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Luca Rigotti, Matthew N. LeRoux and Todd M. Schmit

Charles H. Dyson School of Applied Economics and Management SC
Johnson College of Business
College of Agriculture and Life Sciences
Cornell University, Ithaca, NY 14853-7801

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Abstract
Until recently, lack of customer transaction data at farmers markets prevented strategic vendor decision making. However, emerging point-of-sale technologies adapted to farmers markets address this limitation. We collect point-of-sale data from over 26,000 transactions in 2021 from 10 livestock farms at 22 farmers markets in New York. We find payment type, sale hour, product differentiation, and customer density significantly influence customer transaction size. Marginal expenditure effects on over 30 meat product categories across seven livestock species provide valuable information on alternative product offerings and pricing. The number of product groups (species) and item variety offered by vendors increases transaction size.

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

JEL Codes: M31, Q12, Q13,

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Introduction

Over the past two decades, the growth of farmers' markets (FMs) has been a significant development in the American food landscape, as they are a recognizable direct marketing channel connecting consumers with nearby farmers (Quick et al. 2022). While the number of FMs in the United States has nearly doubled over the past decade, recent research suggests that the growth rate is slowing. Between 2016 and 2017, the number of FMs increased by just 0.2%, in stark contrast to rapid growth rates of previous years (AMS, 2018). Bonanno et al. (2017) suggest that decelerating growth rates indicate FMs are approaching saturation in some areas.

Direct-to-consumer (DTC) marketing has played an important role in local farm revenue, but that effect has also waned. In 2017, the number of farms with DTC sales decreased 10% from their 2012 level (NASS, 2019). This is likely due, in part, to farmers reallocating sales through alternative wholesale marketing channels like grocery stores, restaurants, and/or food distributors (Low et al. 2015). Major food retailers now offer locally sourced foods that are purchasable alongside regular groceries, rendering them more accessible to consumers. Public procurement of local foods has also shifted supply from FMs (Bonanno et al. 2017, Krasnoff et al. 2022). Schmit et al. (2019) suggest that farmers have identified alternative market channels believed to be more profitable than DTC sales. Indeed, Schmit & LeRoux (2014) demonstrate FMs were the worst performing channel in terms of sales per hour of marketing labor on over 30 diversified vegetable farms.

Metz & Scherer (2022) identify five possible reasons for reductions in FM sales: (1) an oversupply of FMs, (2) the unconscious creation and/or misguided beliefs of FMs as spaces of whiteness and upper-middle-class culture, (3) a changing food retail environment that usurps FM patrons, (4) a scarcity of farmers needed to supply DTC sales due to aging of current farmers and a lack of replacements, and (5) the burden of effective market management. Both Helmer (2019) and Metz & Scherer (2022) suggest growth in the number of FMs beyond consumer demand contributes to declining food sales at FMs. Therefore, introducing additional FMs may lead to increased competition for sales and customers, resulting in declining sales of existing products.

FM managers also face challenges retaining current and recruiting new shoppers at FMs due to shifting customer and farmer preferences. Hamilton (2018) describes local food market life cycles where past successful approaches, like product differentiation (branding/labeling), are inadequate in today's markets where price and convenience are top consumer priorities. This compounds with the challenge of FM managers dealing with the complexity of marketing efforts to address a wide range of customer preferences by income, race, and ethnicity. Furthermore, access issues commonly surface as a barrier to shopping at FMs, including travel and parking constraints (Schmit et al. 2019).

Marketing practices by farmers at FMs vary considerably. These practices include product claims/certifications, brochures, recipe cards, product sampling, stall layout/design, price displays, and product handling and preparation information (Cowee et al. 2009). Lin et al. (2008) find consumers at FMs are willing to pay a premium for certified organic vegetables while simultaneously being concerned with product pricing.

Point-of-Sale Systems (POS)

Retailer scanner data (e.g., from grocery stores) refers to the collection of information generated by bar code scanners during the point of sale, such as the stock keeping unit (SKU), time of sale, form of payment, price, and quantity sold (O’Connell et al. 2022; Muth et al. 2020, pp. 1-12). Customer identification may also be recorded, enabling individualized tracking of purchases over time (e.g., through preferred shopper programs). Retailers can more accurately forecast their future needs and negotiate better prices and terms with suppliers by identifying inefficiencies for cost reduction (Pepe & Pepe 2012).

Traditional grocery retailers purchase products for resale. As such, they choose from a wide range of suppliers, brands, and products to address customer demands. Farmers at FMs are also retailers but they are also the producers of the items they bring for sale. Meat vendors must consider the types and variety of products they sell relative to consumer demand, but also need to sell all meat cuts and products from an entire animal (carcass) they produce to avoid costly inventory problems. FM retailers are their own brand and are limited to the species they grow.[1] Consequently, the profit/utility maximizing problem for FM retailers is different, rendering marketing implications from retail grocer research less applicable. The "simpler" supply chains of FM retailers increase the value for their own POS data collection for improved marketing strategy (Wayne et al. n.d). The approach is particularly useful for businesses with high-volume, low-margin sales due to the complexity of variety and price points and variable weight items.

Recent efforts to improve FM returns include the use of POS systems that collect detailed customer transaction information (LeRoux & Schmit 2020). POS systems allow vendors to process all sales from small devices (e.g., tablets and smart phones). They also allow users to manage inventories and supply chains, track sales performance, manage staff, collect customer contact information, and other transaction-specific data (Cote 2015). LeRoux & Schmit (2020) use a POS-focused application at FMs to identify opportunities for increasing customer transaction size (CTS) for fruit and vegetable producers.

[1] Depending on FM rules, FM meat vendors can sell meat products that they do not produce themselves; however this is less common and generally represent a small share of total farm sales.

We contribute to the research in this area by applying and improving upon the methodology of LeRoux & Schmit (2020) for livestock farms selling meat products at FMs. In addition, by aggregating the POS data to daily sales equivalents, the form of data commonly used in the literature, we highlight the limitations such data provide in identifying specific marketing strategies to improve FM sales performance. To this end, we provide specific marketing implications for meat vendors regarding pricing strategy, product variety, differentiation effects, and other factors.

