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Jason P. Brown and Dayton M. Lambert

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Creative Destruction and the Reallocation of Capital in Rural and Urban Areas*

Jason P. Brown†, Dayton M. Lambert‡

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Abstract

We test the implications of Schumpeter's theory of creative destruction on food manufacturer births and deaths using a dynamic, unobserved effects count model with correlated random effects. We find evidence of a creative destruction process via the interaction of previous firm birth and death, which is correlated with higher rates of contemporaneous firm birth and death in a given location. Results support Marshall's notion of "something is in the air" as evidenced by the strong correlation between sources of unobserved heterogeneity in the birth and death processes. Consistent with overall declines in firm birth and death across the U.S. between 2001 and 2019, we find evidence of convergence in birth and death rates across counties. Our results provide insights into capital reallocation across locations. The convergence rate is higher in urban versus rural areas, which have become more static over time.

Keywords: birth, death, creative destruction
JEL Classification Numbers: C35, D21, R12, R30

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†Federal Reserve Bank of Kansas City, jason.brown@kc.frb.org, 1 Memorial Dr., Kansas City, MO 64198

‡Oklahoma State University, dayton.lambert@okstate.edu, Agricultural Economics, 308 Ag Hall, Stillwater, OK, 74078

1 Introduction

Creative destruction is thought to be an important aspect of economic renewal. Agarwal et al. (2007) show that Schumpeter's notion of creative destruction is a primary driver of long-term economic growth. Schumpeter argued that the creative destruction process causes an increase in regional value added through product innovation, the services required to support product development, and the entry of new businesses that displace or diminish the value of incumbent products, services, and providers. The most evident outcome of this process is the birth (entries) and death (exits) of brick-and-mortar establishments, with knock-on effects on employment, local demand, spending patterns, and migration. More generally, business establishment birth and death events reallocate resources to their most efficient use as economic conditions change. Over the past several decades, however, business establishment entry and exit rates have declined significantly, especially in rural areas, prompting further examination of the creative destruction process as a resource reallocation driver (Brown, 2018).

This paper aims to test the relevance of a creative destruction process through the lens of firm location choice, applied to an industry represented in rural and urban areas. How creative destruction influences business establishment births and deaths along the food manufacturing value chain is understudied. The food and beverage industry purchases inputs from the agricultural sector. It transforms raw agricultural materials into value-added products for human and animal consumption. This industry also provides job opportunities to farm-dependent, urban, and peri-urban communities. The food manufacturing sector generated \$164 billion in value-added to the U.S. economy in 2017, accounting for 15 cents of every consumer dollar spent (Committee for Economic Development, 2017). The study period examined here spans from 2001 to 2019. On average, the food manufacturing sector supported 263,574 jobs with a wage bill of \$12.1 billion over this period making it an important industry, especially in rural areas.

We expand on Schumpeter (1943)'s notion of creative-destruction by incorporating insights from the empirical industrial organization literature and endogenous growth theory to help guide our empirical design. Firm entry and exit decisions are assumed to be based on the current state of the industry and expected future states (Ericson and Pakes, 1995). Firms enter the market with uncertainty about their productivity and learn over time, and decide to continue or exit based on this learning (Jovanovic, 1982). New firms bringing technological advancements that increase competitive pressures on existing firms (Aghion and Howitt, 1992). Using these features, we develop and estimate a structural, dynamic, correlated unobserved effects count model to test the implications of Schumpeter's theory of creative destruction on food manufacturer births and deaths.

We use a proprietary data set, the National Establishment Time Series (NETS), to track food manufacturing births and deaths. NETS is currently the only data series outside of confidential Census data that allows for modeling establishment entry-exit churn. The U.S. Census used to collect annual birth-death counts at the county level. However, the lowest level of industry aggregation was at the 2-digit North American Industry Classification System (NAICS). The NETS data includes birth-death count series down to the 6-digit NAICS. This level of detail allows us to disaggregate food manufacturing based on industry cost structure. The model developed here could be used in a causal analysis examining, for example, the impact of federal dollars during the Great Recession on firm location and exit events.

We find evidence of a creative destruction process via the interaction of firm birth and death, which is correlated with higher rates of firm birth and death in a location. However, creative destruction appears to play a more prominent role in reallocating capital in demand-oriented food manufacturers versus supply-oriented ones. The empirical findings support Marshall's notion that "something is in the air," e.g., unobserved agglomeration forces that attract and support economic activity, which we estimate as the correlation between unobservable factors that contribute to the birth and death process. Consistent with overall declines in firm birth and death in the U.S., we find evidence of convergence in birth and death rates across counties. The results provide insights for understanding capital reallocation across locations. We find that the convergence rate is higher in urban versus rural areas, which have become increasingly static over time. As a result of being more static, food manufacturing in rural areas may become less competitive over time and experience further declines and consolidation relative to urban locations.

2 Conceptual Model of Creative Destruction

Schumpeter's theory of creative destruction refers to the process where old firms are destroyed and replaced by new ones. This dynamic process drives innovation and economic growth, leading to constant economic renewal. We expand on Schumpeter (1943) by applying insights from the industrial organization and endogenous growth theory literature to help guide our empirical design. We incorporate the idea that firm entry and exit decisions are based on the current state of the industry and expected future states (Ericson and Pakes, 1995). Firms enter the market with uncertainty about their productivity and learn over time, and decide to continue or exit based on this learning (Jovanovic, 1982). We use steady-state analysis to determine the equilibrium of firms (Hopenhayn, 1992). Innovation is a central driver, with new firms bringing technological advancements that increases competitive pressures on existing firms (Aghion and Howitt, 1992). A conceptual birth/death model is developed below. It is easily extended to the case of food manufacturing firms.

We assume that firm dynamics are driven by the birth and death process. New firms enter markets with new technologies or innovative processes, aiming to capture market share from existing firms. Less productive firms exit the market due to their inability to compete with more efficient firms or new entrants. Firms close when the variable costs of inputs and the interest on entry costs are less than the marginal value of production (Dixit, 1989). Innovation is the primary driver of productivity improvements and firm dynamics. Firms that fail to innovate or adopt new technologies are more likely to exit. Firms have a distribution of productivity levels. Over time, this distribution changes as new, more productive firms enter and less productive firms exit. As a result, the market structure evolves dynamically by the birth and death process. In a perfectly competitive environment, markets will reallocate resources (e.g., labor, physical inputs, land, and leftover depreciated capital) to more productive firms as others exit, which drives economic growth.

The change in the number of firms in a given location evolves over time according to:

$$\frac{dN_{it}}{dt} = \mu_i + \phi_1^b B_{it-1} + \phi_2^b D_{it-1} - (\delta_i + \psi_1^d B_{it-1} + \psi_2^d D_{it-1})N_{it} \tag{1}$$

$$\mu_i = \mu + u_i^{\mu} \tag{2}$$

$$\delta_i = \delta + u_i^{\delta}, \tag{3}$$

where μ_i is the the base rate of firm births in location i modified by an unobserved random effect u_i^{μ}, δ_i is the base rate of firm deaths in location i modified by an unobserved random effect u_i^{δ}, $\phi_1^b B_{it-1}$ and $\phi_2^b D_{it-1}$ capture the effects of the previous period's count of firm birth and death on the current period's birth. A positive value of ϕ would suggest that higher birth/death rates in the previous period cause more firm births in the current period, possibly due to spillover effects or increased market opportunities. The term $(\delta_i + \psi_1^d B_{it-1} + \psi_2^d D_{it-1})$ is the rate at which firms exit the market, and is multiplied by the current number of firms, N_{it}. It captures the effect of previous firm birth and death ψ on the death of firms in the current period. A positive value of ψ indicates that higher firm birth/death in the previous period leads to higher death rates in the current period, potentially due to increased competitive pressures.

