Size, Growth, and Survival in the Upper Austrian Farm Sector

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ABSTRACT. This paper investigates the evolution of the size distribution of more than 40,000 farms in the Upper Austrian farm sector over the period 1980–90. Using Gibrat's Law as our point of departure, we find that smaller farms grow much faster towards some minimum efficient scale of production than farms at or above this threshold size. We furthermore find evidence for the existence of two separate "centres of attraction" of farm size supporting the notion of a "disappearing middle" and the emergence of a bimodal structure of farm sizes. Correcting for size-related attrition bias had very little effect on our results.

1. Introduction

Agriculture in industrialised countries has undergone dramatic changes during the last century. Notable characteristics of this change are (a) the shrinking of the agricultural sector in terms of contribution to GDP, the share of agricultural employees and self employed in the whole labour force as well as the number of farms, and (b) the significant increase in farm productivity and average farm size.[1]

Obviously, the evolution of agriculture has important impacts on individual farmers. The rising size of a farm necessary to provide a reasonable level of farm income forces those with smaller holdings to expand beyond a single family operation, seek off-farm employment or exit from the agricultural sector altogether and thus constitutes a direct link between farm structure (structural change) and individual producer welfare.

But agricultural structure also affects societal welfare in a number of important ways. Larger farms may be more efficient and more inclined to adopt new technologies since they can apply it to a bigger resource base or spread its cost over more units of output. Cheap supply of food directly improves consumer welfare. On the other hand, there is also a significant debate about the effects of farm structure on the environment as well as the safety of food and food products (Atwood and Hallam, 1993). Furthermore, the decline in the number of farmers has been associated with a depopulation of the countryside which may have unfavourable effects with respect to tourism industry. Many current urban dwellers, for example, attach some value to rural areas as places to visit and enjoy nature and some of these activities are viewed of being more enjoyable in a countryside dotted with small well kept farms, as opposed to large industrialised farms. And finally, the size distribution of farms also has some implications for the political economy of agriculture in that operators of large farms may be more motivated and better able to lobby for economic support than operators of small farms.[2]

Studying changes in agricultural structure is interesting in its own right and furthermore may be helpful for policy makers in designing programs to direct changes towards desired ends. How the present farm structure has evolved and will continue to evolve over time constitutes the major purpose of this paper.[3] Do small businesses in the farm sector grow as fast as (or even faster than) large ones? Are there empirical trends crystallising from past performance of farms? What are the implications for the future size distribution of farms? In particular, we test a simple stochastic model which, in many other empirical studies,[4] has been found to explain many of the key aspects of firm (farm) size and growth. This model has that farm growth is determined by random factors that are independent of farm size (i.e. Gibrat's "Law of Proportionate Effects").

Final version accepted on October 10, 1996

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Small Business Economics **10**: 305–312, 1998.

In investigating this issue we make two advances compared to previous studies: First, we take advantage of a wide range of farm sizes in the data to test whether the Law of Proportionate Effects applies to all farm sizes. There is strong empirical evidence suggesting that returns to scale for small farms are much larger than those for medium and large farms (see for example Kumbhakar (1993) and the literature mentioned there). Under these circumstances, one would expect to find smaller farms to either die or adjust upwards rather quickly towards some minimum efficient scale of production while firms at or above the threshold scale have essentially stochastic growth characteristics. According to my knowledge, empirical evidence for the existence of threshold effects in the size-growth relationship for the farm sector is not available yet.[5]

Second, an empirical analysis of growth experience by size of farm, which focuses solely on the growth rates of surviving farms runs the risk of bias arising from sample attrition (Mansfield, 1962). Whereas declining large farms may simply slip downwards through the size distribution for a considerable length of time before exiting altogether, a smaller farm will hit the boundary of extinction much sooner. In any given time interval, therefore, declining small farms are less likely to remain as survivors than declining large farms. Hence growth rates by opening size class estimated on survivors only will, ceteris paribus, be biased towards finding relatively lower growth rates for the larger holdings. In the present paper we check for the impact of this sort of bias by reestimating our basic size-growth regressions within a maximum likelihood sample selection model framework utilising a probit analysis of survival by size of farm.

The rest of the paper is organised as follows: Section 2 discusses the empirical model and briefly describes the data used. The results of the econometric estimations are reported in Section 3. Finally, Section 4 presents the conclusions.

