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Abstract

Producers participating at farmers markets (FMs) operate with limited information about their consumers. Little or no information about consumer behavior is available to producers at FMs to help them make better pricing and strategic decisions on their offerings. Understanding consumer demand for meat products at FMs is essential for producers seeking to enhance market performance and local food systems participation. Price elasticity of demand captures consumer behavior that is relevant to producers. This study estimates price elasticities of demand for beef, pork, and chicken sold at FMs in New York State using detailed point-of-sale (POS) transaction data from multiple farms and FMs during 2021 and 2022. Employing the Linear Approximation Almost Ideal Demand System (LA/AIDS) and Quadratic Almost Ideal Demand System (QU/AIDS) models we account for farm-level and market-level sales heterogeneity while addressing endogeneity concerns related to unit value quality effects and price variation across farms and markets. Our findings indicate that own-price elasticities vary by species, with pork and chicken exhibiting elastic demand, while beef demand is relatively inelastic. Additionally, cross-price elasticities are not statistically significant, suggesting limited substitution between species in FM settings. These results highlight the unique characteristics of FM transactions, where direct producer-consumer relationships and limited product availability influence purchasing behavior. The findings offer valuable insights for FM vendors in optimizing pricing strategies and understanding consumer responsiveness to price changes in local food systems. Given our results and the increasing competition from traditional retailers marketing local products, FM vendors should be more aware of grocery store prices and offerings to refine their pricing strategies and maintain their competitive advantage.

Key Words: farmers markets, livestock farms, marketing, point-of-sale data, price elasticity

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Introduction

Farmers markets (FMs) are important elements for the development of local agriculture value chains. They provide unique opportunities for farmers to offer their products directly to consumers, eliminating the need for intermediaries and allowing farmers to receive full retail prices, albeit with added retail marketing costs such as renting a booth and labor. Consumers benefit from FMs through direct engagement with growers, supporting and learning about local agriculture, and expressing their preferences to producers. FMs facilitate the interaction between producers and consumers, which helps farmers better understand the preferences of their customers, creating a beneficial relationship between them (Fenestra and Lewis, 1999; Adanacioglu, 2021).

Despite the perceived benefits of FMs, there is evidence that their performance, at the farm or market level, is heterogeneous across space (Low et al., 2015). Using consumer surveys, some research has examined the preferences of FM shoppers and their relationships with demographic and market characteristics (Schmit et al., 2019, Abello, et al., 2014; Gumirakiza et al., 2014; Conner et al., 2010; Zepeda, 2009). Vendor performance, as measured in daily sales or customer counts, has been correlated with FM, customer, and community characteristics (Schmit and Gomez, 2011; Stephenson et al., 2008; Varner and Otto, 2008). Although the literature on FMs and customer characteristics is relevant in understanding how the products offered at FMs differ across location, we have not found studies that estimate consumer price elasticities of demand at FMs. Price elasticity of demand is a critical component in price determination and marketing strategy for farm vendors, and particularly relevant given evolving local food systems and growing competition with traditional retailers (Hamilton, 2018; Schmit et al. 2019).

The lack of studies on price elasticity at FMs may be the result of the absence of detailed sales data necessary for their estimation. The extensive literature on retail food product elasticities focusses primarily on conventional retail environments, such as grocery stores, and estimated through aggregated retail disappearance or per capita consumption data provided by the USDA and other sources (for a searchable database see USDA, 2024). Increasing availability of scanner data from grocery stores and household diary/consumer expenditure surveys has allowed a more detailed estimation of price elasticities per category and product levels, and for at-home and away-from-home consumption, but still constrained to traditional retail channels due to data availability (Okrent and Alston, 2012; Muth et al., 2020; Jeon et al., 2023).

The data vacuum for FMs leads to potential inaccuracies when applying traditional retail-based elasticity measures for marketing strategy adjustments and price determination at FMs. Even within the confines of existing published results, the selection of the most applicable retail elasticity is elusive at best. Published retail price elasticities for meats and meat products, for example, range from inelastic to elastic (Capps, 1989; Gallet, 2010; Jeon et al., 2023) an outcome understandably attributable to different empirical approaches, data frequency and aggregation (e.g., transaction, weekly, monthly, annual), product scale (e.g., meat species (beef) versus retail cuts (ground beef)), observational scale (e.g., retail sales, household purchases, customer transaction), and spatial focus (e.g., local, regional, national).

The FM setting is distinct from traditional retail environments since the retailer is both the producer (farmer) and seller (vendor). In this context, sales occur more infrequently (generally weekly and often seasonally), with more limited product variety (especially across species in the case of meats), and with limited restocking due to individual supply constraints based on farm size, seasonality in production, and slaughter dates for livestock. Further, the elasticities from existing literature ignore potential demand-side effects where purchasing behavior may be influenced by the desire to have a direct connection to the producer and support local agriculture and communities.

Recent technology adoption by FM vendors of electronic point-of-sale (POS) systems to process customer sales (cash and credit) provide the means to collect and analyze detailed transaction-level purchasing data akin to grocery store scanner data. We contribute to the literature by developing a novel empirical framework to estimate price elasticities at FMs with a demand systems approach. Given the distinct retail environment, a data aggregation procedure across farms is proposed to estimate consumer price elasticities while contemporaneously incorporating product, farm, and FM effects derived from the detailed POS data. We apply our framework to POS data from a sample of livestock producers selling meat products at FMs in New York State (NYS). We estimate price elasticities at the species level (beef, pork, and chicken) using two model specifications for robustness: the Linear Approximation of the Almost Ideal Demand System (LA/AIDS) and the Quadratic Almost Ideal Demand System (QU/AIDS).

