplify the LST-VAR model, using $\mathbf{y_t}$ as the vector of endogenous variables and $\mathbf{x_t}$ as vector of explanatory variables. We denote the low inflation regime as $\mathbf{B}_1'$ and the high inflation regime as $\mathbf{B}_2'$ for simplicity.

$$\mathbf{y}_t = \mathbf{B}_1' \mathbf{x}_t + \mathbf{G}_t \mathbf{B}_2' \mathbf{x}_t + \varepsilon_t \tag{18}$$

The model has $j = 1, ...p$ dimensions. The null hypothesis is that $\gamma_j = 0, j = 1, ..., p$ and the alternative hypothesise is that at least one $\gamma_j > 0, j = 1, ..., p$. Furthermore, under the null hypothesise $\mathbf{G}_t \equiv (1/2)\mathbf{I}_p$, the system becomes linear and c_j is not defined.

Inserting the new transition function into the LST-VAR system yeilds:

$$\begin{aligned}
\mathbf{y}_t &= \mathbf{B}_1' \mathbf{x}_t + \left(\sum_{i=0}^{n} \mathbf{A}_{n-i} z_t^{n-i} + \mathbf{R}_t\right) \mathbf{B}_2' \mathbf{x}_t + \boldsymbol{\varepsilon}_t \\
&= \left(\mathbf{B}_1' + \mathbf{A}_0 \mathbf{B}_2'\right) \mathbf{x}_t + \sum_{i=1}^{n} \mathbf{A}_i \mathbf{B}_2' \mathbf{x}_t z_t^i + \mathbf{R}_t \mathbf{B}_2' \mathbf{x}_t + \boldsymbol{\varepsilon}_t \\
&= \Theta_0' \mathbf{x}_t + \sum_{i=1}^{n} \Theta_i' \mathbf{x}_t z_t^i + \boldsymbol{\varepsilon}_t^*
\end{aligned} \tag{19}$$

Where $\Theta_0 = \mathbf{B}_1 + \mathbf{B}_2 \mathbf{A}_0, \Theta_i = \mathbf{B}_2 \mathbf{A}_i$, and $\varepsilon_t^* = \mathbf{R}_t \mathbf{B}_2' \mathbf{x}_t + \varepsilon_t$ The null hypothesise for linearity is can be written as $\Theta_1 = ... = \Theta_n = 0$.

We rewrite the above expression as follows: $\mathbf{Y} = \mathbf{X}\Theta_0 + \mathbf{Z}_n \Theta_n + \mathbf{E}$. Where $\mathbf{Y} = (\mathbf{y}_1, \ldots, \mathbf{y}_T)'$, $\mathbf{X} = (\mathbf{x}_1, \ldots, \mathbf{x}_T)'$, $\mathbf{E}^* = (\varepsilon_1^*, \ldots, \boldsymbol{\varepsilon}_T^*)'$, $\Theta_n = (\Theta_1', \ldots, \Theta_n')'$ and

[42] Following Luukkonen et al. (1988) we use n=3

$$\mathbf{Z}_n = \begin{bmatrix} \mathbf{x}_1' z_1 & \mathbf{x}_1' z_1^2 & \dots & \mathbf{x}_1' z_1^n \\ \mathbf{x}_2' z_2 & \mathbf{x}_2' z_2^2 & \dots & \mathbf{x}_2' z_2^n \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{x}_T' z_T & \mathbf{x}_T' z_T^2 & \dots & \mathbf{x}_T' z_T^n \end{bmatrix}$$

The null become: $\Theta_n = 0$ and n indicates the order of the Taylor expansion.

