

GIBRAT'S LAW REVISITED IN A TRANSITION ECONOMY. THE HUNGARIAN CASE

LAJOS ZOLTÁN BAKUCS

research fellow, Institute of Economics, Hungarian Academy of Sciences, H-1112, Budapest,
Budaörsi út 45. Email: bakucs@econ.core.hu

IMRE FERTŐ

senior research fellow, Institute of Economics, Hungarian Academy of Sciences, H-1112,
Budapest, Budaörsi út 45. Email: ferto@econ.core.hu



Paper prepared for presentation at the joint IAAE- 104th EAAE Seminar

Agricultural Economics and Transition:

**„What was expected, what we observed,
the lessons learned.”**

Corvinus University of Budapest (CUB)

Budapest, Hungary. September 6-8, 2007

Copyright 2007 by Lajos Zoltán Bakucs and Imre Fertő. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

ABSTRACT

The paper investigates the validity of Gibrat's Law in Hungarian agriculture. Employing various specifications including OLS, two-step Heckman model and quantile regressions our results strongly reject Gibrat's Law for full sample. Estimations suggest that small farms tend to grow faster than larger ones. However, splitting the sample into two subgroups (corporate and family farms) we found different results. For family farms however, only OLS regression results reject Gibrat's Law, whilst the two-step Heckman models and quantile regression estimates support it. Finally, for corporate farms our results support the Law regardless of the method or size measure used. Our results indicate that there is no difference between family farms and corporate farms according to the growth trajectory.

Keywords: Gibrat's Law, selection bias, quantile regression, transition agriculture

1. INTRODUCTION

There is a continuously growing literature on the agricultural transformation in Central and Eastern European countries (see survey BROOKS and NASH 2002; ROZELLE and SWINNEN 2004). The research has focused on various aspects of transition, including land reform, farm restructuring, price and trade liberalisation and etc. All these economic policy issues have a significant influence upon farm growth in any country. Because of the inherent instabilities associated with the transition period, and the relatively short time (in most Central Eastern European countries the dismantling of the centralised economic structures began only 15 - 16 years ago) farmers had to acquire much needed farm management skills, farm growth rates in a transition economy are expected to be more profoundly influenced by the economic environment. Most of the empirical studies on the farm growth and survival rates use GIBRAT's (1931) as a theoretical departure point in their analysis. Gibrat's Law of Proportionate Effect states that firm growth is a stochastic process resulting from many unobserved random variables; therefore the growth rate of firms (farms) is independent of their initial size at the beginning of the period. The purpose of this paper is to investigate whether Gibrat's Law holds for various subpopulations of Hungarian farms. The farm structure in developed market economies where all similar studies were set is very different from that in the transition economies. The proportion of small farms in transition economies in general, and in Hungary in particular, is much higher, thus this empirical research provides new insights into the farm growth literature. This paper is organised as follows: section 2 presents the theoretical background, section 3 discusses the methodology employed, section 4 presents the dataset and the empirical analysis, and finally, section 5 concludes.

2. LITERATURE REVIEW

Although there is a wealth of literature on whether Gibrat's Law holds on various agricultural sectors, to date no one has studied the law of proportionate growth in a transition economy. Most of the literature (see the recent reviews of SUTTON, 1997 and LOTTI et al., 2003) focuses on the growth of firms and to a lesser extent on the growth of farms. Most studies are limited on testing whether Gibrat's Law holds in a given sector or industry. The empirical research considering the agricultural sector, yielded rather contradictory results. WEISS (1999) focusing on part and full time farms in Upper Austria rejected Gibrat's Law, and found that 'age, schooling and sex of the farm operator, size of farm family, and off-farm employment as well

as initial farm size, significantly influence farm growth and survival'. SHAPIRO et al. (1987) analysed the growth of Canadian farms using census data, and conclude that Gibrat's Law does not hold, that is, small farms tend to grow faster than large ones. On the other hand, UPTON and HAWORTH (1987) using British Farm Business Survey data, BREMMER et al. (2002) using Farm Accountancy Data Network (FADN) data for Netherlands and KOSTOV et al. (2005) using farm census and structural survey data for dairy farms in Northern Ireland, found no evidence (except for the small farms in the case of KOSTOV et al.) to reject Gibrat's Law.

