

Farms and marketing channels: a network-based interpretation of connectivity and resilience

Fahimeh Malekinezhad and Damian Maye

*Countryside and Community Research Institute, University of Gloucestershire,
Cheltenham, UK, and*

Matthew Gorton

*Business School, Newcastle University, Newcastle upon Tyne, UK and
Corvinus University of Budapest, Budapest, Hungary*

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Abstract

Purpose – This study applies social network analysis to examine how 572 UK farm businesses engage with eight marketing channels, aiming to understand how patterns of market access relate to structural position, business characteristics and resilience.

Design/methodology/approach – Measures of degree centrality, core–periphery structure and modularity clustering were used to uncover the relational architecture of the UK farms' marketing channels.

Findings – Findings show that most farms rely on just one or two channels, with those using three or more exhibiting the highest network centrality. The findings highlight the need to distinguish between structural embeddedness and functional integration. A farm may be well connected yet remain marginal in terms of capital flow or market influence.

Practical implications – Policies aiming to strengthen food system resilience must be network-aware and support a plurality of marketing strategies tailored to different farm contexts enabling resilience and innovation to emerge across all parts of the network.

Originality/value – The findings presented herein offer practical recommendations for rural development and national procurement frameworks showing how structural positioning and connectivity can inform typologies for targeted and equitable intervention.

Keywords Local food systems, Social network analysis (SNA), Marketing channels, Farm business resilience, Affiliation network modelling

Paper type Research article

1. Introduction

Local food systems are increasingly recognised as vital for building resilience, enhancing food security and sustaining rural economies (Vafadari *et al.*, 2025; Zhang *et al.*, 2025; Vásquez Neyra *et al.*, 2025, Maye *et al.*, 2025). They are embedded within dense webs of social and economic exchanges (Brinkley *et al.*, 2021; Willis, 2012), often involving complex networks of producers, supply chain actors and consumers (Ilbery and Maye, 2006; Coe *et al.*, 2022). These interdependencies among multiple actors shape how value, trust and sustainability are generated, maintained and transformed (Brinkley *et al.*, 2021). However, despite strong support for developing local food systems, they typically remain small-scale and fragmented in

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practice, with many farms excluded from such distribution networks (Woodward and Hird, 2021). Understanding the relational architecture of these systems, particularly how connections between farms and markets shape resilience, remains poorly understood.

Farms distribute their agricultural outputs through a variety of routes or channels (Jones *et al.*, 2004, Maye *et al.*, 2025). Studies show that farmers increasingly seek diversified marketing pathways to reach consumers and overcome vulnerabilities associated with more conventional and centralised supply chains (Ezenwa; *et al.*, 2024; Lawes-Johnson and Woodward, 2022). Alternatives to traditional, supermarket dominated supply chains include Direct to Consumer (D2C) channels, such as farm shops/e-shops, vegetable box schemes, pick-your-own farms, farmgate sales and farmers' markets, characterised by face-to-face exchange which may enable consumers to know better where, how and by whom their food is produced (Jones *et al.*, 2004; Renting *et al.*, 2003; Pretty, 2001; Christian *et al.*, 2020; Tregear *et al.*, 2025). Beyond D2C models, farmers can utilise various intermediary channels, such as wholesalers, processors, independent retailers, supermarkets and co-operatives (Maye and Ilbery, 2006; Chiffolleau and Dourian, 2020). These actors serve as vital connectors that allow farmers to reach larger markets, which may be inaccessible through direct selling alone.

The value of marketing channel diversity was vividly demonstrated during the COVID-19 pandemic (Lever, 2020; Brinkley *et al.*, 2021; Jones *et al.*, 2022). As highlighted by Defra (2021), the UK food supply chain operates as a highly complex and interconnected web of systems. The pandemic revealed both vulnerabilities and adaptive strengths, showing that resilience depends not only on the availability of multiple supply routes but also on the structural configuration of relationships among producers, retailers and intermediaries. Although local food systems are increasingly recognised as interdependent networks, much empirical research remains focused on individual marketing channels or business-level resilience capacities and outcomes (Lucas *et al.*, 2024; Liang *et al.*, 2025; Malekinezhad *et al.*, 2024). Such limited approaches risk overlooking the broader structural patterns and network dynamics that shape system-wide performance and resilience (Kim *et al.*, 2011).

Bridging social network theory and resilience research, this study conceptualises resilience as emerging from the relational architecture of food systems – that is from how farms are embedded within networks of exchange rather than solely a resource-based perspective. This advances agri-food network theory by reframing resilience as a property of structural configurations that enhance network connectivity and mitigate inequalities in market access. This perspective aligns with recent resilience debates suggesting that being resilient is not merely about possessing resources to overcome shocks (Gibson *et al.*, 2021) but rather the capacity to adapt and respond in a way that enables growth (Jones *et al.*, 2022). In this way, resilience emerges from structural ties – from how different components of a (local) food system, such as farms, consumers and intermediaries, are connected and interact to generate collective adaptive capacity, and transformative potential towards more sustainable and equitable outcomes.

In this context, studies that map geographical and social relations (Ilbery *et al.*, 2006; Lawes-Johnson and Woodward, 2022) make important contributions by highlighting the spatial and infrastructural dimensions of local food systems. However, they also expose persistent data gaps that limit understanding of the relational structures critical to resilience. These gaps are particularly concerning given evidence that the centralised configuration of most food supply chains substantially reduces farmers' share of market value, reinforcing systemic vulnerabilities and inequities (Woodward and Hird, 2021).

Recent UK national strategy documents such as *Sustain and RSPB publication (2021)* and *Local Food Plan (2025b)*, identify the lack of a range of routes to market as a major weakness of contemporary food systems. In response, the *Local Food Plan (2025a)*, calls for regional planning, investment in food infrastructure and public procurement reform to foster a more resilient local food economy. In keeping with this, the Review of *Local Food Plan (2025b)*, argues that resilient local food systems are relational infrastructures, linking producers, intermediaries and consumers through SME-focused and socially embedded supply chains. This aligns with increasing calls to embed network thinking into food system strategy;

an approach championed by [Sustain and RSPB publication \(2021\)](#), which notes that local food outlets return up to £25 to the local economy for every £10 spent, compared to £2.40 via supermarkets.

