

ARTICLE

BRITAIN'S TRADE CHALLENGE: TRACKING THE COSTS IN REAL TIME

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Abstract

Since early 2021, food prices in Britain have increased by 30%. Using monthly microdata, researchers have found that frictions in the UK's new trade relationship with the European Union (EU) play an important part in this inflation. The trade relationship is evolving, with further changes expected in 2024. This article establishes a framework for identifying trade-related inflation in close to real time. Using programming techniques, we collect daily prices of over 100,000 supermarket items, covering 80% of the UK grocery market. We identify 1,200 products from 12 countries with a protected designation of origin (PDO). This allows us to link price changes to individual EU economies. Addressing the predominance of EU PDOs, we employ a large language model to discern product origins from additional web-scraped data, thus broadening our analysis to cover over 67,000 products. Since August 2023, we find that prices for EU-originating food products have increased at a rate of 50% higher than domestically sourced products. This study presents a unique methodological approach to dissecting food sector inflation, which is well-positioned to be used in a policy setting, allowing us to assess the possible impact of impending nontariff barriers at the GB-EU border in 2024.

Keywords: Trade; Prices; Inflation; Artificial intelligence; LLMs; Central Banking

JEL codes: E31; F13; F15; Q11

1. Background: policy and literature

1.1. UK policy

The growing extent of nontariff barriers (NTBs) present at the GB-European Union (EU) border in recent years has been shown to have increased prices (Bakker *et al.*, 2022). Our dataset extends this analysis, providing a process that allows for real-time monitoring.

The EU remains Britain's most important trade partner. Between 1999 and 2007, the EU accounted for over half of UK exports and imports. Although shares have fallen somewhat, the EU still accounts for 42% of exports and 48% of imports. The latter channel—£432 billion of imports—is one conduit through which trade shocks are transmitted. For example, the depreciation of sterling following the EU Referendum is estimated to have increased consumer prices by 2.9%, costing the average household £870 per year (Breinlich *et al.*, 2022). EU imports are also the main channel for inflationary pressure from NTBs.

NTBs will rise in 2024. The UK Government's Border Target Operating Model, published in October 2023, outlines a phased introduction of full controls on imports from the EU to GB (Cabinet Office, 2024). This plan is divided into three key phases as follows:

- a. **31 January 2024:** Health certifications required for EU imports of medium-risk animal products, plants, plant products (e.g., meat, dairy, some fruits and vegetables) and high-risk nonanimal food and feed.

- b. **30 April 2024:** Initiation of risk-based checks (documentary, identity and physical) on imports of medium-risk goods from the EU mentioned above. High-risk plant inspections will shift from destination to Border Control Posts.
- c. **31 October 2024:** Enforcement of Safety and Security declarations for all imports from the EU and applicable territories.

The Cabinet Office guidance suggests that the inflationary impact will be minimal. The additional controls on plant and animal products are estimated to cost businesses £330 million annually, increasing food prices by 0.2% over 3 years (Cabinet Office, 2024). The analysis suggests that costs will depend closely on how businesses adapt their operations and supply chains to integrate the new control regimes. Internal modelling suggests that the impact on food prices ‘will not be significant’. Our paper provides a way to verify these cost estimates.

1.2. Literature

Tariffs have been the traditional trade barrier used by countries seeking to protect domestic producers and are still in widespread use today. The United States, for example, imposed new tariffs in 2018, which targeted approximately \$283 billion of American imports, principally from China. Recent studies find high pass-through rates of tariffs to consumer prices. Flaaen *et al.* (2020) use weekly microdata from retail stores to examine the impact: tariffs on washing machines were found to have a pass-through rate of between 1.08 and 2.25. Similarly, Fajgelbaum *et al.* (2020) find evidence for complete pass-through of tariffs, along with a large decline in imports of targeted products and a significant loss in real incomes. If the impact of NTBs is similar to tariffs, there are reasons to be concerned about the impact on UK households.

For many countries, NTBs have eclipsed tariffs as the primary barrier to trade. The estimated indices for trade restrictiveness show that NTBs are almost as restrictive as tariffs (Looi Kee *et al.*, 2009). This means low tariff rates can give a false picture of ‘free’ trade. In 2018, the EU had an average ad valorem equivalent NTB of 13.1%, contrasting an average tariff rate of just 1.8% (Bakker *et al.*, 2022). These differences mean that while tariff rates may be falling, trade protection may be rising due to NTBs: Niu *et al.* (2018) estimate ad valorem equivalents of NTBs between 1997 and 2015, confirming this concern.

Recognising this, many trade agreements aim to offer a ‘deep’ eradication of barriers. Deep trade agreements go beyond tariffs and quotas and include provisions that reduce NTBs. This can include the mutual recognition of health certifications used for livestock, for example. Dhingra *et al.* (2023) measure the welfare effects of such agreements. They find a substantial impact on trade and argue that agreements that reduce NTBs improve welfare.

A detailed analysis of the 2021 TCA is provided by Freeman *et al.* (2022), who examine UK-EU trade relative to UK trade with the rest of the world using a difference-in-differences event study. They reason that uncertainty and anticipation effects could mean trade impacts may predate new rules being imposed, but they find no evidence of such ‘forward looking’ impacts between 2016 and 2021. Following the TCA, however, they find a sudden and persistent fall in relative UK imports from the EU, estimated at 25%. In contrast, they find a smaller and temporary decline in relative UK exports to the EU, but a large and sustained drop in the number of firms exporting. Low-value trade relationships may have been made unviable, the authors argue.