An important issue in the farm growth studies, is the way, the farm size is defined. These include: acreage farmed, livestock number, total capital value, gross sales, total gross margin and net income. Output value measures however, are subject to inflation, and changes in relative prices. The use of physical input measure may also cause difficulties, since farms are characterised by a non-linear production technology, this changes in size involve changes in the mix and proportions of inputs used.

3. METHODOLOGY

The simplest way to test Gibrat's law is to run an OLS regression, and test the β_1 coefficient associated with the logarithm of the lagged farm size (equation 1):

$$\log S_{i,t} = \beta_0 + \beta_1 \log S_{i,t-1} + \varepsilon \quad (1)$$

where $S_{i,t}$ is the size of farm i at time t , $S_{i,t-1}$ is the size of farm i at the previous period, and ε is a random variable, independent of $S_{i,t-1}$. If $\beta_1 = 1$, then growth rate and initial size are independently distributed and Gibrat's Law holds. If the coefficient is smaller than one, it follows that small farms tend to grow faster than large farms. On the other hand, a coefficient larger than one, means that larger farms grow faster than smaller farms do. The OLS analysis however is only capable to test whether Gibrat's Law holds globally for all farms, regardless of their size. Following KOSTOV et al., (2005) we employ modern quantile regression methods in order to distinguish between farms of different sizes. An important issue in the empirical analysis is the sample selection problem. Since growth rate is only possible to be measured for surviving farms (still operating in period t), and since slow growing farms are most likely to exit, it is easy to see that small, fast growing farms can easily be overrepresented in the sample, thus introducing bias in the results. This problem is of a particular importance in the present paper, since the proportion of small farms in transition economies in general, and in Hungary in particular, is much higher than in developed economies. HECKMAN (1979) introduced a two-step procedure to control for the selection problem. In step one, a farm survival model for the full sample (both surviving and exiting farms) is estimated, using a probit regression. This equation is used to obtain a variable, the inverse of Mill's Ratio for each observation (equation 2):

$$P(f_i = 1) = F(\delta + \gamma \log S_{i,t-1} + \varphi \log S_{i,t-1}^2 + \mu) \quad (2)$$

where $f_i = 1$ denotes survivor, $f_i = 0$ exit, and μ is the disturbance.

In the second step, this additional variable is introduced as a correcting factor into the quantile regression based on a sample that contains only the surviving farms.

The BIERENS and GINTHER's (2001) Integrated Conditional Moment (ICM) test is used to test the appropriateness of the quintile regression models' functional form.

4. EMPIRICAL ANALYSIS AND RESULTS

4.1. Data

The analysis is based on Hungarian Farm Accountancy Data Network (FADN) private farms database. In 2005, the Hungarian FADN system data were collected from 1940 farms above 2 European Size Units based on representative stratified sampling according to four criteria: legal form, farm size, production type and geographic situation. The database contains data of 1546 private farms and of 394 economic organizations, but the number of common observations decreased to 781 farms between 2001 and 2005. Empirical studies usually face the problem of farms exiting the business between the two time points. Dropping these farms from the sample introduces a sample selection bias against the small farms, which are most likely to exit. This issue may be crucial for Hungarian farm structure by dominating a large number of small farms. The farm size is measured by number of farm input or output variables, including total capital value, net income, gross sales, total gross margins, livestock numbers, and acreage farmed. In order to obtain robust results, we use 4 different measures of farm size: acreage, net total revenues, total capital and total labour. Net total revenue and total capital variables were deflated to 2000.

4.2. Empirical results

We present our results in following steps. First, closely related to farm growth issues is the bimodal farm size distribution hypothesis (see WOLF and SUMNER, 2001). The market economy institutions and structures in Hungary have fully developed by 2001 thus we test using Kernel density functions whether a shift towards a bimodal farm structure has taken place by 2005. Figure 1 shows that Kernel density function moved to right indicating a slight concentration in farm structure during analysed period, but the bimodality of Hungarian farm structure can be rejected independently from measures of size.

