

Development and Expansion of Existing Food Price Modelling System

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Executive Summary

In this report, we detail the development and expansion of the existing food price modelling system. The previous modelling approach (detailed in Defra, 2020) was largely premised on developing a framework to address the potential impact of the UK's departure from the EU on retail food prices in the UK. As such, an original feature of that research was to develop an econometric framework of the determinants of UK food prices with considerable attention to the detail of sources of UK raw agricultural and processed food. However, since the delivery of the original food price modelling framework, there have been a number of significant global events (most obviously, the COVID pandemic, the Russia Ukrainian war, the spike in global energy prices and growing awareness of the importance of climate change on food prices) which-given the openness of the UK's food and agricultural sector-would potentially have major impacts on UK retail food prices. In addition to updating the data underlying the previous econometric model, accommodating the factors that would reflect the changes in the global environment was one of the main factors motivating the extension of the food price modelling framework.

In the course of updating the previous framework and incorporating additional variables, we also took the opportunity to extend other aspects of the research developing the econometric approach to modelling UK retail food prices. First, instead of employing a vector autoregressive approach, we applied the local projections econometric methodology that-for our purposes-offers a number of desirable features in terms of estimation, efficiency and incorporating a larger number of variables that would be challenging in the vector autoregressive approach. Second, while the previous research focussed on retail food prices, we have taken the opportunity to estimate econometric models relating to several food and agricultural sub-sectors (bread and cereals, dairy, beef, fruit and vegetables). This is warranted given that the price dynamics at retail, import and domestic agricultural for these sub-sectors differs from the aggregate level. The econometric framework and the variables determining prices at various levels are identical to the aggregate retail food price model but, reflecting differences in the UK's openness to global events in these sectors, energy intensity and characteristics of the supply chain, the impact of the determining factors will likely differ from the aggregate retail food price model and across the various sub-sectors.

Finally, given that we have estimated sub-sector models, we can also tie the potential outcomes of price shocks to health impacts. This draws on work previously commissioned by Defra on estimating demand elasticities and related to that research, nutrient elasticities associated with certain food groups.

Details of the revised approach and selected results are provided in this report.

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1. Introduction

This report outlines the development and extension of the previous food price modelling system that was reported in Defra (2020). The research documented in the previous report detailed the specification of the econometric framework focussed on determining the drivers to UK retail food price inflation: this framework allowed Defra to consider alternative scenarios relating to the drivers of retail food prices. The work for this original model was commissioned in 2015 and was largely focussed on issues relating to the UK's (at the time) potential departure from the European Union (EU) addressing a range of scenarios relating to changes in the prices and the geography of the sources relating to UK food and agricultural imports from the EU and any potential trade deals that the UK government may have pursued. Aside from these specific trade issues, the results from the econometric approach could also be employed to address the effects of other factors determining food price inflation such as effective exchange rates but given the initial motivation was not fully appropriate to adequately address the drivers of UK retail food price inflation that have emerged since the mid-2010s.

Against this background, there is therefore an obvious need for both an upgrade of the econometric model to address Defra's requirement for widening the range of scenarios that need to be addressed to appropriately advise senior civil servants and policymakers. Specifically, there are four main aspects associated with the development and expansion of the existing food price inflation modelling system.

First, as noted, the current econometric model was predicated around the UK's departure from the EU, and therefore provided analysis of the potential outcomes associated with post-Brexit trade agreements that the UK may have sought with other trading partners. However, in terms of the wider macroeconomic context, the departure took place in a relatively low inflation environment with the consequences of the food price spikes of 2007-08 and 2011 having passed. While these issues are still relevant, in more recent years, the macroeconomic context has changed considerably, most notably due to the impact of COVID followed by Russia's invasion of Ukraine which not only impacted on agricultural prices in world markets but also had a significant impact on energy prices. Moreover, due to increasing awareness of climate change, the impact of rising global temperatures and extreme weather on food security has emerged as an additional driver of food prices.

While the annual rate of food inflation averaged around 2 per cent between 2016-2017, in 2022 UK food inflation was around 13 per cent, exceeding headline inflation of 10 per cent and was an important aspect of the recent cost-of-living crisis in the UK. More recently, the election of President Trump and the implementation of an 'America First' trade policy agenda, characterised by country-specific trade deals, pose another dimension to UK's trading arrangements going forward. Taken together, there has been a significant change to the external environment in which the UK food and agricultural sector sit, and associated with this, a wider range of factors to be considered in the update of the model. With the UK best characterised as a relatively small open economy, developing an econometric framework that can quantify the impact on retail food prices of these wider macroeconomic and global events and increasing geo-political risk, is an important input in addressing UK food security concerns.

Second, the domestic policy environment relating to the UK food sector has also changed. Most notable in this regard relates to concerns about the links between health externalities associated with food consumption and how these health externalities vary across the income distribution and across regions in the UK as highlighted by the recent National Food Strategy (2021). Defra has commissioned research from the National Institute of Economic and Social Research (Da Silva *et al.*, 2022) on demand elasticities associated with the consumption of nutrients. Since food prices are a fundamental determinant of food choices particularly at the lower end of the income distribution where households spend around 16 per cent of their disposable income on food, how shocks impacting on the UK food and agricultural sectors are passed through to retail food prices could potentially have important impacts on the health externalities associated with food consumption across the income distribution. As such, one of the main objectives of the research extending the analysis of UK food prices will be to tie the assessment of the pass-through of shocks in the UK food sector on food choices by tying the research reported here with the nutrient demand elasticities reported by NIESR (Da Silva *et al.*, 2022).

Third, the current econometric framework focuses on aggregate retail food price inflation. In face of the multiple shocks that may impact on the UK food and agricultural sectors, it is important for Defra to retain the capacity to address these issues and provide advice to senior ministers at an aggregate level. However, a more granular approach to addressing food pricing issues in specific food and agricultural sectors is also desirable. The requirement for a disaggregate assessment of food pricing issues reflects several issues: (i) retail prices for specific food sectors exhibit different dynamics from the aggregate retail food price index; (ii) similarly, the import price index for specific commodity sectors will also show different patterns of behaviour; (iii) varying degrees of openness to world trade, energy intensity and so on, mean that the contribution of the drivers of import and retail prices will vary across sub-models and differ from the insights that would arise from the aggregate retail price model.

Furthermore, the relevance of these sectoral models extends to policy analyses. First, in relation to the issues associated with healthy food choices, it is necessary to identify issues where these issues are to the fore (for example, a rise in the retail prices of fruit and vegetables will likely influence consumers choosing healthy to unhealthy food options). Second, in the context of recent trade policy issues (whether this relates to UK free trade arrangements with Australia and New Zealand or with a trade agreement with the US), the issues are often tied with agreements in specific sectors (such as beef in the two examples referred to). As such, in the development and expansion of the food inflation econometric model, not only will there be a significant upgrade of model incorporating a wider range of drivers of UK retail food prices as detailed above but also the development of a series of sub-sector models for more disaggregate analysis. These disaggregate econometric models will also be developed in the current extension.

Finally, we have taken advantage of recent advances in econometric practice and adopted a new underlying econometric methodology to generate the impulse response functions that quantify the dynamic effects of the drivers on retail food prices. Specifically, while previous versions of the model used a co-integrated vector autoregression model (C-VAR), the research reported here uses impulse response functions calculated by local projection (Jordà 2005, 2009). This approach has become increasingly popular in applied macroeconomics. We detail the econometric methodology later in this report but, in short, the local projection methodology offers some advantages over the C-VAR approach. Most notably, it offers greater flexibility and has been shown to be more robust to model specification (e.g. lag length) than the C-VAR. It also facilitates the inclusion of a wider set of variables than can be accommodated in the C-VAR and

is relatively easy to implement. In addition, technical issues associated with the identification of shocks are more straightforward to accommodate with the result that the impulse response function from local projection are more reflective of the causal impacts than can be obtained from counterparts derived from a C-VAR. In this study we use the local projection approach to generate cumulative responses (and theoretically consistent confidence intervals) of retail prices over a 24-month time horizon to assess both the level and variance of food prices associated with specific shocks to each driver.

The report is organised as follows. In Section 2, we set out the economic context for the development of a new econometric model of food prices, emphasizing that specifications used previously cannot adequately deal with the more recent challenges to the UK food and agricultural sectors. In Section 3, we outline the conceptual model that underlies the econometric model, detailing relevant drivers of retail food prices. As we show, this conceptual framework will apply to retail food price inflation and five key sub-sectors (bread and cereals, meat, dairy, fruit and vegetable). The revised econometric approach is set out in Section 4 which is followed by a discussion of the variables and the data that is employed to operationalise the specification of the conceptual model. In Section 5, we report the impulse response functions associated with the econometric model and a discussion of the interpretation of the results. We extend the discussion of the results to the sub-sector models which are reported in Section 6. Finally, in Section 7, we discuss the linking of the impulse response results generated in the revised econometric models with the nutrient demand elasticities reported in NIESR (2022). In Section 8, we summarise and conclude on potential future developments in the econometric approaches to addressing UK food price inflation.

2. Previous Econometric Model in a Changed Macroeconomic Environment

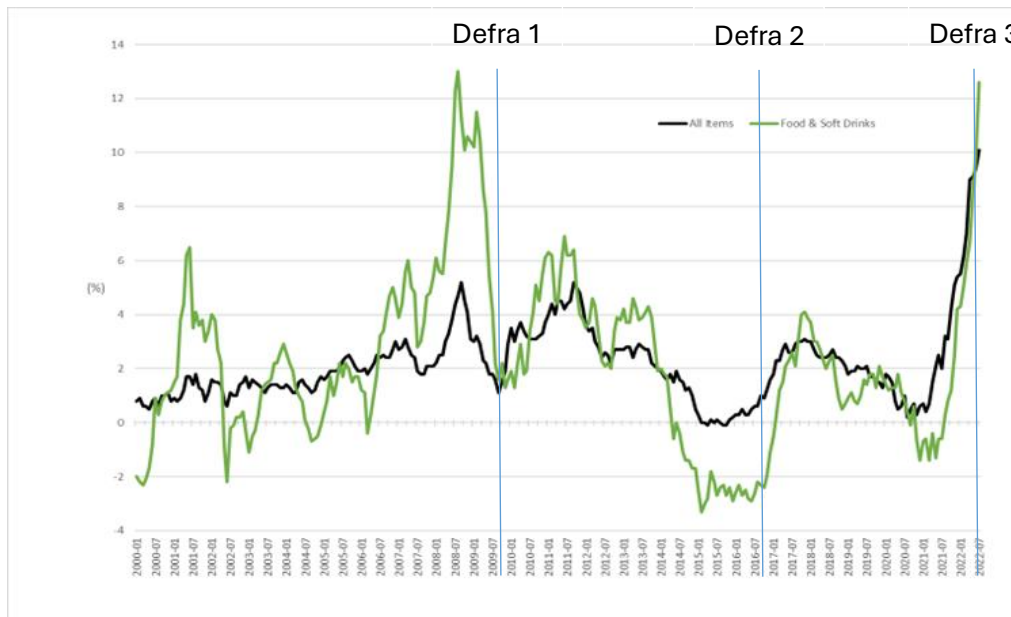
It is useful to start by highlighting the need for the expansion and the development of the underlying econometric analysis of food price inflation in the UK. In Figure 1, we report UK food inflation (annualised monthly) between 2000 and towards the end of 2022 (green line); we also report headline inflation for the same period (black line). As is evident from the figure, food inflation is more volatile than general inflation and, towards the end of 2022, food inflation was reported at around 13 per cent compared with headline inflation of around 10 per cent. In the figure, we also highlight the timing of the econometric analyses for Defra and how they overlapped with the food inflation experience in the UK.

‘Defra 1’ focussed on the aftermath of the world commodity price crises of 2007-08 and involved the development of an econometric framework that could address the drivers of UK food inflation in the context of the then-recent world commodity crises. ‘Defra 2’ involved the development of a model in the context of a period of relatively low (and negative) food price inflation. In this period, concerns about world commodity price spikes had dissipated, and as noted above, the overriding concern related to the potential impacts of changes in trade arrangements arising from UK’s departure from the EU; the EU being the UK’s main trading partner with respect to both raw agricultural and processed food imports. The ‘Defra 2’ econometric modelling addressed issues related to the geography of UK imports and-given the focus on trade arrangements- used highly disaggregated trade data from HMRC on 18 commodity and food chapters disaggregated by region. These specific features of UK imports are retained in the most recent modelling effort (see below).

The current modelling exercise (‘Defra 3’) is associated with the high levels of food price inflation experienced in recent years and heightened geo-political tensions. Not only has the

macroeconomic context changed following the period of the UK's exit from the EU but successive structural shocks related to COVID-19, Russia's invasion of Ukraine in March 2022 and growing concerns about the impact of climate change on food prices have been exacerbated by the impact of US trade policies all of which has resulted in high world agricultural prices and oil price spikes. Looking forward, with on-going global economic and political tensions and given the openness of the UK's food and agricultural sector and dependence on global energy markets, there is a clear need to update the previous econometric modelling framework.

Figure 1: Rates of General and Food Inflation in the UK January 2000 to June 2022



As a preliminary analysis to the econometric model detailed below, we updated the previous model specification by extending the data coverage to February 2023. We retained the same model specification (i.e. applied the co-integrating VAR model) and updated and amended (where necessary) the data series used for each of the variables used in the model¹. The results of this exercise are reported in Table 1.

In Column 1 of Table 1 we report the elasticities of retail food prices with respect to each of the previously used drivers of food prices over the original sample period (1997(6) to 2017(6)). All the estimated elasticities have the anticipated (positive) sign, and the relative values of these elasticities indicate that domestic factors were more likely to be the main drivers of food prices contingent on the magnitude of the shocks². In Column 2, we report the results from the model that was re-estimated using a modified measure of the non-labour cost index in manufacturing which excludes the climate change levy (the one used in the original model has been discontinued). Numerical estimates remain very similar. We then re-estimated the model over the longer data period (which extends to February 2023), which produced some notable changes: the elasticity with respect to domestic labour costs decreases in magnitude and the import price index changes sign which is difficult to rationalise.