The LM-statistic for testing $\Theta_n = 0$ or $\gamma_j = 0, j = 1, ..., p$ is computed as:

$$LM_n = \mathrm{tr}\left\{ \tilde{\mathbf{\Omega}}^{-1} \left(\mathbf{Y} - \mathbf{X}\tilde{\Theta}_0 \right)' \mathbf{Z}_n \left[\mathbf{Z}_n' \left(\mathbf{I}_T - \mathbf{P}_x \right) \mathbf{Z}_n \right]^{-1} \mathbf{Z}_n' \left(\mathbf{Y} - \mathbf{X}\tilde{\Theta}_0 \right) \right\}$$

With $\widetilde{\Omega}$ and $\widetilde{\widetilde{\Theta}_0}$ estimated from the model under the null and $\mathbf{P}_x \equiv \mathbf{X}\left(\mathbf{X}'\mathbf{X}\right)^{-1}\mathbf{X}'$.

The test statistics has, under the null hypothesise, an asymptotic χ^2 distribution and $np(kp+q)$ degrees of freedom. The number of degrees of freedom are equal to the column dimension of $\mathbf{Z}_1$ multiplied with the number of restrictions (p). For more details see, Teräsvirta & Yang (2014).

A3: Estimations with Alternative Structural Order

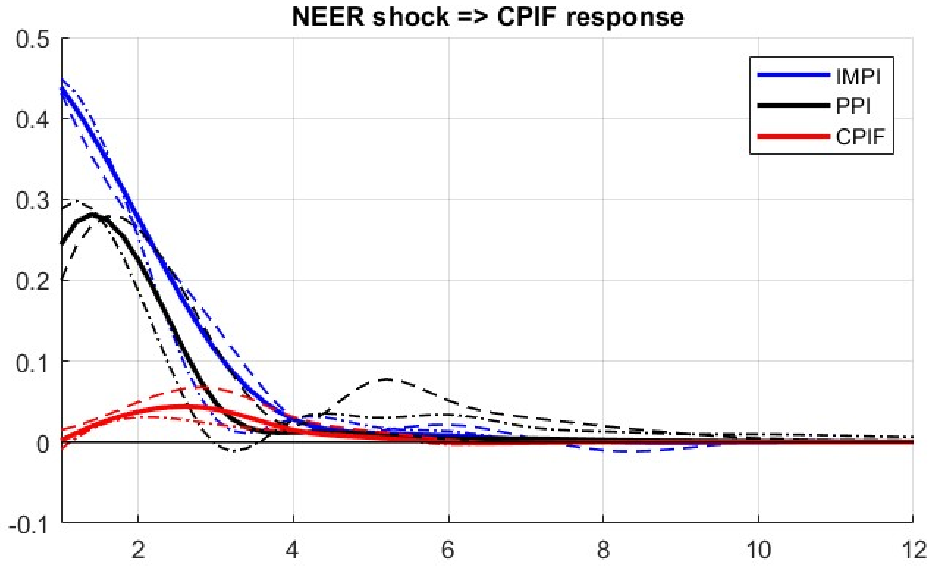

Figure 10: Impulse response functions with alternative structural ordering

Note: The figure shows the impulse response functions for the alternative structural ordering (McCarthy, 2000; Kwon & Shin, 2020). The functions display how a 1% depreciation shock in the exchange rate (NEER) impacts consumer prices (CPIF), producer prices (PPI) and import prices (IMPI) over 12 quarters. The solid lines represent the linear estimations, the dashed line (- -) represent the low regime and the dash-dotted (- . -) represent the high regime. Confidence intervals are not presented in the figure.

