From Soil to Shelf

Fertilizer Price Transmission to Swedish Food Prices After Russia's Invasion of Ukraine

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Abstract

Russia's invasion of Ukraine in February 2022, caused a disruption in global fertilizer markets, raising the question if such input costs shocks transmit to consumer food prices. Using monthly panel data this study examines how the increase in global urea price following Russia's invasion of Ukraine affected Swedish consumer food prices for four food categories with varying degrees of fertilizer dependency: *vegetables*, *sugar*, *fruits and tree nuts* and *pulses*.

Three complementary two-way fixed effects modes are estimated to capture whether urea price changes transmitted to Swedish consumer prices and if the increase was greater following the invasion. The first model finds statistically significant positive urea price transmission for fruits and tree nuts, pulses and sugar, indicating that price shocks in the fertilizer market are transmitted to Swedish consumer food prices. However, the effects are small and do not follow the expected fertilizer dependency order, suggesting that other factors affect how fertilizer prices are transmitted. The second and third models found little to no find significant evidence overall or category-specific level that more fertilizer dependent categories experienced grater price increases following the invasion, with only sugar showing a small but significant price shift relative to pulses.

The findings are consistent with the findings of existing literature on price transmission and suggests that urea prices are associated with Swedish consumer food prices, however, the effects are small. Due to a significant placebo test and some variables having high collinearity the findings should be interpreted with caution. The study contributes to the literature by examining fertilizer price transmission for food categories with varying degree of fertilizer dependency and in a high-income economy.

Keywords: Price transmission, Fertilizer prices, Food prices, Sweden, Panel data, Fixed effects

Table of contents

List of tables

1. Introduction

Following Russia's invasion of Ukraine in February 2022, global fertilizer prices increase by about 50% between February and April 2022. With Russia and Belarus as among the largest exporters of nitrogen, phosphate and potash fertilizers, this price surge was driven by export restriction, supply chains disruptions such as the Black Sea blockade and sanctions placed on Russia (USDA Economic Research Service, 2023). Urea is the most widely traded form of nitrogen fertilizer and is exposed to these disruptions since it is produced from natural gas through the Haber-Bosch process (Smith et al., 2020). Given these disruptions, the question is how much would this affect consumer prices?

Fertilizers is a key input in crop production and shortages, or high prices affects the entire food supply chain. When fertilizer prices increase, farmers may reduce their fertilizer use, switch to less fertilizer intensive crops or reduce production, which in turn can lead to higher commodity prices (USDA Economic Research Services, 2023). However, the extent to which fertilizer price changes transmit is not straightforward. Price transmission along food supply chains is often incomplete, partly because fertilizer is only a small share of the consumer retail price (Meyer & von Cramon-Taubadel, 2004). Moreover, transmission is unlikely to be the same for all food categories, it depends on a variety of factors such as fertilizer dependency, import dependency and supply chain structures. Since these factors differ across food categories, a category specific level analysis can show if there are differences in how they transmit to consumer prices.

Although the price transmission literature shows that transmission along the food supply chain is often incomplete (Meyer & von Cramon-Taubadel, 2004) and previous studies have examined the effects of Russia's invasion of Ukraine on global food systems (El Bilali and Ben Hassen, 2024; Vos et al., 2025), and fertilizer linkage between a single food category (Etienne et al., 2016; Morão, 2025) there are currently none examining how fertilizer price changes transmit to consumer food prices across different food categories in Sweden. This study aims to answer the following question: How did the increase in global fertilizer prices following Russia's invasion of Ukraine affect Swedish retail prices across food categories with varying degrees of fertilizer dependency over the period 2005-2025?

To answer this question, the study uses a panel dataset with monthly observations covering vegetables, sugar, pulses, and fruits and tree nuts, with data spanning from January 2005 to December 2025. The research question it is broken down into three objectives which is answered through three complementary two-way fixed effects panel models. Each model designed to captures a different aspect of the relationship of urea prices, the invasion and consumer food prices. The main explanatory variable is the urea spot price from the World Bank Pink Sheet (UREA_EE_BULK), which tracks the Black Sea urea spot price prior to the invasion and, the Middle East after the invasion (World Bank, 2026). This price series is used rather than a Swedish price because there were no Swedish price series currently public and the Eastern European price reflects the price that Swedish farmers are exposed to, given that Russia and Belarus are among the major nitrogen exporters (USDA Economic Research Services, 2023). To account for fertilizer dependency differences for the different categories, each category got a grade on a scale from 1 to 5 based on their nitrogen application rates form the IFA (2022) report.

Sweden is an interesting case for this study. As an EU member state Sweden is intergrated in the European agricultural markets and subject to EU trade policies, making it directly exposed to the price disruptions following the invasion. While much of the existing research on fertilizer price transmission examines low- and middle-income countries or aggregated EU-level effects, this paper instead focuses on how shocks are transmitted to Sweden’s consumer food prices across food categories with varying degrees of nitrogen fertilizer dependency. The findings can contribute to understanding which food categories are more vulnerable to fertilizer price shocks and can shed light in how fertilizer prices changes transmit to high-income economies, where the supply chain might differ from lower-income countries. From a policy perspective, tracking global fertilizer prices and understanding how different food categories are affected could help governments and food security analysts to prepare for potential price increases before they reach consumers.

2. Previous Research

This section reviews the literature relevant to how fertilizer price shocks may affect consumer food prices. It begins by discussion the disruption Russia's invasion of Ukraine had on global agricultural and fertilizer markets, then reviews broader literature on food prices and price transmission to then narrowing down on fertilizer price shocks specifically and then ending with the research gap this thesis addresses.

2.1 The Russia-Ukraine war and global agricultural markets

Russia and Ukraine played central roles in global agricultural markets, which means that Russia's invasion of Ukraine in 2022 caused a major disruption to the global food systems. Prior to the invasion, the two countries accounted for a large share of grain exports, while Russia and Belarus where major suppliers of global fertilizers, with Russia as one of the largest exporters of nitrogen, phosphate and potash (El Bilali & Ben Hassen, 2024).