2. The empirical model and the data

Casual inspection of the data on farm sizes suggest that the size distribution is highly skewed, with a few large farms, rather more medium-sized farms and a large 'tail' of small farms. Such a size distribution is approximated by a number of related skew distributions, of which the lognormal and the pareto are the most familiar one. These forms arise if each farm faces the same distribution of growth possibilities, and each farm's actual growth is determined by a random sampling from that distribution. We can imagine this process of random growth of farms leading to a lognormal distribution to be made up of three effects (see equation (1)),

$$\frac{S_{i,t}}{S_{i,t-1}} = \alpha S_{i,t-1}^{\beta-1} \varepsilon_{i,t} \tag{1}$$

where $S_{i,t}$ is the size of farm i at time t. The first is a constant growth rate α (of the market) which is common to all farms. The second element is a systematic tendency for the growth of a farm to be related to its opening size. The effect of opening size on growth is determined by the value of β. The third element is a random growth term, $\varepsilon_{i,t}$, which again enters the growth equation multiplicatively. The specific case where $\beta = 1$ is known as "Gibrat's Law of Proportionate Effect", and implies that proportionate changes in size are independent of current size and past history. Farm size has no effect on farm growth. For $\beta > 1$, large farms grow faster than small ones, and vice versa for $\beta < 1$. The latter is termed 'regression': the tendency for a variate to return to the mean size of the population.[6]

Two facts about this model are remarkable: its parsimony and its lack of economics. Several authors have tried to add economics to this model in particular by exploring the implications of the assumption that managers are heterogeneous (see Lucas, 1978, and Jovanovic, 1982) as well as considering the fact that capacity and technology choices involve some degree of sunkness (Cabral, 1995). These models point to a number of socio-economic variables influencing firm performance and moreover provide a theoretical explanation for a relation between size and growth. Testing of Gibrat's Law remains as an important point of departure for the analysis of farm growth.

Stochastic models of firm growth have been subjected to two kinds of empirical tests: the first is to see how closely actual size distributions of firms confirm to the lognormal distribution. This approach has been applied to agricultural holdings in England and Wales by Allanson (1992) who concludes that "the lognormal model provides a satisfactory fit to grouped frequency data on the truncated range of the distributions of holdings and farmland by size of holding" (p. 147). The power of this kind of test however is low, since the relationship of growth rates to size is not explicitly investigated.

The second approach to empirical work in this area is to investigate the relationship of growth and size in a panel of farms.[7] Taking natural logarithms and rearranging terms in equation (1) we get equation (2) (which constitutes a random walk with drift):

$$\ln S_{i,t} = \alpha + \beta \ln S_{i,t-1} + u_{i,t} \qquad (2)$$

where $u_{i,t} = \log \varepsilon_{i,t} \sim N(0, \sigma^2_{\varepsilon,t})$. Econometric estimations of equation (2) for surviving farms in Canada (Shapiro, Bollman and Ehrensaft, 1987) report parameter estimates of $\beta < 1$, which rejects Gibrat's Law and suggests that small farms do grow faster than large farms. However, this second approach, which often focuses solely upon the growth rates of surviving farms runs the risk of bias arising from sample attrition.[8] The appropriate econometric method to avoid this problem is the two-step method suggested by Heckman (1979) which introduces an additional explanatory variable (the inverse Mill's Ratio) obtained from a probit model on farm survival in the least squares regression for surviving farms (2).[9]

Measurement of farm size is not a trivial issue. Output measures, such as gross farm sales, are not available and moreover would be unsatisfactory because of the effects of inflation and changes in relative prices (Gardner and Pope, 1978). The two (input) measures of farm size used in the present study are acres under cultivation and the number of livestock (measured in "Großvieheinheiten").[10] Due to the fact that farms are characterised by a non-linear production technology and changes in farm size typically involve changes in factor proportions and changes in technology, none of these input measures can fully describe farm size and the process of farm growth. Despite this weakness, "input measures . . . , which gauge productive capacity, may come nearer to being good indicators of size that those measured by value of output" (Garcia et al., 1987). An extensive discussion of the problems of adequately measuring farm size is available in Hallam (1993).

The empirical approach in the present paper utilises a panel of more than 40,000 farm households for three years, 1979, 1986, and 1990. Our sample covers all Upper Austrian farms with holdings of more than half a hectare, in 1980 the acreage limitation was increased to 1 hectare.[11] In what follows, we analyses size, growth, and survival of farms in the more recent 1986–90 time period by utilising livestock as our measure of farm size. The results when using the alternative measure of farm size (acres under cultivation) will be described briefly at the end of the following section. Analysing the 1979 to 1990 time period does not provide important additional information, the results, which are very similar to those reported here, are available from the author upon request.