A4: Estimation with Reduced Sample Period

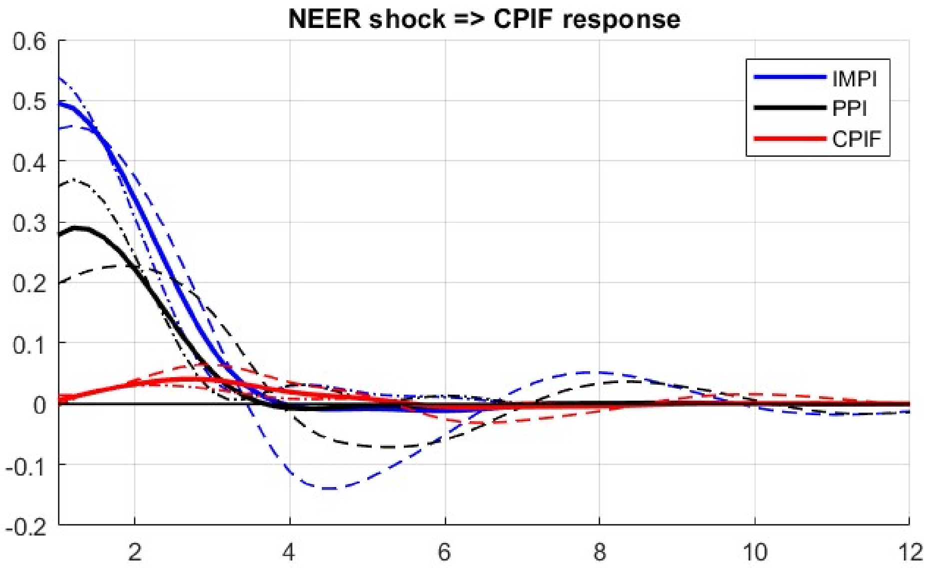

Figure 11: Impulse response function using a reduced sample

Note: The figure shows the impulse response functions for the reduced sample, covering observations from 1995Q1-2019Q4. The functions display how a 1% depreciation shock in the exchange rate (NEER) impacts consumer prices (CPIF), producer prices (PPI) and import prices (IMPI) over 12 quarters. The solid lines represent the linear estimations, the dashed line (- -) represent the low regime and the dash-dotted (- . -) represent the high regime. Confidence intervals are not presented in the figure.

A5: Estimations using Monthly Data

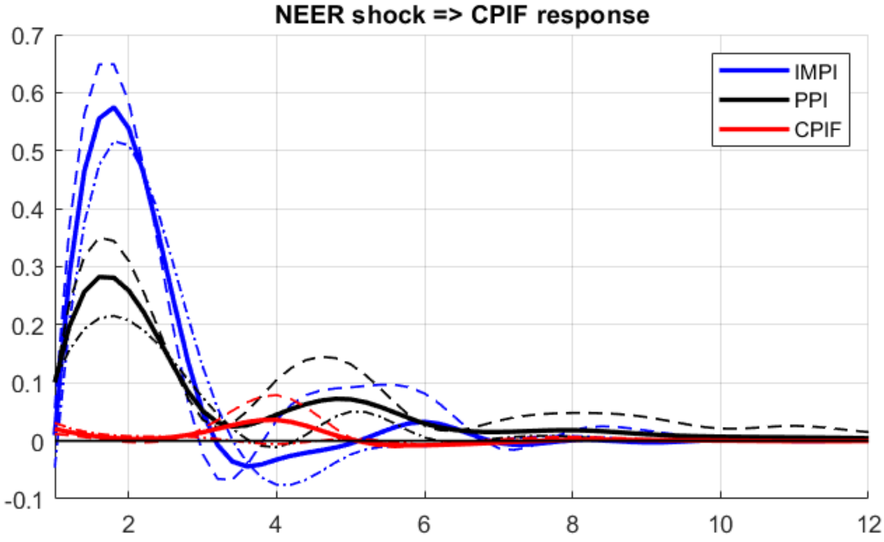

Figure 12: Impulse response function using monthly data

Note: The figure shows the impulse response functions using monthly data for estimations. The functions display how a 1% depreciation shock in the exchange rate (NEER) impacts consumer prices (CPIF), producer prices (PPI) and import prices (IMPI) over 12 months. The solid lines represent the linear estimations, the dashed line (- -) represent the low regime and the dash-dotted (- . -) represent the high regime. Confidence intervals are not presented in the figure.