The invasion disrupted both agricultural supply chain and fertilizer markets. Ukrainian exports drastically decreased due to among other factors infrastructure damage and blockades, while fertilizer prices increased due to export restrictions and sanction related disruptions (Vos et al., 2025; El Bilali & Ben Hassen, 2024). The increase in fertilizer prices was also linked to changes in the energy markets. Nitrogen fertilizers are produced using natural gas through the Haber-Bosch process (Smith et al., 2020). With Russia being one of the major exporters of natural gas and producer of nitrogen fertilizer, both the fertilizer production and trade were affected, contributing to the increase in global fertilizer prices.

2.2 Food prices and their drivers

Food prices are influenced by a wide range of supply and demand factors and a large movement in food prices rarely have a single cause (Headey and Fan, 2008). Much of the modern literature on food price dynamics is tied to the global food crisis of 2007-2009, when the international prices increase dramatically. Headey and Fan (2008) examines this period and argue that the crisis was driven by several factors, including rising energy prices, declining inventories and export restriction.

One important conclusion from this literature is that energy and input costs are important drivers of food prices. Higher energy prices increase transportation costs, production costs and the cost of agricultural inputs such as fertilizer (Headey &

Fan, 2008). Since fertilizer is a key input in food production, changes in fertilizer prices might be transmitted through the supply chain and eventually affect consumer food prices.

2.3 Price Transmission in commodity market

Price transmission refers to how a price change at one stage of a supply chain affects prices at another stage. Ferguson and Ubilava (2022) distinguished between two types of transmission. Horizontal transmission refers to the pass-through of global commodity prices to local markets and vertical price transmission refers to how price changes move through different stages of the supply chain.

For fertilizer price shocks to affect Swedish consumer prices, the increase in global fertilizer prices must first be transmitted to the Swedish fertilizer market. The transmission of fertilizer price shocks to Swedish food prices therefore involves both horizontal and vertical transmission.

Previous research suggests that price transmission is incomplete and might be asymmetric and that it varies across products and markets. Meyer von Cramon-Taubadel (2004) documents that retail prices respond differently to increases and decreases in input costs, indicating that cost changes are not always fully or symmetrically passed through to consumers. They also mention the marketing margin model by Gardner (1975) to help explain why transmission might be limited. In the model, the difference between farm-gate prices and retail prices is determined by conditions on both demand side at retail level and the supply level at the farm level. Because the farm gate is only a small share of the final retail price, with processing, transport and retail costs accounting for the rest of the transmission.

2.4 Fertilizer price shocks and their effects on prices

Several studies have documented relationships between fertilizers and agricultural commodity markets. Among them are Ott (2012), who found that higher crop prices increase the demand for fertilizers contribute to higher fertilizer prices. Similarly, Etienne et al. (2016) finds that ammonia and corn prices have a stable long-run relationship. Although ammonia and corn prices might deviate from their relationship in the short run, they tend to adjust back over time. The authors also find volatility spillovers between the two markets. This suggests a strong connection between fertilizer and crop prices.

Recent studies have focused on the fertilizer price increases following Russia’s invasion of Ukraine. Vos et al. (2025) finds that fertilizer demand declined only a bit despite the large price increases, this because many farmers absorbed the higher costs during a period of relatively favourable harvest expectations. Morão (2025) further shows that fertilizer price shocks explain a large share of the variation in agricultural output prices and played an important part during the 2007-2008 food price crisis ant the during the recent fertilizer market disruption.

The effects of fertilizer price shocks are not the same across countries and products. Although global trade volumes declined slightly following the 2022 price surge, the effects of the associated trade disruptions and price increases varied substantially between countries (Vos et al., 2025).

2.5 Research gap

Despite growing literature on fertilizer price shocks and food price transmission, there are still some gaps. While Meyer and von Cramon-Taubadel (2004) establishes that rpice transmission along the food supply chain is often incomplete and Etienne et al (2016) and Morão (2025) examine how fertilizer crop price relations for a single food category, much of the previous literature focuses on low- and middle-income countries, which leaves us with a limited understanding of how fertilizer price changes transmit consumer food prices in high-income countries, such as Sweden. A few studies examine transmission differs across categories with varying degrees of fertilizer dependency within a single country. This study addresses both gaps by examining category-specific fertilizer price transmission in Sweden, using monthly panel data from January 2005 to December 2025.

3. Data

The analysis is based on monthly panel dataset covering the period January 2005 to December 2025. The dataset includes four Swedish food categories observed over time which allows the study to exploit both variation across categories and over the studied time. This time frame is chosen so that the data cover a long pre-invasion period, so that the effects of Russia's invasion of Ukraine in February 2022 can be compared to. The data are collected from: Statistics Sweden (SCB), the World Bank, the International Fertilizer Association (IFA) and the Swedish Board of Agriculture (Jordbruksverket).

3.1 Dependent variable

The dependent variable is the consumer price index (CPI) for four food categories and obtained from Statistics Sweden (SCB). The categories follow the Classification of Individual Consumption According to Purpose (COICOP), not seasonally adjusted and indexed to 2020 = 100. The groups examined are fruits and tree nuts (COICOP 01.1.6), leafy or stem vegetables (COICOP 01.1.7.1), pulses (COICOP 01.7.6) and sugar from sugarcane and beets (COICOP 01.1.8.1). *Leafy or stem vegetables* will be referred to as vegetables and the category *sugarcane and beets* will be called as sugar.