The quantification of NTB pass-through to consumer prices set out by Bakker *et al.* (2022, 2023) is the closest paper to ours. By matching ONS price microdata with UN data on bilateral trade flows, they are able to estimate a measure of EU trade exposure for individual food items. The authors find that since the EU referendum, UK food products that are more heavily imported from the EU have seen larger price increases. Using a difference-in-differences event study, they find that price increases are driven by food products with high NTBs, with an implied pass-through rate of 50–88%. The cost of this, estimated between 2019 and 2023, is almost £7 billion across UK households. These costs are likely to amplify

preexisting inequality in the United Kingdom, with households in the bottom income decile suffering cost of living increases that are 52% more than those in the top decile.

2. Building the dataset

We utilise a dataset of 20 million British grocery prices compiled by the Data Unit at the Economics Observatory (Davies, McEvoy and Hellings, forthcoming). The data are daily observations from websites of seven of the ten largest British supermarkets. The earliest prices were recorded in July 2023; following a staggered introduction, all seven stores are represented by mid-August.¹ In total, 100,000 prices are added daily, and over 140,000 unique products have been captured.

This article contributes a new dimension: products' countries of origin. The products sold in British supermarkets arrive from around the world, with items in our dataset sourced from 125 countries. Product provenance provides valuable insight into international price dynamics and potential inflationary pressures stemming from external economic factors. This section describes two approaches we use to identify a product's provenance.

2.1. Protected names

Many food and drink product names provide information on their origin. A geographical indication (GI) is a 'distinctive sign used to identify a product whose quality, reputation, or other such characteristics relate to its geographical origin' (European Commission, 2023). Within this umbrella categorisation, there are three systems holding varying degrees of protection.² We utilise the strongest categorisation: Protected Designation of Origin (PDO). This covers food and wine products, specifying that each stage of production, processing and preparation must occur in a specific region.

PDO products have strong links to their place of origin. For instance, "Champagne" from France, "Prosciutto di Parma" from Italy and "Stilton Cheese" from the United Kingdom are all emblematic PDO products that consumers associate with authenticity and region-specific character. For most products sold in supermarkets, retailers can substitute goods sourced from one country with goods sold in another. For example, a retailer can switch suppliers for vegetables in response to a change in NTBs. In contrast, as PDO products' character is defined by their origin, their geographic substitutability is low, and their exposure to NTBs is potentially high.

To match products from our dataset to their PDO counterparts, we use the European Commission's PDO register. By searching product titles for combinations of protected terms, as defined in the European Commission's eAmbrosia database, we identify the origins of over 1,100 products from our wider dataset. The matched origin countries in this subset are legally defined and protected.

Our PDO products are mainly from regions with a tradition of GIs, notably the United Kingdom, France, Italy and Spain. Table 1 describes the price data collected for PDO products; Figure 1 provides a map.

2.2. Large language model text extraction

Many traded products do not have protected names. Our second method aims to assign provenance for a further 67,000 items by parsing item descriptions. Listings on supermarket websites often include an indication of a product's origin. For example, the page of a juice drink might list the source of the fruit and the location where the packaging took place. By parsing these descriptions using a novel large language model (LLM)-driven methodology, we can gain a better understanding of the geographical distribution of product origins.

¹For an extensive explanation of the prices dataset (see Davies, McEvoy and Hellings, forthcoming).

²The European Commission recognises three categories of GI: PDO, Protected Geographical Indication and GI.

Table 1. Summary of PDO products

	France	Spain	Italy	Greece	United Kingdom	Cyprus	Portugal	South Africa
Registered PDO items	478	211	584	113	31	9	97	1
Matched Items	514	179	337	117	59	57	54	27
N price quotes	75168	29041	49406	15739	8308	5999	8798	4222
Mean	20.19	10.38	8.57	2.99	11.28	2.87	12.29	2.51
Std	23.24	5.26	5.83	1.52	11.57	0.66	6.01	0.63
Min	1.42	1.30	1.32	0.79	1.00	0.70	0.79	0.85
25%	8.99	7.49	4.00	2.25	2.50	2.40	8.50	2.25
50%	13.00	9.25	8.00	2.70	3.19	2.85	11.00	2.49
75%	24.99	12.25	10.99	3.25	21.00	3.20	14.50	2.75
Max	300.00	51.00	51.00	12.35	42.00	4.25	38.00	4.10

Notes: Compares the number of PDO items registered in the eAmbrosia Geographical Indicators dataset (as of 20 February 2024) with the count of matching products in our dataset. Top eight countries by matched product count are shown.
Source: Authors’ calculations, European Commission (eAmbrosia).

