WHY DO RURAL FIRMS LIVE LONGER?

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Abstract

Rural firms have a higher survival rate than urban firms. Over the first 13 years after firm entry, the hazard rate for firm exits is persistently higher for urban firms. While differences in firm attributes explain some of the rural-urban gap in firm survival, rural firms retain a survival advantage 18.5% greater than observationally equivalent urban firms. We argue that in competitive markets, the remaining survival advantage for rural firms must be attributable to unobserved factors that must be known at the time of entry. A plausible candidate for such a factor is thinner markets for the capital of failed rural firms. The implied lower salvage value of rural firms suggests that firms sorting into rural markets must have a higher probability of success in order to leave their expected profits equal to what they could earn in an urban market.

JEL: O18, L21, D92
Key words: Rural, urban, entry, exit, survival, sorting , salvage value

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I. Introduction

Entrepreneurship is increasingly being identified as a key determinate of future economic growth.[1] In turn, the growth only occurs if the pace of entrepreneurial entry exceeds the rate of firm exits. Even areas with relatively slow firm birth rates may experience economic expansion if local firms survive and grow. That simple observation turns out to have key implications for rural economic development: rural areas experience lower rates of firm entry. Less well known is that rural firms also have lower rates of firm exit. Understanding the conditions that lead to great rural firm survival relative to their urban counterparts is critical to understanding rural economies can grow.

Economists have long established that business survival is influenced by firm and industry characteristics.[2] More recently, economists have also begun to examine whether business location matters for business survival. Fritsch *et al* (2006) and Falck (2007) found that regional characteristics play an important role in business success. However, little is known about the relative success of rural firms and urban firms.

Figure 1 illustrates the stylized facts that motivate this study: that rural economies are characterized by slow rates of both firm entry and firm exit. We plot firm entry and exit rates in the five most rural and the five most urban states in the US. The rural states consistently have lower firm entry rates than urban states. Less well known is

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[1] See Acs and Armington, Acs et al (2008), Atudretsch et al (2006), and Baumol et al (2007) for recent examples of this literature.

[2] Examples include Audretsch (1991), Audretsch and Mahmood (1995), Esteve-Pérez and Mañez-Castillejo (2008), Mata and Portugal (1994), and Taylor (1999).

that rural states also have lower firm exit rates than the urban states. [3,4] However, in almost all years, the rural firm exit rate is lower than the rural firm entry rate, and so we have net additions of rural firms.[5] Understanding the reasons behind the lower exit rate of new firms in rural areas may identify factors that ultimately can increase entrepreneurial activity and economic growth in these regions.

Urban establishments should have numerous advantages over their rural counterparts. Urban markets are characterized by knowledge spillovers across firms and workers, a large customer base, easy access to information on new technologies, easy availability of differentiated skills in the labor markets, close proximity to suppliers, and superior transportation, telecommunication, and energy infrastructure. Such advantages have been shown to give urban firms a better chance at survival in West Germany, for example (Falck, 2007).

However, it is not obvious that all factors favor urban firm survival. Agglomeration economies in urban areas may be offset by higher input costs such as wages and rents or by having to face a large number of competitors (Arenius and Clercq, 2005). For example, Fritsch *et al* (2006) found that survival rate of newly founded businesses is negatively related with population density in West Germany. Bresnahan and Reiss (1990, 1991) found evidence that in the smallest populated markets, firms can charge monopoly prices. As community population rises, firm

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[3] Davis et al (2008) argue that the churn rate—the combined pace of firm entry and exit, is systematically related to growth by raising the pace of productivity advances.

[4] Plummer and Headd (2008) also found that rural firm death rates are significantly lower than urban firm death rates, but their reported differences were very small.

[5] We get similar patterns when we replicate the graph with the ten most and least rural states, but the urban-rural entry and exit rates are more similar.

entry quickly drives pricing power to the competitive level.

Our analysis of firm survival in rural and urban regions uses Iowa as a case study. The data are particularly suited to address why rural firms live longer. Iowa's 99 counties range from predominantly rural to metropolitan, providing a suitable range of markets to study this issue. The data set focuses on the universe of nonagricultural firms that opened for business in 1992 which holds constant the macroeconomic conditions that prevailed at the time of firm entry. The data is longitudinal which allows us to follow the firms for 13 years. Because two-thirds of U.S. firms fail within 6 years, the period is suitably long to establish whether any differences in survival are permanent or transitory. By holding industry and firm age fixed, we can measure the rural advantage holding constant differences in industry life cycle (Agarwal and Gort, 1994) and opportunities for learning-by-doing (Jovanovic and Lach, 1989). We can also hold fixed regional characteristics, observed and unobserved firm attributes, and factors influencing the strength of the local and industry markets.

In addition, the Iowa data mimic the national pattern of higher rural firm survival rates. Figure 2 shows the proportion of Iowa urban and rural firms that are still in business six years after entry. Seven firm birth-year cohorts are presented, and in all but one, rural firms have a higher survival rate after six years. The higher rural survival rate occurs despite the fact that the Iowa urban firm survival rate is already higher than the national average.

We find that both rural and urban firms face concave exit rates with peak exits at about 5 years. Over the first 13 years after entry, the hazard rate for firm exits is persistently higher for urban firms. Even after controlling for differences in firm, local market and industry factors between urban and rural firms, the rural firms retain a survival advantage over urban firms. The remaining advantage to rural firms is attributable to differences in unobserved, time invariant attributes that exist at the time the firm is born. We argue that the source of this survival advantage is plausibly found in thinner markets for capital in rural areas that lead to a lower salvage value for failed rural firms. Because firms have to take the possibility of failure into account at the time of entry, rural firms must have a higher probability of success in order to leave expected profits equal across rural and urban markets.

II. The Iowa Longitudinal Firm Database

We require longitudinal data on firms from date of entry to exit. Such data are available from the National Establishment Time-Series (NETS) database. NETS is a long-term project of Walls & Associates in conjunction with Dun and Bradstreet (D&B). The NETS database identifies each establishment using a unique DUNS ID number[6]. We use the earliest available Iowa NETS cohort, which includes the universe of establishments born in Iowa in 1992. If an establishment exits in any year between 1992 and 2004, excluding the cases where the firm migrates to another county inside or outside Iowa, it is designated as failing to survive. The sample is right censored in 2005 consequently all of the remaining establishments survived at

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[6] The observation unit in the NETS database is the establishment, which might be a stand-alone firm; one of several branches of a multi-plant firm, or the headquarters of a multi-plant firm. The link between subsidiary establishment and parent firm can be identified, and so we can distinguish the performance of branches and subsidiaries from the performance of independent establishments.

least thirteen years.