Table I provides an analysis of the vital statistics of our sample in the period 1986 to 1990 by splitting the size distribution of farms into 9 different size classes, which have been defined so that the number of farms in each size class is approximately the same. It shows the size distribution of farms in 1986 and then traces their growth to 1990.

Table I shows that of the 43,685 farms in 1986, 39,898 (91.3 %) survived to 1990 and 3,787 did not survive. The very smallest had the lowest survival rate (63.8 %) and the farms in class [8] had the highest survival rate (98.1 %). Of the survivors 22,904 (57.4 %) remained in the same size class, although this in part reflects the fact that 2,175 (651) of them were already in the largest (smallest) size class and could not be promoted (demoted). Of the remaining survivors the majority (9,609 or 24.1%) moved up whereas 7,385 (18.2%) farms moved down one or more size classes. The average annual growth rates of surviving farms and the standard deviation of growth rates for each size class is reported in the final columns of Table I. As expected we find growth rates within each size class to be highly variable.[12] In addition, there is also considerable variation in average growth rates between size classes. The most dynamic farms are the very smallest ones reporting a mean annual growth rate of 40.3%. Although this estimate is clearly influenced by the extreme performance of some farms it is nonetheless substantially higher than the estimates in any other group.

TABLE I
Size, growth and survival of farms 1986–90

Size	All farm (in 1986) No.	Survivors											Average annual growth rate	Std. Dev.
		No.	(in %)	0,1<1 [1]	1,1<3 [2]	3,1<6 [3]	6,1<10 [4]	10,1<15 [5]	15,1<21 [6]	21,1<28 [7]	28,1<36 [8]	>36 [9]		
[1] 0,1<1	2,027	1,293	(63.8)	651	401	142	43	22	21	4	1	8	40.3	52.6
[2] 1,1<3	4,425	3,470	(78.4)	666	1,994	647	63	33	24	21	14	8	–1.1	23.5
[3] 3,1<6	7,508	6,605	(87.9)	452	978	4,092	947	78	22	8	9	19	–2.8	16.3
[4] 6,1<10	6,155	5,702	(92.6)	179	194	892	3,334	929	115	34	11	14	–1.7	13.7
[5] 10,1<15	5,878	5,593	(95.2)	95	87	150	759	2,962	1,295	185	32	28	–0.4	12.2
[6] 15,1<21	6,056	5,868	(96.9)	61	36	52	142	711	3,011	1,567	230	58	0.3	10.3
[7] 21,1<28	5,333	5,210	(97.7)	21	9	18	36	87	661	2,768	1,417	193	0.9	7.6
[8] 28,1<36	3,597	3,527	(98.1)	8	2	7	14	16	75	522	1,917	966	0.6	6.6
[9] >36	2,706	2,630	(97.2)	5	6	5	6	10	14	80	329	2,175	–0.24	7.2
All farms	43,685	39,898	(91.3)	2,138	3,707	6,005	5,344	4,848	5,238	5,189	3,960	3,469	0.6	17.7

3. Results

Our analysis of the relationship between growth and size of farms consists of a series of tests of the null hypothesis embodied in the Law of Proportionate Effect which states that the rate of farm growth is independent of the opening size of the farm. The null hypothesis of no relationship embodied in the Law of Proportionate Effect implies an estimated value of $\beta = 1$ in equation (2). Table II reports the results of estimating equation (2).

According to column [1] of Table II, which reports the results of the OLS estimation of farm size in 1990 on farm size in 1986 for all farms, the parameter estimate for β_1 is less than unity indicating that small farms grow faster than larger ones. The statistical tests clearly reject the null-hypothesis of $\beta_1 = 1$.[13] Whether the OLS-estimates are biased due to serially correlated residuals or due to size related sample attrition (or both) is investigated in the following three columns [2 to 4]. The results reported in column [2] are based on an OLS-estimation of Chesher's (1979) specification ($\ln S_{i,90} = \beta_0 + \beta_1 \ln S_{i,86} + \beta_2 \ln S_{i,79} + u_{i,t}$) and again imply rejection of Gibrat's Law. Given the estimated values of β_1 and β_2 in Table II, estimates for β (from equation (2)) and r (first-order serial correlation term) can be computed from $(\beta, r) = (1/2)[\beta_1 \pm (\beta_1^2 + 4\beta_2)^{1/2}]$. The calculated parameter estimate for β (0.963), although larger than in column [1], is still clearly below unity.