Local and regional food systems continue to evolve and mature, including increasing availability and marketing of local food products in conventional retail settings. Understanding potential differences in elasticities across conventional and FM environments helps inform strategic marketing and pricing strategy for FM producers. To that end, we hypothesize that consumer price sensitivity at FMs is relatively more inelastic than traditional retail settings. We base this on the expectation that consumers have a fundamentally different relationship with the retailer at FMs (i.e., the farmer) that enhances customer loyalty and purchases even in the face of (moderate) price changes.

We also hypothesize that cross-price elasticities at the species level will not be statistically significant as most vendors do not regularly offer a full suite of products from multiple species simultaneously and the expected aversion by customers to switch product species and/or vendors in a dedicated FM shopping trip. Put differently, higher customer loyalty leads to more intentional product purchasing during a shopping trip and limits cross-species purchasing from other vendors. Since not all species may even be available for sale at a given FM, lower availability of multiple species at FM relative to the meat case in traditional grocery stores likely limits cross price effects in the aggregate.

We continue with an outline of the POS data collected and our empirical framework to apply a demand systems approach to a FM setting. Next, the econometric models are developed, and the corresponding results are presented. The discussion concludes with insights into the importance of the models constructed, possible implications for farms and industry, and future research directions.

Data

Our data encompasses over 40,000 unique transactions over time from six farms (retailers) selling beef, pork, and chicken products at fifteen different FMs in 2021 and 2022. Some FMs in our sample feature a single seller from our farm sample, while other FMs have multiple farms selling simultaneously. Due to cost and time constraints to collect the data and farm willingness to participate, we do not collect data from all livestock farms at each FM. Three farms sold products from all three species (beef, pork, and chicken), two sold products from two species, and one focused exclusively on pork. Some multispecies farms sold some species in limited quantity and/or times of the market season.

The data used in this study extends the work of Rigotti et al. (2023), which utilized the Square™ POS system to collect data on customer transactions at FMs to investigate the primary factors influencing customer transaction size. Transaction data includes a unique transaction ID, time and date of sale, sale location, item sales, product descriptions, and quantities purchased. Individual product prices per unit are set by the farmer and input into the POS system (e.g., $6.99/pound). Transaction data collected from farms do not include item prices but rather total sales by product (e.g., $69.90) and quantity sold (e.g., 10 pounds). Product prices per unit are easily calculated based on the dollar amount of item sales and quantity purchased.

Data Processing

Estimating product-level elasticities for FMs requires consideration of the distinct retail environment and supply constraints associated with FM vendors. Traditional retailers restock items via supplemental purchases from their suppliers (predominantly wholesalers). FM vendors are limited in the supply of cuts based on the scale of their farm and the distribution of cuts available from a single carcass (e.g., more pounds of ground beef are available from a beef carcass than pounds of ribeye steaks). In addition, limited slaughter/processing dates within a year may constrain product availability over the course of a market season. Accordingly, "zero sales" of a particular product in a particular week may be the result of "availability and nonpurchase" or "nonavailability" of the product (stockouts). Without additional information, including weeks with zero sales associated with stockouts will bias price elasticity estimates. Since it is unlikely that all products within a species stock out on an individual sales date, we aggregate customer transactions to the species level.[1]

[1] Aggregating to product category levels within species reduces the opportunity for bias but requires a sufficiently long time series for a multi-species demand systems investigation (i.e., a degrees of freedom constraint).

Weekly observations were dropped when any of the farms that sell a particular species had no recorded transactions. These occurrences are likely due to non-attendance at FMs in a particular week or species-level stock outs. In the FM setting, zero sales weeks may also be the result of seasonal FM closures and/or holidays, rather than a genuine absence of sales. These adjustments are critical in a FM context to ensure that zero sales weeks are not erroneously interpreted as changes in demand.

Since not all farms sell all species of meat products, a traditional panel data analysis at the farm level is infeasible for a demand systems approach. In addition, individual farm vendors in our sample change prices relatively infrequently during a market a season. By aggregating transactions across farms and FMs by species and week, we collectively accumulate individual vendor price changes. Having POS data across two market seasons also accommodates price changes across seasons. The process is comparable to aggregated consumer demand analyses using secondary data and whereby we estimate average FM price elasticities across the farm and FM sample.

Endogeneity Controls

Weighted-average prices are computed each week for each species based on product prices and quantity of sales for each farm and FM they attend. The process necessarily involves a distribution of cuts with lower (e.g., ground beef) and higher (e.g., ribeye steaks) prices per pound. In other words, species-level prices represent unit values with endogenous quality effects. Unit values are unreliable indicators of price when the distribution of individual products within the aggregate category varies over time. Such variability introduces bias into the estimation of price effects, especially if changes in quality correlate with other unobserved characteristics (Deaton, 1988; McKelvey, 2011). For example, in the face of rising prices across products for a meat species, customers may opt for more lower-quality cuts and the unit value does not accurately reflect the actual price increase, potentially leading to underestimation of price effects.

Given the underlying POS data, we can control for endogenous quality effects. Specifically, we include control variables representing the composition of meat products purchased each week for each species. Using transaction-level records in the POS data, we calculate weekly sales percentages based on pounds for multiple product categories within each species. Specifically, beef includes six product categories (chuck, loin, rib, round, thin cuts, and trim), pork includes six product categories (belly, butt, ground, ham, loin, and shoulder), and poultry includes two product categories (cuts and whole).[2] By quantifying the percentage of each product category sold relative to the total quantity sold of that species each week, we address the unit value quality problem.

