Measuring and comparing economic resilience within the UK agri-food and drink industry

Technical Annexes

LE
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List of defined terms and acronyms

Defined term/acronym	Meaning
ABS	Annual Business Survey
Actual output	Observed economic activity/output.
AI	Artificial Intelligence
BCM	Business Continuity Management
CAP	Common Agricultural Policy
CEPR	Centre for Economic Policy Research
CGE	Computable General Equilibrium
Common shock	Shock affecting all sectors in the UK agri-food and drink industry.
CPI	Consumer Price Index
DEFRA	Department for Environment, Food and Rural Affairs
DSGE	Dynamic stochastic general equilibrium modelling.
Econometrics	Application of statistical methods to economic data.
FSA	Food Standards Agency
GDP	Gross Domestic Product
GVA	Gross value added. GVA reflects an industry's own-value added as it deducts all the inputs that are not produced by the industry itself but obtained or purchased from other units from the industry's gross output.
HP filter	Hodrick-Prescott filter
Idiosyncratic shock	Opposite of common shock. In the context of this study, an idiosyncratic shock is understood to be a shock only affecting a particular sector.
IoP	Index of Production
NBER	National Bureau of Economic Research (United States)
ONS	Office for National Statistics
Output	Production, proxied by production sold (turnover/value of sales) in this study.
Output gap	Difference between actual and potential output, commonly expressed in percent.
Potential output	Estimated long-run potential level of economic activity/output. Potential output is most commonly estimated by means of statistical procedures that split an output measure time series into cyclical and trend components (see 'time series filters').
RAS	Robotics and Autonomous Systems
Resilience	Ability of an entity or system to return to its original state, or an improved state, following an adverse shock. Attributes of resilience include shock absorption and shock counteraction.
Shock	Risk and challenge affecting the output of a sector.
Shock absorption	Ability to withstand a shock, i.e., the ability to absorb or neuter the adverse effect of a shock so that the end effect is small.
Shock amplification	Extent to which a shock gets amplified, inverse of a sector's ability to absorb or neuter a shock (shock absorption).
Shock counteraction	Ability to recover quickly from a shock after having been adversely affected by a shock.
Shock persistence	Amount of time the effect of a shock lingers, inverse of a sector's ability to recover from a shock (shock counteraction).
SIC	(UK) Standard Industrial Classification of economic activities. Five-digit classification providing the framework for collecting and presenting a large range of statistical data according to economic activity.
Time series filters	Statistical procedures that split the series into cyclical and trend components.
Turnover	Production sold on the market during the reference period (value of sales).

VAR	Vector Auto Regression

Source: London Economics

Introduction to Annexes

The Food Standard Agency has asked London Economics to produce a **‘rough and ready’** but **robust**[1] index of economic resilience for the purpose of conducting cross-sector comparisons and rankings within the UK agri-food and drink industry. The main requirements are as follows.

- The research should be supported by a **review of relevant literature** on the evidence and methodologies used to develop and construct measures of economic resilience at an industrial sector level.
- The index should be **fit for purpose** and **user-friendly** to aid policy design and decisions**.** The analysis further needs to be replicable as the FSA may seek to periodically update and revise the index.
- The index should be constructed at the **most granular sector breakdown possible** given the available data.
- The Food Standard Agency wishes to understand the food and drink sectors’ resilience to a **broad set of risk factors** rather than one particular type of shock, with a focus on macroeconomic risks. Moreover, the approach to developing an economic resilience index should include some sensitivity analysis and investigate whether the ranking of sectors’ resilience varies across different types of shocks (e.g. supply as compared to demand shocks).
- Finally, the FSA wishes to **understand, if possible, what factors make certain sub-sectors more resilient** than others.

The main report – provided in a separate document - sets out our approach and results, including **two complementary indices of resilience** and **recommendations for future research.**

This document provides the Technical Annexes that accompany the main report. They give the following additional background and technical information:

- **Annex 1** provides a review of the relevant **literature on shocks affecting the UK agri-food and drink sector,** including information on the nature of shocks; inter-sectoral transmission of shocks; and the determinants of resilience.
- **Annex 2** outlines important conceptual considerations regarding appropriate measures of sector-level economic activity, an overview of how we define the UK agri-food and drink industry and a review of available **data sources** of sectoral output.
- **Annex 3** provides an introduction into **business cycle analysis** and describes how we derived sector-level output gaps for the purposes of the analysis presented in the main report.
- **Annex 4** provides a descriptive analysis of output levels, output volatility and output gaps in the UK agri-food and drink industry.
- **Annex 5** provides additional information and results for the statistical analysis employed in this paper. In particular, it provides **additional technical information about the statistical method** used to develop the two indices of economic resilience, including a description and **justification of the estimators** used in this study and the **test statistics that informed our main model specification.** Annex 5 also provides **additional regression results** not reported in the main report.
- **Annex 6** contains the results from a preliminary attempt at **structurally identifying common shocks in the data.**

[1] As far as possible within the timescales.

Annex 1 Literature review

Annex 1 Summary: Literature review

This Annex provides a review of the relevant literature on shocks affecting the UK agri-food and drink sector.

First, it provides an overview of the environmental, macroeconomic, business continuity, legal/regulatory, political and technological shocks the sector is exposed to.

Secondly, it provides evidence on inter-sectoral transmission of shocks, in particular as it relates to price transmission.

Finally, this Annex reports the findings from a review of available evidence on determinants of resilience.

A1.1 Shocks and stressors in the UK agri-food and drink sector

Food and drink supply chains in the UK are exposed to multiple internal and external drivers of change. These range from **sudden shocks** such as weather events, changes to food regulations, and animal disease; to **long-term stressors** that in turn increase the systems' vulnerability to shocks and threaten the resources, infrastructure and markets that the food and drink industry relies upon. Climate change is an exemplar of these stressors, increasing the likelihood of weather-related shocks, and threatening to impact the success of certain crops and growing methods in the UK.

This section explores the **types, incidence, and impact of shocks and stressors on the agri-food sector**.

A1.1.1 Environmental

Bio-security

Bio-security in the agri-food context refers to the protection of agriculture and livestock from pests, contamination, and diseases. Alongside the continuous occurance of pre-existing, endemic diseases in the UK, **22 outbreaks of exotic animal diseases** ocured in the UK between 2000 – 2017 (Defra, 2018).

Although rare, **the magnitude of these outbreaks can be severe**. The foot and mouth disease outbreak in 2001 cost the UK food chain approximately **£3.1bn in direct losses**, with 11 million cattle, 42 million sheep, and 6.5 million pigs being slaughtered (Thomson et al., 2002). Export bans were put in place, with mutton and lamb production falling 30% year-on-year (Waage and Mumford, 2007; Defra, 2006). Similar effects emerged from the BSE crisis of 1996, where beef consumption fell by 20% and production 29% year-on-year (Defra, 2006).

In comparison to other EU nations the UK is considered **low risk for bio-security matters** (EC DG for Agriculture and Rural Development, 2017). Nonetheless**, threats are ever-present:** 300 different pests and diseases were intercepted at UK borders in 2017 (House of Lords European Union Committee, 2018). This is indictive of the threat that agricultural trade brings, for example, increased horticultural trade with Asia exposes the UK to new plant diseases (Waage and Mumford, 2008).

Impaired plant and animal health mainly impact the economic performance of agriculture, leading to both **destroyed product** and, more commonly, **increased costs** due to the management and prevention of outbreaks, and the expense of pesticides (EC DG for Agriculture and Rural Development, 2017).

In the longer run, **bio-security threats are expected to increase in the UK** due to climate change, increasing the likelihood of exotic pests and diseases, as they and their carriers become compatible with the altered

UK environment. This concern is matched with a concern that the repeated use of pesticides could lead to a built up of resistance in pests (Defra, 2018). These two factors are examples of longer run stressors affecting UK agriculture.

Bio-diversity

Bio-security risks are further driven by **ever-reducing bio-diversity**. From 1963-2003 UK native plant species dropped 28%, which is a systemic risk factor in agriculture as reductions in diversity, by reducing genetic diversity, can **amplify the damage caused by disease** (Barling et al., 2015). More directly, crop yields are adversely affected by reduced bio-diversity (Bullock et al., 2001), while the reductions in diversity and number of bees is noted to adversely affect the essential 'pollination services' they provide (Breeze et al., 2011).

Weather events

Severe weather events, whether local, regional or national, can have a significant impact on the UK's agri-food supply chain through **losses to agricultural yield and quality**. Severe weather consists of events such as: Volatile rainfall, flooding, heat/drought, high wind, snow/frost/hail, and reductions in air quality due to hot weather and air pollution. These events can also interact with existing problems in bio-security, e.g. wind aiding the migration of insects from the continent or transmitting bluetongue (Benton et al., 2012).

The effect of a severe weather event is **heterogenous** to the type of crop, and possible overlapping weather events. This is illustrated by the effect of high temperatures on maize yield, whereby each degree day above 30 degrees **reduces maize yield by 1%** when water is available and **1.7% when water it is not**. Illustrative examples of the magnitude of weather events include: (i) the flooding of 42,000 Hectares of farmland in 2007 across various English regions, amounting to an average loss per affected farm of £89,415 (compared to average insurance/charity pay-outs of 4720 per farm), and (ii) low temperatures in affecting sugar beet in 2010, writing off 10,000 hectares of crop and costing 15m in the east midlands alone (Benton et al., 2012).

Climate change

The likelihood of weather events affecting UK agricultural **production is considered to be growing with climate change**: heat waves are predicted to be more frequent, higher in temperature and last for longer durations, while short-duration extreme precipitation events are predicted to greatly increase, adding to flooding risk (Benton et al., 2012). Bertrand and Parnaudeau (2015) estimate the sensitivity of UK agricultural GVA to quarterly temperature and precipitation anomalies. Concluding that the impact of temperature and rainfall anomalies in the UK is **£72 and £87 million per year respectively.**

The systemic risks of climate change, i.e. stressors affecting agri-food rather than short-run shocks, are difficult to establish. Soil erosion, acidification (affecting marine stocks), and rising sea levels (in areas such as the Fens where a large proportion of England's acreage is grown in the open), must be weighed against potential benefits (Defra, 2010; Barling et al., 2008; Knox et al., 2015). For example, some projections suggest wheat yield has the potential to increase by 15-23% due to a longer growing seasons (Knox et al., 2015).

A1.1.2 Macroeconomic

Consumer preferences

The agri-food and drink industry is exposed to **volatile and evolving consumer demand**, apparent at every level of the supply chain – acting as both shocks and a stressor to UK agri-food.

Short run demand volatility affecting firms emerges from: panic buying**,** seasonal and weather demand shocks, and food scares. The latter is especially concerning for retailers and their branded suppliers as contamination scares have destroyed brands in the past (Peck, 2006). Demand volatilities also have a unique impact on agriculture. This is because production decisions must be made in advance, and **accurately anticipating demand and market prices is difficult**, yet must be done prior to making production, and production capacity, decisions (Leat and Revoredo-Giha, 2013).

Consumer preferences are **evolving** in the agri-food industry, with consumers placing more value upon ethically and organically sourced foods, healthier products, fresh products, and time saving food innovations such as ready meals (Deloitte, 2017) . Achieving these, considering the strong price pressures in agri-food, places innovation pressure on retailers, who often must adopt **new methods of collaboration** within the supply chain to maintain competitiveness and satisfy these changing preferences. These further place manufacturers under pressure, **requiring more complex, and international, supply chains** - which are more liable to disruption (Colwill et al., 2016).

Food and drink services have a particular pressure to adapt to evolving consumer preferences, being exposed to additional pressures such as: Experience driven behaviour (wanting 'unique, experiences), consumer promiscuity (falling brand loyalty), and increased value scrutiny (Deloitte, 2017).

Exchange rate volatility

Evidence of the agri-food industries exposure to exchange rate volatility is limited. However, there is suggestion in the literature that exchange rate risk does pose a problem in terms of altering the price of traded goods relied on by the UK agri-food sector (EC DG for Agriculture and Rural Development, 2017).

In 2016 UK food production was 60% of food consumption, with the EU accounting for 70% of the UK's imports, 60% of its exports and 27% of UK food consumption (Lang and Schoen, 2016; Parliamentary Office of Science and Technology, 2017). Imports are relied on by all levels of the UK agri-food industry, with imports ranging from animal feed to consumables such as fruit sourced directly by retailers. UK agriculture particularly relies on the EU market for exports, with the EU accounting for 95% of lamb, 90% of beef, 80% of wheat, and 70% of pork exports (Parliamentary Office of Science and Technology, 2017).

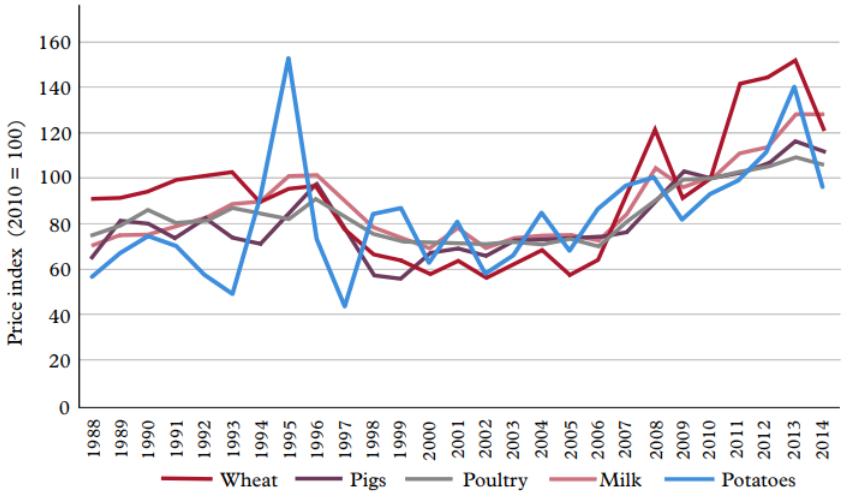
Such a degree of cross-border integration **exposes UK agri-food to exchange rate shocks**, although the effects of this is likely **heterogenous across the agri-food sector** – with some firms relying more on export sales than imports (EC DG for Agriculture and Rural Development, 2017).

Some literature surrounding Brexit suggests that a weakening of the pound adversely affects the agri-food sector (see section 1.15), while some price transmission literature suggests that a weakening of the pound relative to the euro **increases retail-farm price spreads** – i.e. the difference between retail and farm prices. This is interpreted as the exchange rate movement opening farming units up to extended EU competition, by making EU products more price competitive in the UK (London Economics, 2004).

Agricultural commodity price volatility

The volatility of agricultural prices, and agricultural inputs, is an inherent feature of agricultural markets, for example, between April and September 2012 wheat prices rose 38% in response to droughts in the US (Defra, 2017). Price volatility, namely periods of low prices, pose a clear challenge to the incomes of farmers, repeatedly placing them under **financial strain** (House of Lords European Union Committee, 2016).

Figure 1 Real indexed prices for agricultural commodities (UK)



Source: House of Lords European Union Committee (2016); Defra, 'Agriculture in the United Kingdom': https://data.gov.uk/dataset/agriculture_in_the_united_ kingdom

Volatility and low prices further threaten farmers' ability to **anticipate the production needs and investment opportunities of the market** (House of Lords European Union Committee, 2016). Volatility is a normal feature of markets, sending crucial market signals that direct production and investment decisions. However, in agriculture, price volatility is also caused by short-term shocks.

In agriculture demand and supply are inelastic, meaning that large movements in prices are required to balances out shocks. This volatility complicates the allocation decisions of farmers, who, due to the long time to production in agriculture, must judge whether high prices are indictive of market opportunity or events that will not be present in the next cycle.

For example, a period of high prices in the poultry market, due to a disease related culling, may act as a signal to farmers to expand their poultry production. However, when the next production cycle comes around, the outbreak's effect may have dissipated, leading to an oversupply of poultry from farmers who followed the original price signals. This process **reinforces the price volatility and low prices in agriculture**, but crucially, can lead to **sub-optimal investment** in the long run – acting as a stressor for farming resources (House of Lords European Union Committee, 2016).

Exposure to international markets

As discussed above, the UK's agri-food supply chain is integrated with the EU and global markets, relying on both exports and imports. The interconnectedness of the UK and the EU is especially stark: In 2011, 12.58% of the total value-added of UK exports was produced by the EU, of a total of 26.3% that is produced by foreign countries (Bellora et al., 2017).

Despite such agri-food interconnectedness with the EU, **the threat of an EU supply or demand shock on the UK could be limited**. The openness of the UK with regard to agri-food trade allows the UK food chain to be resilient to domestic supply shocks, and importantly shocks to supply from specific countries (Defra, 2010). The **wide range of countries** in which the UK sources its food limits significantly the possible impact of a country specific shock (Parliamentary Office of Science and Technology, 2017). This is truer for large retailers, which can quickly swap sources of supply if required and avoid the fallout of possible shortages (Defra, 2010).

European and global exposure does have the potential to be a source of risk in specific commodities where the UK produces a relatively small amount domestically yet relies on a limited number of overseas suppliers.

These include: (i) Fruit and veg, where imports from Spain and the Netherlands account for 69% of imports for fresh vegetables, and four other nations for 44% of its supply of fresh fruit imports, and (ii) animal feed imports in poultry and pig sectors, namely soy beans, where the bulk of imports come from Argentina and Brazil (Parliamentary Office of Science and Technology, 2017). This exposes the UK to potential supply shortages such as Spanish drought.

It is possible there are some risks that could impact the **supply of a range of countries** simultaneously, and therefore not be dissipated by having a diverse range of countries supplying the UK market. A clear example of this is large scale weather disruption such as a heatwave. The likelihood of such events is growing due to the **deterioration of agro-climatic conditions** in Europe, such as: Increased drought stress and shortening of the active growing season in central and southern Europe, a reduction in livestock production across Europe due to higher temperatures and drought risk having a negative impact on grassland productivity and animal health, and the increased risk of periods of extremely unfavourable climate conditions which increase crop yield variability (EC DG for Agriculture and Rural Development, 2017).

Concern further exists over whether the global supply of seeds is diverse enough. High levels of concentration in global seeds markets could make the industry vulnerable to seed shortages if one company fails, which in turn could affect both UK primary producers and the supply of other nations' good to UK processors and retailers (Defra, 2010).

The globalisation of the seed market further raises concerns of systemic risk in the literature that the UK may no longer have access to seeds that are developed specifically to suit the UK's climate and soil type. Cereals bred for Germany and France may not maximise yields within the UK for example (Barling et al., 2015).

Interest rate

Interest rate variability and its effect on agri-food is not well documented, although it is noted by the literature to have little effect at the EU level as, from a historical perspective, interest rates are currently low and stable. Agri-food investments financed largely by debt could therefore be at risk from interest rate rises, although this is unlikely to especially impact the agri-food sector (EC DG for Agriculture and Rural Development, 2017).

Energy and oil price

The UK agri-food industry, especially agriculture, is particularly **dependent upon energy inputs** in their various forms (Defra, 2010). As a result, shocks to global energy prices have the potential to expose the agri-food industry to extreme **input price volatility**, especially as fertilisers and chemical product prices closely follow the price of oil (EC DG for Agriculture and Rural Development, 2017). Estimates suggest that an increase in the price of oil from $50 to $100 a barrel could increase production costs for livestock products by 3-5%, and crops by 13 % (Defra, 2008).

Labour market

Shocks to the labour supply have the potential to affect the whole agri-food supply chain.

The UK farming and food manufacturing sectors rely heavily on **seasonal and permanent migrant labour**, with census data suggesting that there are 115,000 full-time and 67,000 seasonal migrant agricultural workers as of 2012. Further, 38% of food manufacturing workers are foreign born (Parliamentary Office of Science and Technology, 2017). These features are important for the implications of Brexit on agri-food (see section 1.1.5). Migrant workers, who preform both unskilled and skilled work (e.g. animal husbandry), are a less secure pool of labour, exposing the UK to potential **labour shocks** in the future should immigration policy or economic events encourage the movement of labour (Barling et al., 2015).

Shocks to levels of migrant labour could further pose a particular risk to the UK food service industry, where, for restaurants, 28% of employees were foreign born in 2015 (Deloitte, 2017).

One possible impact that migrant shocks could have on the labour market is **increased labour input costs** (wage costs). These shocks, of migration on wages, are often found to be negligible, with some studies finding that increases in migrant labour lead to small decreases in the incomes of low-skilled workers. The reliability of these studies is limited however as they often focus on: increases in inward migration rather than decreases in migration, and labour market equilibrium outcomes, which cannot fully account for firms adjusting their production decisions (i.e. using more automation in production as labour becomes more expensive) (Bakker and Datta, 2018).

Other large-scale disturbances to the labour supply seem rare, with industrial action in the agri-food sector deemed very unlikely. Human disease pandemics are a noted short-term risk by the literature, suggesting that in extreme circumstances absenteeism rates could climb to 10-15% (Defra, 2006).

A1.1.3 Business continuity

Disruption of critical infrastructure

Disruptions, whether climatic, accidental or malicious, to infrastructure critical to the agri-food industry have the potential to pose a significant threat to the industry and food supply. The literature specifically expresses concern over disturbances to ports and the transport system.

Just-in-time supply chains developed by retailers, whereby very limited stocks are held in store in order to provide continuous variability to consumers, have increased the role of the transport network in the effective management of the food supply chain. Potential shut downs of the transport network have the scope to cause significant disruption to food supplies to both retailers and food processors (Peck, 2006). The magnitude of transport disturbances is hard to ascertain, although it seems that the **scale of retailers in the UK insulates from larger losses**. The fuel protests of 2000, which led to largescale fuel shortages, were a good example of this, with retailers rationing their own forecourts to maintain the supply of essential product lines to stores (Peck, 2006).

Similarly, disruptions to key import and export infrastructure, such as ports becoming inoperable, could cause a significant supply shock to retailers and processors. The magnitude of these shocks depends on the concentration of traded goods across ports, and the ability for these goods to be diverted to other ports. In the UK a substantial share of raw cane sugar, tea, soya beans, coffee and bananas travel through one port, however the potential effects of this are mitigated as there are **sufficient alternative port options** for these commodities in the UK. The channel tunnel has the potential to mitigate a shock to a particular port, although it is difficult to establish what the effect of the channel tunnel being inoperable would be given that import and export volumes need not be tracked across the EU border (Defra, 2010).

Idiosyncratic supply chain shocks

A minor threat to clusters of manufacturers and retailers emerges from what is best described as idiosyncratic supply chain shocks. Whether due to climatic, accidental (e.g. fire or flooding) or malicious reasons (terror attacks), potential loss of site or production capital can disrupt manufacturers and retailers. An example of this is the Buncefield fuel depot explosion in 2005, which resulted in Retailer Marks & Spencer having to close one of its six food depots (Peck, 2006), and the 2006 closure of the McVitie's biscuit factory in Cumbria due to flooding, which lead to their brands being unavailable (Colwill et al., 2016).

Other shocks of this nature include: loss of supplier (e.g. packaging suppliers for manufactures), loss of service provider (e.g. IT support), and reliance of upon IT systems (Peck, 2006).

The likelihood and magnitude of events of this nature are heterogenous, with the literature expressing no concern for clusters of the agri-food industry. Such risks are often accounted for in the **business continuity management systems** of UK supermarkets, and, as a result of their scale and level of vertical integration, non-retail industry units are often **protected from idiosyncratic risks** of this nature (Peck, 2006).

A1.1.4 Legal/regulatory

Food standards and animal welfare regulation

Expansions to food standards and animal welfare regulation have been cited as potential shock to costs for farmers and manufacturers. For example, in 1999 the UK government, in order to raise pig welfare, introduced bans on the use of close-confinement breeding stalls and tethers – increasing the costs of pig farmers materially (Leat and Revoredo-Giha, 2013).

This increase in cost was exasperated by EU wide bans not being instituted until 2006 for tethers and 2013 for sow stalls. This disparity in regulation made EU imports of pork **comparatively cheaper**, introducing competitive pressures on UK pig producers (Leat and Revoredo-Giha, 2013). Likewise, the need to ensure traceability, and segregation of certain ingredients for allergen purposes, is cited by the literature to place a systemic strain on food manufactures (Colwill et al., 2016).

Compliance with regulation could have a further impact food manufactures, as, for example, retailers may use positions of market power to “force the adjustment costs onto their suppliers, which have to accept low prices while meeting the high compliance costs” (Doherty et al., 2019; Henson and Humphrey, 2010).

A1.1.5 Political

Brexit

Changes in trade costs represent one of the major Brexit risk factors for the agri-food industry. Increases in trade costs could affect all levels of the supply chain through **higher input costs and reduced export demand**. The most direct threat to trade costs is tariffs - although significant uncertainty surrounds the likely outcome of tariff barriers after Brexit. Outcomes range from a continuation of zero-tariffs, to Most Favoured Nation tariffs – the tariff countries must impose on the imports of another member of the World Trade Organisation with whom they do not have a preferential trade agreement. Such tariffs are discretionary although must be equal for all nations without a preferential trade agreement. The impact of these tariffs could be devastating for EU-UK trade, with the average tariff that could apply to agricultural import being 18.3%, and for dairy products, one of the most commonly traded goods across the border, average tariffs could stand at 35% (Bakker and Datta, 2018; Bellora et al., 2017).

Non-Tariff barriers after Brexit, should the UK exit the customs union, are **predicted to further effect trade costs**. Examples of these costs include: (i) The cost of declaration, as the UK may need to document any goods travelling into, and from, the EU, (ii) cost associated with increased check times and port traffic , predicted to increase by waiting by 1.4 hours, (iii) animal and food specific trade costs, e.g the number of goods requiring a veterinary check will increase by 325% (Bakker and Datta 2018).

Increased trade costs could be amplified by the likely prolonged **weakening of the pound**. Since the Brexit timeline begun the pound has weakened substantially, increasing the costs of importing food products, and the price of UK exports in foreign markets. As an indicator of this, products with a higher import exposure **experienced an inflation rate around 4% higher than products with a low import exposure since 2016** (Bakker and Datta 2018). Increased import costs could especially harm retailers and food service providers, who rely on a range of foreign goods to satisfy consumer demand. The effect of reduced export competitiveness, due to higher costs to market for exporters, will predominantly harm UK agriculture, which relies on direct trade with the EU (Parliamentary Office of Science and Technology, 2017). One estimate suggests that in the longer run a soft Brexit could reduce household income by £850 a year, compared to a hard Brexit estimate of £1,700. This fall, alongside potential reductions in consumer confidence, could reduce spending and harm the agri-food sector (Bakker and Datta 2018).

Retailing segments of the agri-food industry, such as supermarkets, are suggested by the literature to be well **insulated from reductions in consumer spending** as many of their goods, are inferior goods (increasing in demand as incomes fall), a feature that acts as a countervailing force to other losses. A fall in household income after Brexit would likely impact the profitability of luxury product lines, as demand is diverted to cheaper alternatives (Bakker and Datta 2018; PWC, 2019).

Brexit further poses longer run **supply side risks**. As discussed, the UK agri-food sector is reliant on seasonal and permanent EU migrant labour, of which the availability is not guaranteed after Brexit. Work-related net migration from the EU has dropped dramatically since the referendum (Bakker and Datta 2018), with the number of seasonal workers coming to work on British arms falling by 17% (Downing and Coe, 2018).

Whether induced by changes to immigration policy, or a fall in the UK's attractiveness to agricultural workers, reductions in the labour supply put pressure on the whole agri-food sector, especially agriculture. Studies on the effect of migration on wages suggest that this effect could be negligible, although, as discussed, these often focus on: inward migration shocks rather than decrease in migration, and labour market equilibrium outcomes, which cannot fully account for firms adjusting their production decisions (i.e. using more automation in production) (Bakker and Datta, 2018).

A complication of Brexit for British agriculture, in all Brexit scenarios, is the loss of **Common Agricultural Policy (CAP) payments**. One component of this is the Direct Payment which is paid directly to farmers, and accounted for **56.4%, or £22,400, of average farm business incom**e in 2014/15 (House of Lords European Union Committee, 2016).

The UK government is expected to maintain the current level of funding to 2022, although how much the UK will be able/wiling to allocate farm subsidies after this is uncertain. Reductions, or changes in the allocation mechanism, of farm subsidies, pose a significant source of **income uncertainty** for UK agriculture (Downing and Coe, 2018).

A1.1.6 Technological

Robotics, big data and artificial intelligence

Rapid developments in computing hardware, software and the availability of data, especially satellite data, are changing production practices in the agriculture sector, as they are across many other sectors. These developments are already having an impact on cost structures and are likely to continue to do so as well as having impacts on employment and land use patterns.

The application of high-precision geo-location services in the agricultural sector leads to improved productivity, for example, through improved fertiliser and seed application, and better agronomic decision-making and operations. In particular, augmented GPS receivers enable the use of self-steering (robotic) tractors and harvesters, which greatly improves operational efficiency.

In a small-scale UK survey (London Economics, 2015)[2], nearly all respondents were aware of GNSS-based agriculture technology (96%) and nearly all used it (84%). Of those who did not use GNSS technology, the majority farmed livestock. Popular use cases of GNSS included machinery guidance and automatic steering,

[2] The survey was completed by a total of 50 farmers. Due to this small sample size, results may not be representative for the total agriculture sector in the UK.

land measurement, and information monitoring (e.g. weather, soil and yield). Farmers using GNSS technology found that technology mostly benefitted them through reduced input costs, although increased outputs were also noted as benefits.

Beyond GNSS applications, big data and Artificial Intelligence (AI) can improve agricultural practices in various, sometimes surprising ways. For instance, AI can be used to track individual cows visually through hide pattern and facial recognition. This allows farmers to automatically track the feed and water intake of individual cows (Markets Insider, 2018). AI applied to imagery could also be used to recognise stress levels and diseases in plants (Bagchi, 2018).

The effects of AI and big data can be substantial. One company has developed AI systems for selectively administering weed killer. They claim that this system can reduce the use of agrochemicals by as much as 90% (Gonzalez, 2018). It may also reduce the use of the labour required to identify and remove weeds.

The use of Robotics and Autonomous Systems (RAS) may further improve yield and efficiency in agriculture. RAS technology may for instance be used to develop (UK-RAS Network, 2018):

- in-field assisting and human-augmenting robots, e.g. to carry payloads off the field;
- automated weeding and drilling; or,
- automated harvesting.

UK-RAS (2018), however, recognises that the current landscape of technology developers interested in agriculture is small and fragmented. The expectation is that, for the foreseeable future, fully autonomous agricultural robots are not likely to be fully developed, and instead robots cooperating with humans will be incorporated into existing systems.

The large potential disruptive force of robotics, big data and AI in agriculture (sometimes called ag tech) is evident from investment into the industry. In 2017, around $700 million (£543 million) was invested in ag tech, more than 2015 and 2016 combined – respectively, $223 million (£146 million) and $332 million (£245 million) (Financial Times, 2018).

Bio-fuels

Expansions in the consumption of bio-fuels have the potential to place **longer term systemic risk** onto the UK agri-food industry by **increasing the price of agricultural commodities** (House of Lords European Union Committee, 2016).