Second, we test the Gibrat's Law employing various specifications including simple OLS estimates, two-step Heckman selection model and quantile regressions. Tables 1, 3 and 4 present OLS, two-step Heckman and quantile regression estimates for the total population, family and corporate farms, according to the various size measures used (labour, land, capital, net sales). Third and fourth row of each table presents estimates of the β_0 and β_1 coefficients (see equation 1). Then the $\beta_1 = 1$ null hypothesis (i.e. Gibrat's Law holds) is tested. Rows 6 and 7 of each table present the number of surviving and the number of total farms. Finally, the regression coefficient of determination is shown in the last row. β_0 and β_1 estimates are generally significant, and the R^2 coefficients show that the regressions explain a relatively large part of the variation in the dependent variable. Regardless of the estimation procedure, empirical results provide strong evidence against Gibrat's Law for total sample. In eleven of twelve specifications estimates of β_1 significantly different from zero, and significantly less than one. This confirms that in general smaller farms grow faster than larger farms. Table 2 shows the mean value of various size measures for family, corporate and total farms. Data reveal that the size of family farms is smaller than corporate farms. Interestingly, the average land size and number of labour decreased for corporate farms between 2001 and 2005. Empirical literature emphasise that smaller firms grow faster than larger firms, especially for small newborn firms (LOTTI et al. 2003). One may argue that the growth paths of family and corporate farms are different. Thus, we divide the full sample into two separate groups: family and corporate farms and re-estimate the models by organisation forms.

Compared with the full sample, the picture is more mixed for the family and corporate farms (Tables 3 and 4). For family farms, OLS regression estimates of β_1 are significantly smaller than unity, rejecting Gibrat's Law. Two-step Heckman and quantile regression estimates of β_1

however, are not significantly different from 1, supporting Gibrat's Law. This again provides empirical support for the hypothesis that OLS regression estimates are biased towards the small, fast growing farms, and thus they reject more often Gibrat's Law. In eleven out of twelve cases, β_l regression estimates for corporate farms (Table 4), support the law of proportionate effects.

Third, a useful tool to illustrate the β_l quantile regression estimates, is to plot the coefficient value across the range of quantiles. Figure 2 presents quantile regression estimates along with 95% confidence intervals by size measures and organisational groups. Whenever the confidence intervals include the value of 1, Gibrat's Law holds. Graph results are in line with tables 1, 3 and 4. For all farms, Gibrat's Law is rejected. If family and corporate farms are taken separately, the unity is generally comprised in the 95% confidence intervals.

Finally, we estimate the ICM test statistics to check the appropriateness of the quantile regressions' functional form. Because of the considerable computational burden of estimating ICM statistics, Table 5. presents estimates for the 0.50 quantile only. Several c values are used, since the ICM test statistics is actually a ration of 2 probability measures estimated over a hypercube, whose dimensions are $2c$. Asymptotically, any choice of c is equivalent, however the choice of c has strong influence on the small sample properties (see KOSTOV et al., 2005; BIERENS and GINTHER, 2001 for further details on the test). None of the test statistics computed for the four size measures is significant at 5%, supporting the estimated quantile regression and its conclusions.

5. CONCLUSIONS

In this paper we analyse the concentration process in the Hungarian farms sector, and test the validity of the Law of Proportionate Effects (Gibrat's Law) for Hungarian farms between 2001 and 2005, using four different measures of size. Previous studies found that Gibrat's Law holds when larger farms, but fails to hold when smaller farms are considered. This is mostly due to methodological and sample issues. We used OLS and two additional methods to overcome the bias introduced by small and exiting farms. Our results strongly reject Gibrat's Law if all farms (corporate and family) are considered together, regardless of the size measure used. In line with previous studies our estimations suggest that small farms tend to grow faster than larger ones. However, splitting the full sample into two subgroups yields different results. For family farms however, only OLS regression results reject Gibrat's Law, whilst two-step Heckman and quantile regression estimates support it. Finally, for corporate farms, the Law holds regardless of the method or size measure used. Apart from testing whether Hungarian farms grow independently of their initial size, our study also emphasises the importance of the applied methodology in getting sound results. Our research contributes in some aspects to family farm debate. RIZOV and MATHIJS (2003) using cross section data show that older and larger farms are more likely to survive, farm growth decreases with farm age when farm size is held constant and that learning considerations are important. Our estimations indicate that when farm structure is already stabilised there is no difference between family and corporate farms in terms of growth. However, further research is needed to identify factors explaining the survival and growth across farm types.