Given our data aggregation process, we must also control for endogenous price effects related to differences in the distribution of sales across farms and FMs across each week. To do so, we utilize the transaction-level POS data to compute farm- and FM-level Herfindahl-Hirschman Indices (HHI). This effectively controls for overall prices that may differ across farms and/or offered at different FMs. The indices are formerly presented in equations 1 and 2 for farms and FMs, respectively:

(1) $HHI\_F_{i,t} = \sum_{f=1}^{6} \left[\left(\frac{Q_{f,i,t}}{\sum_{f=1}^{6} Q_{f,i,t}} \right)^2 \right]$ and

(2) $HHI\_M_{i,t} = \sum_{m=1}^{15} \left[\left(\frac{Q_{m,i,t}}{\sum_{m=1}^{15} Q_{m,i,t}} \right)^2 \right]$

for meat species i, farm f, and FM m. Q denotes the quantity sold (in pounds) in week t.[3]

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[2] For detailed information on the items included in each product category, see Rigotti et al. (2023).

[3] An alternative approach would be to include share variables for each farm and FMs, similar to the product category variables above (given the underlying detailed transaction data). However, degrees of freedom concerns (discussed later) and potential multicollinearity issues support the HHI approach.

Descriptive Statistics

Summary statistics provided in Table 1 offer a snapshot into the weekly transactions of beef, pork, and chicken for our farm and FM sample. Following the data construction process above, the final data set encompasses 68 weeks in 2021 and 2022 (i.e., two market seasons).

[TABLE 1]

On average, all sampled farms sold approximately 115 pounds of beef (*Q_BE*), 531 pounds of pork (*Q_PK*), and 217 pounds of chicken (*Q_CH*) each week, with considerable variability across weeks. Weighted-average weekly prices per pound of beef, chicken, and pork sold are $10.68 (*P_BE*), $13.74 (*P_PK*), and $6.79 (*P_CH*), respectively, resulting in average weekly sales (weekly customer expenditure) of $1,247 (*X_BE*), $7,295 (*X_PK*), and $1,470 (*X_CH*), for all three species. Pork dominates expenditure shares with a weekly average of 0.73 (*S_PK*).

The composition of product sales by category and species represents both carcass volume breakdowns and customer product preferences. For example, ground beef and other related trim products (*BE_TR*) represent a majority percentage of beef sales (53%). Similarly, ground pork and sausages make up the majority of pork sales (*PK_GR*, 63%). Chicken sales are predominantly cuts (*CH_CU*, 75%) rather than whole birds. However, as shown in Figure 1, the sales percentages by primary product category for each species vary considerably over time, supporting our inclusion of them as control variables for the unit value issue.

[FIGURE 1]

Relative to traditional industry concentration measures, concentrations of farm sales (*HHI_F*) are relatively high for each meat type (Table 1). Specifically, *HHI_F* values are 0.42, 0.36, and 0.47 for beef, pork, and chicken, all exceeding the 0.25 threshold that generally signifies a high "industry" concentration (Benkard, et al., 2021). This suggests that a small number of farms in our sample hold significant sales shares (i.e., are considerably larger relative to the average). More importantly for our estimation controls, HHI concentrations over farms for each species vary considerably over the 68 weeks with no evident trend (Figure 2).

[FIGURE 2]

HHIs at the FM level (*HHI_M*) are considerably lower (0.24 to 0.29, Table 1) than the HHI values across farms (*HHI_F*), suggesting a more even distribution of sales across markets, on average. Although both *HHI_F* and *HHI_M* show a wide range of values, the variation in *HHI_M* is considerably larger suggesting considerable variation in the distribution of sales across weeks. This is illustrated in Figure 3, indicating higher concentrations of FM sales during the winter months when smaller markets tend to close. Accordingly, the inclusion of both *HHI_F* and *HHI_M* are an effective means to account for farm and FMs endogenous price effects.

[FIGURE 3]

As expected, summer and fall are peak seasons at FMs, accounting for 38% and 32% of the weeks observed in the sample, respectively (Table 1). This seasonal pattern inherently reflects that some FMs in our sample do not operate through the whole year.

Methodology

We estimate FM price elasticities using two different models: LA/AIDS and QU/AIDS. We employ the LA/AIDS model, an efficient version of the more complex AIDS model, developed by Deaton and Muellbauer (1980). The AIDS model is known for its flexibility and the capability to fit well-defined consumer preferences. However, due to the nonlinear nature of the AIDS model's price index, practical applications often favor its linearized form when dealing with aggregated data where price collinearity is a concern (Green et al., 1990). Our empirical LA/AIDS model is formally expressed as:

(3) $share_{i,t} = \alpha_i + \beta_i ln(X/P)_t + \sum_j \gamma_{i,j} lnp_{j,t} + \sum_{j,c} \delta_{i,j,c} QS_{j,c,t} + \sum_j \theta_{i,j} HHI\_F_{j,t}$

$$+ \sum_j \mu_{i,j} HHI\_M_{j,t} + \sum_s \tau_s S_{s,t} + \varepsilon_{i,t}$$

where $share_{i,t}$ is the budget share for species i at week t, X_t is total customer expenditure across all meat species, P_t is the Stone Price Index, and lnp_j are the natural logarithms of the weighted-average species prices. $QS_{j,c,t}$ denote the c^{th} product category quantity percentages for species j (excluding one category to avoid singularity), $HHI\_F_{j,t}$ and $HHI\_M_{j,t}$ represent the species specific HHIs for farm and FMs, respectively, and $S_{s,t}$ are the seasonal dummy variables (excluding one season).