The four food categories were selected according to a few criteria's. First, they had to differ in their degree of fertilizer dependency, which was necessary to answer the research question. Second, each category is a primary agricultural product that is grown directly and which fertilizer are applied directly. Third, they are among the few Swedish consumer price categories indices that are not aggregated together with other foods of differing fertilizer dependency, which would make it difficult to give them an accurate score for the whole category. Fourth, the categories consist primarily of crops that could be grown in the EU or Sweden. This matters because the study uses the Eastern European urea price as a measure for the fertilizer price shock as well as the EU has similar regulations for fertilizer use.

3.2 Urea Price

The main explanatory variable is the price of urea, measured as the Eastern European bulk price in US dollars per metric ton, collected from the World Bank's Commodity Price Data (Pink Sheet). Urea is the most widely traded nitrogen fertilizer and is produced from natural gas, which makes it exposed both supply and energy disruptions caused by the invasion. Eastern European bulk price is used because it is the regional price most closely linked to what Swedish farmers pay for nitrogen fertilizer. Since Russia and Belarus are among the largest suppliers of nitrogen fertilizers to the European market and Sweden imports both its fertilizer and food from these markets, the Eastern European price best captures the price that Swedish farmers and food imports are exposed to following the invasion (Naturskyddsföreningen, 2023).However, Swedish urea prices might serve as a better measure but since a lot of the foods are imported both of EU and worldwide markets, the Swedish prices might be more restrictive than the Eastern European price.

3.3 Fertilizer dependency

To capture differences in fertilizer dependency across food categories, this study assigned each category a score on a scale from 1 to 5 based on the nitrogen fertilizer application rates reported in the IFA Fertilizer Use by Crop report (IFA, 2022). The report provides a global crop-level data on fertilizer use for the 2017-2018 period. On the scale higher values indicate a greater nitrogen dependency. *Vegetables* received the highest score of 5, with an average application rate of 190 kg N/ha. *Sugar* and *fruits and tree nuts* received scores of 4 and 3 respectively, with application rates of 132 and 110 kg N/ha respectively. Pulses can fix atmospheric nitrogen and therefore received the lowest exposure score of 1, with an application rate of 15 kg N/ha.

3.4 Control variables

3.4.1 Import dependency and covid

Import dependency is constructed as one minus Sweden's domestic self-sufficiency rate for each category. Self-sufficiency rates are obtained from the Swedish Board of Agriculture (Jordbruksverket), except for pulses, for which the rate is taken from Lindström and Norberg (2025). Fruits and tree nuts have the highest import dependency, with Sweden only producing a small share of its own fruits and tree nuts, with a value of 0.79. Pulses and vegetables are moderately import-dependent, at 0.67 and 0.60 respectively. Sugar is almost entirely domestically produced from sugar beet and therefore have the lowest import dependency at 0.07.

The COVID-19 pandemic is another source of price disruption that overlaps with the post-invasion period. To account for this, the model includes an interaction term, vulnerability_covid, between import dependency and dummy variable that equal one for the period December 2019 to May 2023, and zero otherwise.

The interaction is included since the pandemic is not expected to have affected all categories the same. Categories with higher import dependency were more exposed to pandemic related supply chain disruptions and this is not captured by the time fixed effects, which only absorbs the common price movements for all categories.

3.4.2 Seasonality

Food prices experience seasonal variation driven by harvest cycles, weather, perishability and storage abilities. If we do not control for this, the control variable for season could be estimated incorrectly. Seasonality grades were assigned based on the average within-year coefficient of variation (CV) for each food category. The CV values were calculated form the consumer price index dataset and is reported in table 6 in the appendix. *Vegetables* exhibit the highest within-year variation, with a CV-value of 10.1, followed by *fruits and tree nuts* with a CV of 2.8. *Pulses* and sugar had lower variation with values 1.9 and 1.6 respectively. Based on these different variations, *vegetables* were assigned a high seasonality grade of 3, *fruits and tree nuts* a medium grade of 2 and *pulses* and *sugar* a low grade of 1.

3.5 Descriptive statistics

Table 1: Descriptive Statistics

	Mean	**Std. Dev.**	**Min**	**Max**
Price Index	92.766	19.388	56.620	171.650
Urea Price Index (lagged)	335.218	136.098	142.625	925.000
Exposure × Post-Invasion	0.365	0.830	0.000	3.000
Vulnerability × COVID-19	0.038	0.164	0.000	0.890
Seasonality × Season	5.625	4.359	1.000	16.000
Lagged Price Index	92.569	19.301	56.620	171.650
Post-Invasion Dummy	0.183	0.386	0.000	1.000
COVID-19 Dummy	0.071	0.258	0.000	1.000
Exposure Index	2.000	0.707	1.000	3.000
Vulnerability Index	0.538	0.329	0.000	0.890
Seasonality Index	2.250	1.300	1.000	4.000
Observations	**1,008**			

Sample: January 2005 – December 2025. Pre-invasion period: January 2005 – January 2022 (N=206 per category). Post-invasion period: February 2022 – December 2025 (N=46 per category). All consumer price indices are indexed to 2020 = 100. Urea price from World Bank Pink Sheet (E. Europe). Exposure index based on IFA (2022). Vulnerability index based on Jordbruksverket (2024).

Table 1 present descriptive statistics for all variables used in the analysis. The consumer price index mean value is 92.77 across all categories and time periods, which is below the 2020 base value. The consumer price index ranges from 56.62 to 171.65 indicating a large price variation across categories and time. The urea price shows the largest variation, with a mean of 335.22 USD per ton and a maximum price of 9.25.

4. Methodology

To examine how the increase in global urea fertilizer prices following Russia's invasion of Ukraine affected Swedish consumer prices across food categories with varying degrees of fertilizer dependency, this study employs three complementary fixed effects panel models with robust standard errors. The analysis uses a monthly panel dataset spanning from January 2005 to December 2025 covering four food categories: vegetables, sugar, pulses, and fruits and tree nuts. Category fixed effects are included to control for time-invariant differences between the categories, while time-fixed effects control for shocks affecting all categories at the same time.