Wheat, sugar beet, maize and barley are all inputs into the production of ethanol, a bio-fuel, yet are also inputs into the UK agri-food sector. This is especially true for UK livestock producers, relying on these inputs for animal feed. Increases in the consumption of bio-fuels are largely attributable to EU policy surrounding biofuels: In 2011 ethanol for example was subsidised between 48 – 54 euro cents per litre (Charles et al., 2013). Bio-fuels often do not make up a trivial amount of specific agricultural markets, for example, in 2011 bio-fuels accounted for 32% of all vegetable oils imported and produced in the EU (Charles et al., 2013).

There is **little reliable evidence** of the effect of biofuels on agricultural commodity prices, namely due to difficulties in disentangling any price movements and additional price volatility caused by the consumption of bio-fuel, and the price effects of an abundance of other factors (e.g income growth, diet changes, weather conditions, productivity gains) (IISD and GSI, 2013).

The direct effect of EU bio-fuel policy changes has been estimated by the literature. Estimates suggest that EU bio-fuel subsidies have **increased the price of wheat** anywhere from 1-13%, and 1-36% for vegetable oils. Given the lack of data, most studies rely on models that rely jointly on economic assumptions and data, the reliability of which is difficult to establish as they only project real world conditions, onto a simplified model of reality. Nonetheless, these suggest that **bio-fuels act as a stressor for agricultural commodity producers**, and by extension, the UK agri-food industry (IISD and GSI, 2013).

Estimates of the cost to animal feed consumers across the EU, based on this range of estimates, range from 7-264 million euros (IISD and GSI, 2013). Although not UK specific, this has likely negatively affected the profitability of UK livestock producers over time.

A1.2 Inter-sectoral transmission of shocks

The impact of shocks and stressors on any particular segment of the agri-food industry **depends on how shocks are dissipated**, or passed along, the supply chain. For example, a demand shock that starts at the retail level – with consumers buying less of a product – may force supermarkets to lower their prices. Whether or not this shock affects the supermarket however depends on their ability to pass this price reduction back along the supply chain (London Economics, 2003).

Understanding how and why shocks dissipate along the supply chain is an essential element of understanding the incidence of shocks and a firm's resilience to them. If firms can partially dissipate shocks across the whole industry, this may make the industry **more resilient** – ensuring that no individual segment experiences the full impact of a shock. Alternatively, if a firm cannot pass on the effects of a shock, or indeed can pass the effects on perfectly, **the shock will be disproportionately experienced by one firm or segment of the agri-food industry**, making certain firms or segments less resilient (Vavra and Goodwin, 2005).

Price transmission studies of the agri-food industry seek to understand **how much a change in the farm price of a product is reflected in the retail price**, and vice versa – whereby price shocks/movements are a proxy for supply or demand shocks in an industry segment. These price interlinkages can be assessed in two distinct ways: (i) By looking at price levels to assess how price changes are passed on across the supply chain, and (ii) by focusing on the pass on of price volatilities, the degree to which price uncertainty or volatility in one part of the supply chain affects that of another. If prices, or price volatilities, were perfectly transmitted across the supply chain, then there would be a strong association between prices and price volatilities at each level of the supply chain.

These studies further seek to understand the heterogeneity of the price transmissions that can occur, for example, **cost increases** at the farm level may be dissipated differently to **cost decreases**, while supply or demand shocks affecting **upstream firms** may not impact **downstream firms** in the same way that downstream supply and demand shocks affect upstream firms. The latter instance would imply that **price transmission asymmetry** exists – where the transmission of a shock, and thereby its incidence, depend on a shock's position within the supply chain[3].

Price transmission studies that assess price levels test whether the prices of products at each end of the supply chain are cointegrated, i.e. follow a long run relationship – this is often done in the framework of an error correction model. Other studies on price level transmission assess the direction of causality between each end of the supply chain – assessing whether shocks to prices at each end of the supply chain affect price spreads equally. Studies focusing on price volatility transmission tend to rely on multivariate generalized autoregressive heteroskedasticity models (MGARCH) to assess the transmission of price volatility across the supply chain – these models measure the degree of volatility in prices and test whether the price volatility of one part of the supply chain is associated to that of another.

[3]http://www.fp7ulysses.eu/publications/ULYSSES%20Working%20Paper%204_Price%20volatility%20transmission%20in%20food%20supply%20chains.pdf).

Literature of the UK has **focused on the assessment of price level transmission**, documented in Table 2, rather than volatility transmission, which is noted as a **significant weakness** in the literature.

Despite many price transmission studies of the UK agri-food supply chain, **strong conclusions cannot be drawn from the literature** and the results in Table 2 should be treated with **caution**. Evidence on the magnitude, and asymmetry, of price transmission is mixed varying both across studies and across different product types. Other studies across Europe and the US similarly offer uncertain conclusions (London Economics, 2004; Vavra and Goodwin, 2005). Furthermore, the time-scales of price transmission, and their relevance to resilience, are not comprehensively explored – i.e. prices may be linked in the long run, but rapid, short-run price transmissions may be more important for a firm's resilience. This further restricts the value of these studies as indicators of the extent of shock dissipation and the effect it has on a firm's resilience.

As can be seen in Table 2, some papers seek to explain the factors that impact price transmission across the supply chain. These should be **treated with even greater caution** than the price transmission estimates. Results are sensitive to changes in specifications, data, and product types, and are further often only speculative. Therefore, more general conclusions based on these should be avoided (London Economics, 2004; Vavra and Goodwin, 2005).

Table 1 Summary of price transmission research

Studies	Products	Price transmission magnitude/ direction	Cited factors influencing transmission
London Economics (2004)	90 products	Varying findings on exact pass through of shocks: For UK apples an increase of producer prices by 1% increases retail prices in the short-run by 0.15%, and 0.46% in the long run. Alternatively, no transmission is found in the wheat industry. Little evidence of systematic asymmetric transmission in the EU and UK food chains; for most commodities, there is evidence of symmetric price transmission. Price transmission in the fruits and vegetables sector appears to be mainly symmetric. The eggs and chicken supply chains show evidence of mainly symmetric price transmission.	No direct assessment of factors, only indirect by looking at retail-farm price spread determinates in the UK. Paper builds semi-structural model to explain variation in price spreads across different product groups. Concluding that: market concentration appears to have no impact, the £/€ exchange rate appears to increase spreads, food processing costs have an impact in some cases, the BSE outbreak increased spreads in the beef market, and EU intervention prices under the Common Agricultural Policy (CAP) decreased prices spreads.
London Economics (2003)	Milk	A unit increase in the retail price of liquid milk is fully transmitted to the farm price, whereas a unit increase in farm prices causes a unit increase of 0.56 in retail prices. Similarly, a unit decrease in farm prices reduces retail price by 0.71.	Differences in market structures; differences in the transmission of information; varying degrees of government intervention

Dawson and Tiffin (1997)	Beef; Pork; Lamb	No cointegrated relationships for UK beef and pork retail-farm prices. Some evidence for Lamb, with prices being set at the retailer level.	Lack of relationship/ retailer price dominance interpreted as evidence of an uncompetitive market and retailer market power.
Tiffin and Dawson (2000)	Lamb	Prices follow a long run relationship, but only in price changes at the retailer level, not the producer level.	
Palaskas (1995)	Pig-meat; Bread; Beef; Butter; Cheese	Estimated elasticity of price transmission greater than 1 for all UK products; implying that a 1% change in producer prices causes a more than 1% increase in consumer prices.	
Davidson et al. (2011)	Index of agricultural prices	Report a cointegrating relationship between agricultural commodity prices and retail prices in the U.K. Long run transmission elasticity predicted to be 0.63.	
García-Germán (2015)	Index of agricultural prices	No cointegrated relationship between agricultural index and retail prices for the UK.	
Bukeviciute et al. (2009)	Index of agricultural prices	Elasticity of consumer food prices to producer food prices of 0.25.	
Ministry of Agriculture, Fisheries and Food (1999)	Beef; Pork; Lamb	Limited cointegrated relationship between prices. Evidence of transmission symmetry for lamb and beef[4]; some evidence of asymmetry for pork – retailers responded less quickly to producer price falls.	
Lloyd et al. (2001)	Beef; Pork; Lamb	Impact of the outbreak of BSE on meat prices. Conclude that retail-farm prices are cointegrated only when accounting for a “food publicity index”, capturing the number of publications in the news about the safety of meat. Conclude that shocks to this index increase wholesale-producer price spreads more than the retail-wholesale price spread – i.e. a food scare will diverge producer and wholesale prices, implying producers feel the shock disproportionately[5].	

A1.3 Evidence on the determinants of resilience

Extent of business continuity planning

[4] García-Germán, S., Bardají, I., & Garrido, A. (2015). Evaluating price transmission between global agricultural markets and consumer food price indices in the European Union. Agricultural Economics, 47(1), 59–70. doi:10.1111/agec.12209

[5] Bukeviciute, L., Dierx, A., Ilzkovitz, F., 2009. The functioning of the food supply chain and its effect on food prices in the European Union. Occasional papers No 47. [Online]. Accessed May 2015, available at http://ec.europa.eu/economy_finance/publications/publication15234_en.pdf; Steal Davidson citation - Davidson, J., Halunga, A., Lloyd, T.A., McCorriston, S., Morgan, C.W., 2011. Explaining UK food price inflation. Working Paper No.1, TRANSFOP project. [Online]. Accessed June 2014, available at http://www.transfop.eu/media/universityofexeter/businessschool/ documents/centres/transfop/UK_Food_Inflation_WP1.pdf

The uptake across the agri-food industry of **business continuity planning** – contingency planning for shocks that interrupt business operations - is an important source of resilience in UK agri-food and drink industry (Defra 2009; Peck 2006). Designated crisis management teams, and the development of procedural guidelines, enhance the ability of firms to effectively and quickly respond to supply chain risks. This is supported by firms having a culture of risk awareness, and further, early warning systems that alert firms to risks faster (Stone and Rahimifard, 2018).

Research by Peck (2006) into the scope of existing business continuity management (BCM) in the UK in the food and drink industry suggest that businesses are aware of their exposure to shocks, and the need for BCM. Among leading supermarkets, wholesalers, manufactures, and suppliers, **BCM is widely recognised**, with businesses pursuing ever wider operational risk management. Supermarkets, despite being inherently resilient due to having **few critical suppliers**, are noted to have especially advanced BCM. This is due to BCM systems being critical in maintaining brand reputation during times of supply stress. This in turn is noted to lead to pressure on firms that supply supermarkets to have logistical flexibility in exceptional circumstances.

By market share, 92% of supermarkets and 41% of wholesalers, are noted to operate with BCM, suggesting it is a source of reliance for retailers more generally (Defra, 2010).

Peck (2006) notes that BCM strengths in food manufacturing are less pronounced, with firms focusing efforts around the protection of key assets, and their ability to 'flex' production across different sites – a contingency that is **likely to be ineffective given the erosion of excess manufacturing capacity in food manufacturing**. Further the study notes that few firms had moved beyond relative crisis management, toward proactive or preventative BCM – a potential source of further resilience.

Access to finance and financial instruments

Having **access to finance** is an essential source of resilience for UK farmers (House of Lords European Union Committee, 2016). Specifically access to lending and products that mitigate price risk are needed for farmers to withstand shocks.

Research by the House of Lords European Union Committee (2016) notes that access to lending is a source of resilience for most farmers in the UK, although for specific groups, namely tenant farmers who do not own their land, **access to finance is limited**. The literature notes that a lot of the willingness of banks to lend to agriculture stems from their **favourable debt to asset ratios** – which is driven by land ownership. Alongside the high capital costs, and thin margins in some seasons, this hampers the ability of tenant and contract farmers to be resilient.

This research further suggests other market-based solutions that boost the resilience of farmers include forward contracts, futures markets, swaps and options, and insurance schemes. The use of these to hedge price movements varies widely, and there are often significant barriers to uptake due to a lack of knowledge and experience among farmers. For example, the use of futures markets is well established in cereals and oilseeds, although less effective, and naturally less common, in perishable good markets.

Across the whole industry, access to finance, whether from institutional lenders or existing business capital, is an important factor in being able to weather shocks (Stone and Rahimifard, 2018).

A1.3.1 The Common Agricultural Policy

Research by the House of Lords European Union Committee (2016) further notes the Common Agricultural Policy (CAP) is noted by the literature to be a source of resilience in UK agriculture. Firstly, the CAP provides **direct financial assistance**, namely the Basic Payment Scheme, of which amounts are based on the amount of land owned. The scheme has also **facilitated one-off payments** that target specific, and struggling sectors, For, example in 2015 €500 million was set aside by the Commission to support farmers after a prolonged period of low prices – consisting of targeted aid to support the dairy sector. These payments protect farmers from shocks, especially price volatility, and are an important source of resilience for periods of low prices.

Secondly, the study also notes that CAP provides a **policy framework for farmers to manage risk**. For example, Rural Development Programmes, the second pillar of CAP finance, can fund financial contributions for crop, plant, and animal insurance to protects against income shocks. They can further compensate in the event adverse shocks, or severe drops in farmer income. These provisions are not currently available within the UK's Rural Development Programme, although grants are available for business development and efforts to improve farm productivity[6].

Some stakeholders within UK farming consulted for this study suggested that the direct payments of CAP may hinder resilience in the long run, reducing incentives to innovate, an encouraging passive, rather than active, risk management.

A1.3.2 Stock levels

The inelastic tendencies of agricultural commodity supply, due to high production lags and high capital costs, mean that the holding of agricultural commodity stocks in other parts of the supply chain can be a significant contributor to the resilience of agriculture (House of Lords European Union Committee, 2016), and the market more generally (Defra, 2009). Having high stock levels allows for an **easily accessible source of supply** which can reduce agricultural price volatility. Reductions in price volatility would benefit UK agriculture (House of Lords European Union Committee, 2016), while the mitigation of periods of high prices could prevent input cost increases for the whole industry.

Given that stock levels of agricultural commodities are historically low (Defra, 2009; House of Lords European Union Committee, 2016), stock levels seem to currently contribute little to the resilience of the UK agri-food industry.

Stock holding at the retail level can too build resilience to short run supply chain shocks (Peck, 2006), although retail stock levels are generally observed by the literature to be in decline. Just-in-time supply chains developed by retailers, whereby very limited stocks are held in store are common practice in the UK (Peck, 2006). For example, from 1996 to 2007 stock levels of frozen goods fell by 24% (Defra, 2009). These falls in stock levels emerge with retail supply chain becoming more responsive (Defra, 2017), reducing resilience across downstream sectors of the agri-food industry.

A1.3.3 Supply chain collaboration

Collaboration is commonly cited by the literature to be an important source of resilience (Zhao et al., 2017). By **aligning incentives**, business supply chain collaboration (e.g. information sharing, communication, and joint decision making) reduces the impact of supply chain disruptions. It further can reduce the incentive to act opportunistically: close inter-firm networks, often developed to reduce costs, encourage mutual loyalty between firms (Zhao et al. 2017).

The supply chain collaborations that result from the scale and centralised structure of UK supermarkets appear to be an important source of resilience for certain sectors in the agri-food industry. **Centralised buying power** in UK supermarkets has led to the emergence of many dedicated **long-term supply**

6 For the current grants of the Rural development programme, see: https://www.gov.uk/topic/farming-food-grants-payments/rural-grants-payments

relationships (Harvey, 2000). One example of this is the ASDA porkLink, see box 1, which has built resilience among one of Scotland's major pork supply chains (Leat and Revoredo-Giha, 2013).

Supermarkets could also be a source of resilience to short-term disruptions, such as the UK fuel shortages of 2000, where supermarkets made their fuel stocks available to suppliers of key products (Peck, 2006).

Box 1 Asda PorkLink: Building resilience through collaboration

Scottish Pig Producers Ltd (SPP), a marketing cooperative, Vion Food Scotland Ltd, a processor, and ADSA, a retailer, form a major pork supply chain in Scotland: PorkLink. The PorkLink agreement between these firms aims to strengthen links across the supply chain, ensuring enhanced quality, supply consistency, and financial stability in the pig-meat sector. Specifically, the agreement is based on the SPP's 12 month rolling contract to supply 3000 pigs a week to ASDA.

The PorkLink supply chain has been recognised as an exemplar for both horizontal and vertical collaboration in the agri-food industry - being commended for building resilience and stability in the pig-meat sector. The agreement alleviates market risk by ensuring market continuity for small scale pig producers, creating price transparency by publishing deadweight average pig price weekly, and offering a price bonus for high-grade pigs. The collaboration bought about by the agreement has further ensured that the industry is more adept at dealing with shocks: In 2001 ASDA assisted producers in managing feed cost rises by supplementing feed by 8 pence per kilogram.

ASDA not only insulates the supply chain from risk, but further encourages expertise and information transfer. ASDA regularly shares information regarding market development and has further collaborated with Vion and the SPP to boost the product development of less popular cuts of pig meat.

The horizontal collaboration brought about by the SPP has likewise reduced market risks. The cooperative provides non-payment insurance for its members and prompt payment, while its ability to engage with larger upstream firms is noted to reduce the transaction costs and uncertainty of marketing activities. The SPP also reduces costs by organising the transport of pigs and their various welfare verifications/ inspections and helps encourage efficiency by disseminating pig production innovations.

Source: Leat and Revoredo-Giha, (2013).

A1.3.4 Traceability and compliance

Research indicates that compliance with regulations (e.g. safety monitoring) and greater frequency of compliance checks are linked to greater internal visibility and awareness of issues, which contribute to increased resilience (Stone et al., 2015).

Compliance with traceability regulation, or indeed the individual furthering of traceability measures, can especially **enhance resilience** (Zhao et al., 2017). Traceability systems are important for recalling contaminated products, building resilience to the effects of contamination scares (Peck, 2006). It can further build resilience by **increasing supply chain visibility and consumer trust** on food safety (Zhao et al, 2017). As an example of this, articles discussing the Fipronil contamination of imported eggs to the UK in 2017 cited that consumers should look for British eggs, harbouring the lion mark, that have been deemed safe (Ward, 2017).

Research into compliance however indicates that focussing on compliance as a tool for business continuity management is **insufficient and a limited source of resilience**; organisations need to take a more **systematic approach** to the business continuity management in order to build the resilience of the food supply chain. Complying with regulatory requirements may transfer the liability for management of operating risks but does not “protect the company concerned from the operational consequences of such failures.” (Peck, 2016).

Similarly, studies suggest that focussing on compliance tends to encourage food suppliers, government and regulators to “legislate the risk out of supply chains” (British Food Journal, 2016); however, increased safety and resilience in the food supply chain requires a holistic approach aiming at prevention of risks, rather than reacting to them (EC DG Environment, 2014).

Other factors

Other factors noted by the literature to affect the resilience of specific firms or sectors are (Stone and Rahimifard, 2018):

- **Flexibility** - the ability of firms and sectors to swap suppliers, share materials, or have staff that fulfil multiple roles.
- **Agility** – the ability for a sector to quickly respond to changes in supply and demand (e.g. manufacturing flexibility of existing products).
- The effectiveness and efficiency of **information flow**.
- The diversity and complexity of inputs, suppliers, and customers.
- The **market power** of a firm, and its subsequent ability to pass on shocks

Annex 2 Data considerations

Annex 2 summary: Data considerations

This Annex describes the data we used for our analysis.

We start with a discussion of alternative indicators of economic activity that could be employed, noting the conceptual advantages and disadvantages of different measures.

Next, we provide an overview of how we define the UK agri-food and drink industry.

The Annex concludes with a review of available data sources of sectoral output, describing the data sources used for the analysis described in the main report as well as the reasons for not using alternative data sources.

A2.1 Indicator of economic activity

In order to assess the resilience of a sector to shocks empirically, thought needs to be given to which measure of economic activity is most relevant to the assessment. Possible alternatives for economic indicators able to capture sectoral business cycles are **output measures** such as gross value added, gross output quantities, gross production value or turnover on the one hand, and **input measures** such as labour inputs, raw material consumption or energy use on the other hand (Eurostat, 2006). The empirical literature concerned with the assessment of economic resilience mostly relies on gross value added (GVA) (Duval et al., 2007; Duval and Vogel, 2008), turnover (Canova et al., 2012) or employment (Blanchard and Wolfers, 2010; Sensier et al., 2016).

While employment data is **readily available** (in **real terms)** (Eurostat, 2006) at a monthly or **quarterly level,** less prone to data revisions (Coyle, 2014) and potentially more relevant from a policy perspective (Sensier et al., 2016), an output-based measure of economic resilience is likely to be better suited to capture sector-level responses to common macroeconomic shocks because employment may be a **lagging economic indicator due to labour market rigidities.** Moreover, as is the case with all input-based indicators, employment is only a good alternative to output measures for business cycle analysis purposes if few **homogeneous input factors** are needed for production and if **substitutive relationships** between input factors are small, which might not be equally the case across all agri-food and drink sectors. In addition, **changes in labour productivity over the modelling period,** which again might not be homogeneous across all food and drink sectors, would have to be explicitly factored in if economic resilience was measured in terms of employment volatility. Finally, an additional problem with the use of employment data might arise for the food and drinks services industry, for which activities of certain companies such as online food delivery companies (e.g. Deliveroo) that are based on self-employment models would not accurately be captured in the employment data.

Among the different types of output measures potentially available for further analysis (GVA, production value and turnover), **GVA (net output) is the preferred measure from a conceptual perspective.** GVA reflects an industry's own-value added as it deducts all the inputs that are not produced by the industry itself but obtained or purchased from other units from the industry's gross output. As such, GVA would be preferable for the index because it abstracts from changes in technical input-output relations (processing techniques) and changes in vertical integration over the modelling period[7]. In practice, very few national

[7] Another reason why GVA rather than gross output (turnover) is often used in economic analysis is that it allows the presentation of the output of different industries without double-counting the output that is being produced by one industry and used as an intermediate input in other industries. In a comparative analysis of sector-wide volatility, however, double-counting is not of any concern.

statistics offices collect high-frequency data on value added, and quarterly or monthly output data is often only available for indicators such as gross production value, output quantities or turnover.

Alternative output measures used in the literature are turnover and output quantities. **Turnover measures production sold on the market during the reference period** as opposed to goods or services produced during the reference period. Hence, if turnover data is not adjusted for changes in stock this can lead to a misinterpretation of turnover indices in terms of business cycle dynamics (Eurostat, 2006).

Despite these conceptual limitations, **turnover-based output measures are often used in the literature** (see for example Canova et al., 2012) because turnover is the only measure that is consistently available across a broad range of sectors. In the context of the agri-food and drink industry, for example, the concept of production cannot be easily defined for the wholesale, retail and service activities. Moreover, for industries with heterogeneous and extensive production ranges, turnover data is a better proxy of output compared to approaches relying on the quantity or value of individual production outputs (Eurostat, 2006).

A2.2 Sub-sectors of the UK agri-food and drink industry

The table below lists all sub-sectors, classified in terms of the UK Standard Industrial Classification (SIC), which form part of the UK agri-food and drink industry. Due to lack of granularity in available quarterly data series of industrial output, the following sectors in the table below are not covered in our analysis:

- 01.2: Growing of perennial crops
- 01.3: Plant propagation
- 01.5: Mixed farming
- 01.6: Support activities to agriculture and post-harvest crop activities
- 03.1: Fishing
- 03.2: Aquaculture
- 46.17: Agents involved in the sale of food; beverages and tobacco
- 47.81: Retail sale via stalls and markets of food; beverages and tobacco products
- 47.8: Retail sale via stalls and markets

The remaining sectors are covered either in terms of full (turnover-based) output, or in case of all primary sectors, by approximations using output quantity- rather than turnover-based indices.

Table 2 Sub-sectors of the UK agri-food and -drink industry, classified in terms of the UK Standard Industrial Classification (SIC)

1-digit sub-classes	2-digit sub-classes	3-digit sub-classes(1)	4-digit sub-classes
A: Agriculture, forestry and fishing	01: Crop and animal production, hunting and related service activities	01.1: Growing of non-perennial crops	01.11: Growing of cereals (except rice), leguminous crops and oil seeds
			01.12: Growing of rice
			01.13: Growing of vegetables and melons, roots and tubers
			01.14: Growing of sugar cane
			01.15: Growing of tobacco
			01.16: Growing of fibre crops
			01.19: Growing of other non-perennial crops
		01.2: Growing of perennial crops	01.21: Growing of grapes
			01.22: Growing of tropical and subtropical fruits
			01.23: Growing of citrus fruits
			01.24: Growing of pome fruits and stone fruits
			01.25: Growing of other tree and bush fruits and nuts
			01.26: Growing of oleaginous fruits
			01.27: Growing of beverage crops
			01.28: Growing of spices, aromatic, drug and pharmaceutical crops
			01.29: Growing of other perennial crops
		01.3: Plant propagation	01.30: Plant propagation
		01.4: Animal production	01.41: Raising of dairy cattle
			01.42: Raising of other cattle and buffaloes
			01.43: Raising of horses and other equines
			01.44: Raising of camels and camelids
			01.45: Raising of sheep and goats
			01.46: Raising of swine/pigs
			01.47: Raising of poultry
			01.49: Raising of other animals
		01.5: Mixed farming	01.50: Mixed farming
		01.6: Support activities to agriculture and post-harvest crop activities	01.61: Support activities for crop production
			01.62: Support activities for animal production
			01.63: Post-harvest crop activities
			01.64: Seed processing for propagation
	03: Fishing and aquaculture	03.1: Fishing	03.11: Marine fishing
			03.12: Freshwater fishing
		03.2: Aquaculture	03.21: Marine aquaculture
			03.22: Freshwater aquaculture
C: Manufacturing	10: Manufacture of food products	10.1: Processing and preserving of meat and production of meat products	10.11: Processing and preserving of meat
			10.12: Processing and preserving of poultry meat
			10.13: Production of meat and poultry meat products
		10.2: Processing and preserving of fish, crustaceans and molluscs	10.20 Processing and preserving of fish; crustaceans and molluscs
		10.3: Processing and preserving of	10.31: Processing and preserving of potatoes
			10.32: Manufacture of fruit and vegetable juice

		fruit and vegetables	10.39: Other processing and preserving of fruit and vegetables
		10.4: Manufacture of vegetable and animal oils and fats	10.41: Manufacture of oils and fats
			10.42: Manufacture of margarine and similar edible fats
		10.5: Manufacture of dairy products	10.51: Operation of dairies and cheese making
			10.52: Manufacture of ice cream
		10.6: Manufacture of grain mill products, starches and starch products	10.61: Manufacture of grain mill products
			10.62: Manufacture of starches and starch products
		10.7: Manufacture of bakery and farinaceous products	10.71: Manufacture of bread; manufacture of fresh pastry goods and cakes
			10.72: Manufacture of rusks and biscuits; manufacture of preserved pastry goods and cakes
			10.73: Manufacture of macaroni; noodles; couscous and similar farinaceous products
		10.8: Manufacture of other food products	10.81: Manufacture of sugar
			10.82: Manufacture of cocoa; chocolate and sugar confectionery
			10.83: Processing of tea and coffee
			10.84: Manufacture of condiments and seasonings
			10.85: Manufacture of prepared meals and dishes
			10.86: Manufacture of homogenised food preparations and dietetic food
			10.89: Manufacture of other food products n.e.c.
		10.9: Manufacture of prepared animal feeds	10.91: Manufacture of prepared feeds for farm animals
			10.92: Manufacture of prepared pet foods
	11: Manufacture of beverages	11.0: Manufacture of beverages	11.01: Distilling; rectifying and blending of spirits
			11.02: Manufacture of wine from grape
			11.03: Manufacture of cider and other fruit wines
			11.04: Manufacture of other non-distilled fermented beverages
			11.05: Manufacture of beer
			11.06: Manufacture of malt
			11.07: Manufacture of soft drinks; production of mineral waters and other bottled waters
G: Wholesale and retail trade; repair of motor vehicles and motorcycles	46: Wholesale trade, except of motor vehicles and motorcycles	46.1: Wholesale on a fee or contract basis	46.17: Agents involved in the sale of food; beverages and tobacco
		46.3: Wholesale of food, beverages and tobacco	46.31: Wholesale of fruit and vegetables
			46.32: Wholesale of meat and meat products
			46.33: Wholesale of dairy products; eggs and edible oils and fats
			46.34: Wholesale of beverages
			46.36: Wholesale of sugar and chocolate and sugar confectionery
			46.37: Wholesale of coffee; tea; cocoa and spices
			46.38: Wholesale of other food; including fish; crustaceans and molluscs
			46.39: Non-specialised wholesale of food; beverages and tobacco
	47: Retail trade, except of motor vehicles and motorcycles	47.1: Retail sale in non-specialised stores	47.11: Retail sale in non-specialised stores with food; beverages or tobacco predominating
		47.2: Retail sale of food, beverages and tobacco in specialised stores	47.21: Retail sale of fruit and vegetables in specialised stores
			47.22: Retail sale of meat and meat products in specialised stores

			47.23: Retail sale of fish; crustaceans and molluscs in specialised stores
			47.24: Retail sale of bread; cakes; flour confectionery and sugar confectionery in specialised stores
			47.25: Retail sale of beverages in specialised stores
			47.29: Other retail sale of food in specialised stores
		47.8: Retail sale via stalls and markets	47.81: Retail sale via stalls and markets of food; beverages and tobacco products
I: Accommodation and food service activities	56: Food and beverage service activities	56.1: Restaurants and mobile food service activities	56.10: Restaurants and mobile food service activities
		56.2: Event catering and other food service activities	56.21: Event catering activities
			56.29: Other food service activities
		56.3: Beverage serving activities	56.30: Beverage serving activities

A2.3 Data sources

As pointed out by Canova et al. (2012), one reason for the relative scarcity of empirical investigations of sector resilience is the **limited availability of appropriate industry data.**

In particular, given the administrative burden associated with detailed business surveys, detailed **information on firm-level output, intermediate inputs and value added is often only collected annually.** With annual data being unable to capture short-term economic cycles and/or to distinguish between sectors' absorption of common shocks and sectors' counteraction to shocks (Pelkmans et al., 2008), however, **quarterly[8] output data is preferred** for the purposes of the current study.