The QU/AIDS model extends the traditional AIDS model by incorporating quadratic Engel curves, allowing for a more detailed analysis of how expenditure shares respond to changes in income (Banks, Blundell, and Lewbel, 1997). Unlike AIDS, which assumes a linear response in expenditure shares to income changes, QU/AIDS adds a quadratic term to capture non-linear variations in consumer behavior (Lakkakula et al., 2016). This enhancement makes QU/AIDS particularly adept at handling complex interactions, providing a more robust understanding of demand elasticity and consumer response to price and income changes. Our empirical QU/AIDS model is formally expressed as:

(4) $share_{i,t} = \alpha_i + \beta_i ln(X/P)_t + \frac{\lambda_i}{b(P)}(ln(X/P)_t)^2 + \sum_j \gamma_{i,j} lnp_{j,t} + \sum_{j,c} \delta_{i,j,c} QS_{j,c,t} +$

$$\sum_j \theta_{i,j} HHI\_F_{j,t} + \sum_j \mu_{i,j} HHI\_M_{j,t} + \sum_s \tau_s S_{s,t} + \varepsilon_{i,t}$$

where $(ln(X/P)_t)^2$ is the quadratic expenditure term allowing for a non-linear response in expenditure and $b(P)$ represents the Cobb-Douglas price aggregator function. The $b(P)$ term serves as a normalizing factor that accounts for the aggregate price level, allowing the quadratic term to reflect the real purchasing power of income rather than nominal income. This improves the model's robustness in capturing consumer behavior as prices fluctuate (Lakkakula et al., 2016).

Conventional adding up, homogeneity, and symmetry restrictions are applied in both models for theoretical consistency, and expressed, respectively, as:

(5) $\sum_i \alpha_i = 1$, $\sum_i \beta_i = 0$, $\sum_i \gamma_{i,j} = 0 \, \forall \, j$,

(6) $\sum_j \gamma_{i,j} = 0 \, \forall \, i$, and

(7) $\gamma_{i,j} = \gamma_{j,i} \, \forall \, i, j$.

Both models are estimated with the *aidsills* package from Stata (Lecocq and Robin, 2015). Finally, expenditure and Marshallian (i.e., uncompensated) own- and cross-price elasticities are derived as (Mustafa et al., 2022):

(8) $\delta_i = 1 + (\frac{\beta_i}{share_i})$,

(9) $\varepsilon_{i,i} = (\gamma_{i,i}/share_i) - 1$, and

(10) $\varepsilon_{i,j} = (\gamma_{i,j}/share_i)$.

Results

Conditional Marshallian price elasticities of demand are presented in Table 2. For ease of exposition, full regression results are presented as supplementary materials in Appendix 1 (LA/AIDS) and Appendix 2 (QU/AIDS).

[Table 2]

The results show strong similarity in own-price elasticities across the LA/AIDS and QU/AIDS models. Both models reveal significant and elastic negative own-price elasticities for pork and chicken. Specifically, in the LA/AIDS model, pork has an own-price elasticity of -1.089 (p-value = 0.000) and chicken -1.239 (p-value = 0.002). The QU/AIDS model yields similar values, with pork at -1.122 (p-value = 0.000) and chicken at -1.195 (p-value = 0.020), but also shows a significant, but inelastic, own-price elasticity for beef of -0.803 (p-value = 0.015). The own-price elasticity for beef in the LA/AIDS model is not statistically significant at the 10% significance level but is of similar magnitude (-0.750, p-value = 0.120).

Cross-price elasticities show no statistical significance in either model. As discussed above, the insignificant cross-price elasticities may reflect the more designated nature of product shopping at FMs and resistance to species switching. The similarity in results across both LA/AIDS and QU/AIDS models reinforces the robustness of these findings and highlights the distinctive consumer preferences present in the FM context.

Robustness Checks

Supplemental regressions using a double log ordinary least squares (OLS) model with robust standard errors and an LA/AIDS model without homogeneity and symmetry constraints were conducted to further assess the robustness of our results (Table 3). The OLS model (equation 11) considers logged quantity for each species ($lnQ_{i,t}$) as the dependent variable, and logged total customer expenditures on meat (lnX_t) as additional independent variable; the rest of the variables are unchanged from our primary AIDS models:

(11) $$lnQ_{i,t} = \alpha_i + \beta_i lnX_t + \sum_j \gamma_{i,j} lnp_{j,t} + \sum_{j,c} \delta_{i,j,c} QS_{j,c,t} + \sum_j \theta_{i,j} HHI\_F_{j,t} + \sum_j \mu_j HHI\_M_{j,t} + \sum_{s-1} \tau_s S_{s,t} + \varepsilon_{j,t}$$

[Table 3]

The unrestricted LA/AIDS model is defined as before (equation 3) but without homogeneity and symmetry constraints (equations 6 and 7).

The double log model demonstrates relatively similar results albeit with higher own price elasticities for beef (-1.378, p-value = 0.028) and chicken (-1.434, p-value = 0.159) and a lower own-price elasticity for pork (-0.719, p-value = 0.094), but all measured with less statistical precision. Further, a negative and statistically significant cross-price elasticity between beef and pork of -1.979 (p-value = 0.072) is inconsistent with traditional expectations. Similar results hold for the unrestricted LA/AIDS model, albeit with higher statistical precision, and implies the regularity conditions (adding-up, homogeneity and symmetry) are important in demand systems analysis in a FM setting. In general, the relatively similar own-price elasticities to our primary models provide some degree of robustness but with regularity conditions important, especially for a relatively small sample size. The QU/AIDS model demonstrates improved performance relative to the restricted LA/AIDS model (Table 2), reinforcing the robustness of our results under comparable regulatory and functional form conditions

Discussion

In relation to our first hypothesis (i.e., more inelastic own price effects), the findings from our preferred QU/AIDS model display higher elasticities compared to the mean values reported in the meta-analyses of Jeon et al. (2023) and Gallet (2010); however, all fall within the range of findings they report. Specifically, Jeon et al. (2023) report mean price elasticities of -0.740 for beef, -0.815 for pork, and -0.609 for chicken, with ranges extending from -2.227 to 0.283, -2.351 to -0.007, and -1.665 to -0.047, respectively. Jeon et al. (2023) discuss the distinction of scanner data in capturing demand elasticity, suggesting that it may lead to more elastic demand estimates than non-scanner data. From this perspective, our results are broadly consistent with traditional retail settings.