A6: Model Trace Plot

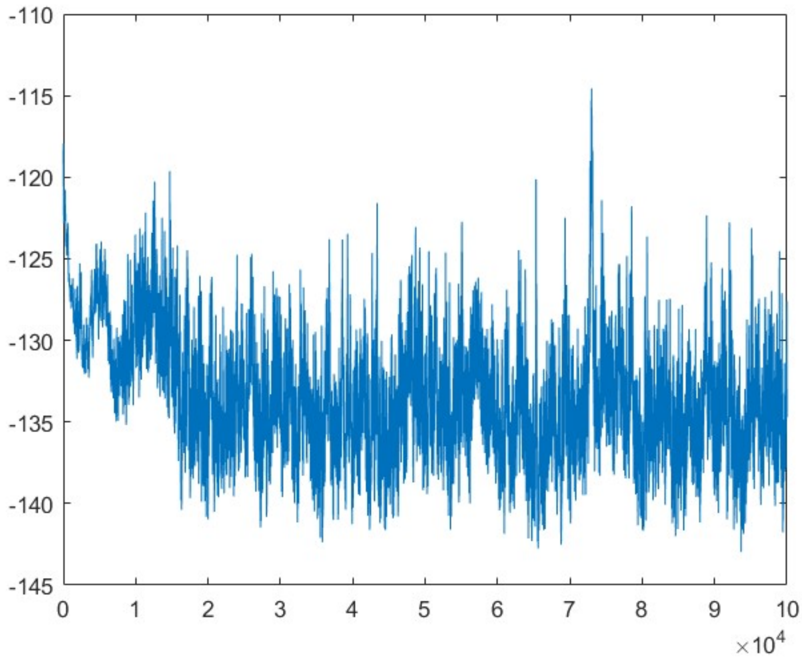

Figure 13: Trace plot for CPIF-specification log likelihood

Note: The trace plot shows the calculated log likelihood for every set of parameters from the Markov Chain Monte Carlo simulation showing the evaluation and progress of the optimization. The x-axis plots the 100 000 draws in order and the y-axis plots the negative log likelihood. A smaller negative log likelyhood is equal to a higher log likelyhood and better model fit.