ACKNOWLEDGEMENTS

Lajos Zoltán Bakucs is grateful for the financial supports to the József Öveges Scholarship.

REFERENCES

- BIERENS, H.J., GINTHER, D.K. (2001): Integrated Conditional Moment Testing of Quantile Regression Models. *Empirical Economics*, Vol. 26, pp. 307 – 324.
- BREMMER, J., OUDE LANSINK, A.G.J.M., OLSON, K.D., BALTUSSEN, W.H.M. AND HUIRE, R.B.M. (2002): Analysis of farm development in Dutch agriculture and horticulture. Paper presented at 13th Congress of International Farm Management Association (IFMA), Wageningen, The Netherlands, 7 – 12 of July.
- BROOKS, K., NASH, J. (2002): The Rural Sector in Transition Economies. In: GARDNER, B. AND RAUSSER, G.C. (eds.). *Handbook of Agricultural Economics*. Vol. 2A. Amsterdam: North-Holland, pp.1547-1592.
- GIBRAT, R. (1931): *Les Inegalites Economiques*. Librairie du Recueil Sirey. Paris.
- HECKMAN, J.J. (1979): Sample selection bias as a specification error. *Econometrica*, Vol. 47(2), pp. 153 – 161.
- KOSTOV, P. M. PATTON, S. MCERLEAN, J. MOSS (2005): Does Gibrat's law hold amongst dairy farmers in Northern Ireland?, paper presented at EAAE 11th Congress, Copenhagen, 24-27 August.
- LOTTI, F., SANTARELLI, E., VIVARELLI, M. (2003): Does Gibrat's Law hold among young, small firms? *Journal of Evolutionary Economics*, Vol. 13(3), pp. 213 – 235.
- RIZOV, M., MATHIJS, E. 2003. Farm Survival and Growth in Transition Economies: Theory and Empirical Evidence from Hungary. *Post-Communist Economies*, Vol. 15 (2) pp. 227-242.
- ROZELLE, S. SWINNEN, J.F.M. (2004): Success and Failure of Reform: Insights from the Transition of Agriculture. *Journal of Economic Literature*, Vol. 42 (2), pp. 404-456.
- SHAPIRO, D., BOLLMAN, R.D., EHRENSAFT, P. (1987): Farm size and growth in Canada. *American Journal of Agricultural Economics*, Vol. 69, pp. 477 – 483.
- SUTTON, J. (1997): Gibrat's Legacy. *Journal of Economic Literature*, Vol. 35, pp. 40 – 59.
- UPTON, M., HAWORTH, S. (1987): The growth of farms. *European Review of Agricultural Economics*, Vol. 14, pp. 351 – 366.
- WEISS, C.R. (1999): Farm Growth and Survival: Econometric Evidence for Individual Farms in Upper Austria. *American Journal of Agricultural Economics*, Vol. 81, pp. 103 -116.
- WOLF, C.A., SUMNER, D.A. (2001): Are Farm Distributions Bimodal? Evidence from Kernel Density Estimates of Dairy Farm Distributions. *American Journal of Agricultural Economics*, Vol. 83(1), pp. 77 – 88.