Inspired by recent policy calls to revisit social relations and market concentration to build resilience and reduce power asymmetries in food supply chains, this study addresses this research gap by applying social network analysis (SNA) to examine how UK farms are connected across multiple marketing channels and how structural positioning within local food networks shapes resilience. It does this by modelling buyer and producer relationships and connections ([Kim et al., 2011](#)). More specifically, SNA allows researchers to map and quantify the structure of food networks and understand how individual firms and marketing outlets are embedded within the system ([Brinkley et al., 2021](#)).

[Han et al. \(2020\)](#) provide a systematic review of SNA applications in supply chain management (SCM), highlighting its potential to uncover not only transactional patterns but also reciprocal and structural interdependencies that drive resilience, innovation and value creation. They argue that SNA helps uncover the nuances of networks, which is vital for understanding local food systems, where value is co-produced through dynamic and multidirectional relationships. While the use of SNA in agri-food research is embryonic, its application in business-to-business (B2B) research is more mature. For example, [Zaefarian et al. \(2022\)](#) provide a comprehensive guide to applying SNA in a B2B context, discussing how this method can uncover interorganisational dynamics and the relational architecture of market participation.

SNA's relational modelling capabilities have increasingly been discussed in SCM to examine how these networks can translate into outcomes like innovation, resilience and competitive performance ([Fouad and Rego, 2024](#); [Wei and Zhou, 2025](#)). However, despite increasing recognition of local food systems as interdependent networks, there remains limited empirical insight into how actors' structural positions within these systems shape their resilience. Consequently, the aim of this study is to employ SNA to examine local food system resilience, conceptualising the latter as a relational property that emerges from network connectivity and structural positioning.

Empirical applications of SNA remain underutilised in agri-food systems generally, and especially in local and short food chain studies, due in part to challenges with data collection and conceptual clarity around network metrics ([Kim et al., 2011](#)). Many existing studies focus on single channels, isolated case studies or public datasets (e.g. agricultural census or farm accounting), which offer little insights into downstream relationships ([Trivette, 2019](#); [Woods et al., 2022](#); [Renting et al., 2003](#)). This limits our understanding of how farms are structurally positioned within broader food networks ([Ricketts Hein et al., 2006](#); [Wei and Zhou, 2025](#)).

The study addresses this research gap by employing an affiliation network approach to examine farm-to-market relationships. The analysis uncovers structural patterns in marketing relationships in terms of diversity and connectivity. Using sales data from 572 farmers across three English regions collected by the National Innovation Centre for Rural Enterprise, matrices were created and analysed with UCINET and Gephi to assess how farms cluster connect by marketing routes, how central or peripheral they are and what this in turn reveals about their stability and growth opportunities.

In particular, the analysis reveals a structural typology of UK farms to help identify patterns of interaction, inclusion, and exclusion. This supports wider calls for network-aware strategies that reflect the economic and relational realities of local food systems ([Brinkley et al., 2021](#)). This builds also on past research focused on food system dimensions ([Gaitán-Cremaschi et al., 2022](#); [Jones et al., 2022](#)) while adding a resilience structural perspective on how farmers engage with markets and networks. Through a structural perspective on farm–market relations, this study advances a relational view of resilience and identifies a typology to understand diversity and provide a basis for more targeted interventions. This opens pathways for longitudinal and multi-actor research on networked resilience in agri-food systems.

2. Methodology

2.1 Survey design, measures and sample

The analysis draws on data collected in 2023 as part of the State of Rural Enterprise survey of farm businesses, commissioned to inform government policy on farm business support. Survey participants were individuals responsible for day-to-day farm operations, selected voluntarily from a random sample drawn from a commercial database of farm contacts. Although the sample covers three English regions, it may underrepresent micro-scale enterprises as well as new, local actors not yet recorded in the database.

A total of 586 farm businesses took part in the survey, administered by commercial market research agency via Computer Assisted Telephone Interviewing, between May and August 2023. Participation was voluntary, with informed consent obtained at the beginning. Respondents could withdraw at any time, and anonymity was maintained in accordance with General Data Protection Regulation (GDPR) guidelines.

This study focuses on marketing channels and business performance data ($n = 572$). Respondents estimated the share of farm sales across eight potential channels and reported their interest in increasing local/direct sales (within 50 miles), along with related motivations, barriers and support needs. Business performance was measured via changes in employment, turnover (agricultural and non-agricultural), government support and the impact of rising costs on cash flow in the past 12 months.

The sample covers three English regions, namely the North East (32%), South West (35%) and West Midlands (33%), capturing the diversity of UK farm types and production systems. Most employ between one and four people (54%), though 13% have 10 and more and 11% have none. Farm types include livestock (59%), crop (26%), mixed (12%) and other (3%). Conventional methods dominate (77%), with 9% organic, 12% mixed and 2% other farming practices. Women hold managerial roles in 55% of farms.

2.2 SNA analytical framework

We apply SNA to investigate how farm businesses are structurally connected to different marketing channels. We used a two-mode network affiliation approach (Nicolosi *et al.*, 2019), in which farm businesses represent one set of nodes and marketing channels the other. The core farm marketing channel sale dataset was transformed into a binary affiliation matrix, with each row representing a farm and each column representing a marketing channel. A value of 1 indicates that a given business uses a specific marketing channel, while 0 denotes no engagement.

Using UCINET (version 6.789; a social network analysis software package) and Gephi version 0.10.1, we analyse the farm-channel supply network. We used UCINET for matrix-based computation of centrality measures and core-periphery structures and Gephi for visualising the network topology and detecting structural clusters. This echoes established analytical routines in marketing-focused SNA (Zaefarian *et al.*, 2022), especially for deriving the farm's position in the overall marketing network and structural clusters of farms.