Assume the economy reaches equilibrium with N^* firms in location i. At equilibrium, the rate of change in the number of firms is zero:

$$\frac{dN_{it}}{dt} = 0 \Rightarrow \mu_i + \phi_1^b B^* + \phi_2^b D^* = (\delta_i + \psi_1^d B^* + \psi_2^d D^*)N_i^* \tag{4}$$

Solving for the equilibrium number of firms N_i^*,

$$N_i^* = \frac{\mu_i + \phi_1^b B^* + \phi_2^b D^*}{\delta_i + \psi_1^d B^* + \psi_2^d D^*}. \tag{5}$$

The equilibrium number of firms N_i^* depends on the base rates of birth and death, the lagged effects of previous births and deaths, and the initial rates of birth and death plus random effects for the location captured in the composite terms μ_i and δ_i. A higher base rate of firm birth (μ) or positive spillover effects from previous births or deaths (ϕ) will increase the equilibrium number of firms. In contrast, a higher base rate of firm death (δ) or positive effects from previous deaths (ψ) will decrease the equilibrium number of firms.

The model provides three implications. First, the continuous reallocation of resources towards more productive firms leads to overall economic growth in the form of a higher equilibrium number of firms. Second, the threat of death provides incentives for firms to innovate continuously. Third, the constant birth and death of firms ensures a dynamic and competitive market environment, as the raw data in Figure 2 suggests. The random effects at the geographical level highlight the potential importance of location-specific factors such as social networks, local knowledge of input markets, and other unobservable factors that could affect firm birth and death.

3 Location Choice in Food Manufacturing

We next look at the factors influencing where food manufacturing firms choose to enter the market. We categorize food manufacturing into demand-oriented or supply-oriented firms based on cost structure (Connor and Schiek, 1997; Lambert and McNamara, 2009). Demand-oriented firms specialize in making fragile or perishable products. These firms locate near demand centers to minimize the cost of distributing their final product. Supply-oriented firms, such as meat packers, ethanol producers, and grain millers, aim to minimize transport costs by locating near raw materials.

We hypothesize that a food manufacturing firm enters a perfectly competitive market when the variable costs of inputs and the interest on entry costs are lower than the long-term expected marginal value of processing and marketing food. Food manufacturers shut down when variable costs, less the interest on the costs of shutting down, exceed the marginal value of production (Dixit, 1989). Once the entry decision is made, profit-maximizing establishments choose production levels such that the marginal value of production equals factor costs. Holding other variables constant, when the cost of an input increases relative to the product's output price, a firm will use less of that factor. Alternatively, when the factor cost-to-output price ratio decreases, a firm will use more of that factor to maximize profit. Businesses unable to achieve these necessary conditions eventually exit the industry and are replaced by more efficient firms.

Food manufacturers consider regional, state, local, and site-specific features when evaluating site feasibility. Factors like market access, agglomeration economies, and infrastructure play a significant role (Goetz, 1997). Heuristically, the location decision of a food manufacturer is a two-stage process (Lambert and McNamara, 2009). The first stage entails selecting a region that broadly coincides with company objectives. In the second stage, firms search for a minimum-cost site inside the targeted region, with proximity to markets, infrastructure, and labor characteristics are the critical location determinants for food processors (Lopez and Henderson, 1989; Leistritz, 1992; Vesecky and Lins, 1995).

The literature identifies agglomeration economies as a critical driver of firm location events. These factors also apply to food manufacturers. Neffke et al. (2011) categorized agglomeration economies into three types: urbanization, Marshall-Arrow-Romer (MAR), and Jacobs externalities. Urbanization externalities encompass the advantages of locating in metropolitan areas. Large cities offer access to product markets, a skilled workforce, business services, and connectivity inside broader infrastructure networks. MAR-type externalities are also called "localization economies" (Viladecans-Marsal, 2004). MAR-type externalities occur when similar enterprises locate near each other. Clustering strengthens the forward and backward linkages along the industry's value chain. Clustering also attracts suppliers and customers, facilitates labor skill pooling, reduces search costs for employers and employees, and fosters information spillovers between industries, fostering innovation through interaction with competitors. Jacobs externalities benefit firms through industry diversity. This type of externality favors innovative solutions to meet production challenges by modifying or copying production processes used by other industries. Firm diversity can also reduce variation in factor costs by expanding input substitution possibilities if production technology allows it (Lambert et al., 2014). Thus, if the industry production technology is Leontief (as we would expect for many food manufacturers), we would expect industry diversity to play a minor role in establishment entry and exit.

4 Statistical Model and Estimation

We develop a dynamic, unobserved effect count model to study the effect of business establishment entries and exits on business creation and destruction. Food manufacturer births and deaths are hypothesized to occur as simultaneous events and depend on previous entry/exit levels, other local economic conditions, and unobserved time-invariant factors associated with a location, all of which influence the establishment productivity. Counties are the geographic unit of analysis. Births and deaths are observed as discrete counts. Three consequential issues include modeling county-level unobserved heterogeneity, handling the initial condition problem familiar to dynamic panel models, modeling the covariance between unobserved county-level effects, and addressing overdispersion.

We follow Wooldridge (2010) to model unobserved heterogeneity at the county level. Unobserved heterogeneity is modeled using two procedures. The first introduces county-level fixed effects to control for time-invariant unobserved heterogeneity particular to a location. The remaining unobserved heterogeneity associated with entry-exit counts is modeled with county-level random effects. Unobserved factors correlated with births and deaths are hypothesized to be correlated, so we allow the county-level random effects for birth and death processes to be correlated.

We start with a generic outcome equation. The data generating process driving location events is assumed to be Poisson-distributed. As usual, the exponential link function is used for the conditional mean of births and deaths. We model dynamic, unobserved heterogeneity, starting with the multiplicative Poisson model for panel data as

$$y_{it}|\mathbf{x}_{it}, \delta_t, c_i \sim \text{Poisson}\left[c_i \cdot \exp(\rho \cdot y_{it-1} + \mathbf{x}_{it}\boldsymbol{\beta} + \delta_t)\right] \tag{6}$$

where i indexes locations, t indexes years, the y_{it} are birth or death counts, the c_i is a random effect, and the δ_t are time effects equally experienced by all counties (for example, macroeconomic shocks). The typical Poisson random effect estimator assumes the unobserved effects are uncorrelated with the explanatory variables and that the outcomes are independent of each other, conditional on the covariates and the unobserved effects. This assumption requires strict exogeneity between the explanatory variables and the random effect;

$$\mathrm{E}(y_{it}|\mathbf{x}_1, \cdots \mathbf{x}_T, \delta_t, \cdots \delta_T, c_i) = c_i \cdot \exp(\rho \cdot y_{it-1} + \mathbf{x}_t\boldsymbol{\beta} + \delta_t). \tag{7}$$

This assumption is relaxed by allowing arbitrary correlation between the unobserved effects and the explanatory variables, which amounts to estimating the c_i with a "fixed effects" estimator.