We continue with a description of the POS data systems and customer transaction data collected, followed by a presentation of the econometric models and empirical results from the customer transaction size (CTS) and daily sales models. We close with implications for farm marketing strategy and future research directions.

Data

Farmers were recruited to participate during the year 2021. Some farmers were using the POS system for this study (Square) at FMs before they enrolled in the study and already had a complete year of data available, while others enrolled and adopted the POS system during 2021 as part of their participation. Farmers were provided in-person and virtual trainings, and, in select cases, the research team worked directly with farmers at FMs to provide additional assistance in familiarizing them with the POS system. Farmers received a set of written instructions on how to download their Square data and send it to the research team. In total, 10 farms selling at 22 different FMs in New York State (NYS) were involved.

POS Data

Farmers submitted two data files (spreadsheets) from Square: a “Transactions” file where each row represents a unique customer purchase and sales over all items purchased; and an “Items” file where each row represents the attributes of each item sold in a particular transaction. The Transactions file includes a unique transaction ID, date and time of the transaction, gross and net sales (i.e., net of coupons, discounts, etc.), payment method (card, cash, or other), shopping basket details, and location of sale. Unique customer IDs and customer characteristics were not collected by the farmers nor associated with a particular transaction.

The Items file provides a detailed list of all the items sold by transaction ID, including information such as item name, item description, SKU or barcode (if applicable), and quantity sold. Transaction IDs are uniquely generated by Square and can be used to cross reference all data in the Items and Transactions files.

Supplementary Data

We collect and merge with the POS data additional data on FMs, farm products, weather, and demographic characteristics of the counties in which the FMs operated. FMs were coded into one of four size categories: *SmallFM* (<11 vendors), *MediumFM*, (11-25 vendors), *LargeFM* (26-50 vendors), or *VeryLargeFM* (>50 vendors).

Farmers provided additional attributes of their products that distinguish them beyond conventional production methods. Conventional products are defined as those without any claims or with claims limited to being “all-natural,” which the USDA defines as “minimally processed” and unrelated to livestock production practices. Additional differentiation for beef, veal, and lamb products were coded if the farm claims the item is “100% grass-fed” or “certified organic.” Additional differentiation for pork and poultry products were coded if the farm claims the item is “pasture raised,” “forest raised,” “certified organic,” or produced with “non-GMO feed.” Additional product differentiation for game species (e.g., rabbit) were coded if the farm claims the item is "certified organic." We create a dummy variable, *Category2*, to identify if additionally differentiated products are included in the customer's shopping basket.

Weather data on average daily temperature (Fahrenheit) and total daily precipitation (inches) were obtained from the National Oceanic and Atmospheric Administration for the county in which the FM was located (NOAA 2021). Hence, weather is invariant across transactions within a day at a specific FM and across FMs within the same county. The 22 FMs included in the POS data are in 13 different counties. A selection of county-level demographic data are also added. These include income per capita (BEA 2022), percent of the population identified as non-white (U.S. Census Bureau 2023), percentage of population living below the poverty level (FRED 2023), child dependency ratio (U.S. Census Bureau 2023), and whether the county is metropolitan or nonmetropolitan (ERS 2020).[2]

Data Processing

Data was processed at the farm level before merging all farm data together. Processing involved creating and keeping variables necessary for statistical analysis and removing irrelevant observations. For example, some farms used their POS system beyond FMs (e.g., for CSA or bulk sales) – these observations are excluded. Since valid FM sales may occur before the official opening or after the official closing time, sales occurring within 1 hour of the FM opening and closing times are retained. Finally, sales during FM hours but labeled as "Custom Amount" are excluded since no identifying item information is included.

Binary variables *PayCash*, *PayCard*, and *PayOther* are created based on Square's payment for each transaction as "Cash", "Card", and "Other", respectively. To provide insights into the temporal dynamics of customer behavior in a FM setting, we create the continuous

[2] The child dependency ratio (CDR) is defined as the number of people aged 0 to 19 divided by the number of people aged 20 and older.

variable *Salehour* denoting the time elapsed (in hours) that a transaction occurred since the opening time of the FM that day. *Cust_density05* is the number of customers served within a 5-minute window around each transaction. *Busy05* is a binary variable that takes a value of 1 if *Cust_density05* is over one standard deviation above its mean for the vendor on that FM day.

We create separate product category dummy variables associated with items included in the customer shopping basket, generally based on primal cuts for meat. Since some vendors also sold non-meat products, we categorize all products for sale. The detailed categorization scheme is available in [redacted]. In total, we define 53 product categories, 34 for meat products. To assess variety affects specific to the range of species offered, a *Product_Groups* variable counts the number of different groups of products and/or species (e.g., beef, pork, lamb, veal, poultry, game species, dairy, and fruits and vegetables) sold by a farm on a particular FM day.

To account for the variety of items within and across product categories, we compute the number of unique items sold on a particular FM day. This serves as a useful measure of overall product variety effects not already captured in the product category and group variables. In this way, item counts represent a further delineation of product categories. For example, prime rib and ribeye steak both fall under the product category *Beef_Rib* but are two separate items. Similarly, three flavors of pork sausage (*Pork_Ground*) are three unique items. Item counts are differentiated by product type: meat (*item_meat*), fruit and vegetable (*item_vegfruit*), dairy (*item_dairy*), and other farm products (*item_OFP)*.

Descriptive Statistics

The POS data included 26,355 total transactions, with an average CTS of \$25.46 (Table 1). CTS ranged from as low as \$0.50 to over \$600. Larger transactions are often associated with purchases made by buyers for restaurants. Regarding payment, 43% of the transactions were in cash, 57% credit card, and only a small fraction using other payment methods. Nearly 75% of transactions include at least one product with a second level of differentiation (*Category2*).