Degree centrality measures the number of marketing channels each business is connected to and the number of businesses linked to each channel. This helps assess the relative prominence of actors and their level of integration within the network. Then, the network was projected into two additional configurations: a farm-to-farm (one-mode) network, in which ties represent shared use of the same marketing channels; and a channel-to-channel (one-mode) network, in which ties represent channels used in combination by the same businesses.

To assess variation in structural positioning, we performed core-periphery analysis on the B2B network. This technique identifies businesses that are part of a densely connected network versus those less connected (Yang *et al.*, 2018; Smith and Sarabi, 2022). Core businesses tend to use multiple shared marketing channels and occupy strategic positions within the network, while peripheral businesses have limited overlap or shared pathways. We also applied modularity-based clustering. This technique helps detect groups that are more connected to each other than to the wider network based on their marketing channels (Ji *et al.*, 2015).

3. Results

3.1 Sales channel connectivity overview

The most common marketing channels are processor (23%), wholesaler and merchant (21%). Auctions/Livestock markets are also common sales channels, contributing to 18% of ties. Overall, farms remain clearly embedded in B2B marketing channels. D2C channels account for 14% of ties. Independent retailers and “other channels” each make up 8% of links. Direct contracts with supermarkets and co-operatives are less common (4% and 5%, respectively).

3.2 Marketing channel use and network centrality

Farms use between one and four channels. Almost half of those sampled (288 out of 572) use only one marketing channel, mostly concentrated in the 151–250° centrality range. Just over a third (36%) of businesses use two channels, with increasing representation in higher degree categories. Overall, 154 businesses fall in the 251–450 range. Only 14% use three or more channels with 3% use four or five and appear more in the highest degree ranges.

Processors, and wholesalers and merchants account for the largest share of sales by value (23 and 24%, respectively) as well as the highest degree of centrality (219 and 195), reflecting frequent co-use with other channels. For example, 58 farms sell via both processors and auctions, 33 distribute via both processors and D2C channels and 45 combine serving wholesalers with D2C sales. Auctions or livestock markets contribute 20% of sales and are used by 169 farms, but with lower centrality (129). D2C ($n = 137$) distribution accounts for a smaller share of sales (11%) but demonstrates high connectivity (centrality = 178), often used alongside sales to independent retailers, wholesalers and merchants, and processors. Distribution via independent retailers ($n = 72$) has moderate centrality (116) and contributes around 5% of total sales. By contrast, contracts with supermarkets, co-operatives and other channels are used by fewer farms ($n = 40, 48$ and 72 , respectively), show lower centrality (65, 49 and 71) and contribute less to overall sales (4%, 6% and 8%). Overall, the results capture the complex set of distribution channels employed by farms.

3.3 Farm structural positioning in the marketing network

As illustrated in [Figure 1](#), of the 572 businesses, 36% ($n = 205$) form a dense central cluster and the remaining 64% ($n = 367$) form the periphery. Membership of central and peripheral categories varies significantly by farm size ($\chi^2 = 21.656$, $df = 2$, $p < 0.001$). Specifically, 43% of large-scale farms (>100 ha) are part of the core, compared to just 16% of small-scale farms (<20 ha), with the latter overwhelmingly peripheral with few links with core nodes (84%). Medium-sized farms (20–100 ha) are better integrated into the network, often bridging between periphery and core (see [Figure 1](#) – bottom left).

3.4 Farm marketing network typologies

Modularity analysis ([Figure 2](#)) identifies four structural clusters of farm businesses. This approach enables a novel use of SNA to develop a typology of farms based on their structural position and marketing connectivity. A detailed comparative analysis follows, illustrating how these clusters engage with different marketing channels ([Table 1](#)).

Cluster 1 (green) consists of 166 nodes (29%), predominantly composed of livestock farms (85%), which farm conventionally (87%) and rely almost exclusively on auctions or livestock markets (100%) for sales, with moderate use of processors (34%). Cluster 2 (purple) consists of 174 nodes (30%) – they are more crop-focused (49%) and the cluster is uniquely defined by its exclusive use of wholesaler and merchant (100%). Cluster 3 (blue), comprising 112 nodes (20%), leads in the use of D2C (56%), independent retailer (35%) and other channels (40%). It also has the highest proportion of farm businesses possessing a contract with a supermarket chain (13%). Cluster 3 has the lowest proportion of conventional farming (59%) and a notably higher presence of organic (16%) and mixed (19%) practices. It shows balanced representation