The most granular monthly and/or quarterly measures of **survey- or financial accounts-based output data[9]** available for the sectors of the UK agri-food industry are **output indices based on**

[8] While monthly output indices are available from both Eurostat and the ONS, monthly data is considered too volatile for the purposes of the present study and month-on-on-month growth rates are less informative than quarterly growth rates. See also: https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/methodologies/ukindexofproductionqmi

[9] While the ONS further publishes estimates of current-price (nominal) quarterly gross value added for some of the sub-sectors considered by this study, those estimates are derived by benchmarking current price output data (the undeflated production and services indices) at an industry level to annual nominal GVA data as part of the supply use balancing process. While this benchmarking process allows to adjust the output measure for intermediate inputs and changes in stocks, it does so at the price of potentially confounding the short-term business dynamics actually observed in the survey data by benchmarking by means of annual data. More importantly, the ONS warns against using these measures as different compilation measures are used for different time periods , especially in more recent years. Moreover, estimates past 2016 rely on the intermediate input estimates of 2016 – implicitly assuming that intermediate inputs are constant in the years after 2016. In addition, the wholesale and retail food sectors are not covered in this series, and neither is the primary sector at a sufficiently granular level. Finally, the ONS does not at present provide estimates of real GVA, which leads to additional issues as appropriate deflators are not always available at the right level of sector aggregation. For these reasons, we proceed using the turnover-based data from the indices of production and the indices of services for our main estimations. We do, however, employ the ONS' estimates of quarterly GVA, deflated using the Consumer Price Index (CPI) for food products, as a robustness test (see Section 5.4.1).

deflated[10] **turnover**[11]**.** These indices are an important feature in the compilation of gross domestic product, and are derived from **turnover reported in the monthly business survey as well as quarterly turnover data derived from HMRC VAT data**. The Office for National Statistics then deflates this turnover-based data **using a producer price index** for the respective industries and indexes the series for comparability at various levels of aggregation.

In spite of the limitations associated with the use of turnover rather than GVA-based output measures highlighted in the previous section, it is common to interpret changes in those turnover-based indices as **proxies for changes in real gross value added**[12][13]**,** and the indices are frequently used in empirical business cycle applications given their fast availability and detailed sector breakdown (Eurostat, 2006).

Data on (turnover-based) output indices was obtained from **both the ONS and Eurostat**[14], in order to maximise industry coverage (see Table 3)[15]. All ONS and Eurostat series used are seasonally and calendar adjusted.

No sufficiently granular quarterly deflated turnover indices exist for the UK **primary sector**[16]**.** In order to include a measure of production for sub-sectors of the primary sector, the following monthly data series were obtained from the **Department for Environment, Food and Rural Affairs (DEFRA):** wheat, barley and oat quantities used by UK breweries, oat millers and flour millers as a proxy for SIC sector 01.11 (Growing of cereals (except rice), leguminous crops and oil seeds); and total egg throughput as a proxy for SIC sector 01.47 (Raising of poultry). Further the following monthly series were obtained from Eurostat: slaughtering of home-fed animals as a proxy for SIC sector 01.4 (Animal production); and total milk production as a proxy for SIC sector 01.41 (Raising of dairy cattle). As discussed in the previous section, the use of output quantities is justifiable in sectors that produce **homogenous goods**.

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[10] Only nominal turnover indices are available for the wholesale industry. Several deflators were considered in order to appropriately deflate the turnover index for this sector, including the Consumer Price Index (CPI), Retail Price Index (RPI), the agricultural price index published by Defra and the price index used to deflate the retail food series in Eurostat's short-term business statistics. Consistent with the approach followed in the quarterly national accounts, the main estimations use CPI (for food products) to deflate wholesale production.

[11] For manufacturing industries, these output indices are named 'indicates of production' (see also here: https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/methodologies/ukindexofproductionqmi

[12] For up to date information on the methodology of compiling the indices of production see Office for National statistics: (https://www.ons.gov.uk/economy/economicoutputandproductivity/output/bulletins/indexofproduction/previousReleases)

[13] In fact, the ONS' estimates of real (chain-volume) quarterly gross value added as published here are based on the indices of production and turnover and as such not adjusted for intermediate inputs or changes in stocks. Given that, we prefer to use the underlying raw data, i.e. the indices of production and deflated turnover, for the purposes of this study rather than the ONS' estimates of real GVA that are based on these measures. The reason for this is the quarterly GVA series does not contain any information for sub-sectors 46.3, 47,11, and 47.2, and only very aggregate data for sub-sector 01. We do, however, rely on the ONS' real GVA dataset for our sensitivity analysis, as the quarterly real GVA series extends back to 1990 (as opposed to the production indices which are only available from 1998).

[14] Eurostat short-term business statistics data is in fact based on the UK Monthly Business Survey (MBS) conducted by the Office for National Statistics. Data is obtained from Eurostat, where possible, to take advantage of the interpolations and cross-sector standardisations carried out by Eurostat. Moreover, an index based on Eurostat data will be more easily replicable by the FSA.

[15] While both the ONS and Eurostat publish equivalent measures of the index of production, differences in quarterly coverage and industry coverage exist: The ONS does not publish quarterly indices for services sectors, and has no data for SIC 47.11, while Eurostat has missing data for SIC 10.2-3 (the level of aggregation published by the ONS), and 56. Eurostat further publishes (turnover-based) output indices for the food wholesale and retail trade sectors 46.3, 47.2, 47.11, which are not available at such a disaggregate level from the ONS.

[16] The aforementioned ONS estimates of quarterly GVA (both the current price and chain-volume measures) include estimates of output for SIC sector 01: Crop and animal production, hunting and related service activities. This includes a wide variety of sub-sectors ranging from the growing of tobacco, biofuels in addition to the growing of crops and raising of poultry and other animals. It further includes services activities such as hunting and trapping, and farm animal boarding and care. In light of this, the measure was deemed insufficiently granular for the purposes of the current study.

The production quantities as published by DEFRA are not seasonally adjusted. For the purposes of the present study, we removed seasonal variations the U.S. Census Bureau's software package for seasonal adjustment, X-12-ARIMA, which is used by many statistics offices internationally including the ONS. This approach allows for seasonality not to be constant over the modelling period.

Table 3 summarises the data sources used to derive output indices across the agri-food industry.

Table 3 Industry coverage and data sources

Industry	Industry name (short)[1]	SIC 2007	Source	Measure of output
Growing of cereals (except rice), leguminous crops and oil seeds	Cereals, crops & seeds	01.11	Defra	Quantities
Animal production (slaughtering)	Slaughtering	01.4	Eurostat	Quantities
Raising of dairy cattle (milk production)	Milk	01.41	Eurostat	Quantities
Raising of poultry (egg production)	Eggs	01.47	Defra	Quantities
Processing and preserving of meat and production of meat products	Meat	10.1	Eurostat	Deflated turnover(2)
Processing and preserving of fish, crustaceans, molluscs, fruit and vegetables	Fish & fruit/vegetables	10.2-3	ONS	Deflated turnover(2)
Manufacture of vegetable and animal oils and fats	Oils & fats	10.4	Eurostat	Deflated turnover(2)
Manufacture of dairy products	Dairy	10.5	Eurostat	Deflated turnover(2)
Manufacture of grain mill products, starches and starch products	Grain mill & starches	10.6	Eurostat	Deflated turnover(2)
Manufacture of bakery and farinaceous products	Bakery	10.7	Eurostat	Deflated turnover(2)
Manufacture of other food products	Other	10.8	Eurostat	Deflated turnover(2)
Manufacture of prepared animal feeds	Animal feeds	10.9	Eurostat	Deflated turnover(2)
Manufacture of soft drinks; production of mineral waters and other bottled waters	Soft drinks	11.07	Eurostat	Deflated turnover(2)
Wholesale of food, beverages and tobacco	Wholesale	46.3	Eurostat	Turnover(3)
Retail sale in non-specialised stores with food; beverages or tobacco predominating	Non-specialised retail	47.11	Eurostat	Deflated turnover
Retail sale of food, beverages and tobacco in specialised stores	Specialised retail	47.2	Eurostat	Deflated turnover
Food and beverage service activities	Services	56	ONS	Deflated turnover

Note: (1) We use abbreviated industry names throughout all graphs in this report. Those abbreviations are reported in column 2 of the table. (2) For the manufacturing industries, output indices are called Indices of Production (IoP). For the sectors under consideration for this study, all of those IoP are based on deflated turnover, and hence those output measures are directly comparable to the turnover-based volume of sales indices used for the trade industries and index of services used for the food and beverage services. (3) Consistent with the approach followed in the quarterly national accounts, our estimations use CPI (for food products) to deflate wholesale production.

Source: London Economics

The table below further provides a more detailed overview of all the data sources considered for this study, along with the rationale for including/excluding them for the purposes of the analysis provided in the main report.

Table 4 Alternative data sources considered for this report

Provider	Dataset	Relevant variable(s)	Sector disaggregation	Frequency	Coverage	Use; purpose; reasons chosen/not chosen
ONS	Annual Business Survey (ABS)	GVA (current basic prices); employment; capex; stocks	SIC level 4	Annual	2008-2017	Not used as an industry output measure; Insufficient frequency. Other measured not used; Turnover and employment are a less preferred measure to deflated turnover and indices of production which encompass deflated turnover. This dataset is also used to construct measure of the ratio of gross value added in turnover – the proportion of turnover that is attributable to gross value added (Simplistically: GVA = turnover – intermediate inputs).
	Annual Business Inquiry (ABI)	GVA (current basic prices)	SIC level 4	Annual	1995-2007	Not used as an industry output measure; Insufficient frequency.
	Index of production time series (ONS series: DIOP)	Index of production	SIC level 3	Annual, Quarterly Monthly	1995-2018	Used as output measure for SIC: 10.2-3 (Only a combined measure is published).
	Index of services time series (ONS series: IOS1)	Index of services (production)	SIC level 3	Annual, Monthly	1995-2018	Used as output measure for SIC: 56. SIC 56 is not available in the quarterly Eurostat data. An average of the monthly figures is taken as a proxy for quarterly figures. Assessing this same relation between SIC 47.2 in the data (Using Eurostat published data at the monthly and quarterly level) suggests that this only results in minor changes to the series; accuracy, with growth rates being preserved.
	Monthly Business Survey	Turnover (current prices)	SIC level 3/4	Annual, Quarterly Monthly	1996-2018	Not used; Turnover is a less preferred measure to deflated turnover and indices of production which consist of deflated turnover.
	Inflation and price indices	Consumer price index (CPI)	-	Annual, Quarterly Monthly	1989-2015	Used to deflate turnover for sector 46.3 (Food wholesale). Several deflators were considered: CPI, RPI, the agricultural price index published by Defra and the price index used to deflate the retail food series in Eurostat's short-term business statistics. Consistent with the approach followed in the quarterly national accounts, the main estimations use CPI to deflate wholesale production.

Eurostat	Short-term business statistics	Volume index of production; deflated turnover; turnover; producer prices; employment; wages; hours worked	SIC level 3	Monthly, Quarterly	1998-2018	Index of production measures are used as output measures for SIC: 10.1 – 10.9 (Excluding 10.2 and 10.3) (Manufacture of food products), and 11.07 (Manufacture of soft drinks; production of mineral waters and other bottled waters). Turnover data is used foe SIC 46.3 (Wholesale of food, beverages and tobacco) This is used given the importance of this sector. This series is deflated (See below).

						Deflated turnover data is used for sectors 47.11 (Retail sale in non-specialised stores with food; beverages or tobacco predominating) and 47.2 (Retail sale of food, beverages and tobacco in specialised stores). Published indices of production consist in most cases of only deflated turnover – as a result these essentially represent the same original survey data as the indices of production. Despite equivalent ONS coverage for many SIC codes Eurostat data is chosen when coverage is shared as it is more easily easier replicable by the FSA. Sector 11.01-6, the manufacturing of alcoholic beverages, has been excluded from the analysis as it is aggregated alongside SIC 12, the manufacture of tobacco products.
	National accounts: Gross value added (NACE Rev. 2 & Total)	Gross value added	SIC level 2	Quarterly	1995-2015	Not used; Insufficient SIC granularity. Used for measure of UK total gross value added at the quarterly level.
	Structural and Demographic Business Statistics (SDBS)	Production (Gross Output); Employment, GVA	SIC level 2	Annual	1995-2017	Not used; Insufficient SIC granularity.
	Primary sector statistics	Various measures of poultry output: e.g. Chicks of laying hen breeds (laying); Various measures of animal slaughtering; milk production	By component of the poultry sector	Monthly	Various -2017	Used as a proxy for the output of certain agricultural units (indices of production do not cover the primary sector): Slaughtering of animals (including bovine, pig, poultry and rabbit meat production) used as a proxy for the output of SIC 01.4. Milk production data used as a proxy for SIC 01.41; the raising of dairy cattle.
EU level analysis of capital (K), labour (L), energy (E), materials (M) and service (S) inputs (EU KLEMS)		GVA (current, basic prices); Gross Output (current basic prices); GVA price indices; employment	SIC level 1 and level 2 groupings for certain manufacturing industries	Annual	1995-2015	Not used; Insufficient SIC granularity.
Department for Environment, Food and Rural Affairs	Farm Business survey	GVA output (Crop, livestock etc); variable/fixed costs; labour costs; labour used; stock levels; output prices	Aggregate, with selected data by farm type	Annual	1995-2017	Not used for output measures; Insufficient frequency.

	Production (Monthly)	Production: Cattle, sheep, pig (slaughter); Eggs (quarterly); Poultry; Cereals production (Wheat)	By product	Monthly	~1990- 2017 (1980 for animal production)	Used as a proxy for the output of certain agricultural units (indices of production do not cover the primary sector): Oats usage for cereals & flour used as a proxy for SIC 01.11 (Growing of cereals (except rice), leguminous crops and oil seeds). This was deemed to better reflect shocks relative to other measures such as: Wheat & barley usage by brewers. Egg throughput data is used as a proxy for 01.47 (Raising of poultry). This was deemed to be a better alternative than Eurostat measures of poultry such as: Chicks of laying hen breeds (laying).

Source: London Economics

Annex 3 Identifying business cycles at the industry level

Annex 3 Summary: Identifying business cycles at the industry level

This Annex provides an overview of the business cycle literature and describes how we derived sectoral output gaps based on available industry output data (see also Annex 2).

In order to establish a meaningful counterfactual to establish how sectoral output would have developed in absence of a (common) shock, we need to explicitly examine business cycles at the sector level (see for example Martin and Sunley, 2014).

While business cycles dates are defined at the national level by established research organisations, e.g. the National Bureau of Economic Research (NBER) in the United States or the Centre for Economic Policy Research (CEPR) in the euro area, no such information is publicly available at the sector level. This section therefore introduces the strategies commonly employed in the business cycle literature to date and quantify the extent of business cycles.

A3.1 Business cycle literature

Business cycles are defined as 'recurrent sequences of alternating phases of expansion and contraction in economic activity' (OECD, 2001). Studies differ in their conceptual definition of 'economic fluctuations', and thus in their approach to identifying business cycles.

- The ***'classical business cycle'* literature** is concerned with fluctuations in the absolute *level* of economic activity (e.g. measured by real GDP) (Harding and Pagan, 2002; OECD, 2001). Studies employing a classical business cycle framework in the context of measuring economic resilience include Artis et al. (2004), Canova et al. (2012), and Sensier et al. (2016).
- The **'*growth cycle*' literature** refers to fluctuations in the deviation of observed economic activity from the estimated long-run potential level, i.e. fluctuations in the *output gap*. This approach involves separating economic output data, at the sector-level, into trend and cyclical components. Duval et al. (2007) and Duval and Vogel (2008) employ this approach in order to estimate the resilience of 20 OECD countries over the period 1982-2003.

We employ a growth cycle approach because it allows us to investigate sectoral deviations from trend in a panel context. In particular, using an output gap measure allows us to simultaneously capture several sectors' deviations from trend in any given quarter, whereas differences in the timing of peaks and troughs between different sub-sectors risks forsaking a proper, synchronised time dimensions for a panel (Canova et al., 2012). Moreover, the computerised procedures commonly used to identify turning points for classical business cycle analysis have been found not to be able to identify turning points in the Eurostat production volume data due to relatively short series and data interpolations (Canova et al., 2012).

A3.2 Measuring potential output and the output gap

The output gap is defined as the **difference between actual and potential output,** and commonly expressed in percent. Potential output is unobservable and has to be constructed based on available data.

Potential output is most commonly estimated by means of **statistical procedures** that split the series into cyclical and trend components. The use of statistical filters is preferred to alternative approaches to defining potential output and the output gap such as economic models or DSGE approaches because they are simple and transparent, and results can be easily reproduced.

We employ the **Hodrick and Prescott (HP) filter** in order to estimate output gaps[17]. The HP filter is the most widely known used univariate method for the estimation of the trend component of a time series, and largely used in scientific papers as well as by international organizations and institutions such as the IMF, OECD, European Central Bank (ECB) and the Economic and Financial Affairs Directorate and in the Economic Directorate of the European Central Bank (Mazzi and Scocco, 2003).

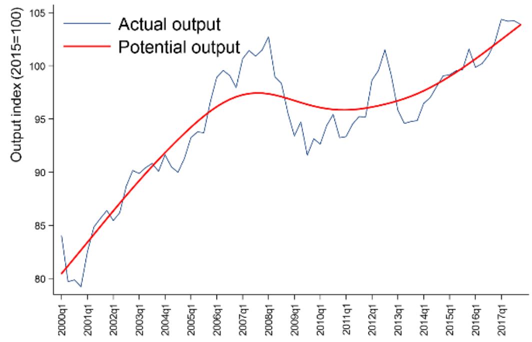
Applying the HP filter to the agri-food indices of production yields **a trend component** and a **cyclical component.** Conceptually, trend production can be understood as **potential output**, representing the **expected value of output in the absence of short-term shocks** but inclusive of longer run productivity or demand shocks that drive trend growth in production. The deviation between the de-trended output series (potential output) and actual output (in percent) in any given quarter can then be interpreted as a reflection of the impact of **any number of shocks that cause deviations from trend in that period**, including cyclical movements in aggregate demand or shocks such as extreme weather conditions.

The figure below illustrates the application of the HP filter and calculation of the output gap for the food and drink services industry (SIC sector 56), illustrating that the output gap increases during recessionary periods such as the Great Recession[18].

[17] While business-cycle features have been shown to be robust to the measurement approach chosen for quantification of potential output (see for example Duval et al., 2007; Duval and Vogel, 2008), we test whether our approach is sensitive to alternative filters in the sensitivity analysis (Section 6.3).

[18] Note that we also observe a falling value of potential or trend output during the Great Recession. There is evidence that large scale macro-shocks can significantly reduce trend growth (Haltmaier, 2012; European Commission, 2009). Such movements could be conceptually understood as a reduction in production capacity in light of reduced output over time.

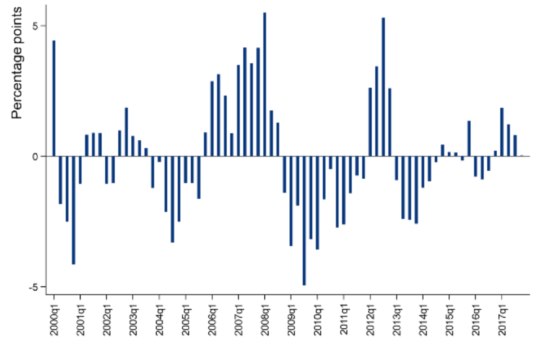
Figure 2 Potential and actual output: Food and beverage services



Note: Potential output is the trend component of the output series for the same sector, derived through application of the Hodrick-Prescott filter.

Source: London Economics' analysis based on data obtained from Eurostat, ONS and Defra.

Figure 3 Output gap: Food and beverage services



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics' analysis based on data obtained from Eurostat, ONS and Defra.

A3.2.1 Further information on the Hodrick-Prescott filter

The Hodrick and Prescott (1997) procedure minimises the following equation:

$\sum_{t=1}^{T}(lnY_t - lnY*_t)^2 + λ*\sum_{t=1}^{T-1}[(lnY*_{t+1} - lnY*_t)(lnY*_t - lnY*_{t-1})]^2$ ……………………………(6),

where Y is actual and Y* is trend output, and λ is a parameter that determines the smoothness of the trend component and consequently the length of the cycle.

Smoothing parameter λ

A pertinent question within literature leveraging Hodrick-Prescott (HP) filters is what value of smoothing parameter λ to select. The smoothing parameter can be understood as the parameter which penalises variability in the trend component of a series. The equation above minimises the difference between actual and the potential output values, while minimising the change in the trend value. These minimisations conflict and λ settles the trade-off between these two objectives.

Small λ imply a trend component more aligned with observed output and hence shorter cycles, while large λ imply a more linear trend in potential output and hence longer cycles. When λ=0, the trend component is simply the series (There is no cyclical component) and when λ approaches infinity the trend approaches a least square fit of a linear trend model (Hodrick and Prescott, 1997).

Implicitly, then, the selection of λ corresponds to an assumption surrounding the length of the business cycle, and how long run deviations from output potential can be.

In line with the literature, we chose λ=1,60019 for our quarterly dataset as a starting point, consistent with the parameter originally suggested by Hodrick and Prescott's (1980; 1997)20 and reflecting the assumption of an average duration of business cycles of 4-6 years (Duval et al., 2007; Duval and Vogel, 2008; Ladiray and Soares, 2003; Phillips and Jin, 2015)21.

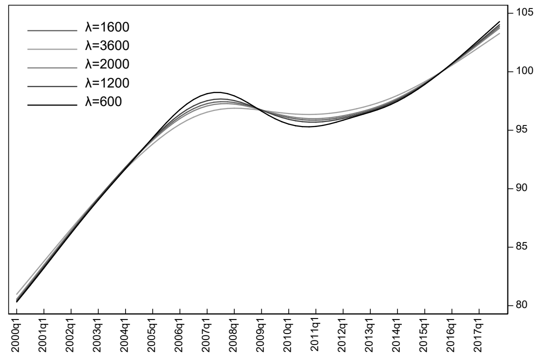
While we test the sensitivity of our results to the this choice of parameter, a preliminary investigation of the data (see Figures below) corroborates the earlier findings of Pesaran and Pesaran (1997, as cited in Duarte and Holden, 2003), who suggested that for the UK the trend series for quarterly data is often not sensitive to values of λ between 600 to 3600.

[19] Separate λ values for each industry were not selected in light of Hodrick and Prescott (1997) specifically recommending that all series be filtered by the same parameter – doing so ensures more reliable comparability.

[20] This choice was derived from an examination of US output data, and chosen to reflect an assumption that a moderately large change in the cyclical component within a quarter is around 5%, and a large change in the trend component within a quarter is around (1/8)%.

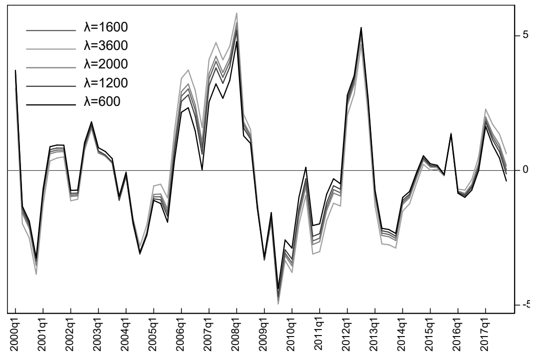
[21] Ravn and Uhlig (2002) extend this assumption to other frequencies, suggesting that a choice of λ=6.25 for annual data and λ=129600 for monthly data is appropriate.

Figure 4 Sensitivity of potential output to λ – trend components



Source: London Economics

FigureFigure 6 Sensitivity of potential output to λ – cyclical components

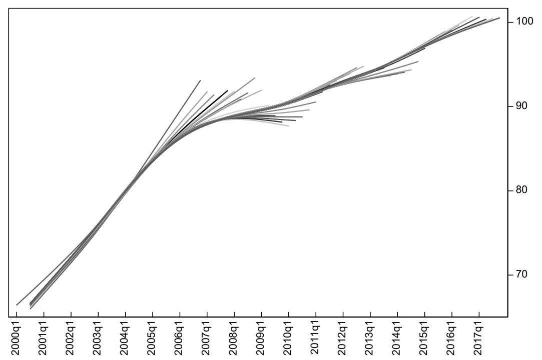


Source: London Economics

A3.2.2 Limitations of the Hodrick-Prescott filter

The HP filter leverages the assumption that **over a subsample we can eliminate noise in the data** (i.e. shocks) by observing what can be understood as, at least simplistically, a moving average of output data. As noted by Guay and St-Amant (2005) this assumes that the unobserved cyclical and trend **components of output are not correlated**, and further that the cyclical process resembles a white noise process – i.e. stipulating that across a sample shocks should approximately average to zero and be normally distributed. This assumption is especially relevant for more granular series, as noted by Grech (2013), showing that the HP filter is less reliable when estimating potential output for small economies or more granular sector breakdowns that exhibit **larger fluctuations, more pronounced trends, and recurrent structural breaks** – causing excess volatility in estimated potential output. The impact of structural breaks is specifically noted by Scacciavillani (1999), who highlights that structural breaks in the series can lead the HP filter to attributing shifts which represent changes in the level of potential output to cyclical and short run movements).

Figure 7 Revisions to potential output: Processing and preserving of fish, crustaceans, molluscs, fruit and vegetables (10.2-3)

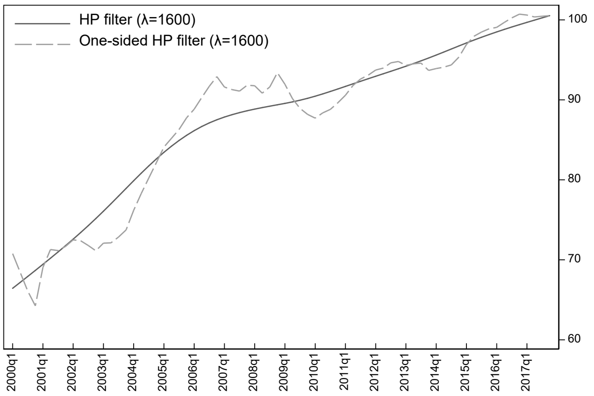


Note: 10.2-3 = Processing and preserving of fish, crustaceans, molluscs, fruit and vegetables.

Source: London Economics

Revisions in and of themselves are too a limitation surrounding the HP filter, with past values of the output gap series being altered by increases in sample size. The figure below shows that this does not pose a problem in general with non-endpoint runs of the series receiving limited revisions when the time sample is extended[22].

Figure 8 Revisions to potential output: Processing and preserving of fish, crustaceans, molluscs, fruit and vegetables (10.2-3)



Note: 10.2-3 = Processing and preserving of fish, crustaceans, molluscs, fruit and vegetables.

Source: London Economics based on data obtained from ONS.

A further concern expressed in the literature is the existence of an end-point problem when using the HP filter. The minimisation that occurs during the HP detrending process gives an undue weight to the last and first data points of the series, resulting in the movements of the end-points of data being disproportionately attributed to movements in trend as opposed to the cyclical component[23].

As a result, when the subsequent series are extended, revisions to the trend at end-points can occur – this can be seen in the Figure below where Baxter & King (1999) note that it takes three additional years for this bias to be fully eliminated. Cotis et al (2005) suggest that there is no practical remedy for this problem. The effect of this bias is considered to not be significant, given that all years in the sample are weighted equally in determining the resilience index – and therefore bias to real-time data should not adversely impact the resilience rankings.

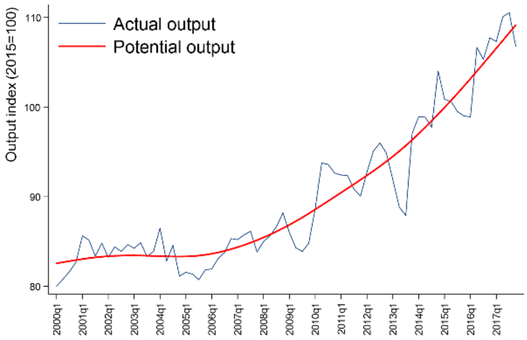
A3.3 Potential output and output gap over time

The figures below show how potential and actual output as well as the output gap developed over the modelling period, separately for each sub-sector.

[22] One method of preventing revisions is to use a one-sided, as opposed to a two-sided, HP filter (Hamilton, 2016). This method only considers past and current values when estimating potential output, depicted in Figure 14. This method has not been considered due to concerns that it amplifies the effect of the end-point problem.

[23] St-Amant and van Norden (1997) note that observations in the middle of the series have a 6 percent weight in the calculation of detrended data while the last observation accounts for 20 percent of the weight.