Sample attrition bias may in principal affect our results (in columns [1] and [2]) because of the greater likelihood that smaller farms will leave the sample than larger farms, ceteris paribus. To allow for such sample attrition bias we re-estimate both equations in a sample selection framework described above. Note that if the disturbances of the survival equation and the farm size equation are uncorrelated ($\rho = 0$), the parameter estimate for β will not be biased even though size may still be a predictor of survival. This is exactly what we observe in columns [3] and [4]. The top half of the table shows the estimates of a very simple probit equation describing the relationship between size and the probability of survival. This model suggests a significant positive impact of farm size on the probability of survival. However, the sample selection terms (ρ) in the size equations (columns [3] and [4]) are small and not statistically significant. The parameter estimates for β, although again somewhat higher than in columns [1] and [2] are still significantly below unity. We thus conclude, that our previous result suggesting that small farms grow faster than large farms is not an artefact of sample selection bias.[14]

So far we have only tested Gibrat's Law for our sample as a whole. Increasing returns to scale up to some threshold level at or above which the returns to scale are constant (as suggested by Simon and Bonini, 1958) would however suggest that our previous results are not stable *within* various size classes. In particular we would expect

TABLE II
The relationship between size, growth, and survival in Upper Austrian farms 1986–90

Equations: $P(d_i = 1) = F[\alpha_0 + \alpha_1 \ln S_{i,86}] + v_{i,t}$ where $d_i = \begin{cases} 1 & \text{survivor 1986–90} \\ 0 & \text{non-survivor} \end{cases}$

$\ln S_{i,90} = \beta_0 + \beta_1 \ln S_{i,86} + \beta_2 \ln S_{i,79} + \beta_3 \ln S^2_{i,86} + \beta_4 \ln S^3_{i,86} + u_{i,t}$

Estimation method:		OLS [1]	OLS [2]	Sample selection [3]	Sample selection [4]	Sample selection [5]
Dependent variable: Probability of survival						
Intercept	α_0			–1.059 (–22.92)	–1.108 (–23.20)	–1.012 (–23.17)
$\ln S_{i,86}$	α_1			0.376 (51.75)	0.385 (51.26)	0.368 (53.44)
Dependent variable: Log of farm size in 1990						
Intercept	β_0	0.473 (11.94)	0.250 (6.29)	0.416 (3.25)	0.198 (1.59)	7.921 (1.44)
$\ln S_{i,86}$	β_1	0.926 (170.51)	0.837 (52.78)	0.933 (56.59)	0.844 (50.77)	–2.515 (–2.09)
$\ln S_{i,79}$	β_2		0.121 (7.34)		0.120 (29.33)	
$(\ln S_{i,86})^2$	β_3					0.498 (6.91)
$(\ln S_{i,86})^3$	β_4					–0.023 (–23.13)
Calculated β			0.963		0.968	
Calculated r			0.126		0.124	
Sigma	σ			0.720 (201.98)	0.709 (225.64)	0.685 (457.34)
Rho	ρ			0.089 (0.54)	0.084 (0.53)	0.001 (0.01)
Log Likelihood		–43,473.2	–42,412.5	–54,786.0	–53,315.0	–52,853.0
LRT		43,510.8	43,921.0	46,643.3	47,007.9	50,509.3
BP		16,065.7	15,413.8			
t-test ($\beta_1 = 1$)		–13.55	–10.26	–4.05	–9.34	
Wald-test (χ^2)		183.50	155.17	16.39	863.23	

Remarks: Numbers in parentheses are t-values, which are heteroscedastic-consistent estimators following the method of White (1980). LRT = likelihood-ratio test. BP = Breusch-Pagan test. F is the cumulative probability function.

to find parameter estimates for β which are significantly below unity for the group of farms below this threshold scale (smaller farms would grow faster towards the minimum efficient scale of production) but would expect opening size to be unrelated to farm growth (i.e. Gibrat's Law to hold) for medium-sized or large farms. Accordingly, the assumption of a linear size-growth relationship is clearly rejected. Model [5] in Table II reports highly significant parameter estimates for $(\ln S_{i,86})^2$ and $(\ln S_{i,86})^3$. For the sake of easier interpretation of these results, we plot the relationship between farm size and farm growth according to model [5] in Figure 1.

