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The Convergence Hypothesis of Financial Ratios : A Non-Parametric Approach

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I. Introduction

In this paper we propose and illustrate a new econometric methodology to test convergence of financial ratios. Financial analysts usually evaluate a firm's performance in relation to comparable companies in terms of aggregate financial measures. They select financial ratios calculated from published financial statements. Financial ratios are primarily used to reduce the relevant information to a limited set of financial indicators and to remove the influence of company size so that comparisons between companies of different scale are possible (Rees, 1995). Barnes (1987) identifies positive and normative uses of financial ratios. The positive uses deal with the estimation of empirical relationships (such as bankruptcy prediction). From a normative point of view a firm's financial ratios are typically compared to an industry benchmark (usually the industry mean) to determine its performance.

In practical ratio analysis company ratios are compared with industry targets. This means that optimal targets are assumed to exist. The deviation from these norms and the adjustment process of a firm's ratios towards the target is important both from a theoretical and a practical point of view. While all previous studies specify more or less advanced partial adjustment models to study financial ratio adjustment dynamics, we will introduce a non-parametric econometric methodology to test the convergence hypothesis.

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The adjustment of financial ratios towards industry targets has been studied in the literature before (Lev, 1969; Frecka and Lee, 1983; Lee and Wu, 1988; Peles and Schneller, 1989, Chen and Ainina, 1994). The focus in this literature is predominantly on various models of adjustment and on the speed of adjustment towards a given target level, usually the industry average, with the maintained hypothesis that convergence exists. Lev (1969) uses a log-linear partial adjustment model to consider financial ratio adjustment processes. Industry norms are defined as past industry averages. He concludes that firms adjust their ratios towards industry averages over time.

Frecka and Lee (1983) extend Lev's model and assume a generalized functional form technique. They find that both the linear and log-linear models are not appropriate as a general rule. Their results are equivalent to Lev's earlier results, but somewhat stronger. Lee and Wu (1988) introduce a generalized partial adjustment - adaptive expectations model and incorporate the persistence of changes in industry averages into the adjustment process. Their empirical results indicate an improvement over the simple partial adjustment model.

The methodology of Peles and Schneller (1989) does not require an a priori knowledge of the level towards ratios are adjusted. They conclude that all examined ratios follow a partial adjustment process with finite adjustment durations. Recently, Chen and Ainina (1994) estimate a partial adjustment model where the speed of adjustment is treated as a time-varying parameter which incorporates the impact of omitted macro or micro economic variables. They use interest rate expectations as a variable and confirm the partial adjustment processes followed by financial ratios.

The overall conclusion is that financial ratios are partially adjusted over time towards an industry target. An important problem associated with the conclusions derived from this technique is Galton's fallacy of regression towards the means.

This means that apparent convergence could be observed due to random shocks or measurement error in a typical adjustment regression. In other words, for the adjustment models considered financial ratios show in a typical adjustment regression a negative coefficient on the initial value of the ratio. This is often interpreted as convergence, however, such a negative coefficient could also arise in the case of non-convergence. The problem is that a single regression coefficient does not reveal much about convergence of the entire cross-section distribution. It is this issue we address in the current paper. We take the literature as given and instead of studying various possible adjustment models we investigate the underlying maintained assumption of convergence.

To do this we use an alternative econometric approach which takes into account movements in the entire cross-section distribution of financial ratios[2]. The data can be structured in Markov transition matrices that map one cross-section distribution of financial ratios into another and contain information on intra-distribution movements. The ergodic distribution derived from this system gives an indication of convergence or divergence of financial ratios over time. This technique avoids Galton's fallacy of regression towards the mean (see also Quah, 1993b).

The remainder of this paper is organized as follows. The next section introduces the empirical methodology. The third section describes the data and reports the empirical results. The fourth section presents the most important conclusions.

II. Methodology

The brief overview of the introduction shows that traditionally some kind of adjustment model was assumed and estimated, replacing the target level of the financial ratio by its industry

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[2] This methodology finds its origins in the literature of convergence in GDP per capita between countries (Quah, 1993a).

average. Implicit in this approach is the view that in each industry there exists a steady state adjustment path.