The most purchased meat product category for beef was *Beef_Trim* (primarily ground beef), accounting for approximately 5% of all transactions (Table 1). For poultry, *Chicken_Meat*, was more frequently purchased than *Chicken_Eggs*. For pork, *Pork_Ground* was the most purchased category, comprising 34% of all transactions and including both fresh ground pork and various sausages. As for lamb, *Lamb_Ground* was most popular, constituting 2% of all transactions. The distribution of category purchases is a function of the number of producers by species (e.g., farms selling pork were the most common), customer demand for alternative products, and the availability of products derived from different parts of the animal carcass (e.g., there are less pounds of *Beef_Rib* than *Beef_Trim*). While fruits and vegetables and other farm products are sold irregularly and/or in limited quantities by meat vendors, some livestock farms regularly sold dairy products, most notably cheese (13%).

There is a wide range in the number of unique meat products (*item_meat*) available across farms, with a mean of 24. This reflects both farm size and the number of species raised. As expected, item variety across other groups (i.e., *item_dairy*, *item_vegfruit*, and *item_OFP*) is much lower.[3] The average number of product groups (*Product_Groups*) sold on a market day is close to 3, and ranges from 1 to 6. Within a 5-minute interval of a transaction occurring, the average number of transactions (*Cust_density05*) is 2.33 across farms and FMs. Further, 17% of transactions occur when farms are particularly busy (*Busy05* = 1).

[3] A minimum of zero on a particular item category implies that at least in one farm did not sell that category of product on particular day. The mean across all farm days for those selling those categories are 24.11, 10.11, 3.31, and 3.72 for *item_meat*, *item_dairy*, *item_vegfruit*, and *item_OFP*, respectively.

Most transactions (63%) occur at large FMs (*LargeFM*), with very large FMs at 28% (*VeryLargeFM*). Since larger markets are likely to have a higher number of shoppers, a positive correlation between market size and transactions is expected. However, the number of transactions is also a function of the number of markets, by size, that the farmers attend. In our case, farms more commonly attended large markets than very large markets.[4]

Methodology

Transaction-level data across all farms are used to examine the association between CTS and several transactional, product category, farm, FM, and county variables. The model reflects an industry average of the factors that impact CTS at FMs. In this way, the regression identifies overarching trends in customer behavior that may not be evident in individual models, enabling farmers, market managers, and other stakeholders to make more informed decisions.

Ordinary Least Squares (OLS) with robust standard errors is employed. The baseline regression model includes 75 transactional variables and 47 variables accounting for FM (*FM*), farm (*F*), day (*DAY*), and month (*MO*) fixed effects. For the i^{th} customer transaction, on the j^{th} date, sold by farmer vendor k, at FM l, the regression is expressed as:

$$\begin{aligned} CTS_{i,j,k,l} &= \beta_0 + \textstyle\sum_{p=1}^{2} \beta_p PMT_{p,i,j,k,l} + \beta_3 Salehour_{i,j,k,l} + \beta_4 Category2_{i,j,k,l} + \sum_{c=5}^{54} \beta_c PROD_{c,i,j,k,l} + \\ &\textstyle\sum_{a=55}^{58} \beta_a ITEM_{a,j,k,l} + \sum_{b=59}^{62} \beta_b ITEM_{b,j,k,l}^2 + \beta_{63} Customer\_Density05_{i,j,k,l} + \\ &\beta_{64} Busy05_{i,j,k,l} + \beta_{65} Product\_Groups_{i,j,k,l} + \textstyle\sum_{m=66}^{68} \beta_m MSIZE_{m,l} + \sum_{cv=69}^{73} \beta_{cv} DEMOG_{cv,l} + \\ &\textstyle\sum_{w=74}^{75} \beta_w W_{w,j,l} + \sum_{l=1}^{21} \delta_l FM_l + \sum_{k=22}^{30} \delta_k F_k + \sum_{d=31}^{36} \delta_d DAY_{d,j} + \sum_{mt=37}^{47} \delta_{mt} MO_{mt,j} + \varepsilon_{i,j,k,l}, \end{aligned} \tag{1}$$

where *PMT* represents payment methods, and *PROD* represents the 10 beef, 8 pork, 7 lamb, 5 poultry, 3 veal and 1 rabbit product categories, as well as the 11 fruits and vegetables, 3 dairy, and honey, beverages, maple syrup, spreads and other farm product categories (Table 1). *ITEM*

[4] Of the total markets in our sample (22), 13.6%, 31.9%, 40.9% and 13.6% were classified as small, medium, large, and very large, respectively.

represents the number of unique products sold in a day by group (i.e., *meat*, *dairy*, *vegfruit*, and *OFP*), *MSIZE* and *DEMOG* represent the FM size and county-level demographic characteristics, respectively, and *W* includes the daily *Precipitation* and *Temperature* variables.

We perform several robustness checks to examine the sensitivity of the results to changes in the model specification and functional form. Since county demographics, weather, and FM fixed effects do not vary by transaction within a FM day, we perform a robustness check by removing them based on a variance inflation factor (VIF) multicollinearity test (Tomaschek et al. 2018). Additionally, we remove product categories from the CTS model as a robustness check to avoid collinearity issues and isolate item variety effects.

Hypotheses

PayCard and *PayOther* identify the association of alternative payment methods on CTS relative to the omitted category *PayCash*. Given constraints to available cash on hand, we hypothesize that the estimated coefficients will both be positive. *SaleHour* captures the effect on CTS over the course of a market day. Given early shoppers are motivated by less customer traffic and/or higher availability of products, we hypothesize the estimated coefficient will be negative.

The estimated influence of customer density at the FM may be positive or negative. A higher number of customers at a particular vendor may signal higher quality products to shoppers and induce them to buy more; however, more crowded stalls can leave less time for personal communication with farmers, leading to lower purchase amounts. When vendors are particularly busy, we expect the negative influence of *Busy05* to outweigh possible positive effects of *Cust_density05* leading to an overall negative effect.

