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Abstract
With the persistent changes in technology and increased competition in food manufacturing, it is important to reassess the effects of agglomeration economies and market access on the performance of firms in the industry. Using survey data from a recent survey of New York State food processors, an ordered logit analysis reveals that firm growth is related to important upstream and downstream market conditions as reflected in increased access to agricultural inputs and growing population centers. The clustering of similar manufacturers has negative effects on firm growth in rural areas, but these effects are not significant in urban areas. For these reasons, policies that promote intra-industry or cross-industry collaboration would likely benefit food manufacturers, but these benefits would not be limited to firms in close geographic proximity to one another. Moreover, in rural areas especially, manufacturing firms and community planners need to be aware of possible negative effects of competition from growing concentrations of firms so that these issues can be addressed before local business growth is adversely affected.

Key Words: food manufacturing, growth, agglomeration economies, firm clustering

JEL classification: O13, Q13, R11

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Introduction

From 1999 through 2008, contributions to Gross Domestic Product (GDP) by food manufacturers in New York State (NYS) have increased nearly 18% (about 2.4% per year); growth in the entire U.S. was similar at around 16% (BEA 2008). The relative importance of food manufacturing to state economies varies; however, growth in NYS has been particularly strong relative to aggregate manufacturing sector performance. The situation with employment is even more revealing. Employment in all manufacturing industries has decreased strongly since 1999 - over 21% in the U.S. and nearly 30% in NYS. However, changes in food manufacturing employment have been considerably more resilient; a 0.2% gain for the U.S. and a drop of only 2% for NYS (U.S. Census 2008a).

With renewed concern at the state and national levels towards creating jobs in manufacturing, it is an opportune time to re-examine the drivers influencing the growth and performance of food manufacturing firms.[1] In stark contrast to much of the past literature that focuses on aggregate changes in the number of establishments and location of food manufacturing firms, we examine this issue at the firm level by exploiting a unique dataset. Our focus is on changes in individual firm revenue growth rather than counts of firms.[2] The model is underpinned by traditional notions of spatial economics and location theory (von Thünen 1826; Marshall 1920; Fuchs 1962), while also considering concepts of agglomeration economies (Ellison and Glaeser 1997; Shields, Barkley, and Emery 2009, Ellison, Glaeser, and Kerr 2010), economic geography (Krugman 1991; Venables 1996; Fujita and Krugman 2004), and rural development (Parr 1993; Walz 1996; Kilkenny 1998a, 1998b).

Ultimately, benefits of agglomeration reflect gains to firms when proximity reduces transport costs (Ellison, Glaeser, and Kerr 2010). Marshall (1920) defined three primary sources where changes in transport costs arise - location near suppliers and/or customers, labor market pooling, and intellectual spillovers. While changes in technology and competition have diminished traditional roles of firm location (e.g., resources and capital can be efficiently sourced from more distant markets), new influences of clusters on innovation, competition, and cooperation have taken on growing importance (Porter 2000).

Accordingly, our objectives are to identify the importance of factors affecting more recent growth in food manufacturing and to develop recommendations for firms and policymakers that support industry growth. To support these objectives, a survey of food manufacturers in New York State (NYS) was conducted.[3] NYS's strong agricultural production base and large nearby populations may benefit food manufacturers located in the state; however, other aspects of the state's business environment may reduce competitiveness (e.g., high taxes, energy and regulatory

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[1] For example, President Obama signed the U.S. Manufacturing Enhancement Act of 2010 (Public Law No. 111-227) to reduce costs, increase production, and create more jobs in manufacturing industries. At the state level, there is renewed interest in increasing the capacity and competitiveness of the food manufacturing sector (Cuomo 2010).

[2] Notable exceptions using firm survey data are Lopez and Henderson (1989), Vesecky and Lins (1995), and Jaenicke et al. (2009); however, none look at the issue of individual firm revenue growth explicitly.

[3] We include both food manufacturing firms (NAICS = 311) and beverage manufacturing firms (NAICS = 3121) in our defined food manufacturing sector.

costs). While some aspects of the business environment cut across all industries, more decisive aspects of the business environment for competitiveness often are cluster-specific; e.g., the presence of particular types of supplies, skills, or universities (Porter 2000).

The approach presented here contributes to the literature in four important areas. First, this study is the first to examine revenue growth at the firm level for food manufacturers. The data used provide a unique perspective of the economic conditions associated with the growth of food manufacturing firms in several sub-sectors. Using an ordered logit modeling approach, we are able to directly measure the effect of various factors on the level of firm revenue growth and provide a more detailed picture the growth factors affecting the industry.

Second, we model within-stream agglomeration, and upstream and downstream co-agglomeration effects simultaneously to compare the relative agglomeration benefits of each, and to better examine the ways in which food manufacturers may benefit from firm clustering. Previous studies have generally included only a subset of these agglomeration variables. In this way, we heuristically incorporate Porter's (1990) more general framework of multi-dimensional clustering effects while maintaining an output focus on one component of the cluster's performance; i.e., food manufacturing revenue growth.

Third, estimating agglomeration economies empirically is difficult because of simultaneity issues between firm clustering and performance (Glaeser and Gottlieb 2009). Our instrumenting approach combines traditional uses of historical population and manufacturing area data with new data on regional purchase coefficients (RPC) reflecting the extent of all user demands met by local production. Sufficiently lagged RPCs should be correlated with firm clustering given apparent opportunities to meet unmet local demand, but should not influence current rates of firm growth for firms already located within these areas.

Finally, to account for the heterogeneous nature of the data that includes representation from both rural and urban processing plants, agglomeration economies are allowed to vary between urban and rural locations. Clusters are present in both areas and their definition and effectiveness can differ at different locations based on the segments in which the member companies compete and the strategies they employ (Porter 2000). With the exception of Lambert, McNamara, and Beeler (2007), previous studies in food manufacturing have not accounted for differences in urban and rural clustering.

We continue with an overview of the conceptual framework and empirical modeling approach. This is followed by a description of the firm survey and county-level data collected, empirical model specifications, and estimation results. We close with some firm and policy implications and directions for future research.

Conceptual Framework

Our conceptual framework follows the theory of firm location as specified by Deller (2009), with a general model of firm location and production following Karlson (1983) and Isik (2004). Consider a firm that sells a single good in m output markets at a price P_i (i = 1, ..., m) facing individual market demands $D_i(P_i)$. Total revenue is

(1) $R = \sum_{i=1}^{m} P_i D_i(P_i)$.

The firm purchases production inputs x_i from market i (i = 1, …, n) and has production function:

$$(2)\ Q = f(x_1, \dots, x_n, F, A(s)),$$

where $Q = \sum_{i=1}^{m} D_i(P_i)$, $f_{x_i} > 0$ and $f_{x_i x_i} < 0$, F are firm-specific factors affecting production (e.g., productivity, specialization), and $A(s)$ are influences on production that arise from the firm's environment at location s through agglomeration economies (Graham and Kim 2008). Specifically, $A = (A^X, A^W, A^U, A^D)$, where A^X include external socioeconomic factors in the firm's local economy, and A^W, A^U, and A^D are agglomeration factors relating to within-stream, upstream, and downstream firm clustering, respectively.