Figure 1 Kernel density function by measure of size

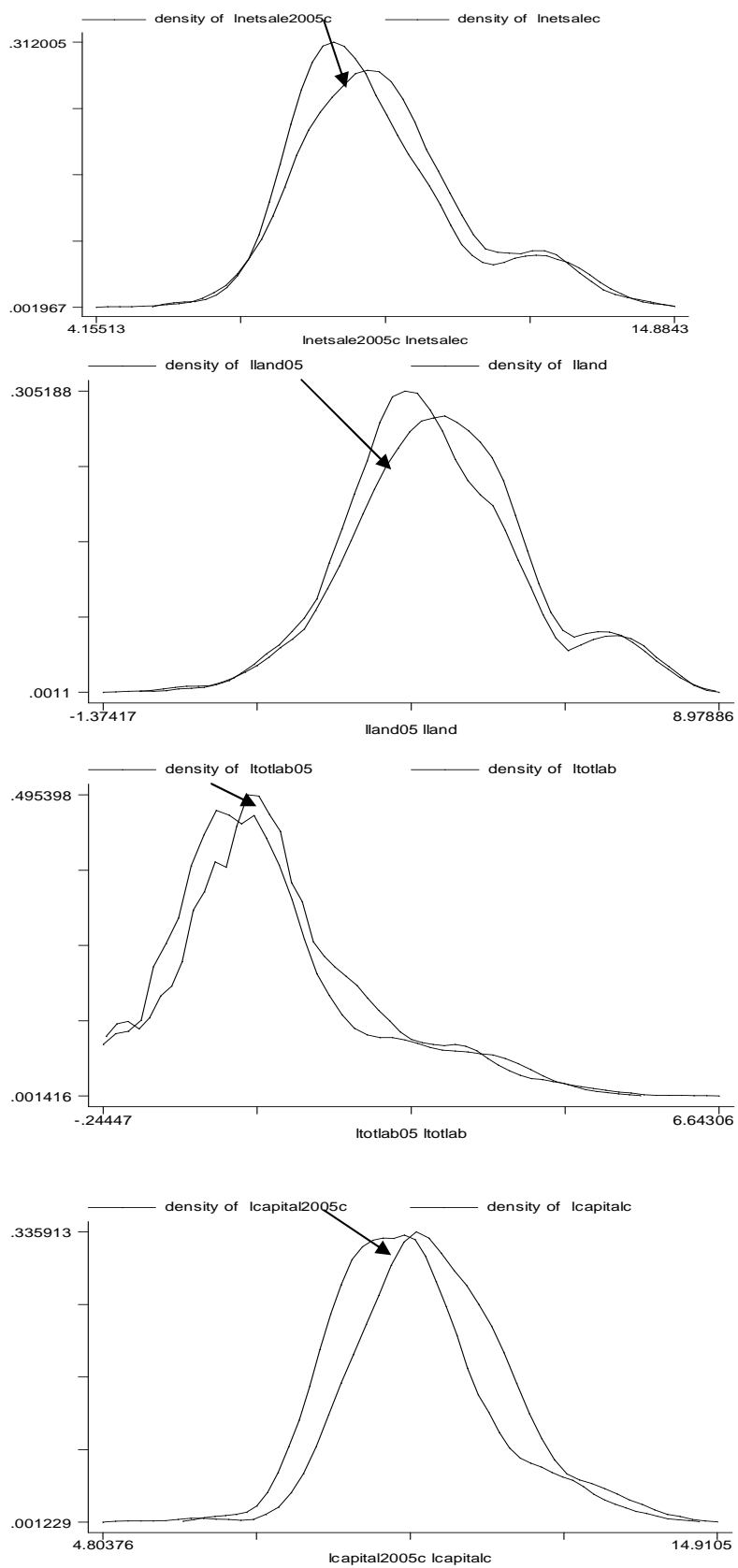
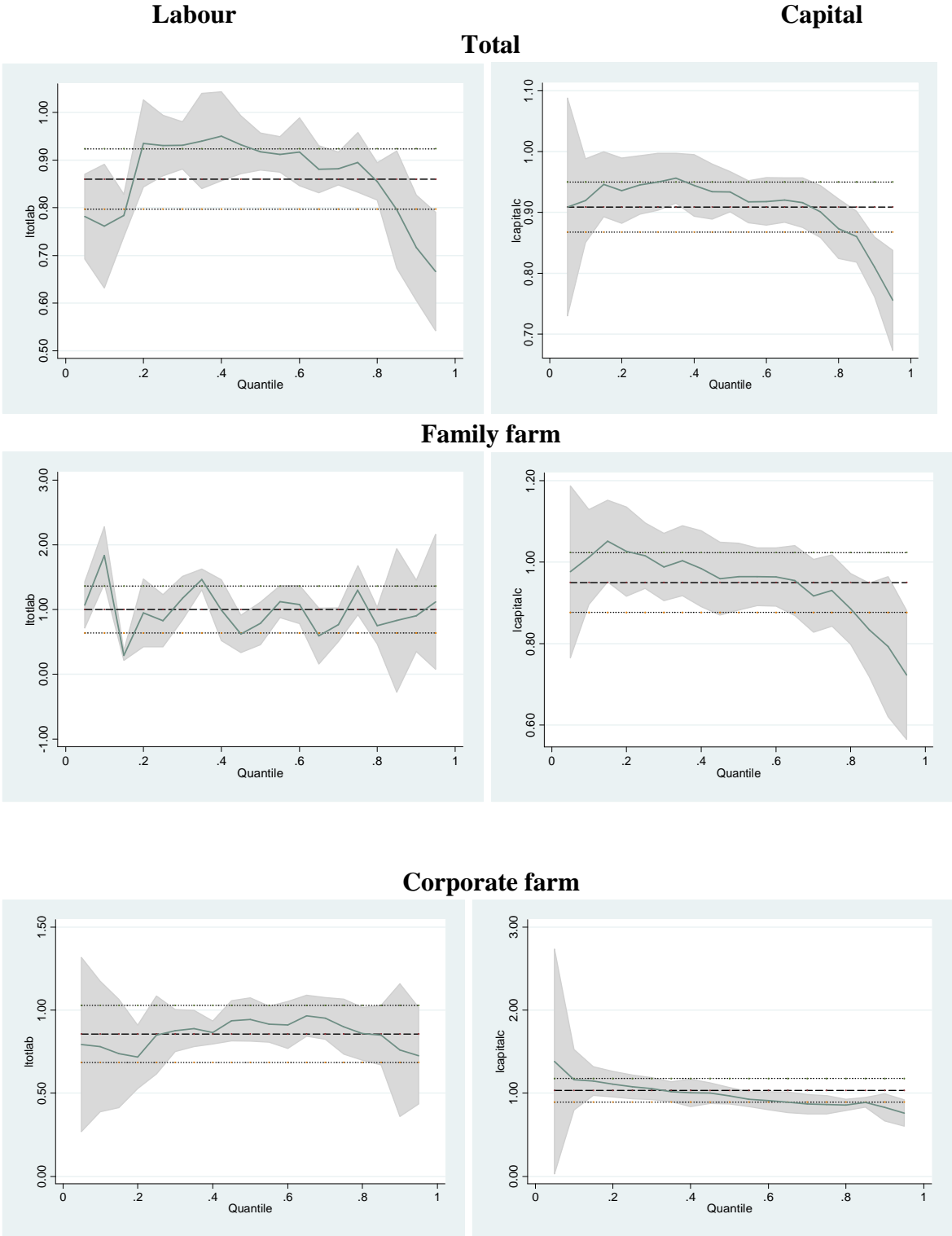