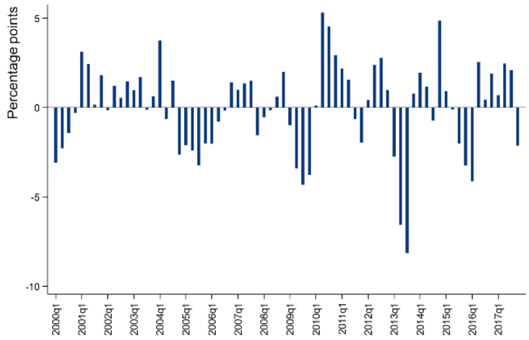
Figure 9 Potential and actual output: 01.11



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

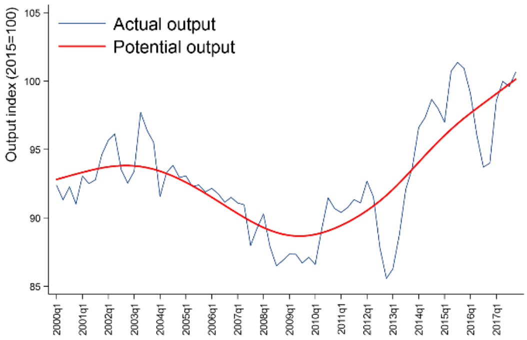
Figure 10 Output gap: 01.11



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

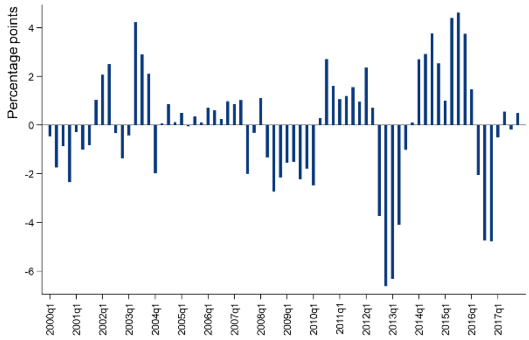
Figure 11 Potential and actual output: 01.41



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

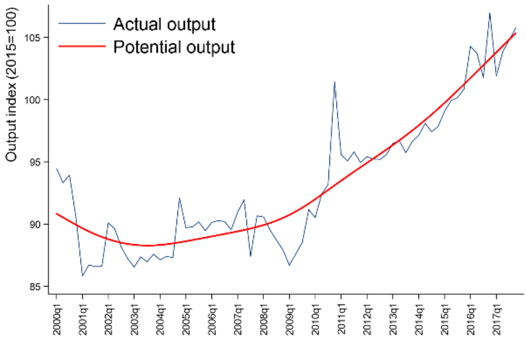
Figure 12 Output gap: 01.41



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

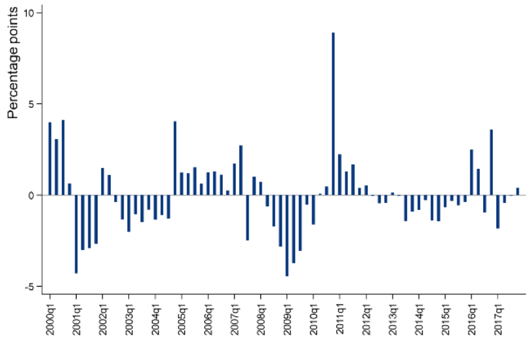
Figure 13 Potential and actual output: 01.4



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

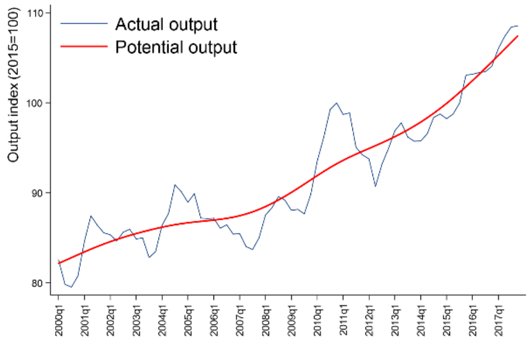
Figure 14 Output gap: 01.4



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

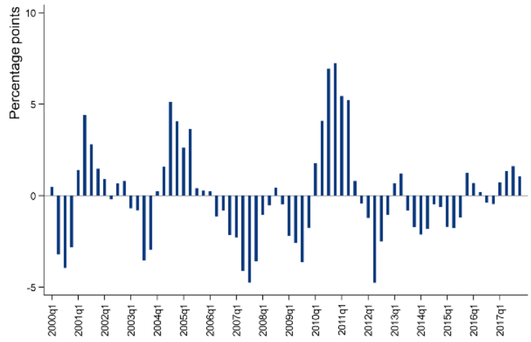
Figure 15 Potential and actual output: 01.47



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

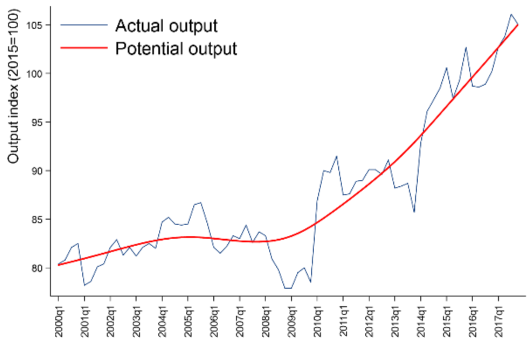
Figure 16 Output gap: 01.47



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

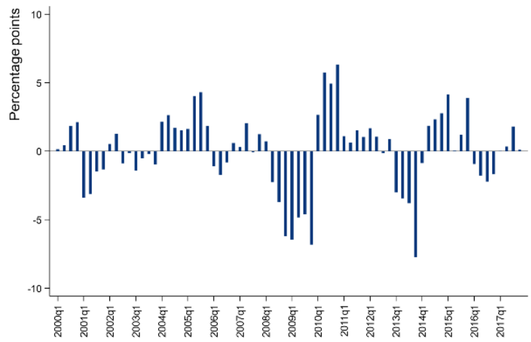
Figure 17 Potential and actual output: 10.1



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

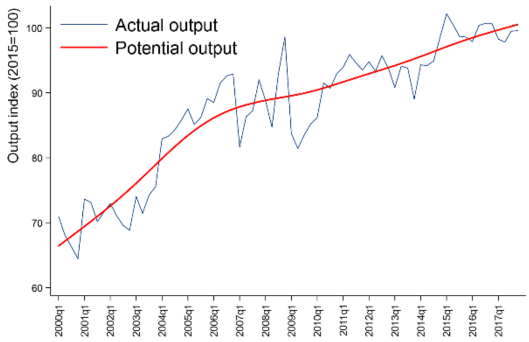
Figure 18 Output gap: 10.1



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

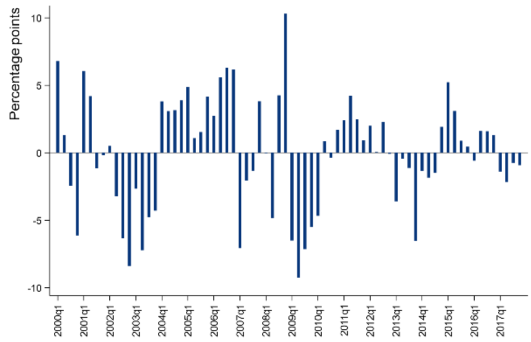
Figure 19 Potential and actual output: 10.2-3



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

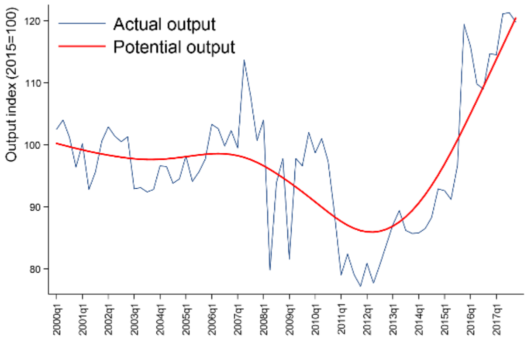
Figure 20 Output gap: 10.2-3



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

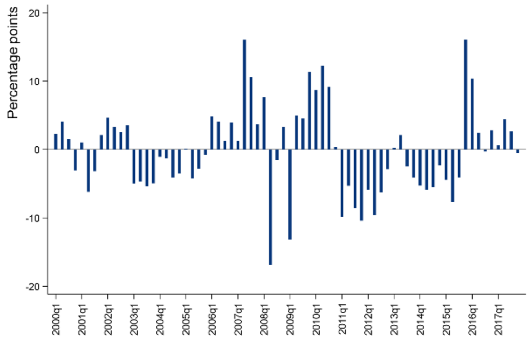
Figure 21 Potential and actual output: 10.4



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

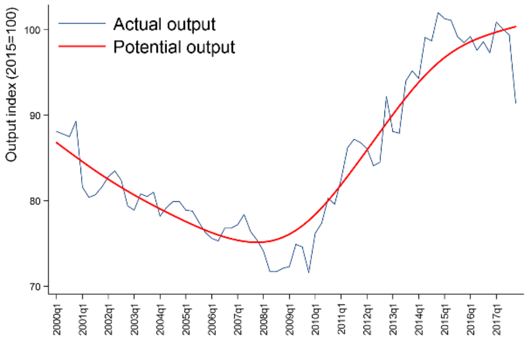
Figure 22 Output gap: 10.4



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

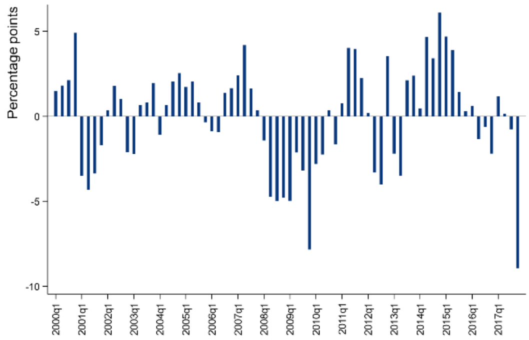
Figure 23 Potential and actual output: 10.5



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

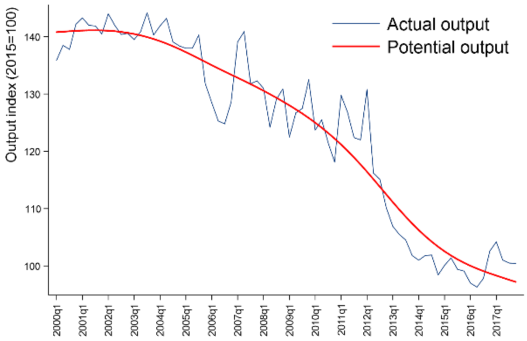
Figure 24 Output gap: 10.5



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

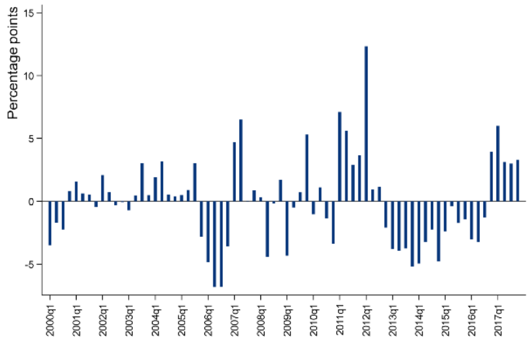
Figure 25 Potential and actual output: 10.6



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

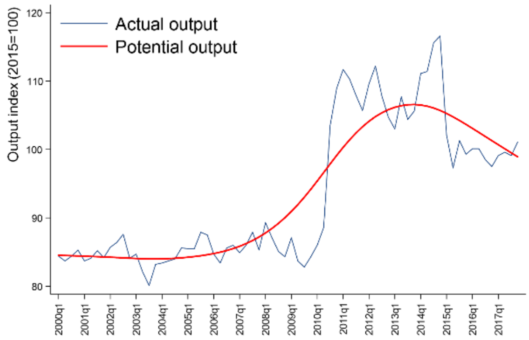
Figure 26 Output gap: 10.6



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

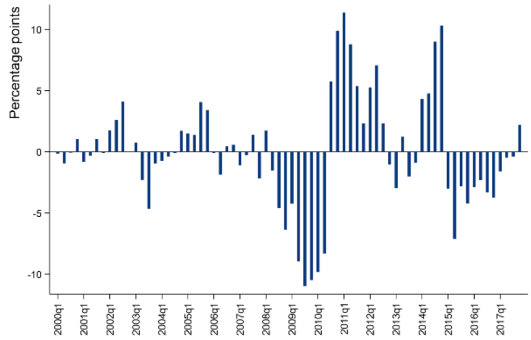
Figure 27 Potential and actual output: 10.7



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

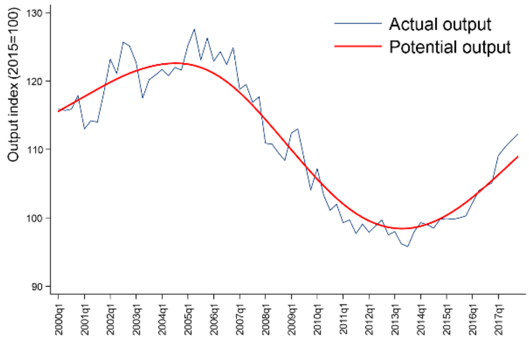
Figure 28 Output gap: 10.7



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

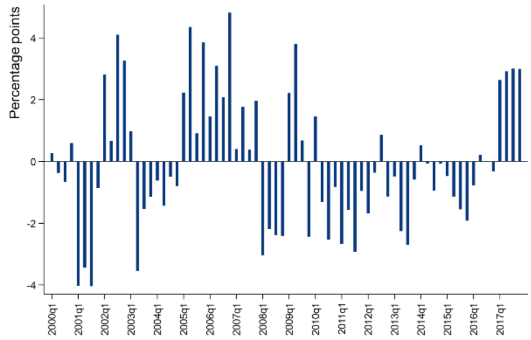
Figure 29 Potential and actual output: 10.8



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

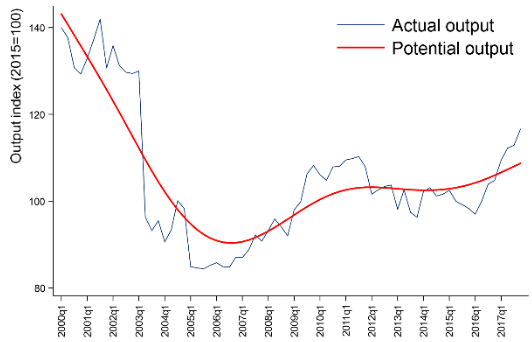
Figure 30 Output gap: 10.8



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

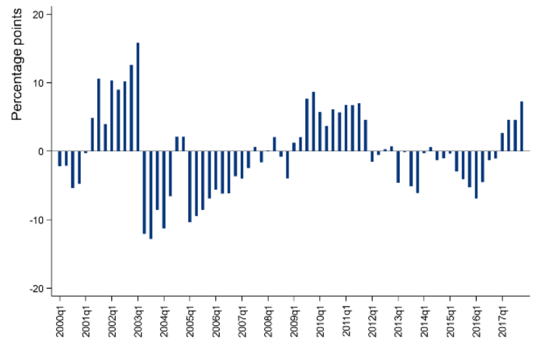
Figure 31 Potential and actual output: 10.9



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

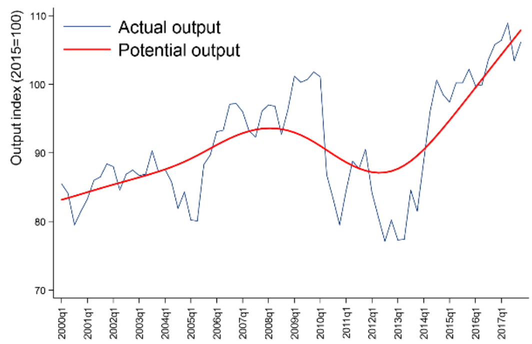
Figure 32 Output gap: 10.9



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

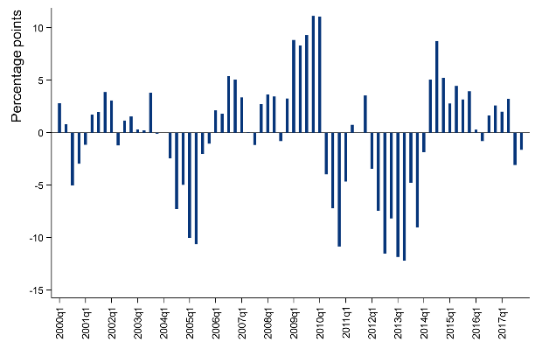
Figure 33 Potential and actual output: 11.07



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

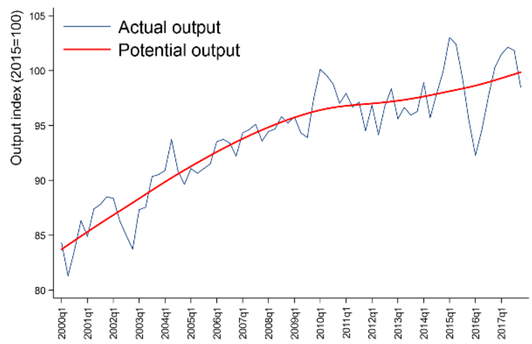
Figure 34 Output gap: 11.07



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

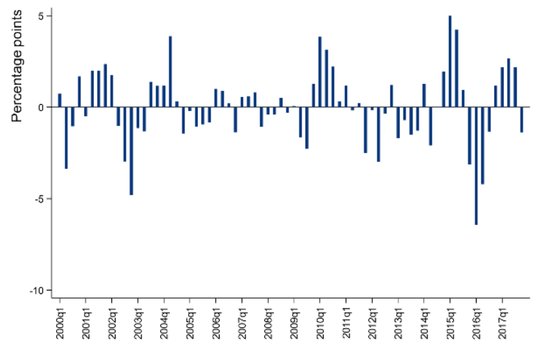
Figure 35 Potential and actual output: 46.3



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

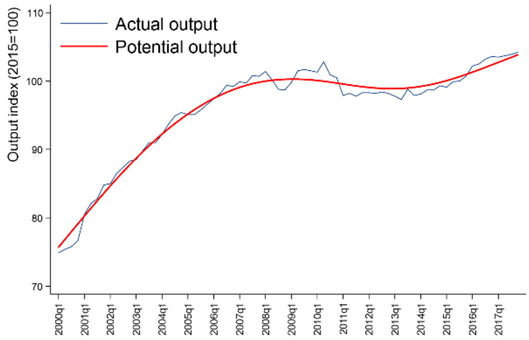
Figure 36 Output gap: 46.3



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

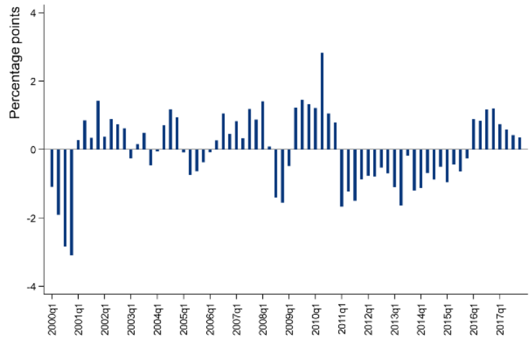
Figure 37 Potential and actual output: 47.11



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

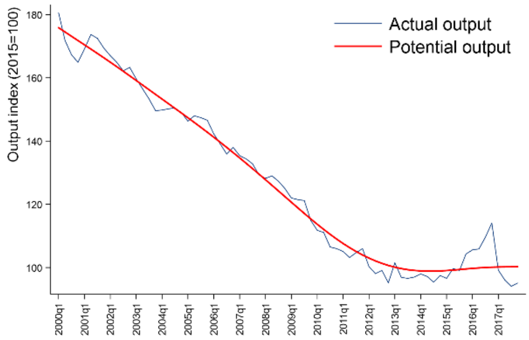
Figure 38 Output gap: 47.11



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

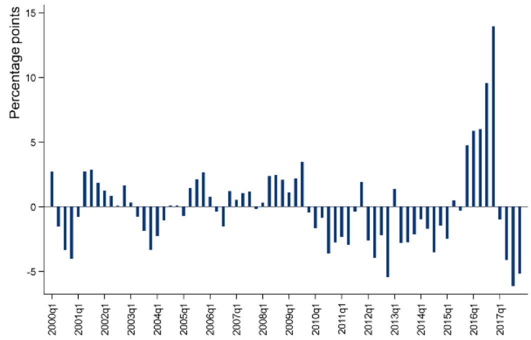
Figure 39 Potential and actual output: 47.2



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

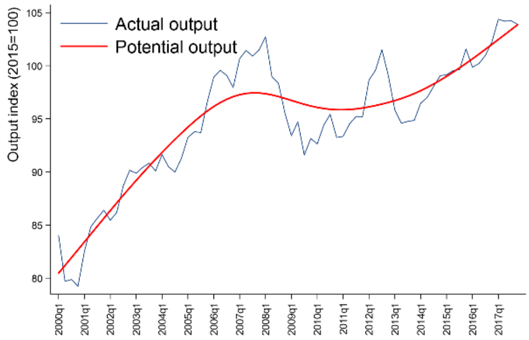
Figure 40 Output gap: 47.2



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

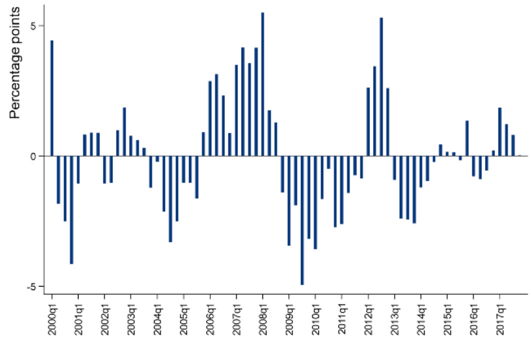
Figure 41 Potential and actual output: 56



Note: Potential output is the trend component of the application of the Hodrick-Prescott filter.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

Figure 42 Output gap: 56



Note: Output gap is the deviation of output from potential expressed in percent.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

Annex 4 Descriptive analysis of output in the UK agri-food and drink industry

Annex 4 Summary: Descriptive analysis of output in the UK agri-food and drinks industry

This Annex provides some background evidence for our analysis by:

- Showing data on output levels and volatility for the various agri-food and drink sectors over time;
- Including a simple analysis of the resilience of the sector following the economic crisis of 2008;
- Providing a preliminary analysis of the association between sectoral and aggregate output gaps.

A4.1 Sector output levels

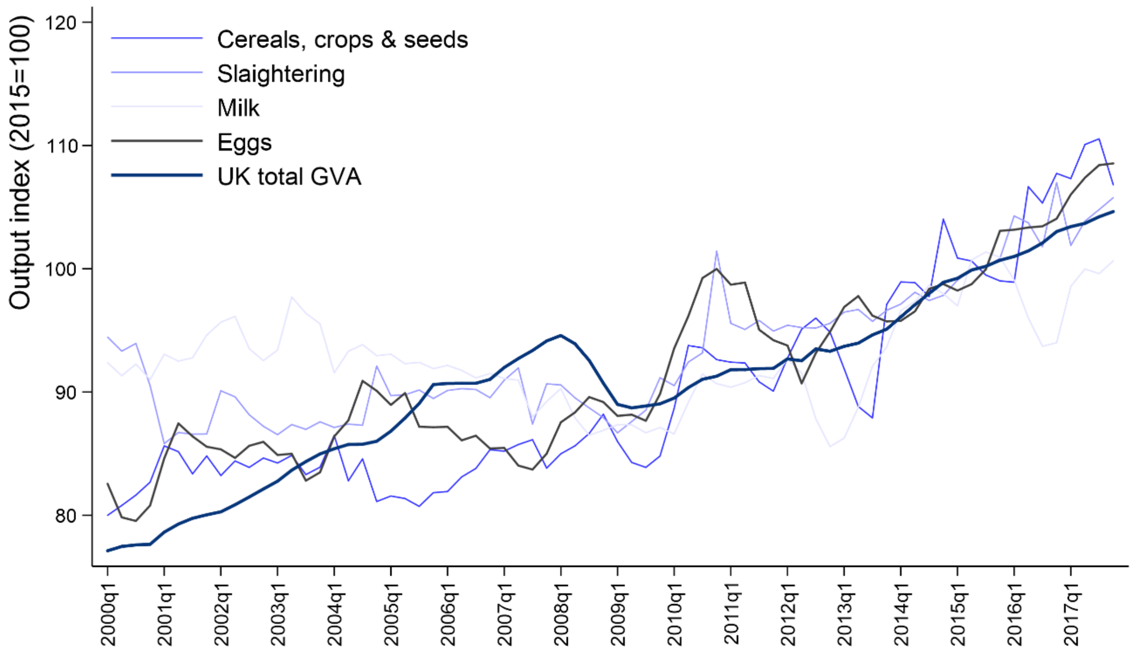
A4.1.1 Output indices over time

The figures below plot UK quarterly total GVA and the quarterly output indices for the sub-sectors of the UK agri-food and drink industry that were used for both the descriptive and statistical analyses underlying this study.

The figures highlight a number of points that further informed our analysis:

- Most output series exhibit a clear upward trend between 2000 and 2017, highlighting the **importance of disentangling trends and shocks within the data** and thus providing further justification for our
- For many series, the trend follows a similar growth path to UK total GVA (e.g. 10.1: processing and preserving of meat and production of meat products). However, the more granular series tend to be more volatile.
- Overall food manufacturing (10) is depicted in the Figure below in order to illustrate the effect that **aggregation has on smoothing volatility in output statistics**. The overall food manufacturing index of production follows a similar trend line to UK total GVA, although is significantly less volatile relative to the movements in SIC 10 subsectors. This highlights the value of granular data in establishing the true extent of output shocks.

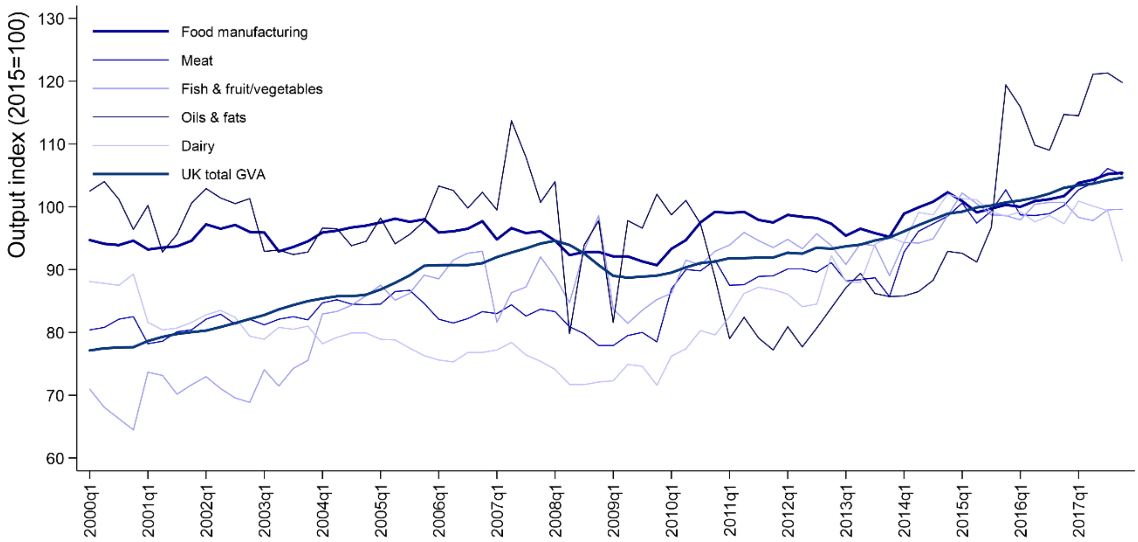
Figure 43 Output indices: Primary sector



Note: UK total GVA = Gross value-added of the UK measured as an index base year 2015 = 100 (source: Eurostat).

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

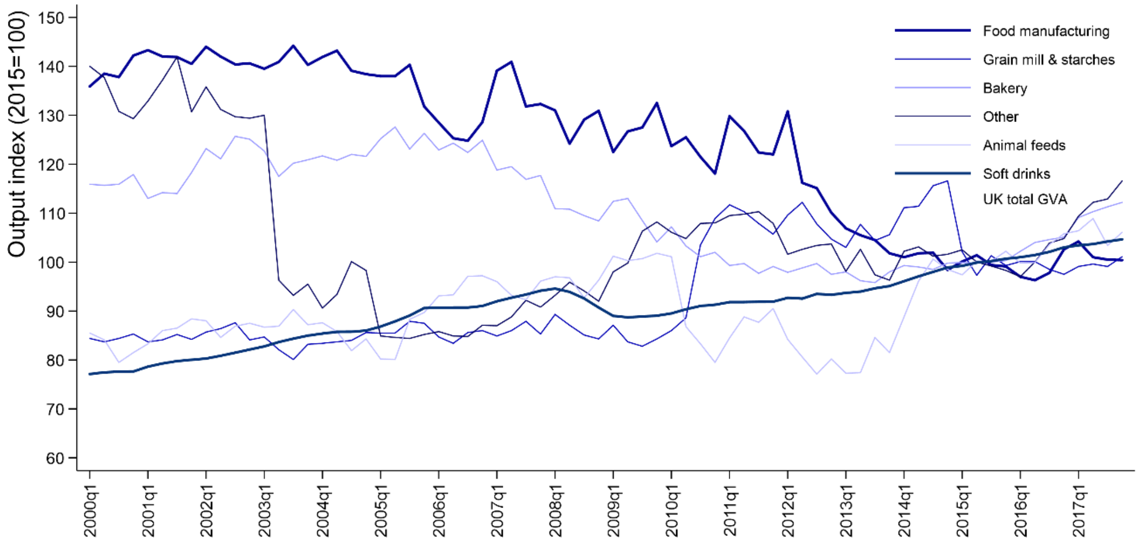
Figure 44 Output indices: Manufacturing sectors (a)



Note: UK total GVA = Gross value-added of the UK measured as an index base year 2015 = 100 (source: Eurostat).

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

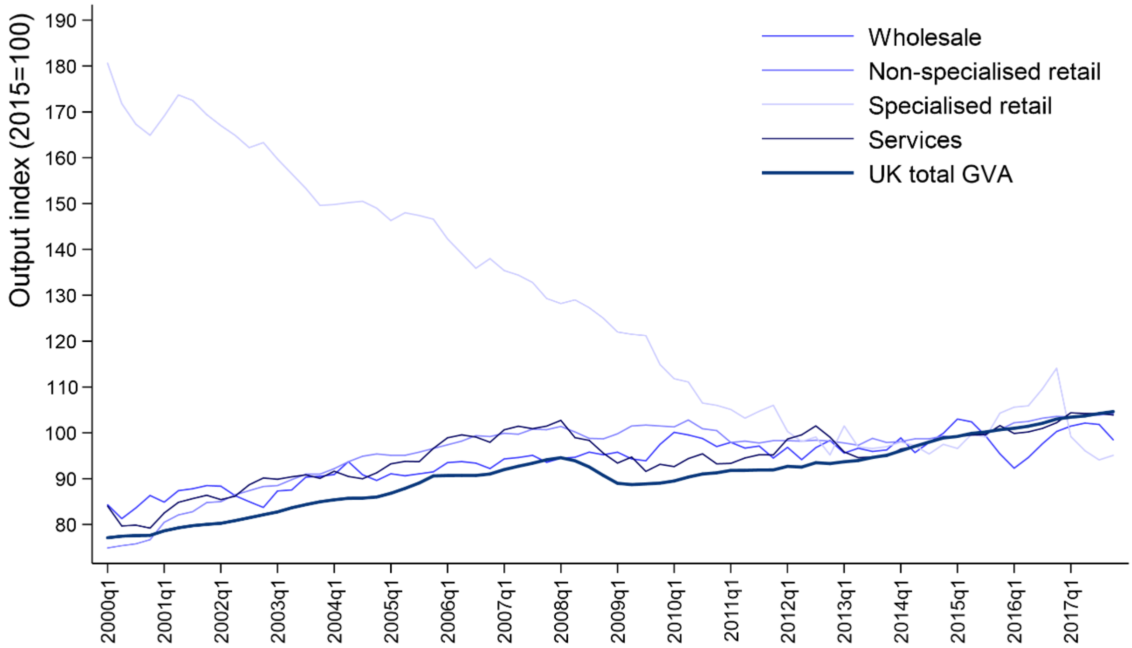
Figure 45 Output indices: Manufacturing sectors (b)



Note: UK total GVA = Gross value-added of the UK measured as an index base year 2015 = 100 (source: Eurostat).

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

Figure 46 Output indices: Beverages, retail, and wholesale sectors



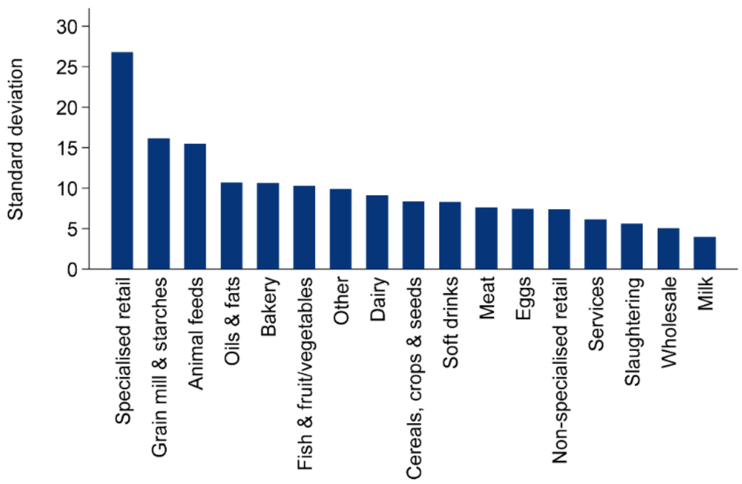
Note: UK total GVA = Gross value-added of the UK measured as an index base year 2015 = 100 (source: Eurostat).

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

A4.1.2 Output volatility

The figure below provides a first indication of output volatility across sectors, showing the variation (measured in standard deviations) of industry-level output levels over the modelling period (2000q1-2017q4). The figure shows that output is most volatile in the non-specialised retail sector (47.2), and least volatile in the milk production sector (01.41). Among the manufacturing industries, output for grain mill products, starches and starch products (10.6) and animal feeds (10.9) tends to be more volatile, while meat production (10.1) is less volatile.