An advantage of the NETS database is that it provides detailed information on each establishment's characteristics at the time of firm birth. This information allows us to control for factors that have been shown to be important in explaining business survival such as firm ownership and firm size (Audretsch and Mahmood, 1995, Mahmood, 2000), but at the time of entry rather than later in the firm life cycle. This side-steps difficulties caused by time varying firm attributes that change endogenously as each firm's path toward survival or death progresses. We also have an unusually long time series on each firm, allowing us to follow firms for more than twice the median life of firms in the United States.[7]

Address information on each firm is used to identify the firm's county of residence which we take to be its primary consumer market. We also use the county designation to merge additional county-level data that measures local market conditions, natural amenities and other characteristics.

The categorization of firms by industry in the NETS database initially used eight digit Standard Industrial Classification (SIC) codes. During the period covered by this study, the Census Bureau switched to the North American Industry Classification System (NAICS). Walls & Associates provides a one-to-one projection table which translates the SIC codes into NAICS codes which allowed us to place each firm into consistent two-digit NAICS codes that spanned the full period between 1992 and 2004.

[7] See Knaup and Piazza (2007) for U.S. firm survival rates.

Looking ahead to our analysis, in 1992, 11,922 firms opened for business in Iowa. After six years, 64% of rural firms and 61% of urban firms were still in business. By 2005, the end of our sample period, 5,176 firms were still operating, 43 percent of the 1992 entry cohort. Only 40% of urban establishments were still alive compared to 45% of the rural firms. The difference in average survival rates between urban and rural areas is statistically significant, and as we saw in Figure 2, is a regular finding for other entry cohorts. We focus on the 1992 firm entry cohort because it affords us the longest time period over which to observe firm success or failure. Of course, the difference in rural-urban firm survival may reflect systematic differences in the types of firms found in those markets, and so we require a more structured analysis to see whether rural firms really have a higher rate of survival.

III. Survival Model

The survival duration of an establishment is defined as a random variable *T*. The hazard function, representing the probability of exit during a time interval $t+\Delta t$, conditional on the establishment being in business at time t is:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t < T < t + \Delta t \mid T \geq t)}{\Delta t} = \frac{f(t)}{S(t)} = -\frac{\partial S(t)/\partial t}{S(t)}, \qquad (1)$$

where $f(t)$ is the density function and $S(t)$ is the survival function. Figure 3 shows the non-parametric estimated hazard curves for our 1992 cohort of Iowa establishments in both rural and urban areas. The curves have an inverse U shape. While some studies found that hazard rates fell monotonically with establishment age (Fritsch, Brixy and Falck(2004), Audretsch(1991), and Evans(1987)), more recent empirical studies have found a concave hazard rate pattern (Mahmood, 2000; Falck, 2007). The bell-shaped hazard function suggests a log-logistic distribution in the accelerated failure time model[8] .

We allow firm *i*'s survival duration *T* to vary with covariates x_i according to the survival function

$$S(t_i, \beta, \gamma) = \frac{1}{1 + (t_i \varphi_i)^{1/\gamma}} \tag{2}$$

where $\varphi_i = \exp(-x_i \beta)$, β is a $p \times 1$ vector of regression parameters and $\gamma > 0$ is an ancillary parameter to be estimated and x_i is a $p \times 1$ characteristics vector, including the firm's own characteristics, location attributes and industry characteristics. If β_j>0 $j = 1, 2, ..., p$, an increase in one of the covariates x_{ij} , holding other covariates constant, will result in a decelerated or degraded failure which indicates an increased survival likelihood. In contrast, β_j<0, indicates an accelerated failure or decreased survival likelihood attributed to the covariate, all else equal.

Homogeneous risk of firm failure

The parameter γ in equation (2) influences the shape of survival and hazard functions. When γ>1, the hazard rate is monotonic in duration. If 0<γ<1, the estimated hazard rate will first increase and then decrease with time, as found in the

[8] The log-logistic model fits the data well. Our conclusion is based on a common diagnostic tool that plots the Cox-Snell residuals against the cumulative hazard function. (Klein and Moeschberger, 1997). If the model is appropriately specified and fits the data, these residuals should have an exponential distribution with its rate parameter equal to one. The plot is shown in Figure A1 in the Appendix. The plot is very close to the 45^0 line, indicating the log-logistic distribution is an appropriate assumption. Other parametric functional forms, such as the Weibull, Log-normal, and Gamma were also investigated and rejected because the residuals are not as close to the 45^0 line as those from the Log-logistic specification, as seen in the Figure A1 In addition, the Cox (1972) proportional semi-parametric hazard model does not fit the data well because the proportional assumptions are violated in general and for nearly half of the covariates included in the estimation.

simple nonparametric hazard shown in Figure 3.

Hypothesis 1: $0 < \gamma < 1$ *in the log-logistic survival model so that firms face a concave failure hazard rate.*

The hazard rate, according to definition (1) is given by

$$h(t_i,\beta,\gamma) = \frac{t_i^{1/\gamma-1}\varphi_i^{1/\gamma}}{\gamma[1+(t_i\varphi_i)^{1/\gamma}]}. \tag{3}$$

The log likelihood is

$$L(\beta,\gamma \mid x_i) = \sum_{i=1}^{n} d_i \ln f(t_i,\beta,\gamma) + \sum_{i=1}^{n} (1-d_i) \ln S(t_i\beta,\gamma) \multimap, \tag{4}$$

where $f(t,\beta,\gamma)$ is the probability density function of survival duration T; and d is a binary variable, equal to one if the establishment exits from the market.

Heterogeneous risk of firm failure

The model above assumes that each individual establishment is exposed to the same risk once characteristics x_i are controlled. However, there may be unobserved factors that influence the mortality of establishments. For example, Jovanovic(1982) assumes firms are heterogeneous in their abilities to learn-by-doing, creating a mixture of firms that differ in productive efficiency. Over time, the inefficient firms decline and fail and the efficient firms grow and survive. If the population is a mixture of individual establishments with different failure risks that are ignored in the estimation, then the hazard rate tends to be underestimated (Hougaard, 1986, Omori and Johnson, 1993).