Let $v(s)$ equal the constant marginal cost of producing one unit of output at location s and $c(s)$ be the associated fixed costs of production. Production costs may vary by location from differences in local factor endowments (e.g., land, labor, and capital), regulatory costs, or other factors. Total production costs (PC) are then:

$$(3)\ PC = v(s) f(x_1, \dots, x_n, F, A(s)) + c(s).$$

Let $d(s, s^i)$ equal the cost of transporting one unit of input from market location s^i (i = 1,…, n), and $t(s, s^i)$ equal the cost of transporting one unit of output from the plant to market location s^i (i = 1,…, m). Total transportation costs (TC) are:

$$(4)\ TC = \sum_{i=1}^{m} t(s, s^i)\, D_i(P_i) + \sum_{i=1}^{n} d(s, s^i) x_i.$$

Combining (1) through (4) yields the profit equation of the firm given location s:

$$(5)\ \pi(P, v, d, t, F, A|s) = \sum_{i=1}^{m} P_i D_i(P_i) - v(s) f(x_1, \dots, x_n, F, A(s)) - c(s)$$
$$- \sum_{i=1}^{m} t(s, s^i) D_i(P_i) - \sum_{i=1}^{n} d(s, s^i) x_i,$$

The choice variables are output prices P_i, input levels x_i, and location s. The optimal solution is characterized by the first-order conditions:

$$(6)\ \frac{\partial \pi}{\partial P_i} = D_i(P_i) + \left(P_i - t(s, s^i)\right)\frac{\partial D_i}{\partial P_i} - \sum_{i=1}^{n}\left(d(s, s^i) + v(s) f_{x_i}\right)\frac{\partial x_i}{\partial P_i} = 0 \quad (i = 1, \dots, m)$$

$$(7)\ \frac{\partial \pi}{\partial x_i} = \sum_{i=1}^{m}\left(P_i - t(s, s^i)\right) f_{x_i} - \left(v(s) f_{x_i} + d(s, s^i)\right) = 0 \quad (i = 1, \dots, n)$$

$$(8)\ \frac{\partial \pi}{\partial s} = v_s f + v(s) f_A \frac{\partial A}{\partial s} + c_s + \sum_{i=1}^{m} \frac{\partial t(s, s^i)}{\partial s} D_i(P_i) + \sum_{i=1}^{n} \frac{\partial d(s, s^i)}{\partial s} x_i = 0$$

Optimal prices P_i^* are selected to maximize demand at each market (equation 6).[4] Optimal input levels x_i^* (given P_i^*) are selected to equate marginal revenue with marginal cost for each input (equation 7). The optimal location is determined from (8) that minimizes production and

[4] Equivalently, summing (6) across all markets m and applying Hotelling's lemma yields the equi-marginal marginal revenue and cost condition for Q^*; i.e., $\sum_{i=1}^{m}\left(P_i - t(s, s^i)\right)\frac{\partial D_i}{\partial P_i} - \sum_{i=1}^{m}\sum_{i=1}^{n}\left(d(s, s^i) + v(s) f_{x_i}\right)\frac{\partial x_i}{\partial P_i} = 0$.

transportation costs, depending on P_i^* and x_i^*.[5] The firm's incentives to locate in a particular location increase with an increase in expected profits. The expected profits increase with an increase in output prices, a decrease in the distance to input and output markets, and a decrease in total cost of production. Optimal output can then be implicitly defined as:

(9) $Q^* = f(P^*, x^*, v, c, d, t, F, A(A^X, A^W(Q^*, Q_-^*), A^U, A^D)|s^*)$.

Since an individual firm's output (Q^*) depends on the agglomeration factors and, in particular, on localization agglomeration economies relative to the production of similar local firms (Q_-^*), optimal outputs of all firms are simultaneously determined; i.e., $A^W = A^W(Q^*, Q_-^*)$. This inherent endogeneity must be addressed in associated empirical applications (Graham and Kim 2008). As an extension, we also assess the influence of related upstream and downstream firms within *A*.

While we investigate firm-level growth (ΔQ^*) rather than firm location (s^*) and production (Q^*) decisions, we conceptually rely on firm location theory for three reasons. First, we examine growth primarily through spatial variables and location theory provides a framework for their inclusion. Second, location theory assumes firms will locate in the most profitable location as determined by spatial factors. The profitability of a location based on the qualities of that location should therefore also influence growth rates of firms; e.g., increases in employment or output. Put another way, location theory conceptually determines areas where firms are most likely to locate and firms already located in these areas should correspondingly have higher rates of growth. Finally, there is empirical support in the literature to evaluate the influence of agglomeration economies on both output and changes in output over time (e.g., Goetz 1997; Isik 2004; Asiseh et al. 2009, 2010).

Empirical Models

In our survey, average annual revenue growth was reported by firms using several ordered categories from strongly negative to strongly positive. As such, an ordered logit approach accommodates our dependent variable of interest. In general, let the observed ordinal growth variable for firm *i* be Y_i underlying a continuous (unmeasured) latent variable Y_i^* using *J* categories and threshold points $\mu_1 < \mu_2 < \cdots < \mu_{J-1}$, or $Y_i = (1 \text{ if } Y_i^* \leq \mu_1, 2 \text{ if } \mu_1 < Y_i^* \leq \mu 2, \ldots, J \text{ if } \mu J-1 < Yi*$. The underlying continuous variable follows a linear model $Yi*=\boldsymbol{Xi\beta}+ei$, where $\boldsymbol{X_i}$ is a vector of firm, market, and agglomeration variables, and the error term e_i has the logistic cdf $F(e_i)$. The standard proportional odds model is (Fullerton 2009):

(10) $Log\left(\frac{Pr(Y_i \leq j|X_i)}{Pr(Y_i > j|X_i)}\right) = \mu_j - \boldsymbol{X_i\beta} \quad j = 1, 2, \ldots, J$

where a positive coefficient within $\boldsymbol{\beta}$ indicates that a unit increase in the associated variable within $\boldsymbol{X}$ leads to a higher level of Y_i. The probability for any given outcome category is:

[5] Note that Deller (2009) follows a two-stage process, where the firm first maximizes (5) assuming a homogenous economic plane (*v* and *c* are fixed) and, in so doing, defines a general location (or region) for the firm. During the second stage, the firm maximizes profits by choosing a specific location within the region assuming transportation costs are constant, but production costs vary based on differences in factor endowments. Following Isik (2004), we allow both production and transportation costs to vary and inherently incorporate other spatial differences within *A*.

$$P(Y_i = 1) = F(\mu_1 - \boldsymbol{X}_i\boldsymbol{\beta})$$
$$P(Y_i = j) = F(\mu_j - \boldsymbol{X}_i\boldsymbol{\beta}) - F(\mu_{j-1} - \boldsymbol{X}_i\boldsymbol{\beta}), \qquad j = 2, \ldots, J-1 \tag{11}$$
$$P(Y_i = J) = 1 - F(\mu_{J-1} - \boldsymbol{X}_i\boldsymbol{\beta})$$

The proportional odds model estimates *J*-1 binary logit models simultaneously, with the μ's and β's estimated by maximum likelihood methods. One of the key assumptions of the model as proposed is that the effects of $\boldsymbol{X}$ on falling in the next highest category of $\boldsymbol{Y}$, relative to all prior categories, is homogeneous across all levels of $\boldsymbol{Y}$. This assumption may be violated for some or all variables in $\boldsymbol{X}$. We investigate relaxing this assumption below (i.e., replacing $\boldsymbol{\beta}$ with $\boldsymbol{\beta}_j$ for some or all j).

While the underlying (latent) continuous model is linear, marginal effects of the probabilities are nonlinear and will depend on the values of the explanatory variables. Specifically, the marginal effect for the ordered logit is (Greene 1997, p. 928):

$$\frac{\partial P(Y_i=1)}{\partial x} = -f(\mu_1 - \boldsymbol{X}_i\boldsymbol{\beta})\boldsymbol{\beta}$$
$$\frac{\partial P(Y_i=j)}{\partial x} = [f(\mu_{j-1} - \boldsymbol{X}_i\boldsymbol{\beta}) - f(\mu_j - \boldsymbol{X}_i\boldsymbol{\beta})]\boldsymbol{\beta}, \; j = 2, \ldots, J-1 \tag{12}$$
$$\frac{\partial P(Y_i=J)}{\partial x} = f(\mu_{J-1} - \boldsymbol{X}_i\boldsymbol{\beta})\boldsymbol{\beta}$$

where f is the logistic pdf. Note that the signs on the marginal effects and the signs on $\boldsymbol{\beta}$ will be the same (opposite) for the highest (lowest) category, but the comparison is ambiguous for the interior categories and depends on the sizes of the densities. In order to assess the robustness of our ordered logit results, we also estimate growth models using least squares procedures where a continuous growth variable is assigned as our dependent variable based on mid-point values of the ordered growth categories.

Data

A plant-level survey was administered to collect information on NYS food manufacturing establishments.[6] The survey was pre-tested with a small group of manufacturers representing various industry sectors and was administered in February 2009 in both mail and online formats.[7] A reminder mailing was sent one month later to firms that had not originally responded. Follow up phone calls and emails were delivered to a number of plants to improve overall response rate.