Figure 47 Volatility: output standard deviation by sector



Note: standard deviation of industry-level output levels over the modelling period (1998q1-2018q3). Please refer to Table 3 for the official SIC codes and full names of the agri-food and drink sectors depicted in the graph above.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

Differences in terms of output volatility across sectors captured in the figure above might be due to either sectors' reaction to common shocks or the industries' exposure to sector-specific shocks. For example, the retail sector might be more volatile compared to the other industries either because it reacts more strongly to common shocks, or because it is exposed to more frequent idiosyncratic shocks than other industries.

Since most comparative studies focus on sectors' ability to common shocks only (see also Chapter 2 of the main report), we continue by examining whether and to what extent movements in the output of individual agri-food and drink sectors are associated with movements in aggregate UK GVA (left) and the total production of the UK agri-food industry[24] (right). This is done by looking at coefficients of correlation.

The figures show that output of the **non-specialised retail trade, wholesale trade and services industries tends to move into the same direction as aggregate GVA**, more so than the primary sector and most manufacturing industries. At the same time, the production of those sectors is more strongly associated with the production movements in total UK agri-food and drink production. The negative correlation between food retail output and aggregate GVA can be explained by differences

[24] Given that production is only available in a non-indexed form for a limited selection of industries this aggregate measure includes the following: 01 - Crop and animal production, hunting and related service activities ; 10 – the manufacture of food products ; 11.07 - manufacture of soft drinks, production of mineral waters and other bottled waters; 56 - Food and beverage service activities.

in growth trends and does not necessarily mean that the specialised retail industry is counter-cyclical (see Annexes 3.3 and 4.1).

Within the manufacturing industries, processing and preserving of fish, crustaceans, molluscs, fruit and vegetables (10.2 and 10.3) is the most strongly associated with both aggregate GVA and agri-food and drink industry output.

Caution should be taken in interpreting these results as being indicative of resilience, however, as the correlations provided below include both associations between short term shocks and longer run trends within each time series. Put differently, the high positive association between, for example, processing and preserving of fish, crustaceans, molluscs, fruit and vegetables (10.2 and 10.3) and UK GVA could be driven purely by a correlation in long-term trends rather than short-term shocks.

Figure 48 Correlation between indices of production and total UK GVA

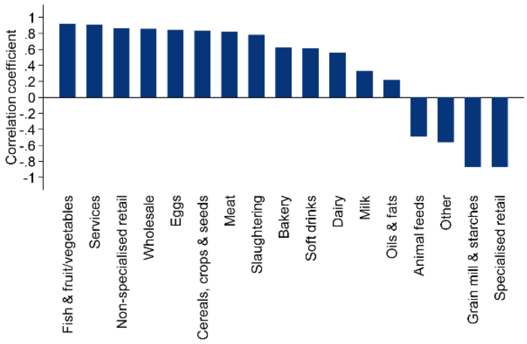
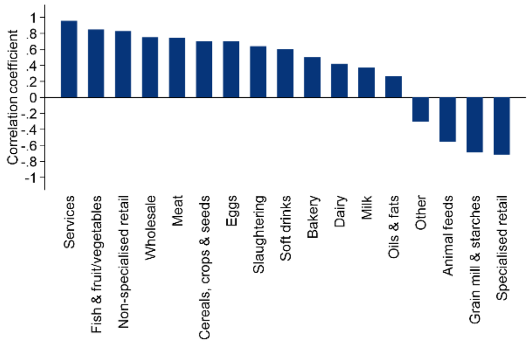


Figure 49 Correlation between indices of production and total agri-food output



Note: correlation coefficients over the modelling period (2000q1-2017q4). Agri-food output (Figure on the right) refers to the combined production of SIC: 01; 10; 11.07; 56. (Detrended with the HP filter λ=1600). Please refer to Table 3 for the official SIC codes and full names of the agri-food and drink sectors depicted in the graph above.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

Box 1 The UK agri-food and drink industry's resilience during the Great Recession (2008)

Adapting the approach used by Tan et al. (2017), the following provides an initial **estimate of the resilience** of the agri-food sector to the global financial crisis that started in 2008. In the absence of any further analysis of the sector-level output time series data, the great recession of 2008 has been chosen as a the time frame for comparison as it offers **an obvious and identifiable business cycle timeline** during which to compare how sectoral output changes respond to a common shock[25].

Following Tan et al. (2017), we rank sectors according to both their relative **shock absorption capacity**[26], defined here as the extent to which a sector **contracted relative to the national**

[25] The recessionary period is defined as 2008q2 to 2009q2, and the recovery period ad 2009q3-2013q3. See: https://www.onsgov.uk/economy/grossdomesticproductgdp/articles/the2008recession10yearson/2018-04-30

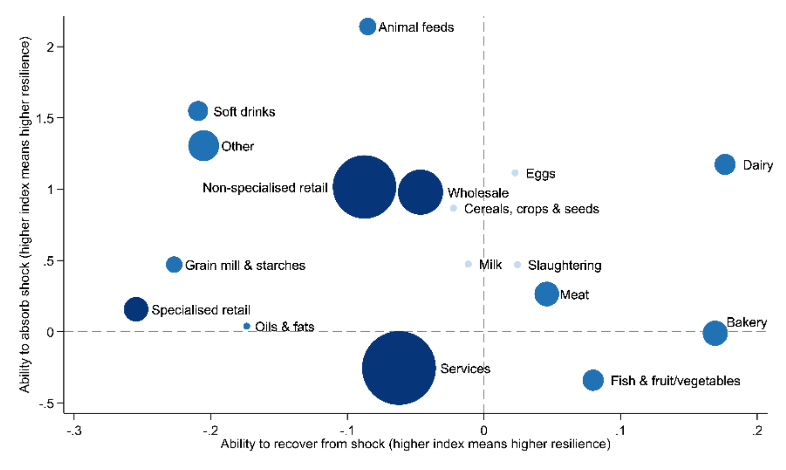
[26] Defined as 'resistance' by Tan et al. (2017).

economy over the recessionary period, and their **shock counteraction capacity**[27]**,** defined as the extent to which an industry **recovered relative to the national economy** during the recovery period. A positive value of shock absorption indicates that a sector's output **contracted more slowly than the national average**, and therefore is an indication of higher resilience. Similarly, a positive value of shock counteraction indicates that sector output **grew faster than the national economy** during the recovery period, and hence suggests that the sector is more resilient.

The figure below shows that the manufacturing of dairy products (10.5) has both relatively **high shock absorption and shock counteraction measures**, suggesting that it is more resilient to macroeconomic shocks than other sectors. Conversely, the food and beverage services industry (56) exhibits negative measures of both shock absorption and shock counteraction, indicating that it **contracted faster than the national economy over the recessionary period** (2008q2-2009q2), and then recovered slower than the national economy over the recovery period (2009q2-2013q3).

Overall, the preliminary analysis shows that most agri-food and drink industries (all sectors apart from the food and drink services industry (56) and the manufacturing of fish/vegetable products (10.2 and 10.3) contracted **less than the national economy** during the recessionary period, implying that the agri-food and drink industry is relatively resilient to macroeconomic shocks. This result is intuitive from an economic perspective, as many food products can be considered to be 'necessity goods'. Necessity goods are products and services that consumers will buy regardless of the changes in their income levels, meaning that those products are less sensitive to income change.

Figure 50 The great recession and recovery (2008-2013)



Note: The size of each marker in the above figure is weighted by each sectors' total GVA in 2017 (Based on the Annual Business Survey (ABS)), with the exception of the primary sector, for which GVA data is not published. Please refer to Table 3 for the official SIC codes and full names of the agri-food and drink sectors depicted in the graph above.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

The descriptive analysis provided in this Section and in Box 1 above is limited in both scope and accuracy. Most importantly, the analysis does not disentangle the effect of shock induced movements in output and trend output growth movements in the series, with for example growth in the aftermath of the Great Recession in the Box above being exclusively attributed to a sector's

[27] Defined as 'recoverability' by Tan et al. (2017).

shock counteraction capacity rather than the likely combination of trend growth and shock counteraction.

Overall, the preliminary analysis provided here highlights the need for taking account of sector-specific business cycle patterns in order to establish a reliable counterfactual (expected industry-level output developments in absence of a shock). This is achieved by looking at de-trended sectoral output series in the next chapter.

A4.2 Sector output gaps

The table below depicts the summary statistics of each sub-sectors' output gap series.

Average quarter on quarter trend growth, the growth in potential output, is broadly consistent in absolute terms across all industries, with **no overt anomalous results**. The maximum average trend growth observed is 1.68% (2013 – 2017) for the manufacture of vegetable and animal oils and fats (10.4), while the lowest observed is -1.68% (2000-2006) for the manufacture of prepared animal feeds (10.9). Although these growth rates are in part dictated by the assumptions surrounding the de-trending technique used to derive the output gaps, these values are indictive of fairly stable movements in trend output from quarter to quarter.

Similarly, the range of output gap values, the maximum positive and negative output gaps respectively (negative referring to when output is below trend), rarely exceed 10%. The series that do exhibit a sharp range of output gap values, for example the manufacture of prepared animal feeds (10.9), also exhibit greater output gap standard deviation across the whole series – indicating that the extremes observed are **reflected in output gap volatility across the whole series** (as opposed to just anomalous values).

Table 5 Summary Statistics

	Standard deviation	Range of output gap		Average Q-on-Q trend growth (%):		
				2000 - 2006	2007 - 2012	2013 - 2017
01.11 - Growing of cereals (except rice), leguminous crops and oil seeds	2.51	-8.15	5.31	0.07	0.46	0.75
01.4 - Animal production (slaughtering)	2.16	-4.46	8.92	-0.06	0.30	0.47
01.41 - Raising of dairy cattle (milk production)	2.33	-6.62	4.62	-0.09	0.05	0.44
01.47 - Raising of poultry (egg production)	2.63	-4.76	7.24	0.22	0.39	0.57
10. 1 - Processing and preserving of meat and production of meat products	2.84	-7.75	6.32	0.11	0.36	0.76
10. 2 and 10.3 - Processing and preserving of fish, crustaceans, molluscs, fruit and vegetables	4.10	-9.26	10.31	1.03	0.29	0.34
10.4 - Manufacture of vegetable and animal oils and fats	6.35	-16.90	16.05	-0.07	-0.54	1.68
10.5 - Manufacture of dairy products	3.01	-8.94	6.10	-0.51	0.69	0.60
10.6 - Manufacture of grain mill products, starches and starch products	3.48	-6.82	12.33	-0.20	-0.71	-0.73
10.7 - Manufacture of bakery and farinaceous products	4.59	-10.99	11.36	0.04	0.89	-0.34
10.8 - Manufacture of other food products	2.16	-4.04	4.82	0.11	-0.79	0.50
10.9 - Manufacture of prepared animal feeds	6.16	-12.84	15.85	-1.68	0.54	0.27
11.07 - Manufacture of soft drinks; production of mineral waters and other bottled waters	5.44	-12.23	11.13	0.40	-0.24	1.06
46.3 - Wholesale of food, beverages and tobacco	2.09	-6.43	4.99	0.41	0.16	0.14
47.11 - Retail sale in non-specialised stores with food; beverages or tobacco predominating	1.09	-3.09	2.82	0.99	0.01	0.24
47.2 - Retail sale of food, beverages and tobacco in specialised stores	3.24	-6.15	13.96	-0.94	-1.26	-0.02
56 -Food and beverage service activities	2.30	-4.95	5.50	0.70	-0.02	0.37

Note: By construction the mean of each output gap series equals 0.
Source: London Economics

We refine our preliminary analysis of correlations between sector-level output levels and aggregate (UK-wide or agri-food industry-wide) output (Section A4.1) by looking at correlations between output gaps.

Figure 51 shows the correlations between each sector's output gap series and the national output gap series (as calculated by the HP filter applied to UK total GVA). The interdependence between sectoral and aggregate output fluctuations presented below differs from the correlations in output levels provided in the previous section, indicating that movements in underlying output trends might have **distorted the earlier correlations** provided.

For example, the food wholesale and retail industries (46.3, 47.11, and 47.2) exhibit significantly less strong associations with aggregate UK output gaps compared to the correlations in levels, which might indicate that there is a st**rong association between the trend components of national GVA and food wholesale/retail output**, while the same does not hold true for cyclical fluctuations.

Figure 51 Correlation: Sector and national output gaps

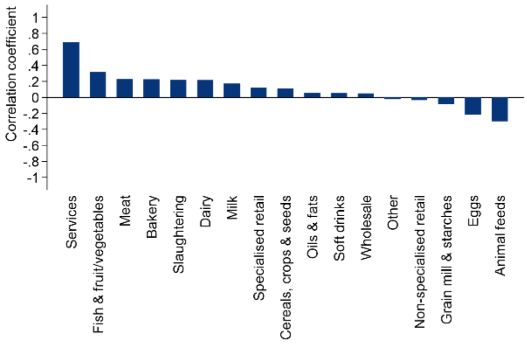
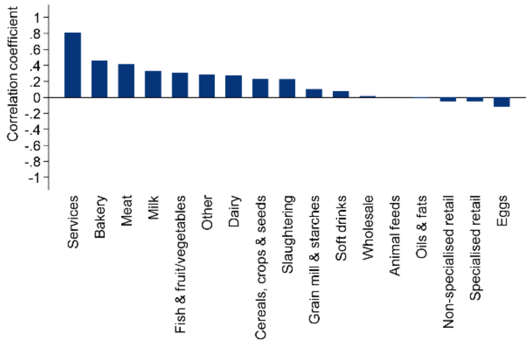


Figure 52 Correlation: Sector and agri-food industry output gaps



Note: correlation coefficients over the modelling period (2000q1-2017q4).

Output gaps are obtained by de-trending the series with the HP filter (λ=1600). Please refer to Table 3 for the official SIC codes and full names of the agri-food and drink sectors depicted in the graph above.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

Figure 52 depicts the pairwise association (correlation) between each sector' output gap and the output gap of the agri-food industry. The figure provides a first indication of either sector resilience or the transmission of shocks between sectors. For example, the high association between the output gap in the services sector and the output gap of the total industry might be due to a stronger impact of industry-wide shocks on the services sector compared to other sectors; however, the high positive correlation could also mean that shocks originating in the services industry are more likely to affect the rest of the UK agri-food and drink industry than shocks originating in other sectors.

Annex 5 Econometric analysis of economic resilience in the UK agri-food and drink industry

Annex 5 Summary: Econometric analysis of economic resilience in the UK agri-food and drink industry

This Annex provides additional information and results for the statistical analysis employed in the main report.

We provide additional technical information about the statistical method used to develop the two indices of economic resilience, starting with a description and justification of the estimator used in the main report as well as related estimators.

We then provide the test statistics that informed our main model specification, in particular stationarity tests to justify why we proceeded by estimation in levels and partial correlation functions and information criteria to justify the chosen order of autocorrelation (lag 1).

We then provide additional regression results not reported in the main body of this report.

A5.1 Estimation method

This section provides further background information on the main estimators used in the main report.

A5.1.1 Multi-factor error structure

Equations (5) and (6) in the main text represent a special case of the following generalised heterogeneous panel data model (as described in Chudik and Pesaran, 2015, or Neal, 2013):

$y_{it} = \phi_i y_{it-1} + \beta_i' x_{it} + u_{it}$……(7)

$u_{it} = c_{yi} + \gamma_i' \lambda_t + \varepsilon_{it}$……(8)

$x_{it} = c_{xi} + \Gamma_i' \lambda_t + v_{it}$……(9)

A5.1.2 Common correlated effects (CCE)

The Pesaran (2006) common correlated effects mean group estimator allows for the empirical setup as laid out in equations (7) to (9), which induces cross-section dependence, time-variant unobservables with heterogeneous impact across panel members and problems of identification (β_i is unidentified if the regressor contains λ_t).

Pesaran (2006) demonstrates that cross section averages of observed (dependent and independent) variables are able to adequately approximate the projection space of the unobserved common factors λ_t (under several conditions) for the case of a static (i.e. $\phi_i = 0 \ \forall$ i) panel.

He suggests running individual Ordinary Least Squares (OLS) regressions for each panel-unit on the following equation augmented by cross-sectional averages:

$y_{it} = \beta_i x_{it} + \delta_{xi} \bar{x}_t + \delta_{yi} \bar{y}_t + \varepsilon_{it}$……(10), where $\bar{x}_t$ and $\bar{y}_t$ are the cross-sectional averages of x_{it} and y_{it} across all panel units. Implicitly the cross-sectional averages are λ_t while γ_i is estimated. Given the group-specific estimation the heterogeneous impacts ϕ_i and γ_i are also given. The CCE then derives a mean group estimate by averaging across the individual coefficients.

A5.1.3 Augmented mean group (AMG) estimator

Eberhardt and Teal (2010) and Bond and Eberhardt (2013) develop the augmented mean group estimator as an alternative to Pesaran (2006). They use a two-step regression that includes a common dynamic effect to the individual panel unit regressions in the second stage. The dynamic effect is estimated through time dummies included in the first stage first-difference pooled regression.

In particular, they first estimate the following pooled first-difference regression augmented with time dummies:

$\Delta y_{it} = \beta \Delta x_{it} + \sum_{t=2}^{T} \mathrm{ct}\Delta \mathrm{Dt} + e_{it}$……………………………………………………………………………………………………(11)

In this pooled first-difference regression, D_t represents time dummies (starting from the second period as they are differenced). The coefficients to the time dummies, c_t , are turned into a variable shared across panel units µt , as a coefficient estimate will exist for each time period in the panel.

Stage two then consists of estimating the following equation:

yit = ai + βixit + diµˆt + eit………(12)

The time dummy coefficient variable included in (12) approximates the unobserved common factors that are potentially driving the variables in each panel unit the coefficients on the (differenced) year dummies are collected. They represent an estimated cross-group average of the evolution of unobservables over time. This is referred to as 'common dynamic process'. Like the CCE, mean group estimates are obtained by averaging coefficients across individual panel members.

A5.1.4 Dynamic common correlated effects (DCCE)

The standard CCE estimation method initially developed by Pesaran (2006) is unsuitable in models with a lagged dependent variable (Everaert and Groote, 2013), as is the augmented mean group estimator developed by Eberhardt and Teal (2010) and Bond and Eberhardt (2013) (see for example Neal, 2013).

Chudik and Pesaran (2015) extend the CCE approach to (heterogeneous) panel data models with lagged dependent variables and/or weakly exogenous regressors. They show that the CCE mean group estimator continues to be valid if a sufficient number of lags of cross-section averages is included in the individual equations of the panel and if the number of cross-section averages is at least as large as the number of unobserved common factors.

A5.1.5 Extensions

Neal (2015) further extends the DCCE estimation approach of Pesaran (2006) and Chudik and Pesaran (2015) by using Generalised Method of Moments (GMM) instead of OLS estimation in the panel-specific regressions, and by using lagged observations of the explanatory variables to form the instrument set. Neal (2015) demonstrates by means of Monte Carlo simulation that exchanging

OLS for GMM allows the CCE estimator to be robust to endogenous regressors in both static and dynamic panel data models, and that the use of GMM significantly improves the small sample properties of the estimator in dynamic panel data models regardless of whether the regressors are strictly exogenous, weakly exogenous, or endogenous. Similar to the original approaches, Neal's (2015) approach is robust to cross-sectional dependence and slope heterogeneity.

A5.1.6 Interpretation of common factors

γ_i – in theory – should capture how the sectors react to common shocks, and hence $\gamma_i'\lambda_t$ as estimated by *xtdcce2* (see below) can be used to rank sectors in terms of their reaction to common shocks (as λ_t is common to all sectors by construction).

It is important to note, however, that while DCCE estimation is often used in empirical applications to overcome the problems of cross-sectional dependence and heterogeneous slope factors discussed previously, it less common in the literature to explicitly estimate and interpret the common factors λ_t and the corresponding heterogeneous coefficients γ_i.

Indeed, (D)CCE estimation treats the set of unobservable common factors as a nuisance, and cross-sectional averages are merely present to blend out the biasing impact of the unobservable common factors. The estimated coefficients on the cross-section averaged variables as well as their average estimates are not, however, directly interpretable in a meaningful way (Eberhardt, 2012). In fact, the cross-sectional averages are approximations of λ_{jt} (where j is the j^{th} factor) and the interpretation of γ_{ji} is not straightforward given that the number of common factors in (D)CCE models is unknown.

However, $\gamma_i'\lambda_t$ contains the unknown number of common factors, and while the size of the coefficient does not have a meaningful interpretation, the relative ranking of sectors in terms of their load factor γ_i can be used to approximate sectors' capacity for absorbing or neutering common shocks.

A5.1.7 Implementation in Stata

We use Jan Dicken's *xtdcce2* command to implement the DCCE estimation in Stata28, and we follow the literature in including $\sqrt[3]{T}=\sqrt[3]{72}\approx 4$ cross-section lags.

We further correct for the small sample time series bias by jackknife correction, as Chudik and Pesaran (2015) find this method is more effective in dealing with the small sample bias than the recursive mean adjustment procedure.

In practice, we obtain estimates of $\gamma_i'\lambda_t$ by taking the difference between the residuals from estimation of (7) (u_{it}, including the common factors) and the residuals from estimation of (10) (ε_{it}, excluding the common factors). Having obtained estimates for $\gamma_i'\lambda_t$ for each period, we then calculate, for each sector, the average across all time periods. Note that this means we arrive at a weighted average of the heterogeneous factor loads γ_i whereby the weights are determined by the extent of the shocks λ_t

[28] *Xtdcce2* is preferred to *xtcce*, since the latter programme does not allow us to drop the panel-unit fixed effect and, more importantly, does not store $\gamma_i'\lambda_t$. It is also preferred to xtmg, which while allowing for estimation using the augmented mean group estimator, does not allow for the dynamic structure of our model and further does not allow to drop the panel-unit fixed effects. Moreover, xtmg provides estimates of γ_i but not of λ_t and thus does not contain the (unknown) number of common factors.

A5.2 Model specification

A5.2.1 Stationarity tests

The first step in setting up the appropriate model structure for the econometric analysis described in Chapter 3 of the main report consists of investigating whether our industry output gap time series are stationary. The table below reports the results for the augmented Dickey Fuller test[29], which tests the null hypothesis that that the variable under consideration contains a unit root. It shows that the null-hypothesis can be rejected at the 1% or 5% confidence level for all sectors, implying that the output gap follows a stationary process in all industries.

Table 6 Augmented Dickey Fuller test results

Sector	Z statistic	Cv1	Cv5	Cv10
01.11	-4.829			
01.4	-5.377			
01.41	-3.495			
01.47	-2.931			
10. 1	-3.822			
10.2/10.3	-5.364			
10.4	-5.089			
10.5	-3.702			
10.6	-4.664	-2.612	-1.950	-1.610
10.7	-3.234			
10.8	-4.550			
10.9	-3.411			
11.07	-3.242			
46.3	-4.694			
47.11	-3.612			
47.2	-3.864			
56	-3.711			
Levin-Lin-Chu unit-root test*	Unadjusted t	-16.7082		
	p-value	0.0000		

Note: *Joint Levin-Lin-Chu unit-root test.

01.11 - Growing of cereals (except rice), leguminous crops and oil seeds; 01.41 - Raising of dairy cattle (milk production); 01.47 - Raising of poultry (egg production; 01.4 - Animal production (slaughtering); 10. 1 - Processing and preserving of meat and production of meat products; 10. 2 and 10.3 - Processing and preserving of fish, crustaceans, molluscs, fruit and vegetables; 10.4 - Manufacture of vegetable and animal oils and fats; 10.5 - Manufacture of dairy products; 10.6 - Manufacture of grain mill products, starches and starch products; 10.7 - Manufacture of bakery and farinaceous products; 10.8 - Manufacture of other food products; 10.9 - Manufacture of prepared animal feeds; 11.07 - Manufacture of soft drinks; production of mineral waters and other bottled waters; 46.3 - Wholesale of food, beverages and tobacco; 47.11 - Retail sale in non-specialised stores with food; beverages or tobacco predominating; 47.2 - Retail sale of food, beverages and tobacco in specialised stores; 56 -Food and beverage service activities.

Source: London Economics analysis based on data obtained from Eurostat, ONS and Defra.

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[29] As is common practice (see for example Enders, 2014), we start with the most general formulation of the augmented Dickey Fuller test that allows for both trends and drifts in the time series. Allowing for trends and drifts if the underlying series does not contain trends/drifts reduces the power of the test, i.e., the ability of the test to reject the null hypothesis if it can be rejected. However, failing to allow for trends and drifts would lead to biased estimates in case the underlying series do contain trend/drift terms. Given that the null-hypothesis is rejected under this general specification despite the implied reduction of power, however, we do have to re-estimate without constant and/or drift terms.

A5.2.2 Order of auto-regression

Having established that the output gap series are stationary, the next step required for arriving at an appropriate model structure is to determine whether and how many lags of the output gap series should be included.

Partial autocorrelation functions

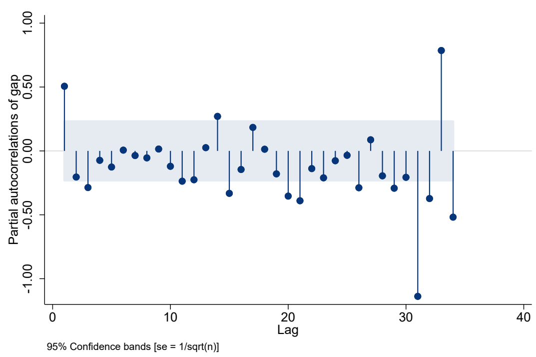
We start by visually inspecting the **partial autocorrelation functions (PACF)** for each sector to tentatively identify the numbers of AR terms that are needed.

The PACF plots visualise the *partial* correlation coefficients between the series and lags of itself. A partial autocorrelation in a time series context is the amount of correlation between a variable and a lag of itself that is **not explained by correlations at all lower-order-lags.** The autocorrelation of a time series Y at lag 1 is the coefficient of correlation between Yt and Yt-1, which is presumably also the correlation between Yt-1 and Yt-2. But if Yt is correlated with Yt-1, and Yt-1 is equally correlated with Yt-2, then we should also expect to find correlation between Yt and Yt-2. In fact, the amount of correlation we should expect at lag 2 is precisely the square of the lag-1 correlation. Thus, the correlation at lag 1 "propagates" to lag 2 and presumably to higher-order lags. The partial autocorrelation at lag 2 is therefore the difference between the actual correlation at lag 2 and the expected correlation due to the propagation of correlation at lag 1.

The patterns of PACFs can be used to determine the appropriate AR structure for a given time series. In particular, if the PACF plot cuts off sharply at lag k (meaning the partial autocorrelation is significantly different from zero at lag k and low in significance at the next higher lag), this is strong evidence of an AR(k) process, i.e. an autoregressive process of lag k .

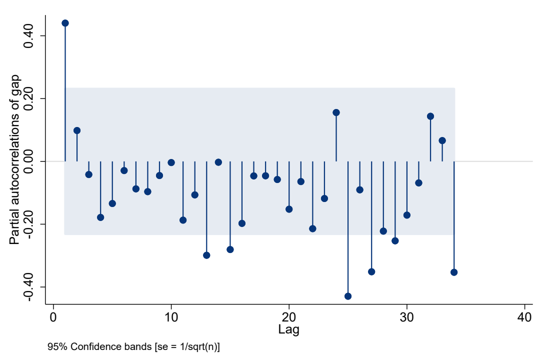
The figures below show the PACF for the sectors under consideration for this study. For most sectors, the PACF plot has a significant spike only at lag 1, meaning that all the higher-order autocorrelations are effectively explained by the lag-1 autocorrelation. This is indicative of an AR(1) process.