This unobserved heterogeneity is measured by a quantity called frailty of individual establishments, defined as a new random variable α. It is incorporated into the individual hazard function as $h(t_i, \beta, \gamma \mid \alpha) = \alpha \cdot h(t_i, \beta, \gamma)$ and $S(t_i, \beta, \gamma \mid \alpha) = \{S(t_i, \beta, \gamma)\}^{\alpha}$. We define α to have mean one and variance θ[9]. Denote $\alpha \sim g(\alpha)$, where $g(\alpha)$ is the density function of α. This cumulative effect of α describes individual establishment's relative exit risk. Establishments with $\alpha > 1$ are more frail for reasons that are uncorrelated with the covariates x_i that are included in the estimation. Bad draws on α create a permanent increased risk of failure for the life of the firm, and could reflect bad luck, bad management, poor technology choices, or any other unmeasured adverse factor. Firms with good α draws will have $\alpha < 1$ which permanently raises their probability of survival, all else being equal (Gutierrez, 2002). As time passes, the establishments tend to become more homogeneous because frail establishments die earlier than robust ones (Vaupel, *et al*, 1979).

In theory, any continuous distribution of α supported on the positive numbers that has mean one and finite variance is allowed. However, the Inverse-Gaussian distribution or Gamma distribution is the common choice for the purpose of mathematical tractability. We chose the Inverse-Gaussian distribution, which makes the population of survivors more homogeneous with the passage of time than does the Gamma distribution (Hougaard, 1984, Hougaard, 1986)[10]. This generates the second hypothesis to be tested:

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[9] For the purpose of identification, expectation of α is assumed to be one. To be computationally convenient, we require that α is independent of *T*.

[10] Because of the small difference in properties between Gamma and Inverse-Gaussian frailty distribution, we did similar analysis when the heterogeneity is specified to have a Gamma distribution, the results are still consistent with the ones we obtain under the assumption of Inverse-Gaussian frailty distribution.

Hypothesis 2: θ≠0, implying that firms differ in unobservable relative risk of failure.

If $\theta=0$, there is no heterogeneity across establishments and so the estimation reduces to the survival function (2) and log likelihood function (4). If $\theta \neq 0$, inclusion of frailty is necessary to capture the excess dispersion in firm hazard rates.

The survival function with heterogeneity incorporated is given by

$$S_\theta(t_i,\beta,\gamma,\theta)=\int_0^\infty S(t\mid\alpha)g(\alpha)d\alpha=\exp\left\{\frac{1}{\theta}\left(1-\sqrt{1-2\theta\ln[S(t_i)]}\right)\right\}, \qquad (5)$$

The log-likelihood with Inverse-Gaussian distributed heterogeneity is the following,

$$\begin{aligned} L(\beta,\gamma,\theta\mid x_i) &= \sum_{i=1}^{n} d_i \ln f_\theta(t_i,\beta,\gamma,\theta)+\sum_{i=1}^{n}(1-d_i)\ln S_\theta(t_i,\beta,\gamma,\theta) \\ &= \sum_{i=1}^{n} d_i \ln h(t_i,\beta,\gamma)-(\theta^{-1}+d_i)\ln[1-\theta\ln S(t_i,\beta,\gamma)] \end{aligned} \qquad (6)$$

where $f_\theta(t,\beta,\gamma,\theta)$ is the corresponding probability density function of $S_\theta(t,\beta,\gamma,\theta)$.

Under either model specification (4) or (6) , we can also consider the effect of observable local market characteristics on firm longevity. Factors that have been identified as contributing to economic growth more generally, such as the education level of the local workforce, strong local markets for credit or product demand, and natural amenities, enter the vector x_i. That allows us to test our third hypothesis:

Hypothesis 3: Business survival depends on favorable local economic, labor market and environmental conditions.

Our primary interest is in assessing whether the impact of these local factors on firm survival differs between urban and rural areas. We can investigate that possibility by altering how the vector of local factors enters the analysis.

Specifically, insert $\phi_i = \exp(-x_{i,-R}\beta_{x,-R}, -R\beta_R)$ into equation (2), where R is a binary variable indicating the establishment is located in a rural county, and $x_{i,-R}$ contains all other covariates included in x_i except the constant term. If $\beta_R > 0$ after controlling for all other covariates, then rural firms have a higher survival rate. This allows us to test our fourth hypothesis:

Hypothesis 4: Holding all firm and local factors constant, rural businesses have a greater survival rate than urban businesses.

IV. Covariates that may influence firm survival

The variables included in the vector x_i represent firm, community and industry characteristics that are believed to affect firm survival. Summary statistics are presented in Table 1.

1. Individual establishment specific characteristics

The NETS database identifies establishment specific characteristics, such as initial establishment size and ownership that may influence the likelihood of survival. The number of employees at time of birth has been hypothesized to raise survival prospects because larger firms have advantages in raising capital, face better tax conditions, and are in a better position to recruit qualified labor (Mahmood, 2000). Innovation rates and technology adoption intensity are found to be positively related with the survival probabilities of establishments (Audretsch and Mahmood, 1994, 1995, and Mahmood, 2000). Additionally, because large firms tend to adopt more advanced technologies in the early stage of technology diffusion, they are more likely to survive than small firms. Finally, the larger sunk costs associated with opening a larger firm implies a higher prior expectation of profitability. Consequently, greater survivorship may simply reflect sorting on expected profits at time of firm birth (Frank, 1988).

Establishment size is categorized into three levels: small, medium and large. A small establishment has no more than five employees. A medium establishment has six to fifty employees and a large establishment has more than fifty employees. Two dummy variables, *Medium* and *Large* are used, reserving small firms as the base. 75.5% of new establishments born in Iowa in 1992 are small and 38.6% of small businesses were still alive in 2005. In contrast, 22% of new establishments are medium sized and their survival rate is 56.2%, 17.6% higher than small establishments.

A second factor that may affect firm survival is ownership structure (Audretsch and Mahmood, 1995). Establishments in our dataset can be independent single entities; a branch or subsidiary of a multi-establishment firm; or the headquarters of a multi-establishment firm. Branches or subsidiaries are more likely to survive than independent firms because branches benefit from the experience and reputation of their parent firm. Of our new business cohort in 1992, 67.6% are independent establishments and 31.0% are branches.