Hausman et al. (1984) (HHG) proposed a conditional, fixed effects procedure for count data models. Their method allows for arbitrary correlation between observed variables and unobserved effects.[1] The procedure relaxes the strict assumption that must be maintained to consistently estimate the parameters of the Poisson model with random effects. There are some drawbacks to this procedure. HHG's fixed effects approach ostensibly permits

[1] HHG's procedure is available in most econometric software packages. For example, in Stata, the `fe` option in `xtpoisson` uses the HHG fixed-effects estimator.

arbitrary correlation between the c_i and the explanatory variables, but the approach does not directly or implicitly estimate the c_i because they are the sum of the counts at location i. This shortcoming is a problem only if interest lies in the distribution of the unobserved effects for exploratory analyses. For this study, the variation in the c_i across counties and the potential correlation between these unobserved effects is important (discussed below). A second, less serious limitation is the lack of built-in or user-written packages for estimating correlated count model systems with HHG fixed effects.

We consider two other conditional maximum likelihood approaches for modeling unobserved heterogeneity in the birth/death models. Both approaches allow arbitrary correlation between the c_i and the exogenous variables. An advantage of both procedures is that they are easy to implement in most econometric software with routines that estimate count, limited-dependent, binary, or other nonlinear models with random effects. Relaxing the strict exogeneity requirement of the random effect Poisson, the conditional mean function results in the sequential moment condition,

$$\mathrm{E}(y_{it}|\mathbf{x}_{i1}, \cdots \mathbf{x}_{it}, \delta_t, c_i) = c_i \cdot \exp(\rho \cdot y_{it-1} + \mathbf{x}_{it}\boldsymbol{\beta} + \delta_t). \tag{8}$$

We also follow Wooldridge (2005)'s procedure to handle the initial condition problem that must be addressed when estimating dynamic, nonlinear panel models with unobserved effects. Ignoring this issue can cause estimates to be biased and inconsistent (Hsiao, 2022). Wooldridge's approach treats the initial condition, y_{i0}, as random variable. The initial conditions and the unobserved effects are integrated out of the likelihood function such that the density of $(y_{i1}, \cdots y_{iT})$ is conditioned on $(y_{i0}, \mathbf{x}_i, c_i)$. The difference is the inclusion of the $\mathbf{x}_i$, rather than $\mathbf{x}_{it}$, which is discussed below. Under this assumption, the unobserved heterogeneity terms are specified as $c_i = r_i \cdot \exp(\xi_0 \cdot y_{i0} + \mathbf{x}_i\boldsymbol{\gamma} + \delta_t)$, where the r_i are random effects with $\mathbb{E}[r_i] = 1$. The conditional mean of the birth/death outcome in period t, conditioned on $(y_{i(t-1)}, \cdots y_{i0}, \mathbf{x}_i, r_i)$ is:

$$\mu_{it} = r_i \cdot \exp(\rho \cdot y_{it-1} + \mathbf{x}_{it}\boldsymbol{\beta} + \xi_o \cdot y_{i0} + \mathbf{x}_i\boldsymbol{\gamma}) \tag{9}$$

We introduce $\mathbf{x}_i$ into the conditional mean function by replacing them with Mundlak instruments, $\overline{\mathbf{x}}_i = \sum_{t=1}^{T} \mathbf{x}_{it}$ (Mundlak, 1978). Since $\overline{\mathbf{x}}_i$ is a linear function of the explanatory variables, $\text{cov}(\overline{\mathbf{x}}_i, r_i) = 0$ (Wooldridge, 2021), and the c_i are correlated with the $\mathbf{x}_{it}$ when $\boldsymbol{\gamma} \neq \mathbf{0}$.[2] The intuition behind Mundlak's approach for modeling unobserved heterogeneity across units is that by adding the time averages as controls, we estimate the effect of changing an explanatory variable while holding the time average of the variable fixed (Wooldridge, 2010). When $\boldsymbol{\gamma} = \mathbf{0}$, the model reduces to the standard random effects Poisson estimator.

Establishment birth and death counts are assumed to be functions of previous births and deaths. We include lagged births and deaths in both conditional means functions for entries and exits. Previous levels of births and deaths co-determine next-period establishment entries and exits, as discussed in the previous section. The observed component of creative destruction, the direct effect, enters the birth-death equations as an interaction term between lagged births and deaths. Taking the natural log of the random effects (denoted with tildes, $\tilde{r}_{bi}$ and $\tilde{r}_{di}$) and moving them inside the exponential operator, the reduced-form birth-death equations are:

$$\begin{aligned}\mu_{bit} = \exp(&\alpha_{b1} \cdot birth_{it-1} + \alpha_{b2} \cdot death_{it-1} + \alpha_{b3} \cdot birth_{it-1} \cdot death_{it-1} + \\ &\mathbf{x}_{it}\boldsymbol{\beta}_b + \delta_{bt} + \overline{\mathbf{x}}_i\boldsymbol{\gamma_b} + \xi_{b1} \cdot birth_{i0} + \tilde{r}_{bi})\end{aligned} \tag{10}$$

$$\begin{aligned}\mu_{dit} = \exp(&\alpha_{d1} \cdot birth_{it-1} + \alpha_{d2} \cdot death_{it-1} + \alpha_{d3} \cdot birth_{it-1} \cdot death_{it-1} + \\ &\mathbf{x}_{it}\boldsymbol{\beta}_d + \delta_{dt} + \overline{\mathbf{x}}_i\boldsymbol{\gamma_d} + \xi_{d2} \cdot death_{i0} + \tilde{r}_{di})\end{aligned} \tag{11}$$

where the "b" and "d" subscripts denote birth and death.

We also allow for arbitrary correlation between the unobserved heterogeneity terms to

[2] For linear models, Mundlak's correlated random effects estimates for time-varying covariates are identical to those of the usual fixed-effects estimator.

capture unobserved effects of the creative destruction process on establishment entry/exit, i.e., the indirect effects. The log-normal $(\tilde{r}_{bi}, \tilde{r}_{di})$ are bivariate random effects that capture unobserved heterogeneity that affect birth and death rates, and are distributed as:

$$\begin{pmatrix} \tilde{r}_{bi} \\ \tilde{r}_{di} \end{pmatrix} \sim \mathcal{MVN}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_{r_b} & \rho\sigma_{r_b}\sigma_{r_d} \\ \rho\sigma_{r_b}\sigma_{r_d} & \sigma^2_{r_d} \end{pmatrix}\right) \tag{12}$$

The covariance between the random effects of the birth and death processes is of particular interest. The sign and significance of the covariance proxy Marshall's idea of unobserved forces of agglomeration economies that attract and sustain economic activity.

An offset variable (not shown in the equations), $\ln estabs_{it}$ enters both equations. The coefficient on the offset variable is restricted to be "1." Including the offset changes the interpretation of the model coefficients as rates (deaths or births per the total number of establishments in a county in period t) (Cameron and Trivedi, 1998).

We estimate the system of equations using Stata's *gsem* procedure, which finds maximum likelihood estimates. The likelihood function for this dynamic, double-outcome Poisson model with correlated random effects is:

$$L(\boldsymbol{\theta}) = \prod_{i=1}^{N}\prod_{t=1}^{T}\int\int\left(\frac{\mu_{bit}^{y_{bit}}\exp(-\mu_{bit})}{y_{bit}!}\cdot\frac{\mu_{dit}^{y_{dit}}\exp(-\mu_{dit})}{y_{dit}!}\right) f(\tilde{r}_{bi}, \tilde{r}_{di}|\boldsymbol{\Sigma})\,\mathrm{d}\tilde{r}_{bi}\,\mathrm{d}\tilde{r}_{di}$$

where $f(\tilde{r}_{bi}, \tilde{r}_{di}|\boldsymbol{\Sigma})$ is the joint density of the random effects, which is bivariate-normal with the covariance matrix $\boldsymbol{\Sigma}$ in equation 12.