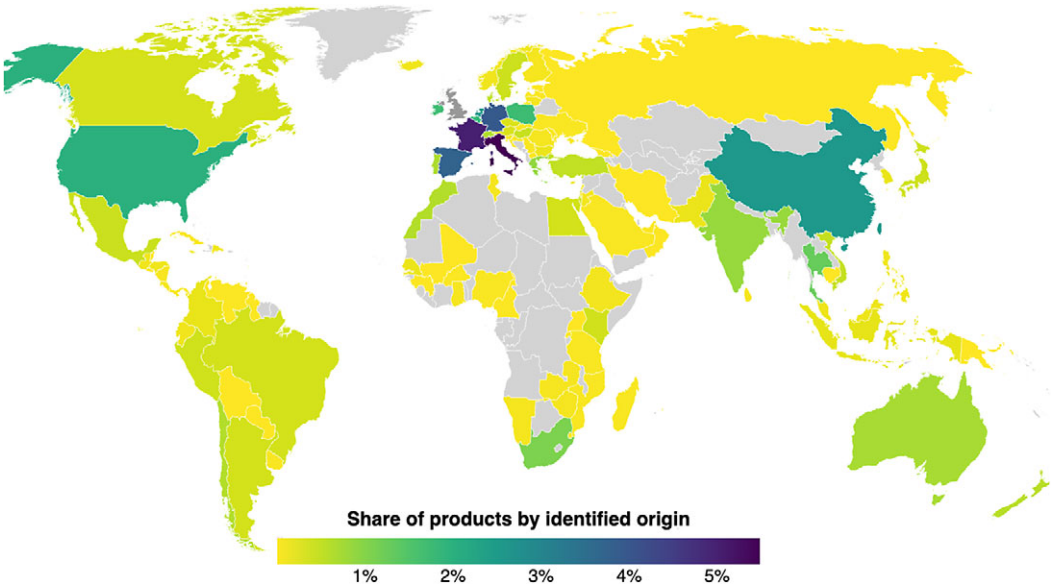


Figure 1. Composition of product origin. Share of products assigned to each country from main prices dataset.
Notes: Excludes products originating from the UK (roughly 50%). Share calculation uses country-of-origin data identified in this paper, covering 67,000 products sold across seven UK supermarkets.
Source: Authors’ calculations.

The challenge we face is the huge number of products on offer, and the complexity and variability in the language that retailers use in their descriptions. To solve this problem, we use an LLM to interpret and extract the relevant country or countries of origin from the text. LLMs are artificial intelligence (AI) tools that have been trained on large amounts of text, enabling them to parse and generate new text. In

practical terms, the LLM acts as a research assistant (RA) tasked with summarising details from text, such as identifying the nuanced mentions of a product's origin within its description.

The proposed LLM is faster than a human RA, and better than a naïve trawl through text using standard search functions. The LLM recognises diverse linguistic expressions that refer to locations identifying, for example, that 'wine from the Rhône Valley' gives an indication of origin. The LLM behaviour here varies between extrapolating for the country (so returning 'France') or allocating the named origin (so returning 'Rhône Valley'). Responses of the latter type are limited in number and so can be manually added to a lookup table and replaced with the actual country. A more traditional method—parsing text for a list of target words, including 'France'—would miss this. Our approach thus increases information capture.

Unlike Champagne or Stilton, many grocery products mention multiple countries in relation to their ingredients. In such cases, we attribute the product to all listed countries, based on an assumption of equivalence for each mentioned origin. For instance, a product described as 'packed in France using meat from France, Germany and Spain' is attributed an origin of (France, Germany and Spain). This pragmatic approach, of course, does not identify the true cost contribution from each location.

We take steps to maximise the accuracy and relevance of the LLM responses we get back from our requests. For each request to the LLM, we provide the product description (text extracted from its individual webpage) along with an array of previous messages. The first message takes the role 'system', which shapes the behaviour of the LLM for the subsequent conversation. The other messages are sample examples of previous user-assistant interactions. Including examples can improve the model's reliability in understanding and executing the task, especially when dealing with nuanced or complex product descriptions. The examples act as blueprints for the model's outputs. By seeing how past queries were structured and answered, the LLM can more accurately mimic this format, improving the consistency of output. Essentially, this serves to dynamically tune the responses to our task, while still leveraging the LLM's preexisting knowledge. The example illustrates a typical interaction (Figure 2).

The LLM responses (which are formatted as JSON data) are then processed, cleaned and merged with our prices databases. This application of LLMs augments our price dataset with origin data for 62% of the daily prices, significantly enhancing our ability to test the role of geography in our food price analysis. We identify a country of origin for over 67,000 products. Of these, less than half (49.4%) originate from the United Kingdom. The distribution of origin among imported products is shown in Figure 3. Italy is the top import source (11%), followed by France (10%) and Germany (8%).

Table 2 shows the price characteristics for the top 15 countries by item count. Beyond the United Kingdom itself, Italy (3,944), France (3,694) and Germany (3,008) are at the top of the ranking, with South Africa (690), India (664) and Australia (629) sitting at the bottom.

Figure 4 shows the distribution of imports between EU and non-EU origins for products in our dataset, by store. The stores are anonymised and given numbers 1–6. All stores import more EU products than non-EU products, although the extent to which this is true varies. For example, store 1 sees 62% of its imports originating from the EU, while for store 5 this is 79%. There is also substantial inter-store variation in the share of UK-sourced products (not shown in the chart), ranging from 46% for store 1–62% for store 5. Store 1 is the only store with more than 50% of products showing non-UK origin.