Figure 53 PACF for 01.11



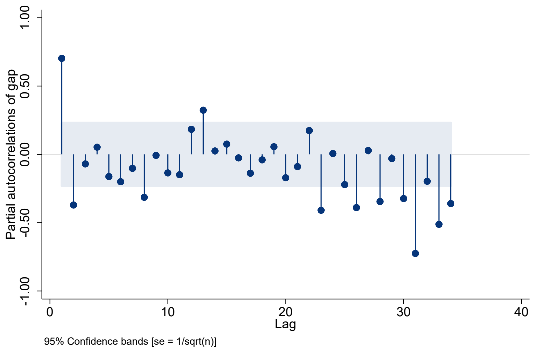
London Economics based on data obtained from Defra

Figure 54 PACF for 01.4



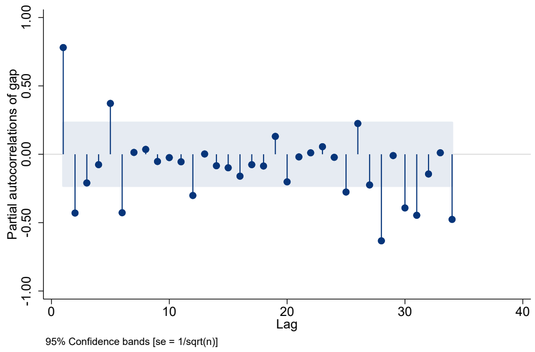
London Economics based on data obtained from Eurostat

Figure 55 PACF for 01.41



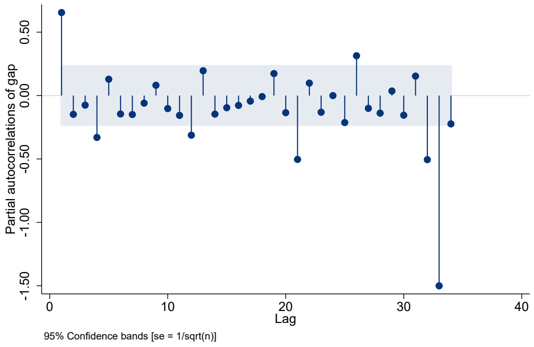
London Economics based on data obtained from Eurostat

Figure 56 PACF for 01.47



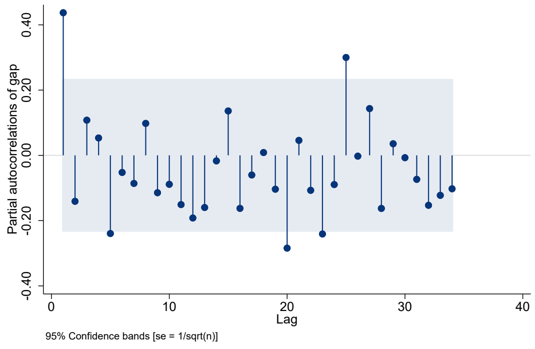
London Economics based on data obtained from Defra

Figure 57 PACF for 10.1



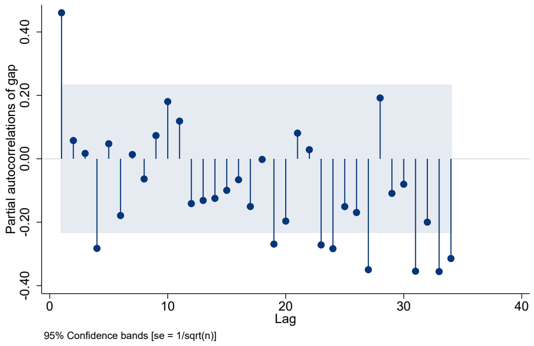
London Economics based on data obtained from Eurostat

Figure 58 PACF for 10.2-3



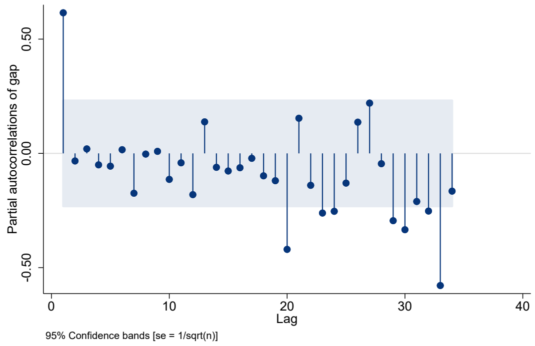
London Economics based on data obtained from Eurostat

Figure 59 PACF for 10.4



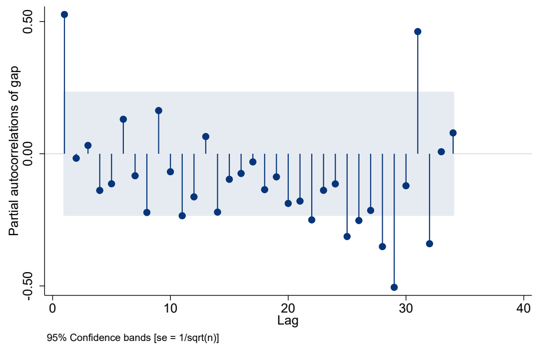
London Economics based on data obtained from Eurostat

Figure 60 PACF for 10.5



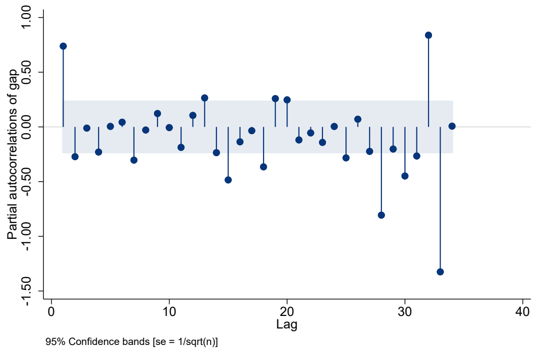
London Economics based on data obtained from Eurostat

Figure 61 PACF for 10.6



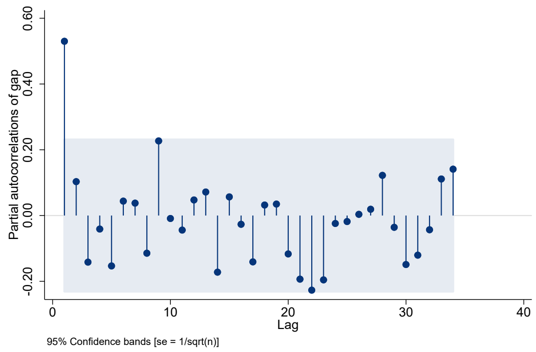
London Economics based on data obtained from Eurostat

Figure 62 PACF for 10.7



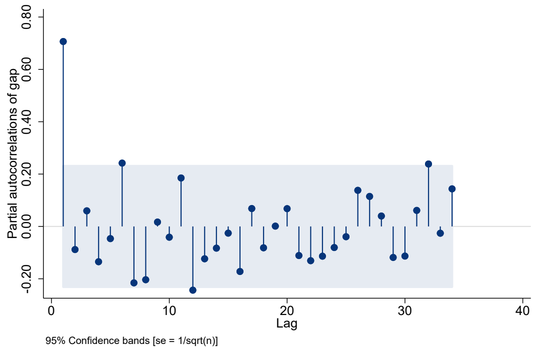
London Economics based on data obtained from Eurostat

Figure 63 PACF for 10.8



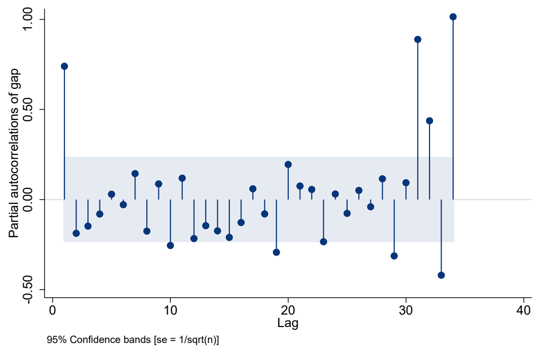
London Economics based on data obtained from Eurostat

Figure 64 PACF for 10.9



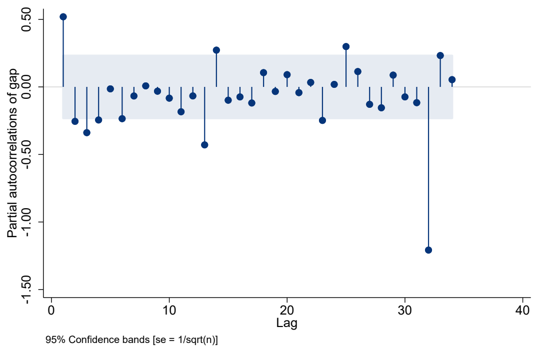
London Economics based on data obtained from Eurostat

Figure 65 PACF for 11.07



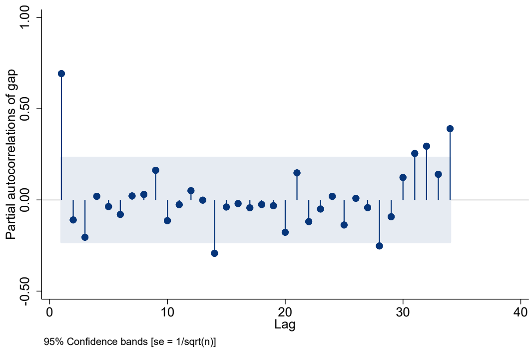
London Economics based on data obtained from Eurostat

Figure 66 PACF for 46.3



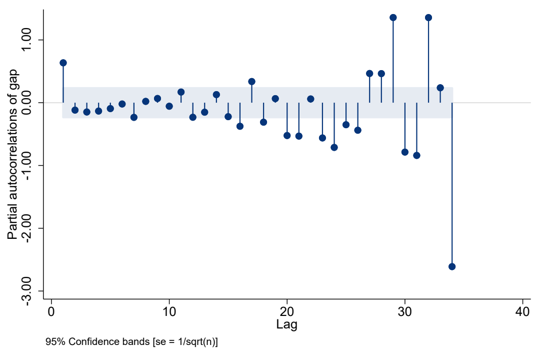
London Economics based on data obtained from Eurostat

Figure 67 PACF for 47.11



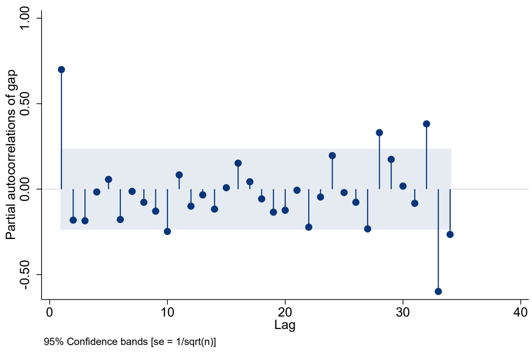
London Economics based on data obtained from Eurostat

Figure 68 PACF for 47.2



London Economics based on data obtained from Eurostat

Figure 69 PACF for 56



London Economics based on data obtained from Eurostat

Information criteria

After visual inspection of the correlation plots, we estimate AR models with up to six lags and compare the different AR-models based on the **Akaike information criterion (AIC)** and **Bayesian information criterion (BIC).** Both the AIC and BIC are lowest for AR(1) models of the output gap across all sectors, indicating that the output gap follows an AR(1) process.

Table 7 Akaike information criteria (AIC) and Bayesian information criteria (BIC) for different model lag lengths

Sector	Lag	AIC	BIC
01.11 - Growing of cereals (except rice), leguminous crops and oil seeds	Lag1	320.274	327.104
	Lag2	340.673	347.503
	Lag3	337.714	344.544
	Lag4	333.865	340.695
	Lag5	335.097	341.927
	Lag6	340.317	347.147
01.41 - Raising of dairy cattle (milk production)	Lag1	282.690	289.520
	Lag2	324.125	330.955
	Lag3	331.048	337.878
	Lag4	330.094	336.924

	Lag5	329.068	335.898
	Lag6	326.721	333.551
01.47 - Raising of poultry (egg production)	Lag1	281.778	288.608
	Lag2	332.717	339.547
	Lag3	347.665	354.495
	Lag4	345.967	352.797
	Lag5	344.791	351.621
	Lag6	343.561	350.391
01.4 - Animal production (slaughtering)	Lag1	303.908	310.738
	Lag2	314.567	321.397
	Lag3	319.380	326.210
	Lag4	319.380	326.210
	Lag5	317.819	324.649
	Lag6	317.948	324.778
10.1 - Processing and preserving of meat and production of meat products	Lag1	319.987	326.817
	Lag2	350.823	357.653
	Lag3	358.714	365.544
	Lag4	357.630	364.460
	Lag5	355.751	362.581
	Lag6	354.453	361.283
10.2/10.3 - Processing and preserving of fish, crustaceans and molluscs/Processing and preserving of fruit and vegetables	Lag1	396.846	403.676
	Lag2	412.068	418.898
	Lag3	412.206	419.036
	Lag4	411.429	418.259
	Lag5	411.458	418.288
	Lag6	408.997	415.827
10.4 - Manufacture of vegetable and animal oils and fats	Lag1	458.451	465.281
	Lag2	470.601	477.431
	Lag3	473.795	480.625
	Lag4	474.180	481.010
	Lag5	474.601	481.431
	Lag6	472.153	478.983
10.5 - Manufacture of dairy products	Lag1	339.407	346.237
	Lag2	360.160	366.990
	Lag3	365.253	372.083
	Lag4	367.376	374.206
	Lag5	367.988	374.818
	Lag6	367.916	374.746
10.6 - Manufacture of grain mill products, starches and starch products	Lag1	365.918	372.748
	Lag2	384.085	390.915
	Lag3	387.558	394.388
	Lag4	388.976	395.806
	Lag5	387.512	394.342
	Lag6	388.875	395.705

10.7 - Manufacture of bakery and farinaceous products	Lag1	373.210	380.040
	Lag2	415.169	421.999
	Lag3	426.297	433.127
	Lag4	428.799	435.629
	Lag5	426.907	433.737
	Lag6	426.597	433.427
10.8 - Manufacture of other food products	Lag1	297.474	304.304
	Lag2	311.521	318.351
	Lag3	319.436	326.266
	Lag4	320.101	326.931
	Lag5	318.422	325.252
	Lag6	319.166	325.996
10.9 - Manufacture of prepared animal feeds	Lag1	423.441	430.271
	Lag2	455.959	462.789
	Lag3	464.713	471.543
	Lag4	469.847	476.677
	Lag5	471.129	477.959
	Lag6	470.605	477.435
11.07 - Manufacture of soft drinks; production of mineral waters and other bottled waters	Lag1	396.694	403.524
	Lag2	436.213	443.043
	Lag3	449.896	456.726
	Lag4	453.214	460.044
	Lag5	452.769	459.599
	Lag6	452.066	458.896
46.3 - Wholesale of food, beverages and tobacco	Lag1	293.067	299.897
	Lag2	314.511	321.341
	Lag3	308.959	315.789
	Lag4	294.814	301.644
	Lag5	303.124	309.954
	Lag6	309.008	315.838
47.11 - Retail sale in non-specialised stores with food; beverages or tobacco predominating	Lag1	173.951	180.781
	Lag2	207.310	214.140
	Lag3	220.011	226.841
	Lag4	221.025	227.855
	Lag5	220.109	226.939
	Lag6	219.169	225.999
47.2 - Retail sale of food, beverages and tobacco in specialised stores	Lag1	343.356	350.186
	Lag2	371.359	378.189
	Lag3	378.549	385.379
	Lag4	377.702	384.532
	Lag5	376.713	383.543
	Lag6	376.331	383.161
56 - Food and beverage service activities	Lag1	277.544	284.374
	Lag2	312.538	319.368

	Lag3	326.506	333.336
	Lag4	329.139	335.969
	Lag5	329.071	335.901
	Lag6	327.101	333.931

A5.3 Additional regression results

This section provides additional regression results, including the resilience indices for additional sensitivity tests and original coefficient estimates for all estimations.

A5.3.1 Further evidence from sensitivity analysis

Alternative estimators

We re-estimate our regression using alternative time series panel estimators, in particular Pesaran' (2006) static common correlated effects estimator, Eberhard and Teal's (2010) augmented common correlated effects estimator, and Neal's (2015) extension of the dynamic common correlated effects estimator using 2SLS and GMM methods (see previous section for further details).

The table below shows that the resilience index in terms of sectors' ability to react to a shock is remarkably robust across the estimators relying on OLS. Neal's (2015) 2SLS and GMM extensions yield slightly different results.

Note that it is not possible to compute the shock absorption index for estimators that cannot be implemented using the *xtdcce2* command in Stata, as alternative commands do not provide the option of calculating the residuals including the common factors[30].

Table 8 Sensitivity of resilience index to alternative estimators

	Shock counteraction index$^{(1)}$	Shock absorption index$^{(2)}$
(Static) Common Correlated Effects	97%	88%
(Static) Augmented Common Correlated Effects$^{(3)}$	76%	
Dynamic Common Correlated Effects (OLS)$^{(3)}$	100%	100%
Dynamic Common Correlated Effects (2SLS)$^{(3)}$	65%	
Dynamic Common Correlated Effects (GMM)$^{(3)}$	44%	

Note: (1) Based on estimates of ϕ_i. (2) Based on Based on estimates of $\gamma_i \lambda_t$. (3) Model includes constant. Estimations are based on a balanced panel for 2000q1-2017q4. We use Jan Dicken's *xtdcce2* command to implement Pesaran's (2006) Common Correlated Effects and Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator. We use Markus Eberhardt's *xtmg* command to implement Eberhardt and Teal's (2010) Augmented Common Correlated Effects estimator. We use Timothy Neal's *xtcce* command to implement Neal's 2SlS and GMM versions of the DCCE estimator.

Source: London Economics analysis

The table below provides the full economic resilience indices for the alternative estimation methods.

[30] $u_{i,t}$

Table 9 Economic resilience indices for alternative estimators

	Ability to react to shock[1]						Ability to absorb shock[2]		
	Main (Dynamic Common Correlated Effects OLS)	(Static) Common Correlated Effects	(Static) Augmented Common Correlated Effects[3]	Dynamic Common Correlated Effects (OLS)[3]	Dynamic Common Correlated Effects (2SLS)[3]	Dynamic Common Correlated Effects (GMM)[3]	Main (Dynamic Common Correlated Effects OLS)	(Static) Common Correlated Effects	Dynamic Common Correlated Effects (OLS)[3]
Cereals, crops and seeds	91 *(2)*	100 *(2)*	80 *(4)*	92 *(2)*	92 *(2)*	50 *(6)*	81 *(12)*	78 *(11)*	81 *(12)*
Slaughtering	100 *(1)*	100 *(1)*	99 *(2)*	100 *(1)*	61 *(4)*	56 *(5)*	92 *(8)*	89 *(7)*	92 *(8)*
Milk	22 *(13)*	19 *(13)*	23 *(13)*	22 *(12)*	48 *(6)*	69 *(3)*	98 *(3)*	93 *(4)*	98 *(3)*
Eggs	8 *(16)*	5 *(16)*	0 *(17)*	8 *(16)*	5 *(15)*	21 *(13)*	94 *(6)*	87 *(9)*	93 *(7)*
Meat	50 *(6)*	61 *(6)*	37 *(10)*	50 *(6)*	47 *(7)*	45 *(9)*	82 *(11)*	66 *(14)*	82 *(9)*
Fish & fruit/vegetables	41 *(7)*	57 *(7)*	100 *(1)*	41 *(7)*	100 *(1)*	100 *(1)*	77 *(13)*	48 *(16)*	77 *(13)*
Oils & fats	33 *(9)*	40 *(10)*	93 *(3)*	33 *(8)*	42 *(8)*	50 *(7)*	0 *(17)*	0 *(17)*	0 *(17)*
Dairy	27 *(11)*	48 *(8)*	48 *(8)*	28 *(11)*	25 *(10)*	37 *(10)*	93 *(7)*	88 *(8)*	94 *(6)*
Grain mill & starches	74 *(3)*	67 *(4)*	74 *(6)*	72 *(3)*	53 *(5)*	60 *(4)*	53 *(16)*	67 *(13)*	53 *(16)*
Bakery	0 *(17)*	0 *(17)*	12 *(15)*	0 *(17)*	22 *(12)*	33 *(11)*	77 *(14)*	73 *(12)*	77 *(14)*
Other	58 *(5)*	69 *(3)*	73 *(7)*	57 *(5)*	18 *(13)*	29 *(12)*	100 *(2)*	100 *(2)*	99 *(2)*
Animal feeds	36 *(8)*	43 *(9)*	22 *(14)*	31 *(9)*	7 *(14)*	11 *(15)*	82 *(9)*	48 *(15)*	82 *(11)*
Soft drinks	16 *(15)*	8 *(15)*	12 *(16)*	16 *(14)*	4 *(16)*	8 *(16)*	82 *(10)*	93 *(5)*	82 *(10)*
Wholesale	*65 (4)*	*66 (5)*	*76 (5)*	*65 (4)*	*76 (3)*	*89 (2)*	*100 (1)*	*92 (6)*	*100 (1)*
Non-specialised retail	32 *(10)*	38 *(11)*	42 *(9)*	30 *(10)*	24 *(11)*	21 *(14)*	97 *(4)*	100 *(1)*	98 *(4)*
Specialised retail	27 *(12)*	31 *(12)*	26 *(11)*	20 *(13)*	30 *(9)*	50 *(8)*	94 *(5)*	100 *(3)*	94 *(5)*
Services	16 *(14)*	14 *(14)*	23 *(12)*	15 *(15)*	0 *(17)*	0 *(17)*	76 *(15)*	80 *(10)*	76 *(15)*

Note: (1) Based on estimates of ϕ_i. (2) Based on Based on estimates of $\gamma_i \lambda_t$. Based on a balanced panel for 2000q1-2017q4. Estimated using Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator, implemented by Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.

Source: London Economics' analysis

Alternative de-trending methods

Since different de-trending methods may yield different growth cycle chronologies (Canova et al., 2012), we replicate the analysis using alternative smoothing parameters for the Hodrick-Prescott filter as well as an alternative time-series filter (developed by Baxter-King).

For the original (main) regressions, we have employed a parameter of λ=1,600, which corresponds to business cycles of between four and six years. For the sensitivity analysis, we consider parameter values of λ=600 and λ=3,600, in line with Pesaran and Pesaran (1997, as cited in Duarte and Holden, 2003). The table below shows that results are remarkably consistent across filtering methods as far as the shock counteraction index is concerned. The shock absorption index changes, however, quite significantly for when the Baxter King filter is used instead of the HP filter.

Table 10 Sensitivity of resilience index to alternative de-trending methods

	Ability to recover from shock(1)	Ability to absorb shock(2)
HP filter, λ=600	95%	99%
HP filter, λ=3,600	97%	99%
BK filter, min=2	85%	49%

Note: (1) Based on estimates of ϕ_i. (2) Based on Based on estimates of $\gamma_i \lambda_t$. Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Source: London Economics

The full economic resilience indices for different time series filtering techniques are provided in the table below.

Table 11 Economic resilience indices for alternative de-trending methods

	Ability to recover from shock(1)				Ability to absorb shock(2)			
	Original (HP, λ=1,600)	HP, λ=600	HP, λ=3600	BK	Original (HP, λ=600)	HP, λ=600	HP, λ=3600	BK
Cereals, crops and seeds	91 (2)	81 (2)	92 (2)	62 (3)	81 (12)	80 (10)	82 (12)	58 (11)
Slaughtering	100 (1)	100 (1)	100 (1)	86 (2)	92 (8)	89 (7)	92 (6)	52 (13)
Milk	22 (13)	13 (15)	26 (9)	0 (17)	98 (3)	92 (4)	99 (2)	98 (2)
Eggs	8 (16)	0 (17)	12 (16)	15 (13)	94 (6)	91 (6)	92 (5)	100 (1)
Meat	50 (6)	51 (7)	47 (5)	57 (5)	82 (11)	75 (13)	87 (9)	46 (14)
Fish & fruit/vegetables	41 (7)	36 (11)	41 (6)	45 (6)	77 (13)	69 (15)	83 (11)	41 (15)
Oils & fats	33 (9)	29 (12)	30 (8)	10 (14)	0 (17)	0 (17)	0 (17)	52 (12)
Dairy	27 (11)	44 (8)	19 (12)	35 (9)	93 (7)	83 (9)	100 (1)	92 (4)
Grain mill & starches	74 (3)	73 (3)	72 (3)	62 (4)	53 (16)	60 (16)	45 (16)	0 (17)
Bakery	0 (17)	1 (16)	0 (17)	2 (16)	77 (14)	73 (14)	80 (13)	96 (3)
Other	58 (5)	63 (4)	36 (7)	43 (7)	100 (2)	100 (1)	92 (7)	79 (8)
Animal feeds	36 (8)	54 (5)	21 (11)	21 (12)	82 (9)	83 (8)	83 (10)	86 (6)
Soft drinks	16 (15)	14 (13)	15 (15)	25 (10)	82 (10)	76 (11)	80 (14)	79 (9)
Wholesale	65 (4)	52 (6)	69 (4)	100 (1)	100 (1)	95 (2)	98 (4)	83 (7)
Non-specialised retail	32 (10)	36 (10)	23 (10)	40 (8)	97 (4)	91 (5)	98 (3)	67 (10)
Specialised retail	27 (12)	40 (9)	16 (14)	23 (11)	94 (5)	94 (3)	90 (8)	86 (5)
Services	16 (14)	14 (14)	17 (13)	8 (15)	76 (15)	76 (12)	75 (15)	40 (16)

Note: HP = Hodrick-Prescott filter; BK = Baxter-King filter. (1) Based on estimates of ϕ_i. (2) Based on Based on estimates of $\gamma_i \lambda_t$. Based on a balanced panel for 2000q1-2017q4. Estimated using Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator, implemented by Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.

Source: London Economics' analysis

Alternative output measure

The table below provides the full economic resilience indices and ranks for the robustness test where we use GVA instead of turnover for developing the index.

Table 12 Economic resilience indices for alternative output measure

	Ability to recover from shock(1)		Ability to absorb shock(2)		Average resilience index	
	Original (turnover)	GVA	Original (turnover)	GVA	Original (turnover)	GVA
Agriculture	39 *(7)*	50 *(3)*	98 *(2)*	19 *(8)*	69 *(8)*	34 *(6)*
Meat	69 *(3)*	26 *(5)*	89 *(4)*	28 *(4)*	79 *(10)*	27 *(5)*
Fish & fruit/vegetables	55 *(4)*	86 *(2)*	69 *(8)*	20 *(7)*	62 *(5)*	53 *(9)*
Oils & fats	39 *(6)*	17 *(9)*	0 *(11)*	100 *(1)*	19 *(1)*	59 *(10)*
Dairy	34 *(8)*	21 *(7)*	100 *(1)*	59 *(2)*	67 *(7)*	40 *(8)*
Grain mill & starches	100 *(1)*	0 *(11)*	40 *(10)*	14 *(9)*	70 *(9)*	7 *(1)*
Bakery	0 *(11)*	100 *(1)*	74 *(6)*	20 *(6)*	37 *(2)*	60 *(11)*
Other	90 *(2)*	15 *(10)*	97 *(3)*	23 *(5)*	94 *(11)*	19 *(3)*
Animal feeds	52 *(5)*	18 *(8)*	79 *(5)*	53 *(3)*	66 *(6)*	36 *(7)*
Soft drinks	14 *(10)*	40 *(4)*	72 *(7)*	0 *(11)*	43 *(3)*	20 *(4)*
Services	28 *(9)*	22 *(6)*	64 *(9)*	13 *(10)*	46 *(4)*	17 *(2)*

Note: Note: (1) Based on estimates of ϕ_i. (2) Based on Based on estimates of $\gamma_i\lambda_t$. Based on a balanced panel for 2000q1-2017q4. Estimated using Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator, implemented by Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics' analysis

Alternative subsamples

The table below provides the full economic resilience indices and ranks for the robustness test where we extend the time period for building the indices.

Table 13 Economic resilience indices for alternative time period

	Ability to recover from shock(1)		Ability to absorb shock(2)		Average resilience index	
	Original (2000q1-2017q4)	Extended time period (1990q1-2018q4)	Original (2000q1-2017q4)	Extended time period (1990q1-2018q4)	Original (2000q1-2017q4)	Extended time period (1990q1-2018q4)
Agriculture	39 *(7)*	48 *(7)*	98 *(2)*	67 *(8)*	69 *(8)*	57 *(4)*
Meat	69 *(3)*	78 *(4)*	89 *(4)*	88 *(4)*	79 *(10)*	83 *(10)*
Fish & fruit/vegetables	55 *(4)*	78 *(3)*	69 *(8)*	83 *(6)*	62 *(5)*	81 *(9)*
Oils & fats	39 *(6)*	4 *(10)*	0 *(11)*	0 *(11)*	19 *(1)*	2 *(1)*
Dairy	34 *(8)*	55 *(6)*	100 *(1)*	96 *(3)*	67 *(7)*	75 *(8)*
Grain mill & starches	100 *(1)*	89 *(2)*	40 *(10)*	48 *(10)*	70 *(9)*	68 *(7)*
Bakery	0 *(11)*	0 *(11)*	74 *(6)*	96 *(2)*	37 *(2)*	48 *(3)*
Other	90 *(2)*	100 *(1)*	97 *(3)*	100 *(1)*	94 *(11)*	100 *(11)*
Animal feeds	52 *(5)*	41 *(8)*	79 *(5)*	85 *(5)*	66 *(6)*	63 *(5)*
Soft drinks	14 *(10)*	27 *(9)*	72 *(7)*	56 *(9)*	43 *(3)*	42 *(2)*
Services	28 *(9)*	60 *(5)*	64 *(9)*	70 *(7)*	46 *(4)*	65 *(6)*

Note: (1) Based on estimates of ϕ_i. (2) Based on Based on estimates of $\gamma_i\lambda_t$. Based on a balanced panel for 2000q1-2017q4. Estimated using Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator, implemented by Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.

Source: London Economics' analysis

The tables below provides the full economic resilience indices and ranks for alternative cross-section samples.

Table 14 Economic resilience indices for alternative cross-section samples (1/2): Ability to recover from shock

	Ability to recover from shock(2)					
	Original (full sample)	**No primary sectors**	**Original (full sample)**	**No manufacturing sectors**	**Original (full sample)**	**No services sectors**
Cereals, crops and seeds			81 *(7)*	0 *(8)*	81 *(9)*	79 *(8)*
Slaughtering			92 *(6)*	63 *(3)*	92 *(5)*	80 *(7)*
Milk			98 *(2)*	51 *(4)*	98 *(2)*	92 *(4)*
Eggs			94 *(5)*	16 *(6)*	94 *(3)*	93 *(2)*
Meat	82 *(8)*	90 *(5)*			82 *(8)*	73 *(9)*
Fish & fruit/vegetables	77 *(9)*	80 *(8)*			77 *(10)*	55 *(11)*
Oils & fats	0 *(13)*	0 *(13)*			0 *(13)*	0 *(13)*
Dairy	93 *(5)*	96 *(2)*			93 *(4)*	93 *(3)*
Grain mill & starches	53 *(12)*	48 *(12)*			53 *(12)*	38 *(12)*
Bakery	77 *(10)*	82 *(7)*			77 *(11)*	64 *(10)*
Other	100 *(2)*	94 *(3)*			100 *(1)*	100 *(1)*
Animal feeds	82 *(6)*	66 *(10)*			82 *(6)*	88 *(5)*
Soft drinks	82 *(7)*	59 *(11)*			82 *(7)*	85 *(6)*
Wholesale	100 *(1)*	100 *(1)*	100 *(1)*	10 *(7)*		
Non-specialised retail	94 *(4)*	93 *(4)*	94 *(4)*	68 *(2)*		
Specialised retail	97 *(3)*	89 *(6)*	97 *(3)*	100 *(1)*		
Services	76 *(11)*	76 *(9)*	76 *(8)*	48 *(5)*		

Table 15 Economic resilience indices for alternative cross-section samples (2/2): Ability to absorb shock

	Ability to absorb shock(2)					
	Original (full sample)	**No primary sectors**	**Original (full sample)**	**No manufacturing sectors**	**Original (full sample)**	**No services sectors**
Cereals, crops and seeds			91 *(2)*	85 *(2)*	91 *(2)*	86 *(2)*
Slaughtering			100 *(1)*	100 *(1)*	100 *(1)*	100 *(1)*
Milk			22 *(6)*	5 *(7)*	22 *(10)*	23 *(10)*
Eggs			8 *(8)*	0 *(8)*	8 *(12)*	9 *(12)*
Meat	50 *(4)*	70 *(4)*			50 *(5)*	53 *(5)*
Fish & fruit/vegetables	41 *(5)*	65 *(5)*			41 *(6)*	35 *(8)*

Oils & fats	33 *(7)*	46 *(9)*			33 *(8)*	36 *(7)*
Dairy	27 *(9)*	48 *(8)*			27 *(9)*	26 *(9)*
Grain mill & starches	74 *(1)*	100 *(1)*			74 *(3)*	72 *(3)*
Bakery	0 *(13)*	0 *(13)*			0 *(13)*	0 *(13)*
Other	58 *(3)*	92 *(3)*			58 *(4)*	54 *(4)*
Animal feeds	36 *(6)*	55 *(7)*			36 *(7)*	38 *(6)*
Soft drinks	16 (12)	32 (11)			16 (11)	15 (11)
Wholesale	65 (2)	93 (2)	65 (3)	56 (3)		
Non-specialised retail	32 (8)	58 (6)	32 (4)	21 (4)		
Specialised retail	27 (10)	42 (10)	27 (5)	14 (5)		
Services	16 (11)	30 (12)	16 (7)	8 (6)		

Note: (1) Based on estimates of ϕ_i. (2) Based on Based on estimates of $\gamma_i \lambda_t$. Based on a balanced panel for 2000q1-2017q4. Estimated using Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator, implemented by Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.

Source: London Economics' analysis

Alternative types of shocks

The table below provides the full economic resilience indices and ranks for alternative types of shocks.