Finally, a dummy variable *Minority* indicates whether the owner is a member of a minority group. Past research has found a positive correlation between minority status and the probability of setting up new businesses (Lee, *et al.*, 2004) because minority groups tend to pool various resources to enable new start-ups (Lee, *et al.*, 2004, Kandel and Lazear, 1992). However, language limitations or social or cultural isolation may limit access to customers, new business opportunities, or new technologies critical to firm survival prospects (Arenius and Clercq, 2005, Ozgen and Baron, 2007).

2. Location specific characteristics

The abundance of local labor, capital, information, or material is critical to the operation of new firms (Stearns, *et al* 1995). Stable and healthy development of a local economy should also increase the likelihood that an establishment can survive. We introduce several factors that represent a firm's local economic environment. We treat a county as the local market in which a firm resides. The 99 counties of Iowa are of roughly comparable size, and so these measures will reflect roughly the same geographic boundaries surrounding the firm.

Rural is a dummy variable, indicating whether the county is urban or rural. The USDA estimates that 53% of Iowa's establishments are located in rural or nonmetro counties (Rural-Urban Continuum Codes 4-9[11]). Firms in urban areas should face higher customer demands and lower search costs for information, and should benefit from lower production costs attributable to agglomeration (Glaeser, *et. al*, 1992). On the other hand, social networks that could result in a loyal customer base are stronger in rural areas (Arenius and Clercq, 2005). Rural firms will also face lower rent, lower labor costs and less competitive pressure. Previous studies have not established whether rural firms have different survival prospects. However, Acs and Malecki (2003) found a higher percentage of high growth firms in smaller Labor Market Areas,

[11] http://www.ers.usda.gov/Data/RuralUrbanContinuumCodes/1993/LookUpRUCC.asp?C=R&ST=IA and http://www.ers.usda.gov/briefing/Rurality/RuralUrbCon/.

suggesting that rural firms may have some advantages over urban firms.

Higher Education is defined as the percentage of college degree holders in a county. In the empirical literature of new business survival, local labor quality is largely neglected. However, establishments can benefit from knowledge spillovers which create innovations, generate exterior learning-by-doing, reduce searching costs, and potentially reduce the hazard of failure (Moretti, 2004). At the same time, more educated residents have more disposable income therefore they will generate higher and more diversified demand for local products and services.

Local Capital is measured by per capita bank deposits (in $millions) in the county. The measure is meant to indicate the availability of loanable funds in the local credit market. While it may seem that credit markets are very efficient at locating and funding promising ventures, banks could play an important role in disseminating information on such opportunities in small or isolated market.

Debt measures log of per capita local public debt in a county. This could be viewed as a measure of expected future tax obligations that must be paid by firms and residents. Heavier tax obligations lower discretionary income of the customers and add cost to the firms, both of which may lower the probability of survival. Both *Debt* and *Local Capital* emphasize the effect of liquidity constraints faced by entrepreneurs. For example, Holtz-Eakin, *et al* (1994) found that liquidity constraints exerted a noticeable influence on the viability of entrepreneurial enterprises.

Entry1991 is the entry rate of new businesses in the county in 1991. The variable is defined as the number of establishments born in the county in 1991 divided by the total number of active establishments in the county in the beginning of 1991. We use this variable as a correction for selection: we only observe firm exits for firms that were induced to enter. It is plausible that exit rates are highest in markets that have the highest firm entry rates, due to low entry costs, or high perceived opportunities. For example, studies show that imposing barriers to exit such as firing restrictions or contracted length of service requirements can also serve as a barrier to firm entry in an industry (Agarwal and Gort, 1994, Eaton and Lipsey, 1980, Macdonald, 1986). However, it is still not clear if entry costs at a national or regional level affect new business survival probabilities. If true, then our exit rates will be subject to substantial selection bias that could cloud our interpretation of the results. If *Entry1991* successfully serves as a control for selection, we should find that high values of *Entry1991* will raise the likelihood of exit and lower firm survival.

Amenity is an index from one to seven which represents the quality of natural amenities in the county. As defined by the Economic Research Service of the USDA, a higher number means better weather and better access to naturally occurring topographic or geological features. *Water* measures the water coverage in a county. Higher levels of amenity and more water in a county may attract employment and tourists. Henderson (2007) finds that local growth is enhanced by better amenities and water coverage in a local region.

Highway is a dummy variable indicating that the county has an interstate highway. The presence of transportation infrastructure reduces the average cost of production for firms by reducing distribution costs and input acquiring costs from the distant markets and supports the local employment growth (Henderson, 2007).

3. Sector-specific market growth and industrial structure

A firm should find it easier to survive in a sector with increasing demand. The market growth variable *Growth* is measured by the annual percentage change in employment in the national two digit industry in the four year period between 1998 and 2002, the midpoint of our sample period. Data are compiled from the March Current Population Surveys from the US Census Bureau. We expect that establishments are more likely to be viable in industries that are experiencing higher growth.

Concentration defines the sales percentage of the biggest four firms in a specific 4 digit NAICS coded industry in Iowa in 1991. A high concentration ratio suggests high entry barriers in the industry. New firms that enter those markets will face pressures to drop out, even as the older incumbent firms are insulated from competing with new entrants. One example is in the retail sector where big firms tend to drive out small firms (Jia, 2008).

V. Empirical Results

Regression results from the survival model specified in equation (6) are shown in Table 2. *Hypothesis 1* cannot be rejected. The estimated shape parameter γ is 0.4 and statistically significant, supporting our use of the log-logistic specification. This implies a bell shaped hazard function for firm failures consistent with the patterns shown in Figure 3.

The variance of the Inverse-Gaussian frailty θ is 2.04 and a likelihood ratio test easily rejects the hypothesis that individual establishments have a homogeneous exit rate distribution after controlling for the observables. Consistent with *Hypothesis 2*, there are significant time-invariant unobserved traits that affect the likelihood of firm survival. That firms differ in frailty means that over time, firms with bad draws from the α distribution at time of birth cannot compete and are forced to exit the market. The process continues until vulnerable establishments are shaken out, and only the strong establishments with good α draws remain active in the market.