3. Results

3.1. Frequency and size of price changes

The United Kingdom has continued to experience food inflation during our period of study. Between August 2023 and February 2024, CPI inflation for food was 0.67%. Microdata tend to show how prices ebb and flow (there are price cuts, even in inflationary periods) and that the net proportion of prices rising is a simple and powerful predictor of inflation (Davies, 2021). We find a consistently positive net balance—that is, more rises than cuts—during our period of study, in line with the aggregate data.

```
prior_messages = [
    {
        "role": "system",
        "content": "You are an assistant tasked with identifying the country of origin for products based on their details. Some products have multiple countries of origin, so you may return a list of countries. You must only return a JSON object. Provide a brief reason for your answer. You may return an empty list if you fail to find the country of origin."
    },
    {
        "role": "user",
        "content": '''{"product_title": "Sainsbury's Brussels Pâté 170g", "Description": "Smooth pork liver Brussels style pâté produced in Belgium.", "Country of Origin": "Packed in Belgium, for Sainsbury's Supermarkets Ltd, London EC1N 2HT using pork and pork liver from the Netherlands."}'''
    },
    {
        "role": "assistant",
        "content": '''{"origin": ["Belgium", "Netherlands"], "reason": "Packed in Belgium. Uses pork from the Netherlands."}'''
    },
]
```

Figure 2. Example instructions to LLM. Simplified array of system and example messages. These are passed to the LLM with each request. Notes: Full message available in Figure 5 in Annex. We use OpenAI’s gpt-3.5-turbo-1106 chat completions model.

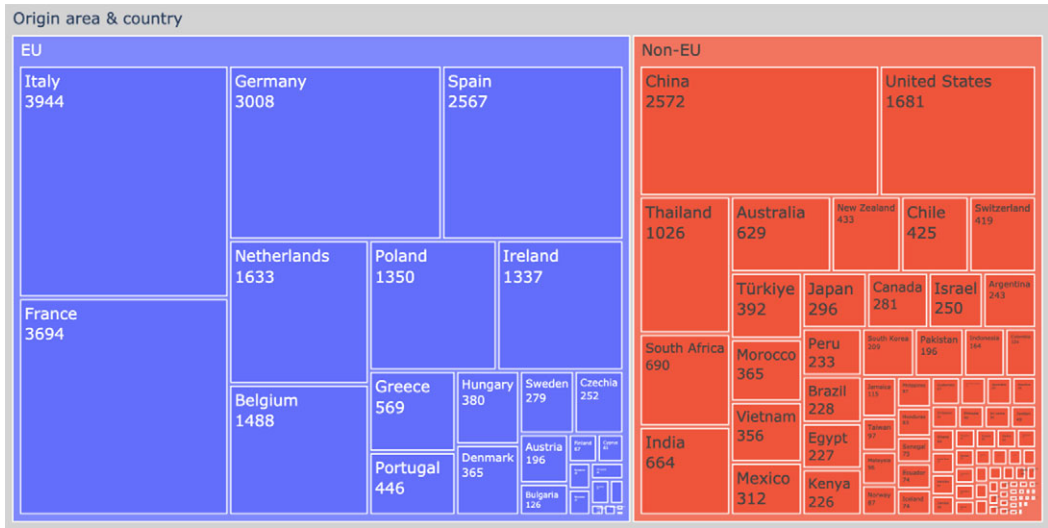


Figure 3. Composition of product origin. Total number of products assigned to each country from main prices dataset. Notes: Includes all products with an identified non-UK origin from our dataset of UK supermarket prices, irrespective of product category. Source: Authors’ calculations.

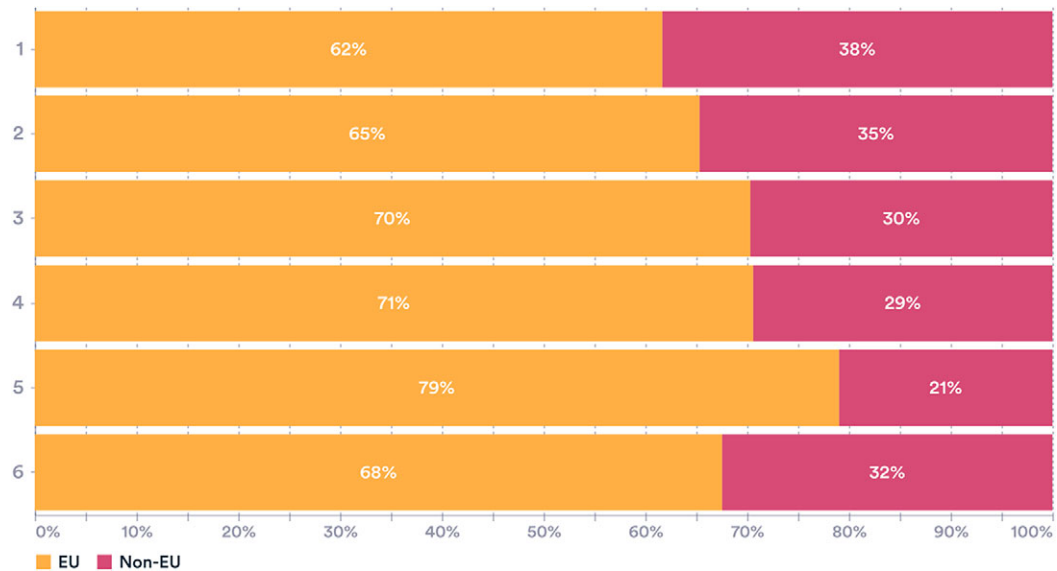
Imported foods changed price more frequently than those produced in the United Kingdom. Across our period, 0.41% of the daily price quote pairs for UK products saw price rises (Table 3). Products originating from the EU were more likely to increase in price (0.55% frequency), as well as non-EU products (0.5% frequency). These internationally sourced products are also more likely to experience price cuts. Across each geography, price rises were more common than price cuts. Net rises were highest for non-EU products, at 0.12%. Net rises for EU products was 0.11%, while for UK products the figure was 0.09%.

