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A DYNAMIC ANALYSIS OF FIRM GROWTH IN SWEDISH BANKING

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Abstract

This paper examines the firm size-growth relationship using a balanced panel of surviving Swedish banks spanning the post-regulatory reform period (1995-2002). Univariate as well as multivariate tests of the law of proportionate effect (LPE) are performed, using a recently developed dynamic panel econometric method, i.e. the GMM-system estimator. Regardless of model specification (univariate, bivariate or multivariate) the LPE is always accepted. In the multivariate specification, all firm performance indicators turned out to be insignificant. Hence stochastic rather than systematic factors determined growth performance during the period under consideration.

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1. INTRODUCTION

It is a well known fact that if a typical firm's growth rate during a year is independent of its size and growth in previous years (or, equivalently, if logarithmic firm sizes are subject to sequences of purely random shocks), the firm size distribution within the industry will become increasingly skewed and dominated by a small number of large firms, eventually turning to the log-normal distribution. Whether this non-relationship between growth and size, referred in the literature to as Gibrat's law or the law of proportionate effect (LPE), adequately describes intra-industry firm size distributions has been the focus of empirical studies for many decades. However, a majority of these studies have concerned the manufacturing industry, while studies based on services such as banking are quite few in number. With reference to manufacturing, recent studies (e.g. ...) consistently find an inverse size-growth relationship, thus contradicting the LPE. The evidence of such a relationship is convincing enough for Geroski (1995) to regard it as a stylized result, while Sutton (1997) concludes that the proportional rate of firm growth, conditional on survival, decreases with size. For services, however, Audretsch *et al.* (2004) present compelling theoretical reasons why the LPE could be expected to hold. For banking specifically, the empirical evidence concerning the LPE is somewhat mixed. On the whole, however, the existing evidence does not suggest either a strong or a consistent relationship between size and growth in banking, thus indicating that the LPE may indeed offer a reasonable description of the firm growth process (Goddard *et al.*, 2001).

The aim of this paper is to contribute to this strand of research by examining whether Sutton's (1997) statistical regularities and Geroski's (1995) stylized results

for the validity of the LPE, based on evidence from the manufacturing industry, apply to the Swedish banking industry. This is accomplished by estimating a dynamic firm growth model, using firm-level data and recently developed dynamic panel data econometric methods, i.e. the GMM-system estimator. In addition to performing the widely used univariate test of the LPE, multivariate growth estimation is also conducted. The multivariate model is based on the notion that the univariate specification is the reduced form of an unspecified structural model. Accordingly, if the univariate test rejects the LPE, and for example, larger banks grow faster than smaller banks, they may do so for specific reasons which a multivariate model incorporating various bank performance indicators is able to control for.

Due to the short time series dimension of the data set, the sample only considers banks which were in operation and survived during the whole period under examination (i.e. 1995-2002). The exclusion of banks due to insufficient data or banks which exited, entered or were taken over may create sample selection bias. However, the data set does represent a heterogeneous cross-section of banks, covering around 90 % of the industry in terms of total assets.

The paper is organized as follows. Section 2 reviews the evolutionary and stochastic literature on firm growth, as well as the empirical evidence concerning the LPE within banking. Section 3 presents the growth model as well as the methodology employed. Section 4 discusses the sample and presents some descriptive statistics. In addition, variables used in the analysis are defined. Section 5 presents the results and discusses their implications. Finally, section 6 concludes.

2. RELATED LITERATURE

2.1 Evolutionary and stochastic firm growth theory: the law of proportionate effect (LPE)

To date a large number of studies on the subject of firm growth theory has been undertaken.¹ One important part of this research embraces theories which postulate certain outcomes for firm size distribution and industrial concentration, i.e. theories on stochastic and evolutionary growth.² Stochastic firm growth theories emanate from Gibrat (1931), whose law of proportionate effect postulates that the proportionate growth rate of incumbent firms is completely randomly determined and hence independent of systematic factors such as initial size or previous growth rates. In other words, factors that influence firm growth, such as growth of demand, managerial talent, innovation, organisational structure and luck, are distributed across firms in a manner which cannot be predicted from information about firm's current size or its previous growth performance (cf. Goddard *et al.*, 2001). As well-known, the implication of the LPE is a firm-size distribution which over time becomes increasingly skewed, and in the limit will approximate certain theoretical distributions, including the log-normal, Pareto and Yule distributions.³ Thus, the

¹ Hart (2000) provides an extensive review of the theoretical and empirical literature on firm growth.

² This literature is thoroughly reviewed by Sutton (1997).

³ The formal demonstration below is based on Steindl (1965) and reproduced in Sutton (1997, 1998): Let x_t and ε_t denote the size of a firm at time t and a random variable capturing the proportionate rate of growth between $(t-1)$ and t so that:

$$x_t - x_{t-1} = \varepsilon_t x_{t-1} \quad [\text{i}]$$

implying

$$x_t = (1 + \varepsilon_t)x_{t-1} = x_0(1 + \varepsilon_1)(1 + \varepsilon_2) \cdots (1 + \varepsilon_t). \quad [\text{ii}]$$

Now, for short time intervals, it is reasonable to consider ε_t as small, justifying the approximation $\ln(1 + \varepsilon_t) \approx \varepsilon_t$. Thus, taking logs, condition [ii] becomes:

$$\ln x_t \approx \ln x_0 + \varepsilon_1 + \varepsilon_2 + \dots + \varepsilon_t. \quad [\text{iii}]$$

industry will tend to become more concentrated and dominated by a handful of large firms, despite the absence of systematic factors (e.g. scale economies or superior x-efficiency) that would enable large banks to grow faster, implying increased dispersion in sizes.

While Gibrat's theory had little immediate impact, the 1950s and 1960s saw a revival of stochastic firm growth theory.⁴ The new models retained the law to specify the size-growth relationship for surviving firms, but elaborated in particular on the assumptions made about entry and exit and their role in influencing the size-growth relationship (e.g. Hart and Prais, 1956; Ijiri and Simon, 1977). Meanwhile, a growing number of empirical tests of the LPE were conducted, which can be grouped into two main categorical approaches. The first category comprises studies which base their analysis on empirical firm size distributions, and which tests for the LPE using goodness-of-fit tests (Hart and Prais, 1956; Simon and Bonnini, 1958; Steindl, 1965; and Ijiri and Simon, 1977). The second category consists of studies which examine the size-growth relationship using more direct tests, based on regression analysis (Hart and Prais, 1956; Hart, 1962; Mansfield, 1962). As remarked by Goddard *et al.* (2001), Hart (1962) identified the following implications of the LPE: (1) large and small firms should have the same average proportional growth; (2) no heteroscedasticity in growth rates; (3) the firm size distribution should be log-normal; and (4) the relative dispersion of firm sizes should increase over time. Using these properties as a basis for regression-based tests, Hart (1962) found no evidence against

By assuming the increments ε_t to be independent variates with mean m and variance σ^2 , we have that as $t \rightarrow \infty$, the term $\ln x_0$ will be small compared to $\ln x_t$, so that $\ln x_t$ is approximated by a normal distribution with mean mt and variance $\sigma^2 t$. In other words, the limiting distribution is lognormal.