An original listing of 3,893 establishments (excluding animal food and maple product processors) was developed using several sources of information.[8] For reference, the U.S. Census reported 4,377 establishments in 2008, 51% of which were small establishments with no

[6] Multiple plants owned by the same firm were surveyed individually. The majority of responding plants (89%) belonged to single-plant firms (Hall 2010). For ease of exposition, firm, establishment, and plant are used interchangeably.

[7] A copy of the final survey is available from the corresponding author upon request.

[8] Plant-level databases were purchased from *Manufacturers News* and *Harris Interactive*. Publicly available data sources included USDA Meat and Poultry Inspection Database, New York State Cattle Health Assurance Program, New York State Department of Agriculture and Markets Food Safety Inspection Service, New York MarketMaker, and the New York State Wine and Grape Foundation.

employee payroll (2008a, 2008b). After deleting establishments no longer in operation or whose surveys were returned as undeliverable, the net count of surveyed plants was 3,460. A total of 399 surveys were returned (13%).

While the overall response rate is relatively low, a wide distribution of plants by size, location, and industry sector was received. Figure 1 shows the distribution of plants by industry sector relative to U.S. Census estimates (2008a, 2008b). Bakery and tortilla (beverages) sector responses under (over) represented Census estimates; however, when these two sectors are excluded, the remaining distribution of sectors is comparatively more representative.[9] Responses from non-employer firms in our sample (11.0%) were also below that of Census estimates (51.2%); however, the distributions of plants with payroll by employee size are quite similar (Figure 2).

Plant Variables

Responding plants have been in business an average of 30 years (*Years*, Table 1). While not shown, grain and oilseed milling plants (*N* = 5) have been in operation the longest (85 years on average), and alcoholic beverage processors (*N*=74) the shortest (15 years). The younger age of alcoholic beverage manufacturers reflects the strong growth in new wineries in the state over the last several years. Many responses were from small firms; overall, the average firm had about 28 employees (*Employees*, Table 1). A sufficient number of alcoholic beverage (21%), bakery and tortilla (17%), meat processing (14%), dairy product (10%), fruit and vegetable (11%), and sugar and confectionary (5%) plants permitted the assessment of sector-specific effects. The remaining plants (22%) were included in the *Other* category (Table 1).[10]

Average annual revenue growth for the past three years was reported by firms using nine ordered categories.[11] Since independently characterizing four levels of negative and positive growth may be problematic statistically and intuitively difficult to distinguish, growth categories were aggregated to five (*Rev_Cat*): (*i*) strongly negative, less than -10%, (*ii*) moderately negative,-1% to -10%, (*iii*) zero, (*iv*) moderately positive, 1% to 10%, and (*v*) strongly positive, more than 10%. The percent of plants reporting positive growth were in the strong majority (71%, Table 1); however, this could be the result of selection bias since firms experiencing negative revenue growth would be more likely to have stopped operating by the time of the survey. That said, there were a number of firms reporting negative growth (21%), some quite strongly (Table 1).

Using the nine original growth categories, a continuous variable (*Rgrowth*) was also created by assigning the mid-point level for each category (extreme categories were set at values corresponding to their minimum level). In this format, average annual growth across all firms was 5.0% (Table 1). A standard deviation of over twice this level is indicative of considerable firm heterogeneity.

County Variables

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[9] Beverages as defined here include both alcoholic and non-alcoholic beverage manufacturing establishments.

[10] Grain and oilseed millers (*N*=5), seafood processors (*N*=11), and non-alcoholic beverage manufacturers (*N*=9) were included in the *Other* category along with other food manufacturers (*N*=51).

[11] The original survey categories were: less than -20%, -11% to -20%, -5% to -10%, -1% to -4%, 0%, 1% to 4%, 5% to 10%, 11% to 20%, and more than 20%.

To identify within stream agglomeration effects, the percent of workers employed in a sector is commonly used since the level of employment is generally considered a good measure of industry size (Rainey and McNamara 1999; Gabe 2005). Results from this survey, however, indicated that many firms had only a few or no paid employees. As a result, the percent of all establishments in a county in food manufacturing (*Cluster_Within*) was used. Food manufacturers represented about 0.6% of all firms in counties where surveyed firms resided, and ranged from 0.1% to 2.6% (Table 1).

Given that food manufacturing occurs in both rural and urban areas, we examine whether within stream cluster effects vary across this dimension. Firms located in urban areas likely have different cost structures than firms located in rural areas and, therefore, may have differential benefits from clustering. Additionally, smaller populations in rural counties may make rural processors more sensitive to competition effects from other processors in the area. Of the 62 counties in NYS, 13 were identified as urban counties (*Urban*) and 42% of surveyed plants were located in urban counties (Table 1).[12]

Rather than farm counts, county cash receipts from crops and livestock sales per 100,000 people (*Cluster_Upstream*) was used as an indicator of upstream clustering, intended to measure the concentration of agricultural production in the area. As expected, upstream clustering was generally lowest in or near urban counties and, on average, was $0.75 across all plant-county observations (Table 1).

The county-level number of establishments of merchant wholesalers (nondurable goods), retail food and beverage stores, and food services and drinking places per capita was used to model downstream clustering effects (*Cluster_Downstream*).[13] It was hypothesized that downstream clustering will have a positive effect on firm growth as a demand-pull component, although this measure has not been used in previous studies. Within NYS, downstream clustering appears to be greatest in counties near metropolitan areas, but low within the counties containing the metropolitan areas themselves. On average, 6.1 establishments per capita existed in counties where surveyed firms were located (Table 1).

About 38% of all plant sales from our sample were direct to consumers (Hall 2010). As such, downstream effects may also be captured by spatial differences in consumer populations. To address this, we include variables representing county-level population densities (*Density*) and population growth rates (*Popn_Growth*) (Table 1). Attributes of the local labor conditions were proxied by county-level manufacturing wage rates (*Wages*), and averaged over $51 thousand per person per year across all plant-county observations (Table 1).

Previous studies have suggested that tax rates and available infrastructure will affect firm costs (Goetz 1997; Lambert, McNamara, and Beeler 2007). However, most taxes and other governmental costs of operating are state-level costs and do not vary between counties. NYS also has numerous programs to offset governmental costs for selected firms, which makes accurate

[12] Counties with over 80% of households located in urbanized areas were defined as urban. U.S. Census Bureau (2009a) define an urbanized area as a census block group with a population density of at least 1,000 people per square mile and surrounding census blocks with an overall density of at least 500 people per square mile.
[13] Food and beverage wholesalers are a large proportion of the wholesale nondurable goods sector. However, due to the limits of available county-level data, we were unable to separate out food and beverage wholesalers explicitly.

measures of county differences in governmental costs infeasible from available data sources. Likewise, within the state, nearly all counties provide access to highways, the typical proxy for infrastructure. As such, these spatial cost factors were not considered.

Empirical Specification

The underlying linear model specification is expressed as function of firm, market, and agglomeration factors, or

$$\text{(13)}\quad Rev_{Cat_{i,j}} = \mu_j + \beta_1 Years_i + \beta_2 Years_i^2 + \beta_3 Employees_i + \beta_4 Employees_i^2$$

$$+\textstyle\sum_{k=1}^{K-1} \gamma_k Industry_{i,k} + \delta_1 Wages_{i,c} + \delta_2 Density_{i,c} + \delta_3 PopnGrowtH_j$$

$$+\delta_4 ClusterWitHin_{i,c} + \delta_5 ClusterWitHin_{i,c} \cdot Urban_{i,c} + \delta_6 ClusterUpstream_{i,c}$$

$$+\delta_7 ClusterDownstream_{i,c} + \textstyle\sum_{k=1}^{K-1} \alpha_k Industry_{i,k} \cdot Wages_{i,c} + \sum_{r=1}^{R-1} \varphi_r Region_{i,r} + e_i$$

for plant i in industry sector k and located in county c of state region r. The μ_j's (j=1, ..., 4), β's, γ's, δ's, α's, and φ's are parameters to be estimated, and e_i is the error term with logistic cdf. Given the large range in plant ages and number of employees, these factor effects are allowed to vary nonlinearly with growth. The γ's represent sector fixed effects, while variables associated with the δ's represent county-level variables given plant i's location. Within-stream agglomeration economies are allowed to vary based on a plant's location in an urban or non-urban county, while county labor wage effects are allowed to vary by sector.[14] Regional fixed effects (φ_r) are used to identify possible differences in firm performance across geographic regions of the state defined by the Empire State Development.