4.1 Lag length selection

The study utilizes two types of lags. First, because consumer prices tend to stay close to the previous month's level, a lag on the dependent variable was applied. The lag length was selected using the Schwarz Bayesian Information Criterion (SBIC). Second, because a fertilizer price shock does not transmit instantly, a lag was applied to account for the delay for the shock to reach consumer prices. The lag was determined using cross-correlation analysis.

4.1.1 Schwarz Bayesian Information criterion (SBIC)

The optimal lag length of dependent variable in each regression was determined for each category using the Schwarz Bayesian Information Criterion (SBIC). The BIC is a model selection criterion that helps identify the preferred degree for polynomial regressions. The results with the lowest BIC value were selected (Schwarz, 1978).

Table 7 in appendix presents the resulting lag length for each food category. *Fruits and tree nuts*, and *pulses* both received an optimal lag of 1 month. *Sugar* received a lag of 2 months and vegetables required a longer lag of 6 months.

4.1.2 Cross-correlation

To determine the appropriate lag length for the urea price variable, a cross-correlation analysis was conducted between the urea price and the consumer price index for each food category. Cross-correlation measures the relationship two time series across different time lags by shifting one series relative to the other and recalculate each lag. The lag with the strongest correlation indicates the time delay at which two variables are most closely related (Derrick &Thomas, 2004).

Table 8 presents in the appendix presents the cross-correlation and the selected lag length for each food category and the chosen lag length. For vegetables, the strongest correlation (0.293) occurs at lag 6, indicating a transmission delay of six months. For fruits and tree nuts, the strongest lag occurs at lag 11 to 13 months, where lag was selected for the analysis. Although sugar exhibited the highest correlation (0.527) at lag 20, a 12-month lag was selected instead. For pulses, the highest correlation (0.358) occurred between lags 15 and 16 but 12 was selected was once again. A 15-to-20-month delay would substantially limit the study's ability to capture the effect of the invasion within the sample period and run the risk of capturing broader long-term trends unrelated to the fertilizer price transmission. The 12-month lag was therefore chosen as a compromise, allowing the analysis to account for the long transmission delay.

4.2 The three models

This study answers the research question through three complementary two-way fixed effects models that captures different dimensions of the relationship between urea prices and consumer prices. The first model examines category-specific urea price transmission, estimating whether changes in urea prices are associated with consumer price changes and if the relationship differs across food categories. The second model interacts each category's fertilizer exposure level with a post-invasion indicator to estimate if more fertilizer dependent categories experienced relatively larger increases following Russia's invasion of Ukraine. The third model examines category specific post-invasion effects by estimating whether each food category experienced different price shift relative to pulses.

4.2.1 Category-Specific Urea Price Transmission

The first model estimates whether changes in global urea prices are transmitted to Swedish consumer prices, and if it the transmission varies across food categories. The main explanatory variable β_{1i} is estimated for each category through an interaction between the lagged urea price and each category's fertilizer dependency grade. This mode uses the whole sample period (2005-2025) to examine the long-run relationship between fertilizer prices and consumer prices across the categories.

$$Y_{it} = \beta_0 + \sum_{c=1}^{4} \beta_{1,c} 1[i = c]\left(\text{Urea}_{\text{t-k}_c} \times \text{Exposure}_c\right) + \beta_2(\text{Vulnerability}_i \times \text{COVID19}_t) + \sum_s \beta_3 \text{Season}_{s,t} + \sum_m \sum_s \beta_4\left(\text{Seasonality}_{m,i} \times \text{Season}_{s,t}\right) + \rho Y_{i,t-q} + \mu_i + \lambda_t + \varepsilon_{it}$$

The dependent variable Y_{it} measures the consumer price index for food category i at time t. β_0 is the intercept. β_1 captures the price level shift for each food category j following Russia's invasion of Ukraine multiplied with nitrogen fertilizer dependency for each category, relative to the reference category pulses. β_2 measures the interaction Vulnerability_i and COVID19_t, where vulnerability is how import dependent Sweden is in category i and COVID-19 is a dummy variable that takes the value 1 for the period December 2019 to May 2023 and zero otherwise. β_3 captures the within-year seasonal variation in prices through seasonal dummy variables indicating whether an observation occurs in spring, summer or autumn, relative to the reference category winter. β_4 is an interaction term between seasonality and season. Season is a categorical variable that indicates whether an observation occurs in spring, summer, autumn or winter. Seasonality is a measure assigned to each category, taking the value low (1), medium (2) or high (3), and reflects the extent to which prices in that category vary over the year. The purpose of this interaction term is to capture how different seasons affect food prices, while controlling for that seasonal variation differs between the different food categories. ρ lagged dependent variable that controls for price persistence, with lag length q that is selected using the SBIC. μ_i and λ_t represents the category and time fixed effects respectively, while ε_{it} is the error term.

4.2.2 Overall Effect

To capture whether more fertilizer dependent categories experienced relatively larger increases following Russia's invasion of Ukraine, the second model interacts the exposure level with a post-invasion dummy. This is accpmlished by estimating a single coefficient on the interaction between fertilizer dependency grade (1-5) and a post-invasion dummy variable.

$$Y_{it} = \beta_0 + \beta_1(\text{Exposure}_\text{i} \times \text{Post}_\text{t}) + \beta_2(\text{Vulnerability}_\text{i} \times \text{COVID19}_\text{t}) + \sum_s \beta_{3,s}\text{Season}_{\text{s,t}}$$
$$+ \sum_m \sum_s \beta_4(\text{Seasonality}_{\text{m,i}} \times \text{Season}_{\text{s,t}}) + \rho Y_{i,t-q} + \mu_i + \lambda_t + \varepsilon_{it}$$

The dependent variable measures consumer price index for food category i at time t. β_0 is the intercept. β_1 is an interaction between the fertilizer dependency grade (1-5) and the post-invasion dummy. Exposure_i assigns each food category a grade on a scale from 1 to 5 based on their fertilizer dependency. $\text{Post-Invasion}_{-t}$ is a dummy variable that takes the value one from February 2022 and onward, otherwise zero. β_1 captures whether more fertilizer-dependent categories experienced larger price increases following the invasion, estimated as one overall coefficient across all categories. $\beta_2, \beta_3, \beta_4$, ρ, μ_i, λ_t and ε_{it} are defined the same as in the first model.