¹ Notable in this regard was the discontinuation of the data series used for manufacturing input costs in the food supply chain. This series was replaced by an alternative measure of input costs that excluded the climate change levy.

² This differs from the insights from Defra 1 where-not surprisingly given the background of the commodity price spikes of 2007-08 and 2011-international factors were the main drivers of UK retail food prices.

However, as noted, extending the data series to the end of 2022 covers the COVID-19 period and geopolitical developments. Incorporating a dummy variable to account for the more recent period, produces results that retain the effects obtained in the ‘Defra 2’ model reported in column 2. Notably, the impact of domestic labour costs returned to its initial value and the sign of the elasticity of import prices on retail prices returned to being positive. Despite the recovery of these results, the impact of import prices is shown to be much lower than the original results and the impact is not statistically significant. Overall, this preliminary investigation highlights that there are likely missing variables that are not accounted for in the ‘Defra 2’ specification and that these variables reflect changes in the global context which impacts on UK retail price inflation. This leads to an updated specification of the econometric model which we report next³.

Table 1: ‘Defra 2’ Specification: Original Results and Revised with Updated Data

Elasticity of UK retail food prices with respect to:	1 Defra 2 Model	2 Defra 2 model (ex. climate levy)	3 Defra 2 model (ex. climate levy)	4 Defra 2 model (ex. climate levy, COVID Dummy)
	1997(6) to 2017(6)	1997(6) to 2017(6)	1997(6) to 2023(2)	1997(6) to 2023(2)
UK agricultural output prices	0.242 (0.001)	0.247 (0.002)	0.363 (0.000)	0.327 (0.000)
UK labour costs	0.256 (0.000)	0.244 (0.000)	0.043 (0.491)	0.147 (0.005)
UK non-labour manufacturing costs	0.143 (0.050)	0.164 (0.030)	0.430 (0.000)	0.254 (0.002)
Import prices	0.162 (0.012)	0.151 (0.041)	-0.076 (0.215)	0.056 (0.188)
COVID Dummy				-0.015 (0.173)
Elasticity of UK agricultural output index with respect to:				
Effective exchange rate for agricultural imports	0.906 (0.006)	0.643 (0.008)	0.702 (0.001)	0.724 (0.000)
Import price index for raw agricultural products	1.440 (0.000)	1.372 (0.000)	1.339 (0.000)	1.415 (0.000)
COVID Dummy				-0.081 (0.019)

3. Conceptual Framework

As detailed above, the aim is to develop an aggregate econometric model that will form the basis for assessing the impact of macroeconomic and global shocks that impact on UK food and agricultural imports. This will be complemented by a series of sub-sector econometric models that will be more pertinent to addressing the impact of events that impact on specific agricultural sectors. The aggregate and sub-sector models adopt a common specification in terms of variables; however, lag structures, trends and seasonals are tailored to the characteristics of

³ Detailing the causes of inflation more generally through the COVID period is subject to on-going research. See, for example, Ball *et al.* (2022) and Bernanke and Blanchard (2025).

specific sectors. For example, storage (or lack of) may be a feature of some sectors as will seasonal factors, entailing that there are likely to be differences in the specification of say, beef and fruit models.

In this section, we detail the conceptual framework that underpins the econometric models that are estimated below. We outline first, the framework that applies to the aggregate food inflation model. This is followed by an outline of how the specification of the aggregate model is amended when applied to the sub-sector models. Details on the data used follows in Section 3.

In essence, the conceptual framework applied in the extension and development of the food inflation model is similar in principle to that employed in ‘Defra 2’. Specifically, there are two relationships that are captured in this model: first, is a ‘vertical’ relationship that ties the cost drivers of retail food prices throughout the food supply chain (such as, the price of domestic and imported products, labour costs in manufacturing and so on) along with a measure of consumer demand; as such, the econometric model produces estimates of the pass-through of shocks to the drivers of food price inflation.

Second, we develop separate models for two key factors that drive retail food prices, that are of key policy interest, namely domestic agricultural prices and the prices of food imports. By allowing each factor to be explained by its own set of determinants, the overall model offers additional insight into the scenarios that are of potential concern to policymakers. For example, in addition to quantifying the effects of domestic agricultural output on retail prices, we can assess the effects of factors such as agricultural input prices or domestic weather on agricultural output prices (and, in turn, retail food prices). Similarly, factors that impact on the price of food imports such as the exchange rate and global energy shocks can also be assessed, both in terms of their impacts on the price of food imports but also their effects on retail food prices.

In the ‘Defra 2’ econometric model these vertical and horizontal relationships that underpinned UK retail food price inflation were estimated in a vector autoregressive (VAR) framework that tied the vertical and horizontal relationships in a single framework. One drawback of this approach is that the factors that can be accommodated is rather limited owing to the ‘curse of dimensionality’ for which VAR based methods are prone. By stepping outside the VAR, we can estimate these relationships in richer detail using ‘stand-alone’ models, the results of which are tied together. As we note below, the econometric approach we employ to deal with these relationships in the current version have several advantages over the previous (C-VAR) approach.

Aggregate Retail Food Inflation Model

There are three components to the conceptual framework: a retail price model capturing relationships and the pass-through of costs in the food supply chain; an import price model reflecting the factors that determine the UK prices of agricultural and food imports; and a domestic agricultural price model capturing the main drivers of prices of agricultural products that enter the UK food supply chain. Modelling the three relationships separately has several advantages.

First, we can accommodate a wider range of factors that would be difficult to estimate in the context of a VAR model which is more readily applicable when the number of determining factors is small (typically less than five). Second, separating determinants of retail prices from import (and domestic agricultural price) price levels is consistent with recent research. For example, Cavallo *et al.* (2021) highlight the significance of separating pass-through issues at the border from those at retail; Amiti *et al.* (2024) focus on import price inflation as a distinct causal factor

determining the impact of global factors on the domestic macroeconomic environment. Third, our adopted approach offers more flexibility in terms of undertaking scenario analysis: if the advisor is intending to address only the impact of an x per cent change on import or domestic agricultural prices on retail prices, she can; but if she chooses to provide more information on the underlying driver of this shock (for example, by how much will global energy prices determine the change in import prices or how much of a change in domestic agricultural input prices will change domestic agricultural prices), this will remain an option, enabling a richer assessment of the causes and effects of shocks to be made, than would be possible with VAR based methods.

The conceptual framework we employ is summarised in Figure 2 which sets out the variables that enter each of the three models. In the following section, we highlight the main challenges relating to the data that is employed.

- *Retail Food Price Model.*

This model (highlighted in the green box) captures vertical relations in the UK food supply chain. Except for a variable representing consumer demand, all other variables are associated with costs passing through from upstream stages to retail. There are four components of the supply chain costs we account for: labour costs; non-labour costs (which covers all other costs emanating from upstream suppliers and will include energy and natural gas costs); domestic agricultural prices which are essentially farm gate prices that enter the supply chain; and the price of imported food and agricultural products. Note that, since we are focusing on retail prices, these import prices include processed and raw agricultural products and is a bespoke measure of these imports that enter the UK. The construction of this data, the like of which unavailable from official sources, is detailed below. Finally, we have a variable that reflects supply chain pressures that may impact on food suppliers; this is outlined in the data section below, but it serves to capture frictions in the global supply chain that UK processor and manufacturer face. While this variable is particularly relevant to the COVID period, reflecting (difficulties in shopping behaviour, the move away from eating out and difficulties in transportation and obtaining supplies), it will also serve as a measure of future food supply chain issues, should they arise. For example, these may include difficulties in employing labour in the agricultural sector, supply chain disturbances due to geo-political events and human or animal/phytosanitary outbreaks that may arise in the future.

- *Domestic Farm Price Model*

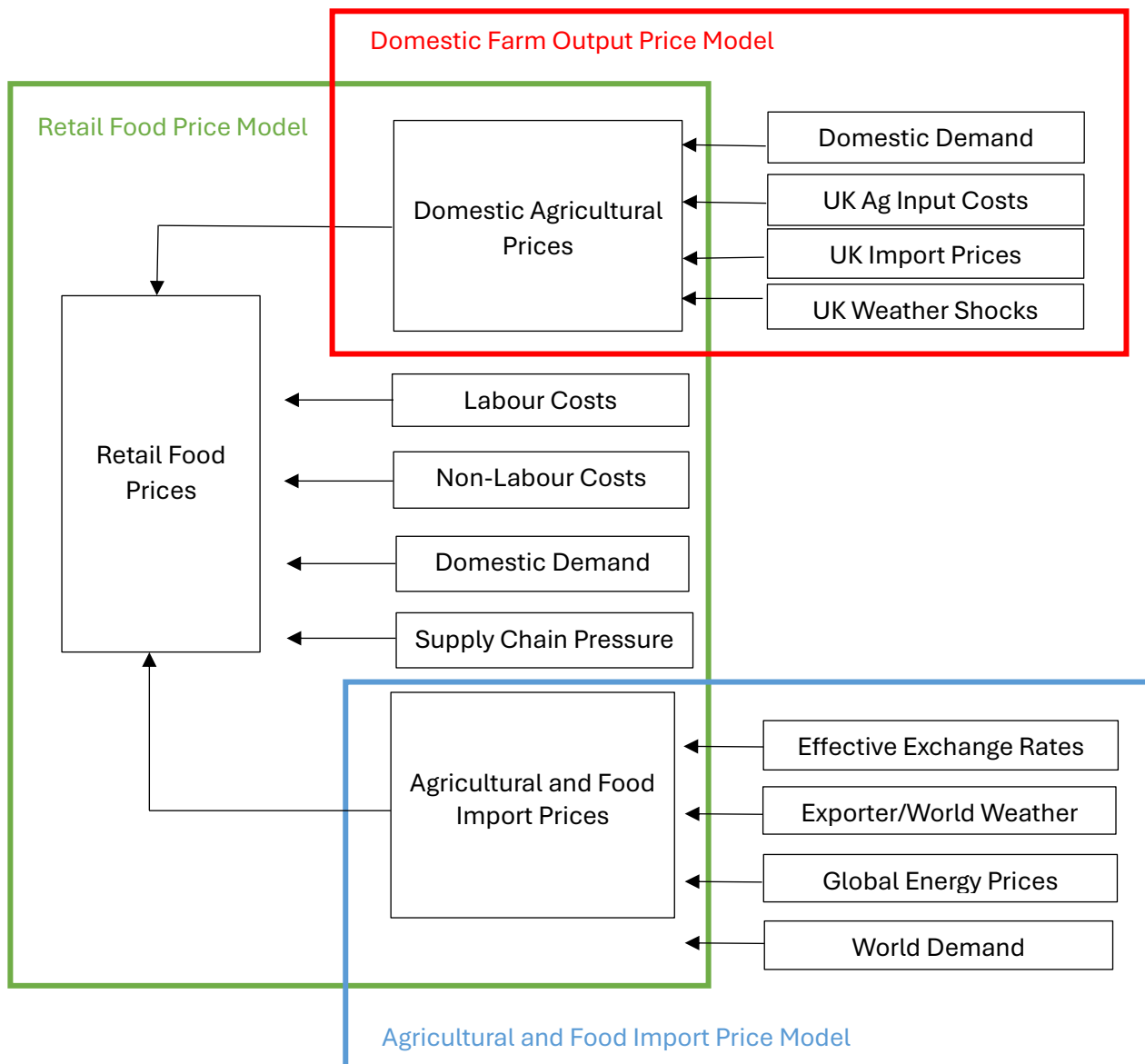
In this model, we are highlighting the factors that determine domestic agricultural prices. These include domestic demand (reflecting the derived demand for agricultural products); agricultural input costs (such as energy, agrochemicals and machinery) that may impact on farm production; UK import prices which, given the UK's exposure to imports and the potential parity between UK and world prices, is an important driver of domestic prices; and finally, UK (anomalous) weather. We detail the measure of this weather variable below.

- *Import Price Model*

In this model, we have created a bespoke measure of the prices of processed food and raw agricultural commodities that enter the UK (details below). The determinants of these import prices are the UK effective exchange rate; global energy prices; and global demand pressures. Given that the UK can reasonably be considered a small country in world food

markets, if global demand for commodities rise, this will increase the import price of food and agricultural products to the UK. In addition, given the concerns about the increasing frequency of extreme weather and how this may impact on agricultural markets, we also include a measure of global weather anomalies that relate to both temperature and precipitation.