⁴ See Steindl, (1965) for a review.

the LPE for various industries during the 1930s, 1940s and 1950s. As pointed out by Sutton (1997), the contribution of Mansfield (1962) is of particular interest. Mansfield points out that the previous inconclusive findings about the validity of the LPE emanates from using three different types of samples: (1) all firms (including those that fail to survive during the period); (2) surviving firms only; and (3) well-established firms (i.e. firms which have reached the minimum efficient scale⁵ (MES) of operation, and thus have exhausted economies of scale). Overall, Mansfield concludes that smaller firms have higher and more variable growth rates than large firms, while there is support for the LPE for firms operating above the MES.

A problem with tests based on empirical firm size distributions (category 1) is that they are essentially static, while regression based tests are able to incorporate dynamic influences on firm size distributions, such as persistence of growth or heteroscedasticity in growth rates. Following Chesher (1979), more recent regression-based tests tend to be dynamic⁶ (i.e. allow for the effects of growth persistence on the model).

In the late 1970s and 1980s, following a revival of empirical work in the area, a number of economic (i.e. not entirely stochastic) models of firm growth were introduced. These models introduced stochastic elements into conventional maximizing models (e.g. Jovanovic (1982); Sutton, (1991; 1997; 1998)). In Jovanovic (1982), each firm's cost curve is subjected to randomly distributed firm-specific shocks. Over time a firm learns about the effects of these shocks on its efficiency. Firms experiencing favourable shocks grow and survive. Others do not grow and may

⁵ MES is defined as the output level at which a firms average cost curve stops falling.

⁶ With reference to banking, see e.g. Tschoegl (1983), Vander Venet (1999) and Wilson and Williams(2000).

decline and even leave the industry (cf. Hart, 2000). Accordingly, larger firms are likely to be older than smaller firms, since they have benefit from learning economies of scale, enabling them to avoid making costly mistakes. The implication is that large firms' growth is subject to less variation than that of smaller firms (cf. Goddard *et al.*, 2001). More recently, Sutton (1991, 1997, 1998) argues for the need of an integrated theory capable of explaining variations between industries in concentration and in the shape of their firm size distributions. In Sutton (1998), markets that tend to fragment into separate submarkets remain less concentrated than those that tend to remain homogeneous. For any given concentration ratio, firm size distributions are modelled as the outcome of a dynamic process in which there is a fixed probability that any submarket will be contested by an entrant, which may be either an established firm operating in other submarkets or a new firm. It is possible to derive a theoretical firm size distribution that would apply if the probability of successfully contesting a new submarket were the same for established and new firms. In Sutton's framework, this case is analogous to the LPE. Departures from this theoretical size distribution would occur if established firms enjoyed advantages over new firms, affording a higher probability of successfully contesting new submarkets as they arise (cf. Goddard *et al.* 2001).

Nelson and Winter (1982) propose an evolutionary model of firm growth. The evolutionary approach to firm growth implies that there is some serial correlation in growth: "success breeds success and failure breeds failure". Thus this is in contrast to purely stochastic models of growth, such as the LPE, which postulate that the proportionate growth of surviving firms is random and hence independent of previous success (cf. Hart, 2000). The model by Nelson and Winter (1982) avoids strict

maximizing assumptions in favour of weaker rationality assumptions, and raises some fundamental questions as to the appropriateness of making strong rationality and informational assumptions on agents who face continuing technological change (cf. Sutton (1998), p. 244). Instead of optimising, agents tend to react automatically to changes in the market environment using routines which are specific to the firm. Successful routines which have produced growth in the past, are likely to do so in the future. It is true that circumstances change, but successful firms have successful routines for changing previous methods to meet new market environments (cf. Hart, 2000).

The relative importance of systematic and stochastic factors in the growth model may be indicated by the degree of serial correlation in growth. Systematic factors are expected to produce persistent company growth and hence a high degree of serial correlation (*ibid*), in consistency with evolutionary theories of firm growth. This is in contrast to stochastic growth models such as the LPE which postulate that the proportionate growth of surviving firms is purely random.

2.2 The LPE and banking – prior results

The overwhelming majority of previous empirical tests of the LPE have been based on cross-sectional regressions of logarithmic growth over a certain time interval on initial log size, sometimes (more recently) including a term accounting for persistency of growth. The first researchers who tested for the LPE using banking data were Aldaheff & Aldaheff (1964), who compared growth rates for the 200 largest banks to the average of the whole sample, and obtained that the group of large banks tended to grow more slowly than average for the period 1930-1960. Rhoades & Yeats

(1974) deal with a sample of 600 US banks for the period 1960-71, where they also were able to distinguish between internal and external (merger) growth. The conclusion reached was that the group of medium-sized banks experienced the highest internal growth. Tschoegl (1983) tests the hypothesis of no size-growth relationship for a sample of the largest international banks during the span 1969-77. In addition, two other hypotheses relating to the LPE were tested: (2) variability of growth between banks is independent of initial size; and (3) growth does not persist from one period to the next. The acceptance of these three propositions implies that concentration will increase over time, and that the LPE is valid in its strongest form. Tschoegl (1983) found no significant size-growth relationship. However, the variability of growth was found to decline with size, indicating that smaller banks exhibit more variable growth rates than larger banks, contradicting the LPE in its strongest form. Finally, the growth persistence was positive but insignificant. Vennet (2001) investigates growth patterns for the (aggregate) bank sectors in 23 OECD countries, including Sweden, for the time span 1985-94. For the sub-period 1985-89, size convergence was obtained, implying that smaller bank sectors were catching up with the larger ones. Enlarged access to revenue sources, growing internationalization of trade in financial services and increased competition were suggested as explanations for this finding. In contrast, the results for the period 1990-94 supported the LPE, indicating that the largest banks were reclaiming their dominance over world banking. Moreover, the results are robust to whether the conventional size measure (i.e. total assets) or the composite size measure (i.e. off-balance-sheet activities are included as well) is considered.