Given the wide variation in product scales and methodologies across existing studies and meta-analyses, we focus our comparison on four studies identified during the literature review that estimate elasticities at the species level and use an AIDS framework (Table 4). The range and averages from these studies reveal that our results are consistent for beef and pork, but higher for chicken.

[Table 4]

Of these four studies, only one, Tonsor and Bina (2023), uses retailer scanner data and with data over a comparable time period. In this case, both the level of the own-price elasticities for beef and pork and their relative relation (i.e., pork higher than beef) are reasonably consistent. However, estimated elasticities for chicken are far different, where we report the most elastic response in deference to Tonsor and Bina (2023) and of the other AIDS model estimates in Table 4 that show it is the most inelastic response.

Traditional retail grocers have been leveraging locally sourced products in their marketing since the 1990s to compete with FMs and other direct-to-consumer options and meet increasing demands by their customers for local products (Guptill and Wilkins, 2002) The convenience of one-stop shopping and flexible hours make grocery stores an attractive option. Based on a recent national FM customer survey, Schmit et al. (2019) discusses evolving consumer preferences for locally sourced products and the associated price sensitivity at FMs, reflecting a dynamic marketplace environment. Schmit et al. (2019) divide consumers into strong customers (i.e., same or higher level of FM shopping relative to the prior year), decreasing customers (i.e., attendance and purchases at FMs decreased from the prior year), and non-FM customers (i.e., never a customer or no longer participate in them). They find the top reasons consumers shop less at FMs is due to growing availability and convenience of shopping for local foods at traditional grocers and a perception of higher prices at FMs. As the demand for local foods evolves, traditional retailers will continue to adapt their offerings and reflective of increasing competition among alternative market channels

Conclusions

The utilization of vendor scanner data at FMs, an empirical framework that recognizes the unique retail conditions farmers face as both producers and retailers, and the estimation of price elasticities of demand enhances the understanding of consumer behavior in local foods direct-to-consumer markets. An evolving local foods marketplace and growing competition among traditional retail settings is consistent with the higher estimated elasticities than originally hypothesized. To the consumer interested in supporting local food economies, buying local products at either the FM or the grocery store likely meets that desire. The stronger connection to the producer (farmer) through interaction likely remains a salient advantage for FM vendors, but relatively less important, on average, than in years past given growing competition and convenience effects for consumers in traditional retail settings.

Accordingly, FM vendors and FM managers should consider additional marketing features (e.g., tastings, farm stories, customer stories, recipes, announcing product availability in advance) and market (e.g., marketing promotions to the public on vendor offerings) to better take advantage of the in-person customer-to-farmer interface. Furthermore, heightened attention by FM vendors to understand what local products are available in their local traditional retail settings, the characteristics of those products, and the prices offered are necessary for identifying competitive advantages to inform marketing strategy and price setting.

While the insights from existing literature and results from our FM application underline the complexity of interpreting demand elasticities and emphasize the importance of incorporating diverse market and consumer considerations into marketing and business strategies, there are limitations in our research. The limited number of farms and FMs in our dataset understandably restricts the generalizability of our findings. Additional studies across space will help recognize potential differences due, in part, to community and customer characteristics. Collecting data over longer time periods with additional farm data will be important in capturing sufficient price variation to further understanding consumer price sensitivity at FMs. While our approach intentionally seeks to estimate average consumer demand elasticities at FMs through a multi-farm, multi-market sample, considering a specific FM with sufficient producers and products and collecting data from all farm vendors at it may better identify both own- and cross-price effects withing a given FM setting.

Econometrically, incorporating price endogeneity concern through an instrumental variables approach would help address potential biases in the estimated effects. Disaggregating species into more narrowly defined product groups (such as high and low-priced products), categories, or cuts will allow for a more nuanced analysis of consumer responses to price changes at FMs, including cross-price effects, among competing products within a species, conditional on sufficient data for their analysis and more farm-level information on inventory constraints (stock outs).

Overcoming these data limitations would allow for a more comprehensive analysis of demand elasticity and build on the empirical framework proposed. Doing so will further inform marketing strategy and price determination for farm vendors as they adapt to evolving market trends and consumer preferences.

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Table 1. Summary Descriptive Statistics