Table 16 Economic resilience indices for alternative types of shocks

	Ability to recover from shock(1)			Ability to absorb shock(2)		
	Original (full sample)	Supply(3)	Demand(4)	Original (full sample)	Supply (3)	Demand(4)
Cereals, crops and seeds	91 *(2)*	100 *(1)*	77 *(2)*	81 *(12)*	24 *(12)*	54 *(5)*
Slaughtering	100 *(1)*	94 *(2)*	100 *(1)*	92 *(8)*	37 *(8)*	17 *(15)*
Milk	22 *(13)*	30 *(13)*	21 *(13)*	98 *(3)*	44 *(6)*	41 *(9)*
Eggs	8 *(16)*	10 *(15)*	6 *(16)*	94 *(6)*	7 *(16)*	35 *(10)*
Meat	50 *(6)*	60 *(6)*	42 *(8)*	82 *(11)*	29 *(11)*	57 *(3)*
Fish & fruit/vegetables	41 *(7)*	39 *(8)*	44 *(6)*	77 *(13)*	8 *(15)*	0 *(16)*
Oils & fats	33 *(9)*	30 *(12)*	27 *(10)*	0 *(17)*	100 *(1)*	57 *(4)*
Dairy	27 *(11)*	37 *(11)*	27 *(12)*	93 *(7)*	24 *(13)*	53 *(7)*
Grain mill & starches	74 *(3)*	67 *(5)*	73 *(3)*	53 *(16)*	0 *(17)*	100 *(1)*
Bakery	0 *(17)*	0 *(17)*	0 *(17)*	77 *(14)*	17 *(14)*	0 *(17)*
Other	58 *(5)*	77 *(3)*	57 *(5)*	100 *(2)*	68 *(3)*	32 *(12)*
Animal feeds	36 *(8)*	37 *(10)*	44 *(7)*	82 *(9)*	30 *(10)*	86 *(2)*
Soft drinks	16 *(15)*	47 *(7)*	14 *(15)*	82 *(10)*	93 *(2)*	25 *(14)*
Wholesale	65 *(4)*	69 *(4)*	59 *(4)*	100 *(1)*	30 *(9)*	43 *(8)*
Non-specialised retail	32 *(10)*	38 *(9)*	31 *(9)*	94 *(5)*	38 *(7)*	33 *(11)*
Specialised retail	27 *(12)*	13 *(14)*	21 *(14)*	97 *(4)*	47 *(5)*	53 *(6)*
Services	16 *(14)*	6 *(16)*	27 *(11)*	76 *(15)*	63 *(4)*	28 *(13)*

Note: (1) Based on estimates of ϕ_i. (2) Based on Based on estimates of $\gamma_i \lambda_t$. (3) Supply shock: Primary sector production shock. Based on a balanced panel for 2000q1-2017q4. (4) Demand shock: Household non-durable and services expenditure shock. Estimated using Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator, implemented by Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.

Source: London Economics' analysis

A5.3.2 Full regression outputs

This chapter reports the coefficient estimates that were used to derive the resilience indices reported in the main report. In addition to the coefficient estimates, the tables below also report the estimated half-life of a shock on sectoral output gaps, which is calculated based on the persistence coefficients ϕ_i[31] and defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock.

[31] The implied half-life of s shock in an AR(1) model can be calculated as ln(0.5)/ln($\boldsymbol{\phi_i}$).

Main results

Table 17 Main results

	Implied half-life of a shock(1)	ϕ_i(2)	$\gamma_i\ \lambda_t$(3)
Cereals, crops and seeds	0.69	.368**	-0.041
Slaughtering	0.61	.321*	-0.016
Milk	2.12	.721***	0.000
Eggs	2.96	.791***	-0.011
Meat	1.26	.578***	-0.040
Fish & fruit/vegetables	1.47	.625***	-0.053
Oils & fats	1.71	.667***	-0.249
Dairy	1.91	.695***	-0.012
Grain mill & starches	0.88	.457***	-0.114
Bakery	3.83	.834***	-0.053
Other	1.11	.536***	0.005
Animal feeds	1.62	.651***	-0.039
Soft drinks	2.45	.753***	-0.040
Wholesale	1.01	.503***	0.006
Non-specialised retail	1.74	.671***	-0.001
Specialised retail	1.91	.696*	-0.009
Services	2.41	.75***	-0.056
R-squared	0.44	0.44	0.44
Obs	1,139	1,139	1,139

Note: (1) The half-life of a shock is defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock. It is calculated as ln(0.5)/ln(ϕ_i). (2) Used to derive the shock counteraction index. Lower levels of ϕ_i imply lower persistence of the impact of a shock (higher resilience). (3) Used to derive the shock absorption index. Lower (more negative) levels of $\gamma_i\lambda_t$ imply higher amplification of a common shock (lower resilience). Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics analysis

Alternative estimators

Table 18 Dynamic Common Correlated Effects with a constant

	Implied half-life of a shock(1)	ϕ_i (2)	$\gamma_i\ \lambda_t$ (3)
Cereals, crops and seeds	0.69	.368**	-0.041
Slaughtering	0.62	.325*	-0.015
Milk	2.15	.725***	0.000
Eggs	2.98	.792***	-0.011
Meat	1.26	.578***	-0.040
Fish & fruit/vegetables	1.48	.627***	-0.052
Oils & fats	1.70	.666***	-0.248
Dairy	1.89	.693***	-0.010
Grain mill & starches	0.91	.466***	-0.114
Bakery	3.86	.835***	-0.053
Other	1.15	.546***	0.005
Animal feeds	1.76	.675***	-0.041
Soft drinks	2.45	.754***	-0.040
Wholesale	1.01	.503***	0.006
Non-specialised retail	1.81	.682***	0.000
Specialised retail	2.23	.733*	-0.008
Services	2.53	.76***	-0.055
R-squared	0.44	0.44	0.44
Obs	1139	1139	1139

Note: (1) The half-life of a shock is defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock. It is calculated as ln(0.5)/ln($\boldsymbol{\phi_i}$). (2) Used to derive the shock counteraction index. Lower levels of ϕ_i imply lower persistence of the impact of a shock (higher resilience). (3) Used to derive the shock absorption index. Lower (more negative) levels of $\gamma_i\lambda_t$ imply higher amplification of a common shock (lower resilience). Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics analysis

Table 19 Static Common Correlated Effects

	Implied half-life of a shock[1]	ϕ_i[2]	$\gamma_i\ \lambda_t$[3]
Cereals, crops and seeds	0.71	.377***	-0.039
Slaughtering	0.71	.376**	-0.023
Milk	2.08	.716***	-0.018
Eggs	2.73	.775***	-0.026
Meat	1.13	.54***	-0.057
Fish & fruit/vegetables	1.18	.556***	-0.081
Oils & fats	1.49	.628***	-0.149
Dairy	1.34	.596***	-0.025
Grain mill & starches	1.04	.514***	-0.055
Bakery	3.06	.797***	-0.046
Other	1.02	.507***	-0.008
Animal feeds	1.44	.617***	-0.081
Soft drinks	2.57	.764***	-0.018
Wholesale	1.06	.521***	-0.019
Non-specialised retail	1.54	.637***	-0.008
Specialised retail	1.71	.667**	-0.008
Services	2.27	.737***	-0.037
R-squared	0.41	0.41	0.41
Obs	1207	1207	1207

Note: (1) The half-life of a shock is defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock. It is calculated as ln(0.5)/ln(ϕ_i). (2) Used to derive the shock counteraction index. Lower levels of ϕ_i imply lower persistence of the impact of a shock (higher resilience). (3) Used to derive the shock absorption index. Lower (more negative) levels of $\gamma_i\lambda_t$ imply higher amplification of a common shock (lower resilience). Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics analysis

Table 20 Static augmented Common Correlated Effects

	Implied half-life of a shock[1]	ϕ_i[2]
Cereals, crops and seeds	1.02	.506***
Slaughtering	0.84	.44***
Milk	1.97	.703***
Eggs	2.80	.78***
Meat	1.64	.655***
Fish & fruit/vegetables	0.84	.437***
Oils & fats	0.89	.46***
Dairy	1.43	.615***
Grain mill & starches	1.08	.527***
Bakery	2.29	.738***
Other	1.09	.53***
Animal feeds	2.00	.707***
Soft drinks	2.30	.74***
Wholesale	1.06	.519***
Non-specialised retail	1.53	.636***
Specialised retail	1.89	.693***
Services	1.94	.7***
R-squared	.	.
Obs	1,207	1,207

Note: (1) The half-life of a shock is defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock. It is calculated as ln(0.5)/ln($\boldsymbol{\phi_i}$). (2) Used to derive the shock counteraction index. Lower levels of ϕ_i imply lower persistence of the impact of a shock (higher resilience). (3) Used to derive the shock absorption index. Lower (more negative) levels of $\gamma_i\lambda_t$ imply higher amplification of a common shock (lower resilience). Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics analysis

Table 21 Dynamic Common Correlated Effects (2-stage least squares)

	Implied half-life of a shock(1)	ϕ_i(2)
Cereals, crops and seeds	0.52	.262***
Slaughtering	0.77	.405***
Milk	0.91	.467***
Eggs	1.73	.669***
Meat	0.93	.473***
Fish & fruit/vegetables	0.46	.225***
Oils & fats	0.98	.493***
Dairy	1.25	.574***
Grain mill & starches	0.85	.443***
Bakery	1.30	.587***
Other	1.38	.606***
Animal feeds	1.67	.66***
Soft drinks	1.74	.672***
Wholesale	0.64	.336***
Non-specialised retail	1.28	.582***
Specialised retail	1.16	.55***
Services	1.88	.691***
R-squared	0.41	0.41
Obs	1207	1207

Note: (1) The half-life of a shock is defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock. It is calculated as ln(0.5)/ln($\boldsymbol{\phi_i}$). (2) Used to derive the shock counteraction index. Lower levels of ϕ_i imply lower persistence of the impact of a shock (higher resilience). (3) Used to derive the shock absorption index. Lower (more negative) levels of $\gamma_i\lambda_t$ imply higher amplification of a common shock (lower resilience). Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics analysis

Table 22 Dynamic Common Correlated Effects (generalised method of moments)

	Implied half-life of a shock[1]	ϕ_i[2]
Cereals, crops and seeds	1.00	.501***
Slaughtering	0.94	.476***
Milk	0.79	.414***
Eggs	1.56	.641***
Meat	1.08	.527***
Fish & fruit/vegetables	0.53	.268***
Oils & fats	1.01	.504***
Dairy	1.22	.567***
Grain mill & starches	0.88	.456***
Bakery	1.30	.586***
Other	1.36	.602***
Animal feeds	1.83	.685***
Soft drinks	1.95	.701***
Wholesale	0.61	.318***
Non-specialised retail	1.56	.641***
Specialised retail	1.01	.505***
Services	2.29	.739***
R-squared	.	.
Obs	1173	1173

Note: (1) The half-life of a shock is defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock. It is calculated as ln(0.5)/ln(ϕ_i). (2) Used to derive the shock counteraction index. Lower levels of ϕ_i imply lower persistence of the impact of a shock (higher resilience). (3) Used to derive the shock absorption index. Lower (more negative) levels of $\gamma_i\lambda_t$ imply higher amplification of a common shock (lower resilience). Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics analysis

Alternative de-trending methods

Table 23 Smaller smoothing factor (λ=600)

	Implied half-life of a shock(1)	ϕ_i(2)	$\gamma_i\ \lambda_t$(3)
Cereals, crops and seeds	0.65	.343**	-0.039
Slaughtering	0.50	.249	-0.016
Milk	1.88	.692***	-0.010
Eggs	2.47	.755***	-0.013
Meat	0.99	.495***	-0.051
Fish & fruit/vegetables	1.24	.573***	-0.065
Oils & fats	1.40	.609***	-0.229
Dairy	1.10	.532***	-0.032
Grain mill & starches	0.72	.384***	-0.086
Bakery	2.39	.748***	-0.054
Other	0.83	.435**	0.009
Animal feeds	0.95	.484***	-0.031
Soft drinks	1.83	.684***	-0.048
Wholesale	0.97	.491***	-0.001
Non-specialised retail	1.24	.571***	-0.012
Specialised retail	1.17	.553	-0.006
Services	1.84	.686***	-0.049
R-squared	0.34	0.34	0.34
Obs	1139	1139	1139

Note: (1) The half-life of a shock is defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock. It is calculated as ln(0.5)/ln(ϕ_i). (2) Used to derive the shock counteraction index. Lower levels of ϕ_i imply lower persistence of the impact of a shock (higher resilience). (3) Used to derive the shock absorption index. Lower (more negative) levels of $\gamma_i \lambda_t$ imply higher amplification of a common shock (lower resilience). Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics analysis

Table 24 Larger smoothing factor (λ=3600)

	Implied half-life of a shock[1]	ϕ_i[2]	$\gamma_i\ \lambda_t$[3]
Cereals, crops and seeds	0.74	.393***	-0.034
Slaughtering	0.67	.354*	-0.008
Milk	2.24	.734***	0.013
Eggs	3.29	.81***	-0.007
Meat	1.49	.628***	-0.019
Fish & fruit/vegetables	1.66	.658***	-0.032
Oils & fats	2.06	.714***	-0.263
Dairy	2.71	.775***	0.015
Grain mill & starches	1.00	.499***	-0.136
Bakery	5.01	.871***	-0.040
Other	1.85	.687***	-0.008
Animal feeds	2.53	.761***	-0.031
Soft drinks	3.03	.796***	-0.042
Wholesale	1.05	.516***	0.010
Non-specialised retail	2.43	.752***	0.011
Specialised retail	2.93	.79**	-0.012
Services	2.82	.782***	-0.054
R-squared	0.52	0.52	0.52
Obs	1139	1139	1139

Note: (1) The half-life of a shock is defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock. It is calculated as ln(0.5)/ln($\boldsymbol{\phi_i}$). (2) Used to derive the shock counteraction index. Lower levels of ϕ_i imply lower persistence of the impact of a shock (higher resilience). (3) Used to derive the shock absorption index. Lower (more negative) levels of $\gamma_i\lambda_t$ imply higher amplification of a common shock (lower resilience). Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics analysis

Table 25 Baxter-King filter

	Implied half-life of a shock(1)	ϕ_i(2)	$\gamma_i\ \lambda_t$(3)
Cereals, crops and seeds	0.81	.426**	-0.144
Slaughtering	0.51	.258	-0.177
Milk	4.49	.857***	0.067
Eggs	2.43	.752***	0.077
Meat	0.90	.461**	-0.208
Fish & fruit/vegetables	1.14	.545***	-0.237
Oils & fats	2.93	.789***	-0.175
Dairy	1.43	.616***	0.036
Grain mill & starches	0.81	.427***	-0.450
Bakery	4.05	.843***	0.058
Other	1.19	.558***	-0.032
Animal feeds	2.05	.713***	0.001
Soft drinks	1.84	.686***	-0.032
Wholesale	0.38	0.163	-0.014
Non-specialised retail	1.26	.577***	-0.100
Specialised retail	1.93	.699*	0.002
Services	3.14	.802***	-0.237
R-squared	0.46	0.46	0.46
Obs	731	731	731

Note: (1) The half-life of a shock is defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock. It is calculated as $\ln(0.5)/\ln(\boldsymbol{\phi_i})$. (2) Used to derive the shock counteraction index. Lower levels of ϕ_i imply lower persistence of the impact of a shock (higher resilience). (3) Used to derive the shock absorption index. Lower (more negative) levels of $\gamma_i\lambda_t$ imply higher amplification of a common shock (lower resilience). Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics analysis

Alternative output measure

Table 26 Use of GVA-based output gap measure

	Implied half-life of a shock[1]	ϕ_i[2]	$\gamma_i\ \lambda_t$[3]
Agriculture	3.44	.818***	0.019
Meat	5.11	.873***	0.049
Fish & fruit/vegetables	2.21	.731***	0.022
Oils & fats	6.25	.895***	0.293
Dairy	5.74	.886***	0.155
Grain mill & starches	10.49	.936***	0.000
Bakery	1.93	.698***	0.022
Other	6.56	.9***	0.032
Animal feeds	6.12	.893***	0.133
Soft drinks	3.98	.84***	-0.047
Services	5.64	.884***	-0.002
Agriculture	3.44	.818***	0.019
R-squared	0.77	0.77	0.77
Obs	737	737	737

Note: (1) The half-life of a shock is defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock. It is calculated as $\ln(0.5)/\ln(\boldsymbol{\phi_i})$. (2) Used to derive the shock counteraction index. Lower levels of ϕ_i imply lower persistence of the impact of a shock (higher resilience). (3) Used to derive the shock absorption index. Lower (more negative) levels of $\gamma_i \lambda_t$ imply higher amplification of a common shock (lower resilience). Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics analysis

Alternative subsamples

Table 27 Extended time period (1990q1-2018q4)

	Implied half-life of a shock[(1)]	ϕ_i[(2)]	$\gamma_i\ \lambda_t$[(3)]
Agriculture	1.77	.675***	-0.029
Meat	1.14	.546***	-0.014
Fish & fruit/vegetables	1.14	.544***	-0.018
Oils & fats	4.72	.863***	-0.076
Dairy	1.58	.645***	-0.009
Grain mill & starches	1.00	.5***	-0.042
Bakery	5.50	.882***	-0.008
Other	0.87	.451***	-0.006
Animal feeds	1.98	.705***	-0.016
Soft drinks	2.58	.765***	-0.036
Services	1.47	.623***	-0.026
R-squared	0.47	0.47	0.47
Obs	1221	1221	1221

Note: (1) The half-life of a shock is defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock. It is calculated as ln(0.5)/ln($\boldsymbol{\phi_i}$). (2) Used to derive the shock counteraction index. Lower levels of ϕ_i imply lower persistence of the impact of a shock (higher resilience). (3) Used to derive the shock absorption index. Lower (more negative) levels of $\gamma_i\lambda_t$ imply higher amplification of a common shock (lower resilience). Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics analysis

Table 28 Excluding the manufacturing sector

	Implied half-life of a shock[(1)]	ϕ_i[(2)]	$\gamma_i\ \lambda_t$[(3)]
Cereals, crops and seeds	0.78	.412***	-0.044
Slaughtering	0.66	.348***	-0.005
Milk	2.52	.759***	-0.013
Eggs	2.80	.78***	-0.034
Wholesale	1.12	.54***	-0.038
Non-specialised retail	2.12	.721***	-0.003
Specialised retail	1.86	.689***	0.017
Services	2.36	.746***	-0.015
R-squared	0.43	0.43	0.43
Obs	536	536	536

Note: (1) The half-life of a shock is defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock. It is calculated as ln(0.5)/ln($\boldsymbol{\phi_i}$). (2) Used to derive the shock counteraction index. Lower levels of ϕ_i imply lower persistence of the impact of a shock (higher resilience). (3) Used to derive the shock absorption index. Lower (more negative) levels of $\gamma_i\lambda_t$ imply higher amplification of a common shock (lower resilience). Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics analysis

Table 29 Excluding the primary sector

	Implied half-life of a shock[1]	ϕ_i[2]	$\gamma_i \lambda_t$[3]
Meat	1.37	.604***	-0.013
Fish & fruit/vegetables	1.45	.621***	-0.037
Oils & fats	1.87	.69***	-0.235
Dairy	1.83	.684***	0.002
Grain mill & starches	0.98	.492***	-0.116
Bakery	4.59	.86***	-0.033
Other	1.06	.519***	-0.001
Animal feeds	1.66	.658***	-0.073
Soft drinks	2.33	.742***	-0.090
Wholesale	1.05	.518***	0.012
Non-specialised retail	2.00	.707	-0.005
Specialised retail	1.59	.647***	-0.014
Services	2.40	.749***	-0.046
R-squared	0.45	.45	0.45
Obs	871	871	871

Note: (1) The half-life of a shock is defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock. It is calculated as ln(0.5)/ln($\boldsymbol{\phi}_i$). (2) Used to derive the shock counteraction index. Lower levels of ϕ_i imply lower persistence of the impact of a shock (higher resilience). (3) Used to derive the shock absorption index. Lower (more negative) levels of $\gamma_i\lambda_t$ imply higher amplification of a common shock (lower resilience). Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics analysis

Table 30 Excluding the services sector

	Implied half-life of a shock[1]	ϕ_i[2]	$\gamma_i \lambda_t$[3]
Cereals, crops and seeds	0.71	.379**	-0.035
Slaughtering	0.59	.306	-0.033
Milk	2.02	.71***	-0.007
Eggs	2.87	.786***	-0.005
Meat	1.18	.555***	-0.047
Fish & fruit/vegetables	1.59	.646***	-0.085
Oils & fats	1.57	.643***	-0.203
Dairy	1.90	.694***	-0.005
Grain mill & starches	0.87	.451***	-0.122
Bakery	3.79	.833***	-0.067
Other	1.16	.549***	0.011
Animal feeds	1.50	.631***	-0.016
Soft drinks	2.47	.755***	-0.022
R-squared	0.43	0.43	0.43
Obs	871	871	871

Note: (1) The half-life of a shock is defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock. It is calculated as ln(0.5)/ln($\boldsymbol{\phi}_i$). (2) Used to derive the shock counteraction index. Lower levels of ϕ_i imply lower persistence of the impact of a shock (higher resilience). (3) Used to derive the shock absorption index. Lower (more negative) levels of $\gamma_i\lambda_t$ imply higher amplification of a common shock (lower resilience). Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics analysis

Alternative types of shocks

Table 31 Demand shocks

	Implied half-life of a shock[(1)]	ϕ_i[(2)]	$\gamma_i\ \lambda_t$[(3)]
Cereals, crops and seeds	0.75	.399***	-0.178
Slaughtering	0.52	0.266	0.375
Milk	2.14	.723***	0.025
Eggs	3.34	.813***	0.108
Meat	1.37	.603***	-0.219
Fish & fruit/vegetables	1.32	.593***	0.629
Oils & fats	1.85	.688***	-0.214
Dairy	1.88	.692***	-0.152
Grain mill & starches	0.81	.425***	-.853**
Bakery	4.17	.847***	0.629
Other	1.04	.514***	0.16
Animal feeds	1.33	.593***	-0.649
Soft drinks	2.62	.768***	0.259
Wholesale	1.01	.503***	-0.009
Non-specialised retail	2.17	.727**	-0.156
Specialised retail	1.72	.668***	0.136
Services	1.86	.688***	0.218
R-squared	0.43	0.43	0.43
Obs	1139	1139	1139

Note: (1) The half-life of a shock is defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock. It is calculated as ln(0.5)/ln($\boldsymbol{\phi_i}$). (2) Used to derive the shock counteraction index. Lower levels of ϕ_i imply lower persistence of the impact of a shock (higher resilience). (3) Used to derive the shock absorption index. Lower (more negative) levels of $\gamma_i\lambda_t$ imply higher amplification of a common shock (lower resilience). Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics analysis

Table 32 Supply shocks

	Implied half-life of a shock(1)	ϕ_i(2)	$\gamma_i\ \lambda_t$(3)
Cereals, crops and seeds	0.65	.343**	0.031
Slaughtering	0.70	.373**	0.002
Milk	1.93	.698***	-0.013
Eggs	3.12	.801***	.07*
Meat	1.14	.544***	0.021
Fish & fruit/vegetables	1.61	.651***	0.068
Oils & fats	1.92	.697***	-.139***
Dairy	1.67	.66***	0.032
Grain mill & starches	1.03	.51***	.085**
Bakery	4.24	.849***	0.046
Other	0.89	.46***	-0.067
Animal feeds	1.67	.66***	0.018
Soft drinks	1.40	.61***	-.123***
Wholesale	0.99	.497***	0.018
Non-specialised retail	2.80	.781**	-0.02
Specialised retail	1.66	.658***	-0.001
Services	3.43	.817***	-0.057
R-squared	0.44	0.44	0.44
Obs	1139	1139	1139

Note: (1) The half-life of a shock is defined as the average number of quarters that it takes a sector to return half-way between current output and potential output in the aftermath of a shock. It is calculated as $\ln(0.5)/\ln(\boldsymbol{\phi_i})$. (2) Used to derive the shock counteraction index. Lower levels of ϕ_i imply lower persistence of the impact of a shock (higher resilience). (3) Used to derive the shock absorption index. Lower (more negative) levels of $\gamma_i\lambda_t$ imply higher amplification of a common shock (lower resilience). Estimations are based on a balanced panel for 2000q1-2017q4. We use Chudik and Pesaran's (2015) Dynamic Common Correlated Effects estimator and implement using Jan Dicken's *xtdcce2* command in Stata.

Please refer to Annex 2 for the official SIC codes and full names of the agri-food and drink sectors depicted in the table above.
Source: London Economics analysis

Annex 6 Structural identification of sector-level shocks

This Annex contains the results from a preliminary attempt at **structurally identifying common shocks in the data.**

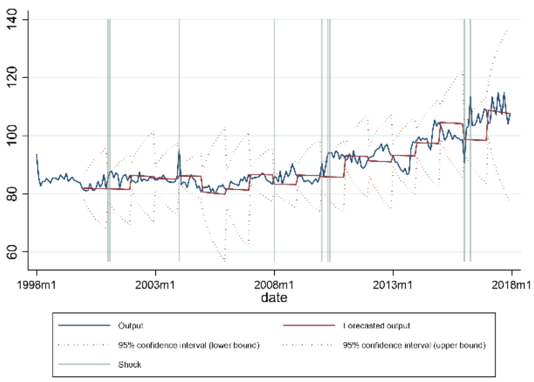
The analysis shows that it is **difficult to detect clearly discernible shocks that are common to all UK agri-food and drink sectors** in the data.

This provides further justification for the statistical approach employed in the main report, which does not explicitly identify the (nature of the) common shocks.

The figures below summarise the results from the sector-specific autoregressive model predictions that were used in an attempt to structurally identify stressors and risks that have affected multiple sub-sectors of the UK agri-food and drink industry over the modelling period ('common shocks'). This approach was considered as an alternative to modelling the shock absorption capacity of sectors through interpretation of the common factors in a mean multi-factor error setting.

Visual inspection of the figures below underlines the concerns raised in the main body of the text regarding the difficulty in directly identifying common shock variables for the purposes of this study, with no single quarter over the modelling period seeing more than half of the sectors affected by a common shock.

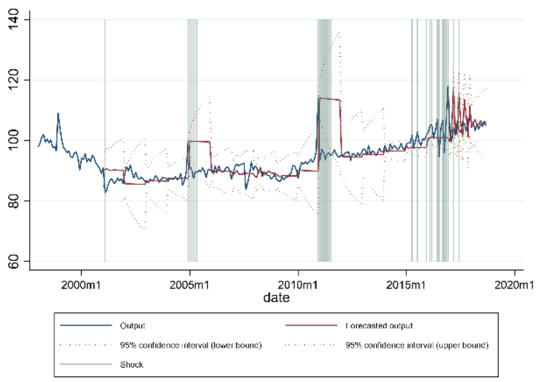
Figure 70 Shocks in sector 01.11



Note: 01.11 = Growing of cereals (except rice), leguminous crops and oil seeds

London Economics based on data obtained from Defra

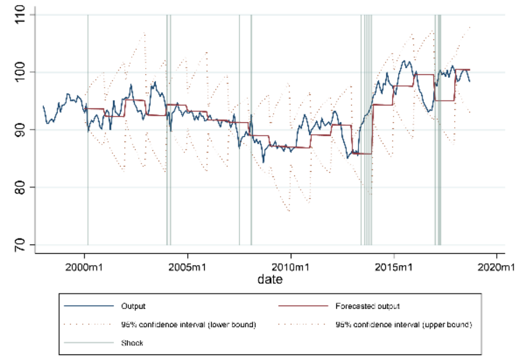
Figure 71 Shocks in sector 01.4



Note: 01.4 = Animal production (slaughtering)

London Economics based on data obtained from Eurostat

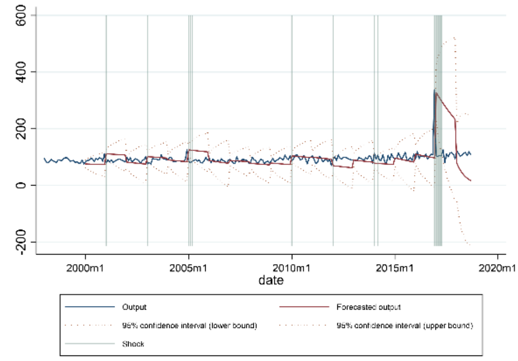
Figure 72 Shocks in sector 01.41



Note: 01.41 = Raising of dairy cattle (milk production)

London Economics based on data obtained from Eurostat

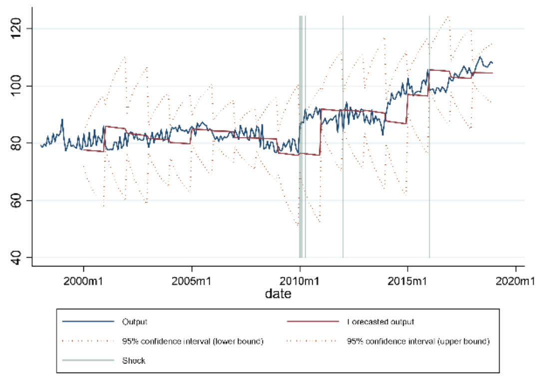
Figure 73 Shocks in sector 01.47



Note: 01.47= Raising of poultry (egg production)

London Economics based on data obtained from Eurostat

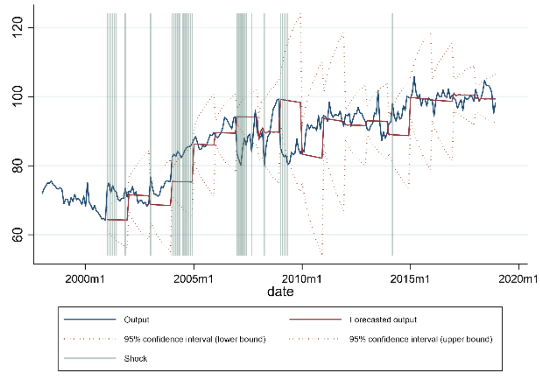
Figure 74 Shocks in sector 10.1



Note: 10.1 = Processing and preserving of meat and production of meat products

London Economics based on data obtained from Eurostat

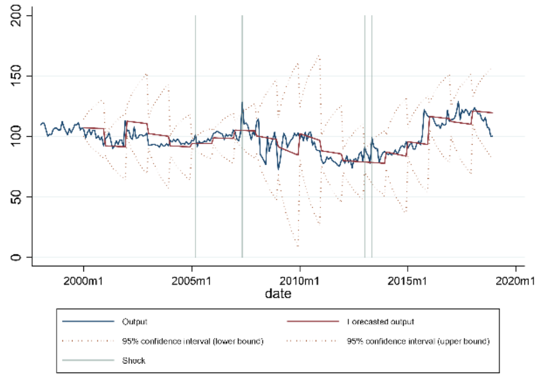
Figure 75 Shocks in sector 10.2-3



Note: 10.2-3 = Processing and preserving of fish, crustaceans, molluscs, fruit and vegetables