Figure 2: Conceptual Framework for Assessing the Determinants of UK Retail Food Prices



Sub-Sector Retail Price Models

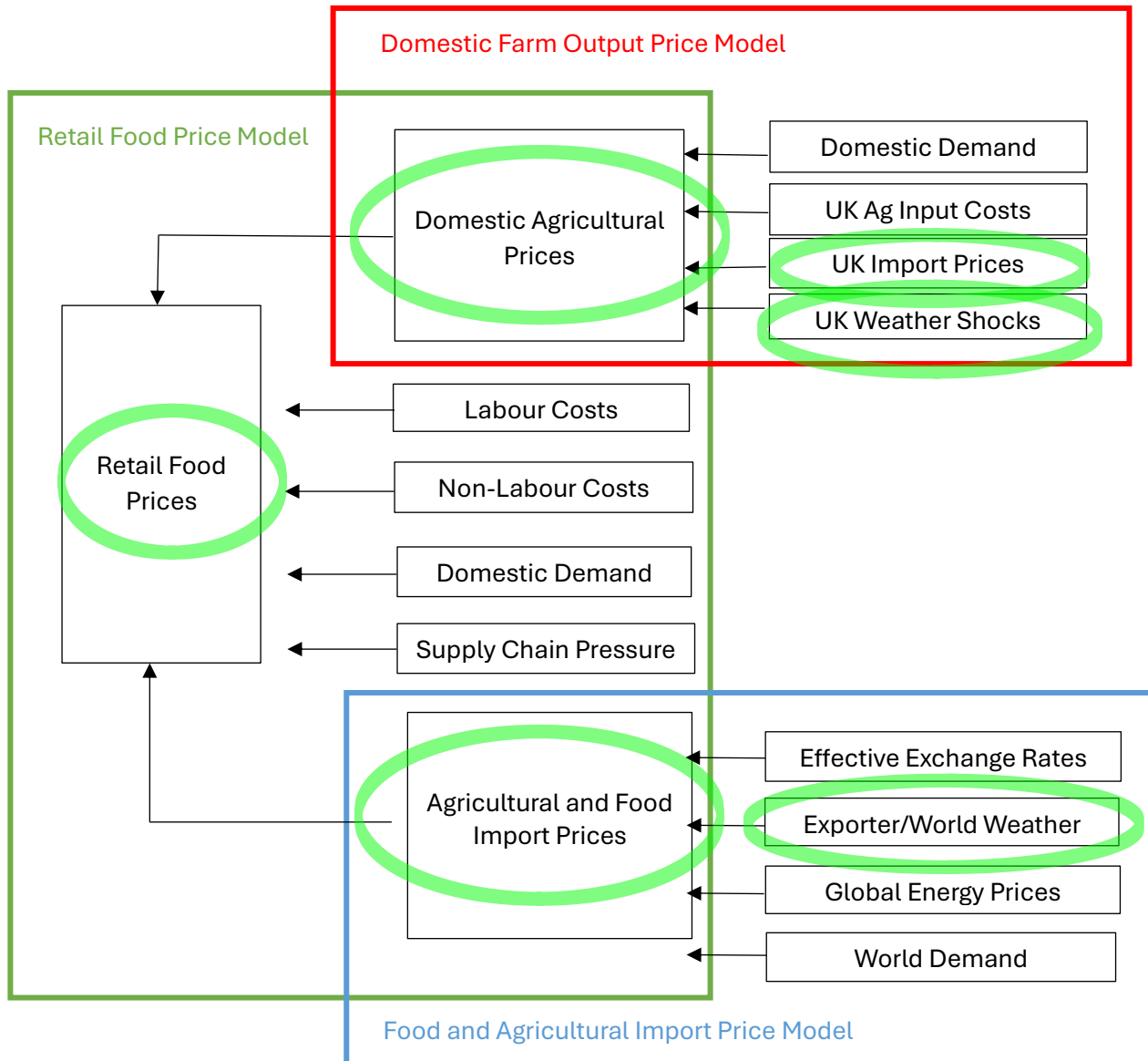
The conceptual framework that is applied to the sub-sector models is specified along the same lines to that for aggregate food inflation. There are some obvious differences, however. The most obvious difference is that the retail price variables are specific to each sector. As we can see from Figure 3, which presents data on retail and imports prices for each of the five sub-sector models we estimate (beef, dairy and cheese, bread and cereals, fruit and vegetables), the dynamics of each price series varies considerably. By extension, the factors that drive these price series will also differ reflecting their sector specific nature. For example, the trade variables are sector specific and not a weighted aggregate of all food and commodity sectors. Similarly, the weather variables (both domestic and global) are sector specific in that they measure weather (temperature and precipitation) conditions on land that supports specific agricultural activity. In Figure 4, we present the conceptual framework but, in this figure, we highlight (ringed green) where the sector-specific variables differ from the aggregate model.

To illustrate the issues, take for example a sub-sector model that applies to the UK beef sector. In this case, the retail prices will relate to beef prices at the retail level; domestic agricultural prices will be beef prices at the farm gate; agricultural import prices will specifically measure beef import prices; and the weather variables will apply to the beef sector both domestically and globally respectively. The interpretation of the impact of shocks that apply in specific sectors is identical to those for the aggregate retail price model. One caveat to note however is that the econometric specification may differ in some cases: for example, for storable commodities, the lag length in the specification may differ from those sectors where agricultural commodities are non-storable.

Figure 3: Retail and Import Price Dynamics Across Selected Sub-Sector



Figure 4: Conceptual framework for Assessing Determinants of Sub-Sector Prices



4. Data

Surveying the conceptual framework outlined in Figures 2 and 4 shows that we require data for 15 variables.⁴ For many of these, the data is readily available from the UK Office for National Statistics (i.e. aggregate retail and sector specific price data, labour and non-labour costs) and Defra (i.e. agricultural input prices). Other variables (such as energy prices, a measure of demand and supply chain pressure) have been obtained from alternative official sources, namely the IMF, OECD and the Federal Reserve Bank of New York. Given that they have not been used in previous food pricing work, we describe in more detail at the end of this section. However, for a set of other

⁴ Definitions and links to all data sources are provided in Appendix 1.

variables, the construction of bespoke measures was necessary. We begin by describing the construction of these measures in detail.

Construction of Bespoke data used in the project

- UK imported prices of food and agricultural products
- the effective exchange rate,
- domestic and global weather

UK Agriculture and Food import Prices

This is a bespoke measure of import prices that relates to what the UK imports covering both processed food and agricultural imports and the geography relating to the sourcing of those imports. This bespoke measure was detailed in the previous Defra report (Defra 2021) but for the sake of being self-contained, we repeat the details of the variable construction here and present the updated data.

The trade data was sourced from the HMRC database (<https://www.uktradeinfo.com/Statistics/>). While trade data are available at a highly disaggregated level, we worked with a relatively high level of commodity aggregation at the HS two-digit level (e.g. meat, cereals, sugar etc.) and identified eight suppliers classified at a regional level. The issue of aggregation is important as the data we have can be disaggregated to any commodity at the six-digit level and by any single country. It was useful to keep a relatively high level of aggregation, however, the more disaggregated the data become (by commodity and country), the more likely it is that null entries would be encountered. Given that the price indices we created comprise unit values (value divided by volume), trade must take place for a price to be calculated. Highly detailed product classifications at the individual country level thus confound the creation of price indices, particularly at the monthly frequency (reflecting, for example, seasonal issues).

Country Aggregation

HMRC provides import data by country although for practical reasons we aggregated by geographical regions which can be downloaded directly from the HMRC website. The regions are:

- European Union
- Non-European Union suppliers split between
 - Asia and Oceania
 - Eastern Europe
 - Latin America and the Caribbean
 - Middle East and North Africa
 - North America
 - Sub-Saharan Africa
 - Western Europe excluding the EU.

Product Aggregation

The commodity groups (called chapters in the HMRC classification system) that we used are from the first four sections of the 99 sections into which HMRC classify all imports. These represent the sections covering agricultural and food imports. The chapters that comprise the first four sections of the HS2 classification are presented in Box 1 below.

We excluded the chapters in these sections that are not food or beverages, namely Chapters 05 (products of animal origin, not elsewhere specified or included), 06 (live trees and other plants; bulbs, roots and the like; cut flowers and ornamental foliage), 13 (lac; gums, resins and other vegetable saps and extracts), 14 (vegetable plaiting materials; vegetable products not elsewhere specified or included), 23 (residues and waste from the food industries; prepared animal fodder) and 24 (tobacco and manufactured tobacco substitutes). This leaves 18 chapters.

Given the broad nature of some of the commodity categories, we split Chapter 17 (sugars and sugar confectionery) and Chapter 18 (cocoa and cocoa preparations) corresponding to their raw and processed constituents to give the 20 groups listed in Table 4. Further, to ensure a correspondence between the retail food price index and the food and commodity chapters for the import price index, in relation to Chapter 22, we excluded the sub-categories of this Chapter that related to alcoholic beverages.⁵ Finally, note that the designation of ‘raw’ and ‘processed’ chapters is in concordance with the FAO’s Food Price Index that essentially relates to raw (unprocessed or with limited processing) commodities and therefore allowed us to compare directly the newly derived import price index for the UK with an ‘off-the-shelf’ world commodity price index.

Import Price Indices

A key objective of the data construction exercise was to create indices of aggregate import prices based on highly granular (eight regions and 20 HS2 commodity groups) import data obtained from HMRC. In all, there were five steps to the process that creates the import data, which is summarised in Figure 5 (see Appendix 2 for details). In Step I, the value and volume of imports from the 8 regions in each of 20 groups covering commodities, food and beverages imported into the UK were assembled from the HMRC online database. Given the monthly frequency of the data, spanning 338 observations from 1996(1) to 2023(2), this represents a total of $(338 \times 20 \times 8 =)$ 54,080 observations for import values and a similar number for import volume. In Step II, each value series was divided by the corresponding volume series to yield unit value series at monthly frequency. This gives $(8 \times 20 =)$ 160-unit value series, each containing 338 monthly observations. In Step III, we created basic indices of unit values by region for each of the 20 product groups that are relative to the unit value in the chosen base year. In Step IV, the regional price indices were aggregated to form price indices of each of the 20 groups imported into the UK. These represent the average price (in £ sterling) of imports into the UK in the 20 commodity, food and beverage groups considering the geography of trade. While useful in themselves, these series were combined to form aggregate price series weighted by the value share of trade. We created three such aggregate series that reflect: (i) the import price of agricultural commodities imported into the UK; (ii) the import price of processed food and beverages; and (iii) an all commodities food and beverages index.

The basic unit of analysis is the region-commodity combination. Should we wish in future work to increase the granularity of the analysis (for example, split North America into constituent countries), it will be possible to do so. Each step in the figure will remain; however, the detail within the boxes will be increased.

⁵ Note that alcoholic beverages were included in the series developed for Defra 2.

Box 1: HS2 Product Classifications

SECTION I LIVE ANIMALS; ANIMAL PRODUCTS

- 01 Live animals.
- 02 Meat and edible meat offal.
- 03 Fish and crustaceans, molluscs and other aquatic invertebrates.
- 04 Dairy produce; birds' eggs; natural honey; edible products of animal origin, not elsewhere specified or included.
- 05 Products of animal origin, not elsewhere specified or included.

SECTION II VEGETABLE PRODUCTS

- 06 Live trees and other plants; bulbs, roots and the like; cut flowers and ornamental foliage.
- 07 Edible vegetables and certain roots and tubers.
- 08 Edible fruit and nuts; peel of citrus fruit or melons.
- 09 Coffee, tea, mate and spices.
- 10 Cereals.
- 11 Products of the milling industry; malt; starches; inulin; wheat gluten.
- 12 Oil seeds and oleaginous fruits; miscellaneous grains, seeds and fruit; industrial or medicinal plants; straw and fodder.
- 13 Lac; gums, resins and other vegetable saps and extracts.
- 14 Vegetable plaiting materials; vegetable products not elsewhere specified or included.

SECTION III ANIMAL OR VEGETABLE FATS AND OILS AND THEIR CLEAVAGE PRODUCTS; PREPARED EDIBLE FATS; ANIMAL OR VEGETABLE WAXES

- 15 Animal or vegetable fats and oils and their cleavage products; prepared edible fats; animal or vegetable waxes.

SECTION IV PREPARED FOODSTUFFS; BEVERAGES, SPIRITS AND VINEGAR; TOBACCO AND MANUFACTURED TOBACCO SUBSTITUTES

- 16 Preparations of meat, of fish or of crustaceans, molluscs or other aquatic invertebrates.
- 17 Sugars and sugar confectionery.
- 18 Cocoa and cocoa preparations.
- 19 Preparations of cereals, flour, starch or milk; pastry cooks' products.
- 20 Preparations of vegetables, fruit, nuts or other parts of plants.
- 21 Miscellaneous edible preparations.
- 22 Beverages, spirits and vinegar.
- 23 Residues and waste from the food industries; prepared animal fodder.
- 24 Tobacco and manufactured tobacco substitutes.