In order to investigate convergence we propose a non-parametric econometric strategy which is not tied to the restrictive assumptions of the nature of the adjustment model and which takes into account the dynamic evolution of the entire cross-section distribution (and not just one point of the distribution such as a regression coefficient or a standard deviation), thereby avoiding Galton's fallacy of regression towards the mean. By way of illustration, this fallacy arises when convergence is investigated by for example regressing the average adjustment on the initial value of the financial ratio as in equation (1)

$$(1) \quad [x_{it} - x_{it0}]/d = \alpha_0 + \alpha_1 x_{it0} + \epsilon_{it},$$

where x stands for a financial ratio, subscript i denotes firm i, subscript t stands for time, t0 denotes the time subscript in the initial period, d=t-t0 and ϵ is a white noise error term. A negative coefficient of α_1 would be interpreted as convergence, i.e. firms with a low initial value of x will increase x on average and vice versa, implying convergence towards the mean value of x. Yet, a negative coefficient on x_{it0} could be perfectly consistent with a non-collapsing cross-section distribution (e.g. Quah, 1993a; Konings, 1995).

The simplest way to illustrate this is by an example. Imagine the following relationship for x,

$$(2) \quad x_{it} = \beta_0 + \beta_1 z_i + \mu_{it}$$

where z is a variable determining the financial ratio and μ_{it} is a white noise error term. Then a regression as (1), conditioning on the information set at time t, I_t implies

$$(3) \quad E[x_{it} - x_{it0} | I_t]/d = \beta_0 + \beta_1 z_i - \beta_0 - \beta_1 z_i - \mu_{it-1}$$
$$= - \mu_{it-1}$$

Thus due to a temporary random shock (or measurement error) firms with a low initial value will seem to grow on average and vice versa.

To avoid this fallacy of regression toward the mean we will summarize the cross-section distribution of financial ratios in Markov transition matrices (Quah, 1993b). Let F_t denote the distribution of financial ratios across firms at time t and let the evolution of F_t be described by the following law of motion:

$$(4) \quad F_{t+1} = M \cdot F_t,$$

where M maps one distribution into another and shows how points in F_t end up in F_{t+1}. Notice that aggregate statistics such as means or standard deviations do not reveal any hidden intra-distribution mobility. Equation (4) is first-order and generalisations to second order or more specifications are possible. Furthermore there is no a priori reason why the relation should be time variant. Nevertheless it is a first step in analysing the dynamics in the cross-section distribution of financial ratios. Iteration of (4) gives a predictor for future cross-section distributions or

$$(5) \quad F_{t+s} = (M \cdot M \cdot \ldots . M) \cdot F_t = M^s \cdot F_t;$$

If s goes to infinity, the long-run or ergodic distribution of financial ratios can be characterised. This would mean that $[I^d - M]F = 0$, or the ergodic distribution can be derived from computing the eigenvector belonging to the eigenvalue of 1. This ergodic distribution can give an indication of convergence or divergence. Divergence might occur if the sequence $\{F_{t+s}\}$ tends to for example a bimodal distribution, while convergence if the sequence tends towards a point mass. The speed of convergence and the cross-sectional mobility properties can be studied by certain (spectral) characteristics of the operator M. We will restrict our attention to the issue of convergence.

We took each financial ratio relative to its industry weighted average. This normalisation controls for common aggregate movements (trends). Moreover, this allows us to infer easily whether there is convergence, i.e. a point mass at 1. To compute M we discretised the set of possible values of financial ratios into five roughly equal sized categories. Thus initially we imposed a uniform distribution on the set of the observed values. We experimented with alternative initial distributions, with a different number of size classes and with models having dynamics beyond the first order, but this did not fundamentally change our results reported here. The 5 by 5 Markov chain transition matrix M describes the probabilities that a firm in state j transits to state k in the next period and they are computed by the relative frequencies or

$$(6) \quad m_{jk} = n_{jk}/n_j,$$

where n_{jk} stands for the number of firms moving from state j to state k and n_j stands for the number of firms in state j.

III. Data and results

The dataset we have at our disposal covers all firms which have to submit full company accounts to the Central Accounts Administration in Belgium in the period 1986 - 1994. Companies are not included in the dataset if they do not exceed more than one of the following criteria: (1) average number of employees during the period: 50, (2) annual turnover in Belgian francs: 170 million or (3) balance sheet total in Belgian francs: 85 million; unless the average number of employees during the period exceeds 100. Industrial classification is based upon the NACE code (Nomenclature des Activités Economiques dans la Communauté Européenne). The industries selected are NACE 483 (processing of plastics) and NACE 7232 (road haulage), with respectively 216 and 383 companies on average each year.

The set of financial ratios selected for this study is the same as the set used in Lev (1969), Frecka and Lee (1983), Lee and Wu (1988), Peles and Schneller (1989) and Chen and Ainina (1994). They represent the most important categories of financial ratios. These ratios are the current ratio, the acid test (both short term liquidity), the net operating income to total assets ratio (return on investment), the equity to total debt ratio (long term solvency), the sales to total assets ratio (long term capital turnover) and the sales to inventory ratio (short term capital turnover).