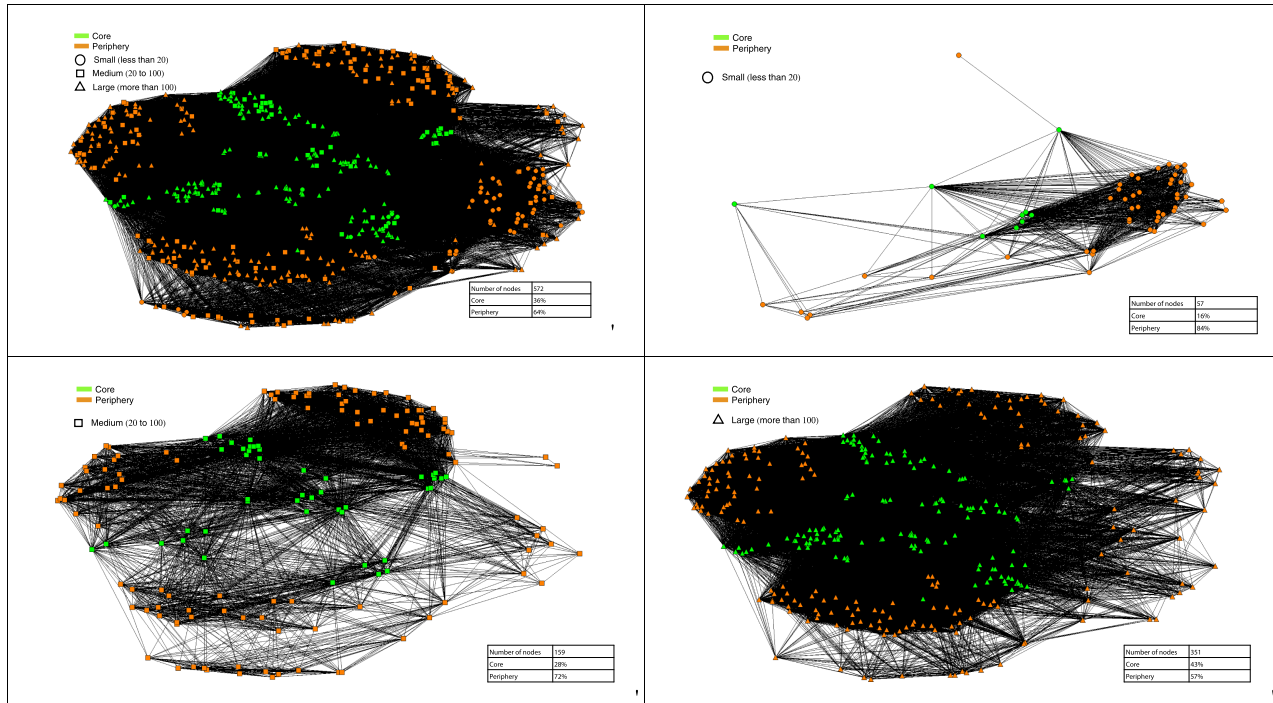


Figure 1. Core-periphery configuration of the farm businesses in the marketing network and by farm size. Note: The core-periphery fit score is 0.618. Source(s): Authors' own work

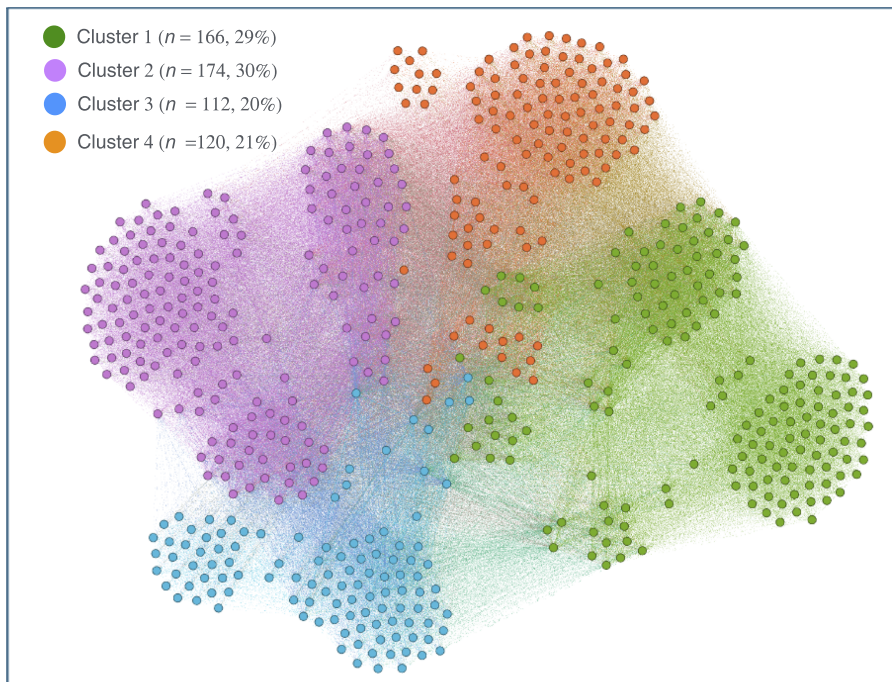


Figure 2. Farm marketing network typologies identified via modularity analysis. The modularity score of 0.296 suggests a moderately strong community structure with some cross-cluster connectivity. Source(s): Authors' own work

between livestock (39%), crop farms (40%) and relatively higher percentage in “other” (13%) compared to other clusters. Finally, Cluster 4 (orange), comprising 120 nodes (21%), are predominantly livestock farms (83%) with a heavily reliance on sales to processors (90%), with additional use of co-operatives (21%), the highest among all clusters.

Table 1 profiles the characteristics of each cluster. Cluster 3 is characterised by a high concentration of small-scale farms (40%). In contrast, Clusters 1, 2 and 4 consist largely of medium- and large-sized farms. Cluster 1 has the highest proportion of farms with no employees or only one to four employees. Geographically, Clusters 1 and 4 are strongly skewed to the North East (52%) and South West (58%) regions, respectively, whereas Clusters 2 and 3 have higher representation from the West Midlands region (44% and 42%, respectively).

3.5 Cluster perspectives on local sales development

Table 2 presents only responses from producers who like to increase the percentage of their total sales accounted for direct or local sales channels unless all D2C sales within 50 miles of farm is 100%. Among those who provided valid responses (excluding missing data), 34% expressed a desire to increase their share of sales through direct or local channels, while 66% did not. The table excludes 5.1% of respondents who reported selling all (100%) of their direct-to-consumer products within 50 miles of the farm. There is a statistically significant difference in interest in expanding local or direct sales across clusters ($p < 0.001$), but there are no statistically significant differences in the reasons, barriers (except for “Other”) or support needs ($p > 0.05$).

Interests: Cluster 2 exhibits the highest interest in increasing local or direct sales (47%), followed by Cluster 3 (34%). Clusters 1 (28%) and 4 (23%) have the lowest levels of interest.