Table 4: Commodity Groups and Corresponding HMRC Chapter Classifications

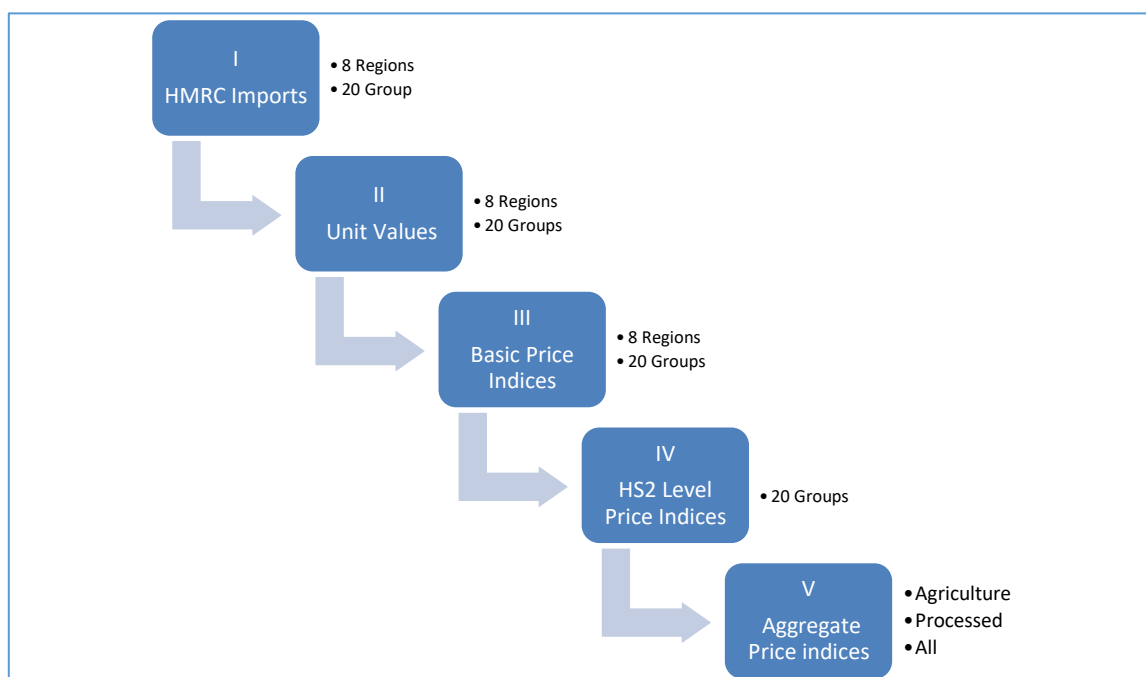
Commodity Group label	HMRC Commodity Chapters (HS Level codes)	Raw or Processed
01	Live Animals (HS01)	Raw
02	Meat and Offal (HS02)	Raw
03	Fish. (HS03)	Raw
04	Dairy Produce (HS04)	Raw
07	Edible Vegetables (HS07)	Raw
08	Edible Fruit (HS08)	Raw
09	Coffee, Tea, Mate (HS09)	Raw
10	Cereals (HS10)	Raw
11	Products of Milling Industry (HS11)	Raw
12	Oilseeds (HS12)	Raw
15	Animal or Vegetable Fats (HS15)	Raw
16	Preparations of Meat, Fish etc. (HS16)	Processed
1701	Sugars (17.01) ¹	Raw
1702	Confectionery (17.02, , 1703 and 17.04) ²	Processed
1801	Cocoa (18.01 and 18.02) ³	Raw
1802	Cocoa Preparations (18.03, 18.04, 18.05 and 18.06) ⁴	Processed
19	Preparations of Cereals, Flour (HS19)	Processed
20	Preparations of Vegetables (HS20)	Processed
21	Miscellaneous Edible Preparations (HS21)	Processed
2202	Non alcoholic beverages and Vinegar (HS22) ⁵	Processed

Source: HMRC

Notes: ¹ 1701 Cane or beet sugar and chemically pure sucrose, in solid form. ² 1702 Sugars, including lactose, maltose, glucose or fructose in solid form; sugar syrups without added; flavouring or colouring matter; artificial honey, whether or not mixed with natural honey; caramel; 1703 Molasses; resulting from the extraction or refining of sugar; 1704 Sugar confectionery (including white chocolate), not containing cocoa. ³ 1801 Cocoa beans; whole or broken, raw or roasted; 1802 Cocoa; shells, husks, skins and other cocoa waste. ⁴ 1803 Cocoa; paste; whether or not defatted; 1804 Cocoa; butter, fat and oil; 1805 Cocoa; powder, not containing added sugar or other sweetening matter; 1806 Chocolate and other food preparations containing cocoa. ⁵ 2202 Non-alcoholic beverages and vinegars.

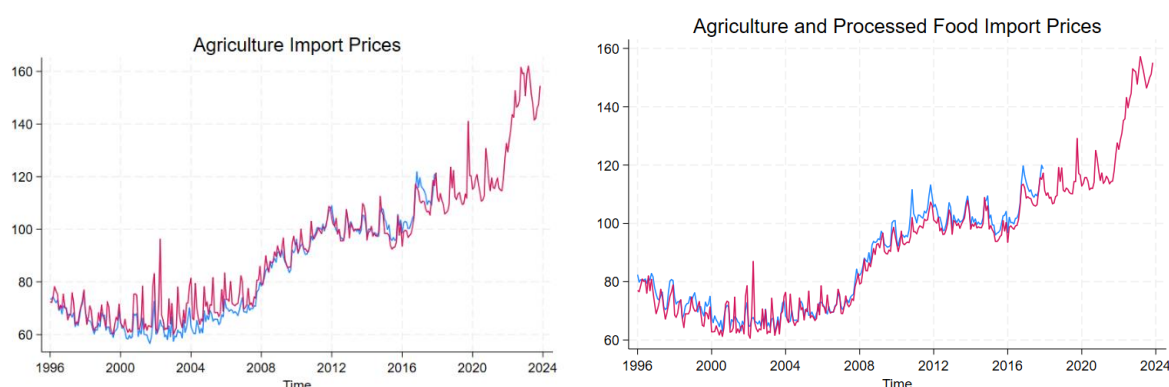
Figure 5: Creation of the Import Price Indices - A Five Step Process

Import Price Indices



In Figure 6, we report the original and updated import price indices; on the left-hand side, we have the bespoke import price index for raw agricultural commodities and, on the right-hand side, the corresponding index for raw agricultural and processed food imports. The blue line indicates the derived price indices used in Defra 2 with the red line reflecting the price indices up to 2024. As can be seen, import prices continued to rise in the post-2016 period reflecting global events.

Figure 6: Updated Import Price Indices

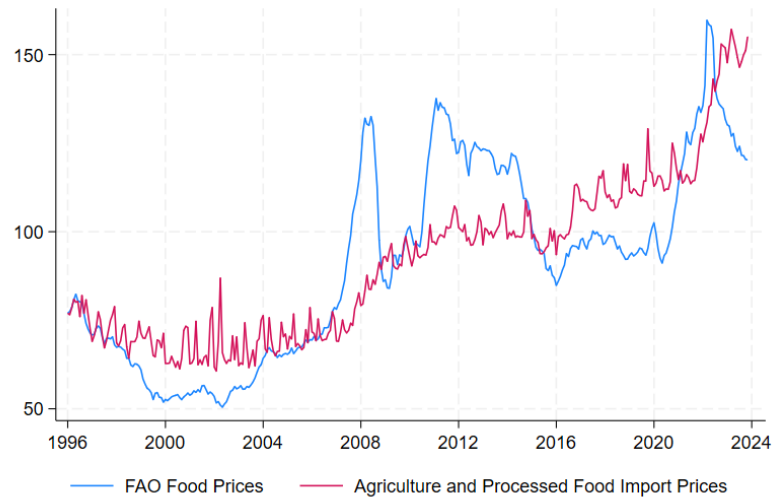


Source: Own Derivations

In Figure 7, we report the comparison between the FAO Food Price Index and the bespoke measure of UK index of agricultural and food commodities derived here. Although the UK import price index tracks events on world commodity markets as one would expect, nevertheless UK import prices are less volatile than the world prices partly reflecting differences in weights between the two indices, the effects (to the extent that they apply) of UK trade policy instruments

and that we are accounting also for processed food imports where processed food prices are typically less volatile than raw agricultural commodities.

Figure 7: UK Agricultural and Processed Food Import Prices Compared with FAO Food Price Index



Source: Own Derivations

Effective Exchange Rates

Owing to the importance of imports of food and drink to the UK food chain, exchange rates are an important determinant of domestic retail food inflation. Results from previous work (see Davidson *et al.*, 2016) confirmed the important role played by the (US\$:£) exchange rate on domestic food prices. As set out in Section 4, exchange rates also feature in the current specification but need to be measured appropriately for the purposes at hand. Specifically, since the emphasis in the current model is on the source of imported commodities, we will need to incorporate an *effective* exchange rate, where the weights reflect the relative importance of key currencies used to purchase UK agricultural and processed food imports. This difference has implications for: (i) the interpretation of the exchange rate and how it is specified in the model; (ii) how the exchange rate is measured; and (iii) the effect of alternative trade agreement scenarios (future changes to the geography of UK food and agricultural imports will change the importance of each currency in the effective exchange rate).

We therefore created an effective exchange rate which reflected the basket of exchange rates associated with where the UK sources its imports from. Although effective exchange rates are available from external sources (e.g. from the Bank of England, the Bank for International Settlements or the IMF), none of these were suitable for the purpose at hand. This is because the weights on these publicly available effective exchange rate indices specifically exclude agricultural and food trade. By reflecting the trade in manufactured goods (and, in some cases, trade in services also), such series misrepresent the costs of UK food trade. This made creation of a bespoke effective exchange rate series necessary.

Ideally, an effective exchange rate should weight the basket of currencies used by source of imports. However, since we are dealing with regions, we could not apply single country exchange rates; also, since we are aggregating across sub-commodity price indices, no single weighting can be applied since the import weights on grains, for example, will differ from that for non-

alcoholic beverages. Setting aside the regional aggregation for the moment, one way to deal with this is to create an effective exchange rate index corresponding to each commodity chapter and then subsequently apply the same weights to the $j=1, \dots, 20$ effective exchange rates that have been derived for the import price index. However, we had to make compromises in the number of bilateral weights that should be included, and we needed to make some decisions to make the derivation functional. To this end, we assume that trade with EU partners was denominated in Euros, and that trade with non-EU regions was denominated in US dollars. The effective exchange rate weighted with reference to raw agricultural and processed food is presented in Figure 8 below.

Figure 8: Sterling Effective Exchange Rate Weighted by Agricultural and Processed Food



Source: Own Derivations

Weather Data

In recent years, the increasing frequency of extreme weather events and food prices has attracted attention in both academic and public policy circles as well as the media. This is reflected in a substantial body of research linking the impact of weather events to changes in agricultural yields. The UK's recent Food Security Report (HMSO, 2024) has also highlighted the potential concerns associated with the exposure of UK food supplies to on-going climate change. However, the impact on the UK is not clear-cut. Thus, while much of the scientific research on climate change and extreme weather and agricultural yields has focussed on a few key staple crops, when widened to account for a larger range of crops, the links between yields and extreme weather become more ambiguous. This has also been noted in the UK food strategy report (see also Agnolucci *et al.*, 2020).

Furthermore, the effect varies across space: in some areas, extreme weather will reduce yields but in others, yields will increase. Even within relatively close geographic regions for the same commodity, climate change could increase yields and, for others, decrease yields. Reflecting the growing concern with the links between weather and general inflation, there has also been a nascent literature on how extreme weather may drive inflation. Insights from this recent research (see for example, Ciccarelli *et al.*, 2024) has shown that the main sector where extreme weather is likely to impact on inflation is via food prices.

To account for this increasing concern between extreme weather and retail food prices, we explicitly account for weather events in the expanded econometric model. A full discussion of the

literature on food prices and extreme weather and the construction of the weather variables can be found in Lin *et al.* (2025). In short, we construct two weather variables as follows.

Our principal data is based on ERA5-Land developed by the European Centre for Medium-Range Weather Forecasts (ECMWF) that provides global gridded weather data at a high spatial resolution ($0.1^\circ \times 0.1^\circ$, approximately 11km x 11km grid squares). ERA5-Land data records hourly readings for key variables such as total precipitation (mm) and 2-metre air temperature ($^\circ\text{C}$). Spanning a period of 1950 to the present, ERA5-Land enables flexible temporal aggregation and is accessed via the Copernicus Climate Data Store. These data underpin the calculation of country-level temperature and precipitation anomalies that we construct, making ERA5-Land the foundational source for the weather variables created for this study.

To obtain measures of ‘extreme weather’, we follow best practice in the climate literature and construct weather anomaly series, which reflect the deviations in temperature and precipitation from a baseline reference period (1950-1979). The anomaly calculation comprises two main steps. First, a reference baseline is computed by calculating the mean temperature and precipitation per month in each grid cell during the reference period. This baseline will be used to represent the normal or expected climatic conditions for each specific grid location. Second, the temperature and precipitation anomalies are then calculated for each grid cell individually. For each observation period (i.e., month), the observed values of temperature and precipitation are subtracted from the respective reference period means. This gives the anomaly value for each grid cell, showing how each specific location deviates from its long-term average.

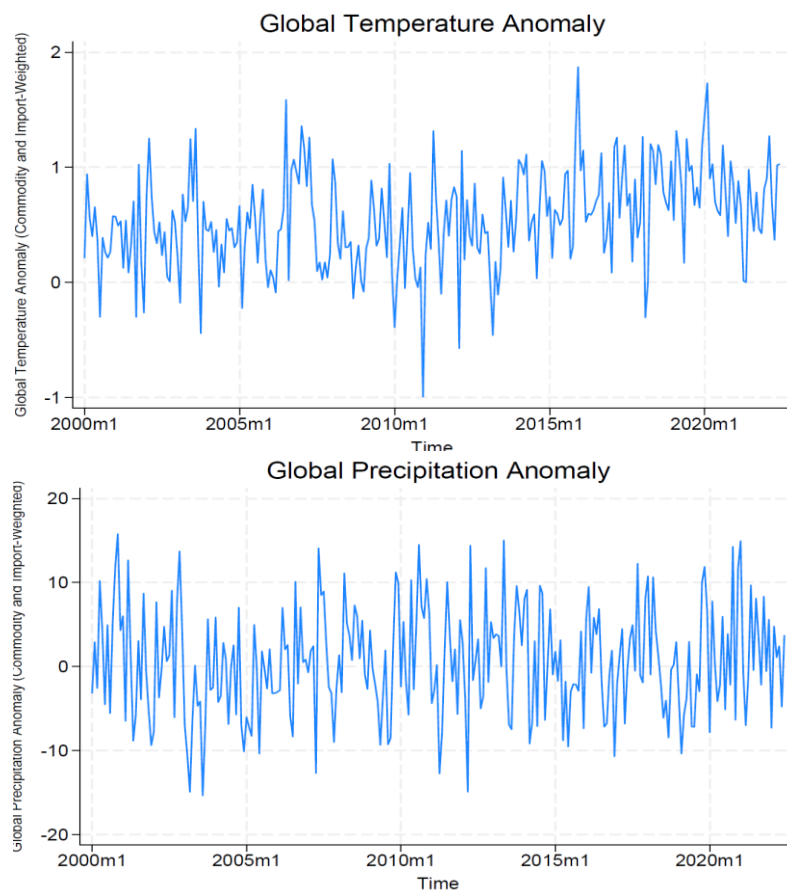
The next step involves identifying where in world agricultural production takes place. To achieve this, we employ FAO’s Global Agro-Ecological Zones (GAEZ) crop area dataset for 2015, which provides spatially detailed and globally consistent estimates of cropland area dedicated to different crops thus exclude urban and other non-agricultural land). The GAEZ dataset provides information on monthly crop-specific harvested areas across countries, enabling the computation of weights based on the share of each crop in total harvested land. This weighting system is applied during weather data aggregation, ensuring that climate metrics are representative of agricultural conditions that are most relevant to national crop production patterns. The crop area data from GAEZ ensures precise alignment of climate analysis with agricultural land use.