4.2.3 Category-Specific Post-Invasion Effect

The third model estimates category-specific post-invasion effects for each food category through a triple interaction between category, the fertilizer dependency grade and a post-invasion dummy, relative to the reference category. Pulses were chosen as the reference category since they have the lowest fertilizer dependency.

$$Y_{it} = \beta_0 + \sum_j \beta_{1,j}(1[\text{category}_i = j] \times \text{Post}_t) + \beta_2(\text{Vulnerability}_i \times \text{COVID19}_t) + \sum_s \beta_{3,s}\text{Season}_{s,t} + \sum_m \sum_s \beta_{4,m,s}(\text{Seasonality}_{m,i} \times \text{Season}_{s,t}) + \rho Y_{i,t-q} + \mu_i + \lambda_t + \varepsilon_{it}$$

The dependent variable measures the consumer price index for food category i at time t. β_0 is the intercept. β_1 is a triple interaction between category j, exposure level and post-invasion. It captures how the price index for category j was affected in the post-invasion period relative to pulses, multiplied with the category's fertilizer dependency. $\beta_2, \beta_3, \beta_4, \rho, \mu_i, \lambda_t$ and ε_{it} are defined the same as in the first model.

4.3 Validity and Robustness

To assess the reliability of the study's result, a robustness check and a multicollinearity test were conducted. First, multicollinearity was tested using variance inflation factors (VIF) for all explanatory variables in the three models. VIF measure how much of the variance of an estimated coefficient increases due to correlation with other variables in the model. A VIF 1 indicates no correlation with the other predictors. VIF values above 4 has moderate correlation and need further investigations and values above 10 indicate a problematic multicollinearity.

Second, a placebo test was conducted by replacing the actual invasion date of February 2022 with a hypothetical invasion date of February 2017. The date was set before the actual invasion so that the pre-invasion time will not be contaminated by the actual invasion. If the results are driven by the specific shock of Russia's invasion, then the placebo coefficient should be statistically insignificant.

5. Results

5.1 Category Specific Urea Price Transmission

Table 2: Two-Way Fixed Effects – Category × Exposure Urea Interactions

	Price Index
category_id # exposure_urea	
fruits_nuts	0.006*
	(0.001)
pulses	0.023***
	(0.002)
sugar	0.008***
	(0.000)
vegetables	0.003
	(0.001)
vulnerability_covid	3.951
	(2.699)
seasonality_season	−1.691
	(0.783)
price_opt_lag	0.701*
	(0.149)
Observations	**966**
R-squared (within)	**0.916**
Number of groups	**4**
Time FE	**Yes**
Category FE	**Yes**

Robust standard errors in parentheses, clustered by category_id. * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table 2 present the results for the first panel fixed effects model, which examines how the different categories react to changes in urea price. The model contains 966 observations, which is fewer than models 2 and 3 that has 998 observations, this is because of the category-specific transmission lags applied to the urea price variable. The model includes category and time fixed effects, with robust standard errors. The within R^2 is 0.921 which indicates that the model explain 92.1% of the variation within consumer price indices over time within the food category is explained by the model's explanatory variables.

Three out of four food categories for the category-specific urea price coefficient show positive and statistically significant results. *Fruits and tree nuts* are statistically significant at the 10% level, and one unit increase in the exposure-weighted urea price is associated with a 0.006 index point increase. Since the index is normalised to 2020 = 100 these equals to 0.006 percentage points relative to 2020s price level, given all other factors are constant. For *pulses*, a one unit increase in the exposure-weighted urea price is associated with a 0.023 index point increase, i.e. indicating a 0.023 percentage point increase relative to the price levels in 2020, given all other factors are constant. The coefficient for pulses is statistically significant at the 1% level. Sugar is significant at the 1% level, and a one unit increase in the exposure-weighted urea price is associated with a 0.008 index point increase. The coefficient indicates that the price increased with 0.008 percentage point relative to 2020s price levels, given everything else equal. For *vegetables*, a one unit increase in the exposure-weighted urea price is associated with 0.004 index point increase, indicating a 0.004 percentage point increase relative to the price levels in 2020. However, the coefficient for vegetables is not significant and therefore, there is no statistically significant evidence of the urea price transmission to consumer prices for vegetables. Overall, the significant coefficients are small, indicating that the urea price changes do not have large effect on Swedish consumer food prices.

The control variable vulnerability_covid has a coefficient of 3.951 and represent a single overall coefficient estimated across all categories. However, it is not statistically significant and therefore do not provide statistically significant evidence of a varying covid effect for categories with different import dependency levels.

The coefficient on seasonality_season is −1.69 and represents the pooled effect of seasonality across all categories. However, the coefficient is not statistically significant and do not provide evidence that more seasonally dependent categories experience larger price declines across the seasonal cycle.

The lagged dependent variables coefficient is 0.701 and is statistically significant at the 10%, indicating strong price persistence This suggests that consumer food prices adjust slowly and not directly after a change.. A one index point increase in the consumer price index in the previous period, at the optimal lag q is associated with 0.701 percentage point increase in the current period, holding all other factors constant. The lagged dependent variable is significant at the 10% level, indicating that there is a price persistence, with about 70% of a price change carrying over to the current period.