We expect shopping baskets with at least one *Category2* product will be higher than those with none. Product category variables estimate the marginal expenditure effect on CTS, *ceterus* *paribus*, when purchasing these products. As such, all estimated coefficients (reflecting both price and quantity effects) should be positive. We anticipate that increases in the variety of meat items for sale (*item_meat*) will have a positive impact on CTS but that it increases at a decreasing rate and eventually declines (i.e., too much variety can be harmful). Accordingly, we include variety effects in both level and quadratic forms, where we expect the coefficients to be positive and negative, respectively.[5]

Based on the literature using more aggregate data, we expect per capita income (*IncomePC*), racial diversity (*Pcnt_NonW*), and child dependency (*CDR*) will have positive effects, while poverty rate (*Pcnt_BPov*) and *Nonmetro* will be negative. However, as these variables are not specific to individual transactions and are limited in precision, their inclusion assumes that they adequately represent the distribution of shoppers at the FM, which may not be accurate (hence our robustness checks on their exclusion).

As most FMs operate in outdoor locations (with varying levels of infrastructure), weather may influence customer attendance and shopping behavior. Unlike shopping at a traditional grocer, shopping at a FM may also be part of a larger social outing for which weather can play a role in food products purchased. Accordingly, we expect a negative association with *Precipitation* and a positive association with *Temperature*. Month (*MO*) fixed effects control for seasonality in customer purchasing habits, while day (*DAY*) fixed effects control for within-week differences in shopping behavior.

Aggregated Models

Complementary OLS models are estimated for daily sales (DS) and average daily customer transaction size model (ACTS) by aggregating the transactional-level data to a daily level by

[5] Sensitivity analysis is conducted to evaluate linear versus quadratic functional forms, and aggregate vs disaggregate variety effects across product groups.

farm, FM, and date. We construct daily variables for the DS and ACTS models consistent with those represented in the CTS model, albeit with different interpretation. For example, the product category variable *Beef_Trim* = 1 in the CTS model implies that a beef trim product is included in the customer's shopping basket, while the comparable variable in the DS and ACTS model represents whether there were positive sales that day of beef trim. Unless a category (or portion of the carcass) has a particularly large (or small) value relative to others, we do not expect product category effects to be statistically significant in the daily models.

If vendors also count the number of sales or customers on a day (relatively uncommon), dividing total daily sales by number of customers yields an average customer transaction size for the day (ACTS). Variables not applicable to daily models (i.e., *salehour*, *Cust_density05*, and *Busy05*) are excluded. In addition, since all farms in the sample produce and sell at least one type of *Category2* meat it is excluded.

Results - CTS

As shown in Table 2, the baseline CTS regression model performs reasonably well in the context of explained variation ($R^2 = 0.49$). Except for FM and weather fixed effects, the remaining fixed effect controls are all jointly significant. This is particularly so for months capturing seasonal influences in both farm meat product supply and customer purchase behavior (e.g., farmers supplying turkeys around Thanksgiving and higher customer spending around holidays months).[6] The lack of joint statistical significance for FMs is likely due to collinearity issues between the FMs and days of the week, as most markets occur on Saturday in the sample. The significance of the day fixed effects can be attributed to the fact that consumers have greater flexibility to attend

[6] While the county-level demographic variables reveal joint significance (Table 2), only *IncomePC* (not shown) was individually significant and with a small positive effect; i.e., for each $10,000 increase in county per capita income, CTS increases a little over $1.

the market on different days of the week and may have more time to spend. Finally, statistically significant farm fixed effects can be attributed to the heterogeneity of farm characteristics and marketing ability not otherwise captured in the model.

Payment methods have a significant impact on CTS (Table 2), where the use of credit cards contributes an additional $2.28 relative to cash sales, while other payment methods (e.g., SNAP, coupon, checks) contribute an additional $5.02. The estimated coefficient on *Salehour* implies that for every additional hour during the market day CTS decreases by $0.36. Customer density (*Cust_Density05*) is associated with lower CTS. Specifically, for every additional customer served within a 5-minute interval, CTS decreases $0.42. That decrease goes to $0.81 (p value = 0.01) when the vendor is very busy (i.e., *Busy05* = 1).[7]

The negative effect on *Category2* appears counterintuitive as these products are likely to be higher priced than those without and with consumers willing to pay more for them. Specifically, CTS decreases $3.32 when at least one product in the shopping basket is a Category2 product. This finding suggests that products with a second level of differentiation may not be as attractive or may be perceived as less valuable. Another possible explanation is that farmers who sell products with a second level of differentiation have prices less than comparable products of other vendors in the sample without Category2 designation. This is particularly salient for samples with a relatively small number of farmers, as in our case (N = 10 farms). Indeed, supplemental price analyses reveal that farmers selling Category2 beef products were priced lower than other farms without that distinction. For pork, this was also true, but with less prevalence.

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[7] $\frac{\partial CTS}{\partial density} | Busy05 = 1 = \beta_{Customer_{density05}} + \beta_{Busy05} = -0.42 - 0.39 = -0.81$ (p value = 0.01).

As expected, all product category effects for common products are positive and statistically significant.[8] For example, *Beef_trim*, the most commonly purchased beef category (usually the ground beef product), has an estimated coefficient of $14.44, indicating that consumers, on average, bought around two pounds of beef trim (i.e., the average price of ground beef is $6.41/lb). *Pork_Ground*, which is largely pork sausages, has a marginal contribution of $18.35, suggesting that consumers are buying, on average, just over one package of sausage (i.e., the average price for sausages is around $14/package).

No statistically significant effects are found for *item* counts besides the level *item_dairy* term (Table 2). Significance is a function of both the number of farms selling the categories (*meat*, *dairy*, *vegfruit*, and *OFP*) and to the degree that the individual farm results are consistent with each other (i.e., farms of different sizes have different ranges of *item* counts). Only two of the livestock farms (with single species sales) had statistical significance for *item_meat* variety effects in the individual farm regressions ([redacted]).[9]

However, item variety is, in part, reflected in the product category variables already defined in the model; i.e., a collinearity issue. In other words, more product categories are, in and of themselves, a dimension of variety. To test this explicitly, we run a second CTS regression with all product category variables excluded (Table 3). Here, *item_meat* is positive and statistically significant, with each additional unique item contributing an additional $0.38 to CTS. The insignificance on the quadratic term reveals a simple result: more product variety increases CTS. The nonsignificant *item* result in the baseline model suggests farmers are, on average, providing sufficient meat product variety to their customers.