Table 2. Summary of prices dataset by country

	N	Item share	Obs ('000)	Mean price	p50	p10	p90
United Kingdom	35,754	49.4%	5,025	3.80	2.40	1.00	7.00
Italy	3,944	5.4%	552	4.45	2.75	0.99	10.00
France	3,694	5.1%	517	7.39	3.65	1.29	15.50
Germany	3,008	4.2%	418	4.78	2.75	1.00	10.00
China	2,572	3.6%	351	5.96	4.00	1.20	12.00
Spain	2,567	3.5%	349	4.00	2.50	0.99	9.50
United States	1,681	2.3%	237	7.21	4.95	1.60	15.00
Netherlands	1,633	2.3%	239	3.25	2.30	0.99	5.75
Belgium	1,488	2.1%	206	4.03	2.50	1.20	10.00
Poland	1,350	1.9%	197	4.53	2.50	1.10	10.25
Ireland	1,337	1.8%	208	4.78	2.75	1.30	11.03
Thailand	1,026	1.4%	155	2.86	2.40	1.10	4.50
South Africa	690	1.0%	92	4.23	2.50	1.00	9.50
India	664	0.9%	102	3.34	2.29	1.15	5.50
Australia	629	0.9%	88	8.25	7.49	2.69	15.50

Notes: N refers to the number of products assigned to each country (equivalent to Figure 3). Obs refers to the quantity of price quotes for those N products. This includes all products collected in the main prices dataset and so may include nonfood items sold by UK supermarkets. These nonfood items are removed prior to further analysis by matching each product with a food/drink COICOP division.

Source: Authors' calculations.

**Figure 4.** Distribution of import origins by store. Food & drink (including alcoholic) items.

Notes: Share of products by region of origin. Stores anonymised to IDs 1–6. Share of unallocated products ranges from 20 to 50% across the stores. Share of UK products ranges from 46 to 62% across the stores.

Source: Authors' calculations.

Table 3. Frequency of price changes by origin of product

	Obs (m)	Frequency	Up	Down
United Kingdom	3.75	0.72%	0.41%	0.32%
EU	2.60	0.99%	0.55%	0.44%
Non-EU	1.27	0.88%	0.50%	0.38%
Total	12.34	0.77%	0.43%	0.34%

Notes: ‘Obs’ is a count of price quote pairs available for products from each region. These are consecutive daily price observations for all products originating from that area. ‘Total’ includes observations from all products in our dataset and so includes products whose origin was not identified by the LLM. Tables 3–5 consider the price change dynamics across every available price quote pair—that is, consecutive price observations for any specific product. ‘Frequency’ gives the proportion of consecutive price observations that represented a price change in any direction, while ‘Up’ and ‘Down’ split these by price rises and price cuts.
Source: Authors’ calculations.

Table 4. Size of price changes by origin

	Price rises		Price falls	
	Median	Mean	Median	Mean
United Kingdom	22.2%	25.5%	–20.6%	–21.6%
EU	22.5%	27.8%	–20.4%	–22.4%
Non-EU	17.0%	21.7%	–18.8%	–19.4%
Total	20.4%	26.0%	–20.0%	–21.8%

Notes: These values correspond to the observations detailed in Table 3. The mean and median values are each conditional on a price change occurring.
Source: Authors’ calculations.

Goods from the EU saw slightly more substantial price moves (mean and median price changes) than those from the United Kingdom, with both the EU and United Kingdom showing larger moves than non-EU imported foods³. EU products exhibited the largest mean price changes, with a mean rise of 27.8% against a mean fall of –22.4% (Table 4). The median price rise and fall is grouped around 20%, which may be driven by sales (Anderson *et al.*, 2017).

We are also able to investigate price dynamics for individual countries. The 10 countries with the highest quantity available price quote pairs are shown in Table 5. Food from France showed the highest frequency of price changes at 1.47% (0.79% were up, 0.68% were down). The United States and Italy, similarly, see frequent price changes. Domestic (i.e., UK origin) foods changed prices much less, as did foods from Belgium and China. The size of price changes also varies by country (Table 10, Annex).

3.2. Weighted price change

The importance of the price changes identified in our data rests on the food products weight in UK consumer expenditure. We capture this using a modified Laspeyres Price Index. Since we know the retailer selling each product, we can include retailer-specific ratings based on each supermarket’s market share (w_s). We also include product-specific CPI weights (w_i) by matching our products to COICOP

³Figures 8 and 9, available in the Annex, plot the distribution of price changes for all products by region of origin, showing the typical size of any observed price changes. Figure 8 considers only price changes in January 2024, with each region seeing a median positive change: 3.6% (non-EU), 5.3% (UK) and 6.2% (EU). Figure 9 considers only price changes in February 2024, showing divergence between EU and non-EU products. Here, EU products show a median price increase (3.8%), while both non-EU (–5%) and UK (–3.6%) products show a median price decrease.

Table 5. Frequency of price changes by country

	Obs (m)	Frequency	Up	Down
United Kingdom	3.75	0.72%	0.41%	0.32%
Italy	0.44	1.02%	0.55%	0.47%
France	0.39	1.47%	0.79%	0.68%
Germany	0.29	0.86%	0.47%	0.39%
Spain	0.27	0.97%	0.59%	0.37%
China	0.19	0.46%	0.23%	0.23%
United States	0.18	1.11%	0.62%	0.48%
Netherlands	0.19	0.94%	0.55%	0.38%
Ireland	0.16	0.82%	0.46%	0.36%
Belgium	0.14	0.70%	0.40%	0.30%

Notes: 'Obs' is a count of price quote pairs. These are consecutive daily price observations for all products originating from that area.