5.2 Overall Post-Invasion Effect

Table 3: Two-Way Fixed Effects – Overall Post-Invasion Exposure

	Price Index
exposure_post	−0.768
	(1.603)
vulnerability_covid	2.540
	(2.930)
seasonality_season	−1.752
	(0.760)
price_opt_lag	0.701*
	(0.200)
Observations	**998**
R-squared (within)	**0.912**
Number of groups	**4**
Time FE	**Yes**
Category FE	**Yes**

Robust standard errors in parentheses, clustered by category_id. * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table 3 presents the results from the second panel fixed effects model, examining whether more fertilizer dependent categories experienced relatively larger increases following Russia's invasion of Ukraine. The model has 998 observations, includes category- and time fixed effects, with robust standard errors. The model shows a good fit, with an R^2 of 0.912, indicating that the model's explanatory variables explain about 91.2% of the variation within the consumer prices indices over time.

The coefficient for exposure_post is the pooled results for all categories and is −0.768, suggesting a small decrease in consumer prices following the invasion. A one unit increase in the exposure-weighted post-invasion variable is associated with a 0.768 percentage point decrease in the consumer price index relative to the 2020 price level, holding all other factors constant. However, the coefficient is not statistically significant, which means that there is no statistically significant evidence that more fertilizer dependent categories experienced relatively larger price increases following the invasion.

The coefficient for vulnerability_covid is 2.540 but statistically insignificant, indicating that there is no statistically significant varying covid effect for categories with different import-dependency.

The pooled variable Seasonality_season has a coefficient of −1.752 but is not statistically significant. This means that the results do not provide evidence that more seasonally dependent categories experience larger price declines across the seasonal cycle.

The lagged dependent variable shows a coefficient of 0.701, with a significance level of 10%. This indicates that one index point increase in the consumer price index in the previous period, at the category-specific optimal lag q, is associated with a 0.701 percentage point increase in the current period, relative to 2020 price levels, holding all other factor constant. With a significance level at 10%, the variable indicates price persistence, with about 70.1% of a price change carrying over to the current period, indicating a slow response to price changes in consumer prices.

5.3 Category-Specific Post-Invasion Effect

Table 4: Two-Way Fixed Effects – Category-Specific Post-invasion Effects Relative to Pulses

	Price Index
fruits_post	−1.795
	(0.846)
sugar_post	1.493*
	(0.577)
veg_post	−1.814
	(0.825)
vulnerability_covid	9.173
	(5.420)
seasonality_season	−1.546
	(0.658)
price_opt_lag	0.536*
	(0.225)

Observations	**998**
R-squared (within)	**0.921**
Number of groups	**4**
Time FE	**Yes**
Category FE	**Yes**

Robust standard errors in parentheses, clustered by category_id. * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table 5 presents the results from the third panel fixed effects model, which examines the category specific price level after Russia's invasion of Ukraine, relative to pulses. The model has 998 observations, includes both category- and time fixed effects, with robust standard errors. The model is a good fit, the within R^2 is 0.921, indicating that the model's explanatory variables explain 92.1% of the variation within the consumer price indices over time.

The main coefficients are the category-specific post-invasion variables capturing the post-invasion price level shift for each category relative to pulses, indicating whether categories with different levels of fertilizer dependency experienced price changes following the invasion. A one unit increase in the exposure-weighted post-invasion variable for *fruits and tree nuts* is associated with 1.795 percentage point decrease relative to pulses, relative to the 2020 price level, holding all other factors constant. For *vegetables*, a one unit increase in the exposure weighted post-invasion variable is associated with 1.814 percentage point decrease relative to pulses, relative to 2020s price level, given all other factors are constant. The coefficients for those *fruits and tree nuts* and *vegetables* are not statistically significant and do not provide statistically significant evidence of price decreases following the invasion. *Sugar* is statistically significant at the 10% level, a one unit increase in the exposure-weighted post-invasion variable is associated with 1.493 percentage point increase relative to pulses, relative to 2020 price level.

The lagged dependent variables coefficient indicates that one index point increase in the consumer price index in the previous period, at the optimal lag q is associated with 0.536 percentage point increase in the current period, relative to the 2020 price level, holding all other factors constant. The lagged dependent variable is significant at the 10% level, indicating an existing price persistence, with about 53.6% of a price change carrying over to the current period.

5.4 Robustness

5.4.1 Variance Inflation Factors (VIF)

Table 9 in the appendix presents the results from the variance inflation factors (VIF) test. As described in methodology, values above 4 indicate moderate correlation and values above 10 indicate problematic multicollinearity.

Models 2 and 3 show mean VIF values of 1.95 and 1.90 respectively, with all individual values below 2.5. These low values indicate that the explanatory variables in these models are not substantially correlated with each other, indicating that the standard errors are not overestimated by multicollinearity. This indicates that the results for models 2 and 3 are not affected by multicollinearity and that the significance reflects the actual relationship rather than issues caused by correlated variables.

Model 1 shows a higher mean VIF value of 6.58, indicating moderate correlation. Most of the individual variables is below the problematic threshold of 10, suggesting no to little concern for majority of the explanatory variables. However, vegetables exceed the problematic threshold for both the interaction term and the category term, with value of 13.16 and 15.38 respectively. Pulses and Sugar are close to the threshold but remain just below the problematic threshold. The higher VIF values indicate that the standard errors for the affected category-specific urea price coefficients are overestimated, which might make it difficult to capture statistically significant effects.

5.4.2 Placebo Invasion date

Table 10 in the appendix presents the results for a placebo test that replaces the invasion date with a hypothetical treatment date of February 2017. Model 1, the coefficients for urea interaction terms for *fruits and tree nuts*, *pulses* and *sugar* are 0.009, 0.033 and 0.009 respectively and is statistically significant. Indicating that one unit increase in the exposure-weighted urea price is associated with an increase in percentage points in the consumer price for those categories, given all other factors constant. The coefficient for Vegetables is 0.001 but is not statistically significant and do not provide evidence of urea prices transmitting to vegetable prices.