Effects of firm attributes, location, and industry characteristics on survival

From Table 2, we find that survival probability is significantly affected by firm attributes, local market attributes and industry fixed effects, based on the global tests on the coefficients of variables in these three categories. Establishments' own characteristics significantly affect the survival of new businesses. Consistent with previous findings, establishments with bigger initial size are less likely to fail than smaller ones. The effect is even stronger for large firms than for medium firms. Figure 4(a) shows that the medium and large establishments have much lower exit hazard rates than do small establishments. The mortality rate peaks at four to five years for small establishments. However, the critical duration extends to six to seven years for medium establishments and to seven to eight years for large establishments. Once establishments survive eleven years, they are exposed to very similar low mortality rates, regardless of initial size.

Also consistent with previous findings, establishments born as branches or subsidiaries are more likely to survive. Headquarters with multiple branches, once in the market, are more likely to survive than independent establishments. Their estimated hazard functions are shown in Figure 4(b). The maximum mortality for independent firms peaks at age four. However, the maximum hazard for branches and headquarters peaks in their seventh year.

Regional factors also influence firm survival, consistent with *Hypothesis 3*. Firm survival likelihood is improved in counties with higher proportions of college graduates and counties with water amenities such as lakes and streams. Firm chance of survival is lower in counties with high levels of per capita public debt. Other factors such as local access to loanable funds or highways do not affect firm survival, nor do other amenities such as weather or topography.[12]

Firm survival probability is also affected by selection. Firms that enter in counties with higher entry rates are also more likely to exit. We interpret this as evidence of sorting on the strength of the local market. In stronger markets, more marginal firms are willing to enter, and faltering firms are more apt to exit because they have ready access to new buyers willing to try their hand at entrepreneurship. In markets with poorer prospects and few entrepreneurs willing to purchase the assets of the weak, only firms with more certain success will enter.

Firm survival and exit rates differ significantly across industries. Firms survive more readily in industries with faster growth nationally. Administrative and waste management establishments have the highest risk of failure, followed by the entertainment and recreation services and professional services, retail and wholesale

[12] There is not much variation across these counties in weather or topography, and so the lack of importance in this application may not hold for samples with greater variation in local amenities.

industries.

Rural – urban differentials in survival patterns

Comparing Tables 1 and 2 allow us to identify the factors that help explain the higher rural firm survival rate. Factors that have a positive effect on survival and have higher means in rural areas will raise average rural establishment survival. Factors that lower survival and have lower means in rural areas will also raise average rural survival rates. The factors that give rural firms a survival advantage are all factors that lower firm survival: rural areas have lower public debt, lower firm entry rates, and fewer construction, professional service, administrative service and arts/entertainment firms. Urban establishments have advantages because they are larger, more likely to be branches or headquarters, have better access to an educated workforce and water resources, and atypically are in growing industries.

Even after controlling for all these factors that might explain the differences in survival rates across urban and rural counties, we cannot reject *Hypothesis 4* that establishments located in rural counties are more likely to survive than those in urban counties. As shown in Table 2, the rural firms have a 18.5% higher survival probability that is significant at the 10% level.[13] Furthermore, as shown in Figure 4(c),

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[13] Average survival odds are defined as $Odds_x \equiv \frac{S(t,\beta,\gamma \mid x)}{1-S(t,\beta,\gamma \mid x)} = (t\exp(-x\beta))^{-1/\gamma}$ when α is held at one. And the corresponding odds ratio between rural and urban firms is

$$OR_R = \frac{Odds_{R=1}}{Odds_{R=0}} = \exp(\frac{\beta_R}{\gamma}) = 1.185.$$

the failure hazard rate is greater for urban than rural firms for the first nine years after entry.

Why does a rural firm tend to live longer than an otherwise observationally equivalent urban firm? It is possible that the attributes included in Table 2 have different marginal impacts on firm survival in rural compared to urban markets, and those different marginal effects generate different survival patterns. To test that, we replicated the estimation strategy used in Table 2 separately for the urban and rural firms and tested for differences in the coefficients across the urban and rural markets. We cannot reject the null hypothesis that the firm survival coefficients are the same across the rural and urban markets, supporting the survival specification used in Table 2.

In competitive markets, a known persistent higher probability of rural firm survival must be accompanied by a higher cost of rural firm entry in order to leave expected profits equal at the margin across urban and rural markets. Our remaining task is to suggest a plausible candidate for the higher rural entry cost. We suggest that the most likely candidate is a weaker market for the capital of failed rural firms that lowers the expected salvage value of a rural firm at the time of entry compared to the salvage value of that same firm in an urban market.

It is commonly known that low population density and poor access to educated labor, capital and infrastructure deter rural firm entry (Reynolds, *et al,* 1995). But those same factors limit the potential market for the plant and equipment of the rural firms that do enter and subsequently fail. The lower expected salvage value of rural firms at the time of entry implies that rural firms must have a higher probability of success to justify opening business in the rural rather than in the urban market.

To make a simple example that clarifies the argument, suppose that a firm considering opening in an urban (*U*) or rural (*R*) market has exactly the same expected revenue and cost stream in both markets. Conditional on survival, assume expected profit is π_S in both *U* and *R*. A firm will only open for business if the expected return from using capital in operation exceeds the value of that same capital in alternative uses. Consequently, it must be true that $\pi_S > \pi_F^j,\ j = U, R$, where π_F^j is the salvage value (or opportunity cost) of the firm's capital in market *j*. Suppose that the salvage value is higher in *U*, and so $\pi_F^U > \pi_F^R$. Using p_j as the probability of firm success in region *j*, we can write expected profit at time of entry as $E(\pi) = p_j \pi_S + (1 - p_j)\pi_F^j,\ j = U, R$. If there is free entry into both markets *U* and *R*, $E(\pi)$ must be the same in *U* and *R*, which can only be true if $p_R > p_U$. Hence, firms that sort themselves into rural markets will only do so if they expect a higher survival probability than they would in an urban market.

We test this sorting hypothesis using a bivariate probit model. Firms jointly choose whether to enter a rural or urban market in 1992, and whether to stay in business by 2005. The decisions are based on the observed characteristics included in Table 2 excluding the location characteristics. We have to exclude the location characteristics because they are selected jointly with the urban- rural location and are therefore endogenous.

The error terms include unobserved factors that sort firms into and out of business and into and out of rural markets. If our sorting mechanism is valid, we should find that the errors are positively correlated: unobserved factors that cause a firm to enter a rural market (such as low π_F^R) must also raise the likelihood of survival p_R .[14]

The results are shown in Table 3. The correlation of unobservables contributing to rural entry and survival is significantly positive, indicating that unobserved regional attributes that induce rural firm entry also raise the probability of firm survival. The implication from our hypothesized sorting mechanism cannot be rejected. We also find that firms that self select into rural areas are small, independent and owned by non-minority entrepreneurs. These rural firms are more likely to be in competitive industries. Manufacturing and mining firms, atypically locate in rural areas while construction, wholesale, finance real estate and professional firms select urban markets.