[8] *Lamb_Shoulder* and *Dairy_Yogurt* are very uncommon, with only 30 and 9 transactions in the data, respectively.
[9] Sensitivity analyses of *item* effects in both functional form (linear only) and aggregation across groupings reveal similar results.

Although the relationship between FM size and CTS was not statistically significant, the increasing negative effects and level of statistical significance, provides some evidence of higher competition as markets grow and more options for customers to purchase similar products from different vendors.

Robustness Checks

Given the strong implied assumptions with their inclusion and lack of statistical significance (but for income), the first robustness check removes all county-level demographic variables from the baseline CTS model. While not shown, the results demonstrate that the other estimated parameters are robust to their inclusion or not, with only modest changes in estimated coefficients (but not statistical significance) for the FM size variables, i.e., other variables that do not change across customer transactions within a FM.

A second robustness check further removed FM fixed effects and weather variables (jointly insignificant). Again, the transactional variables are robust to their inclusion or not. Only one variable changed in statistical significance, *VeryLargeFM*. This is likely due to collinearity effects between market size and FM fixed effects. It also strengthens our argument earlier of customers shopping around with additional vendors as FM size grows.

Results – DS and ACTS

Regression results for the DS model are shown in Table 4. Specific marketing implications from this model are modest, at best. For example, since less than 7% of farm/FM days had sales without credit cards and other forms of payment were rare (Table 1), insignificant results on forms of payment are expected. Further, as expected, most product category variables are insignificant except for particularly valuable/invaluable portions of a meat species carcass (or product types available for dairy). For example, leg (+), loin (+) and shoulder (-) primals for lamb, belly (+), loin (+), and shoulder (+) for pork, other (+) for veal (e.g., prepared burgers, pot pies, and stews), and cheese (+) and yogurt (-) for dairy.

The linear and quadratic coefficients on *item_meat* suggests a U-shaped response to variety, indicating that vendors should aim to sell at least twelve unique meat items to ensure they are in the upward sloping portion of the sales curve. For context, the average number of items sold per day across all farms in the sample was 24 (Table 1). Finally, since larger markets have more shoppers, the positive effects on FM size are expected; however, identifying how to increase CTS at those markets (Table 2) is equally important.

The ACTS model results (Table 5) also provide limited information to guide marketing strategy for meat vendors. Only six product categories show significant results and are reflective of generally higher cost products such as pork loin (*Pork_Loin*), whole turkeys (*Turkey_Meat*), *Lamb_Other* (e.g., prepared burgers, pot pies, and stews), *Beef_Offal* (Fat, Soup Bones, Shanks, Meaty Bones, Marrow Bones, and Osso Bucco), *Beef_Other*, and *Beef_Thincuts*. The results are consistent with the CTS model, but far different in magnitude. For example, *Pork_Loin* had a marginal expenditure effect of $28.00 in the CTS model, but only $1.71 in the (aggregated) ACTS. Interpretation is important: the latter represents the change in ACTS when selling *Pork_Loin* on a particular day, rather than the change in CTS when a customer purchases *Pork_Loin*.

Conclusions and Implications

Our findings reveal that farms can employ alternative marketing strategies at FMs to enhance CTS relative to more limited data and research focused on daily sales. The CTS model reveals marketing strategies that cannot be captured by the more common DS model nor ACTS models, particularly in relation to payment methods, product differentiation, and project category effects.

These insights can help farmers identify effective marketing strategies that target specific customer segments and product variety to enhance sales performance and overall profitability.

Day and Month. The empirical results reveal that Sunday had the largest CTS, with a significant positive impact of \$3.28 ($p = 0.01$) compared to Saturday. This suggests that Sunday markets present an opportunity for higher customer purchases, possibly due to shoppers having more time to spend. Month fixed effects show significant impacts on CTS during holiday months: November and December for Thanksgiving, Hanukkah, and Christmas, and March and April for Easter, Passover, and Eid al-Fitr. To capitalize on this increased consumer demand, farmers can consider increasing both volume and prices during these months. Offering bundled meat products at discounted prices, such as turkey, ham, and roast beef, can also incentivize customers to make larger purchases in a single transaction.

Product Categories. Product category effects on CTS offer valuable insights for farmers to enhance sales and profitability. Trim beef products serve as a prime example, with a significant marginal value contribution of \$14.44 to the average basket size. Ground beef, the category's most popular product, is priced at an average of \$6.41 per pound across all farms, which is less than half of its actual marginal value. This suggests that farmers can leverage pricing strategies, such as increasing their prices or offering bundle products, to attract customers to boost their basket size. Ground pork products also present opportunities, with an average value of \$14.00 and a marginal value expenditure of \$18.35, allowing farmers to capitalize on pricing adjustments. Bundling can provide savings to vendors and simplify the decision-making process of customers, leading to increased likelihood of purchasing (Carroll et al., 2022).

Forms of Payment. Diverse payment options improve CTS. Therefore, it is recommended that farmers adopt alternative payment options to attract more customers and boost sales. In the case of those already accepting credit cards, making sure that this is clear to approaching customers is essential. Despite concerns about fees and transaction process inconvenience, the benefits of accepting credit card payments for farmers estimated here clearly outweigh traditional merchant credit card fees. Establishing a minimum payment amount and optimizing market stall design can help streamline the payment process and mitigate any perceived inconvenience.

Customer Density and Time of Day. With respect to the negative *saleHour* effect, farmers should prioritize offering the best quality products early in the day when customers, such as restaurant owners and grocery, rather than casual, shoppers, are seeking high-quality options. As time passes, farmers can increase CTS by offering special deals on remaining products, considering the decreasing item availability and the cost of unsold inventory. As producers and retailers, meat vendors should regularly monitor their inventory and adjust their offerings accordingly to improve sales and minimize waste. Negative customer density effects emphasize the need for farm vendors to manage customer flow effectively without compromising sales. Strategies may include increasing staff during busy periods, adjusting product offerings to reduce wait times (e.g., offering more grab-and-go options), redesigning stall layout for efficiency, and implementing marketing tactics to simplify purchases, such as bundled-product offerings or incentives for bigger transactions.