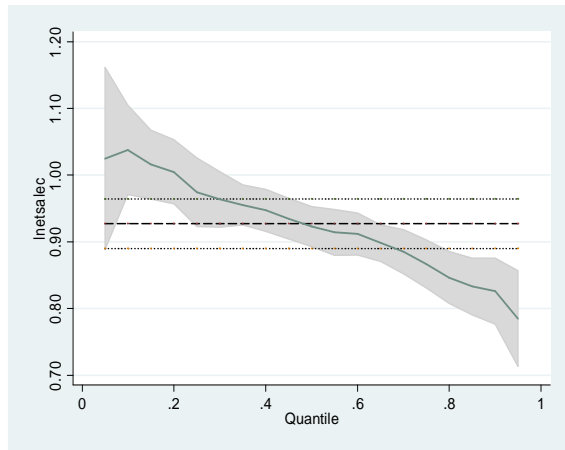
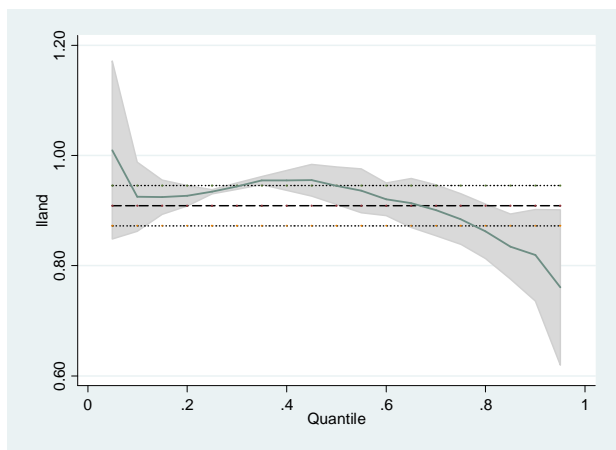
Figure 2 Quantile regression estimates by size measures and organisation groups