VI. Conclusions and discussions

This study uses a unique longitudinal data set to analyze the factors that explain a previously unexplored phenomenon: the higher survival probability of rural establishments. We show that across states and across years within states, rural firms are less likely to exit. As one might expect, many factors actually favor urban firm survival: urban firms are bigger, have better access to educated workers and water, are more likely part of a multiplant firm, and are more likely in growing sectors of the economy. Rural firms have advantages in that they are in markets with a lower public

[14] We did add the location characteristics into the survival equation while excluding them from the rural-urban equation to test the robustness of our results. We obtained similar results for the establishment and industry coefficients reported in Table 3. In addition, the critical error correlation estimate was still positive and significant.

debt load and lower firm entry rates. Nevertheless, even after controlling for these characteristics, there remains a significant survival advantage for rural firms that persist even 13 years after entry.

We argue that a plausible explanation for this persistent survival advantage for rural firms would be a lower expected salvage value of capital should a rural firm go out of business. At the time of entry, firms must take into account the possibility that they will fail and the resources they can still claim in the event they do not survive. Thin markets for capital in rural areas mean that the same firm will expect lower salvage value in rural areas which requires a higher probability of success in order to leave expected profits in rural and urban areas equal. We show evidence that indeed, unobserved factors that lead a firm to enter a rural market are correlated with higher firm success, consistent with our presumption that firms self-select into rural markets based on higher expected likelihood of success.

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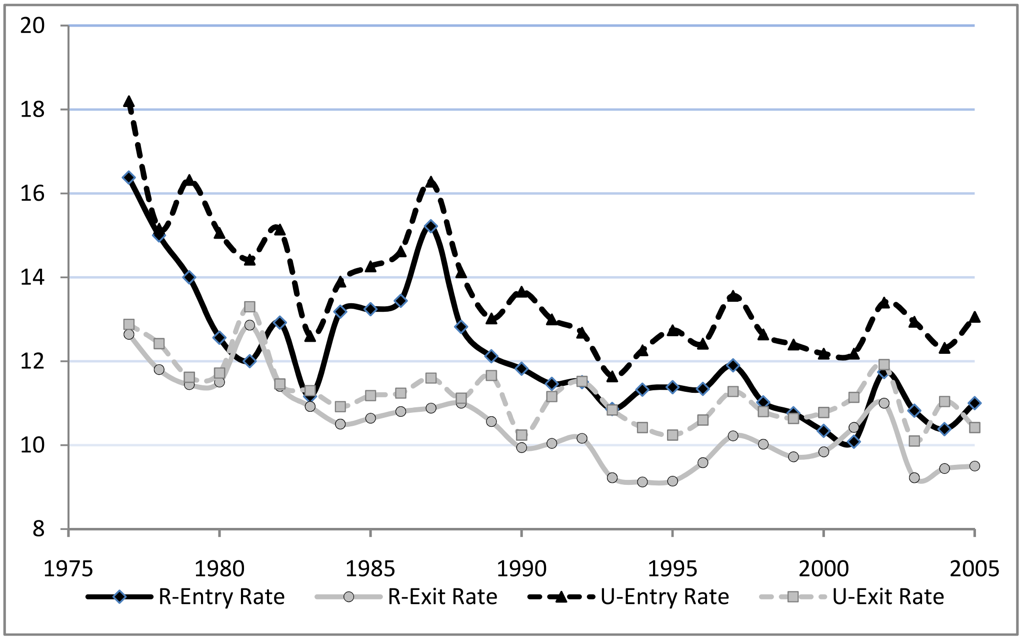
Figure 1 Entry and exit rates in rural and urban states, 1977-2005



Note: The five most rural states include Vermont, Maine, West Virginia, Mississippi, and South Dakota. Average rural population density in these states is 55%. The five most urban states include California, New Jersey, Nevada, Hawaii, and Massachusetts with average rural population density of 7%. Data source: http://www.ces.census.gov/index.php/bds/.