Wilson and Williams (2000), tested for the LPE using a sample of banks from four European countries for the period 1990-96. For the purposes of robustness, several definitions of size were considered (total assets, equity and off-balance sheet activities). With the exception for Italy, no significant size-growth relationship was found. Large banks were found to have less variable growth rates (in line with the results of Tschoegl (1983)), suggesting that large banks enjoys diversification advantages (Singh and Whittington, 1968) and/or that they were able to benefit from learning economies of scale (Jovanovic, 1982).

Hartwick and Adams (2002) examine the relationship between size and growth in the UK life insurance industry, using 1987-1996 data in a multivariate setting. With reference to the whole period, no significant size-growth relationship was obtained. However, more diversified life insurance firms experienced higher growth rates on average than more specialized life insurers. Other firm-specific determinants of growth, i.e. profitability, cost efficiency, company type and organisational form turned out to be insignificant.

Goddard *et al.* (2002) investigated the size-growth relationship of US credit unions during the 1990s, using univariate and multivariate cross-sectional and panel estimation techniques. In general, larger credit unions were found to grow faster than their smaller counterparts. However, the authors were able to identify specific reasons why larger firms were able to grow faster, as most of the financial structure and performance characteristics used in the multivariate model were found to have a significant influence on the size-growth relationship. Thus, growth was not randomly driven but highly systematic.

3. METHODOLOGY

3.1 Estimation technique

This chapter describes the model framework and subsequently presents the empirical model to be estimated. It is assumed that performance measures such as firm profit rate and firm growth evolve according to first-order autoregressive-distributed lag models of the form:

$$\mathbf{y}_{i,t} = \alpha \mathbf{y}_{i,t-1} + \beta^T \mathbf{x}_{i,t} + (\eta_i + \mathbf{v}_{i,t}); \quad i = 1, \dots, N; \quad t = 2, \dots, T \quad [1]$$

where $\mathbf{y}_{i,t}$ represents a firm-level performance observation in period t ; $\mathbf{x}_{i,t}$ a vector of additional covariates; η_i an unobserved bank-specific time-invariant effect allowing for heterogeneity in the means of $\mathbf{y}_{i,t}$ across banks; and $\mathbf{v}_{i,t}$ is a disturbance term, assumed independent across individuals and serially uncorrelated. The error term is also assumed to satisfy $E(\mathbf{v}_{i,t}) = 0$ and $\text{var}(\mathbf{v}_{i,t}) = \sigma_v^2 > 0$.

In dynamic panel models involving individual effects such as [1], the Ordinary Least Squares (OLS) estimator $\hat{\alpha}$ is known to be inconsistent, due to the correlation between the lagged dependent variable, $\mathbf{y}_{i,t-1}$ (a regressor) and the individual effects η_i . Moreover, this correlation and hence the inconsistency of $\hat{\alpha}$ still persists in panels where either the cross-sectional dimension (N) or time dimension (T) increases asymptotically towards infinity. Standard results for omitted variable bias indicate that, at least in large samples, the OLS levels estimator is biased upwards (cf. Bond, 2002).

Through the transformation (first-differencing) of equation [1] which eliminates the individual effects η_i prior to estimation, the Within estimator eliminates this source of inconsistency, while simultaneously introducing a non-negligible correlation between the transformed lagged dependent variable and the transformed error term, unless T is very large. In micro panels (i.e. large N, fixed T) the Within estimator is consistent only in the extreme case where all regressors are strictly exogenous with respect to the error term ($\eta_i + \nu_{i,t}$). Otherwise, standard results for omitted variables bias indicate that the Within estimator, at least in large samples, is inconsistent and biased in a dynamic panel data model (ibid.). Also the random effects GLS estimator is inconsistent and biased in such models (cf. Baltagi, 2001).

Holtz-Eakin, Newey and Rosen (1988) and Arellano and Bond (1991) propose a consistent instrumental variable estimator for the first-order autoregressive panel data model, based on the generalized method of moments⁷ (GMM) approach. This two-stage, asymptotically efficient GMM estimator, referred to as the Arellano and Bond estimator or, alternatively, the *difference estimator* (GMM-DIF), also extends naturally to autoregressive-distributed lag models, and so it is appropriate to use not only for performing reduced-form analysis but for estimating structural, multivariate models such as equation [1] as well. The GMM approach starts with transforming the model (through e.g. first-differencing or orthogonal deviations⁸) to get rid of the individual effects.

⁷ See Hansen (1982).

⁸ The orthogonal deviations transformation (Arellano, 1988; Arellano and Bover, 1995) is an alternative to first-differencing, which involves first-differencing followed by a GLS transformation to remove the resulting serial correlation induced by first-differencing. Although first-differencing and orthogonal deviations generate quite similar parameter estimates, the latter method has been shown to offer superior efficiency in models with predetermined variables (Maeshiro and Vali, 1988). Formally, the transformation involves subtracting from each observation the average of future observations in the sample for the same individual, followed by a weighting to standardize the variances:

The first-differenced model is given by:

$$\Delta y_{i,t} = \alpha \Delta y_{i,t-1} + \beta^T \Delta x_{i,t} + \Delta v_{i,t}; \quad i = 1, \dots, N; \quad t = 3, \dots, T \quad [2]$$

where Δ denotes the first difference operator.

The resulting correlation between the transformed lagged dependent variable $\Delta y_{i,t-1}$ and the transformed error term $\Delta v_{i,t}$ necessitates the use of instrumental variables estimation. The GMM-DIF estimator utilizes the set of orthogonality conditions that exist between lagged *levels* of the dependent and independent variables (instruments) and the transformed (first-differenced) equations, given by [2]. At this stage, it is reasonable to assume (i) that the original time-varying component of the error term, $v_{i,t}$ is serially uncorrelated and (ii) that the regressors, $x_{i,t}$ are weakly exogenous (predetermined) with respect to $v_{i,t}$:

$$\begin{aligned} E[x_{i,t} v_{i,t}] &= 0 \text{ for } s = 1, \dots, t; t = 2, \dots, T \\ E[x_{i,t} v_{i,t}] &\neq 0 \text{ for } s = t + 1, \dots, T; t = 2, \dots, T \end{aligned} \quad [3]$$