Variable	Description	Mean	Std. dev.	Min	Max
Product Sales					
Q_BE	Weekly quantity of beef sold (lbs)	115.10	40.26	37.28	201.82
P_BE	Weighted average price of beef	10.68	1.35	8.21	13.47
X_BE	Weekly expenditure of beef	1,246.56	507.22	328.69	2,598.32
Q_PK	Weekly quantity of pork sold (lbs)	531.17	125.73	250.59	819.24
P_PK	Weighted average price of pork	13.74	1.00	11.54	15.60
X_PK	Weekly expenditure of pork	7,295.15	1,772.61	3,026.94	10,861.81
Q_CH	Weekly quantity of chicken sold (lbs)	216.84	90.76	39.08	453.55
P_CH	Weighted average price of chicken	6.79	0.59	5.69	8.85
X_CH	Weekly expenditure of chicken	1,469.79	624.52	222.36	3,138.84
S_BE	Weekly expenditure share of beef	0.12	0.04	0.06	0.29
S_CH	Weekly expenditure share of chicken	0.15	0.05	0.02	0.28
S_PK	Weekly expenditure share of pork	0.73	0.08	0.43	0.88
X_Total	Weekly total expenditure	10011.50	2314.24	5947.02	13909.29
Product Category Composition Controls					
BE_CH	Beef chuck	6.80	3.80	1.09	17.86
BE_LO	Beef loin	20.87	6.87	3.57	41.25
BE_RI	Beef rib	11.33	5.62	0.00	24.72
BE_RO	Beef round	2.20	2.65	0.00	13.54
BE_TC	Beef thin cuts	5.69	3.59	0.00	17.39
BE_TR	Beef trim	53.11	7.01	41.67	70.31
CH_WO	Chicken whole	25.51	8.63	9.52	64.71
CH_CU	Chicken cuts	74.50	8.63	35.29	90.48
PO_BE	Pork belly	18.02	3.74	11.05	28.62
PO_BU	Pork butt	1.15	0.69	0.00	2.91
PO_GR	Pork ground	63.32	5.17	50.26	75.18
PO_HA	Pork ham	2.15	1.01	0.24	5.83
PO_LO	Pork loin	12.36	3.00	6.47	17.93
PO_SH	Pork shoulder	3.00	1.58	0.00	7.83
Herfindahl-Hirschman Indices (HHI) across Farms and Locations (FMs)					
HHI_F_PK	HHI farm index for pork	0.37	0.08	0.23	0.54
HHI_F_BE	HHI farm index for beef	0.42	0.07	0.34	0.65
HHI_F_CH	HHI farm index for chicken	0.47	0.10	0.34	0.73
HHI_M_PK	HHI farmers market index for pork	0.24	0.11	0.12	0.55
HHI_M_BE	HHI farmers market index for beef	0.26	0.10	0.14	0.65
HHI_M_CH	HHI farmers market index for chicken	0.29	0.11	0.15	0.61
Seasonality					
summer	Week in June, July or August	0.38	0.49	0.00	1.00
fall	Week in September, October, or November	0.32	0.47	0.00	1.00
winter	Week in December, January, or February	0.15	0.36	0.00	1.00
spring	Week in March, April, or May	0.15	0.36	0.00	1.00

Number of observations: 68. For detailed information on the items included in each product category, refer to Rigotti et al. (2023).

Table 2. Uncompensated farmers market price elasticities, primary models.

	P_Beef	P_Pork	P_Chicken
LA/AIDS[a]			
Q_Beef	-0.750	-0.319	-0.408
Q_Pork	-0.125	-1.089***	-0.021
Q_Chicken	0.414	0.717	-1.239***
QU/AIDS[a]			
Q_Beef	-0.803**	-0.218	-0.075
Q_Pork	-0.093	-1.122***	0.025
Q_Chicken	0.203	0.783	-1.195**

***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

[a] Adding Up, Homogeneity and Symmetry are imposed

Table 3. Farmers market price elasticities, robustness checks

	P_Beef	P_Pork	P_Chicken
OLS Double-Log			
Q_Beef	-1.378**	-1.979*	0.283
Q_Pork	0.023	-0.719*	-0.007
Q_Chicken	0.529	-0.883	-1.434
LA/AIDS (without homogeneity and symmetry)			
Q_Beef	-1.167**	-1.956*	0.274
Q_Pork	0.019	-0.732**	0.003
Q_Chicken	0.048	0.311	-1.250***

***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 4. Comparison of Retail Elasticities for Meat Species Utilizing AIDS Framework.

	Retailer Scanner Data			**Consumption Data**		
	Farmers Markets	Farmers Markets	Tonsor and Bina (2023)	Zhou (2015)	Sulgham and Zapata (2006)	Chen (1998)
Time	2021-2022	2021-2022	2022	1970-2006	1975-2002	1958-1985
Model	LA/AIDS	QU/AIDS	G/AIDS	LA/AIDS	AIDS	LA/AIDS
Frequency	Weekly	Weekly	Weekly	Annual	Quarterly	Annual
Level	NYS	NYS	U.S.	U.S.	U.S.	U.S.
Beef	-0.750	-0.803	-0.675	-0.979	-0.964	-1.173
Pork	-1.089	-1.122	-1.362	-0.999	-0.822	-1.192
Chicken	-1.239	-1.195	-0.381	-0.135	-0.306	-0.999