Source: Authors' calculations.

divisions.⁴ Baskets of products that are available on two dates $(0, t)$ are constructed and the weighted price ratios are calculated. Weighting by CPI weights, store market shares and the number of prices from a given store s and type i , $N_{i,s}$, the price index at time t is equal to:

$$p^{0,t} = \sum_{S=1}^S \sum_{i=1}^{N_s} \sum_{j=1}^{N_{sj}} \left(\frac{w_i w_s}{N_{sj}} \times \frac{p_j^t}{p_j^0} \right)$$

As a benchmark, the official UK CPI index shows food prices to have increased by 0.7% between August 2023 and February 2024.⁵ Our index suggests that imported foods contributed almost twice as much (2% and 1.9%, respectively, for non-EU and EU origins) to domestically sourced (1.3%) goods of rises in UK supermarket prices (Table 6).

Turning to country of origin, the weighted price change of products purchased in the United Kingdom varies substantially. According to our dataset, products purchased in the United Kingdom originating from South Africa (4.6%), Spain (4.5%) and Thailand (4%) have increased the most over the period of study (see Table 7). In contrast, the weighted price change for products originating from France (1.4%), Ireland (1.6%) and Italy (1.7%) is the lowest in our dataset.

3.3. Inflation risks by product type

Our data allow us to identify pricing 'risk' by product type. Table 8 displays the top five products by import destination. Focusing on the EU, the table displays the top 10 items by the share of items imported from the chosen destination. For example, in our dataset, 77% of 'olive oil' is bought from EU countries. Baby food (70%) and wine (55%) are the next most concentrated item types in terms of UK imports from the EU.

As outlined in Section 1, on 31 January 2024, the UK introduced new border controls concerning 'medium-risk' and 'high-risk' food products. This means health certifications are now required for EU

⁴The Classification of Individual Consumption According to Purpose (COICOP) system was developed by the UN and classifies areas of consumer expenditure by their purpose.

⁵Between August and December 2023, alcohol in the CPI shows a -0.3% price change. In this period, we also see a price drop across each type of sparkling wine (see Figure 6 in Annex), with wines without protected names seeing the biggest price falls.

Table 6. Size of price changes by origin—whole period

	Products	Price rises		Price falls		Weighted price change
		Median	Mean	Median	Mean	
United Kingdom	3819	9.1%	13.7%	−11.8%	−14.4%	1.3%
EU	2650	10.5%	15.1%	−11.8%	−14.0%	1.9%
Non-EU	1719	9.1%	12.6%	−12.5%	−13.7%	2.0%
Total	11,401	10.0%	13.7%	−12.9%	−14.8%	1.1%

Notes: Tables 6 and 7 present the price changes and a price-change metric across the entire dataset. ‘Product’ refers to the number of unique products. This is calculated using a single period, with prices p_0 and p_1 for each product found in mid-August 2023 and mid-February 2024, respectively. These estimates are not directly comparable to an inflation rate. Mean and median changes are conditional on there being a price change.
Source: Authors’ calculations.

Table 7. Size of price changes by country—whole period

	Products	Price rises		Price falls		Weighted price change
		Median	Mean	Median	Mean	
United Kingdom	3819	9.1%	13.7%	−11.8%	−14.4%	1.3%
France	576	9.4%	12.9%	−14.3%	−14.9%	1.4%
Italy	573	11.8%	17.2%	−11.1%	−13.1%	1.7%
Spain	462	12.5%	18.7%	−8.3%	−11.8%	4.5%
Netherlands	258	7.1%	13.6%	−6.9%	−12.7%	3.0%
South Africa	252	10.5%	15.4%	−11.9%	−12.2%	4.6%
Ireland	220	11.8%	13.7%	−16.7%	−16.8%	1.6%
Australia	211	8.2%	10.9%	−12.5%	−11.6%	3.6%
Chile	184	9.4%	13.4%	−9.5%	−10.9%	2.9%
Thailand	179	8.3%	11.5%	−15.8%	−15.7%	4.0%

Notes: Equivalent conditions to Table 6. Top 10 countries with highest number of products matched from prices dataset.
Source: Authors’ calculations.

imports of medium-risk animal products, plants and plant products (e.g., meat, dairy, some fruits and vegetables). According to our dataset, meat products see an exposure of between 14 and 35%. Milk has a relatively small exposure, at 8–10%, while milk derivatives (e.g., cheese, yogurt etc.) have a higher exposure, between 25 and 46%.

The next policy changes are due on 30 April 2024 and 31 October 2024. In April, risk-based checks (documentary, identity and physical) on imports of the same medium-risk goods⁶ from the EU will be initiated. From October, safety and security certificates will be required. Although many fruit and vegetables are classified as medium risk, a temporary policy of ‘easement’ ensures these are being treated as low risk until October. Table 9 provides our best assessment of the exposure to EU imports at these three states.

Initial changes in January and April 2024 primarily affect meat and dairy products, with exposure ranging from 3% for eggs to 46% for cheese (other dairy products). October 2024 is expected to see the

⁶For a full list of import risk categories and related rules for animals and animal related products, see guidance from DEFRA here: <https://www.gov.uk/government/publications/risk-categories-for-animal-and-animal-product-imports-to-great-britain>

Table 8. Top product type by origin

COICOP category	Total products	Share of category
EU		
Olive oil	149	77%
Baby food	1467	70%
Wine from grapes	2833	55%
Edible ices and ice cream	1057	49%
Pasta products and couscous	1261	48%
Non-EU		
Frozen fish and seafood	363	46–56%
Other preserved or processed fish and seafood	845	45%
Wine from grapes	2833	41%
Fresh or chilled fruit	937	39%
Fresh or chilled seafood	159	31%
United Kingdom		
Eggs	92	97%
Milk (low-fat and whole)	295	87–92%
Poultry	912	84%
Pork	627	82%
Breakfast cereals	1778	82%

Notes: Shares and product counts relate to the sample of goods in the main prices dataset, including products with both an identified origin and a matched COICOP category, giving a pool of 28k items. Share ranges used for combined COICOP categories.