Given the validity of these assumptions, Arellano and Bond (1991) propose to use all available lags of the dependent and the independent variables to form an optimal instrumental variable matrix of the form:

$$\mathbf{Z}_{di} = \text{diag} (y_{i,1} \dots y_{i,t} \ x_{i,1} \dots x_{i,t+1}) \text{ for } t = 1, \dots, T - 2 \quad [4]$$

$$\mathbf{x}_{i,t}^* = \left(x_{i,t} - \frac{x_{i,t+1} + \dots + x_{i,T}}{T-t} \right) \left(\frac{T-t}{T-t+1} \right)^{1/2} \text{ for } t = 1, \dots, T-1.$$

where $x_{i,t}$ denotes any variable (dependent and independent). This transformation also preserves orthogonality among the transformed errors, that is, if the original errors are uncorrelated, so are the transformed errors.

where each row corresponds to the first-differenced equations for $t=3, \dots, T$ for institution i . Given the assumption of predetermined explanatory variables, \mathbf{Z}_i is of dimension $(T-2) \times (T-2) \{ (k-1)(T+1) + (T-1) \} / 2$ (where k denotes the number of explanatory variables including $\mathbf{y}_{i,t-1}$), and constructed according to the orthogonal moment conditions:

$$E[\mathbf{y}_{i,t-s} \cdot (\Delta \mathbf{v}_{i,t})] = 0 \quad \text{for } s \geq 2; t = 3, \dots, T \quad [5]$$

$$E[\mathbf{x}_{i,t-s} \cdot (\Delta \mathbf{v}_{i,t})] = 0 \quad \text{for } s \geq 2; t = 3, \dots, T \quad [6]$$

These conditions may be compactly written as:

$$E[\mathbf{Z}_{di}^T \Delta \mathbf{v}_i] = 0 \quad \text{for } i = 1, \dots, N \quad [7]$$

where $\Delta \mathbf{v}_i = \{\Delta \mathbf{v}_{i,3}, \Delta \mathbf{v}_{i,4}, \dots, \Delta \mathbf{v}_{i,T}\}^T$; T in superscript denotes the transpose.

The corresponding sample moment conditions used to calculate the asymptotically efficient (as $N \rightarrow \infty$, for fixed T) GMM-DIF estimator δ are given by:

$$\mathbf{m}_N(\delta) = N^{-1} \sum_{i=1}^N \mathbf{Z}_{di}^T \Delta \mathbf{v}_i \quad [8]$$

The GMM-DIF estimator $\hat{\delta}_{GMM}$ is then defined as the value of δ which minimizes the criterion function:

$$\mathbf{Q}_N(\delta) = \mathbf{m}_N(\delta)^T \mathbf{W}_N \mathbf{m}_N(\delta) \quad [9]$$

and the resulting estimator is given by:

$$\hat{\delta}_{GMM} = (\Delta \mathbf{x}^T \mathbf{Z}_d \mathbf{W}_N \mathbf{Z}_d^T \Delta \mathbf{x})^{-1} \Delta \mathbf{x}^T \mathbf{Z}_d \mathbf{W}_N \mathbf{Z}_d^T \Delta \mathbf{y} \quad [10]$$

where \mathbf{W}_N is a stochastic positive definite weighting matrix, which is different in the first step and the second-step estimation (cf. Arellano and Bond, 1991). In the first

step, the error terms $v_{i,t}$ are assumed to be independent and homoscedastic across institutions and over time. In the second step, these assumptions are relaxed and the residuals from the first step are used to construct a consistent estimate of the variance-covariance matrix, thus enabling the calculation of an asymptotically more efficient second-step estimator.

A well-known problem with the GMM-DIF estimator is its poor finite sample properties (in terms of bias and efficiency) when the lagged levels of the variables used as instruments are only weakly correlated with subsequent first differences, so that the instruments available for the regression equations in first-differences are weak (cf. Alonso-Borrego and Arellano (1999) and Blundell and Bond (1998)). This problem is expected to occur in the presence of highly persistent explanatory variables (i.e. when series have unit root or near-unit root properties). If for example the variable $y_{i,t}$ contains a unit root, implying a “true” value of the autoregressive parameter α equal to unity, the moment conditions stated in [4] are not sufficient to identify the autoregressive parameter α (cf. Arellano and Bover, 1995) while if α is high but less than unity, the GMM-DIF estimate of this parameter is expected to be biased downwards (in the direction of the *Within estimator*) and imprecisely estimated (cf. Blundell and Bond, 1998).

In order to improve upon the finite sample properties associated with the standard GMM-DIF estimator when the instruments available for the first-differenced equations are weak, Arellano and Bover (1995) and Blundell and Bond (1998) introduce an extended GMM estimator, the so-called *system estimator* (GMM-SYS) which in addition to the lagged *levels* of the variables as instruments for the

differenced equations uses lagged *first-differences* of the variables as instruments for the untransformed (*level*) equations. Both Monte Carlo simulations and empirical experience have shown that the GMM-SYS estimator has much smaller finite sample bias and much greater precision when estimating autoregressive parameters using persistent series (cf. Blundell, Bond and Windmeijer (2000) and Bond (2002)).

When (and if) the GMM-SYS procedure is employed, the following additional assumption is imposed: (iii) while correlation between the levels of the regressors and η_i is allowed for, it is assumed to be time-invariant (or put differently, each series of $(y_{i,t}, x_{i,t})$ is assumed to be mean-stationary). This implies there is no correlation between the *differences* of the regressors and η_i , so that suitably lagged values of $\Delta y_{i,t}$ and $\Delta x_{i,t}$ qualify as instruments for the level equations (cf. Bond, 2002). Given that all available lags of $(y_{i,t-1}, x_{i,t})$ are used as instruments in the differenced equations, only the most recent difference of these variables is used as an instrument in the level equations. Higher order lags become redundant in this situation (Arellano and Bover, 1995). Thus in addition to the moment conditions given by [6], the system estimator utilizes:

$$E[\Delta y_{i,t-s} \cdot (\eta_i + v_{i,t})] = 0 \quad \text{for } s = 1 \quad [11]$$

$$E[\Delta x_{i,t-s} \cdot (\eta_i + v_{i,t})] = 0 \quad \text{for } s = 1 \quad [12]$$

or, in more compact notation:

$$E[Z_{si}^T p_i] = 0 \quad \text{for } i = 1, \dots, N \quad [13]$$

where

$$p_i = [\Delta v_i \quad v_i]^T \quad \text{and the "system instrumental matrix" } Z_{si} \text{ is a block-}$$

diagonal matrix given by:

$$\mathbf{Z}_{si} = \begin{bmatrix} \mathbf{Z}_{di} & 0 \\ 0 & \mathbf{Z}_{ii} \end{bmatrix} \quad [14]$$

where \mathbf{Z}_{ii} is a block-diagonal matrix containing the non-redundant instruments available for the level equations (cf. Blundell, Bond and Windmeijer, 2000).