To accurately measure the effect of firm clustering, it is necessary to account for simultaneity in the determination of firm growth and geographic clustering of these same types of firms (Graham and Kim 2008). Geographic location may also possess an unaccounted for (unobservable) attribute that simultaneously increases the rate of growth of local firms and attracts more firms to the area. To account for endogeneity, we follow a two-stage prediction substitution (2SPS) approach addressed by Terza, Basu, and Rathouz (2008), similar to two-stage least squares (2SLS). In the first-stage, reduced form regressions are estimated with any consistent estimation type. Predicted values for the endogenous variables are then generated and used in the second stage. To accommodate the use of predicted values we report bootstrapped standard errors in the second stage results (Pagan 1984; Terza, Basu, and Rathouz 2008; Beine, Lodigiani, and Vermeulen 2010).

Addressing the endogenity issue requires finding suitable instruments. In their study addressing the impact of firm clustering on sales of organic food processors, Jaenicke et al. (2009) use additional survey variables as instruments for their clustering variable. In contrast, we use historical census variables as suggested by Rice, Venables, and Patacchini (2006), as well as lagged commodity demand-side market factors not previously used in the literature.

[14] Preliminary specifications also included urban interaction effects with upstream and downstream agglomeration factors. Neither was significant at any reasonable degree of statistical significance. Similarly, only the interaction wage effect associated with the alcoholic beverage sector (*Alc_Bev*) was statistically significant. For a more parsimonious specification, other sector-wage interaction effects were excluded in the final models estimated.

First, population and manufacturing area data from the 1920 U.S. Census should be an adequate indicator of current population and manufacturing areas but should not be correlated with the performance of modern firms. County values of manufacturing production per capita (*Manuf_1920*) and county population per square mile (*Density_1920*) from the 1920 census were used as instruments (Table 1). The validity of these instruments rests on the assumption that the exogenous factors that influenced the pattern of population and firm settlement in the early-1900's are unrelated to firm growth more recently, apart from their effect through present-day populations (Rice, Venables, and Patacchini 2006).

Second, lagged demand-side market influences are included using county-level regional purchase coefficients (RPC) for manufactured food commodities. RPCs represent the proportion of total demand for a commodity (e.g., manufactured food products) by all users (e.g., wholesalers, retailers, consumers, other food manufacturers) in a study area that is supplied by producers located within that area (MIG 2011). Sufficiently lagged RPCs should be correlated with firm clustering given apparent opportunities to address unmet local demand, but should not influence current rates of firm growth by firms already located within those areas. We include county-level food manufacturing RPCs for 1998 (*RPC_1998*, Table 1) in the first-stage equation. Including additional variables from $\boldsymbol{X}$, the first stage was modeled as:

$$(14)\quad ClusterWithin_j = \theta_0 + \theta_1 Manuf1920_j + \theta_2 Density1920_j + \theta_3 RPC1998_j$$
$$+ \theta_4 Wages_j + \theta_5 PopnGrowth_j + \theta_6 ClusterUpstream_j$$
$$+ \theta_7 ClusterDownstream_j + \textstyle\sum_{r=1}^{R-1} \vartheta_r Region_r + \varepsilon_j$$

Results and Discussion

Ordinary least squares results for the first-stage equation are shown in Table 2. Historical manufacturing production per capita (*Manuf_1920*) is negatively associated with current food manufacturing clustering, while historical population density effects were not significant. Higher levels of lagged RPCs were positively associated with firm clustering. Higher levels of agricultural production also support higher manufacturing clustering, while the opposite was true for downstream buyers. The latter may be the result of inadequate infrastructure for manufacturing within areas with concentrated retail firms.

An over-identifying restrictions test was performed to statistically test for correlation of our instruments with the error term; i.e., a likelihood ratio test that compares the likelihood function of the second-stage estimates with the likelihood function of a specification that additionally includes the instruments from the first stage (Beine, Lodigiani, and Vermeulen 2010). As shown at the bottom of Table 3, the test confirms the statistical validity of our instruments.

The ordered logit results using maximum likelihood are shown in Table 3 following the proportional odds assumption ($\boldsymbol{\beta}_j = \boldsymbol{\beta}\ \forall\, j$). Likelihood ratio tests suggested that the parallel regressions assumption had been violated.[15] This test is known to be liberal for small samples, implying that the p□-value for the test could be artificially small (Peterson and Harrell 1990). Stokes, Davis, and Koch (2000, p. 249) suggest doing cross-tabulations of the response with each predictor involved; if all cell counts are about five or larger, the sample size should be adequate.

[15] Model 1 $\chi^2(54) = 95.52$ (p-value < 0.001), Model 2 $\chi^2(81) = 130.52$ (p-value < 0.001).

Brant tests (Greene 2007, p. E22-E28) indicated that the firm-level variables *Years* and *Employees* contributed significantly to the overall test result; however, neither variable satisfied the cross-tabulation criteria. Given these data deficiencies, the standard proportional odds model was retained.

A likelihood ratio test that Model 1 (no regional fixed effects) is nested in Model 2 (regional fixed effects) cannot be rejected ($\chi^2(9) = 12.44$, *p*-value = 0.19). This is confirmed with the lower Akaike Information Criterion (AIC) score for the restricted model. Accordingly, the discussion of results will follow from Model 1 (Table 3). Odds ratios for variables with interaction or quadratic terms were computed at sample means. Regression results treating the dependent variable as continuous are included in the appendix (Table A1). The robustness of our ordered logit models are supported based on empirical results similar in signs and level of significance. Due to the spatial nature of the data, we test for spatial autocorrelation using Moran's I statistic (Moran 1950). An estimated *z*-statistic of -1.31 (*p*-value = 0.19) implies we cannot reject the null hypothesis of uncorrelated residuals.

Firm and Labor Measures

If not capital constrained, younger firms have been shown to grow at a more rapid pace and the growth rates of smaller firms are higher and more variable (Wijewardena and Tibbits 1999; Heshmati 2001; Davidsson et al 2002). For this sample of firms, older firms were associated with lower rates of growth, although the effect diminishes as firms age (*Years*, Table 3). When evaluated at sample means, the odds ratio indicates that for a one-year increase in age of plant, the odds of being in a higher growth category decrease by about 1%.[16] At one standard deviation less the mean age, this increases to 2%. The comparable elasticity from the continuous model is -0.27 (Table A1).

In contrast, larger plants in the sample were associated with higher growth rates, but the effect diminishes as plants increase employees. Again, the odds ratio is modest; a one-person increase in the number of employees increases the odds of being in a higher growth category by about 1%. While small at the unit level, changes in employee numbers are often associated with relatively large adjustments; i.e., cumulative effects could be sizable. The comparable elasticity measure is 0.21 (Table A1). Smaller firms were expected to grow at a higher rate; however, many smaller plants in this sample reported they had little intention of increasing size in the future. Specifically, 52% of large plants (over 50 employees) expected to increase employee staffing in the next three years, compared to only 34% of small plants (one to nine employees) and 17% of non-employer firms (Hall 2010).

When other factors were accounted for, few differences in revenue growth existed across industry sectors (Table 3).[17] One clear exception is in alcoholic beverages, although the sector

[16] A more precise definition would be for a one-year increase in plant age, the odds of being in a strongly positive growth category versus the combined categories below it are 0.99 greater, other variables constant. The same change in odds would exist, for example, if comparing the combined moderately and strongly positive growth categories versus the combined zero and negative growth categories. The odds ratio interpretation is relative to a change from the lower aggregate category to the higher aggregate category, as defined by a particular cut point chosen.