Given the bivariate normal distribution of the random effects, the integration over $\tilde{r}_{bi}$ and $\tilde{r}_{di}$ is generally intractable analytically. Therefore, numerical methods such as Gaussian quadrature, simulated maximum likelihood, or Bayesian methods like Markov Chain Monte Carlo (MCMC) are typically used to estimate this model. The *gsem* procedure in Stata uses Gaussian quadrature to integrate out the random effects.[3] We used a combination of the Newton-Raphson and Broyden-Fletcher-Goldfarb-Shanno maximization options, switching

[3] `https://www.stata.com/manuals/semgsem.pdf`

between each solver after five iterations until convergence.

A well-known problem with Poisson regression is the assumption that the conditional mean equals its variance. We attempted to estimate negative binomial regressions as a first step, but most of the models failed to converge. Instead, we use cluster-robust standard errors, with the county fips code as cluster identifiers.

5 Establishment Data and Location Factors

Our dependent variables are constructed from establishment birth and death counts and tabulated at the yearly-industry-county level from the National Establishment Time Series (NETS) database. We focus specifically on the food manufacturing sector (NAICS 311), how birth-death rates vary between urban and rural locations, and whether the creative destruction process is fundamentally different in these areas. The NETS Database is constructed from "snapshots" taken every January from 1990 to 2020 of all active Dun and Bradstreet establishments. We restrict the sample to construct food manufacturers between 2001 and 2019. The variables "first year"/"last year" were used to flag establishment birth/death. Counts by county-year were tabulated for manufacturing industries (Table 1). NETS data only contains information on SIC industry codes. We used a public website to assign the set of NAICS industries to their corresponding SIC.[4]

We show a time series of birth and death rates of food manufactures in Figure 1. Panels a and b report birth and death as percentage of total manufacturing establishment for the demand- and supply-oriented samples. The birth and death rates are generally higher for demand-oriented establishments compared to supply. Birth and death rates for demand-oriented establishments increased between 2002 and 2019, with sharp increases around the Global Financial Crisis in 2008 for deaths and in 2010 for births. In contrast, supply-oriented birth and death rates were mostly flat over the same period, but with the same spikes in 2008 (deaths) and 2010 (births). For much of the sample period, the birth rate was above

[4] `https://siccode.com/naics-to-sic-conversion`

the death rate for demand-oriented establishments, indicating that the sector experienced growth. In contrast, the death rate is generally above the birth rate for supply-oriented establishments, suggesting that the sector experienced consolidation.

We also explore these trends across the urban-rural continuum. The second row of Figure 1 reports tabulations of the same data by urban and rural counties.[5] Birth rates in urban areas are higher than rural areas in every year of the sample for both demand- and supply-oriented establishments. Supply-oriented death rates are also higher in urban versus rural locations. However, death rates for demand-oriented establishments are slightly higher in rural areas in most years. Similar to the findings in Brown (2018), differences in birth and death rates in urban versus rural areas widened over the sample period, indicating that food manufacturing in rural areas became less dynamic compared to urban areas.

Location factors included in $\mathbf{x}_{it}$ control for urban agglomeration, local agglomeration, labor availability, industrial diversity, and rurality measures hypothesized to influence food manufacturer establishment births and deaths. Measures include the natural log of population density, the natural log real per-capita income, the unemployment rate, a location quotient for the agricultural sector (NAICS 11), a location quotient for demand- or supply-oriented food manufacturers, and an industry diversity index. The Economic Research Service's rural-urban continuum code (RUCC) is also included as a control. The RUCCs range from discrete values of 1 to 9, with 1 indicating counties in metropolitan areas with 1 million population or more and 9 indicating nonmetropolitan counties that are completely rural or less than 2,500 urban population and nonadjacent to a metropolitan area.[6]

Population density is included to proxy land available for expansion, pressure on land values, and settlement patterns. Real per-capita income is a proxy for buying power and local demand potential for manufactured processed foods. Population density and per-capita income are hypothesized to be positively associated with the establishment births of

[5] An urban county has a Rural Urban Continuum Code between 1 and 3, while rural counties are between 4 and 9.
[6] `https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/`

demand-oriented food manufactures. The converse is expected to be true for establishment deaths of demand-orientated businesses. Conversely, population density is expected to have a negative effect on supply-oriented business births. We have no *a priori* expectations concerning supply-oriented food manufacturer deaths. Population and personal income per-capita are from the Bureau of Economic Analysis. The income measure was converted to real 2012 dollars using the Bureau of Labor Statistics Consumer Price Index for Urban All Items. Land area is from the U.S. Census Bureau. It is used to calculate population density (population per square mile).[7]

The unemployment rate is a proxy for labor availability. We hypothesize that this variable will be positively associated with establishment births for food manufacturers. The converse is true for business closures. County-level unemployment rates are from BLS, Local Area Unemployment Statistics.[8]

The location quotient for the agricultural sector, farms, and related businesses (NAICS 11) is a proxy for the local availability of raw materials for food manufacturers. The demand and supply location quotients are constructed with firms listed in Table 1, and based on Lambert and McNamara (2009)'s definitions characterizing the cost structures of supply and demand-oriented food manufacturers. We expect that this location quotient will be positively associated with supply-oriented manufacturers births because locating near bulky agricultural inputs will cost less to transport. The importance of this variable concerning demand-orientated establishment births and deaths is expected to be comparatively weaker.

We use an Ethnolinguistic Fractionalization Index (ELF) proposed by Bossert et al. (2011) to proxy county-level industry diversity. The ELF is calculated as $1 - \sum_{k=1}^{108} s_{ikt}^2$, where s is the share of industries in a NAICS category, i indexes counties, t indexes years, k indexes the 108 3-digit NAICS industries. The ELF is "1" minus a Herfindahl-type index of concentration. Industry mix decreases as the index approaches "0." We expect the pace of food manufacturing entry will increase with higher-level values for ELF. We are agnostic

[7] `https://www.census.gov/library/publications/2011/compendia/usa-counties-2011.html#LND`
[8] `https://www.bls.gov/lau/`

about the expected relationship with this variable and establishment death. We used Watson and Allward (2023)'s *Tapestry* employment data to construct the location quotients and the industry diversity index.[9]

Summary statistics of the dependent variables and location factors are in Table 2. We provide separate summary statistics for each sample covering the period 2001 to 2019 because the set of counties included in each sample of demand and supply establishments varies. On average, counties had more establishment births than deaths for demand-oriented establishments. In contrast, on average, counties had more deaths than births of supply oriented establishments. This trend is consistent with ongoing consolidation in the agricultural processing sector. Table 3 shows the definition of the rural-urban codes across counties, with 1 being counties in the largest urban areas and 9 counties that are the most remote.