Combined with the gridded weather anomaly data, we can now derive temperature and precipitation anomalies that apply to specific crops/commodities at the grid ($0.1^\circ \times 0.1^\circ$) level. Specifically, for each commodity, temperature and precipitation anomalies are calculated using the weather data for the areas where the commodity is cultivated. This is done by identifying the grid cells within the commodity’s cultivated regions and computing the temperature and precipitation anomalies specific to those areas. The anomalies for each commodity are then aggregated from grid-level values to the country level. Each grid cell’s anomaly is therefore weighted by the percentage of land used for the commodity in that cell. For example, if a grid cell has a larger proportion of land used for maize cultivation, the anomaly for maize in that grid cell will have a greater influence on the final country-level anomaly for maize.

Our overall aim is to derive a measure of the UK’s exposure to anomalous weather for the agricultural commodities and processed food which the UK imports. This then requires a final aggregation of the crop/commodity specific anomalies detailed above. For this, we match the crops/commodities covered by the IMF Commodity Price Index where the weights relate to the value of imports of the specific commodity to the total value of commodity imports where the baseline commodity imports relate to the relative importance of agricultural commodities in the IMF Commodity Price Index. The global weather anomalies for temperature and precipitation are

reported in Figure 10. Note that, given the rationale above linking extreme weather and the geographical and commodity variation on the impact on yields, we are agnostic about the direction of impact of extreme weather on UK food and agricultural import prices. Finally, although the measure we report here applies to global measures, we apply the same procedure to measuring temperature and precipitation anomalies that impact on UK domestic agricultural production.

Figure 10: Global Weather Anomalies



Source: Own Derivations

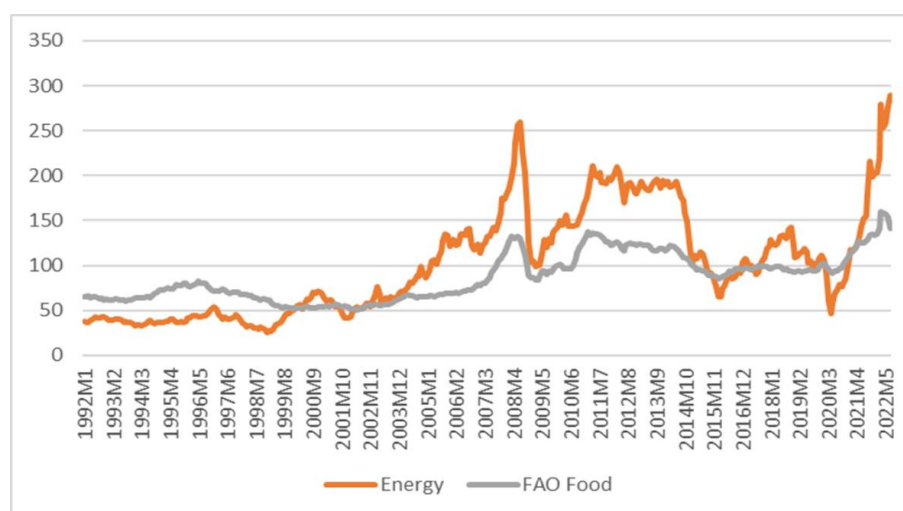
Other variables from Official Sources

Energy Prices

In the updated food inflation model, we account directly for energy prices. This largely reflects the broader scope of the updated model (the Defra 2 model being primarily designed to assess the effects of changes in trading patterns). While there is a logic for including energy in any quantitative model of food prices given the energy intensity associated with production (most obviously since fertiliser production requires energy as a feedstock), the link has not always been strong empirically, particularly during periods of low energy prices. Peersman (2023) explores this time-varying issue in some detail. Consequently, in the context of relatively low food inflation the mid-2010s, energy was not accounted for in Defra 2. However, in earlier analysis of UK food inflation following the commodity price spikes of 2007-08 and 2011 (see Davidson *et al.*, 2016), the link between oil and commodity prices was established relating to biofuel production in the US being a significant contributor to world commodity price spikes. Figure 9 highlights the

relationship between world energy prices and world commodity prices (as measured by the FAO's Food Price Index).

Figure 9: Relationship Between World Energy and Food Prices



Source: IMF and FAO

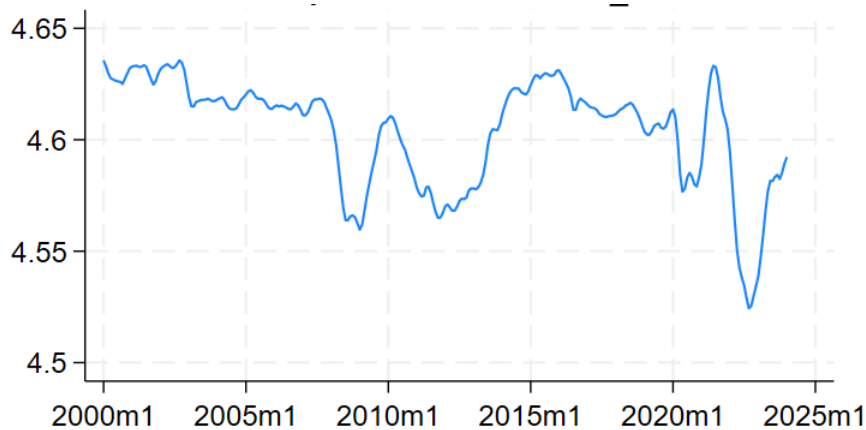
Global geo-political events in recent years are associated with a significant rise in oil and gas prices and represent a major driving force behind the 'cost-of- living crisis' that has impacted UK consumers. Given the integral role that energy plays in all production processes, it is noteworthy that global energy shocks impact through multiple channels in the updated model of retail food prices. As described in the conceptual model Figure 2 and 4, energy shocks propagate through principally three mechanisms that are represented by the three variables:

- Agricultural Input Price Index, which represents the costs of fertilizer and fuels in the Domestic Agricultural Price model.
- Global Energy Price Index in the Agricultural and Food Import Price model
- Non-Labour Costs, which includes the costs of fuels such oil and natural gas in UK food manufacturing.

Demand Factors

Accounting for the role of demand as a driver of food and agricultural prices features in each of the components of the conceptual framework outlined above. Notably, domestic demand factors may be a driver of retail food prices but also a derived demand for agricultural output and therefore features in the agricultural price model. Note that, in the context of a price model, domestic demand plays a potentially important role: given that demand for food is generally price inelastic, imply that changes in quantities bring forth relatively large changes in price. Although demand had been accounted for in Defra 2, it was measured by unemployment, which is not an accurate macroeconomic variable to capture food demand as it is slow moving and may not necessarily reflect income pressures for all groups who may not necessarily be unemployed. In practice, demand effects in Defra 2 were only marginally significant. In this revised model, we therefore measure domestic demand by the UK consumer confidence index produced by the OECD. The data is presented in Figure 11.

Figure 11: UK Consumer Confidence Index



Source: OECD

We also account for global demand in the import price model. The rationale here is that rising demand that impact on economic activity will stimulate the demand for commodities, both food and energy. In turn, this will increase world prices which will be reflected in higher import prices for food and agricultural products imported by the UK. The measure we use for this is the OECD consumer confidence index which is reported in Figure 12.

Figure 12: OECD Consumer Confidence Index



Source: OECD

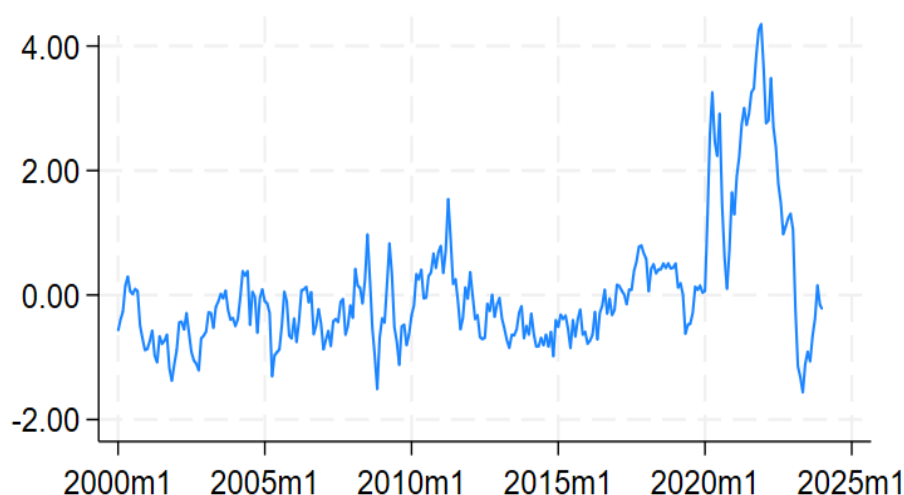
Supply Chain Pressure Index

Finally, in the retail price model shown in Figure 2, we also include a measure to account for frictions in the UK's domestic and global supply chain, the Global Supply Chain Pressure Index (GSCPI) published by the Federal Reserve Bank of New York. Although other variables cover demand and costs that drive retail prices, the GSCPI measures wider supply chain pressures, both domestic and global relevant to the UK supply chain (it is also available for six other major economies). Benigno *et al.* (2022) discuss the basis of the supply chain pressure index and how it relates to addressing changes in the rate of inflation. Back-dated to 1997, the index was developed in the aftermath of the COVID-19 pandemic to gauge the importance of frictions and disruptions to global supply chains. As such, the index incorporates several relevant supply chain indicators, primarily the delivery time, backlogs and stock level components of the Purchasing

Managers Index, which are combined with world freight rates, potential bottlenecks, and uncertainties about the global economic and political environment. The index is presented in Figure 13. It is evident from the figure that the UK supply chain pressure index peaked during the COVID-19 period.

While this measure captures aspects of costs that other more direct cost variables do not, from an econometric perspective, it also removes the need to include a dummy variable for the COVID-19 period and hence addresses the issues relating to the performance of the econometric model as outlined in Section 1 above. Moreover, from a forward-looking perspective, by including the GSCPI, the updated model will also facilitate the assessment of potential future scenarios relating to transportation issues, and human and animal/phytosanitary concerns and geo-political events. Given the vulnerability of key pinch-points in global trade routes (e.g. the Suez Canal or Panama Canal) to disruption the capability of the food price model is enhanced.

Figure 13: UK Supply Chain Pressure Index



Source: Federal Reserve of New York

Summing Up

The development and expansion of the food inflation model have required a substantial upgrade to update bespoke data and incorporate new variables that involve a considerable degree of originality. The extension of the model back up the supply chain to incorporate the drivers of domestic agricultural output prices and the price of imported food and agricultural commodities represent a significant uprating of the model's functionality compared to Defra 2. Doing so permits a more accurate account of the factors that determine retail food prices both at the aggregate and sub-sector model levels and permit greater scope for the development of the scenario modelling tool. Aside from expanding the range of factors that determine food and agricultural prices at different parts of the food chain, we also employ a different econometric approach to estimating the relationship among these variables which we turn to next.

5. Econometric Issues

Local Projections versus VARs

As discussed above, the econometric methodology applied to address UK food inflation issues in Defra 1 and 2 was a co-integrated VAR model. In the development of the current modelling framework, as well as the addition of more variables that underpin UK food inflation, we apply a

new method called Local Projection, as developed originally by Jordà (2005, 2009), to generate the impulse response functions that are of primary interest. The method has become an increasingly employed alternative to the estimation of VARs in empirical macroeconomics for reason that we briefly review. An overview of recent developments in the local projections methodology can be found in Jordà and Taylor (2025).

To begin, it is important to recognise that local projection (LP) methodology produces essentially the same output as a C-VAR, namely the impulse response functions that measure the dynamic response of retail food prices over a given time horizon. The way the impulses are generated is however quite different: whereas the impulse response function is derived from a non-linear combination of the coefficients of an underlying VAR, the impulse response function is estimated directly by local projection. The simplicity this affords offers several advantages that accounts for the popularity of the technique, advantages that are applicable to research on food inflation.

From a theoretical standpoint, it has been shown that the two methods for deriving the impulse responses are asymptotically equivalent under relatively general conditions (see, Plagborg-Møller and Wolf, 2021). However, generating impulse responses via the technique of local projection avoids the complexity often associated with VAR models. As explained below, the impulse response functions are relatively easy to estimate through a series of ordinary least squares regressions that impose few restrictions on the shape of the Impulse response function, which mean that inference is substantially more robust to misspecification than VAR models (Montiel Olea *et al.*, 2024). Moreover, as essentially a single equation approach, the local projection method is both tractable and avoids the ‘curse of dimensionality’ or complexity that characterise the VAR (which is a system of equations). It also affords considerable flexibility in terms of specification, easily accommodating a range of controls and interaction effects that would present a considerable challenge to a VAR. The single equation nature of local projection also means that it is straightforward to generate statistical confidence intervals.

In relation to the discussion in Section 2, we estimate three sets of local projections: (i) the retail food inflation model (ii) the food import price model and (iii) the domestic farmgate output price model. Each set of impulse response function is estimated at the aggregate level (i.e. food) as well as five separate sub-sector model (bread and cereals, beef, cheese, fresh vegetables and fresh fruit).