Source: Authors' calculations.

end of the easement policy for fruit and vegetables, marking a significant increase in exposure to 35% and 31%, respectively, for these categories.

To assess the potential effect of future NTBs, having a clear understanding of item origin is useful. Our new dataset and country-matching analysis provide an indication of potential exposure to item- and category-specific NTBs.

4. Conclusion: policy implications

Our paper has shown how an efficient (i.e., fast and cheap) use of the latest software can help produce an inflation risk register for UK trade. There is a three-stage introduction of full controls on EU imports this year: we show where the main concerns should be, and the first place to look for inflationary impact.

More generally, this study shows how web-scraped consumer prices offer a complement to traditional data gathering methods. It enriches official price microdata with greater detail and scope to assist agencies, including the ONS in their creation and curation of economic indicators. Daily updates on pricing dynamics should also allow policymaking institutions, such as the Bank of England and the HM Treasury, to observe the real-time impact of shocks and policy decisions. Related work shows how real-time measures of inflation may be calculated (Davies and McElvoy, 2024). This may prove useful, particularly in times of economic stress.

The origins of inflation matter. Our fine data on prices also allow us to track those origins. This can feed into policy decisions concerning price stability as well as building resilience to international price

Table 9. New EU food regulations

Date	Total product count	Main products	EU share of category
January/April 2024	11.1k	Other meats and edible offal	28–35%
		Beef and veal	22%
		Pork	17%
		Poultry	14%
		Lamb and goat	3%
		Other preserved and processed seafood	25%
		Fish and seafood	6–8%
		Other dairy	25–46%
		Milk	8–10%
		Eggs	3%
October 2024	13.9k	Fresh fruit	35%
		Fresh vegetables	31%

Notes: Data reflect products tracked from July 2023 to January 2024, corresponding to ‘food and drink’ COICOP groups. Out of 51k identified products, 28k were matched with a country/region of origin across six supermarkets. ‘Product count’ pertains only to these matched items; actual numbers affected by checks are likely higher. ‘Other dairy’ combines cheese, yogurt and similar products. ‘Fresh vegetables’ category excludes potatoes.
Source: Authors’ calculations.

shocks. Our new country-of-origin dataset can inform trade policy decisions by revealing trends in import diversity and dependence; this may be useful in trade negotiations. These data also help paint a picture of supply chains, their resilience and potential fragility.

Acknowledgements. The authors are grateful for the conversations with Swati Dhingra and discussions about related research with Josh de Lyon, Nikhil Datta and Jan Bakker. The authors are also grateful to the participants at the NIESR conference on the Economic Impact of Brexit who gave useful comments. Finn McEvoy was instrumental in gathering price data. Ahmet Aydin, Liam Greenhough and Elishama Tizora at the Office for National Statistics provided helpful comments on their project. James Kean provided excellent research assistance. All errors, omissions and opinions in this article are their own.

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Annex

```
prior_messages = [
    {
        "role": "system",
        "content": "You are an assistant tasked with identifying the country of origin for products based on their details. Some products have multiple countries of origin, so you may return a list of countries. You must only return a JSON object. Provide a brief reason for your answer. You may return an empty list if you fail to find the country of origin."
    },
    {
        "role": "user",
        "content": '''{"product_title": "Sainsbury's Brussels Pâté 170g", "Description": "Smooth pork liver Brussels style pâté produced in Belgium.", "Country of Origin": "Packed in Belgium, for Sainsbury's Supermarkets Ltd, London EC1N 2HT using pork and pork liver from the Netherlands."}'''
    },
    {
        "role": "assistant",
        "content": '''{"origin": ["Belgium", "Netherlands"], "reason": "Packed in Belgium. Uses pork from the Netherlands."}'''
    },
    {
        "role": "user",
        "content": '{"product_title": "Corona Extra Premium Lager Beer Bottles 12 x 330ml", "Description": "Golden lager with a crisp but refreshing bitterness. Born in Mexico and brought up on the beach, Corona is lighter than traditional beers. A great pairing for several cuisines: in particular Thai, Chinese and Mexican.", "Country of Origin": "United Kingdom", "Origin": "Brewed in UK"}'''
    },
    {
        "role": "assistant",
        "content": '{"origin": ["United Kingdom"], "reason": "Brewed in the UK."}'
    }
]
```

Figure 5. Actual system and example messages provided to GPT-API with each request. These are passed to the LLM with each request. Notes: We use OpenAI's gpt-3.5-turbo-1106 chat completions model.

Table 10. Size of price changes, by country

	Price rises		Price falls	
	Median	Mean	Median	Mean
United Kingdom	22.2%	25.5%	−20.6%	−21.6%
Italy	21.2%	24.5%	−20.0%	−20.1%
France	23.0%	27.5%	−20.4%	−22.1%
Germany	28.2%	40.1%	−25.0%	−27.2%
Spain	15.4%	19.7%	−20.0%	−18.7%
China	25.0%	28.8%	−21.1%	−22.9%
United States	18.2%	24.8%	−20.0%	−21.0%
Netherlands	18.4%	22.5%	−20.0%	−20.9%
Ireland	20.5%	25.7%	−20.6%	−21.1%
Belgium	20.0%	24.7%	−20.0%	−21.1%

Notes: These values correspond to the observations detailed in Table 5.
Source: Authors’ calculations.