6 Findings

6.1 Empirical Estimates

We begin by comparing counts and rates of birth and death across demand-oriented and supply-oriented food manufacturing establishments. From 2002 to 2019, birth and death rates in demand-oriented establishments were higher than those of supply-oriented establishments. Normalizing the counts of birth and death by total establishments reported in Table 2 reveals that birth/death rates were also higher for demand-oriented establishments (10/7%) followed by supply oriented businesses (5/5%). Figure 2 shows that food manufacturing establishment birth and death are positively correlated with each other contemporaneously was well as with birth and death in the previous year. Across the two groupings of establishments, the correlations are strongest among birth in year t and death in $t-1$ (0.69-0.71) and birth in year t and birth in $t-1$ (0.75-0.81).

[9] `https://www.uidaho.edu/cals/tapestry`. The authors used an imputation algorithm to overcome suppressed employment data.

Descriptive statistics in Table 2 show similar average county-level real per-capita income, unemployment rates, agricultural employment location quotients, and economic diversity indexes where food manufacturing births and deaths occurred across the three sub-samples. With these general associations in mind, we turn to discussing the regression results. Because coefficients from a nonlinear model are a function of the data, we report estimated marginal effects across the two samples in Table 4. The marginal effects are an average across each cross-sectional unit. We also report delta-method standard errors for these estimates. For completeness, we report coefficient estimates for the demand and supply sub-samples in Tables A1 and A2 of the appendix. Consistent across establishment categories, the marginal effects on $Birth_{t-1}$ and $Death_{t-1}$ are negative and statistically significant in the birth equation. Negative values indicate convergence in the reallocation of capital for areas with higher births and deaths in the previous year, typically having lower births in the current year. We find that an additional birth/death in the prior year is associated with approximately a 0.3/0.5 percent point reduction in the birth rate of demand-oriented establishments and a 1/0.9 percentage point reduction in the birth rate of supply-oriented establishments. While these effects are notable relative to the average birth and death rates, convergence in birth rates appears to be more economically significant than creative destruction. We find limited evidence of a direct creative destruction process in play (industry churn) with the marginal effect on the interaction of $Birth_{t-1} \times Death_{t-1}$ positive and significant, but only in the birth equation. The interpretation is that a higher birth and death rate in a county in the previous year correlates with more establishment births the following year. A one-unit change in the interaction term is associated with a 1 percent increase in the birth rate.

One feature of this model that has not been previously explored is the correlation between the location-specific random effects. We report the variance and covariance estimates in log-normal form, which are used to construct correlation coefficients. For the two sub-samples, the correlation coefficients of the random effects between firm birth and death range from 0.68 to 0.99, being the highest for demand-oriented establishments. The correlation between the random effects are interpreted in the spirit of Alfred Marshall's observations on agglomeration economies.

> "When an industry has thus chosen a locality for itself, it is likely to stay there long: so great are the advantages which people following the same skilled trade from near neighborhood to one another. The mysteries of the trade become no mysteries; but are as it were in the air..." – Alfred Marshall (1890)

Population density is positively correlated with establishment births for both firm types, indicating that more densely populated areas tend to experience higher establishment births. Real per-capita income is only significant in the death equation. Higher real per-capita income is associated with higher establishment deaths in the supply sub-sample. However, in the demand-oriented sample, higher real per-capita income is negatively correlated with death. The difference in the marginal effect signs across the samples suggests that the relative importance of access to consumers with higher incomes and areas with potentially higher production costs. The unemployment rate, a proxy for labor availability, is positively correlated with demand-oriented births and supply-oriented deaths. Establishments with the flexibility to locate in many areas may not rely as much on labor in their production process and interpret areas with higher unemployment as having more economic stress. One consistent finding is the negative relationship between establishment birth and death in more rural versus urban areas. As the RUCC code increases, the county is classified as more rural, which is associated with fewer establishment births and deaths.

We explore how the marginal effects of lagged birth and death vary across the rural-urban continuum. Table 5 reports the marginal effects on lagged birth and death for demand-oriented food manufacturing births, deaths, and their interaction. The table shows that the reallocation of capital across counties is predominantly an urban phenomenon and mostly from firm birth in the previous year. The marginal effects on lagged birth and death are very close to zero in the most rural areas, suggesting that convergence in birth and death rates has mostly played out over the sample period. For this reason, we are unable to estimate the standard errors on the marginal effects for the most rural areas in most cases for the interaction between birth and death. This suggests that, through the lens of food manufacturers, rural industries are less dynamic compared to those located in urban areas.

6.2 Revisiting Conceptual Predictions

Recall that the model predictions in Section 2 were 1) continuous reallocation of resources towards more productive firms leads to overall economic growth in the form of a higher equilibrium number of firms, 2) the specter of death provides incentives for firms to innovate continuously, and 3) constant birth and death of firms ensure a dynamic and competitive market environment.

We run simulations on the equilibrium count of firms using the conceptual model and estimates of key parameters using the econometric results, as well as sample averages for the demand-oriented manufacturing establishments. Table 6 shows the starting values for parameters and the averages for demand and supply-oriented firms. Figure 3 traces out how the equilibrium values of establishments (N^*) change with changes in relationships with previous births and deaths. The first row of the figure's panels shows that negative values on the coefficient of previous birth and death work to reduce the overall number of establishments. The second row of panels in Figure 3 indicates that as higher rates of previous birth and death both lead to more death, the equilibrium number of firms decreases.

The core prediction of the creative destruction process is that firm birth leads to death and firm death leads to birth. However, the empirical results suggests that the creative destruction process has not exactly transpired in this manner for the food manufacturing sector. We find that previous births are positively correlated with deaths, although this relationship is not statistically significant. Moreover, previous deaths are negatively associated with births. While the measure of churn, the interaction of previous births and deaths, is positively correlated with more births, the relationship does not appear to be economically significant. The empirical results suggest that rather than birth leading to death and death leading to birth, there is more of a convergence process across locations in that both previous births and deaths are associated with lower firm births. These findings suggest that factors other than those endorsed by Schumpeter are driving firm entry and exits of food manufacturing establishments. The findings are consistent with the aggregate decline in firm dynamism documented by previous research (Decker et al., 2017).

7 Conclusion

Firm birth and death rates have declined dramatically over the past several decades. The decline has called into question the relevance of Schumpeter's theory of creative destruction. Previous research has shown that while smaller areas have historically had lower rates of firm birth and death compared to larger urban areas, less populated areas may have become even more static after the Great Recession of 2008.

We expand on Schumpeter's ideas by incorporating insights from empirical industrial organization and endogenous growth theory literature. The conceptual model we develop uses steady-state analysis to determine the equilibrium of firms. We estimate coefficients of key parameters in the conceptual model using structural estimation of a dynamic, unobserved effects count model on food manufacturer births and deaths. We find evidence of a creative destruction process via the interaction of firm birth and death that is correlated with higher rates of firm birth and death in a given location. The birth-death count model strongly supports Marshall's notion of "something is in the air" as random effects in the birth and death process are highly correlated, which captures unobserved effects attributable to agglomeration externalities.

Consistent with overall declines in firm birth and death across the U.S., we find evidence of convergence in birth and death rates for food manufacturers across counties. Convergence in birth rates appears to be more economically significant than creative destruction. The results have implications for considering capital reallocation across locations. We find that the convergence rate is higher in larger urban versus rural areas, which is consistent with rural areas becoming relatively more static over time. If rural areas become more static, firms within the same industry may risk becoming less productive in rural versus larger urban areas. As a result, the gap between rural and urban economic fortunes may also widen.