The response variable in each set is the relevant price variable. For example, in the aggregate retail food price model this will be consumer prices index for food, the domestic agricultural output index and the index of imported agricultural and food prices. Each impulse response function measures the effect on these variables of a shock to each of drivers of these prices, as detailed in the conceptual framework in Figure 2, with the other variables included as controls.

Impulse Response Functions estimated by Local Projection

Local projection impulse responses are relatively straightforward to estimate which adds to the attractiveness of the approach. Following Jordà (2005), local projections can be derived from the following regression where Δy_{t+h} is our variable of interest, s_t is the shock variable we want to isolate and the vector $\mathbf{Z}_t$ includes the appropriate controls and lags of y_t :

$$\Delta y_{t+h} = \alpha_h + \beta_h s_t + \gamma_h \mathbf{Z}_t + \varepsilon_{t+h}; \quad h = 0, 1, \dots, H \quad (1)$$

Three comments are noteworthy. First, the dependent variable $\Delta y_{t+h} = y_{t+h} - y_{t-1}$ is the change in the variable of interest between its value before the shock, and its value h periods after. This

variable, often called the ‘long difference’, thus measures the accumulated impact of the shock. While it is standard practice to use a levels specification, where y_{t+h} (the value of the dependent variable h period after the shock) is used, results from Piger and Stockwell (2024) show the long difference has superior statistical properties.

Second, equation (1) is a single equation that is estimated H times. In each of these H regressions the variables on the right hand side remain the same but the dependent variable increases sequentially. As a result, β_h measures the effect of a shock to a variable s at time t on the change in y between its base level before the shock and its value in $t + h$. The impulse response coefficients are therefore the estimates of $\beta_1, \beta_2, \dots, \beta_H$ obtained from the H regressions and can be estimated with ordinary least squares which simplifies the estimating procedure considerably.

Third, in order for the impulse response function to show the causal effect of shocks on the variable of interest, the variable s_t must be identified, or expressed more technically, exogenous and unanticipated (i.e. $E(s_t, \varepsilon_{t+h}) = 0$). This applies to both VARs and local projections yet is far easier to implement in LP because predictable changes in s can be filtered out prior to estimation of (1). Hence, the impulse response functions generated by local projection provide a better estimate of the causal effects that are typically sought (see below).

Finally, by incorporating an extra lag of the dependent variable in (1), produces what is known as a lag-augmented local projection, which greatly simplifies statistical inference. Specifically, and in contrast to a C-VAR, standard critical values apply irrespective of whether the data are stationary or non-stationary (see Montiel-Olea and Plagborg-Møller (2021)). While standard errors of the impulse response coefficients correctly convey the precision with which each coefficient is estimated, they take no account of the sequence in which any one coefficient appears. As a result, presenting the confidence interval for a set of impulse response coefficients will typically give an overly pessimistic impression of significance (i.e. wide confidence intervals).⁶ For this reason, recent work (e.g. Taylor and Jorda 2025) proposes the use significance bands as a basis for statistical inference. Where confidence intervals are used owing to their familiarity, it is common to report 68% confidence intervals, a practice that is adopted in the empirical analysis reported below.

Identification of Shocks (Hamilton Filter)

As noted above, for the identification of the impulse response to the variable of interest, the shock to the variable s_t should be exogenous and unanticipated. To see the relevance of this, consider Figure 9 and assume that the policymaker is interested in the impact of energy prices on commodity prices. But energy prices may have a trend (at least over certain periods), or be characterised by cyclical or seasonal patterns, such that trying to identify the impact of a change in energy prices may conflate these other features of energy price dynamics. Moreover, both commodity and energy prices may have a common influence that may not be explicitly accounted for and therefore may impact in deriving what the impact of a ‘shock’ may be; for example, high levels of economic growth would increase the demand for both commodity and energy prices thus driving both up simultaneously.

To address these issues, it is therefore necessary to account for these features of the variable of interest; in the example here, to take out the trend, cyclical and seasonal factors such that only the unanticipated features of the energy prices are accounted for. To do this, we apply the

⁶ This is analogous to the case of a regression with collinear regressors individual t ratios can be quite small even though and F test would strongly reject the null that the coefficients were jointly zero.

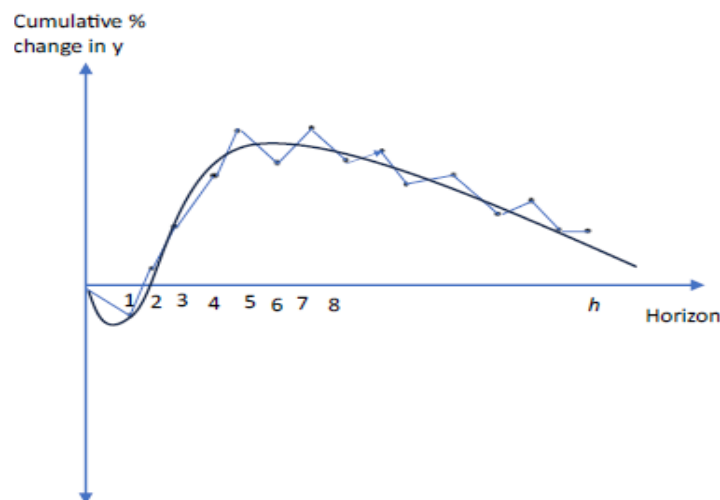
procedure proposed by Hamilton (2018); we refer to this as the ‘Hamilton filter’ and apply it to all the ‘shock’ variables s_t in deriving the impulse response functions as set out above.

Smooth Local Projections

Impulse response functions estimated by local projection often exhibit jagged response patterns, unlike VAR-generated impulse responses which generally exhibit smoother responses. This is because, unlike those obtained from a VAR, the coefficients of an impulse response function estimate by local projection are directly estimated from the data. Recent developments in the literature on local projections show that the impulse response functions can be smoothed if desired which-in the context of the STEFI policy tool-may be a featured that would be attractive (see Jorda and Taylor, 2025).

As an intuitive representation of a smoothed local projection impulse response function, consider Figure 14. Assume that the issue of interest is how retail food prices respond to a shock in domestic agricultural input prices where the coefficients of the impulse response function (i.e. $\beta_1, \beta_2 \dots \beta_H$) are represented by dots. The line through these dots therefore represents the smoothed local projections. While any smoothing algorithm can be applied, the LOESS (Locally Estimated Scatterplot Smoothing) method provides a flexible and tractable approach. Fitting simple models to localised segments of the data, the principal attraction of LOESS is that it does not require that a global function to fit the data is specified. We adopt this approach and present smoothed local projections based on this technique.

Figure 14: Smoothed Local Projections



Empirical Considerations

The impulse response functions that are presented in the following section are based on extensive testing and evaluation. The lag length of the empirical models of (1) is based on the Akaike Information criterion from lag 13 and standard errors are heteroskedasticity robust. As mentioned above, owing to the use of lag augmentation, the order of integration (i.e. whether the data is stationary or not) is not a practical consideration in local projection. As a result, we proceed directly to the presentation of the results.

6. Results

Aggregate (Food) Level

In this section, we present the local projection impulse response results for the aggregate model. As detailed in Figure 2, the impulse response functions relate to the impact of the determining variables conditional on the controls in the specified models. The impulse responses are cumulative, and the response horizons are set at 24 months. With the exception of the weather variables (see later), the impulse response coefficients can be interpreted as an elasticity, and therefore estimate the causal impact of a one percent change in the shock at time t on the response variable (also measured in percent) in periods $t, t + 1, t + 2, \dots, t + 24$. For example, the first impulse response coefficient measures the contemporaneous or impact elasticity; an impulse response elasticity of 0.2 at time period 4 implies that the response variable is estimated to increase by 0.2 per cent following a shock of 1 per cent five periods ago. The response is scalable so, if the effect of a 10% is desired, the responses should be multiplied by 10.

As discussed above, 68 per cent confidence intervals are also reported as a guide to the statistical significance of the effects at specific time horizons. We interpret each impulse response coefficient whose confidence interval does not include zero (i.e. the horizontal axis) as having a statistically significant effect.

Three aspects of the impulse response are typically of interest:

- Sign and magnitude of the responses
- Dynamic pattern (i.e. lagged responses)
- Persistence of effect

Retail Price Model (Figure 15)

The responses of retail food prices with respect to domestic agricultural prices, the overall import price index (the combination of raw agricultural and processed food products), domestic labour, non-labour manufacturing costs, consumer confidence (our proxy for demand factors) and the supply chain index, all have the anticipated signs.

In terms of the estimated magnitude of the elasticities, retail prices are most elastic with respect to domestic demand (1.5) and most inelastic with respect to global supply chain pressure (0.025). Note here that while the elasticity with respect to supply chain pressure is small, the index is prone to large changes. For example, estimates suggest that a doubling of the index implies price increases of around 2.5 percentage points.

Changes to domestic demand are estimated to take the longest time to percolate into food prices whereas shocks to the domestic chain are generally transmitted rapidly with maximum impacts emerging about 15 months after the shock. All shocks have a persistent effect, except for labour costs.

Import Price Model (Figure 16)

The impulse response functions for drivers of import prices (as set out in Figures 2 and 4) are presented in Figure 16. Note that these impulse response functions shown relate to imports of raw agricultural and processed food imports combined. In terms of global demand, global energy and the effective exchange rate, all responses have the anticipated signs. Changes in global

demand take around 12 months to show up in UK retail prices, echoing the results for changes in domestic demand. Exchange rate and global energy prices impart more immediate effects although the timing varies: exchange rates reach maximum effect with 9 months whereas global energy prices take around 12 months to reach peak impact in retail food prices. All shocks have persistent effects.

With reference to the weather anomalies, we treat positive and negative anomalies separately so that drier (cooler) than usual weather is allowed to effect retail prices differently to wetter (hotter) weather. Positive and negative weather anomalies relate to different concerns about how weather shocks may impact on import prices: for example, the effects of flooding may be different to the effect of droughts. Each impulse response measures the effect of more extreme weather (e.g. hotter than usual or cooler than usual temperatures). Note also that the weather anomalies are measured in their natural units of measurement: degrees Celsius for temperature and mm per month for precipitation, so the impulse response coefficients represent semi-elasticities, i.e. the percentage effect on import prices of a shock of known size (in °C or mm per month). The figures depict the dynamic effects of typical (i.e. one standard deviation) shocks.

Results suggest that as far as UK imports of both processed and raw foods are concerned cooler than usual global temperatures increase prices whereas warmer temperature have no discernible impact. For global precipitation, wetter than usual months (floods) raise import prices, whereas drier than usual months lower import prices. While the dynamics differ, peak impact occur some 18 months following the shocks.

Domestic Agricultural Price Model (Figure 17)

Finally, we present the impulse response results for the domestic agricultural output price model. These are presented in Figure 17. Farm input costs increase farmgate prices, as anticipated. Estimated effects are transmitted immediately; peak impact in month 5 with an elasticity of 0.4 and subsequently dissipate.

Import prices also impact on domestic agricultural output prices although weaker than might be expected and with considerable delay. One caveat to note is that the impact of import prices relates to the all-import price index to ensure compatibility with the model specifications reported in Figures 15 and 16. We should note the impulse response functions relating to raw agricultural import prices indicates a stronger and more immediate impact on domestic agricultural prices than the results reported for the combination of raw agricultural and processed food imports.

Also, as noted for the import price model, we have split the weather anomalies between positive and negative temperature and precipitation anomalies and again we note the interpretation of the negative anomaly effects as detailed above. Results suggest that cooler and wetter weather increase domestic prices; hotter and drier weather having impacts that are not statistically different from zero.