Thus the GMM-SYS estimator combines in a system the moment conditions given by [6] and [11]. In analogy with the difference estimator, the model is estimated in a two-step procedure which generates consistent and efficient estimates.

As pointed out by Arellano and Bond (1991), an estimator that uses lags as instruments loses its consistency if the assumption of no serial correlation in the error terms fails to hold. It is thus essential to make sure that the instruments used are valid (i.e. test the assumption of no serial correlation). Two such tests proposed by Arellano and Bond (1991) are Sargan's (1958) test of over-identifying restrictions and a direct-test of no second-order serial correlation in the differenced error term, i.e. $E[\Delta \mathbf{v}_{i,t} \Delta \mathbf{v}_{i,t-2}] = 0$.⁹ The Sargan test tests the overall validity of the instruments based on the sample counterparts to the moment conditions [6] and [11]. Under the null hypothesis the instruments are uncorrelated with the residuals (and hence acceptable). The test statistic is asymptotically chi-squared distributed with degrees of freedom equal to the difference between the number of instruments and regressors. The serial correlation test is asymptotically standard-normal distributed under the null hypothesis of no serial correlation.

⁹ Even if $\mathbf{v}_{i,t}$ is serially uncorrelated, the differenced error term can be first-order serially correlated, i.e. $E[\Delta \mathbf{v}_{i,t} \Delta \mathbf{v}_{i,t-1}] = 0$, need not hold. However, the validity of $E[\Delta \mathbf{v}_{i,t} \Delta \mathbf{v}_{i,t-2}] = 0$ is crucial for the GMM estimator to be consistent.

Monte Carlo studies have shown that the estimated asymptotic standard errors of the two-step GMM estimator are severely biased in small samples (Arellano and Bond, 1991), while the one-step standard errors are virtually unbiased (cf. Windmeijer, 2000). On the other hand, the one-step coefficient estimates are not asymptotically efficient. Therefore, in accordance with common practice, the *two-step* coefficient estimates along with the *one-step* standard errors will be reported in the estimations below.

3.2 Growth dynamics and tests of the LPE

In section two it was shown that if the LPE is in operation, the industry structure will evolve in such a way that the within-industry firm size distribution becomes increasingly skewed and dominated by a small number of large firms. Or, put differently, if factors that influence the growth prospects of firms, such as growth of demand, managerial talent, organisational structure or luck (cf. Goddard *et al.*, 2001) are distributed completely randomly over time and across firms (i.e. if logarithmic firm sizes are subject to a sequence of purely random shocks) then the generated firm size distribution will be approximately lognormal in form. Two striking aspects of this well-known result are: (i) even in the absence of any consistent relationship between size and growth, concentration will tend to increase over time, and (ii) previous research have established that the predictions of the law are fairly consistent with the empirical firm size distribution observed in many industries. In light of these considerations, the very purpose of this section is to test if the highly concentrated banking industry indeed is a result of a pure random growth process (LPE), or if there are systematic factors (e.g. superior efficiency performance of large

banks) which have enabled larger banks to seize most of the growth / investment opportunities.

Prior regression-based tests of the LPE have typically been based on an AR(1) model of the form:

$$\Delta y_{i,t} = (\alpha - 1)y_{i,t-1} + \delta_t + (\eta_i + \nu_{i,t}); \quad \nu_{i,t} = \rho\nu_{i,t-1} + \varepsilon_{i,t} \quad [15]$$

where $y_{i,t}$ is the logarithmic size of institution i at time t ; $\Delta y_{i,t}$ the logarithmic growth rate of firm i ; δ_t allows for time effects; while $(\eta_i + \nu_{i,t})$ is the composite error term discussed previously. The individual effects are assumed to be distributed with $E(\eta_i) = \mu_\eta$ and $\text{var}(\eta_i) = \sigma_\eta^2$. The parameter α determines the size-growth relationship, while ρ captures potential first-order serial correlation in the time-varying part of the error term. Finally, $\varepsilon_{i,t}$ is a random disturbance, assumed normally and iid distributed with $E(\varepsilon_{i,t}) = 0$ and $\text{var}(\varepsilon_{i,t}) = \sigma_\varepsilon^2 > 0$. Model [15] is the logarithmic correspondence of the stochastic growth model proposed by Ijiri and Simon (1977). By applying the logarithmic transformation to the data, distortions arising from inflation and other influences on the chosen size measure common to all banks are effectively eliminated (cf. Goddard *et al.*, 2001) so that size is adequately measured by e.g. the log of total assets. The analysis of the size-growth relationship amounts to testing the null hypothesis of $\alpha = 1$, under which growth is non-explosive and unrelated to size (consistent with the LPE) vs. the alternative of a significant size-growth relationship, i.e. $\alpha < 1$ or $\alpha > 1$. If $\alpha < 1$, then small firms tend to growth faster than large firms, possibly as a result of superior flexibility or innovativeness of small banks. This suggests that over time, the size of all banks is reverting towards some long-run mean value, and so there is no tendency for industrial concentration to

increase. Under mean-reversion ($\alpha < 1$) it is assumed that $\eta_i > 0$, and the average log size to which bank i tends to revert back to is given by $\eta_i / (1 - \alpha)$. If $\eta_i = \eta$ ($\sigma_\eta^2 = 0$), there is a common long-term mean size for all banks, while if $\eta_i \neq \eta$ ($\sigma_\eta^2 > 0$) there are heterogeneous, bank-specific long-term values. On the other hand, if $\alpha \geq 1$, there is no mean-reversion, implying increased concentration over time. If $\alpha > 1$, larger banks tend to grow proportionately faster than smaller banks, possibly through superior efficiency due to scale or scope economies, x-efficiency, or through the exercise of market power (cf. Wilson and Williams, 2000). Growth trajectories are explosive implying rapidly increased size dispersion. This can go on for a finite period but is unlikely to last for long. If, on the other hand, $\alpha = 1$, there is no size-growth relationship. Nevertheless, as mentioned in section 2, size dispersion will tend to widen over time as some banks by chance will get slightly more than their fair share of growth opportunities while the opposite is true for “bad luck” banks. When $\alpha \geq 1$, the individual effects η_i have no interpretation in terms of mean-reversion, and it is assumed that $\eta_i = \eta = 0$.¹⁰