We observe a negative relationship between initial farm size and farm growth for the group of small (below threshold size $\underline{S}$) and the very largest farms (above threshold size $\overline{S}$). This suggests that within these two groups smaller farms are growing faster than the large ones implying a tendency for farms to regress towards a "centre of attraction" in each of the two subsamples of large and small farms. These "centres of attraction" are defined as the intersection of the growth path with the zero-growth line. The most surprising result shown in Figure 1 however concerns the medium-sized

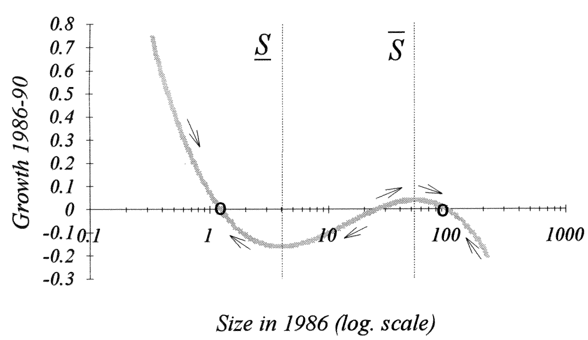

Fig. 1.

farms (between $\underline{S}$ and $\overline{S}$). In this size class the calculated growth path has a positive slope and larger farms grow faster than smaller ones. Thus, the medium-sized farm class is an "unstable class" in that larger farms are growing and will move towards the next higher size class whereas the smaller farms are declining and will eventually move down into the smallest size class. These significant non-linearities in the growth path of farms observed in the present study cast some doubt upon empirical studies assuming a linear size-growth relationship over the entire spectrum of farm sizes. Our results suggest the existence of threshold effects and provide some support for the notion of a "disappearing middle" in the Upper Austrian farm sector (bi-modal distribution).[15]

These results were confirmed by a number of estimation experiments for various subsamples. Estimating equation (2) separately for each of the nine size classes defined in Table I shows the same pattern for estimates of β. The estimated parameter is significantly below unity for size classes [1], [2] and [9] and significantly above unity for medium-sized farms (size classes [3] to [6]). In the size classes [7] and [8], β is not significantly different from unity at the 5% level. These results, which are also available upon request, again suggest the existence of two "centres of attraction" of farm size.

Using area under cultivation as our measure of farm size does not modify these results significantly. The negative relationship between initial size and farm growth turns out to be weaker, which is consistent with the observation that economies of scale are more important for livestock farms than for crop production activities (Hallam, 1993).

Of course the location of the two "centres of attraction" on the size scale in Figure 1 will depend on a number of additional factors influencing farm growth. Due to the fact that the present analysis does not take into account various socio-economic factors influencing farm performance (such as age and human capital of the farm operator, regional factors, size and structure of the farm family, . . .), our results should be interpreted as pointing to an empirical trend rather than fully describing an economic adjustment process. A more detailed analysis of the impact of farm and household characteristics on farm size and growth is, however, beyond the scope of the present paper.[16]

4. Conclusions

The goal of this paper was to study the evolution of the size distribution of farms in the Upper Austrian farm sector empirically. Using Gibrat's Law as our point of departure, we find that growth rates are not independent from initial farm size as assumed by Gibrat's Law. In particular, smaller farms are found to grow much faster towards some minimum efficient scale of production than farms at or above this threshold size. A more detailed analysis of medium-sized to large farms gives some evidence for the existence of a second threshold size, which, together with the above mentioned observation would suggest the existence of two separate "centres of attraction" of farm size. This gives some support to the notion of a "disappearing middle" and the emergence of a bimodal structure of farm sizes in the Upper Austrian farm sector. Correcting for size-related attrition bias had very little effect on our results.

However, it is important to note that the present analysis does not take into account factors influencing farm performance other than initial farm size. The fact that we focus on this very narrow aspect (as it is suggested by Gibrat's Law) does not imply, that we regard all other influences as negligible. Instead, we consider our results as a starting point for further detailed analysis of the social dynamics which condition individual and group responses in a sector where small businesses are an essential element of the economic environment.

Acknowledgements

I wish to thank Ernst Fürst for providing the data and Paul Allanson, Michael Pfaffermayr, the participants of a EAAE seminar at Ancona and three anonymous referees for constructive comments on an earlier version of this paper.

Notes

1 This can be illustrated briefly in case of Austria. During the second half of this century, gross domestic product originating in the farm sector fell form 16.11% in 1954 to

2.28% 1993, the percentage of labour force employed in agriculture even dropped from 30.3% to 5.2% during the same period and the number of farms dwindled from 396,530 in 1960 to 267,444 in 1993 (by 32.6%). At the same time, the index of farm output per man hour rose from 58.9 in 1960 to 296.9 in 1993 using 1970 = 100 as a base and average farm size increased from 19.4 ha per farm in 1960 to 28.1 ha in 1993.