Figure 15: Impulse Response Functions for Retail Price Model

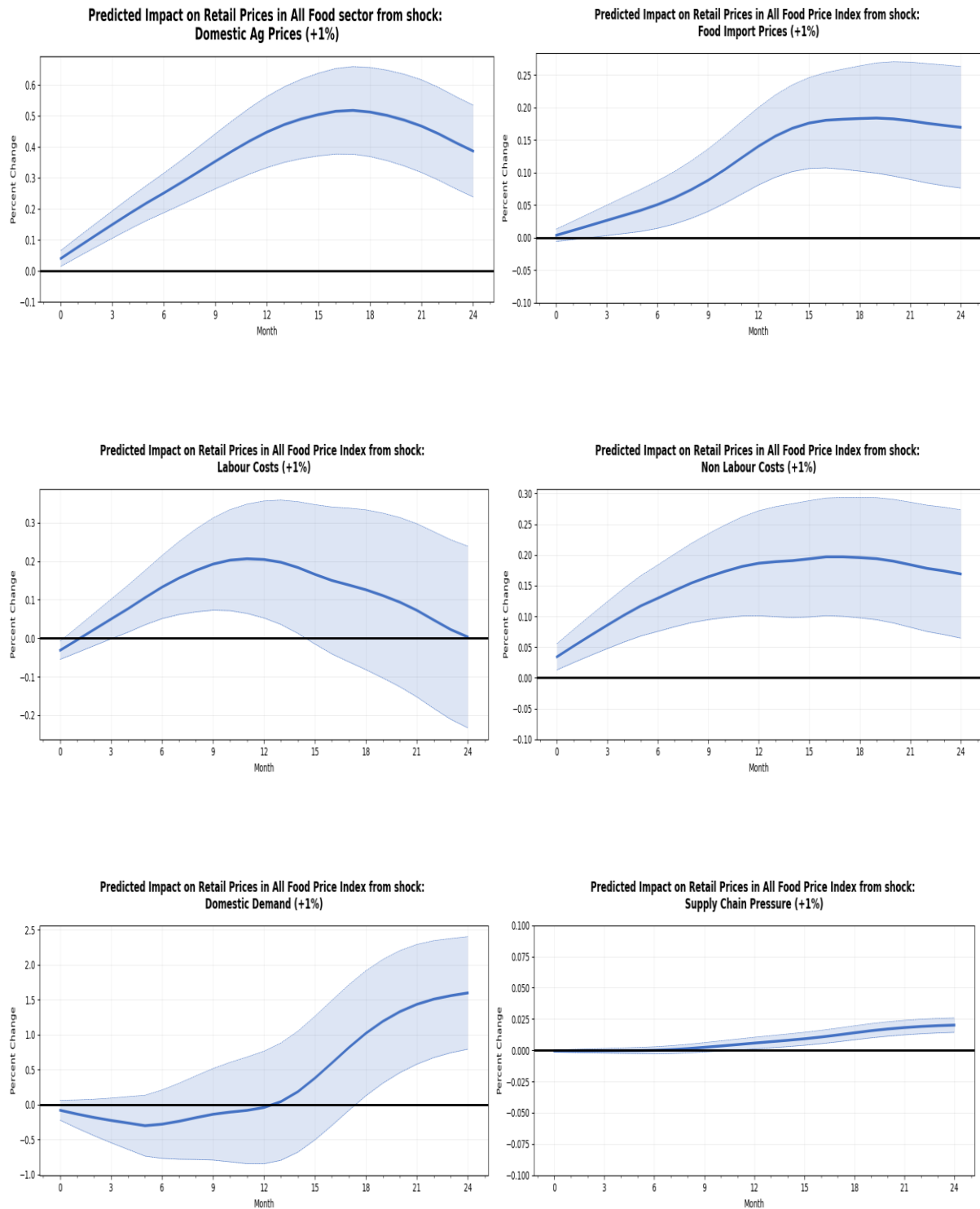


Figure 16: Impulse Response Functions for Import Price Model

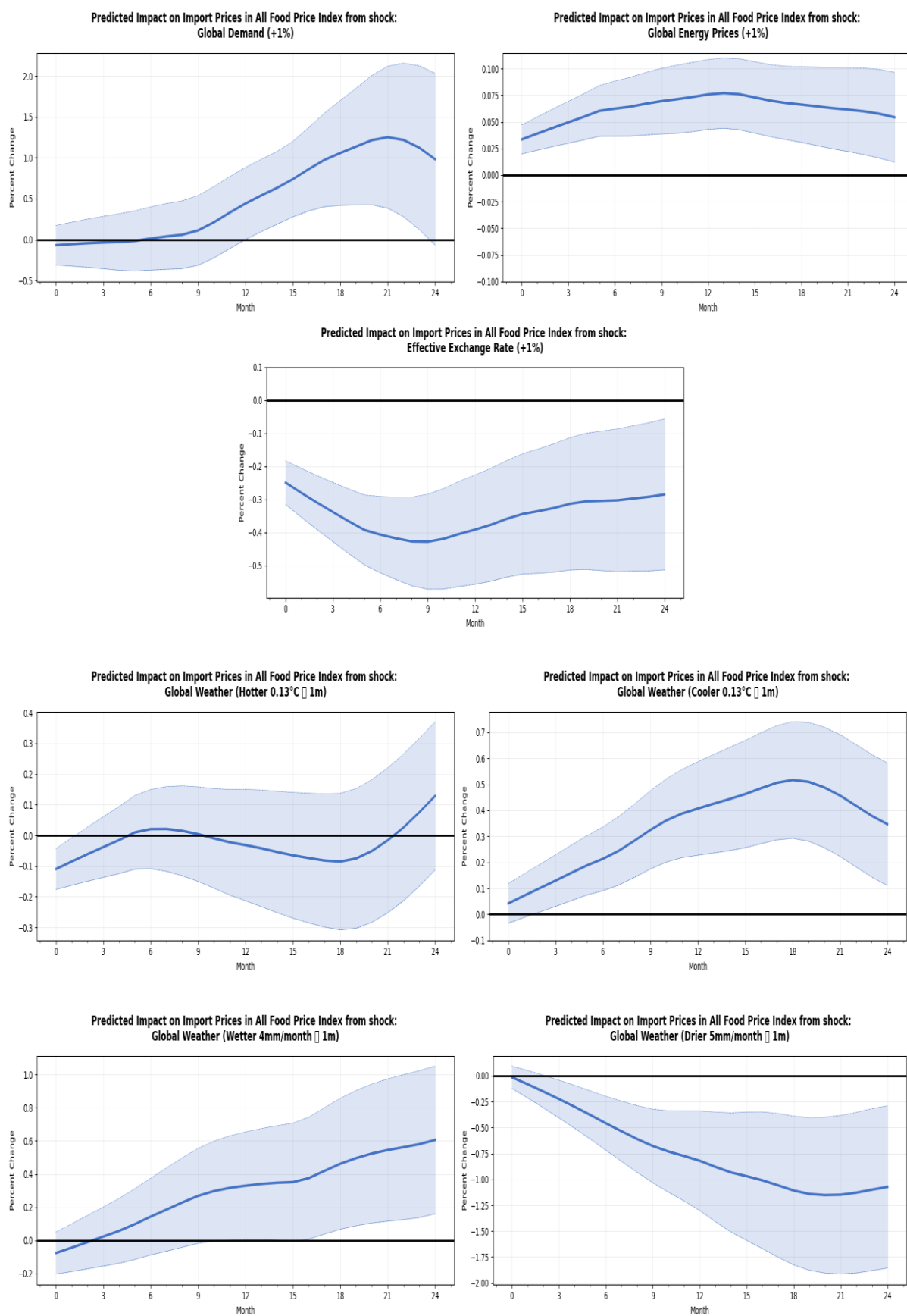
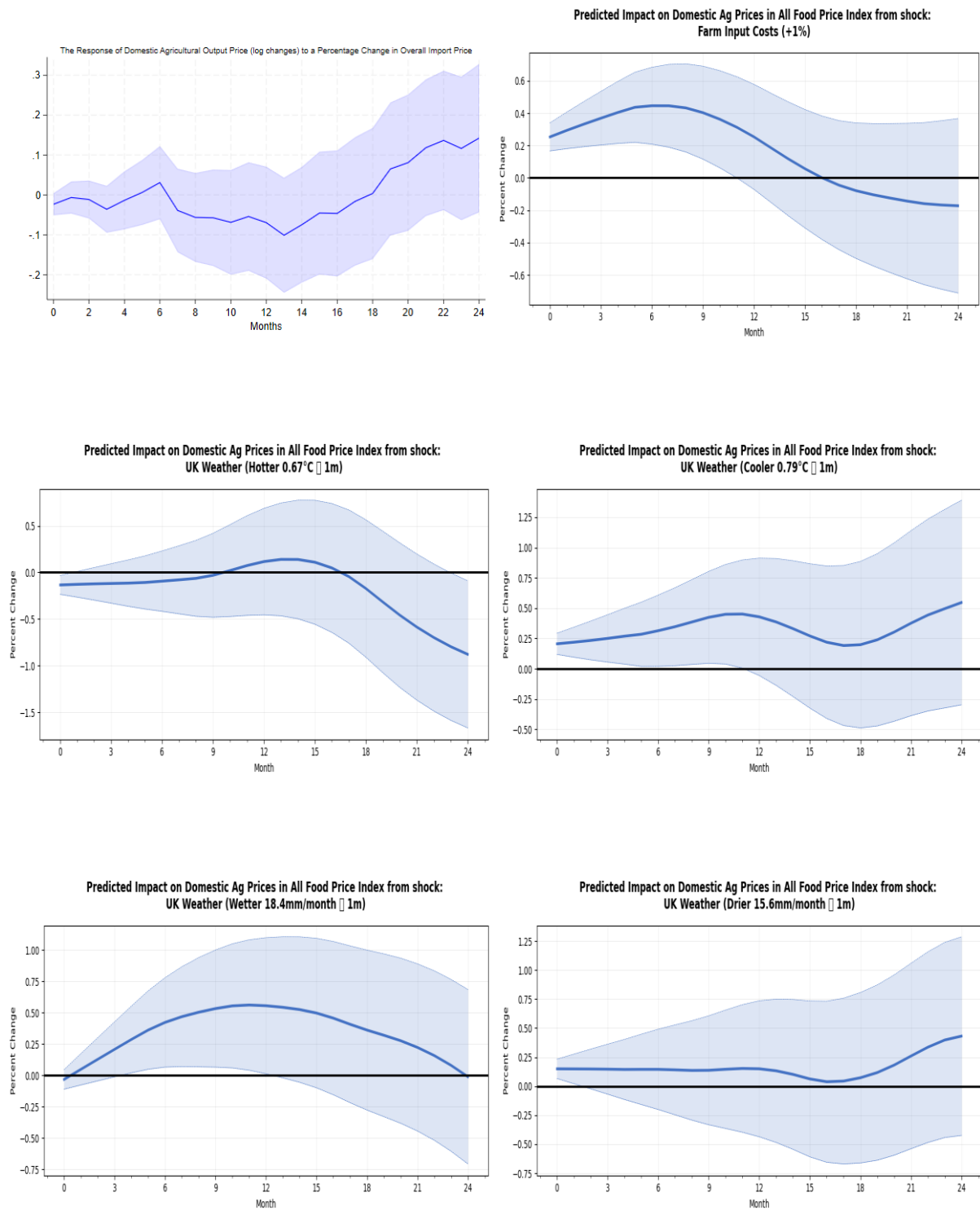


Figure 17: Impulse Response Functions for Domestic Agricultural Price Model



Summary

The results reported for all models detailed in the framework presented in Figure 4 are consistent with economic intuition. The weather variables require a more nuanced interpretation but are also consistent with results from the academic literature and the commentary of climate change effects reported in the Food Security Report (HMSO, 2024) *i.e.* the impact of extreme weather will depend on where and when it occurs and will vary across different food groups. The duration of the weather shock is also pertinent to the impact.

Finally, as detailed in Figure 3, price dynamics at retail, import and domestic agriculture vary across commodity and food sectors. As discussed, we have applied the same modelling framework and the identical econometric specification for 5 sector-specific models. Given the number of impulse response results that are generated; to save space, we do not report them here other than to note that, not unsurprisingly, the responses of retail, import and domestic agricultural prices vary considerably across the sub-models that we estimate.

7. Health-Related Impacts: Tying Price Transmission with Nutrient Elasticities

A further motivation for the update to the existing food price modelling system was to identify the potential health impacts of price changes. The intention here is to tie the results from the updated food price modelling effort with the NIESR report (Da Silva *et al.*, 2022) on estimating demand elasticities for food and drink products. As part of that study, the authors derived the nutrient content of food and drink products and the corresponding nutrient elasticities which are defined as the percentage change in nutrients associated with specific food products for a percentage change in the corresponding prices. The overall nutrient content for specific food comprises of the following components: energy (kcal), protein, carbohydrate, sugar, fat, saturated fat, fibre and sodium). For each nutrient, they estimate specific elasticities. Table 2 of their report details the nutrient elasticities for specific food groups.

Since nutrient elasticities vary by sub-group, the appropriate tie with the econometric approach we detail here is with (some of) the sub-models. As noted, we have estimated retail food price models for beef, dairy and cheese, bread and cereals, fruit and vegetables. The sub-models that tie with Table 3 in the NIESR report are beef, dairy products and ambient bakery products. There are no nutrient elasticities reported for fruit and vegetables. Consequently, the results from the sub-models that we estimate can be tied directly to these nutrient elasticities to assess the potential health outcomes of retail price changes in specific food sectors.

8. Summary and Conclusion

The research reported here involves a considerable upgrade on food inflation modelling compared with the previous exercise carried out in 2017 and detailed in Defra (2020). Since the timing of the original research, there has been significant global events (the COVID pandemic, the Russian Ukrainian War and the consequent increase in global energy prices) that warranted a significant upgrade of the previous food inflation model. In this report we have set out the revised modelling framework that involves several new variables (reflecting the changes in the global economy) and associated with this, an extension of the framework employed to model the determinants of UK retail food prices. In the course of the upgrade, we have also estimated several sub-sector models of retail prices and, where possible tied the output of these models with the likely health impacts of retail price changes.

A feature of the upgraded food inflation model is the application of a different econometric methodology: the local projections approach-while producing impulse response coefficients consistent with a VAR approach, offers some more desirable features that would be more difficult to institute in a VAR context. In addition, the approach outlined in this report would also provide the capability to update the modelling approach as more data becomes available or where the modelling effort would require amendment to address at present unforeseen geopolitical or economic events.