Figure 2: Iowa urban and rural 6-year firm survival rates by year of startup

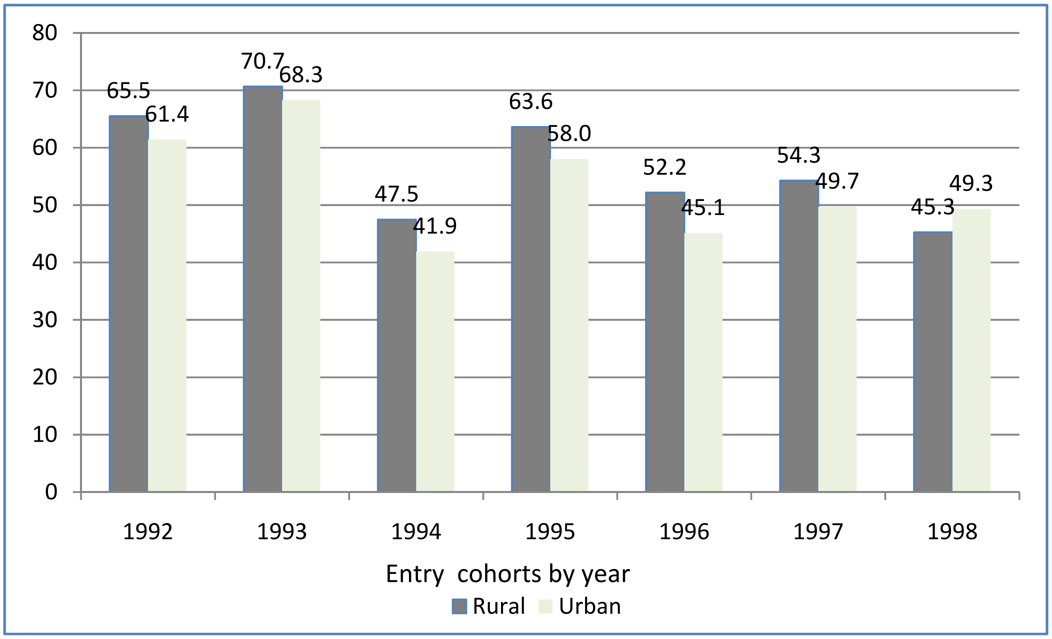
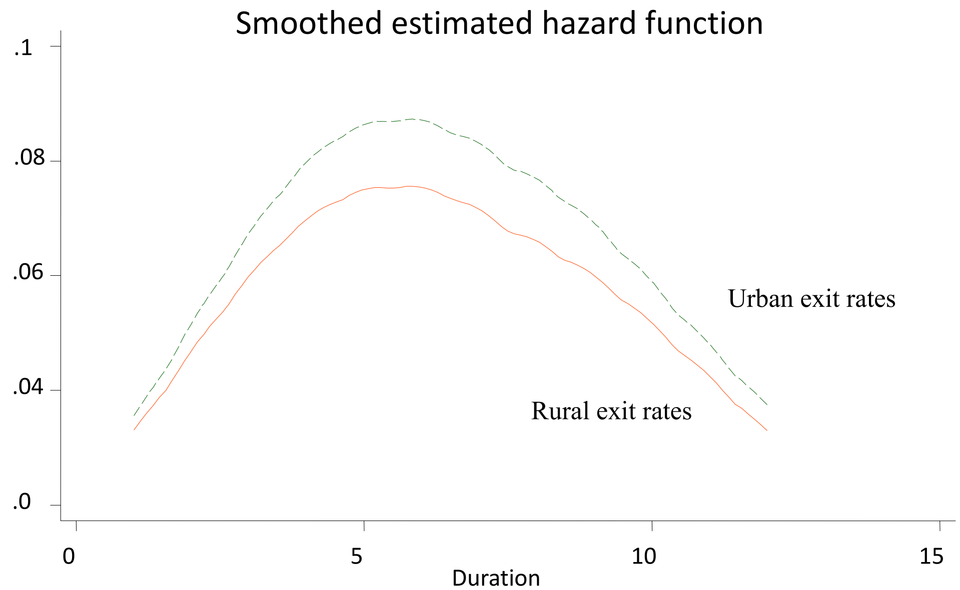


Figure 3 Estimated non-parametric hazard rate function for firm exits, by firm location



Note: log-rank test of equality in survival functions between rural and urban firms is rejected at 1% level($\chi^2(1) = 28.56$).

Table 1 Descriptive statistics of variables and definitions.

Variable	Description	Rural		Urban		Difference	p-value
		Mean	Std. D	Mean	Std. D	(rural-urban)	
Survival duration							
T	Life of establishments	9.069	4.231	8.694	4.234	0.376***	0.000
Establishment characteristics							
Minority	1 if the owner is from a minority, 0 otherwise	0.001	0.038	0.005	0.069	-0.003***	0.001
Medium	1 if number of employees in the establishment is between 6 and 50, 0 otherwise	0.198	0.398	0.242	0.428	-0.045***	0.000
Large	1 if number of employees in the establishment is more than 50, 0 otherwise	0.020	0.140	0.029	0.169	-0.009***	0.001
Branch	1 if the establishment is a branch of a multi-establishment firm, 0 otherwise	0.294	0.456	0.322	0.467	-0.028***	0.001
Headquarters	1 if the establishment is the headquarter, 0 otherwise	0.012	0.110	0.017	0.128	-0.004**	0.045
Location characteristics							
Education [a]	The proportion of residents with a at least college degree in the county	13.594	5.852	21.572	6.935	-7.978***	0.000
Local Capital [a]	The per capita deposits in the county in 2003	17.873	4.343	17.844	7.003	0.029	0.786
Debt [a]	Log (debt in 1997 / population in 2000) in a county	-0.027	0.591	0.516	0.343	-0.543***	0.000
Entry1991	The entry rate in the county where the establishment is located	0.026	0.007	0.043	0.010	-0.017***	0.000
Amenities [a]	Natural amenities scale(1-7 with 7 meaning most natural amenities)	2.345	0.495	2.538	0.499	-0.193***	0.000
Water [a]	Percentage of water areas in a county	0.849	1.194	1.834	1.314	-0.986***	0.000
Highway [a]	1 if the county is close to a highway, 0 otherwise	0.259	0.438	0.945	0.227	-0.687***	0.000
Industry characteristics							
Growth b	The annual percentage change in employment in US industries	1.527	1.583	1.671	1.597	-0.144***	0.000
Concentration	Concentration ratio of the four largest firms in 4-digit NAICS industries	0.232	0.267	0.238	0.225	-0.006	0.224
21	Mining	0.002	0.042	0.001	0.027	0.001	0.111

23	Construction	0.078	0.268	0.089	0.284	-0.011**	0.033
31	Manufacturing	0.049	0.216	0.045	0.207	0.004	0.284
42	Wholesale trade	0.065	0.247	0.067	0.249	-0.001	0.765
44-45	Retail trade	0.193	0.394	0.160	0.367	0.033***	0.000
48-49	Transportation and warehousing	0.042	0.200	0.036	0.186	0.006*	0.087
51	Information	0.015	0.122	0.016	0.124	0.000	0.877
52	Finance and insurance	0.046	0.210	0.059	0.235	-0.012***	0.003
53	Real estate and rental and leasing	0.055	0.229	0.051	0.219	0.005	0.256
54	Professional and technical services	0.063	0.244	0.100	0.301	-0.037***	0.000
56	Administrative and waste services	0.043	0.203	0.060	0.238	-0.017***	0.000
61	Educational services	0.018	0.134	0.014	0.119	0.004*	0.088
62	Health care and social assistance	0.086	0.280	0.083	0.275	0.003	0.568
71	Arts, entertainment, and recreation	0.020	0.139	0.026	0.159	-0.006**	0.029
72	Accommodation and food services	0.058	0.234	0.048	0.214	0.010**	0.018
81	Other services, except public administration	0.167	0.373	0.147	0.354	0.020***	0.004

***: significant at 1%; **: significant at 5%; *: significant at 10%.

a. Data source: USDA

b. Data source: US Census Bureau

Table 2 Regression results from log-logistic survival model.