[2] In many countries, payments from government commodity programs tend to be disproportionally concentrated on larger farms.

[3] Despite the importance of this topic, theoretical and empirical research into the evolution of farm structure and structural change is comparatively limited. This may be due to the fact that theoretical models strictly based on standard cost theory are not able to explain the 'stylised facts' of farm structure and structural change, in that "the theory either predicts the facts incorrectly or makes no predictions al all" (Ijiri and Simon, 1977). The reasons for the lack of empirical work on farm structure and structural change are discussed in Allanson (1992).

[4] The validity of Gibrat's Law for manufacturing industries has been extensively tested (see Evans, 1987, for the U.S., Wagner, 1992, for Germany, and Dunne and Hughes, 1994, for the U.K.).

[5] The existence of threshold effects in the size-growth relationship has first been suggested by Simon and Bonini (1958), empirical evidence has recently been provided for U.K. business firms by Dunne and Hughes (1994).

[6] In addition, the value of β has important implications for the development of market concentration if the distribution of farms is approximately lognormal. The outcome of the stochastic process described in (1) with $\beta = 1$ is a random walk where the variance of farm size increases steadily over time. Hence, concentration in the farm sector increases over time. More details on the interpretation of β with respect to the convergence or divergence of a population can be found in Friedman (1992).

[7] A summary of empirical studies for the non-farm sector is available in Wagner (1992).

[8] Additional econometric issues, such as serial correlation and growth persistence as well as size related heteroscedasticity have also been investigated, the results are reported in an Appendix which is available upon request.

[9] The Heckman estimator is consistent, albeit not fully efficient. Efficient estimates can be obtained by applying an iterative procedure which uses the estimates from the Heckman procedure as starting values and will lead, on convergence, to the maximum likelihood estimates (see Maddala, 1983, p. 222f).

[10] This measure, which is used as the pivotal measure of size in livestock farming in the official statistics aggregates different types of animals according to their live weight into a single index.

[11] A detailed description of the data is available in Fürst (1993).

[12] Table I reports an inverse relationship between size and the standard deviation of growth rates suggesting that the residuals of an OLS estimation of (2) are unlikely to be homoscedastic. All statistical tests reported below are thus based on standard errors obtained from White's (1980) heteroscedasticity consistent estimator.

[13] Hypothesis testing based on the t-statistic may involve two different problems here. First, it has been pointed out that classical hypothesis testing at a fixed level of significance increasingly distorts the interpretation of the data against the null hypothesis as the sample size grows. A good treatment of this phenomenon is found in Leamer's 1978 book (chapter 4). In the present case, the high values for the Wald-tests reported in Table II still suggest rejection of Gibrat's Law when using higher critical values for the Test-statistics as suggested by Leamer. Secondly, we mentioned above that statistical tests of Gibrat's Law involves examining whether the hypothesis of a random walk can be rejected or not. In time series terminology, this requires testing whether the farm size series contains a unit root. Since the underlying process is non-stationary, the asymptotic theory set out for stationary models does not apply. The limiting distribution is not normal and an alternative "t-statistic", tabulated by Dickey, has to be used. In the present case, the unit root test is more complicated than in time-series models since our data only include a very short time-series dimension (T) but a very rich cross-section dimension (N). In a recent paper, Quah (1994) has shown that the asymptotic distribution derived for panel data can be understood as a mixture of the standard normal and the Dickey asymptotics. His tabulations of the distribution from Monte Carlo simulations reveals that the critical points for the case of a large N and a small T are very close to those obtained from the standard normal.

[14] While caution is always advisable in distinguishing sample selection from non-linearities (see Maddala, 1983, p. 271), sensitivity tests suggest that the lack of correlation between the survival and the farm size equation is robust to alternative assumptions concerning sample censoring and non-linearities. Specifying a richer empirical model in order to "explain" the observed exit behaviour of farmers in more detail is however beyond the scope of the present paper. The determinants of farm exits are investigated in Weiss (1996).

[15] See Munton and Marsden (1991) for an extensive discussion of this "dualist thesis" of structural change in advanced agriculture.

[16] An interesting issue for future research would be to investigate, whether these two "gravitation points" of farm size might be related to the distinction between full- and part-time farmers in our sample. Different forms of farm organisation are unlikely to have an identical "optimal" level of farm size but would rather correspond to different "centres of attraction" of farm size (see Schmitt, 1993).

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