[17] While the sector effects are largely insignificant relative to the *Other* category, the signs and magnitudes of the estimated coefficients are reasonably consistent with secondary data estimates of annualized changes in revenues

fixed effect is strongly influenced by local wage rates (i.e., the interaction effect with wages is negative and significant). The change in odds for alcoholic beverage firms being in a higher growth category is not statistically different from zero at mean wage levels (Table 3), but the odds are 2.19 (0.48) times greater when wages are one standard deviation below (above) the mean, both statistically significant at the 5% level. Given that many of these plants were wineries that produce as well as process the input commodity (grapes), labor costs were expected to be particularly important. Marginal industry effects for the continuous growth variable were -0.64 (p-value = 0.72), -5.37 (p-value = 0.03), and 4.10 (p-value = 0.05) evaluated at mean wages and mean wages plus and minus one standard deviation, respectively (Table A1).

Excluding alcoholic beverage processors, average county manufacturing wages (*Wages*) did not significantly influence revenue growth of the firms in our sample. This may be due to the characteristics of our sample, primarily small establishments, many with no or few paid employees. The literature, in general, has found mixed results (negative: Goetz 1997; Henderson and McNamara 2000; Rainey and McNamara 1999; positive: Brown, Florax, and McNamara 2008). If wage rates are positively correlated with workforce education (a generally positive influence), the sign is ambiguous *a priori*.[18]

Within-Stream Agglomeration

Within-stream agglomeration effects (*Cluster_Within*) were found to have important effects on revenue growth in rural areas; a one-percentage point increase in the concentration of local (county) food manufacturers decreases the odds of being in a higher revenue growth category by a sizeable 68% (Table 3). The magnitude of a unit change is relatively large; however, considering average clustering in our sample was only 0.59% (Table 1). Comparatively, the continuous model results would indicate a growth elasticity with respect to within-stream clustering in rural areas of -0.71 (p-value = 0.02, Table A1). Part of the reason for the negative agglomeration effects in rural areas may be because 44% of rural establishments in our sample sold at least 75% of their products direct-to-consumers (D2C), and it is likely that much of these sales go to consumers living near the firm location (Hall 2010). These firms will face more direct competition from collocated food processors than firms selling primarily to downstream retailers or wholesalers.

The interaction term (*Cluster_Within*Urban*) suggests that agglomeration effects in urban areas are significantly above those in rural areas. When combined with the direct effect on *Cluster_Within*, the odds ratio would imply that a one percentage point increase in within-stream clustering in urban areas increases the odds of being in a higher revenue growth category by 55% (Table 3); the comparative elasticity from the continuous model is 0.41 (p-value = 0.25, Table A1). However, in both cases, the total effect is not statistically different from zero. The lack of statistical significance for urban within stream clustering may be primarily due to the sample size of urban manufacturers. Even though 146 plants in our sample were from urban areas, these plants were divided among only 13 counties (43 counties were rural). Since the clustering

from 2006 through 2008; i.e., meat = -1.9%, bakery = -1.4%, sugar = -0.8%, fruit and vegetable = 2.4%, dairy = 4.3%, other = 12.1%, and alcoholic beverage = 21.4% (MIG 2011).

[18] Worker education variables were not available, population education variables were considered in preliminary specifications; however, the results were not statistically significant. The results reported here are robust to their inclusion or not.

variables vary by county, it is likely that less variation in within-stream clustering existed across urban counties, reducing the power to find a significant effect.

Agglomeration benefits accruing through urbanization benefits have been shown to be more important than localization effects (Harrison, Kelley, and Gant 1996). If so, we would expect to see evidence of urbanization economies through downstream population-based effects. Localization economies may still arise in urban areas. For example, food processors may concentrate in a small neighborhood of a large metropolitan city and benefit from the cooperative activities this close location provides, or certain districts of a city may provide access to unique infrastructure (e.g., areas surrounding a port or rail terminal). County-level measures may not be of sufficient detail to detect these effects. Data at a more micro level would be needed to effectively pick up localization economies within metropolitan areas.

The effect of within-stream firm clustering is mixed in the literature. Using county-level data, Goetz (1997) found evidence of negative agglomeration effects, while Henderson and McNamara (2000) found positive agglomeration effects for large food manufacturers only. Neither distinguishes between urban and rural areas. Asiseh et al. (2009, 2010) show within-stream agglomeration economies at the state level can be important, but the effect depends on the firm size considered relative to sizes of the clustering firms. In contrast to our results, Lambert, McNamara, and Beeler (2007) found positive county-level agglomeration benefits in rural areas. This literature suggests that the distribution of firms by size, rather than simply the extent of their presence, may influence whether positive localization benefits arise. However, statistical tests failed to find significant differences in agglomeration benefits by firm size in our sample.

Upstream Agglomeration

As expected, upstream clustering (*Cluster_Upstream*) was strongly associated with revenue growth; for a one unit increase in upstream clustering, the odds of being in a higher growth category increases by nearly 56%; similar in magnitude to the within-stream effects (Table 3); the comparable growth elasticity is 0.41 (Table A1). The result is consistent with other studies (Goetz 1997; Henderson and McNamara 2000; Davis and Schluter 2005; Asiseh et al. 2009, 2010).

Measures of county agricultural production may also be an indicator of rurality and the associated qualities of rural areas, such as availability of land (Goetz 1997). Most likely, some of our sample from rural areas benefit from close access to agricultural inputs (e.g., milk processors, grain millers), while other types of firms may benefit from other aspects of rural areas (e.g., wineries).

Downstream Agglomeration

Downstream firm clustering did not have a significant effect on revenue growth, likely due, in part, to the makeup of our sample wherein a large share of farm sales is D2C. The benefits of locating near a cluster of foodservice and/or food wholesale and retail firms may accrue to a smaller percentage of our sample that access and utilize these sales channels. In addition, our downstream clustering measure included all nondurable goods wholesalers. While food and beverage products represent a relatively large portion of this category, including non-food-related firms may diminish the effect for the category as a whole.[19]

Previous studies have stressed the importance of access to product markets and have found evidence of beneficial effects to firms by locating near urban areas, notably attributed to output market access provided by large populations (Henderson and McNamara 2000; Davis and Schluter 2005; Lambert, McNamara, and Beeler 2007). Using state-level data, Asiseh et al. (2010) find proximity to output markets important for small dairy manufacturing establishments but not for medium or large establishments, perhaps a result of larger sales distribution areas that go beyond state boundaries.

Somewhat surprising, population density (*Density*) was negatively associated with revenue growth; for a one-unit increase in population per square mile, the odds of being in a higher growth category decreases by about 12% (Table 3). This may be due, in part, to more limited infrastructural or operational capacities and/or congestion issues in highly residential areas. Rainey and Murova (2002) found population density to have a positive effect on growth in the number of manufacturing establishments, while Goetz (1997) and Lambert, McNamara, and Beeler (2007) found large local populations (not population densities) increased the growth of food manufacturing establishments.

Although no previous studies included population growth, we expect that growing local populations (rather than just the size of the population) would be important. The empirical results support this hypothesis; for a one-percentage point increase in population growth rates, the odds of being in a higher growth category increases by 7.5% (Table 3). With the continuous model, a one-percentage point increase in population growth increases annual revenue growth by 0.26 percentage points (Table A1).

Another possibility for why we see mixed results is that urban areas, in general, tend to have the highest rates of population growth. In NYS, recent population growth has been highest in the Mid-Hudson, Long Island, Capital, and New York City regions, all areas close to New York City. As such, if county population growth rates were not controlled for, we would expect to see signs of revenue growth in these more dense urban and urban-fringe areas. When population growth rates are included, we see negative effects on growth from urbanization as proxied for by *Density*. Our results suggest that urban effects may be the result of population shifts rather than other particular qualities of urban areas.

Marginal Probability Effects

While estimated logit coefficients effectively summarize changes in odds of moving into higher growth categories, the changes are constant across category comparisons (as restricted in the proportional odds model). The same cannot be said of changes in probabilities associated with any one category as an underlying explanatory variable changes. Marginal effects of each continuous variable, holding all else constant at their mean, are shown in Table 4. We follow

[19] A clear direction for future research is to examine more closely how available data sources can specifically account for food manufacturing downstream firm clustering effects.