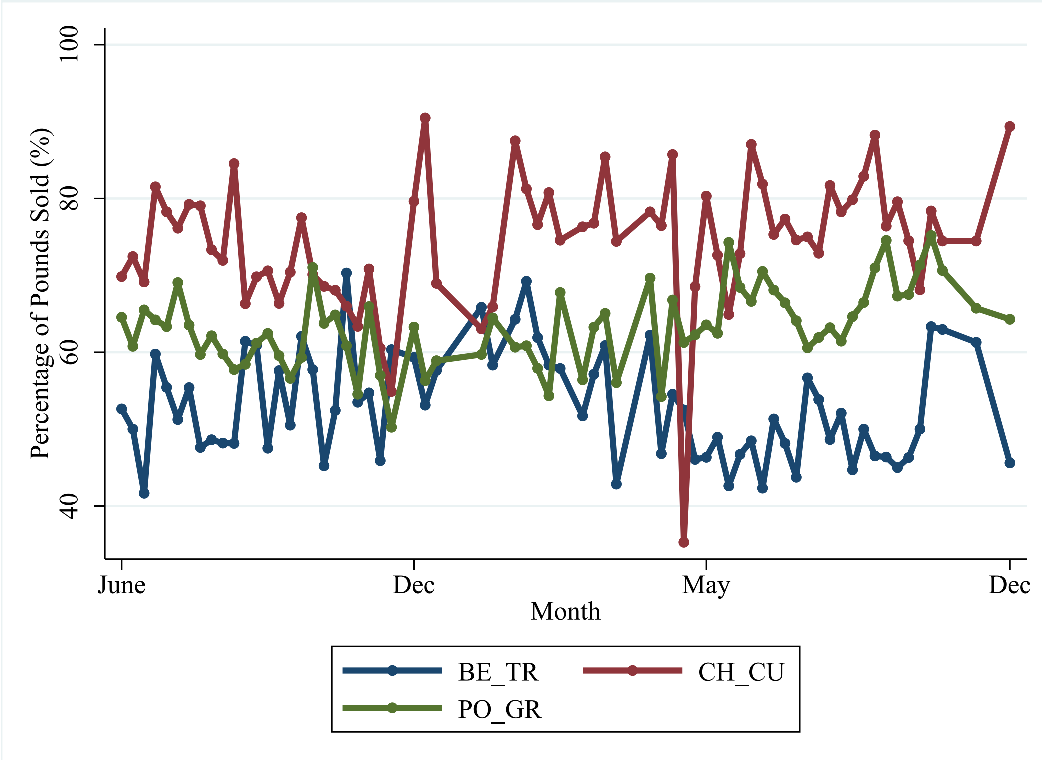

Figure 1. Variation in Sales Percentages by Product Category and Species Over Time