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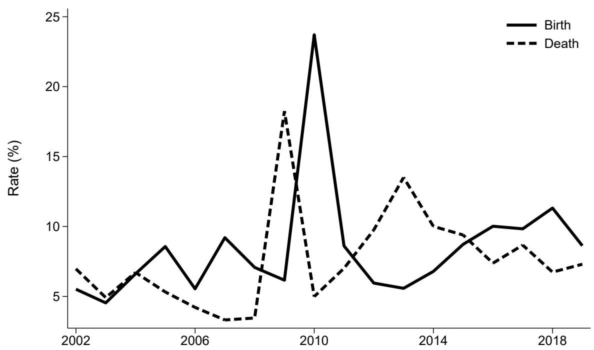
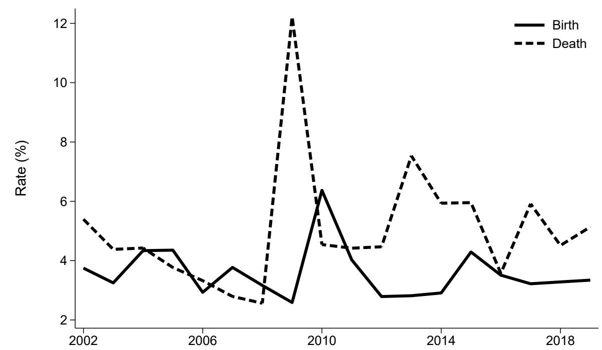
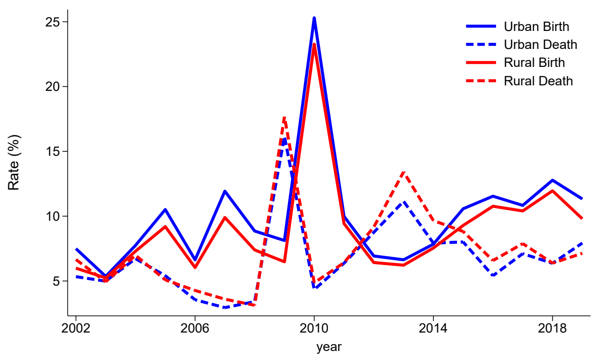


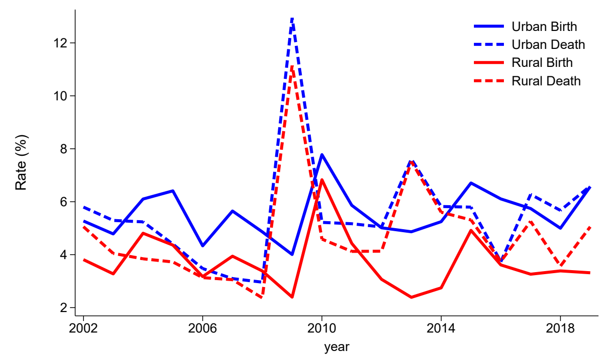
(a) Demand-Oriented



(b) Supply-Oriented



(c) Demand-Oriented



(d) Supply-Oriented

Figure 1: Food Manufacturing Birth and Death Rates

Source: NETS.

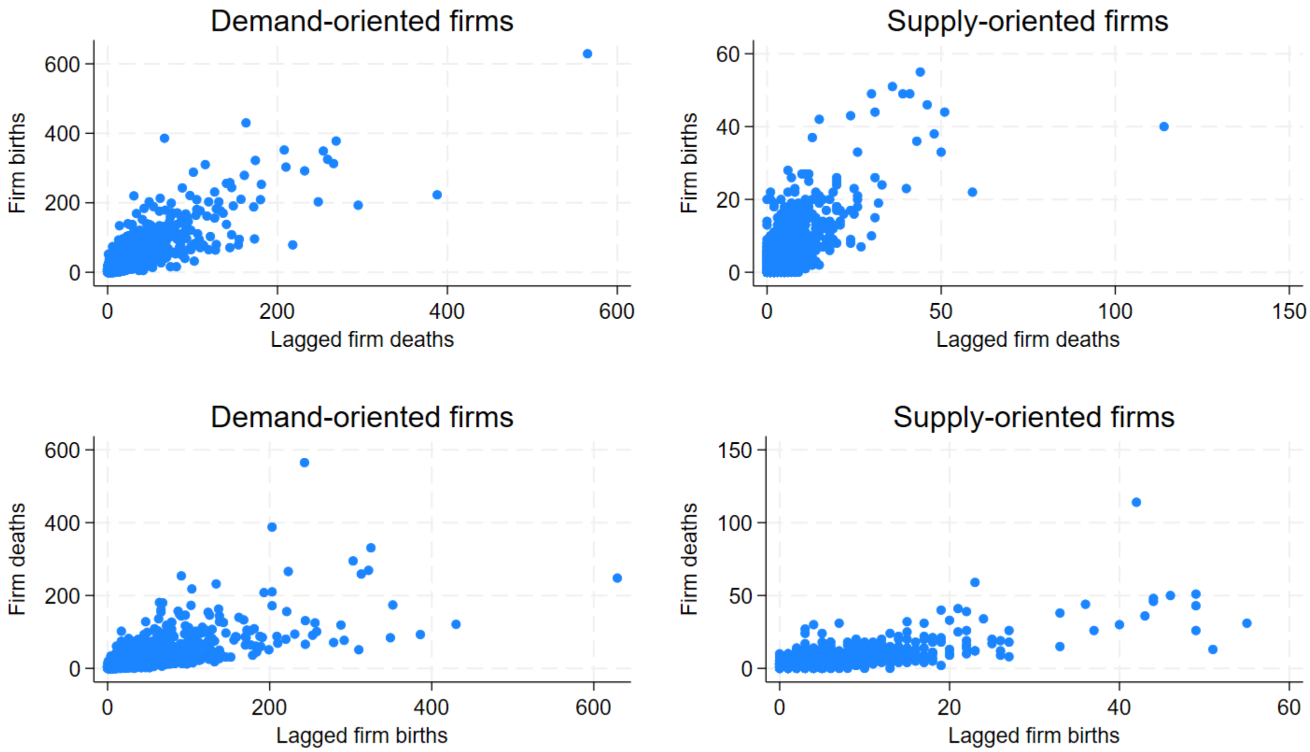


Figure 2: Establishment Births and Deaths

Source: NETS.