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Appendix Table 1 - Variables Used and Data Sources

Variables	Definition	Source	Series Code	Sample	Notes
AGGREGTE FOOD PRICE MODEL					
FCPI	UK Consumer Retail Food Price Index.	Office for National Statistics (ONS) https://www.ons.gov.uk/economy/inflationandpriceindices/timeseries/d7bu/m23?referrer=search&searchTerm=d7bu	D7BU	2000(1)–2023(2) 2016(M1)=100	Food and non-alcoholic beverages at retail
DAOPI	Index of UK agricultural output prices at the farm-gate.	DEFRA			Index 2016=100
DLC	Index of domestic Labour costs defined as average Earnings index for the UK (seasonally adjusted).	Office for National Statistics (ONS).	KAB9		Denoted LMNQ previously. 2016=100. Re-based to 2023(M2) =100.
UKMOPI	Price index of goods sold by UK manufacturers i.e. the price of goods output (produced) by the UK manufacturer and sold within the	Office for National Statistics (ONS)	JVZ7		Index 2016=100. See https://www.ons.gov.uk/economy/inflationandpriceindices/bulletins/producerpriceinflation/july2018 for details

	UK market (Output PPI).				
UKFMOPI	Price index of goods sold by UK food manufacturers i.e. the price of goods output (produced) by the UK food manufacturer and sold within the UK market. (Output PPI)	Office for National Statistics (ONS)	K37L	2000(1)-2023(2) Index 2016=100	See above for details
UKMIC	UK manufacturing input costs including fuel and materials	Office for National Statistics (ONS)	K646	2000(1)-2023-(2)	See above for details
UKFMIC	UK food manufacturing input costs including fuel and materials	Office for National Statistics (ONS)	MC35	2000(1)-2023(2)	See above for details
UKFIC	Inputs into Production of Food, Beverages and Tobacco Products (UK Non-Labor Cost)	Office for National Statistics (ONS)			
EERAM	Effective Exchange Rate for agricultural and manufactured food imports into the UK.	Authors' calculations.		Index 2016=100	Based on HMRC chapters covering agricultural commodity and food products (01-15, 1701,1801)
EERA	Effective Exchange Rate for agricultural imports into the UK	Authors' calculations.		Index 2016=100	Agricultural commodities only (HMRC Chapters 01-15, 1701,1801)

EERM	Effective Exchange Rate for manufactured food into the UK	Authors' calculations.	Index 2016=100	Processed food products only (16, 1702,1802,19-22)
IPAM	Import Price Index for agricultural and manufactured food imports into the UK.	Authors' calculations.	Index 2016=100	Based on HMRC chapters covering agricultural commodity and food products (01-16, 1701,1801, 2202)
IPA	Import Price Index for agricultural products into the UK	Authors' calculations.	Index 2016=100	Based on HMRC chapters covering agricultural commodities only (01-15, 1701,1801)
IPM	Import Price Index for manufactured food products into the UK	Authors' calculations.	Index 2016=100	Based on HMRC Processed food products only (16, 1702,1802,19-2202)
ENERGY	Global energy price index, expressed in nominal U.S. dollars.	World Bank Commodity Price Data		
UK CCI	UK Consumer Confidence Index	OECD		
OECD CLI	OECD Composite Leading Indicator	OECD		
AIP	Agricultural Input Price index	DEFRA		
GSCPI	Global Supply Chain Pressure Index	Federal Reserve Bank of New York		
UKP	UK precipitation	Authors' calculations	mm/month	Based on ERA5 data

UKPA	UK precipitation anomaly	Authors' calculations	mm/month	Based on ERA5 data
UKPAP	Positive UK precipitation anomalies	Authors' calculations	mm/month	Based on ERA5 data
UKPAN	Negative UK precipitation anomalies	Authors' calculations	mm/month	Based on ERA5 data
UKT	UK temperature	Authors' calculations	Degrees Celsius	Based on ERA5 data
UKTA	UK temperature anomaly	Authors' calculations	Degrees Celsius	Based on ERA5 data
UKTAP	Positive UK temperature anomalies	Authors' calculations	Degrees Celsius	Based on ERA5 data
UKTAN	Negative UK temperature anomalies	Authors' calculations	Degrees Celsius	Based on ERA5 data
GPA	Global precipitation anomaly (import-commodity-weighted)	Authors' calculations	mm/month	ERA5 data, weighted by HMRC trade statistics and commodity cultivation area data.
GPAP	Positive global precipitation anomalies(import-commodity-weighted)	Authors' calculations	mm/month	ERA5 data, weighted by HMRC trade statistics and commodity cultivation area data.

GPAN	Negative global precipitation anomalies (import-commodity-weighted)	Authors' calculations	mm/month	ERA5 data, weighted by HMRC trade statistics and commodity cultivation area data.
GTA	Global temperature anomaly (import-commodity-weighted)	Authors' calculations	Degrees Celsius	ERA5 data, weighted by HMRC trade statistics and commodity cultivation area data.
GTAP	Positive global temperature anomalies (import-commodity-weighted)	Authors' calculations	Degrees Celsius	ERA5 data, weighted by HMRC trade statistics and commodity cultivation area data.
GTAN	Positive global temperature anomalies (import-commodity-weighted)	Authors' calculations	Degrees Celsius	ERA5 data, weighted by HMRC trade statistics and commodity cultivation area data.

Appendix 2: Creation of the Data

Price Indices –Some technical background

In general, the expenditure on a group of $i = 1, \dots, n$ products at a point t is $\sum_{i=1}^n (p_{i,t} \times q_{i,t})$ where $p_{i,t}$ and $q_{i,t}$ are the prices and quantities of each product in the group. If, across two periods (say 0 and t), the same quantities of each product were sold so that $q_{i,0} = q_{i,t} = q_i$, but under different prices, then a simple price index would take the form:

$$\frac{\sum_{i=1}^n (p_{i,t} q_i)}{\sum_{i=1}^n (p_{i,0} q_i)} \quad (\text{A1})$$

However, since quantities are likely to be different at the two points in time, we needed to account for the changing relative importance of each product in the price index. This was achieved by weighting each price by the quantity. However, if we did this simply by using:

$$\frac{\sum_{i=1}^n (p_{i,t} q_{i,t})}{\sum_{i=1}^n (p_{i,0} q_{i,0})} \quad (\text{A2})$$

this new index would not distinguish changes in quantities from changes in prices and as a result the index is as much a quantity index as a price index (doubling prices keeping quantities constant would double the index but so would doubling the quantity keeping the price constant). In order to gain a pure price index, we needed to control for changes in quantities and the most common way to do this is by using a weighting scheme that is fixed to some point in the sample so that the index measures price changes alone relative to the level in some base (Laspeyres) or current (Paasche) period.

A simple Laspeyres price index is computed as:

$$P_t = \frac{\sum_{i=1}^n (p_{i,t} q_{i,0})}{\sum_{i=1}^n (p_{i,0} q_{i,0})} \quad (\text{A3})$$

where P_t is the index of the price levels for the group of n products at point t relative to their values at $t = 0$, the base period (usually the first year). Note that we can rewrite the Laspeyres Price index using expenditure weights rather than quantities. Defining $E_{i,0}$ as the expenditure in the base period then $E_{i,0} = p_{i,0} q_{i,0}$ and therefore $q_{i,0} = \frac{E_{i,0}}{p_{i,0}}$. Substituting these into the Laspeyres price index above gives:

$$P_t = \frac{\sum_{i=1}^n (p_{i,t} q_{i,0})}{\sum_{i=1}^n (p_{i,0} q_{i,0})} = \frac{\sum_{i=1}^n \left[p_{i,t} \frac{E_{i,0}}{p_{i,0}} \right]}{\sum_{i=1}^n E_{i,0}} = \frac{\sum_{i=1}^n \left[\frac{p_{i,t}}{p_{i,0}} E_{i,0} \right]}{\sum_{i=1}^n E_{i,0}} = \sum_{i=1}^n s_{i,0} \left(\frac{p_{i,t}}{p_{i,0}} \right) \quad (\text{A4})$$

from which we can see that the price index is the sum of the relative prices multiplied by the share of the prices in the base period.

There are a wide range of price indices that can be used each with their own advantages and disadvantages. While the most used is the Laspeyres index which uses weights that are fixed to a specific time or time span, a chain-linked Laspeyres index updates weights every period and as a result overcomes the problem of outdated weights. This is advantageous when the weights are changing systematically over time. We use the Laspeyres index approach in the derivation of the

import price indices to facilitate a comparison between the new import price indices for UK food and agricultural imports and other commodity price indices widely available such as the FAO Food Price Index.

Import Prices (Unit Values)

For each of our 20 commodity groups, we created unit value series for each of the 8 geographical regions. These are then weighted by the value share of the region to produce an overall unit value for each commodity group. All the unit value series are expressed in £/unit of net mass (typically kg).

In what follows, superscripts denote the commodity groups (01, 02 . . . 22) and subscripts denoting the i^{th} region and t^{th} time period, so that, for example, a unit value index for HS01 (live animals) denoted UV_t^{01} based on imports from the eight regions is given by:

$$UV_t^{01} = \sum_{i=1}^8 s_{i,t}^{01} UV_{i,t}^{01} \quad (A6)$$

UV_t^{01} : the weighted average unit value (£/kg) of live animals at time t from all overseas (EU and Non-EU) sources.

$UV_{i,t}^{01}$: the unit value (£/kg) of live animals imported from the i^{th} region at time t ;

$s_{i,t}^{01}$: the value share of live animal imports coming from the i^{th} supplier at time t (i.e. the proportion of the value of live animals coming from the i^{th} region).

Being unit values, they are derived from the value and quantity of imports and are hence expressed in £/kg. As a result, they were useful for addressing issues relating to changing the geography of UK trade associated with relative prices. Unlike the price indices that were subsequently created and which were normalised to a specific base year, the unit values are in absolute (rather than relative terms) and hence explicitly allow us to acknowledge different price levels from different sources. This is pertinent for addressing post-Brexit issues further down the line. As a result, these unit values formed the basic data for subsequent manipulation and from which the price indices were created.

The Laspeyres weighting scheme used by the FAO

The Laspeyres (historical base period) weighting scheme measures changes in prices relative to the prices of a composition of products imported in a base period, which in its simplest form is a single period at the start of the sample. Other choices of base period could have been used. Given the volatility of commodity prices, it is typical to use an average value over a relatively long period to lessen the effect of this period-on-period variation in composition. Looking at the construction of other commodity price indices (e.g. the UN FAO Food Price Index), we worked with the Laspeyres index with the base period for constructing shares and the base period as the 3-year average for the middle years in our time series (i.e. 2002-2004). In a recent note (FAO, 2014), the FAO show that it would not seem to matter, at least with working with world prices, whether the base year is different (say, due to the commodity crises in 2007-08 and 2011) or whether an alternative price index is used (e.g. Paasche or other alternatives). As a result, we used a Laspeyres index where the base period is an average of the data in 2002-2004. This is consistent with the FAO commodity series and thus facilitated a direct comparison with their overall commodity price index as well as the sub-component (e.g. meat or sugar) of the main index.

Price indices for each commodity group by region

In this section, we detail the creation of Laspeyres price indices by region for each of the 20 commodity groups using FAO (2002-2004) weighting (Step III). These regional price indices were then combined to form a price index at the commodity group level (Step IV). As before, we will illustrate the methods using the nomenclature introduced previously, so that:

$$PILF_t^{01} = \sum_{i=1}^8 s_{i,0}^{01} \left(\frac{UV_{i,t}^{01}}{UV_{i,0}^{01}} \right) \quad (A7)$$

is the Laspeyres price for index live animals at time t from all sources using FAO (2002-04) expenditure weights with:

$\left(\frac{UV_{i,t}^{01}}{UV_{i,0}^{01}} \right) = PILF_{i,t}^{01}$ being the price index of live animals from region $i = 1, \dots, 8$ at time t relative to the base period (average of 2002-2004) and $s_{i,0}^{01}$ is the value share live animals imports coming from region $i = 1, \dots, 8$ at time t relative to the base period (average of 2002-2004).

This price index was then weighted by the value share of live animals in total imports to form the aggregate import price series (see below). For each of these commodity group level indices, the regional weights differ, being specific to each commodity group.

Aggregate Price Indices

The aggregate import price index using Laspeyres weighting at time t is given by:

$$PILF_t = \sum_{c=1}^{20} w_{c,t} PILF_t^c \quad (A8)$$

where $PILF_t$ is the import price index aggregated across all sub-commodity price indices at time t , $PILF_t^c$, and $w_{c,t}$ is the weight of each commodity group in total agricultural and food imports with the weights based on the share of the import value of the chapter in the total value of imports at time t . As a complement to this overall import price index, we also created indices for agricultural commodity imports based on 13 unprocessed commodity groups (HS2 groups 01, 02, 03, 04, 07, 08, 09, 10, 11, 12, 15, 1701 and 1801) and another series for processed products based on 7 food and beverage groups covering processed and manufactured products (HS2 groups 16, 1702, 1802, 19, 20, 21 and 2202). The weights $w_{c,t}$ change reflecting the importance of each commodity group level in the aggregate in which it belongs.

Effective Exchange rates

The effective exchange rates (continuing the example presented in outlining the construction of the import price indices above) for live animals at time t is given by:

$$EER_t^{01} = s_{1,0}^{01} ER_t^{eu} + \sum_{i=2}^8 s_{i,0}^{01} ER_t^{usd} \quad (8)$$

$s_{1,0}^{01}$ is the import share of live animals imports from Euro countries; $s_{i,0}^{01}$ is the share from region $i = 2, \dots, 8$ at time t ; ER_t^{eu} and ER_t^{usd} are the exchange rate Euro to £ Sterling and US\$ into £ Sterling at time t .

Effective Exchange Rate for Agricultural Products

The aggregate agricultural effective exchange rate at time t is given by:

$$EER_t^{agri} = \sum_{c=1}^{13} w_{c,t}^{agri} EER_t^c \quad (9)$$

where EER_t^{agri} is the aggregate agricultural effective exchange rate at time t , $w_{c,t}^{agri}$ is the weight of the chapter c in total agricultural import value at time t , and the EER_t^c is the effective exchange rates for chapter c at time t . It is worth noting that the aggregate agricultural effective exchange rate will involve the HS2 groups 01, 02, 03, 04, 07, 08, 09, 10, 11, 12, 15, 1701 and 1801.

Effective Exchange Rate for Processed Products

The aggregate processed effective exchange rate at time t is given by:

$$EER_t^{pro} = \sum_{c=1}^7 w_{c,t}^{pro} EER_t^c \quad (10)$$

where EER_t^{pro} is the aggregate processed effective exchange rate at time t , $w_{c,t}^{pro}$ and EER_t^c are the weight of the chapter in the total processed import value and the corresponding effective exchange rate. The calculation is based on the processed products (HS2 groups 16, 1702, 1802, 19, 20, 21 and 2202).

Effective Exchange Rate for All (agricultural and processed) Products

The aggregate effective exchange rate at time t is given by:

$$EER_t = \sum_{c=1}^{20} w_{c,t} EER_t^c \quad (11)$$

where the EER_t is computed for the whole 20 chapters, $w_{c,t}$ represents the import share of the chapter in the total import value at time t , its corresponding effective exchange rate is denoted as EER_t^c