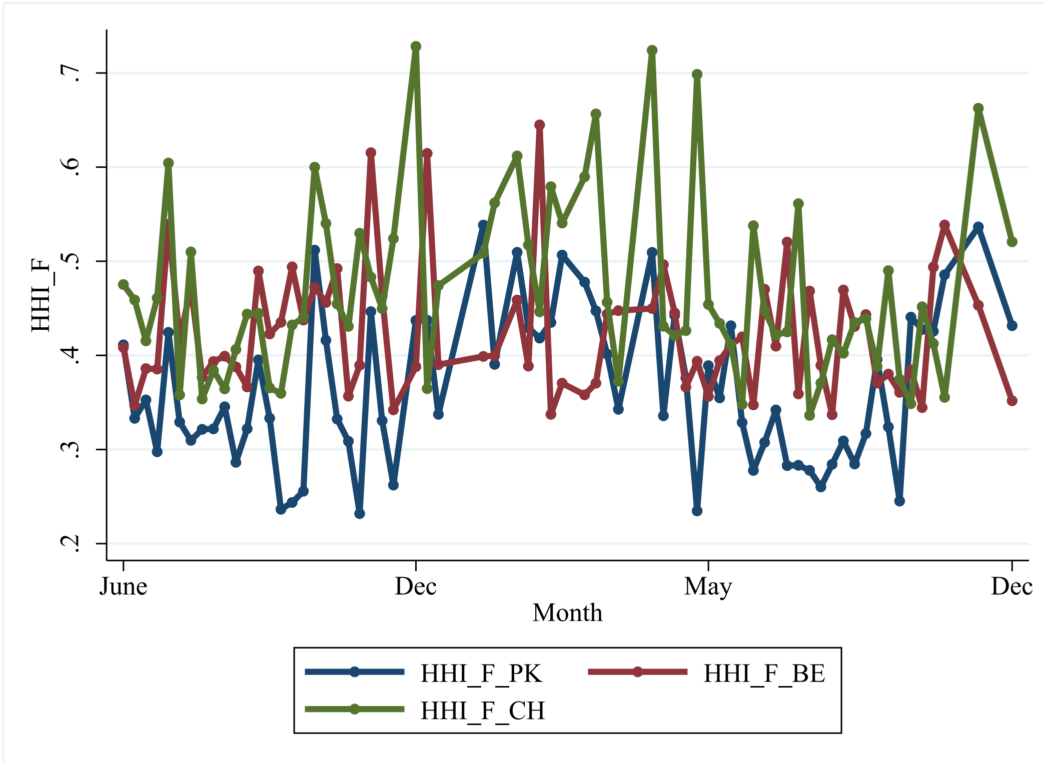

Figure 2. Temporal Variation in Farm Sales Concentration (HHI) by Species

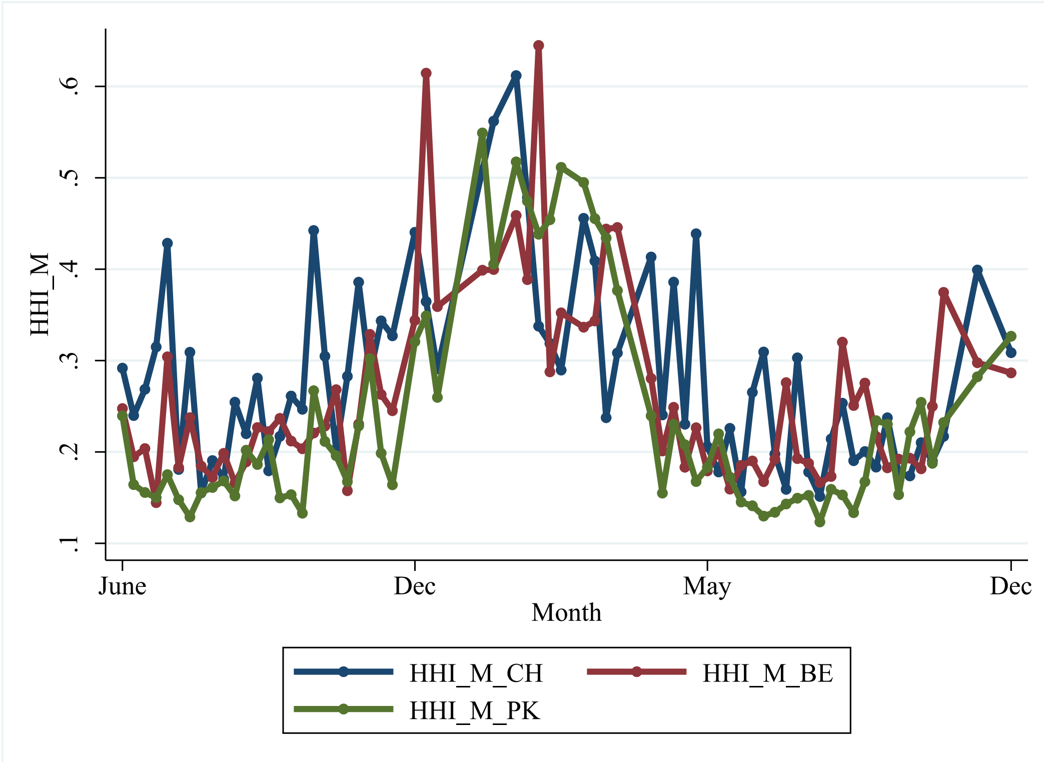

Figure 3. Temporal Variation in FMs Sales Concentration (HHI) by Species

Appendix 1. Regression Results LA/AIDS Model

	Beef			Pork			Chicken		
Variable	**Coeff.**		**Std. err.**	**Coeff.**		**Std. err.**	**Coeff.**		**Std. err.**
lnPR_BE	0.013		0.068	-0.017		0.137	0.004		0.091
lnPR_PK	-0.017		0.106	-0.159		0.238	0.176		0.163
lnPR_CH	0.004		0.069	0.176		0.157	-0.180		0.113
lnX	-0.042		0.035	0.172	***	0.063	-0.130	***	0.043
fall	0.027	***	0.010	-0.019		0.018	-0.008		0.013
winter	0.046		0.022	0.036		0.043	-0.082	***	0.030
spring	0.006		0.018	0.095	***	0.035	-0.101	***	0.024
BE_LO	0.000		0.001	0.000		0.003	-0.001		0.002
BE_RI	0.002		0.002	-0.003		0.003	0.000		0.002
BE_RO	0.002		0.002	0.000		0.004	-0.002		0.003
BE_TC	0.003	**	0.002	-0.001		0.003	-0.002		0.002
BE_TR	-0.001		0.001	0.001		0.003	0.000		0.002
CH_CU	-0.001		0.001	0.000		0.001	0.001		0.001
PO_BU	0.007		0.009	-0.017		0.016	0.010		0.011
PO_GR	0.002	**	0.001	-0.005	**	0.002	0.003	**	0.002
PO_HA	0.005		0.005	-0.013		0.009	0.009		0.006
PO_LO	0.004	**	0.002	-0.006		0.004	0.002		0.003
PO_SH	0.001		0.003	0.005		0.006	-0.006		0.004
HHI_F_BE	0.144		0.094	-0.479	***	0.182	0.335	***	0.125
HHI_F_CH	-0.070		0.064	-0.151		0.125	0.221	*	0.086
HHI_F_PK	-0.077		0.127	0.504	**	0.245	-0.426	**	0.168
HHI_M_BE	-0.145		0.098	0.348	*	0.189	-0.203		0.129
HHI_M_CH	0.084		0.070	0.075		0.137	-0.159	*	0.094
HHI_M_PK	-0.072		0.096	-0.218		0.186	0.290	**	0.127
Intercept	0.309		0.236	-0.011		0.432	0.702	**	0.294
R-squared			0.6431			0.6704			0.6265

***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively. Observation: 68

Appendix 2. QUAIDS model regression results

	Beef			Pork			Chicken		
Variable	**Coeff.**		**Std. err.**	**Coeff.**		**Std. err.**	**Coeff.**		**Std. err.**
lnPR_BE	-0.751	*	0.439	0.882	*	0.489	-0.131		0.467
lnPR_PK	0.882	*	0.503	-1.131		1.036	0.249		0.664
lnPR_CH	-0.131		0.487	0.249		0.687	-0.118		0.212
lnX	0.498	***	0.131	-0.586	*	0.310	0.088		0.319
lnX^2	-0.033	***	0.009	0.047	***	0.015	-0.014		0.019
fall	0.033	***	0.009	-0.027		0.019	-0.006		0.013
winter	0.056	***	0.021	0.021		0.041	-0.077	***	0.029
spring	0.018		0.017	0.079	**	0.034	-0.097	***	0.024
BE_LO	0.000		0.001	0.000		0.002	-0.001		0.002
BE_RI	0.002		0.001	-0.003		0.003	0.000		0.002
BE_RO	0.002		0.002	-0.001		0.004	-0.002		0.003
BE_TC	0.003	*	0.002	-0.001		0.003	-0.002		0.002
BE_TR	-0.001		0.001	0.000		0.002	0.000		0.002
CH_CU	-0.001	**	0.001	0.001		0.001	0.000		0.001
PO_BU	0.004		0.008	-0.014		0.016	0.011		0.011
PO_GR	0.002		0.001	-0.004	**	0.002	0.003	*	0.002
PO_HA	0.002		0.005	-0.009		0.009	0.007		0.006
PO_LO	0.004	*	0.002	-0.006		0.004	0.002		0.003
PO_SH	0.001		0.003	0.004		0.006	-0.005		0.004
HHI_F_BE	0.129		0.094	-0.468	***	0.182	0.339	***	0.126
HHI_F_CH	-0.065		0.062	-0.162		0.123	0.227	***	0.086
HHI_F_PK	-0.084		0.122	0.532	**	0.237	-0.448	***	0.166
HHI_M_BE	-0.151		0.095	0.366	**	0.184	-0.215	*	0.129
HHI_M_CH	0.083		0.068	0.079		0.133	-0.162	*	0.093
HHI_M_PK	-0.056		0.090	-0.239		0.179	0.294	**	0.125
Intercept	-1.751	***	0.525	2.894	**	1.358	-0.143		1.288
R-squared			0.6593			0.6750			0.6232

***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively. Observations: 68

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