A7: Parameter Trace Plot

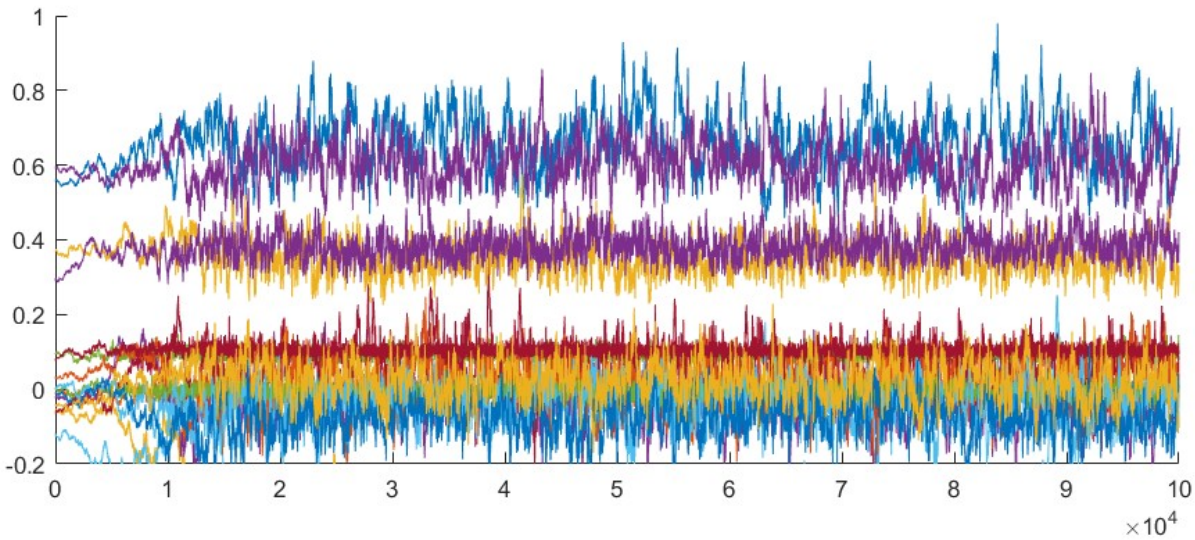

Figure 14: Trace plot for CPIF parameter values

Note: The trace plot shows the evaluation of the parameter values and is obtained from the Markov Chain Monte Carlo simulation. The x-axis plots the 100,000 draws in order, and the y-axis plots the estimated coefficient. White noise behavior indicates that we are sampling from the target distribution.

A8: Autocorrelation and Normality Test

Table 5: Ljung-Box and Jarque-Bera test for the model's residuals

	Ljung-Box								Jarque-Bera	
	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p
Lags	2	2	4	4	6	6	8	8	–	–
GDP	1.0752	0.5841	1.5722	0.8138	1.5851	0.9536	2.6589	0.9539	6.6652	0.0217
PR	0.7136	0.6999	4.7784	0.0665	10.3971	0.1089	11.6637	0.1669	2.9211	0.2321
NEER	3.2035	0.2015	6.7931	0.3108	6.3061	0.3898	8.4534	0.3905	2.3055	0.3158
CPIF	9.9481	0.0069	11.4336	0.0009	25.2551	0.0003	39.9468	0.0003	2.6834	0.2141
Joint	14.940	–	24.573	–	43.543	–	62.721	–	14.575	–
Critical value	15.723	–	26.323	–	55.787	–	79.921	–	15.712	–

Note: The table shows the obtained chi-square values (χ^2) and p-values (p) for the Ljung-Box and Jarque-Bera tests conducted for the residuals of the endogenous variables: gross domestic product (GDP), policy rate (PR), exchange rate (NEER), and consumer prices (CPIF). The Ljung-Box test is evaluated for lags 2-8. The tests are also carried out for the residuals on the entire model in a joint test (Joint). The critical values used to evaluate hypotheses for the joint tests are shown on the bottom row.

A9: Residual Plot

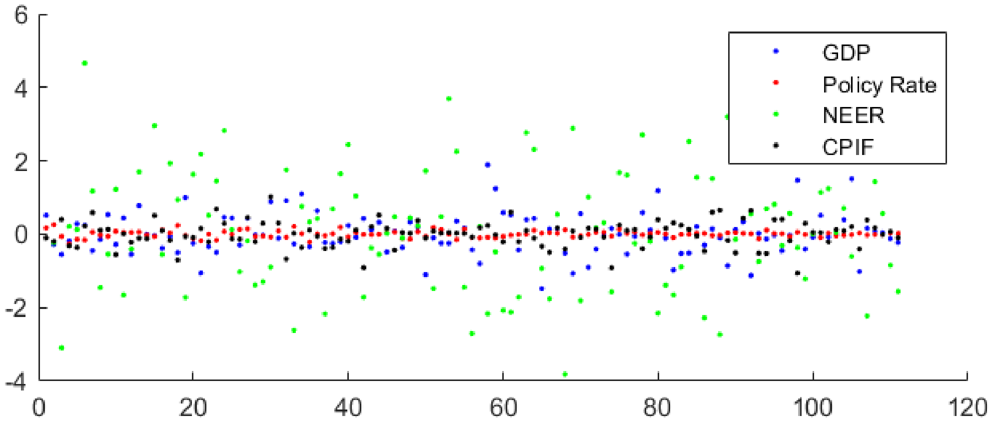

Figure 15: Residual plot

Note: The figure plots the residuals from the model's endogenous variables: gross domestic product (GDP), Policy rate, exchange rate (NEER) and consumer prices (CPIF) for 113 observations.