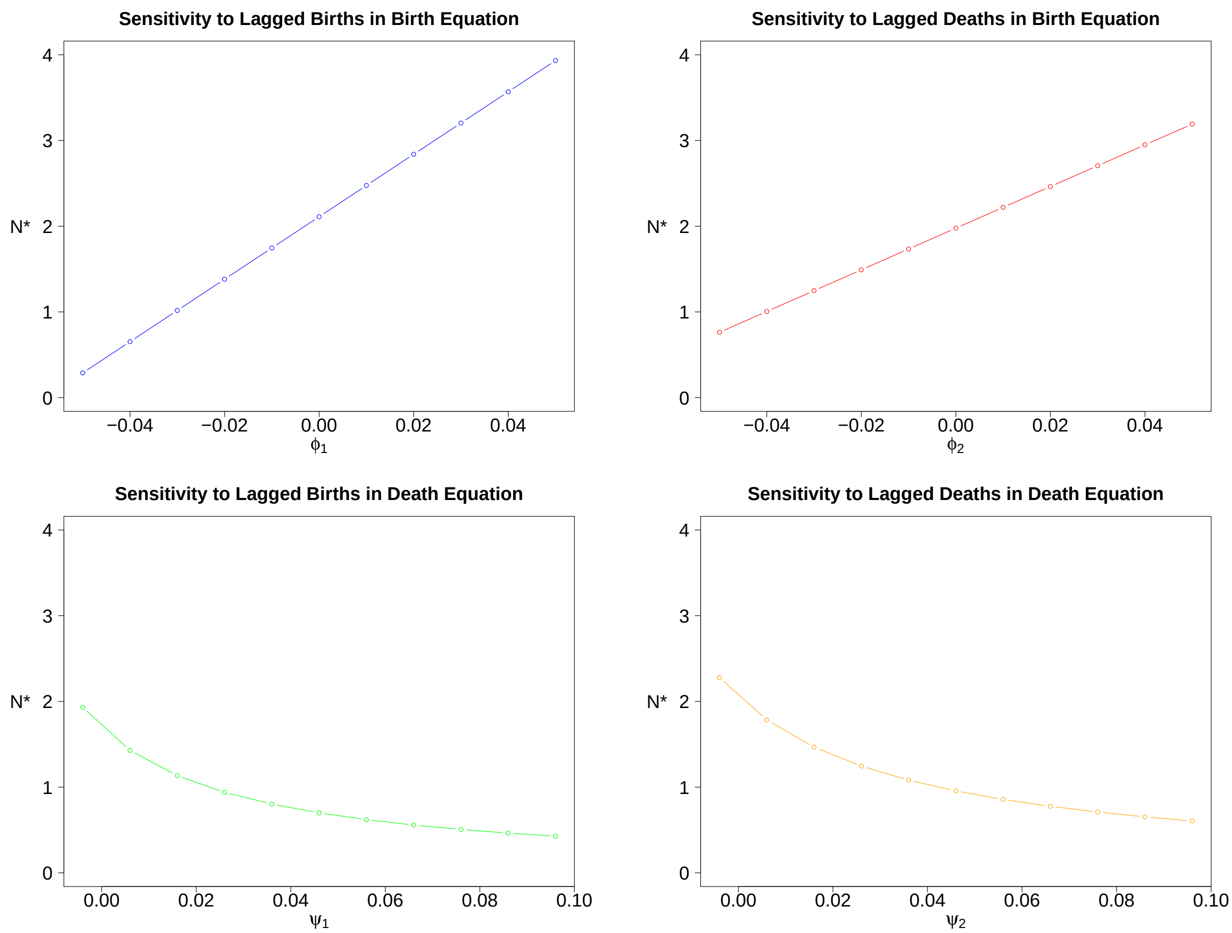


Figure 3: Equilibrium Sensitivity to Changes in Model Parameters

Notes: Parameters ϕ_1, ϕ_2, ψ_1 and ψ_2 correspond to coefficients of previous birth and death which impact the equilibrium number of firms as derived in equation 5.

Table 1: Food Manufacturing Establishments by Cost Structure

Firm type	Specialization	NAICS	SIC
Demand	Fluid milk manufacturing	311511	2026
	Ice cream and frozen dessert manufacturing	311520	2024
	Retail bakeries	311811	5461
	Commercial bakeries	311812	2051
	Dry pasta manufacturing	311823	2098
	Other snack food manufacturing	311919	2096
	Mayonnaise, dressing, and other prepared sauce	311941	2035
	Soft drink and ice manufacturing	31211	2086, 2097
	Breweries	312120	2082
Supply	Flour milling and malt manufacturing	31121	2041, 2083
	Sugar manufacturing	31131	2061, 2062, 2063
	Frozen fruit, juice, and vegetable manufacturing	311411	2037
	Fruit and vegetable canning, pickling, and drying	31142	2032, 2033, 2034
	Creamery butter manufacturing	311512	2021
	Cheese manufacturing	311513	2022
	Dry, condensed, and evaporated dairy products	311514	2023
	Animal slaughtering and processing	31161	0751, 2011, 2013, 2015, 5147
	Seafood product preparation and packaging	3117	2077, 2091, 2092
	Coffee and tea manufacturing	31192	2095
	Tobacco manufacturing	3122	2111, 2121, 2131, 2141

Notes: Modified after Connor and Schiek (1997) and Lambert and McNamara (2009).

Table 2: Descriptive Statistics

(a) Demand-oriented food manufacturers

	Mean	SD	Min	Max
Birth_t	3.24	12.71	0.00	629.00
Death_t	2.24	9.02	0.00	565.00
$\text{Total Establishments}_t$	31.85	117.09	1.00	3952.00
$\text{Ln Pop Density}_{t-1}$	4.08	1.56	-2.48	11.22
Ln Real PCI_{t-1}	10.48	0.23	9.69	12.27
Unemp Rate_{t-1}	6.25	2.65	1.07	29.39
LQ_{t-1}^{Ag}	2.55	4.41	0.00	78.35
LQ_{t-1}^{Demand}	0.87	2.20	0.00	62.88
Diversity_{t-1}	0.94	0.05	0.21	0.97
Rural-Urban CC	4.68	2.52	1.00	9.00
Year	2010.59	5.17	2002	2019
N	45611			

(b) Supply-oriented food manufacturers

	Mean	SD	Min	Max
Birth_t	0.43	1.59	0.00	55.00
Death_t	0.45	1.66	0.00	114.00
$\text{Total Establishments}_t$	8.43	23.75	1.00	753.00
$\text{Ln Pop Density}_{t-1}$	4.08	1.63	-3.28	11.22
Ln Real PCI_{t-1}	10.49	0.23	9.69	12.27
Unemp Rate_{t-1}	6.17	2.63	1.07	29.39
LQ_{t-1}^{Ag}	2.69	4.47	0.00	47.07
LQ_{t-1}^{Supply}	2.19	9.96	0.00	243.65
Diversity_{t-1}	0.93	0.05	0.35	0.97
Rural-Urban CC	4.68	2.57	1.00	9.00
Year	2010.43	5.17	2002	2019
N	42468			

Table 3: Rural-Urban Continuum Code Definitions

Metropolitan counties	
Code	Description
1	Counties in metro areas of 1 million population or more
2	Counties in metro areas of 250,000 to 1 million population
3	Counties in metro areas of fewer than 250,000 population
Nonmetropolitan counties	
Code	Description
4	Urban population of 20,000 or more, adjacent to a metro area
5	Urban population of 20,000 or more, not adjacent to a metro area
6	Urban population of 5,000 to 20,000, adjacent to a metro area
7	Urban population of 5,000 to 20,000, not adjacent to a metro area
8	Urban population of fewer than 5,000, adjacent to a metro area
9	Urban population of fewer than 5,000, not adjacent to a metro area

Source: USDA Economic Research Service. https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/

Table 4: Marginal Effects of Location Factors of Food Manufacturing Birth and Death