Model 2, the coefficient for exposure post-invasion is now statistically significant at the 5% level and is -1.168. This suggests that the prices decreased with 1.168% following the invasion relative to 2020s price levels, holding all other factors constant.

Model 3, all coefficients for the category specific exposure post-invasion variable is now statistically significant at the 5% level. A one unit increase in the exposure-weighted post-invasion variable for *fruits and tree nuts* is associated with 0.853 percentage point increase relative to pulses, relative to the 2020 price level, holding all other factors constant. For sugar and vegetables,

The placebo tests have fewer observations because the sample was restricted to January 2005 to January 2022 so that the post-invasion is not contaminated by the actual post-invasion. The first model has fewer observations than the others because of the lagged urea price.

Overall, the significant placebo results suggests that the main findings should be interpreted with caution since the placebo test picked up underlying trends. The results from the first model should also be interpreted with caution since the results are affected by multicollinearity. The low VIF values in the second and third model confirms that the results are not affected by multicollinearity.

6. Discussion

6.1 Main findings

This study examines how the increase in global urea fertilizer price following Russia's invasion of Ukraine in February 2022 affected Swedish consumer food prices across all four categories with varying degrees of fertilizer dependency. Three complementary two-way fixed effects panel models were estimated, with the first one examining whether urea price changes transmitted differently across food categories by estimating a category specific urea price coefficient for each category, the second model examines whether fertilizer dependent food categories experienced an increase in price following the invasion and the third model examines whether each category experienced a change relative to pulses following the invasion.

In model 1, *sugar*, *fruits and tree nuts* and *pulses* categories show positive relationship between urea prices and consumer price index that is statistically significant. The positive coefficients are consistent with what was expected that a higher urea price is associated with higher consumer food prices. However, what was surprising was that the categories with the highest fertilizer dependency was not associated with the highest price increase. Pulses, that significantly lower fertilizer application rates than the other categories had the largest coefficient, while vegetables that was the category with the highest dependency had the smallest and an insignificant result. This suggests that fertilizer dependency does not determine how strong the transmission is and that other factors might have a larger effect on consumer prices. However, the results for vegetables in model 1 should be interpreted with caution since the vegetables showed problematic VIF values. The high VIF values for vegetables suggest that the standard error for this coefficient is likely overestimated due to multicollinearity.

The high R^2 values for the three models with the small amount of statistically significant coefficient is interesting. However, this might be due to the lagged dependent variable being included, since a large share of this month's variation is explained by the previous period, at the category-specific optimal lag q. The time fixed effects capture price movements that affect all categories at the time, such as general food price inflation and category fixed effects capture permanent differences between categories, most of the variation is captured by these which means that the urea price among with the rest of the remaining variables accounts for a small part.

6.2 Comparison with previous literature

The finding that urea price transmit to consumer food price for three out of four categories in the category-specific urea price transmission model is consistent with previous literature on fertilizer and crop markets. Etienne et al (2016) show that fertilizer and crop prices are closely connected in the long run and Morão (2025) found that fertilizer price shocks explain a large part of the variation in output price. The positive and significant coefficient in this study supports this evidence of fertilizer price changes transmitting consumer food prices. However, similar to Morão (2025) and Etienne et al. (2016), the results in this study indicate that the fertilizer price transmissions to consumer food prices are heterogenous across the food categories and categories with higher fertilizer dependency do not necessarily exhibit stronger transmission effects.

However, the effects are small is this model, which is consistent with Gardner's (1975) marketing margin model that Meyer and von Cramon-Taubadel (2004) discusses in their study. They show that changes in agricultural markets often is incomplete and asymmetric. Since fertilizer is only a small part of what consumers pay, the rest is factors such as processing, transport and retails margins, A large increase in fertilizer prices is therefore only reflects a small increase in the consumer food prices, which is what this study finds.

The finding that pulses show the largest transmission coefficient despite having the lowest fertilizer application rate is unexpected and not explained by the previous research. Headey and Fan (2008) discuss that not only one factors drive price transmission and with this study examining categories, many of which are fresh produce, other factors such as transport or processing that is not included in these models might play a bigger part in this case. This is something that is interesting to further investigate in future research.

6.3 Limitations

A few limitations of this study should be acknowledged. First, the panel dataset includes only four food categories, which limits the study's ability to detect statistically significant effects and the generalisability of the findings. With only four category clusters, the overall F-statistics cannot be computed when standard errors are clustered at the category level using vce(robust). When the models were estimated without the clustered standard errors, the F-statistics were computed but the standard errors may be unreliable due to potential serial correlation within categories. Clustered standard errors are preferred in this study since they account for within-category serial correlation and heteroskedasticity, providing more conservative results despite the loss of the overall F-statistics. If not included, the standard errors will be smaller and therefore the results might appear statistically significant than they are. Although clustered standard errors are better in a larger number of clusters, the benefits from including them are still preferred over ignoring correlation within the categories.

Second, the VIF values indicate that the results for the second and third model are reliable, with values well below the moderate and problematic correlation threshold. However, a problem with the first model is that the categories have high VIF values in general. This is a problem since the category-specific variables share the urea price series, which means that a large part of their variation is the same. With all the category coefficients being moderate, close problematic or problematic values, the results for those coefficients should be interpreted with caution. As a result, the standard errors for these coefficients are overestimated, reducing the reliability of the p-values and making it harder to estimate statistically significant effects. The results for vegetables should be interpreted with caution since they this category had high VIF values, that indicated problematic multicollinearity. As a results, the insignificant coefficient may reflect reduced statistical precision rather than there not being any transmission effect.

Third, the significant placebo test presents an important limitation. The results presented statistically significant coefficients when the hypothetical invasion date was used, a period where no treatment occurred. This suggests that the models might be picking up pre-existing patterns or patterns that these models don't control for. One possible explanation is that the vulnerability_covid variable did not capture the full effects of the invasion, that the placebo post-invasion variables captured. Since the pandemic occurred during the placebo post-invasion period, it is not unlikely that the main coefficients for models 2 and 3 are inflated and therefore become significant. This limits the interpretation of the main results for the second and third model, the results might not be interpreted inconclusive rather than there is no effect.