In this paper, it is initially assumed that size follows the simple univariate data generating process described by [15]. Goddard *et al.* (2001) suggests a useful reformulation of [15] for the purposes of panel estimation:

$$\Delta y_{i,t} = (\alpha - 1)y_{i,t-1} + \rho \Delta y_{i,t-1} + \delta_t + \eta_i(1 - \rho) + \xi_{i,t} \quad [16]$$

¹⁰ As remarked by Goddard *et al.*, (2002), $\eta_i \neq 0$ would allow for a deterministic trend specific to each bank, which could exist but which would be very difficult to identify unless the number of observations per bank is quite large. The possibility of a common deterministic trend is captured, however, through the time effects, δ_t .

where $\xi_{i,t} = \varepsilon_{i,t} + \rho(1 - \alpha)y_{i,t-2}$, implying $\xi_{i,t} = \varepsilon_{i,t}$ under the null hypothesis of no size-growth relationship ($\alpha = 1$).

In accordance with model [16], we say that the LPE is satisfied if $(\alpha - 1)$ is not significantly different from zero, and violated otherwise. Serial correlation in the error term will be reflected in a positive value of the growth persistence parameter ρ . As pointed out by Chesher (1979), a proper test of the LPE requires the model to incorporate a term capturing growth persistence, since otherwise (as long as ρ is non-zero) the estimate of α will be inconsistent and biased (towards unity). Accordingly, to consider the LPE as a reasonable description of the bank growth process, we need to test both $(\alpha - 1) = 0$ and the hypothesis of no persistence in growth rate ($\rho = 0$).¹¹

A weakness with the univariate model is that it is purely stochastic and thus suffers from a lack of economic foundation. Although frequently applied in the empirical literature, it has been criticised by e.g. Geroski *et al.* (1997), who argue that the acceptance of the law may be more a consequence of the overly simplicity of the model. In this context, Goddard *et al.* (2004) point out that the univariate specification can be regarded as the reduced-form of a larger, but often unspecified, structural model. In light of this insight, the following augmented, multivariate growth model is considered:

$$\Delta y_{i,t} = (\alpha - 1)y_{i,t-1} + \rho \Delta y_{i,t-1} + \beta_1^T \mathbf{x}_{i,t}^1 + \beta_2^T \mathbf{x}_i^2 + \delta_i + \eta_i(1 - \rho) + \xi_{i,t} \quad [17]$$

where $\mathbf{x}_{i,t}^1$ and \mathbf{x}_i^2 denote, respectively, a vector of time-varying and time-invariant systematic influences (i.e. bank performance indicators) on firm growth. All variables

¹¹ Tschoegl (1983) proposes a third test – that of independence between size and variability in growth rates.

in $x_{i,t}^1$ are assumed to be potentially correlated with the η_i , and predetermined with respect to the disturbance term. The time-invariant covariates (when included), are also assumed to be potentially correlated with η_i .¹²

Models [16] and [17] are estimated using the GMM technique described above. Because size follows a unit-root process under the null, the extended GMM estimator (i.e. GMM-SYS) is considered as appropriate, while the usual panel estimators or the GMM-DIF estimator are all expected to perform poorly. Thus although several estimators are considered (for comparison purposes), the interpretations will be based on the most reliable results, i.e. those produced by the GMM-SYS estimator.

4. DATA

4.1 Variable definitions and determinants of bank growth

Following Tschoegl (1983), this paper adopts (the log of) total assets as a measure of size.¹³ Both total assets and total equity represents widely accepted measures of bank size ever since, and total assets has subsequently been employed in empirical tests of the LPE within the financial industry by e.g. Wilson and Williams (2000); Vennet (2001); Hardwick and Adams (2002); Goddard, McKillop and Wilson (2002); and Goddard, Molyneux and Wilson (2004).

¹² These assumptions maintain consistency with the instrumental matrix defined above.

¹³ Some recent empirical tests of the LPE within a banking context also tries to accommodate for the shift in banking activities towards increased engagement in off-balance-sheet business activities (e.g. Vennet, 2001; Goddard *et al.*, 2001; 2004). Without referring to banking in particular, other size measures frequently applied are value-added, the log of employment or the log of sales.

With reference to the structural bank growth model given by [17], it should be emphasised that the banking literature on determinants of growth is still in its infancy.¹⁴ The present paper examines some plausible bank-specific determinants, defined in table 1. The time-varying variables (all except *STATUS*) are allowed to enter subject to a time lag.

Table 1 – Bank performance indicators

Control variable (sign prediction)	Definition
ROA (+)	Profitability; Return on total assets
EFFIC (-)	Total operating costs / total revenues
INT_MIX (?)	Total non-interest revenues / Total revenues
STATUS (?)	Ownership status, i.e. Commercial or Savings banks

First, high profits (*ROA*) are expected to contribute positively to growth, since the higher the level of retained profits, the more capital available. Second, the variable *EFFIC* intends to capture operational efficiency. A high cost-income ratio indicates suboptimal performance and should impact negatively on growth. These variables were also used by e.g. Vennet (2001) and Goddard, McKillop and Wilson (2002). The variable *INT_MIX* attempts to control for the degree of diversification of the business

¹⁴ Possible determinants of growth (apart from size) for banking have been examined by Cyree, Wansley and Boehm (2000), Vennet (2001) and Goddard *et al.*, (2004); for the life insurance industry by Hardwick and Adams (2002); and for the credit union industry by Goddard, McKillop and Wilson (2002).

portfolio, although the *a priori* relationship with growth is not unambiguous. On the one hand, a more diversified bank could be expected to operate more efficiently in the presence of scope economies, and hence be able to achieve higher average growth rates. On the other hand, increased diversification lowers risk, and therefore permits banks to settle for a lower return on capital, with adverse effects for growth as a consequence. Finally, it seems likely that ownership characteristics may have an impact on profitability and hence on growth performance, since commercial banks are profit maximizing institutions while savings institutions may pursue other objectives (cf. Goddard *et al.*, 2004).

4.2 The sample

The data set used consists of annual observations (account data) for banks which were in operation during the whole period, i.e. 1995-2002 (hence, a balanced panel). The short maximum time series dimension of the data set necessitates the use of a balanced panel, although this may create a potential problem with sample selection bias. In particular, banks that were formed during the period, as well as foreign banks which operate as subsidiaries or branches, have been excluded. Anyway, the remaining 79 commercial and savings institutions represent a heterogeneous cross section of banks, covering around 90 % in terms of total assets of the whole market. Sample statistics for the included banks are reported in Table 2.