Product Differentiation. Products with a second level of differentiation were shown to have a significant negative impact on CTS, suggesting that vendors in our sample are incorrectly pricing their differentiated products compared to other farmer's non-differentiated products. Vendors should assess consumer demand and the effect on the overall basket size before introducing such products, considering pricing and their own marginal costs. Despite this, there is a growing trend towards second level differentiated products, especially in the organic meat market with an expected CAGR of 8.6% from 2022 through 2027 (Mordor Intelligence n.d). Vendors should engage in marketing efforts to improve communications with consumers about the value and benefits of these products and provide clear signage and labels for them.

Product Variety. Adding more species increases item variety and the number of product categories, indirectly capturing item variety through expanded category variables. Marginal expenditure effects of product categories are useful for assessing customer demand and pricing strategy, but they decrease the independent variation in item count variables. Results with significant product category effects and insignificant item variety effects suggests the variety offered by farms in our sample through product categories is sufficient for consumers. In short, item variety is important to attract customers and increase CTS.

FM targeting. As expected, total daily sales are positively associated with the size of the FM, largely due to higher shopper traffic. Attending larger FMs can help address inventory challenges by vendors as both retailers and producers of the products they sell. However, the effect on CTS appears to be negative, suggesting that customers may spread their purchases across multiple vendors. To improve CTS, vendors should focus on farm and product differentiation, building customer relationships, and highlighting product quality to encourage larger transactions and boost sales.

The CTS results are shown to be robust to alternative restricting assumptions; however, to enhance the validity of our results, a larger and more diverse sample of participating farmers is recommended. This would involve including a broader range of livestock species and locations of FMs. Additionally, incorporating data on specific market rules and operating characteristics, such as restrictions on selling other producers' products and the market's infrastructure and operating schedule, will provide valuable insights for farmers when deciding FMs to attend.

While we control for general socioeconomic and demographic characteristics in communities where FMs are located, including specific customer information (e.g., race, ethnicity, age, income) would be a valuable next step in this research. Some farms already include specific customer codes in their data; expanding on this, perhaps with even a limited set of customers can prove useful in refining marketing strategies to a vendors' known customer base. Additionally, expanding the study to different regions of the United States would provide insights into regional variation in customer behavior, if any. Addressing these issues is a top priority for our ongoing research.

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Table 1. Summary Statistics, Customer Transaction Data

Variables	Description	Mean	SD	Min	Max
Transaction Variables					
NetSales	Average customer transaction purchase	25.46	25.21	0.50	618.3
PayCash	Transaction paid with cash = 1, else =0	0.43	0.5	0	1
PayCard	Transaction paid with debit or credit card = 1, else = 0	0.57	0.5	0	1
PayOther	Transaction paid with other methods (coupon, SNAP, check) = 1, else =0	0.01	0.09	0	1
Salehour	Hour of market sale	4.43	1.57	-0.63	11.65
Category2	Transaction contained a Category2 product (2nd level of differentiation) =1, else = 0	0.74	0.44	0	1
Meat and Dairy Product Category Variables (Equals 1 if shopping basket contains that item, else equal 0)					
Beef_Chuck	Chuck roast/steak, Flatiron steak, Denver/Ranch steak, Hanger steak, Mock Tender, Petite Tender, Chuck Eye, Pot Roast	0.01	0.07	0	1
Beef_Loin	Tenderloin, Strip Steak, NY Strip, Porterhouse steak, T-bone steak, Top Sirloin, Sirloin Roast, Sirloin steak, Tri-Tip	0.01	0.12	0	1
Beef_Offal	Fat, Suet, Soup Bones, Shanks, Meaty Bones, Marrow Bones, Dog Bones, Osso Bucco	0.01	0.10	0	1
Beef_Organs	Oxtail, Kidney, Heart, Tongue, Liver	0.00	0.02	0	1
Beef_Other	Prepared, cooked foods such as burgers, pot pies, stock, broth, stews, and soups.	0.00	0.02	0	1
Beef_Processed	Jerky, Sausage, Snack sticks, Hot Dogs, Croghan Bologna, Beef Links	0.03	0.18	0	1
Beef_Rib	Rib steak, Ribeye steak, Delmonico, Rib roast, Short Ribs, Prime Rib	0.01	0.10	0	1
Beef_Round	Sirloin Tip, Top/Bottom/Eye Round Roast/Steak, Cube Steak, Minute Steak, Sandwich Steak, Rump Roast, Shaved Steak, London Broil	0.00	0.04	0	1
Beef_Thincuts	Brisket, Flank Steak, Skirt Steak, Beef Bacon	0.01	0.07	0	1
Beef_Trim	Ground beef, Patties, Stew meat, Kabobs	0.05	0.21	0	1
Chicken_Eggs	Chicken Eggs	0.07	0.26	0	1
Chicken_Meat	Whole, half, chicken cuts	0.10	0.29	0	1
Chicken_Other	Prepared, cooked foods such as burgers, pot pies, stock, broth, stews, and soups.	0.00	0.06	0	1
Duck_Meat	Whole and half	0.00	0.04	0	1
Lamb_Ground	Ground lamb, lamb sausage, etc.	0.02	0.15	0	1
Lamb_Leg	Leg Roast, Leg Chops, Sirloin Chops	0.01	0.07	0	1
Lamb_Loin	Short loin, Rack, Loin chops	0.01	0.10	0	1
Lamb_Offal	Lamb shank, heart, tongue, soup bones, liver, etc.	0.00	0.06	0	1
Lamb_Other	Prepared, cooked foods such as burgers, pot pies, stock, broth, stews, and soups.	0.01	0.11	0	1
Lamb_Rib	Lamb Breast, Rib chops	0.00	0.03	0	1
Lamb_Shoulder	Shoulder roast, Square-cut shoulder, shoulder chops	0.00	0.03	0	1
Pork_Belly	Spareribs, bacon, St. Louis ribs, Side pork, Fresh Belly	0.13	0.33	0	1
Pork_Butt	Butt roast, butt steaks	0.01	0.09	0	1
Pork_Ground	Ground pork, sausage	0.34	0.48	0	1
Pork_Ham	Fresh or smoked, whole ham, ham slices, ham steaks	0.01	0.12	0	1
Pork_Loin	Loin chops, pork chops, loin roast, back ribs, country style ribs, Tenderloin, Sirloin, Cutlet, Canadian bacon	0.14	0.35	0	1
Pork_Offal	Lard, jowl, heart, tongue, soup bones, fat, lard, Guanciale, Guanciale bacon, jowl bacon, leaf lard, hock, smoked hock	0.01	0.12	0	1
Pork_Other	Prepared, cooked foods such as burgers, pot pies, stock, broth, stews, and soups.	0.07	0.26	0	1
Pork_Shoulder	Picnic roast, shoulder roast, Cottage bacon	0.02	0.14	0	1
Rabbit_Meat	Whole	0.00	0.05	0	1
Turkey_Meat	Whole, half, turkey cuts	0.00	0.03	0	1
Veal_Cuts	Cutlets, other cuts, roasts	0.00	0.06	0	1
Veal_Ground	Ground Veal	0.00	0.07	0	1
Veal_Other	Prepared, cooked foods such as burgers, pot pies, stock, broth, stews, and soups	0.00	0.04	0	1
Dairy_Cheese	All cheeses	0.13	0.34	0	1
Dairy_Milk	Fluid milk (2%, whole, chocolate, etc.)	0.05	0.22	0	1
Dairy_Yogurt	All yogurt	0.01	0.11	0	1