Bartus (2005) when considering variables with interaction or quadratic terms, with standard errors estimated using the delta method.[20]

The results in Table 4 are consistent with our discussion of odds ratios, but provide further detail on probability changes. For example, a marginal increase in a plant's age (*Years*) decreases its probability of being in the strongly positive growth category by 0.17%, while it increases the probabilities of being in negative growth categories (Table 4). The opposite can be said about the number of employees.

What is also apparent is that firm-level marginal effects are much smaller than those associated with agglomeration effects and, to a lesser extent, population growth and density effects. For example, a marginal increase in the extent of firm clustering in rural areas decreases the probability of remaining in the strongly positive growth category by 23.1%; probability changes are -9.0% and -5.9% for the moderately negative and strongly negative categories, respectively. The marginal effects of wages within the alcoholic beverage sector are also quite strong at the extreme levels of growth, both positive and negative.

Implications and Conclusions

The viability of the manufacturing sector in NYS relative to other areas of the U.S. is of growing concern, and policy makers are increasingly looking towards agriculturally based opportunities to better take advantage of the large and diverse agricultural production sectors. With considerable changes in technology and competition over time, the effects of agglomeration economies and firm clustering on firm performance deserves renewed attention. This paper focused on determining the primary factors affecting firm growth for food manufacturing operations in NYS use a unique plant-level dataset, and particular attention to firm agglomeration and market access effects.

As expected, younger firms had higher annual revenue growth rates than larger, more established firms. However, this result has additional implications. Anecdotal evidence from follow up focus groups indicated that little incentives exist for established, older firms to maintain the size of their operations, relative to programs aimed at new start-ups or expansions of firms to create new jobs. Lower growth rates estimated here may be a consequence of such policies (or lack thereof). Policies focused on employee seniority incentives could be considered when more moderated growth for established firms is insufficient for long-term viability.

Larger firms were estimated to have higher rates of growth, consistent with other survey results that indicated a much lower proportion of smaller firms were expecting to increase employee staffing or capital spending in the future. This result may be highlighting difficulties faced by smaller firms looking to increase plant size, but may be limited in doing so due to capital constraints or more limited access to larger downstream markets due to insufficient product volumes for buyers. As such, the result provides some evidence of a need for additional support mechanisms (public or private) for beginning/small firms to improve their potential for successful expansion.

[20] The margeeff and lincom commands in Stata (version 11.1) were used to estimate marginal effects.

Increased access to raw agricultural inputs and growing population centers were important upstream and downstream market conditions to improving firm growth. Policy options that improve efficiencies of market access should improve the growth of the industry. This might include investments in transportation infrastructure or programs that provide better communication and collaboration between food processors and agricultural producers. New York City is the largest source of consumption in the region and upstate food manufacturers may not be accessing this market as much as they could be.[21] Additional programs that bring upstate food manufacturing products to New York City area markets may be a source of potential growth.

Increased food manufacturing firm concentration reduced growth rates in rural areas, presumably from higher competition effects with local firms primarily serving more local markets. With growing interest in developing local and regional food systems within smaller, rural communities, community planners and plant management need to be aware of competition issues and consider the development of policies or operational procedures reinforcing holistic community food-systems planning and the availability of collaborative firm activities that can offset negative competition effects.

Within-stream agglomeration benefits were not significant for food manufacturers located in urban areas; perhaps a result of how mechanisms through which agglomeration benefits accrue in food manufacturing may differ from other industries. Agglomeration benefits in some industries require a dense location of firms; e.g., firms in a technology cluster need to be located in the same area so that the specialized labor pool can be shared. However, external economies of scale in food manufacturing can often be created through cooperation between firms located in opposite corners of the state, just as easily as firms on opposite sides of the street.

Follow-up focus groups provided anecdotal evidence of the ways in which these firms have benefitted from collaborations with other firms, including purchasing inputs with other similar firms to negotiate lower prices and using group distribution and sales. State industry associations were also beneficial in providing marketing and branding for their members, lobbying activities, and sharing knowledge and operational information. Statewide trade associations could also explain why Goetz (1997) found positive agglomeration effects at the state-level but negative effects at the county-level. A large concentration of food manufacturers at the state-level could provide benefits to those firms through well-funded state trade associations, while a large concentration of firms in a single county would not benefit those firms in the same way.

Policies that promote intra-industry or cross-industry collaboration would likely benefit food manufacturers and fall in line with Porter's cluster upgrading concepts (1990), but these policies would not necessarily require geographic proximity between firms. Barkley and Henry (1997) argue that in order for industry clusters to be successful, changes must be made in political, economic, and institutional conditions to discourage competition between firms and encourage collective activities. It is simply not enough for firms to locate close to one another and expect to see benefits from this location. Firms located close to other related firms must actively try to create collaborative actions to attain beneficial outcomes and improved firm performance.

[21] On average, only 9.2% of upstate food manufacturing output in the sample was sold to downstate buyers (Hall 2010).

The results from this analysis contribute new insights into how localization economies impact the performance of the food manufacturing industry, and additionally raise some new questions. Our conclusions further support the contention that market access is one of the most influential location factors on the performance of food manufacturers, yet firm growth near large population centers is explained more by growth in population than by the absolute size of the population itself. More analysis of these population effects is needed to better understand and differentiate dynamic population effects. Additionally, we failed to find significant agglomeration economies from the presence of retail, wholesale, and foodservice firms, yet the market access created by close location to these firms is likely to be beneficial to food manufacturers in general. The pathways through which food manufacturing firms create market access are somewhat ambiguous in previous research. Further study on sales channel effectiveness and preferential supply chains to markets is needed.

It also remains somewhat unclear as to the source of agglomeration benefits accrued to food manufacturers in close location to one another. While our analysis finds a negative effect on firm growth in rural areas, past research has found positive effects, and different effects have been found by size and industry sectors within food manufacturing. We present some evidence of collaborative activities, but the actual manner in which close proximity between firms creates beneficial collaborations has not been fully investigated. Further research is needed to better understand the dynamics of urbanization and localization economies for food manufacturing firms that are likely to be highly dependent on the distributional choices made by firms to alternative market channels.

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Table 1. Summary statistics of model variables (*N*=348)

Variable	Level	Description	Source	Mean	Std. Dev.	Min	Max
Dependent variables:							
Rgrowth	Firm	Annualized revenue growth, past three years, mid-point values of nine growth categories.	survey	5.01	10.23	-20.00	20.00
Revcat=1	Firm	Strongly negative annualized revenue growth, past three years, less than -10%	survey	0.08	0.27	0.00	1.00
Revcat=2	Firm	Moderately negative annualized revenue growth, past three years, -1% to -10%	survey	0.13	0.33	0.00	1.00
Revcat=3	Firm	Zero annualized revenue growth, past three years, 0%	survey	0.08	0.26	0.00	1.00
Revcat=4	Firm	Moderately positive annualized revenue growth, past three years, 1% to 10%	survey	0.45	0.49	0.00	1.00
Revcat=5	Firm	Strongly positive annualized revenue growth, past three years, more than 10%	survey	0.26	0.44	0.00	1.00
Firm-level variables:							
Years	Firm	Number of years plant has been operating	survey	29.34	30.77	1.00	212.00
Employees	Firm	Number of full- and part-time employees	survey	28.38	52.65	0.00	375.00
Sugar	Firm	Sugar and confectionary product manufacturing (NAICS 3113)=1, else=0	survey	0.05	0.22	0.00	1.00
Fruit_Veg	Firm	Fruit and vegetable manufacturing (NAICS 3114)=1, else=0	survey	0.11	0.32	0.00	1.00
Dairy	Firm	Dairy product manufacturing (NAICS 3115)=1, else=0	survey	0.10	0.30	0.00	1.00
Meat	Firm	Animal slaughtering and processing (NAICS 3116)=1, else=0	survey	0.14	0.35	0.00	1.00
Bakery	Firm	Bakeries and tortilla manufacturing (NAICS 3118)=1, else=0	survey	0.17	0.37	0.00	1.00
Alc_Bev	Firm	Alcoholic beverage manufacturing (NAICS 31212-31214)=1, else=0	survey	0.21	0.41	0.00	1.00
Other	Firm	Other food manufacturing (NAICS 3112, 3117, 31211, 3119)=1, else=0	survey	0.22	0.41	0.00	1.00