Fourth, another limitation was the construction of the category-specific post-invasion variable. Pulses were selected as the reference category since they had the lowest nitrogen application rates and therefore the lowest fertilizer dependency. However, the results from the first model revealed that pulse shad the largest urea price transmission coefficient of all categories, suggesting that their prices are more sensitive to urea price changes then what was expected from their exposure level. Since the third model's post-invasion effects are measured relative to pulses, they are measured to the category that had the strongest transmission. Ideally, the post-invasion for each category would have been measured relative to its own pre-invasion price levels, providing a comparison of how much each category’s price changed following the invasion.

7. Conclusion

This study examines how the increase in global urea fertilizer prices following Russia's invasion of Ukraine affected Swedish consumer food prices across four food categories with varying degrees of fertilizer dependency, using panel data from January 2005 to December 2025.

The results indicate that urea price is positively associated with Swedish consumer food prices for three out of four categories, suggesting that price shocks in the fertilizer market are transmitted to retail food prices. However, the effects are small and do not follow the expected fertilizer dependency order, indicating that other factors than fertilizer exposure affect the transmission. Due to significant placebo test and multicollinearity issues, the findings should be interpreted with cautions and not as causal effects.

From a policy perspective, tracking global fertilizer prices and monitoring their category-specific impacts can make it possible for governments and analysts to minimize the negative effect before it affects consumer.

Future research could improve this study by including more food categories, constructing the variables in ways that does not lead to multicollinearity issues and lastly by having a longer post-invasion period.

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Appendix 1

Table 5: Average Within-Year Coefficient of Variation (CV) and Seasonality Grades by Food Category

Food Category	Mean Within-Year CV (%)	Seasonality Grade
Vegetables	10.12	3 (High)
Fruits and tree nuts	2.77	2 (Medium)
Pulses	1.92	1 (Low)
Sugar	1.63	1 (Low)

Note: CV = (standard deviation / mean) × 100, calculated within each calendar year and averaged across 2005–2025. Source: Authors' calculations based on SCB data.

Table 6: Schwarz Bayesian Information Criterion (SBIC)

Category	Selected lag	Criterion
Sugar	2	SBIC
Fruits and tree nuts	1	SBIC
Pulses	1	SBIC
Vegetables	6	SBIC

Table 7: Cross-correlation

Food Category	Max Cross-Correlation (Lag)	Chosen Lag (*t-n*)
Fruits & Nuts	-11 to -13 (0.271)	12 months
Vegetables	-6 (0.293)	6 months
Sugar	-20 (0.537)	12 months
Pulses	-15 to -16 (0.358)	12 months

Table 8: Variance Inflation Factors (VIF) – All Models

Model 1			Model 2			Model 3		
Variable	VIF	1/VIF	Variable	VIF	1/VIF	Variable	VIF	1/VIF
cat_id # exp_urea			exposure_post	1.79	0.558	fruits_post	1.39	0.722
fruits & nuts	5.29	0.189	vulnerability_covid	1.14	0.879	sugar_post	1.74	0.574
pulses	5.09	0.196	seasonality_season	2.32	0.432	veg_post	1.28	0.780
sugar	5.45	0.184	price_opt_lag	2.03	0.493	vulnerability_covid	1.17	0.852
veg	**13.16**	0.076				seasonality_season	2.32	0.431

exposure_post	2.56	0.391	category_id			price_opt_lag	2.08	0.481
vulnerability_covid	1.18	0.846	pulses	2.18	0.458			
seasonality_season	2.33	0.429	sugar	2.52	0.397	category_id		
price_opt_lag	2.21	0.452	veg	1.66	0.603	pulses	2.39	0.419
category_id						sugar	2.75	0.364
pulses	9.77	0.102				veg	1.99	0.503
sugar	9.99	0.100						
veg	**15.38**	0.065						
Mean VIF	**6.58**		**Mean VIF**	**1.95**		**Mean VIF**	**1.90**	

Note: Values in bold exceed VIF = 10. Model 1 includes category fixed effects and category-interacted slope terms; elevated VIF values reflect a known structural feature of this specification. Category 1 = Vegetables, Category 2 = Fruits and tree nuts, Category 3 = Pulses, Category 4 = Sugar.

Table 9: Placebo Test 2017 - All Models

	Placebo Model 1	**Placebo Model 2**	**Placebo Model 3**
category_id # exp_urea_placebo			
fruits & nuts	0.009**		
	(0.002)		
pulses	0.033**		
	(0.007)		
sugar	0.009***		
	(0.001)		
veg	0.001		
	(0.001)		
exposure_placebo	−1.859***	−1.168**	
	(0.294)	(0.300)	
vulnerability_covid	4.984	6.908	−1.777**
	(3.148)	(3.932)	(0.523)
seasonality_season	−1.386*	−1.520*	−1.322*
	(0.550)	(0.573)	(0.522)

price_opt_lag	0.345	0.365	0.218
	(0.236)	(0.257)	(0.204)
fruits_placebo_post			0.853**
			(0.243)
sugar_placebo_post			−12.084**
			(3.199)
veg_placebo_post			−3.351**
			(0.845)
Constant	35.866	48.638*	58.631**
	(19.758)	(18.845)	(15.640)
Observations	778	810	810
R-squared (within)	0.805	0.795	0.815
Time FE	Yes	Yes	Yes
Category FE	Yes	Yes	Yes

Note: Robust standard errors in parentheses, clustered by category_id. * p < 0.10 ** p < 0.05 *** p < 0.01 Category 1 = Vegetables, Category 2 = Fruits and tree nuts, Category 3 = Pulses, Category 4 = Sugar.

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