Number of observations: 26,355. Product category statistics for nonmeat/dairy products are available in [redacted])

Table 1. Summary Statistics, Customer Transaction Data, continued

Variable	Description	Mean	SD	Min	Max
Farm Variables					
item_meat	Number of unique meat products sold in a day, by farm and market	24.11	9.89	0	47
item_dairy	Number of unique dairy products sold in a day, by farm and market	3.45	5.30	0	31
item_vegfruit	Number of unique vegetable and/or fruit products sold in a day, by farm and market	0.51	1.53	0	13
item_OFP	Number of unique other products sold in a day, by farm and market	0.90	2.32	0	13
Product_Groups[1]	Number of product groups sold within a day, by farm and market	2.77	1.79	1	6
Custr_density05	Average number of transactions occurring within a 5-minute interval, by farm and market	2.33	1.25	1	8
Busy05	If Customer_density05 > Mean of Customer_density05 +1 standard deviation = 1, else = 0	0.17	0.37	0	1

Number of observations: 26,355. Product category statistics for nonmeat/dairy products are available in [redacted])

[1]Product groups include beef, pork, lamb, veal, poultry, game species, dairy, and fruits and vegetables.

Table 2. Regression results of Customer Transaction Size, with product category variables

Variable	Coef.		Std. Err.	Variable	Coef.		Std. Err.
PayCard	2.28	***	0.29	Veal_Cuts	25.50	***	5.58
PayOther	5.02	**	2.16	Veal_Ground	22.11	***	3.63
salehour	-0.36	***	0.09	Veal_Other	34.41	***	10.08
Category2	-3.32	***	0.48	Rabbit_Meat	31.60	***	2.79
Beef_Chuck	32.64	***	2.63	Dairy_Cheese	11.57	***	0.46
Beef_Loin	26.72	***	1.16	Dairy_Milk	5.86	***	1.11
Beef_Offal	16.76	***	1.23	Dairy_Yogurt	6.28		4.16
Beef_Organs	8.86	***	2.71	Product_Groups	0.46		0.28
Beef_Other	9.46	***	3.27	item_meat	-0.08		0.10
Beef_Processed	15.72	***	0.63	item_meat2	0.00		0.00
Beef_Rib	27.84	***	1.56	item_dairy	0.42	*	0.24
Beef_Round	17.70	***	2.86	item_dairy2	-0.01		0.01
Beef_Thincuts	30.91	***	2.26	item_vegfruit	-0.14		0.29
Beef_Trim	14.44	***	0.75	item_vegfruit2	0.02		0.03
Chicken_Eggs	8.02	***	0.54	item_OFP	0.35		0.23
Chicken_Meat	26.71	***	0.80	item_OFP2	-0.02		0.02
Chicken_Other	12.76	***	2.51	Cust_density05	-0.42	***	0.15
Duck_Meat	41.07	***	2.61	Busy05	-0.39		0.43
Turkey_Meat	69.37	***	8.67	MediumFM	-0.91		1.35
Lamb_Ground	19.22	***	1.36	LargeFM	-1.34		1.65
Lamb_Leg	47.52	***	2.84	VeryLargeFM	-3.52		2.77
Lamb_Loin	31.80	***	1.87	Intercept	-16.93		10.49
Lamb_Offal	26.22	***	5.52	**Fixed effects/joint significance**			**F-stat**
Lamb_Other	7.41	***	1.62	Nondairy/meat PCs	Yes	***	36.00
Lamb_Rib	48.22	***	6.08	County demogs	Yes	***	6.01
Lamb_Shoulder	7.58		5.87	Weather	Yes		0.16
Pork_Belly	18.29	***	0.47	Day of week	Yes	**	2.76
Pork_Butt	31.32	***	1.20	Month	Yes	***	5.49
Pork_Ground	18.35	***	0.45	Farmers Market	Yes		0.74
Pork_Ham	18.24	***	0.91	Farm	Yes	***	8.94
Pork_Loin	28.00	***	0.53	Observations			26,355
Pork_Offal	15.09	***	1.19	R-squared			0.485
Pork_Other	16.36	***	0.57	***, **, and * represent statistical significance at			
Pork_Shoulder	24.81	***	1.32	the 1%, 5% and 10% levels, respectively.			