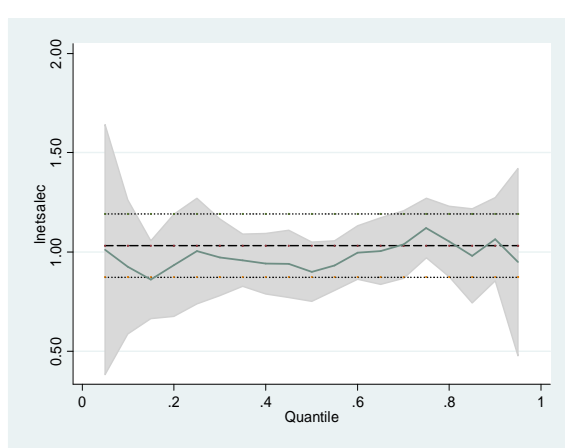
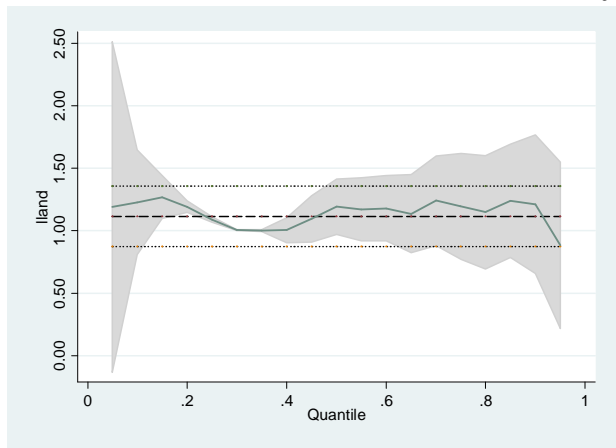
Land

Total

Net Sales



Family farm



Corporate farm

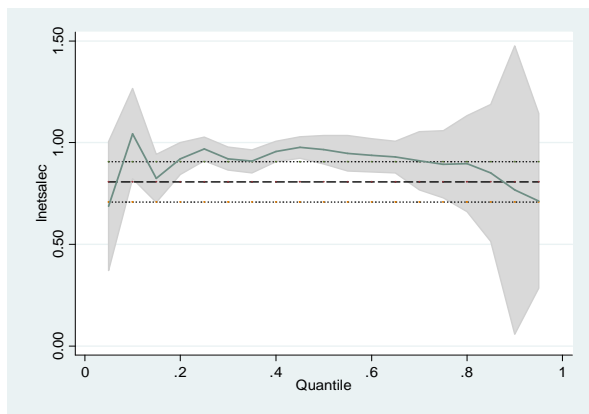
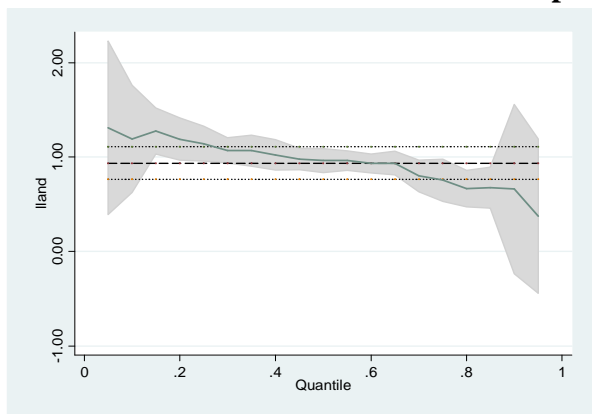


Table 1 OLS, Two-Step Heckmann and Quantile Regression estimates for total sample by measures of size