Table 2: Variables used in the analysis – Sample statistics

Variable	Mean	Std. Dev	Median	Min	Max
SIZE	6.767	1.992	6.387	3.279	13.76
GROWTH	0.06486	0.1472	0.04563	-1.228	1.153

ROA	0.01742	0.01120	0.01612	-0.04125	0.08261
EFFIC	0.4877	0.1306	0.4794	0.1419	1.096
INT_MIX	0.1426	0.06501	0.1423	0	0.4763

5. RESULTS

The first part of this section presents the estimation results, while the second part interprets the results. For the purposes of comparison, the dynamic growth equation has been estimated using several techniques, although we know that only the GMM estimators are consistent, and that GMM-SYS provides efficiency gains as long as the additional level moment conditions given by [13] are valid. In particular, if the model involves highly persistent series (so that lagged levels of the corresponding variables constitute weak instruments) then the standard difference GMM estimator is likely to be subject to serious finite sample bias in the direction of the Within estimator (i.e. downwards), while the system GMM estimator has much smaller finite sample bias and much greater precision. This outcome was shown by Blundell and Bond (1998) for simple AR (1) models but is also likely to be true in multivariate models (Blundell, Bond and Windmeijer, 2000). If the first-differenced GMM estimates are close to the Within estimates but differ substantially from the system GMM estimates, this is an indication of weak instrument bias of the differenced estimator, i.e. lagged levels of the variables used as instruments only weakly identify the parameters. In order to detect and avoid potential problems with finite sample bias due to weak instruments, Bond (2002) suggests investigating the series individually, as well as comparing the consistent GMM estimators with other panel estimators which are known to be biased in opposite directions. Accordingly, Table 3 reports

simple AR(1) specifications for the different series, where the panel OLS and the Within estimator are included for comparison.

Starting with *size*, the system GMM estimate of the autoregressive parameter is very close to unity and estimated with great precision. By contrast, the differenced GMM estimator is not only seriously biased downwards and similar in magnitude to the Within estimator, but also inefficient. This is as expected since the series is highly persistent. The panel OLS estimate, which is unbiased under the null of $\alpha = 1$, while upward biased under the alternative of $\alpha < 1$ (cf. Bond, Nauges and Windmeijer, 2002), is very similar in magnitude to that of the system GMM, and indicates that *size* indeed is an integrated variable, in accordance with the LPE. By contrast, the other individual series appear to be either stationary but highly persistent (*efficiency* and *output mix*), or stationary and not highly persistent (*profits*). Thus since three out of four series are highly persistent, the standard GMM estimator is expected to suffer from serious finite sample bias while the system GMM technique should give reasonable results, given the validity of the level moment conditions.

Table 3: AR(1) Model estimates (Unit root test)

	Panel OLS	Within	GMM-DIF	GMM-SYS
<u>Size</u>				
<i>Size_{i,t-1}</i>	1.00*** (241.)	0.315** (3.31)	0.248 (1.10)	0.984*** (50.2)
AR(2) test	[0.305]	[0.550]	[0.785]	[0.334]
Sargan test	–	–	[0.001]	[0.005]

<u>Profitability</u>				
<i>Roa_{i,t-1}</i>	0.586*** (9.78)	0.149** (3.02)	0.294*** (5.03)	0.283*** (3.92)
AR(2) test	[0.915]	[0.000]	[0.370]	[0.373]
Sargan test	–	–	[0.085]	[0.189]
<u>Efficiency</u>				
<i>Eff_{i,t-1}</i>	0.883*** (24.7)	0.340*** (6.51)	0.384** (2.41)	0.774*** (16.5)
AR(2) test	[0.336]	[0.010]	[0.412]	[0.619]
Sargan test	–	–	[0.190]	[0.378]
<u>Output mix</u>				
<i>Mix_{i,t-1}</i>	0.977*** (26.7)	0.604*** (4.49)	0.149 (1.03)	0.884*** (5.19)
AR(2) test	[0.028]	[0.010]	[0.713]	[0.576]
Sargan test	–	–	[0.002]	[0.007]

Note: Two-step coefficient estimates are reported together with t-ratios based on finite sample corrected standard errors (in brackets); p-values in square brackets. Year dummies included.

Table 4 reports dynamic growth estimation results for the GMM system estimator¹⁵, which, for reasons outlined above, are considered as the most relevant, while the results for the other estimators are added for comparison and presented in the appendix. With reference to the GMM estimators, it is assumed that all explanatory variables are predetermined, in consistency with the instrumental matrix given by [14]. In the estimations however not all available instruments were used,

¹⁵ All dynamic panel estimation results are obtained using the DPD package for OX (Doornik *et al.*, 2002).

since despite the fact that additional instruments increase efficiency of the GMM procedure, they may also increase the downward bias in small samples (Kiviet, 1995).

Table 4: Growth model estimates – GMM-SYS estimation results

DepVar = $Grow_{i,t}$	Univariate	Bivariate	Multivariate
<i>Size_{i,t-1}</i>	-0.0157 (-1.36)	-0.0233 (-1.56)	-0.00541 (-0.254)
<i>Grw_{i,t-1}</i>	0.00795 (0.252)	0.00246 (0.122)	-0.0187 (-1.45)
<i>Roa_{i,t-1}</i>	–	-0.0557 (-0.236)	-0.0817 (-0.0391)
<i>Mix_{i,t-1}</i>	–	–	0.396 (1.60)
<i>Eff_{i,t-1}</i>	–	–	-0.0691 (-0.512)
<i>Type</i>	–	–	0.0549 (0.598)
Time dummies	[0.000]	[0.000]	[0.000]
Wald joint (χ^2)	[0.422]	[0.413]	[0.241]
Sargan's test	[0.003] (21)	[0.040] (43)	[0.179] (59)
AR(2) test	[0.692]	[0.658]	[0.451]

Matrix of instruments	<i>size(2,5); $\Delta size(1,1)$</i>	<i>size(2,5), roa(2,5); $\Delta size(1,1), \Delta roa(1,1)$</i>	<i>size(2,3), roa(2,3), eff(2,3), mix(2,3); $\Delta size(1,1), \Delta roa(1,1),$ $\Delta eff(1,1), \Delta mix(1,1)$</i>
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Note: two-step coefficient estimates are reported together with t-ratios based on finite sample corrected standard errors (in brackets); p-values in square brackets.
of firms= 79; # of obs= 395 (balanced panel)

Starting with the univariate estimation results¹⁶, a slightly negative size coefficient is obtained, indicating that smaller banks were growing faster than larger ones during the period under examination. However, the coefficient is insignificant at any reasonable level. The coefficient of growth persistence takes a positive value, although insignificant as well. Consequently the Wald joint test (i.e. test of joint significance of the independent variables, excluding time dummies), is not able to reject the null hypothesis that all the corresponding coefficients are equal to zero. Furthermore, the two tests of instrument validity give inconsistent results – the acceptance of the autocorrelation test indicates validity of instruments and hence consistency of the GMM estimator while the overidentification test of instruments (Sargan) does not.