Table 3. Regression results of Customer Transaction Size (CTS), without product category variables

Variable	Coef.		Std. Err.
PayCard	7.72	***	0.33
PayOther	8.56	***	2.27
salehour	-0.85	***	0.10
Category2	15.41	***	0.34
Product_Groups	0.42		0.33
item_meat	0.38	***	0.12
item_meat2	0.00		0.00
item_dairy	-0.34		0.32
item_dairy2	0.02		0.01
item_vegfruit	-0.23		0.32
item_vegfruit2	0.03		0.03
item_OFP	0.43		0.28
item_OFP2	-0.02		0.03
Cust_density05	-1.11	***	0.18
Busy05	-0.05		0.55
MediumFM	-1.54		1.62
LargeFM	0.00		1.97
VeryLargeFM	0.01		3.43
Intercept	-13.66		12.96
Fixed effects/joint significance			**F-stat**
Nondairy/meat PCs	No		
County demogs	Yes		1.54
Weather	Yes		0.02
Day of week	Yes	***	8.35
Month	Yes	***	4.19
Farmers Market	Yes	***	5.46
Farm	Yes	***	6.29
Observations			26,355
R-squared			0.199

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

Table 4. Regression Results of Daily Sales.

Variable	Coef.		Std. Err.
Card_accept	35.78		36.99
Other_accept	-21.71		54.53
Beef_Chuck	-44.35		44.13
Beef_Loin	-0.14		39.67
Beef_Offal	-25.20		40.20
Beef_Organs	-153.03		144.03
Beef_Other	-102.34		77.82
Beef_Processed	27.05		49.01
Beef_Rib	40.20		-40.56
Beef_Round	-75.87		57.21
Beef_Thincuts	68.50		51.20
Beef_Trim	62.02		54.18
Chicken_Eggs	78.20		56.42
Chicken_Meat	20.21		46.20
Chicken_Other	38.92		73.77
Duck_Meat	66.10		63.99
Turkey_Meat	162.55		105.48
Lamb_Ground	67.95		78.84
Lamb_Leg	286.21	**	114.30
Lamb_Loin	189.64	*	99.90
Lamb_Offal	78.31		86.88
Lamb_Other	-89.63		115.04
Lamb_Rib	193.26		200.85
Lamb_Shoulder	-247.80	*	147.29
Pork_Belly	76.92	***	28.81
Pork_Butt	25.03		26.31
Pork_Ground	3.41		42.56
Pork_Ham	58.75		41.18
Pork_Loin	104.91	***	30.60
Pork_Offal	83.97		62.38
Pork_Other	121.57		254.95
Pork_Shoulder	153.80	**	63.86

Variable	Coef.		Std. Err.
Veal_Cuts	53.76		51.08
Veal_Ground	-0.52		54.03
Veal_Other	149.86	**	74.24
Rabbit_Meat	17.39		58.54
Dairy_Cheese	258.20	**	110.80
Dairy_Milk	162.20		183.53
Dairy_Yogurt	-369.61	*	200.09
Product_Groups	-38.01		31.30
item_meat	-46.87	***	15.61
item_meat2	1.98	***	0.44
item_dairy	31.38		23.47
item_dairy2	-0.68		0.87
item_vegfruit	-97.82	***	28.71
item_vegfruit2	8.27	***	2.50
item_OFP	23.34		27.61
item_OFP2	-0.93		2.97
MediumFM	377.32		229.36
LargeFM	701.00	***	235.64
VeryLargeFM	599.30	***	159.99
Intercept	-2940.98	**	1409.99
Fixed effects/joint significance			**F-stat**
Nondairy/meat PCs	Yes		1.32
County demogs	Yes	***	16.58
Weather	Yes		0.88
Day of the week	Yes		1.82
Month	Yes	*	1.80
Farmers Market	Yes	***	4.09
Farm	Yes		1.72
Observations			644
R-squared			0.925

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

Table 5. Regression Results of Average Customer Transaction Size.

Variable	Coef.		Std. Err.
Card_Accept	0.19		1.63
Other_Accept	0.74		0.78
Beef_Chuck	0.89		0.92
Beef_Loin	-0.35		1.02
Beef_Offal	1.55	*	0.86
Beef_Organs	0.21		1.67
Beef_Other	-3.74	*	2.16
Beef_Processed	-1.38		1.35
Beef_Rib	0.29		0.91
Beef_Round	0.47		0.91
Beef_Thincuts	1.93	**	0.89
Beef_Trim	-0.43		1.75
Chicken_Eggs	0.40		1.01
Chicken_Meat	1.18		1.06
Chicken_Other	1.73		2.40
Duck_Meat	1.69		1.42
Turkey_Meat	3.88	**	1.59
Lamb_Ground	-0.68		2.09
Lamb_Leg	-3.87		4.60
Lamb_Loin	-2.18		1.98
Lamb_Offal	-3.43		2.46
Lamb_Other	-5.61	*	3.31
Lamb_Rib	3.90		2.95
Lamb_Shoulder	-0.28		2.22
Pork_Belly	0.16		0.83
Pork_Butt	0.04		0.59
Pork_Ground	-0.29		1.29
Pork_Ham	-0.46		0.57
Pork_Loin	1.71	**	0.79
Pork_Offal	0.24		0.71
Pork_Other	-2.05		2.08
Pork_Shoulder	0.92		0.89

Variable	Coef.		Std. Err.
Veal_Cuts	-0.06		1.24
Veal_Ground	-0.15		0.97
Veal_Other	1.33		1.95
Rabbit_Meat	1.41		1.45
Dairy_Cheese	3.09		2.20
Dairy_Milk	1.45		3.00
Dairy_Yogurt	-5.96		3.73
Product_Groups	0.29		0.79
item_meat	0.37		0.30
item_meat2	0.00		0.01
item_dairy	-0.60		0.47
item_dairy2	0.02		0.02
item_vegfruit	-2.48	***	0.75
item_vegfruit2	0.15	**	0.07
item_OFP	0.23		0.48
item_OFP2	0.05		0.05
MediumFM	2.06		4.19
LargeFM	-6.33		4.96
VeryLargeFM	-5.54		4.20
Intercept	-5.92		27.40
Fixed effects/joint significance			**F-stat**
Nondairy/meat PCs	Yes		1.08
County demogs	Yes	***	7.13
Weather	Yes		0.16
Day of the week	Yes		1.68
Month	Yes		1.10
Farmers Market	Yes	***	5.73
Farm	Yes		0.56
Observations			644
R-squared			0.80

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

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