	Variable	Coefficient	t statistic
Establishment characteristics	Minority	0.197	1.40
	Medium	0.320	11.27***
	Large	0.423	5.54***
	Branch	0.442	17.24***
	Headquarters	0.347	3.51***
	LR test $\chi^2(5) = 662.3$		p-value <0.001
Location characteristics	Rural	0.068	1.91*
	Education	0.007	3.59***
	Local Capital	0.002	0.80
	Debt	-0.028	-2.07**
	Entry1991	-2.547	-1.90*
	Amenities	0.000	-0.01
	Water	0.023	1.99**
	Highway	-0.020	-0.64
	LR test $\chi^2(8) = 36.1$		p-value <0.001
Industry characteristics	Growth	0.038	3.10**
	Concentration	-0.035	-0.55
	Mining	-0.223	-0.79
	Construction	-0.148	-1.96**
	Wholesale	-0.149	-2.39**
	Retail	-0.206	-3.26***
	Transportation	0.014	0.20
	Information	-0.163	-1.44
	Finance/Insurance	-0.085	-1.05
	Real estate	-0.112	-1.35
	Professional service	-0.211	-2.36**
	Administrative service	-0.252	-3.39***
	Heal care	-0.109	-1.48
	Arts/Entertainment	-0.236	-2.39**
	Accommodation	0.007	0.09
	Private services	-0.060	-0.86
	LR test of industry types $\chi^2(14) = 57.2$		p-value <0.001
Constant		1.669	15.23***
γ		0.401	[0.009]***
θ		2.044	[0.176]***
Log likelihood		-12400.8	
Number of observations		10827	
Likelihood Ratio test		$\chi^2(29) = 758.8$	p-value <0.001
Likelihood Ratio test [a] $\theta = 0$		$\overline{\chi}^2(01) = 431.5$	p-value <0.001

Note: number in the bracket parenthesis is standard error. LR tests reported below establishment characteristics, location and industry characteristics are global tests of zero coefficients of variables in each groups. [a]. The distribution of the LR test statistic is not the usual chi-square with 1 degree of freedom, but instead a 50:50 mixture of a chi-square with no degrees of freedom and a chi-square with 1 degree of freedom (Stata). ***: significant at 1%; **: significant at 5%; *: significant at 10%.

Figure 4 Estimated average hazard functions in different groups

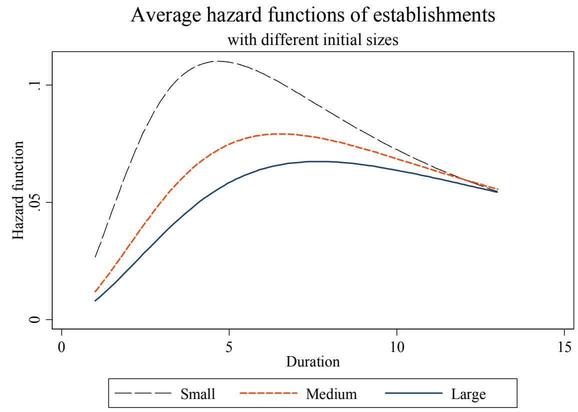


Figure 4(a)

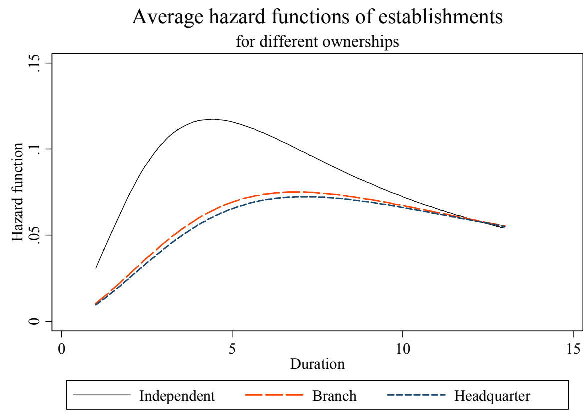


Figure 4(b)

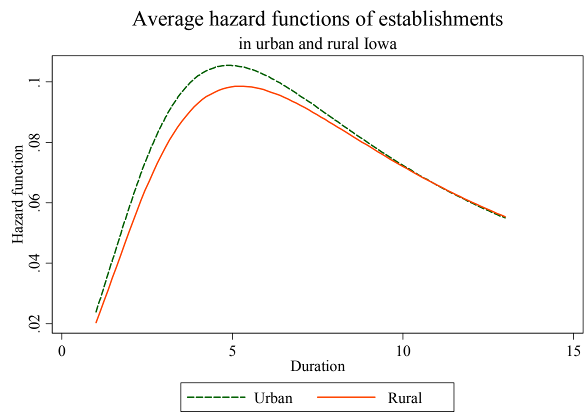


Figure 4(c)

Table 3 Bivariate probit models of location selection and survival of rural and urban firms

	Survival		Rural	
	Coefficient	**t statistic**	**Coefficient**	**t statistic**
Establishment characteristics				
Minority	-0.566	-2.38**	-0.725	-3.12***
Medium	0.298	9.06***	-0.202	-6.17***
Large	0.469	5.55***	-0.240	-2.91***
Branch	0.438	14.59***	-0.072	-2.40**
Headquarters	0.493	4.68***	-0.220	-2.09**
Industry characteristics				
Growth	0.011	0.71	0.013	0.91
Concentration	-0.193	-2.57***	-0.139	-2.04**
Mining	-0.163	-0.49	0.521	1.49
Construction	-0.086	-0.93	-0.381	-4.23***
Wholesale	-0.180	-2.36**	-0.196	-2.65***
Retail	-0.137	-1.80*	-0.103	-1.40
Transportation	-0.034	-0.38	-0.080	-0.90
Information	-0.043	-0.32	-0.150	-1.15
Finance/Insurance	-0.061	-0.61	-0.359	-3.69***
Real estate	-0.168	-1.64	-0.248	-2.49**
Professional service	-0.072	-0.66	-0.552	-5.20***
Administrative service	-0.163	-1.77*	-0.465	-5.17***
Heal care	-0.024	-0.27	-0.192	-2.22**
Arts/Entertainment	-0.235	-1.89*	-0.399	-3.32***
Accommodation	-0.043	-0.47	-0.062	-0.70
Private services	-0.026	-0.31	-0.201	-2.45**
Constant	-0.348	-5.03***	0.375	5.63***
Rho	0.080[0.015]***			
Log likelihood	-14407.707			
Number of observations	10827			

Note: number in the bracket parenthesis is standard error.
***: significant at 1%; **: significant at 5%; *: significant at 10%.

Appendix

Figure A1 Examination of Log-logistic distributional assumption.