Table 1. Farm characteristics and distribution of marketing channels by clusters

| | Cluster 1 (n = 166, 29%) | Cluster 2 (n = 174, 30%) | Cluster 3 (n = 112, 20%) | Cluster 4 (n = 120, 21%) | Asymptotic significance (2-sided) |
|----------------------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|---|
| <i>Marketing channels</i> | | | | | |
| Direct to consumers | 11% | 24% | 56% | 12% | <0.001 |
| Independent retailers | 5% | 13% | 35% | 3% | <0.001 |
| Contract with supermarket | 2% | 9% | 13% | 6% | <0.003 |
| Processors | 34% | 28% | 5% | 90% | <0.001 |
| Co-operatives | 7% | 6% | 2% | 21% | <0.001 |
| Auctions or livestock market | 100% | 0% | 3% | 0% | <0.001 |
| Other channels | 0% | 7% | 40% | 13% | <0.001 |
| <i>Region</i> | | | | | |
| North East | 52% | 29% | 23% | 17% | |
| South West | 25% | 27% | 35% | 58% | |
| West Midlands | 23% | 44% | 42% | 25% | |
| <i>Number of employees</i> | | | | | |
| 0 | 16% | 10% | 9% | 8% | <0.001 |
| 1–4 | 70% | 48% | 45% | 49% | |
| 5–9 | 10% | 22% | 26% | 32% | |
| 10 or more | 4% | 20% | 21% | 11% | |
| <i>Land size (ha)</i> | | | | | |
| Small – less than 20 | 1% | 6% | 40% | 1% | <0.001 |
| Medium – 20–100 | 43% | 18% | 24% | 25% | |
| Large – more than 100 | 55% | 76% | 36% | 74% | |
| <i>Farm type</i> | | | | | |
| Livestock | 85% | 31% | 39% | 83% | <0.001 |
| Crop | 6% | 49% | 40% | 8% | |
| Mixed | 8% | 20% | 7% | 9% | |
| Others | 1% | 1% | 13% | 0% | |
| <i>Farming practices</i> | | | | | |
| Conventional | 87% | 80% | 59% | 75% | <0.001 |
| Organic | 4% | 7% | 16% | 13% | |
| Mixed | 8% | 11% | 19% | 10% | |
| Other farming practices | 0% | 2% | 6% | 3% | |
| <i>Core–peripheral structure</i> | | | | | |
| Core | 51% | 48% | 7% | 24% | <0.024 |
| Periphery | 49% | 52% | 93% | 76% | |

Source(s): Authors' own work

Reasons: Improving margins or accessing new market opportunities is the top reason in all clusters, with 95% in Clusters 1 and 2 and slightly lower (but still strong) in Clusters 3 (83%) and 4 (81%). To diversify income or reduce risk is particularly strong in Cluster 3 (88%). Supporting community or local initiatives are prioritised by Clusters 1 (79%) and 2 (77%) but lowered by Cluster 3 (58%). Gaining greater control over how the product is sold is most cited in Clusters 1 (79%) and 4 (77%) and lower in Cluster 3 (54%). These differences were not statistically significant.

Barriers: Limited demand or insufficient economic opportunity is consistently the most reported barrier in all clusters (50–64%). Lack of time is also equally reported across all clusters (50–55%). Lack of appropriate market infrastructure is significant, particularly for Clusters 1 (60%) and 2 (59%), declining to 42% in Cluster 4. Lack of labour supply or suitable employees is most acute in Cluster 3 (54%). Lack of appropriate skills or knowledge is notably high in Clusters 2 (45%) and 4 (38%). Lack of appropriate digital and transport infrastructure is less commonly reported, particularly in Clusters 1 and 4. The “Other” barrier shows a statistically significant difference across clusters ($p = 0.025$).

Table 2. Direct sales engagement, motivations, barriers and support needs by clusters

| Expanding local sales | Categories | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 | Asymptotic significance (two-sided) |
|-----------------------|---|-----------|-----------|-----------|-----------|-------------------------------------|
| Engagement | Yes | 28% | 47% | 34% | 23% | 0.000 |
| | No | 72% | 53% | 66% | 77% | |
| Motivations | To improve margins or access new market opportunities | 95% | 95% | 83% | 81% | 0.053 |
| | To gain greater control over how the product is sold | 79% | 67% | 54% | 77% | 0.156 |
| | To diversify income or reduce risk | 74% | 76% | 88% | 73% | 0.577 |
| | To support local or community initiatives | 79% | 77% | 58% | 62% | 0.141 |
| | Something else | 14% | 36% | 38% | 27% | 0.071 |
| Barriers | Limited demand or insufficient economic opportunity | 64% | 61% | 58% | 50% | 0.701 |
| | Lack of appropriate skills or knowledge | 26% | 45% | 25% | 38% | 0.131 |
| | Lack of time | 50% | 55% | 50% | 50% | 0.957 |
| | Lack of labour supply or suitable employees | 43% | 42% | 54% | 46% | 0.781 |
| | Lack of appropriate market infrastructure | 60% | 59% | 54% | 42% | 0.481 |
| | Lack of appropriate digital infrastructure | 21% | 27% | 29% | 15% | 0.584 |
| | Lack of appropriate transport infrastructure | 12% | 17% | 17% | 12% | 0.861 |
| | Other | 14% | 20% | 46% | 27% | 0.025 |
| Support needs | Advice on advertising or marketing communications | 52% | 65% | 58% | 65% | 0.559 |
| | Market research | 48% | 67% | 63% | 62% | 0.262 |
| | Technical advice | 45% | 64% | 58% | 65% | 0.235 |
| | Financial advice (budgeting, investments, cash flow) | 45% | 50% | 42% | 62% | 0.492 |
| | None – do not need advisory support | 17% | 9% | 8% | 4% | 0.353 |

Source(s): Authors' own work

Support needed: Advice on advertising or marketing communications is widely sought, particularly in Clusters 2 and 4 (both 65%). Market research is most cited in Clusters 2, 3 and 4 (62–67%) compared to Cluster 1 (48%). Technical and financial advices are notably important for Clusters 2 and 4. Cluster 4 expresses the lowest response for “do not need advisory support” (4%), whereas Cluster 1 (17%) is most likely to report needing no support. However, these differences were not statistically significant.

3.6 Economic performance and financial resilience by cluster

Table 3 profiles the economic performance of clusters in the past 12 months. Statistically significant differences were found for farm turnover, non-farm income, received government financial support, income change and the impact of rising costs on cash flow ($p < 0.05$). However, differences in employment change were not statistically significant ($p = 0.056$).

Employment change: Most farms reported increased employment over the past year, with Cluster 1 leading (90%), followed by Cluster 4 (82%). Reported decreases ranged from 8% to 16% across clusters. This difference was not statistically significant.