Table 1. Summary statistics of model variables (*N*=348), continued

Variable	Level	Description	Source	Mean	Std. Dev.	Min	Max
County-level variables:							
Cluster_Within	County	Percent of establishments in food and beverage manufacturing (NAICS = 3112-3119, 3121)	U.S. Census 2008a, 2008b	0.59	0.56	0.10	2.63
Cluster_Upstream	County	Cash value of crops and livestock per 100,000 people	NASS 2009; U.S. Census 2009b	0.75	0.98	0.00	5.52
Cluster_Downstream	County	Number of establishments per capita in food and beverage wholesale, retail, and service (NAICS = 424, 445, 722)	U.S. Census 2008a, 2008b, 2009b	6.06	16.04	0.55	219.21
Urban	County	Urban county = 1 if at least 80% of households located in an urbanized area, else 0	U.S. Census 2009b	0.42	0.49	0.00	1.00
Density	County	Population (000) per square mile	U.S. Census 2009b	5.12	12.04	0.02	52.42
Popn_Growth	County	Percent change in population from April 2000 to July 2008	U.S. Census 2009b	1.26	3.72	-5.08	11.21
Wages	County	Average annual pay for manufacturing employees ($000)	BLS 2008	51.37	14.48	28.75	97.38
Manuf_1920	County	1920 manufacturing production ($) per capita	U.S. Census 2004	0.62	0.37	0.08	1.54
Density_1920	County	1920 population (000) per square mile	U.S. Census 2004	5.37	18.92	0.02	103.82
RPC_1998	County	1998 regional purchase coefficient	MIG 2011	0.19	0.25	0.00	1.00

Table 2. First-stage regression results on food manufacturing establishment clustering.[a]

Variable	Coefficient (std. error)
Manuf_1920	-0.263**
	(0.103)
Density_1920	-0.003
	(0.006)
RPC_1998	0.444***
	(0.087)
Wages	-0.002
	(0.018)
Density	0.007
	(0.016)
Popn_Growth	-0.010
	(0.010)
Cluster_Upstream	0.246***
	(0.036)
Cluster_Downstream	-0.005***
	(0.001)
Regional fixed effects	Yes
R-square	0.594
F(17)	28.360
Prob > F	< 0.001

[a] Dependent variable is *Cluster_Within*. ***, **, * represent significance at the 10, 5, and 1 percent significance level, respectively.

Table 3. Ordered logistic regression results of plant revenue growth[a]

	Model 1		Model 2	
Variable	Coefficient (std error)	Odds Ratio[b]	Coefficient (std error)	Odds Ratio[b]
Years	-0.018***	0.991**	-0.019***	0.991**
	(0.006)		(0.006)	
Years^2	0.0002*		0.0002*	
	(0.0001)		(0.0001)	
Employees	0.010**	1.008**	0.010**	1.008**
	(0.005)		(0.005)	
Employees^2	-0.00003		-0.00003	
	(0.00002)		(0.003)	
Sugar	-0.596	0.551	-0.580	0.560
	(0.461)		(0.534)	
Fruit_Veg	-0.086	0.918	-0.222	0.800
	(0.449)		(0.507)	
Dairy	0.058	1.059	0.118	0.889
	(0.419)		(0.500)	
Meat	-0.353	0.702	-0.482	0.617
	(0.385)		(0.384)	
Bakery	-0.260	0.771	-0.299	0.741
	(0.411)		(0.441)	
Alc_Bev [c]	2.733***	1.020	2.478**	0.867
	(0.975)		(1.076)	
Wages	0.005	1.005	0.005	1.005
	(0.008)		(0.008)	
*Wages*Alc_Bev* [d]	-0.053***	0.953***	-0.051***	0.955**
	(0.020)		(0.020)	
Density	-0.021**	0.979**	-0.015	0.985
	(0.009)		(0.029)	
Popn_Growth	0.072**	1.075**	0.069	1.071
	(0.036)		(0.055)	
Cluster_Within [e,f]	-1.135**	0.321**	-0.405	0.667
	(0.518)		(1.185)	
*Cluster_Within*Urban* [g]	1.576***	1.554	1.694**	3.629
	(0.588)		(0.854)	
Cluster_Upstream	0.442*	1.556*	0.318	1.375
	(0.268)		(0.396)	
Cluster_Downstream	0.003	1.003	0.009	1.009
	(0.009)		(0.013)	

Observations	348	348
Regional Fixed Effects	No	Yes
Log Likelihood	-452.682	-446.462
AIC	949.364	954.924
Overid (LR test, *p*-val)	0.261	0.583

[a] Estimated intercept terms for threshold points are excluded. Annual plant revenue growth categories include: (1) strongly negative (less than -10%), (2) modestly negative (-1% to -10%), (3) zero (0%), (4) modestly positive (1% to 10%), and (5) strongly positive (more than 10%).
***, **, * represent significance at the 1, 5, and 10 percent significance level, respectively.
[b] Odds ratios for variables with quadratic terms are computed at sample means.
[c] Odds ratio for alcoholic beverage industry computed at sample mean wages.
[d] Odds ratio for wages in the alcoholic beverage industry only.
E *Cluster_Within* uses predicted values from first-stage equation (Table 2). Robust standard errors computed using bootstrapping.
[f] Odds ratio for within stream clustering in rural areas.
[g] Odds ratio for within stream clustering in urban areas.

Table 4. Marginal probability effects evaluated at sample means[a]

	Strongly Negative	Moderately Negative	No Change	Moderately Positive	Strongly Positive
Years	0.0004**	0.0007 *	0.0004 *	0.0003	-0.0017 *
	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0010)
Employees	-0.0004**	-0.0006 **	-0.0003 **	-0.0002	0.0016 **
	(0.0002)	(0.0003)	(0.0001)	(0.0004)	(0.0008)
Wages (*Alc_Bev*=1)[b]	0.0025***	0.0038 ***	0.0020 ***	0.0015	-0.0097 **
	(0.0008)	(0.0012)	(0.0008)	(0.0024)	(0.0043)
Wages (*Alc_Bev*=0)[c]	-0.0003	-0.0004	-0.0002	-0.0001	0.0010
	(0.0004)	(0.0007)	(0.0003)	(0.0004)	(0.0017)
Density	0.001**	0.002 **	0.0008 **	-0.0000	-0.004 **
	(0.0005)	(0.001)	(0.0004)	(0.0004)	(0.002)
Popn_Growth	-0.004**	-0.006 *	-0.003 **	0.001	0.014 **
	(0.002)	(0.003)	(0.001)	(0.001)	(0.007)
Cluster_Within (*Urban=0*)[d]	0.059*	0.090 **	0.046 **	0.035	-0.231 **
	(0.032)	(0.041)	(0.023)	(0.050)	(0.107)
Cluster_Within (*Urban*=1)[e]	-0.023	-0.035	-0.018	-0.013	0.089
	(0.029)	(0.045)	(0.022)	(0.020)	(0.107)
Cluster_Upstream	-0.027	-0.038 *	-0.018	0.001	0.083 *
	(0.018)	(0.022)	(0.011)	(0.008)	(0.050)
Cluster_Downstream	-0.0002	-0.0002	-0.0001	0.0000	0.0006
	(0.0006)	(0.0008)	(0.0004)	(0.0000)	(0.002)

[a] Annual plant revenue growth categories include: (1) strong negative (less than -10%), (2) modest negative (-1% to -10%), (3) unchanged (0%), (4) modest positive (1% to 10%), and (5) strong positive (more than 10%). ***, **, * represent significance at the 1, 5, and 10 percent significance level, respectively.

[b] Marginal effect for wages in alcoholic beverage industry.

[c] Marginal effect for wages in non-alcoholic beverage industries.

[f] Marginal effect for within stream clustering in rural areas.

[g] Marginal effect for within stream clustering in urban areas.