	Demand-Oriented		Supply-Oriented	
	Birth	Death	Birth	Death
Birth_{t-1}	-0.0033***	0.0011	-0.0117***	0.0002
	(0.0006)	(0.0007)	(0.0020)	(0.0017)
Death_{t-1}	-0.0049***	0.0012	-0.009***	0.0017
	(0.0007)	(0.0007)	(0.0011)	(0.0011)
$\text{Birth}_{t-1} \times \text{Death}_{t-1}$	0.00002***	-0.00000000	0.0003***	-0.00004
	(0.000003)	(0.00000002)	(0.00005)	(0.00004)
Ln Pop Density_{t-1}	1.2224***	-0.0935	0.2224***	-0.0313
	(0.1961)	(0.1244)	(0.0642)	(0.0570)
Ln Real PCI_{t-1}	-0.1690	-0.2935*	-0.0903	0.3143***
	(0.2177)	(0.1713)	(0.0718)	(0.0638)
Unemp Rate_{t-1}	0.0326***	0.0033	0.0031	0.0120***
	(0.0103)	(0.0097)	(0.0039)	(0.0035)
LQ_{t-1}^{Ag}	0.0212	-0.0132	-0.0027	-0.0002
	(0.0192)	(0.0169)	(0.0055)	(0.0051)
LQ_{t-1}^{Demand}	-0.0264	-0.0189		
	(0.0188)	(0.0151)		
LQ_{t-1}^{Supply}			0.0005	0.0016
			(0.0012)	(0.0013)
Diversity_{t-1}	0.0207	-0.0959	-0.1154	0.5640
	(1.5149)	(1.2573)	(0.5183)	(0.3546)
Rural-Urban CC	-0.0991***	0.0005	-0.0192***	-0.010***
	(0.0099)	(0.0084)	(0.0033)	(0.0032)
$\sigma^2_{r_b}$	0.0165***		0.0413***	
	(0.0014)		(0.0061)	
$\sigma^2_{r_d}$	0.0122***		0.0312***	
	(0.0013)		(0.0051)	
$\text{cov}(r_d, r_b)$	0.0139***		0.0358***	
	(0.0012)		(0.0048)	
ρ	0.98		0.99	
N	45,611		42,468	

Notes: * p<0.10, ** p<0.05, *** p<0.01. Delta-method standard errors are in parentheses.

Table 5: Marginal Effects of Location Factors of "Demand" Food Manufacturing Birth and Death, by Rural-Urban Continuum Code

	1	2	3	4	5	6	7	8	9
$Birth_{t-1}$									
B	-0.0168***	-0.0062***	-0.0027***	-0.0017***	-0.0016***	-0.0005***	-0.0004***	-0.0003***	-0.0002***
	(0.0032)	(0.0012)	(0.0005)	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.00003)
D	0.0045	0.0018	0.0008	0.0005	0.0005	0.0002	0.0002	0.0001	0.0001
	(0.0030)	(0.0012)	(0.0005)	(0.0004)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$Death_{t-1}$									
B	-0.0245***	-0.0091***	-0.0039***	-0.0025***	-0.0023***	-0.0008***	-0.0006***	-0.0004***	-0.0003***
	(0.0038)	(0.0014)	(0.0006)	(0.0004)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.00004)
D	0.0049	0.0019	0.0009	0.0006	0.0006	0.0002	0.0002	0.0001	0.0001
	(0.0031)	(0.0012)	(0.0005)	(0.0004)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Birth×Death									
B	0.0001***	0.00003***	0.00001***	0.00001***	0.00001***	0.000002	0.000002	0.000001	0.000001
	(0.00002)	(0.00001)	(0.000003)	(0.000002)	(0.000002)	(0.000002)	(0.000002)	(0.0281)	(0.4292)
D	-0.000000	-0.000000	-0.000000	-0.000000	-0.000000	-0.000000	-0.000000	-0.000000	-0.000000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
N	6,719	5,544	5,516	3,828	1,857	9,519	6,991	2,239	3,398

Notes: "B" and "D" correspond to the birth and death equations. * p<0.10, ** p<0.05, *** p<0.01. Delta-method standard errors are in parentheses.

Table 6: Parameters, values, and definitions for the Schumpeter's creative destruction model

Parameter	**Value**	**Definition**
ϕ_1^b	-0.003	Coefficient for the lagged birth on new firm entries
ϕ_2^b	0.001	Coefficient for the lagged death on new firm entries
ψ_1^d	-0.005	Coefficient for the lagged birth on firm deaths
ψ_2^d	0.001	Coefficient for the lagged death on firm deaths
ρ	0.98	Correlation coefficient between the random effects for birth and death rates
σ_μ	0.128	Standard deviation of the random effect for the birth rate
σ_δ	0.11	Standard deviation of the random effect for the death rate
Data	**Value**	**Definition**
μ	0.10	Base rate of firm birth
δ	0.07	Base rate of firm death
B_{t-1}	3	Lagged count of firm birth
D_{t-1}	2	Lagged count of firm death

Notes: Paramter values are from the econometric results in Tables 4 and A1 for the demand-oriented sample. Data values are sample averages from the demand-oriented sample.

Appendix

Table A1: Coefficients of Location Factors on Demand Food Manufacturing Birth and Death

	Birth	Death
Birth_{t-1}	-0.0012***	0.0005
	(0.0002)	(0.0003)
Death_{t-1}	-0.0018***	0.0005
	(0.0003)	(0.0003)
$\text{Birth}_{t-1} \times \text{Death}_{t-1}$	0.000006***	-0.000000
	(0.000001)	(0.000001)
Ln Pop Density_{t-1}	0.4413***	-0.0426
	(0.0712)	(0.0567)
Ln Real PCI_{t-1}	-0.0610	-0.1337*
	(0.0786)	(0.0781)
Unemp Rate_{t-1}	0.0118***	0.0015
	(0.0037)	(0.0044)
LQ_{t-1}^{Ag}	0.0077	-0.0060
	(0.0069)	(0.0077)
LQ_{t-1}^{Demand}	-0.0095	-0.0086
	(0.0068)	(0.0069)
Diversity_{t-1}	0.0075	-0.0437
	(0.5469)	(0.5728)
Rural-Urban CC	-0.0358***	0.0002
	(0.0036)	(0.0038)
$\sigma^2_{r_b}$	0.0165***	
	(0.0014)	
$\sigma^2_{r_d}$	0.0122***	
	(0.0013)	
$\text{cov}(r_d, r_b)$	0.0139***	
	(0.0012)	
ρ	0.98	
N	45,611	

Notes: * p<0.10, ** p<0.05, *** p<0.01. Clustered standard errors by county are in parentheses.

Table A2: Coefficients of Location Factors on Supply Food Manufacturing Birth and Death

	Birth	Death
Birth_{t-1}	-0.0262***	0.0004
	(0.0044)	(0.0037)
Death_{t-1}	-0.0207***	0.0036
	(0.0025)	(0.0024)
$\text{Birth}_{t-1} \times \text{Death}_{t-1}$	0.0006***	-0.0001
	(0.000001)	(0.00001)
Ln Pop Density_{t-1}	0.4979***	-0.0681
	(0.1460)	(0.1231)
Ln Real PCI_{t-1}	-0.2023	0.6775***
	(0.1612)	(0.1367)
Unemp Rate_{t-1}	0.0071	0.0258***
	(0.0087)	(0.0076)
LQ^{Ag}_{t-1}	-0.0060	-0.0004
	(0.0123)	(0.0110)
LQ^{Supply}_{t-1}	0.0011	0.0034
	(0.0027)	(0.0027)
Diversity_{t-1}	-0.2592	1.2160
	(1.1638)	(0.7643)
Rural-Urban CC	-0.0432***	-0.0214***
	(0.0074)	(0.0068)
$\sigma^2_{r_b}$	0.0417***	
	(0.0061)	
$\sigma^2_{r_d}$	0.0312***	
	(0.0051)	
$\text{cov}(r_d, r_b)$	0.0360***	
	(0.0048)	
ρ	0.99	
N	42468	

Notes: * p<0.10, ** p<0.05, *** p<0.01. Clustered standard errors by county are in parentheses.