Table 3. Distribution of financial performance by clusters

| Indicator | Category | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 | Asymptotic significance (two-sided) |
|---|----------------------------|-----------|-----------|-----------|-----------|-------------------------------------|
| Employment change (in past 12 months) | Decreased | 8% | 14% | 16% | 12% | 0.056 |
| | Or, stayed the same | 2% | 8% | 6% | 8% | |
| Farm turnover (in past 12 months) | Increased | 90% | 78% | 77% | 80% | 0.000 |
| | Up to £50,000 | 23% | 8% | 31% | 9% | |
| | £50,001–£100,000 | 29% | 15% | 15% | 9% | |
| | £100,001–£250,000 | 29% | 18% | 18% | 19% | |
| | £250,001–£500,000 | 10% | 20% | 15% | 17% | |
| | £500,001–£750,000 | 3% | 9% | 6% | 8% | |
| | £750,001–£1 million | 1% | 7% | 4% | 13% | |
| | £1–£2 million | 3% | 14% | 7% | 13% | |
| | £2–£5 million | 1% | 9% | 3% | 9% | |
| | £5–£10 million | 1% | 2% | 0% | 2% | |
| | £15–£25 million | 0% | 0% | 1% | 0% | |
| | More than £25 million | 0% | 0% | 0% | 1% | |
| Non-farm income | Yes | 32% | 46% | 41% | 27% | 0.002 |
| | No | 68% | 54% | 59% | 73% | |
| Received government financial support (in past 12 months) | Up to £50,000 | 86% | 69% | 88% | 83% | 0.004 |
| | £50,001–£100,000 | 12% | 21% | 7% | 11% | |
| | £100,001–£250,000 | 2% | 8% | 5% | 3% | |
| | £250,001–£500,000 | 0% | 2% | 1% | 2% | |
| | £500,001–£750,000 | 0% | 0% | 0% | 1% | |
| | £750,001–£1 million | 0% | 0% | 0% | 1% | |
| Income change (in past 12 months) | Decreased | 14% | 25% | 23% | 33% | 0.001 |
| | Or stayed roughly the same | 45% | 42% | 28% | 32% | |
| Impact of rising costs on cash flow (in past 12 months) | Increased | 41% | 33% | 50% | 36% | 0.022 |
| | Yes | 89% | 84% | 75% | 81% | |
| | No | 11% | 16% | 25% | 19% | |

Source(s): Authors' own work

Farm turnover: Cluster 3 includes more low-turnover farms (31% ≤ £50 k) and fewer in higher turnover categories. Clusters 2 and 4 have 60% and 64% of farms earning over £250,000, with around 25% reporting turnover above £1 million. Cluster 1 consists mainly of farms earning between £50,000 and £250,000, with only limited representation above £500,000 (9%).

Non-farm income: Clusters 2 and 3 reported the highest levels of non-farm income (46% and 41%, respectively). Clusters 1 and 4 earn most of their income from farm operations (68% and 73%, respectively).

Government financial support: The majority of businesses received up to £50k in support, especially in Cluster 3 (88%), Cluster 1 (86%) and Cluster 4 (83%). However, Cluster 2 stands out, with 31% receiving support above this threshold.

Income change: Cluster 3 registers the highest income growth (50%). Conversely, Cluster 4 shows the greatest decrease (33%). Cluster 1 maintains a relatively stable profile, with 41% growth and only 14% decrease.

Impact of rising costs: Rising costs have impacted the majority in all clusters. However, Cluster 3 is the least affected (75%) compared to Cluster 1 (89%), Cluster 2 (84%) and Cluster 4 (81%).

To assess whether farm characteristics influence SNA cluster–resilience relationships, we conducted subgroup analyses across several variables (Table A1) Appendix. Significant differences in turnover and income change are apparent across livestock farms, all regions and medium- and large-sized farms. Livestock and medium-sized farms in Clusters 1 and 3 are more concentrated in lower-turnover bands yet often reported stronger income resilience, while Clusters 2 and 4 are skewed toward medium-to-higher turnover categories without consistently better income outcomes. Medium-sized farms showed clear cluster variations in turnover, income change and employment growth, with Cluster 3 most likely to report income increases. Large-scale farms also displayed pronounced turnover and income differences, again with Cluster 3 performing best. The latter links with arguments that direct-to-consumer marketing channels and reduced reliance on auction marts and processors are associated with greater farm resilience and lower income volatility (Key, 2024).

Large-scale farms also differ in non-farm income, with Clusters 2 and 3 more diversified than Cluster 4. Clusters also differ in terms of government support received, with Cluster 2 most likely and Cluster 3 least likely to obtain >£50k (circa £66,000) in government support. Overall, network position is strongly associated with financial resilience even after accounting for key farm characteristics.

4. Discussion

This study analyses how farm businesses in England are structurally positioned within marketing networks. We draw on the structured approach outlined by Zaefarian *et al.* (2022) and Han *et al.* (2020). The former emphasises the importance of examining actors within broader community clusters, highlighting the need to investigate relational interdependencies and network configurations. Our approach aligns with this call, as we mapped farm–market structures within the agri-food context. The study demonstrates the effectiveness of SNA for capturing relationships within agri-food systems, aiding the identification of four distinct structural clusters.

Applying SNA reveals a complex web of distribution channels, within which some farms are more central and others peripheral. Centrality in this context reflects stronger structural connectivity and relational ties in relation to distribution channels. The analysis reveals, for example, that while half of the surveyed farms rely on a single marketing channel, those using two or more demonstrate markedly higher network embeddedness. These data are important because network centrality frequently aligns with economic performance, particularly for farms linked to dominant channels like processors and wholesalers. These channels not only hold the highest degree centrality scores but also account for the largest share of farm sales (23% and 24%, respectively), functioning as economic anchors for large-scale, market-integrated farms. Significant contributions to sales (20%) are also made by auction markets, despite their moderate connectivity, likely due to their high-value livestock trade. In contrast, the D2C route to market is highly used but contributes less to total sales (11%), suggesting that they are low volume and cannot accommodate all of a particular farm's output. They may be important though in offering relatively high margin sales which also promote local visibility, yield intelligence on consumer preferences and contribute to business resilience (Malak-Rawlikowska *et al.*, 2019; Woodward and Hird, 2021, Maye *et al.*, 2025). This highlights a critical point: high centrality does not always connect to economic dominance. Different channels contribute distinct forms of value, some economic while others relational and/or strategic.