Tables A1-A3 display the corresponding results for the panel OLS, fixed effects, and the standard GMM estimator. As expected, the magnitude of the panel OLS lagged size estimate exceeds the system GMM, while the other estimators are biased downwards. The coefficient of this variable is significant in all cases, while the coefficient of growth persistence is always insignificant except in the standard GMM regression.

¹⁶ All reported results refer to the whole cohort of banks.

In the bivariate estimation, where profits (*ROA*) are allowed to have an impact on growth subject to a time lag, the GMM-SYS estimations of lagged size and lagged growth are insignificant, thus consistent with the univariate results and the LPE. Unexpectedly, the coefficient on *ROA* is negative, although insignificant. In the multivariate estimations, the coefficients of lagged size and growth are again insignificant. Except for *ROA*, the coefficients of the control variables have their expected signs although they are all insignificant. Accordingly, the null hypothesis of joint insignificance (Wald test) is accepted also for the bivariate and the multivariate case. Furthermore, while the two tests of instrument validity give mixed results for the bivariate estimation (like the univariate case), they are both accepted in the multivariate case, as reflected by the relatively large p-values reported in table 4.

Thus on the whole the results are consistent with a firm growth process driven by stochastic rather than systematic factors. The obtained findings of an essentially randomly determined firm growth process are in line with what Goddard *et al.* (2001, p 190) concludes in their review chapter on banking and the LPE, i.e. that there is little empirical evidence to suggest either a strong or consistent relationship between size and growth in banking, and that, on the whole, the LPE may indeed offer a reasonable description of the growth process.

6. CONCLUDING REMARKS

This paper has examined the size-growth relationship using a balanced panel of surviving Swedish banks spanning the post-regulatory reform period (1995-2002). Univariate as well as multivariate tests of the law of proportionate effect (LPE) have

been conducted using recently developed dynamic panel econometric methods (GMM-system estimator). Regardless of model specification (univariate, bivariate or multivariate) the LPE is always accepted. In the multivariate specification, all firm performance indicators turned out to be insignificant. Hence stochastic rather than systematic factors determined growth performance during the period under consideration.

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APPENDIX:

Table A1: Growth model estimates – Panel OLS results

DepVar = $Grow_{i,t}$	Univariate	Bivariate	Multivariate
$Sze_{i,t-1}$	0.00528** (2.10)	0.00584** (2.36)	0.00113 (0.251)

<i>Grw</i> _{<i>i,t-1</i>}	-0.0131 (-0.697)	-0.0121 (-0.632)	-0.0120 (-0.696)
<i>Roa</i> _{<i>i,t-1</i>}	–	0.949 (1.29)	1.24 (1.45)
<i>Mix</i> _{<i>i,t-1</i>}	–	–	0.0244 (0.182)
<i>Eff</i> _{<i>i,t-1</i>}	–	–	0.0442 (0.525)
<i>Type</i>	–	–	0.0445 (1.19)
Time dummies	[0.000]	[0.000]	[0.000]
Wald joint (χ^2)	[0.092]	[0.060]	[0.330]
AR(2) test	[0.479]	[0.486]	[0.464]

Note: t-ratios in brackets and p-values in square brackets. # of firms= 79;

of obs= 474 (balanced panel)

Table A2: Growth model estimates – Fixed effects estimation results

DepVar = <i>Grow</i> _{<i>i,t</i>}	Univariate	Bivariate	Multivariate
<i>Sze</i> _{<i>i,t-1</i>}	-0.384*** (-9.79)	-0.387*** (-9.51)	-0.400*** (-11.6)
<i>Grw</i> _{<i>i,t-1</i>}	-0.0194	-0.0194	-0.0219

	(-1.15)	(-1.15)	(-1.31)
<i>Roa</i> _{<i>i,t-1</i>}	–	-0.430 (-0.323)	-0.912 (-0.585)
<i>Mix</i> _{<i>i,t-1</i>}	–	–	0.431*** (2.89)
<i>Eff</i> _{<i>i,t-1</i>}	–	–	-0.127 (-1.01)
<i>Type</i>	–	–	–
Time dummies	[0.000]	[0.000]	[0.000]
Wald joint (χ^2)	[0.000]	[0.000]	[0.000]
AR(2) test	[0.020]	[0.031]	[0.046]

Note: t-ratios in brackets and p-values in square brackets. # of firms= 79;

of obs= 474 (balanced panel)

Table A3: Growth model estimates – GMM-DIF estimation results

DepVar = $Grow_{i,t}$	Univariate	Bivariate	Multivariate
<i>Sze</i> _{<i>i,t-1</i>}	-0.812***	-0.816***	-0.671***

	(-4.56)	(-6.02)	(-4.58)
<i>Grw</i> _{<i>i,t-1</i>}	-0.0447** (-2.05)	-0.0383* (-1.85)	-0.0306 (-1.59)
<i>Roa</i> _{<i>i,t-1</i>}	–	-2.27* (-1.73)	-2.00 (-1.09)
<i>Mix</i> _{<i>i,t-1</i>}	–	–	0.187 (0.596)
<i>Eff</i> _{<i>i,t-1</i>}	–	–	-0.258 (-1.33)
<i>Type</i>	–		-0.0232 (-0.857)
Time dummies	[0.000]	[0.000]	[0.000]
Wald joint (χ^2)	[0.000]	[0.000]	[0.000]
Sargan's test	[0.000] (12)	[0.007] (31)	[0.250] (63)
AR(2) test	[0.059]	[0.106]	[0.105]
Matrix of instruments	<i>sze(2,5)</i>	<i>sze(2,5), roa(2,5)</i>	<i>sze(2,4), roa(2,4), eff(2,4), mix(2,4)</i>

Note: two-step coefficient estimates are reported together with t-ratios

based on finite sample corrected standard errors (in brackets) ;

p-values in square brackets. # of firms= 79; # of obs= 395 (balanced panel)