London Economics based on data obtained from the ONS

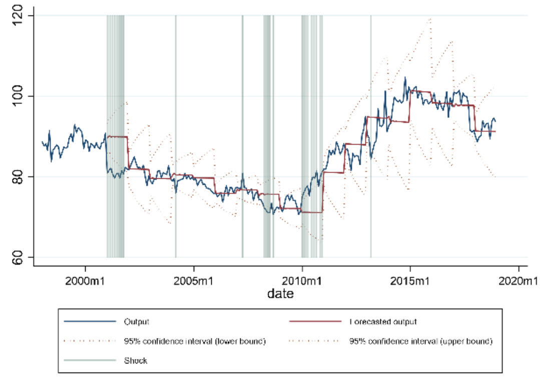
Figure 76 Shocks in sector 10.4



Note: 10.4 = Manufacture of vegetable and animal oils and fats

London Economics based on data obtained from Eurostat

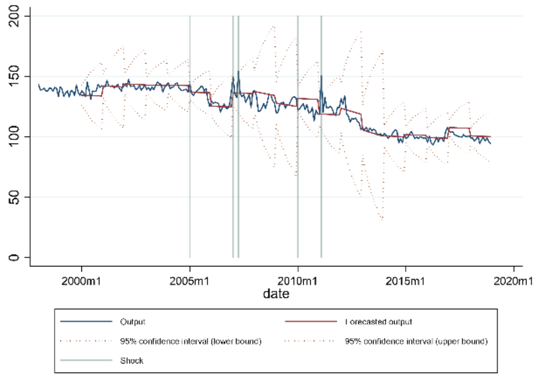
Figure 77 Shocks in sector 10.5



Note: 10.5 = Manufacture of dairy products

London Economics based on data obtained from Eurostat

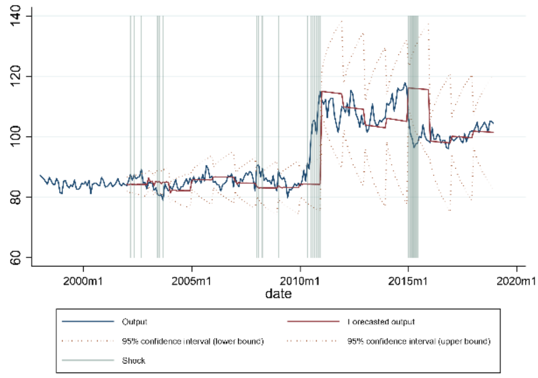
Figure 78 Shocks in sector 10.6



Note: 10.6 = Manufacture of grain mill products, starches and starch products

London Economics based on data obtained from Eurostat

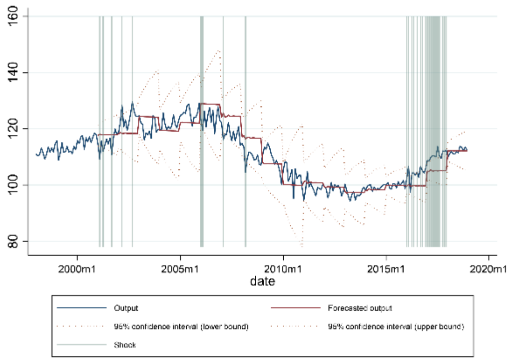
Figure 79 Shocks in sector 10.7



Note: 10.7 = Manufacture of bakery and farinaceous products

London Economics based on data obtained from Eurostat

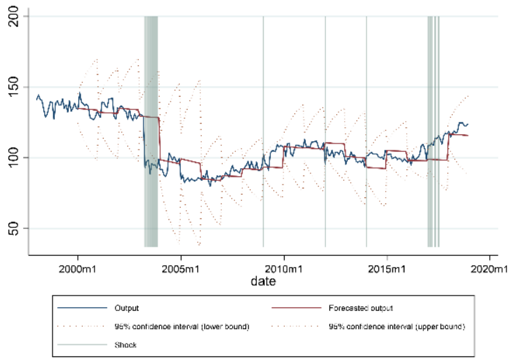
Figure 80 Shocks in sector 10.8



Note: 10.8 = Manufacture of other food products

London Economics based on data obtained from Eurostat

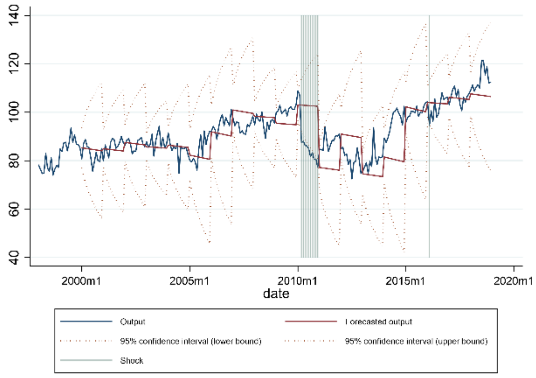
Figure 81 Shocks in sector 10.9



Note: 10.9 = Manufacture of prepared animal feeds

London Economics based on data obtained from Eurostat

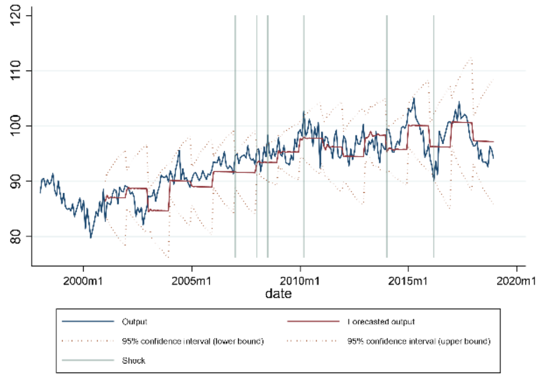
Figure 82 Shocks in sector 11.07



Note: 11.07 = Manufacture of soft drinks; production of mineral waters and other bottled waters

London Economics based on data obtained from Eurostat

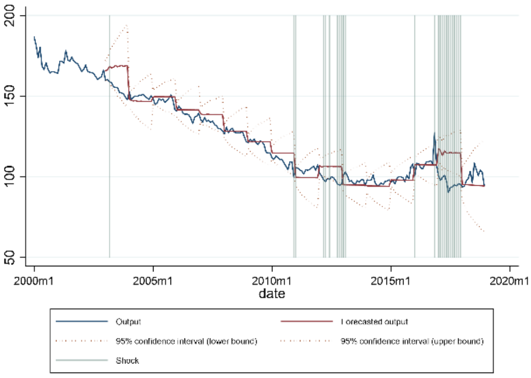
Figure 83 Shocks in sector 46.3



Note: 46.3 = Wholesale of food, beverages and tobacco

London Economics based on data obtained from Eurostat

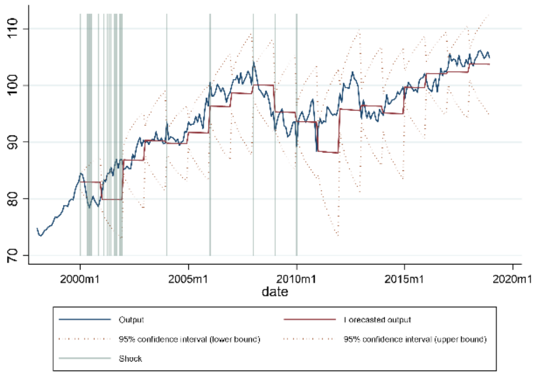
Figure 84 Shocks in sector 47.2



Note: 47.2 = Retail sale of food, beverages and tobacco in specialised stores

London Economics based on data obtained from Eurostat

Figure 85 Shocks in sector 56



Note: 56 = Food and beverage service activities

London Economics based on data obtained from the ONS

References

Advantage West Midlands (2010). Community Economic Resilience Index.

Agenor, Pierre-Richard; McDermott, C. John; Prasad, Eswar S.; Agenor, Pierre-Richard; McDermott, C. John; Prasad, Eswar S.. (2000). Macroeconomic fluctuations in developing countries : some stylized facts. The World Bank economic review. -- Vol. 14, no. 2 (May 2000), pp. 251-285.

Artis. M., Marcellino, M. and Proietti, T. (2004). Characterising the business cycle for accession countries. Available at: https://econwpa.ub.uni-muenchen.de/econ-wp/em/papers/0403/0403006.pdf

Atkins, J., Mazzi, S. and Easter, C. (2000). A Commonwealth Vulnerability Index for Developing Countries: The Position of Small States. London: Commonwealth Secretariat.

Backus, David K., and Patrick J. Kehoe. (1992). International Evidence on the Historical Properties of Business Cycles. American Economic Review 82:4 864–888.

Bagchi, A. (2018). Artificial Intelligence in Agriculture. For Mindtree. Retrieved from: https://www.mindtree.com/sites/default/files/2018-04/Artificial%20Intelligence%20in%20Agriculture.pdf

Bakker, Jan and Datta, Nikhil (2018). The impact of Brexit on the UK dairy sector. LSE consulting. Available at: http://www.lse.ac.uk/business-and-consultancy/consulting/assets/documents/the-impact-of-brexit-on-the-uk-dairy-sector.pdf

Barling, D., Sharpe, R. and Lang, T. (2015). Rethinking Britain's Food Security. Available at: https://www.researchgate.net/publication/228661417_Rethinking_Britain's_Food_Security

Bassanini, A. and R. Duval (2006), Reassessing the Role of Policies and Institutions for Labour Market Performance: A Consolidated Analysis, OECD Economics Department Working Paper No. 486.

Baxter, M., & King, R. G. (1999). Measuring business cycles–Approximate band-pass filters for economic time series. The Review of Economics and Statistics, 81(4), 575–593.

Baxter, Marianne, and Robert King. (1999). Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series. American Economic Review 81:4 573–593.

Bellora, C., Emlinger, C., Fouré, J. And Guimbard, H. (2017). Research for AGRI Committee, EU – UK agricultural trade: state of play and possible impacts of Brexit, Policy Department for Structural and Cohesion Policies, Brussels.

Benton, T. et al. (2012). Severe Weather and UK Food Chain Resilience. Biotechnology and Biological Sciences Research Council. Available at: http://www.foodsecurity.ac.uk/assets/pdfs/frp-severe-weather-uk-food-chain-resilience.pdf

Bertrand, J. and Parnaudeau, M. (2015) Ranking the Impact of Climate Variability on UK Retail Sectors: A Path to Resilience. Available at: http://dx.doi.org/10.2139/ssrn.2675965

Blanchard and Quah (1989). The dynamic effects of aggregate demand and supply disturbances. National Bureau of Economic Research Working Paper Series, No. 2737 (October).

Bry and Boschan (1971). Cyclical Analysis of Time Series: Selected Procedures and Computer Programs. National Bureau of Economic Research, Technical Paper, No. 20.

Blanchard, O. and J. Wolfers (2000), "The Role of Shocks and Institutions in the Rise of European Unemployment: The Aggregate Evidence", Economic Journal, Vol. 110, No. 462.

Breeze, A.P. Bailey, K.G. Balcombe, S.G. Potts. (2011) Pollination services in the UK: How important are honeybees? Agriculture, Ecosystems & Environment, 142(3–4), 137-143.

Briguglio (2003). Available at: https://www.um.edu.mt/__data/assets/pdf_file/0019/44137/vulnerability_paper_sep03.pdf

Briguglio, L. and Vella, S. (2015). Profiling economic vulnerability and resilience in small states: conceptual underpinnings. Available at: https://www.researchgate.net/profile/Lino_Briguglio/publication/268411725_PROFILING_ECONOMIC_VULNERABILITY_AND_RESILIENCE_IN_SMALL_STATES_CONCEPTUAL_UNDERPINNINGS/links/54cc74df0cf29ca810f53c98.pdf

Briguglio, L., Cordina, G., Bugeja, S., & Farrugia, N. (2006). Conceptualizing and Measuring Economic Resilience. Working Paper. Retrieved from https://www.um.edu.mt/__data/assets/pdf_file/0013/44122/resilience_index.pdf

British Food journal (2016), A Conceptual understanding of Criminality and Integrity Challenges in Food supply chains

Bruneau, M., Chang, s., Eguchi, R., Lee, G., O'Rourke, T., & Reinhorn, A. (2003). A framework to quantitatively assess and enhance seismic resilience of communities. Earthquake Spectra, 733-752.

Bukeviciute, L., Dierx, A., Ilzkovitz, F. (2009). The functioning of the food supply chain and its effect on food prices in the European Union.Occasional papers No 47.

Bullock, J. M., Pywell, R.F., Burke, M. J. W. and Walker, K. J. (2001). Restoration of biodiversity enhances agricultural production. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1046/j.1461-0248.2001.00215.x

Burton, C. G. (2012). The development of metrics for community resilience to natural disasters. Ph.D. thesis. University of South Carolina.

Canova, F., Coutinho, L., & Kontolemis, Z. (2012). Measuring the macroeconomic resilience of industrial sectors in the EU and assessing the role of product market regulations. European Economy Occasional Paper 112.

Cellini and Cuccia (2014). The economic resilience of the tourism industry in Italy: What the Great Recession data shows. Available at: https://core.ac.uk/download/pdf/31055619.pdf

Charles, I. Gerasimchuk, R. Bridle, T. Moerenhout, E. Asmelash and Laan, T. (2013). Biofuels—At What Cost? A Review of Costs and Benefits of EU Biofuel Policies, International Institute for Sustainable Development (IISD), Geneva, Switzerland. Available at: http://www.iisd.org/gsi/sites/default/files/biofuels subsidies eu review.pdf

Chudik, A. and Pesaran, M. H. and (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors, *Journal of Econometrics, 188*(2), 393-420.

Colwill, J., Despoudi, s. and Bhamra, R.S., (2016). A review of resilience within the UK food manufacturing sector. In Goh, Y.M. and Case, K. (eds.), Advances in Manufacturing Technology: Proceedings of the 14th International Conference on Manufacturing Research, Loughborough University, September 68, 451-456.

Cooley, Thomas J., and Lee E. Ohanian. (1991). The Cyclical Behavior of Prices. Journal of Monetary Economics 28:1 (1991), 25–60.

Cotis, J. P., Elmeskov, J., & Mourougane, A. (2005). Estimates of potential output: Benefits and pitfalls from a policy perspective. In Reichlin, L. (Ed.), The Euro Area business cycle: Stylized facts and measurement issues. London: CEPR.

Cutter, S. L., Burton, C. G., & Emrich, C. T. (2010). Disaster resilience indicators for benchmarking baseline conditions. Homeland Security Emergency Management, 7.

Dawson, P. J. and Tiffin, R. (1997). Estimating marketing margins in the meat sector using cointegration analysis. Agricultural Economics Society Annual Conference, University of Edinburgh, 21-24 March.

Deloitte (2017). Changing tastes: The UK casual dining market. Available at: https://www2.deloitte.com/content/dam/Deloitte/uk/Documents/ConsumerIndustrialProducts/deloitte-uk-casual-dining-market.pdf

Department for Environment Food & Rural Affairs. (2010). UK Food Security Assessment: Detailed Analysis. (https://webarchive.nationalarchives.gov.uk/20130402191230/http:/archive.defra.gov.uk/foodfarm/food/pdf/food-assess100105.pdf)

Department for Environment, Food and Rural Affairs. (2008). The Impact of Biofuels on Commodity Prices. Available at: https://sugarcane.org/wp-content/uploads/2018/04/The-Impact-of-Biofuels-on-Commodity-Prices.pdfCLES (2010)

Department for Environment, Food and Rural Affairs. (2017). Food Statistics Pocketbook 2016. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/608426/foodpocketbook-2016report-rev-12apr17.pdf Department for Environment Food & Rural Affairs. (2018). UK Biological Security Strategy. Available at: https://www.gov.uk/government/publications/biological-security-strategy

Dickerson, A.P., Gibson, H.D. & Tsakalotos, E. (1998) Business Cycle Correspondence in the European Union. Empirica 25: 49. https://doi.org/10.1023/A:1006888704954

Doherty B, Ensor J, Heron T and Prado P. (2019). Food Systems Resilience: Towards an Interdisciplinary Research Agenda [version 1; referees: awaiting peer review]. Emerald Open Res 2019, 1:4.

Downing, E. and Coe, S. (2018). Brexit: Future UK agriculture policy, House of Commons Library Briefing Paper 8218, 31 January 2018, House of Commons Library, Westminster.

Duarte, Agustin & Holden, Ken. (2003). The business cycle in the G-7 economies. International Journal of Forecasting. 19. 685-700.

Duval, R., Elmeskov, J. and Vogel, L. (2007), Structural Policies and Economic Resilience to Shocks, OECD Economics Department Working Papers, No. 567, OECD.

Duval and Vogel (2008). Economic resilience to shocks: the role of structural policies. OECD Economic Studies, No. 44, 2008/1.

Eberhardt (2012). Estimating panel time-series models with heterogeneous slopes. *The Stata Journal, 12*(1), 61-71.

Eberhard and Teal (2010). Productivity analysis in global manufacturing production. Available at: http://degit.sam.sdu.dk/papers/degit_15/c015_019.pdf

European Commission Directorate General for Environment (2014). Sustainable food, [Online] Available: http://ec.europa.eu/environment/eussd/food.htm

European Commission Directorate-General for Agriculture and Rural Development (2017). Study on risk management in EU agriculture. Available at: https://publications.europa.eu/en/publication-detail/-/publication/5a935010-af78-11e8-99ee-01aa75ed71a1/language-en/format-PDF

Eurostat (2006). Methodology of short-term business statistics. Interpretation and guidelines. Available at: https://ec.europa.eu/eurostat/documents/3859598/5895945/KS-BG-06-001-EN.PDF/609c47c3-220a-48b4-874f-d9c589bf302c?version=1.0

Everaert, G. and de Groote, T. (2016). Common Correlated Effects Estimation of Dynamic Panels with Cross-Sectional Dependence, *Econometric Reviews, 35*(3), 428-463.

European Commission. (2009). Impact of the current economic and financial crisis on potential output. European Economy: occasional paper 49. Retrieved from http://ec.europa.eu/economy_finance/publications/publication15479_en.pdf

Financial Times (2018, January 8). Ag tech fundraising doubles as farmers seek disruptive solutions. Retrieved from: https://www.ft.com/content/02950380-d6f2-11e7-a303-9060cb1e5f44

Food Chain Analysis Group. Department for Environment Food & Rural Affairs. (2006). Food Security and the UK: An Evidence and Analysis Paper. Available at: https://webarchive.nationalarchives.gov.uk/20130404001020/http:/archive.defra.gov.uk/evidence/economics/foodfarm/reports/documents/foodsecurity.pdf

García-Germán, S. , Bardají, I. and Garrido, A. (2016). Evaluating price transmission between global agricultural markets and consumer food price indices in the European Union. Agricultural Economics, 47: 59-70.

Gonzalez, C. (2018). Farm Robotics are Taking A Giant Automated Leap Forward. In: Machine Design. Retrieved from: https://www.machinedesign.com/motion-control/farm-robotics-are-taking-giant-automated-leap-forward

Graveline, N. and Gremont, M. (2017). Measuring and understanding the microeconomic resilience of businesses to lifeline service interruptions due to natural disasters. International Journal of Disaster Risk Reduction, vol. 24, pp.526-538. Available at: https://hal.archives-ouvertes.fr/hal-01631780/document

Grech (2013). Adapting the Hodrick-Prescott Filter for Very Small Open Economies. International Journal of Economics and Finance; Vol. 5, No. 8

Grenouilleau, D., Ratto, M. and Roeger, W. (2007). Adjustment to shocks: a comparison between the Euro area and the US using estimated DSGE models. European Commission DG ECFIN and DG JRC (June).

Guay, A., & St-Amant, P. (2005). Do the Hodrick-Prescott and Baxter-King filters provide a good approximation of business cycles? ENSAE: Annales d'Economie et de Statistique, No.77. Retrieved from http://www.er.uqam.ca/nobel/r27460/files/Hodrick_Prescott.pdf

Haltmaier, J. (2012). Do recessions affect potential output?. Board of Governors of the Federal Reserve System: International Finance Discussion Paper No 1066.

Hamilton, J. D. (2016). Why you should never use the Hodrick-Prescott filter. The Review of Economics and Statistics, 100(5), 831–843.

Harding, Don & Pagan, Adrian, 2002. "Dissecting the cycle: a methodological investigation," Journal of Monetary Economics, Elsevier, vol. 49(2), pages 365-381, March.

Harvey, M. (2000). Innovation and competition in UK supermarkets, Supply Chain Management: An International Journal, 5(1), 15-21.

Henson S, Humphrey J (2010): Understanding the complexities of private standards in global agri-food chains as they impact developing countries. J Dev Stud.;46(9): 1628–1646.

Henson, S. and Humphrey, J. (2010). Understanding the complexities of private standards in global agri-food chains as they impact developing countries, Journal of Development Studies, 46(9), 1628–1646.

Henson, S. and Humphrey, J. (2010). Understanding the Complexities of Private Standards in Global Agri-Food Chains as They Impact Developing Countries, The Journal of Development Studies,46:9, 1628-1646.https://doi.org/10.1080/00220381003706494

HM Government (2018). UK Biological Security Strategy. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/730213/2018_UK_Biological_Security_Strategy.pdf

HM Treasury (2010). Glossary of treasury Terms. Available at: https://web.archive.org/web/20121102095705/http://www.hm-treasury.gov.uk/junebudget_glossary.htm

Hodrick, Robert J. and Edward C. Prescott. (1981). Postwar U.S. Business Cycles: An Empirical Investigation.Working paper, Northwestern University.

Hodrick, Robert J. and Edward C. Prescott. (1997). Postwar U.S. Business Cycles: An Empirical Investigation," Journal of Money, Credit and Banking, 29(1): 1-16.

House of Lords, European Union Committee (2016). Responding to price volatility: creating a more resilient agricultural sector. Available at: https://publications.parliament.uk/pa/ld201516/ldselect/ldeucom/146/146.pdf

House of Lords, European Union Committee (2018). Brexit: plant and animal biosecurity. Available at: https://publications.parliament.uk/pa/ld201719/ldselect/ldeucom/191/191.pdf

James D. Hamilton. (2017). Why You Should Never Use the Hodrick-Prescott Filter. NBER Working Papers23429, National Bureau of Economic Research, Inc.

Jordan, E., Javernick-Will, A., & Amadei, B. (2011). Pathways to communicate recovery and resilience. Proceedings of the engineering project organizations conference. Colorado, USA.

Knox, J., Morris, J. and Hess, T. Identifying future risks to UK agricultural crop production: Putting climate change in context, Outlook on Agriculture, 39(4), 249–256.

Ladiray, Dominique. Soares, Regina. (2003). Cycles in the Euro-zone. Statistical working papers. ISBN: 92-894-5387-7

Lang, T. and Schoen, V. (2016). Food, the UK and the EU: Brexit or Bremain? UK: Food Research Collaboration. Available at: http://openaccess.city.ac.uk/14896/1/FRC%20Brexit%2007%2003%2016.pdf

Leat, P. and Revoredo-Giha, C. (2013). Risk and resilience in agri-food supply chains: the case of the ASDA PorkLink supply chain in Scotland. Supply Chain Management: An International Journal, 18(2), 219-231.

Lloyd, Tim & Mccorriston, Steve & Morgan, Wyn & Rayner, Anthony. (2001). The Impact of Food Scares on Beef and Inter-Related Meat Markets.

London Economics (2015) Satellite Technologies in UK agriculture: A Pathfinder study funded under the National Space Technology Programme (NSTP)

London Economics, (2003). Examination of UK Milk Prices and Financial Returns, Report prepared for The Milk Development Council, February.

London Economics, (2004). Investigation of the determinants of farm-retail price spreads, Final report to DEFRA, UK.

Markets Insider (2018, January 31). Cargill brings facial recognition capability to farmers through strategic equity investment in Cainthus. Retrieved from: https://markets.businessinsider.com/news/stocks/cargill-brings-facial-recognition-capability-to-farmers-through-strategic-equity-investment-in-cainthus-1001718115

Martin, R. (2012). Regional economic resilience, hysteresis and recessionary shocks. Journal of Economic Geography, 12, 1–32. Available at:
http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.852.6915&rep=rep1&type=pdf

Martin, R. and Sunley, P. (2014). On the Notion of Regional Economic Resilience: Conceptualisation and Explanation. Available at:
https://www.geog.cam.ac.uk/research/projects/cger/Onthenotion.pdf

Mayunga, J. S. (2007). Understanding and applying the concept of community disaster resilience: a capita-based approach. Summer Academy for Social Vulnerability and Resilience Building Working Paper.

Mazzi, G. L. and Scocco, M. (2003).Business cycles analysis and related software applications. European Commission Working Papers and Studies. Available at: https://ec.europa.eu/eurostat/documents/3888793/5815721/KS-AN-03-013-EN.PDF/fd190454-cdf9-494d-8d2d-e32e326c8818

McKinnon, R. (1963). Optimum Currency Areas, American Economic Review, 53(4), 717-725.

McNaughton, R. B and Gray, B. (2017). Entrepreneurship and resilient communities – introduction to the special issue, *Journal of Enterprising Communities: People and Places in the Global Economy, 11*(1), 2-19.

Ministry of Agriculture, Fisheries and Food. (1999). A report of an investigation into the relationship between producer, wholesale and retail prices of beef, lamb and pork. Ministry of Agriculture, Fisheries and Food, HMSO, London.

Mongelli, F. P. (2008). European economic and monetary integration and the optimum currency are a theory. European Commission Directorate-General for Economic and Financial Affairs, European Economy Economic Papers, 30 (February).

Mundell, R. A. (1961). A Theory of Optimum Currency Areas, American Economic Review, 51(4), 657-665.

Neal, T. (2015). Estimating Heterogeneous Coefficients in Panel Data Models with Endogenous Regressors and Common Factors. Working Paper: Panel data estimation with common factors and endogeneity.

Organisation for Economic Co-operation and Development (2001). Glossary of statistical terms. Business cycles. Available at: https://stats.oecd.org/glossary/detail.asp?ID=244

Organisation for Economic Co-operation and Development (2016). OECD G20 Policy Paper on Economic Resilience and Structural Policies. Available at: http://www.g20.utoronto.ca/2017/2017-Germany-G20-policy-paper.pdf

Palaskas, S. (1995): "Statistical Analysis of Price Transmission in the European Union", Journal of Agricultural Economics, 41, 61-69.

Parliamentary Office of Science and Technology (2017). Security of UK Food Supply Available at: https://researchbriefings.parliament.uk/ResearchBriefing/Summary/POST-PN-0556

Peck, H. (2006). Resilience in the food chain: a study of business continuity management in the food and drink industry. Research report for Defra. Available at: http://randd.defra.gov.uk/Default.aspx?Menu=Menu&Module=More&Location=None&Completed=0&ProjectID=13607

Pelkmans, J., Montoya, L. A., & Maravalle, A. (2008). How product market reforms lubricate shock adjustment in the euro area (No. 341). Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

Pesaran, M.H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. Econometrica, 74(4), p.967-1012

Pesaran, M. H. (2004). General diagnostic tests for cross-section dependence in panels, IZA Discussion Paper No. 1240 (August).

Phillips, Peter C. B. and Jin, Sainan. (2015) Business Cycles, Trend Elimination, and the HP Filter . Cowles Foundation Discussion Paper No. 2005. Available at SSRN: https://ssrn.com/abstract=2622477 or http://dx.doi.org/10.2139/ssrn.2622477

PWC (2019). Brexit and the UK food sector. Available at: https://www.pwc.co.uk/industries/retail-consumer/insights/the-consumer-global-m-and-a-trends-in-the-consumer-sector/brexit-and-the-uk-food-sector.html

Ravn, Morten O., and Harald Uhlig. (2002). On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations. Review of Economics and Statistics, 84(2): 371-380.

Rose, A. Z., Oladosu, G., Lee, B. and Asay, G. B. (2009). The economic impacts of the September 11 terrorist attacks: A computable general equilibrium analysis. *Peace Economics, Peace Science and Public Policy, 15*(2) (September).

Rose, A. and Krausmann, E. (2013). An economic framework for the development of a resilience index for business recovery. International Journal of Disaster Risk Reduction, 73-83.

Rose, A. and Liao, S.-Y. (2005). Modeling Regional Economic Resilience to Disasters: A Computable General Equilibrium Analysis of Water Service Disruptions. Journal of Regional Science, 45(1), 75-112.

Scacciavillani, F., & Swagel, P. (1999). Measures of potential output: An application to Israel. International Monetary Fund: working paper WP/99/96. Retrieved from www.imf.org/external/pubs/ft/wp/1999/wp9996.pdf

Sensier, M. and Artis, M. (2014). The Resilience of Employment in Wales Through Recession and into Recovery, Regional Studies, 50(4), 1-14.

Sensier, M., Bristow, G. and Healy, A. (2016). Measuring Regional Economic Resilience across Europe: Operationalising a complex concept. Available at: http://orca.cf.ac.uk/83009/2/SEA%20paper%20Final%20Accepted%20Dec%202%202015.pdf

St-Amant, P., & Van Norden, S. (1997). Measurement of the output gap: A discussion of recent research at the Bank of Canada. Bank of Canada: technical report No.79.

Stone, J. and Rahimifard, S. (2018). Resilience in agri-food supply chains: a critical analysis of the literature and synthesis of a novel framework. Supply Chain Management: An International Journal, 23(3), 207-238.

Stone, J., Rahimifard, S. and Woolley, E. (2015). An overview of resilience factors in food supply chains. Presented at the 11th Biennial Conference of the European Society for Ecological Economics, Leeds, 30th June- 3rd July.

Tan, J., Lo, K., Qiu, F., Liu, W., Li, J. and Zhang, P. (2017). Regional economic resilience: resistance and recoverability of resource-based cities during economic crises in Northeast China. Sustainability 2017, 9, 2136.

Thompson, D., Muriel, P., Russell, D., Osborne, P., Bromley, A., Rowland, M., Creigh-Tyte, S. and Brown C. (2002). Economic costs of the foot and mouth disease outbreak in the United Kingdom in 2001, Revue Scientifique et Technique, 21(3), 675–87.

Tiffin, R. and Dawson, P.J. (2000). Structural breaks, cointegration and the farm retail price spread for lamb. Applied Economics, 32, 1281-1286

UK-RAS Network (2018). Agricultural Robotics: The Future of Robotic Agriculture

Vavra, P. and Goodwin, B. (2005). Analysis of Price Transmission Along the Food Chain, OECD Food, Agriculture and Fisheries Papers, No. 3, OECD Publishing, Paris.

Waage, J. K. and Mumford, J. D. (2008). Agricultural biosecurity, Philosophical Transactions of the Royal Society B, 363, 863–876.

Ward, V. (2017). More than 20,000 contaminated eggs sold and consumed in Britain, FSA says. Telegraph. Available at: https://www.telegraph.co.uk/news/2017/08/07/eggs-contamination-scare-distributed-britain/

Wells, J. (1997). Composite Vulnerability Index: A Revised Report, London: Commonwealth Secretariat.

Zhao, G., Liu, S. and Lopez, C. (2017). A literature review on risk sources and resilience factors in agrifood supply chains. In: Camarinha-Matos, L.M., Afsarmanesh, H., Fornasiero, R. (eds.) *Conference* on Virtual Enterprises (PROVE), Sep 2017, Vicenza, Italy. IFIP Advances in Information and Communication Technology, 506, 739-752.

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