Table A1. Two Stage Least Squares regression results on plant revenue growth[a]

	Model 1C		Model 2C	
Variable	Coefficient (std error)	Elasticity[b]	Coefficient (std error)	Elasticity[b]
Years	-0.087*** (0.030)	-0.268**	-0.090*** (0.030)	-0.278**
Years^2	0.0007** (0.0003)		0.0007** (0.0003)	
Employees	0.041** (0.021)	0.206**	0.037* (0.021)	0.186**
Employees^2	-0.00009 (0.00009)		-0.00007 (0.00009)	
Sugar	-4.112 (2.758)		-3.923 (2.790)	
Fruit_Veg	-1.772 (2.010)		-2.914 (2.037)	
Dairy	0.209 (2.169)		-1.116 (2.236)	
Meat	-2.453 (1.885)		-3.168* (1.894)	
Bakery	-2.047 (1.753)		-2.306 (1.784)	
Alc_Bev [c]	16.181*** (5.265)	-0.635	13.900*** (5.295)	-1.265
Wages	0.058 (0.046)	0.596	0.080 (0.054)	0.824
*Wages**Alc_Bev* [d]	-0.327*** (0.101)	-2.762***	-0.295*** (0.103)	-2.205**
Density	-0.070 (0.055)	-0.071	-0.088 (0.138)	-0.089
Popn_Growth	0.258* (0.160)	0.065*	0.317 (0.258)	0.080
Cluster_Within [e,f]	-6.003** (2.631)	-0.707**	-2.780** (1.438)	-0.328**
*Cluster_Within**Urban* [g]	9.466*** (3.228)	0.408	10.018** (4.474)	0.853
Cluster_Upstream	2.723** (1.289)	0.411**	2.004* (1.064)	0.303*
Cluster_Downstream	0.016 (0.038)	0.019	0.047 (0.037)	0.056

Intercept	3.575	0.450
	(3.240)	(3.711)
Observations	348	348
Regional Fixed Effects	No	Yes
R^2	0.118	0.153
Log Likelihood	-1280.507	-1273.514
AIC	2599.015	2603.027

[a] Original annual plant revenue growth categories include: (1) less than -20%, (2) -11% to -20%, (3) -5% to -10%, (4) -1% to -4%), (5) 0%, (6) 1% to 4%, (7) 5% to 10%, (8) 11% to 20%, and (9) more than 20%. Mid-point values were assigned for all interior categories; extreme category values were set at -20% and 20%, respectively.
***, **, * represent significance at the 1, 5, and 10 percent significance level, respectively.
[b] Elasticities for variables with quadratic terms are computed at sample means.
[c] Marginal effect for alcoholic beverage industry computed at sample mean wages.
[d] Elasticity for wages in the alcoholic beverage industry only.
[e] *Cluster_Within* uses predicted values from first-stage equation (Table 2). Robust standard errors computed using bootstrapping.
[f] Elasticity for within stream clustering in rural areas.
[g] Elasticity for within stream clustering in urban areas.

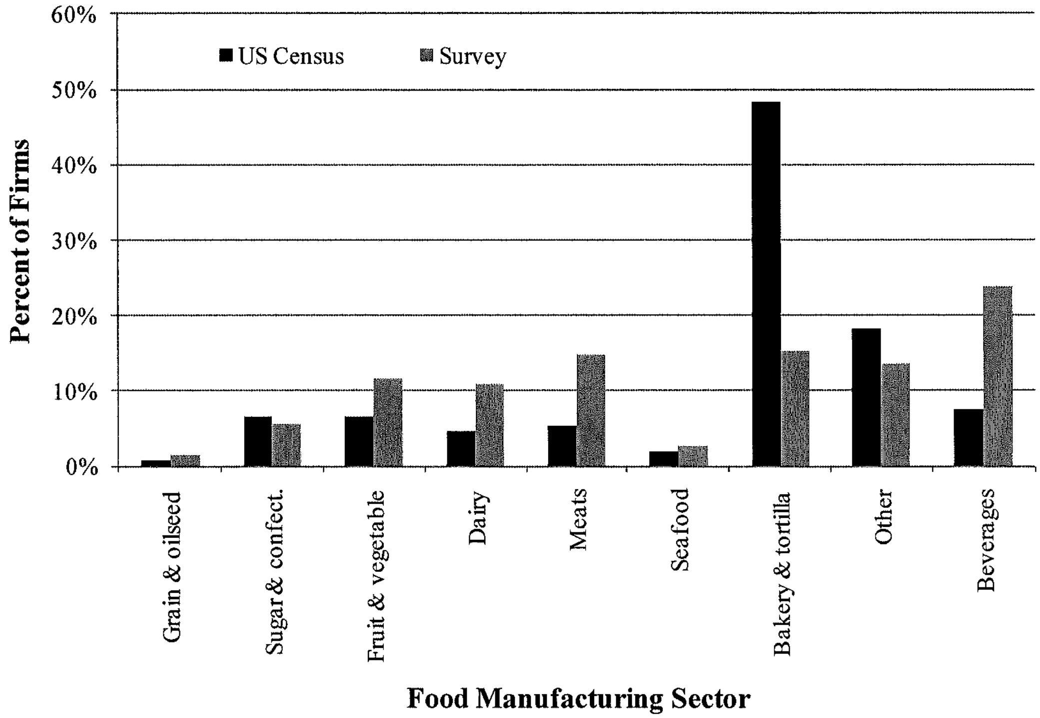

Figure 1. Distribution of food manufacturing plants by industry sector (Source: U.S. Census 2008a, 2008b; survey).

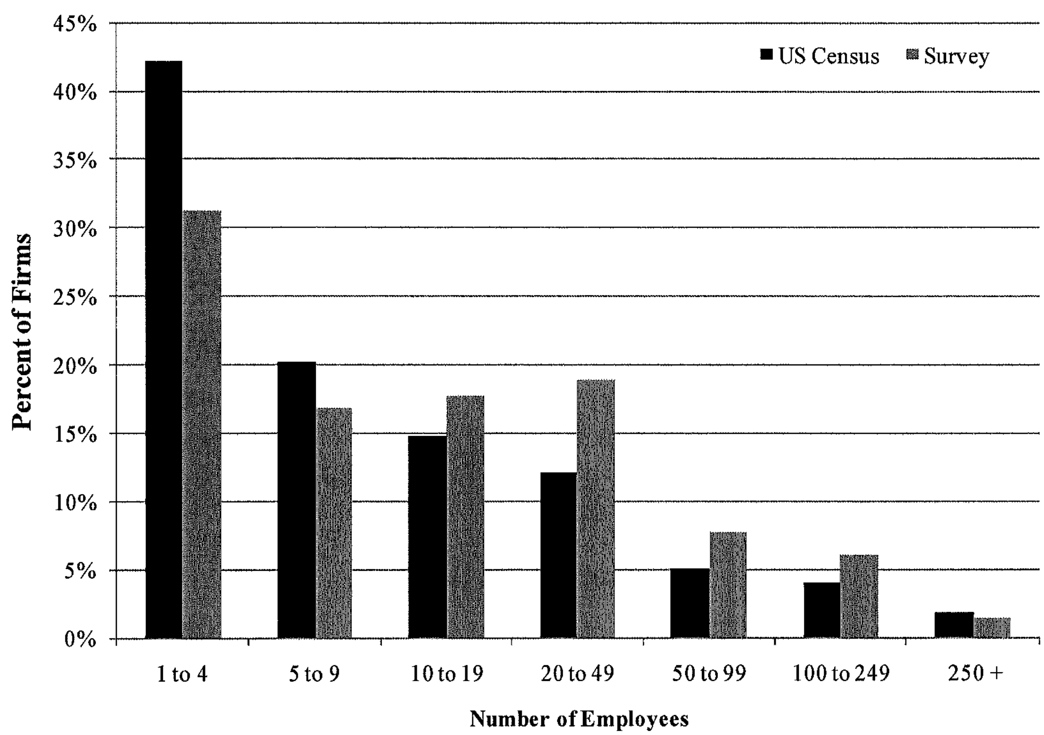

Figure 2. Distribution of food manufacturing plants by number of employees, employers only (Source: U.S. Census 2008a; survey).

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