	Labour			Land			Capital			Net Sales		
	<i>OLS</i>	<i>Heckmann</i>	<i>Quantile</i>	<i>OLS</i>	<i>Heckmann</i>	<i>Quantile</i>	<i>OLS</i>	<i>Heckmann</i>	<i>Quantile</i>	<i>OLS</i>	<i>Heckmann</i>	<i>Quantile</i>
β_0	0.5532***	-2.950	-3.39***	0.496***	0.945*	0.620	1.608***	0.915**	0.940**	1.224***	-0.293	0.354
β_1	0.717***	0.8601***	0.917***	0.921***	0.909***	0.944***	0.884***	0.908***	0.933***	0.887***	0.927***	0.922***
H0: $\beta_1=1$	158.01***	0.99	17.43***	45.12***	19.95***	10.19***	34.48***	15.81***	15.64***	47.10***	6.87***	25.27***
N surv	775	775	775	752	752	752	776	776	776	778	778	778
N total		1748			1684			1749			1750	
R ²	0.5792		0.3651	0.8659		0.6912	0.7584		0.5636	0.7959		0.5895

Table 2 Mean of size variables by organisation forms

	Sale (HUF)		Capital (HUF)		Labour (man)		Land (hectares)	
	2001	2005	2001	2005	2001	2005	2001	2005
	family farms	10974,6	14528,1	20409,3	35320,7	5,0	5,7	72,7
corporate farms	280300,8	273396,5	175150,7	233395,6	46,9	37,0	905,1	886,9
total farms	62356,9	63915,3	49931,1	73109,6	13,0	11,7	231,5	243,5

Table 3 OLS, Two-Step Heckmann and Quantile Regression estimates for family farms by measures of size

	Labour			Land			Capital			Net Sales		
	<i>OLS</i>	<i>Heckmann</i>	<i>Quantile</i>	<i>OLS</i>	<i>Heckmann</i>	<i>Quantile</i>	<i>OLS</i>	<i>Heckmann</i>	<i>Quantile</i>	<i>OLS</i>	<i>Heckmann</i>	<i>Quantile</i>
β_0	0.784***	5.917	-2.464	0.493***	-2.454	-3.216*	1.410***	0.650	0.529	1.717***	-1.520	1.076
β_1	0.495***	0.998	0.785***	0.926***	1.115**	1.192***	0.906***	0.949***	0.964***	0.830***	1.031***	0.900***
H0: $\beta_1=1$	165.47***	0.00	0.1990	14.47***	0.06	2.92*	11.87***	1.58	0.73	23.38***	0.04	1.72
N surv	632	632	632	617	617	617	631	631	631	629	629	629
N total		1386			1348			1384			1380	
R ²	0.230		0.1264	0.7757		0.6093	0.7126		0.5059	0.5534		0.4055

Table 4 OLS, Two-Step Heckmann and Quantile Regression estimates for corporate farms by measures of size

	Labour			Land			Capital			Net Sales		
	<i>OLS</i>	<i>Heckmann</i>	<i>Quantile</i>	<i>OLS</i>	<i>Heckmann</i>	<i>Quantile</i>	<i>OLS</i>	<i>Heckmann</i>	<i>Quantile</i>	<i>OLS</i>	<i>Heckmann</i>	<i>Quantile</i>
β_0	0.680	-0.629	-1.028	0.050	1.258	0.405	1.372*	-2.405	0.491	0.804	4.044	0.625
β_1	0.757***	0.856***	0.943***	0.983***	0.935***	0.965***	0.899***	1.034***	0.968***	0.927***	0.807***	0.965***
H0: $\beta_1=1$	18.52***	1.57	0.72	0.64	0.24	0.29	2.29	0.06	0.38	1.72	1.77	0.94
N surv	143	143	143	135	135	135	145	145	145	149	149	149
N total		362			336			365			370	
R ²	0.7075		0.5440	0.9061		0.7478	0.6791		0.5321	0.8477		0.6767

Table 5 ICM tests by size of measures and organisation types for quantile n=0.50

c	total			family			corporate		
	1	5	10	1	5	10	1	5	10
Labour	3.643	2.378	1.941	4.300	2.691	1.999	0.050	0.286	0.448
Land	0.149	1.805	0.935	0.045	0.4406	0.305	0.106	0.323	0.910
Capital	0.104	0.643	0.636	0.093	0.552	0.555	0.145	0.521	1.009
Net sales	0.094	1.269	1.897	0.123	1.228	1.596	0.125	0.953	1.138

Note: critical values 10 per cent: 3.23; 5 per cent: 4.26