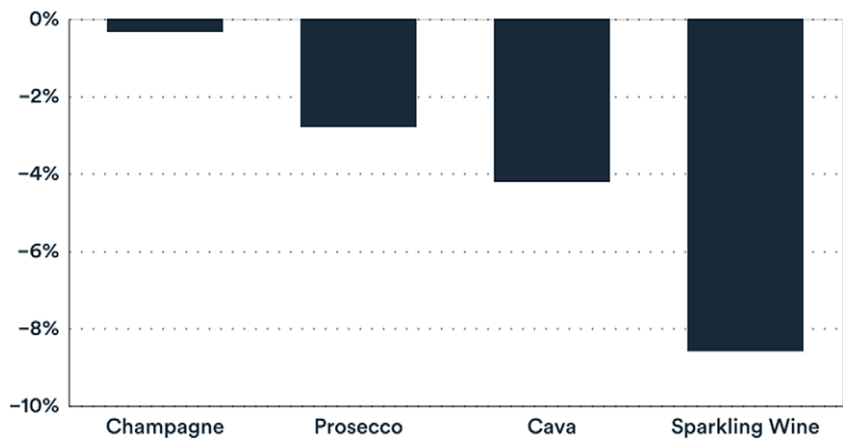


Figure 6. Price change of sparkling wine. Weighted price change of major types of sparkling wine, between August 2023 and January 2024.
Notes: We find 174 Champagne products, 133 Prosecco products, 39 Cava products, and 27 Sparkling Wine products.
Source: Authors’ calculations.

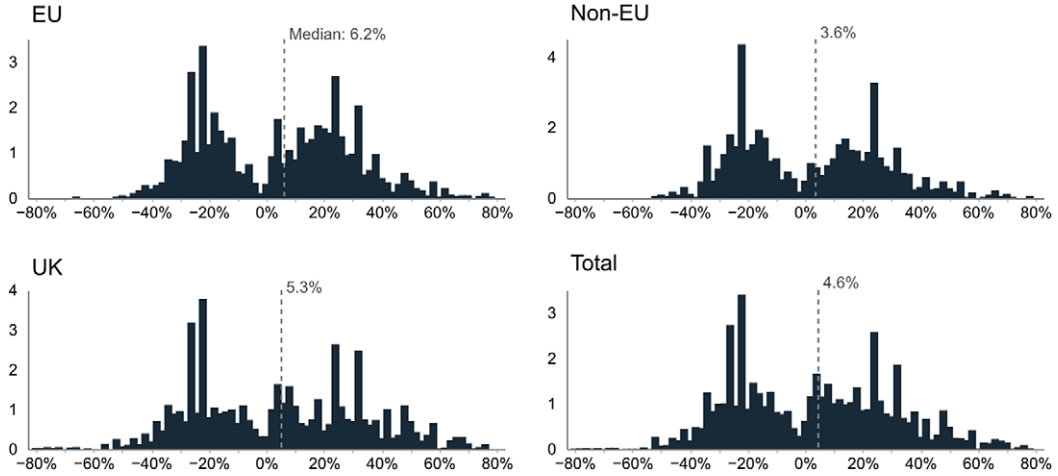


Figure 7. Price change distributions. January 2024.

Notes: Includes all price changes. Excludes products with multiple origin areas.

Source: Authors' calculations.

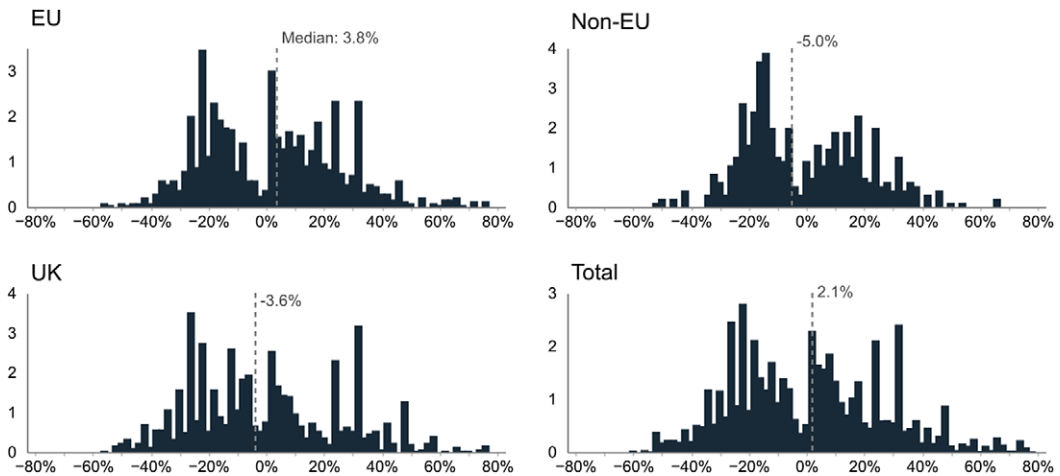


Figure 8. Price change distributions. February 2024.

Notes: Includes all price changes. Excludes products with multiple origin areas.

Source: Authors' calculations.