The strong centrality of diversified farms reflects a broader pattern of strategic adaptation across the network. Many farms adopt multi-channel marketing strategies not simply to expand market reach but also to navigate constraints, particularly barriers to expanding local sales (see Table 2), a pattern also noted in previous studies (Benedek *et al.*, 2018; Milford *et al.*, 2021). These behaviours align with the Local Food Plan (2025a) recommendations, which promote marketing diversity as a core strategy for building resilience. By combining volume-oriented and relational channels such as wholesaling alongside direct-to-consumer sales, farms improve their network visibility and adaptability. Farms using two or three channels are overrepresented in the higher centrality tiers, reinforcing the point that diversification is a structural asset. This structural centrality is often accompanied by signs of financial resilience, for example Cluster 3, though largely peripheral (see Table 3), demonstrates the highest reported income growth (50%) and the lowest impact of rising costs (75%).

However, being well-connected within the network does not always translate into economic influence or financial autonomy. Some structurally central farms remain weak in terms of income, and most farms have little market power. For example, Cluster 4, while high-earning and centrally positioned, registers the highest decreases in income and exhibits the highest demand for external advisory services particularly in marketing, technical support and financial planning. This highlights an important distinction: structural centrality does not necessarily reflect economic resilience. Therefore, building a resilient food system requires recognising the different roles marketing channels play (Vergamini *et al.*, 2019), with some farms integrated into dominant supply chains, while others are more rooted in local, community-based economies.

At the structural level, the results reveal a clear asymmetry within the network. A small core of highly connected businesses exists alongside a larger group of farms that remain structurally peripheral. The latter is especially evident in Clusters 3 and 4, where 93% and 76% of farms, respectively, occupy peripheral positions. Yet, as shown in Cluster 3, a peripheral location in the network does not hinder income growth or adaptive behaviour such as demand for advisory support. These farms are often smaller in scale, highly specialised or deeply embedded in local contexts. Cluster 3 illustrates that peripheral positioning in a network can coexist with financial resilience, marked by strong income growth and flexible marketing strategies. This indicates that this group may include more niche or less traditional farming types suggesting a diverse group in terms of production focus (high in selecting other channels). Consistent with Driessen's (2022) analysis, such farms express interest in collaborative mechanisms like food hubs as tools to improve market access and enhance resilience, which opens up questions about co-operative arrangements and the capacity and operability of collective market infrastructures.

Structural disparities in network positions are related to farm size. Large-scale farms dominate the network central position, while small-scale farms are structurally peripheral with limited ties. Medium-sized farms bridge core and peripheral actors while adopting more diverse marketing configurations. These dynamics echo national findings from Local Food Plan (2025a), which identifies consistent barriers across the United Kingdom, particularly a lack of aggregation infrastructure, policy coordination and equitable access to procurement channels for smaller producers.

In sum, the network analysis illustrates both the economic centrality of a few dominant sales channels and the structural marginalisation of many smaller and less diversified farms. Half of the surveyed farms remain reliant on a single marketing channel. This suggests that multichannel engagement, particularly expanding local sales, remains limited due to a lack of appropriate market infrastructure. Addressing this constraint can contribute to improving farm resilience.

4.1 Theoretical and practical contributions

4.1.1 Theoretical contributions. This study contributes to agri-food network and resilience theory by integrating structural network concepts – centrality, embeddedness and modularity – into the analysis of local food systems. It extends prior work in food geography and SCM by

demonstrating that relational positioning, rather than channel diversity or scale, explains variations in adaptive capacity and inclusion (Tregear *et al.*, 2025; Borgatti and Li, 2009; Woods *et al.*, 2022). Practically, resilience is a relational outcome shaped by structural positioning within the marketing network. Identifying key connector farms or clusters that play strategic roles in the flow of goods and information – and directing support toward these critical nodes rather than distributing resources uniformly – can enhance the overall resilience and inclusivity of the food system. Accordingly, resilience should be understood as a property of the entire marketing network rather than the characteristics of individual farms. This “network-aware” understanding of resilience strengthens both conceptual and applied frameworks for food system research.

4.1.2 Practical implications. The analysis can inform the development of local, regional and national food strategies, identifying opportunities for adding value as well as vulnerabilities. For instance, recent discussions regarding the bargaining power of farmers often focus on the power of supermarkets and potential mechanisms to constrain the latter in their relationships with suppliers. However, as illustrated in this study, only a small minority of farmers deal directly with supermarket chains. The development of food strategies at any spatial level requires a detailed understanding of marketing channels.

As noted by O’Neill (2024), debates on local food strategies and short food supply chains often focus on small-scale farms, assuming that large-scale producers lack interest. However, the results of this study highlight that interest in engaging more in direct sales is widespread across the farming sector, including predominantly arable, large-scale farms (Cluster 2) (see also Maye *et al.*, 2025). Consequently, it is important that food strategies are inclusionary and recognise the widespread interest in developing new marketing channels across a diverse set of producers and current distribution arrangements. In motivating farmers to participate in new marketing arrangements, it is important to note that motivations vary: for some improving margins or accessing new market opportunities matter most, while for others diversifying risks or contributing to local initiatives takes precedence. Moreover, the salience of specific drivers does not fit neatly with particular clusters and instead different structural networks embody a diversity of motivations. This suggests that local food initiatives should avoid having a single objective but rather develop strategies which can achieve multiple objectives. This way they are likely to appeal and retain a much larger critical mass of actors. Similarly, the barriers to engagement in direct marketing arrangements, and the forms of support that enable such engagement, are well-understood and common across different clusters (Table 2). For the development of local food initiatives, it also highlights the importance of integrated advice relating to marketing as well as the technical and financial aspects of new operations.