A10: Log likelihood Test for γ

Table 6: Gamma test

γ	Log Likelihood
0	157.63
5	161.32
10	162.45
20	162.77
30	162.71
40	162.70
50	162.66
100	162.44
500	162.20

Note: The table shows the log likelihood values for different values of the speed of transition parameter γ. The preferred value is highlighted in grey. Higher log likelihood indicates of better model fit.

A11: IRF for Policy Rate Chocks

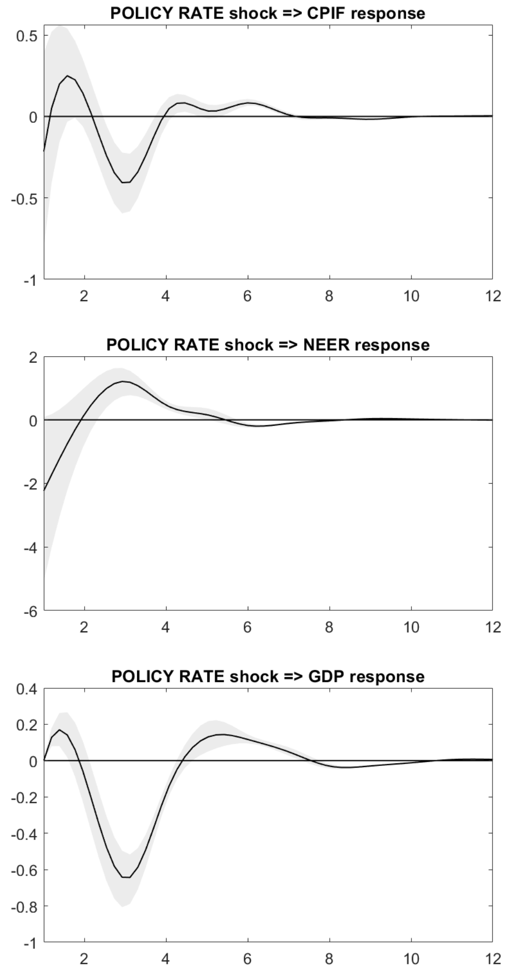

Figure 16: Impulse response function from the Policy Rate

Note: The table presents impulse response functions from a 1% shock in the Policy rate to consumer prices (CPIF), the exchange rate (NEER), and gross domestic product (GDP). The confidence intervals are 90%.

A12: Link to Code Used

The code used and developed for this thesis could be found at https://github.com/MalteMeuller/Master-Thesis. The data wrangling and initial tests are conducted in R. The optimization routines is performed in MATLAB and based of the code developed by Auerbach and Gorodnichenko's (2012) which could be found here:
https://www.aeaweb.org/articles?id=10.1257/pol.4.2.1

A13: Data Sources

QUARTERLY DATA

Variable name	Description	Frequency	Changes made	Source
GDP	Gross domestic product, Consumer side	Quarterly	Seasonally adjusted, log difference	SCB
POLRATE	Policy Rate	Daily	Detrended with HP Filter, quarterly means	Riksbank
CPIF	Consumer price index with fixed interest rate	Monthly	Quarterly means, log difference	SCB
PPI	Producer price index	Monthly	Quarterly means, log difference	SCB
IMPI	Import price index	Monthly	Quarterly means, log difference	SCB
NEER	KIX weighted nominal effective exchange rate	Daily	Quarterly means, log difference	Riksbank
KIX-GDP	KIX weighted GDP	Quarterly	Log difference	Riksbank
KIX-CPI	KIX weighted CPI	Monthly	Log difference	Riksbank
KIX-POLRATE	KIX weighted policy rate	Monthly	HP-filtered	Riksbank

MONTHLY DATA

Variable name	Description	Frequency	Changes made	Source
IPI	Swedish industrial production index	Monthly	Log difference	Riksbank
World-IPI	World industrial production index	Monthly	Log difference	Riksbank

Note : In the main specification, we use data on a quarterly frequency. The monthly specification uses the same variables as the quarterly specification except for the measures GDP and KIX-GDP, which we replace with industrial production indices.