Policy initiatives often mistakenly focus on just the upsides of the change they are seeking to foster (Cadario and Chandon, 2020). However, behavioural change often depends less on increasing motivation but rather identifying ways of overcoming barriers to performing actions (Altmann *et al.*, 2022). For local food strategies, this implies developing approaches which allow farmers to engage with new direct marketing channels but with low personal time, other labour and infrastructure requirements. This suggests that collective approaches to marketing, sales and infrastructure may be most appropriate. This fits with multiple previous studies which demonstrate that farmers can benefit from collaborating in sales, marketing and distribution – for instance in achieving better prices in a B2B context (Zou and Wang, 2022), providing a wider and more attractive range of produce for direct-to-consumer channels (Michel-Villarreal *et al.*, 2021) and cutting transport costs and related carbon emissions (Paciarotti and Torregiani, 2021).

Finally, the study demonstrates the practical relevance of SNA for identifying key actors which occupy strategic positions within a network (Mbaru and Barnes, 2017). The adoption of innovations often depends on peer-to-peer learning led by a critical actor who is well connected and respected in a particular network (Rogers, 2003). SNA can help identify such critical actors, who are vital to behavioural change initiatives (Shelton *et al.*, 2019).

4.2 Future research

Future research could explore how connections between farms and markets evolve over time through longitudinal data, particularly in response to policy shifts or major disruptions such as economic crises that reshape dynamic networks. Furthermore, integrating the human and relational dimensions of these connections would offer a more holistic understanding of how the food system operates, as trust and interpersonal relations help shape structural interactions in supply chains (Lado *et al.*, 2008). Including intermediaries in such analyses would further illuminate the relational infrastructure of the food system and the interdependencies that sustain it, particularly through a direct SNA approach that incorporates tie-strength weights to represent the intensity of exchange relationships.

4.2.1 Conclusions. Resilience in UK local food systems is not simply a function of farm type or scale but is fundamentally shaped by structural positioning within marketing networks (Pretty, 2001). Farms that engage in multi-channel strategies combining high-volume with community-based, relational routes tend to occupy more central positions, benefiting from stronger connectivity, adaptability and often improved economic outcomes. However, centrality does not guarantee market power. Crucially, the findings underscore the benefit of multi-channel engagement as a means to enhance resilience by spreading risk and enabling adaptive responses to disruption (Rivington *et al.*, 2021).

This study shows that structural inequalities within local food networks, combined with diverse farm-level strategies, require tailored policy responses. While core actors play vital roles, enabling access for peripheral farms is essential for building inclusive and resilient food systems. Moving beyond one-size-fits-all approaches, targeted support should include infrastructure investment, marketing diversification, knowledge exchange, non-farming income opportunities and support for farms that strengthen the wider network.

Ultimately, resilient local food systems require recognising their modular and uneven structure and designing interventions that foster resilience. The latter requires a network-aware perspective that understands who is connected to whom, through what marketing channels and within which spatial and structural configurations. This means recognising not only who participates in the market, but how they are positioned, how they interact and what opportunities or constraints flow from those relationships. Such structural understanding (considering, for example, not only farm businesses as individual entities but market relations with intermediary and retail actors as combined arrangements and infrastructures at regional scales) offers a critical foundation for designing targeted, equitable interventions that support diverse forms of resilience in the United Kingdom's evolving agri-food system. This demonstrates the usefulness of SNA approach in revealing critical elements such as structural positioning and connectivity for developing typologies that can inform policy and guide targeted interventions. By applying SNA to reveal patterns of connectivity and asymmetry, we in turn extend resilience theory into a more network-based domain and provide a foundation for future comparative and longitudinal research in agri-food systems.

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(The Appendix follows overleaf)

Table A1. Significant subgroup results linking SNA cluster typology and resilience outcomes (non-significant comparisons excluded)

| Farm characteristic/ Indicator | Subgroup showing significant difference | Resilience indicator (past 12 months) | Pattern of difference across SNA clusters | p-Value |
|-----------------------------------|---|---------------------------------------|---|---------|
| Farm type | Livestock | Income change | C3 most likely to report income increases, C2 least likely | 0.002 |
| Region | North East | Farm turnover | C1 and C3 more likely to be in lower turnover bands | 0.017 |
| | South West | Farm turnover | Clusters differ significantly across turnover bands | 0.001 |
| | | Income change | C1 most likely to report income increases | 0.018 |
| Land Size (ha) | West Midlands | Farm turnover | C1 more likely in low turnover, C4 more likely in mid-high turnover | 0.013 |
| | Medium (20–100 ha) | Farm turnover | Turnover varies clearly across clusters | 0.001 |
| | | Income change | C3 most likely to report income increase | 0.038 |
| Number of employees | Large (>100 ha) | Employment change | C1 and C4 show the highest employment growth | 0.021 |
| | | Farm turnover | Strong turnover differences observed | 0.001 |
| | | Income change | C3 shows the strongest income performance | 0.005 |
| | | Employment change | C1 and C3 show the highest increases, C2 the lowest (borderline) | 0.052 |
| Non-farm income | 1–4 | Income change | C3 most likely to report income increases, C4 least likely | 0.004 |
| | 5–9 | Income change | C3 highest income increases, C2 lowest | 0.003 |
| | 10 or more | Impact of rising costs | C1 and C4 most affected by rising costs | 0.026 |
| Income change | Large farms | Non-farm income | C2 and C3 more diversified, C4 least diversified | 0.001 |
| Impact of rising costs | Multiple subgroups | Income change | C3 consistently shows the highest income growth across subgroups | 0.005 |
| | Employees (10 or more) | Impact of rising costs | C1 and C4 show the highest cost-related cash-flow impacts | 0.026 |

Source(s): Authors' own work

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Corresponding author

Fahimeh Malekinezhad can be contacted at: fmalekinezhad@glos.ac.uk