Basic data are financial ratios for a given company relative to the weighted average of the industry considered. The set of possible values of these ratios are discretized by dividing the data in equal size categories. Low numbered states refer to low values for the observed financial ratios. Tables 1 to 12 show the average one-year transition matrices for the different ratios in the selected industries. In the left column we indicated in brackets the average number of firms in each initial state for the sample period. In the top row the upper end points in each category are given. Thus in Table 1 for instance convergence would occur if a point mass would be observed in the third category for the upper end point is 1.182 and thus the mean, 1, should fall in this category. The transition probabilities, which are in fact equivalent to maximum likelihood estimates, are given in the various cells of the matrix. The ergodic or steady state distributions of the average one-year transition matrix are presented in the bottom row of these tables.

Table 1 and Table 2 report the results of the current ratio. Consider for example the first size class in the processing of plastics industry. Table 1 shows that on average 56% of the companies with the smallest current ratio in a given year remained in that size class the next year. Another 27% went to the second size class and the other companies moved to higher size classes (even 3% to the highest size class).

Persistence is shown by the diagonal elements. There is more persistence in the smallest and the largest size classes for the industries selected. This means that companies with small or large financial ratios in comparison to the industry average are more likely to stay in that size class. It is clear that there is a very high intra-distribution mobility with the highest mobility in the third size class. Only 39% of the companies in NACE 483 and 37% in NACE 7232 stays on average in the third size class.

The ergodic distribution is given in the last row of the tables. It is found by computing the eigenvector associated with an eigenvalue of 1 from this matrix. This distribution is the long run steady state distribution of current ratio considered. There is no convergence because the ergodic distributions do not tend towards a point mass at 1. In contrast, they rather seem to stay uniformly distributed with a weak tendency of bimodality. In the processing of plastics industry for example, 16% of the companies eventually end up in the smallest size class and 21% in the highest size class.

	0.762	0.943	1.182	1.561	40.102
1 (193)	0.56	0.27	0.11	0.03	0.03
2 (179)	0.18	0.42	0.32	0.06	0.01
3 (205)	0.06	0.21	0.39	0.25	0.09
4 (195)	0.03	0.11	0.13	0.43	0.30
5 (210)	0.05	0.07	0.08	0.19	0.61
Ergodic	0.160	0.217	0.213	0.193	0.217

Table 1: Average first order Markov transition matrix for the current ratio (NACE 483)

	0.719	0.875	1.064	1.359	21.334
1 (304)	0.53	0.24	0.11	0.05	0.06
2 (320)	0.25	0.43	0.17	0.08	0.06
3 (297)	0.09	0.22	0.37	0.22	0.09
4 (299)	0.06	0.06	0.21	0.47	0.20
5 (309)	0.03	0.04	0.05	0.20	0.69
Ergodic	0.176	0.178	0.170	0.214	0.262

Table 2: Average first order Markov transition matrix for the current ratio (NACE 7232)

Tables 3 and 4 describe the transition matrix and ergodic distribution for the acid test or quick ratio. The results of this ratio are close to these of the current ratio. There is an important intra distribution mobility with higher persistence in the extreme classes. It cannot be said that there is convergence for this ratio in the industries considered. The ergodic distributions tend towards uniform distributions with a weak bimodal tendency.

	0.705	0.941	1.185	1.695	59.207
1 (191)	0.64	0.19	0.08	0.05	0.04
2 (200)	0.21	0.46	0.24	0.06	0.02
3 (193)	0.09	0.19	0.35	0.27	0.09
4 (199)	0.10	0.07	0.18	0.44	0.22
5 (199)	0.09	0.05	0.06	0.15	0.65
Ergodic	0.259	0.194	0.173	0.181	0.193

Table 3: Average first order Markov transition matrix for the acid test (NACE 483)

	0.688	0.851	1.052	1.388	22.450
1 (297)	0.55	0.25	0.08	0.07	0.05
2 (308)	0.26	0.41	0.20	0.07	0.05
3 (311)	0.11	0.19	0.39	0.23	0.08
4 (304)	0.04	0.05	0.24	0.49	0.17
5 (302)	0.03	0.03	0.09	0.17	0.67
Ergodic	0.182	0.175	0.202	0.219	0.222

Table 4: Average first order Markov transition matrix for the acid test (NACE 7232)

Results for the return on investment ratio can be derived from Tables 5 and 6. This ratio shows the largest transition probabilities. When compared to other ratios, this ratio shows the highest mobility over time. Persistence for the road haulage companies is for example limited to 43% and 48% in the extreme size classes and to 26% in the third size class. The probability that a company in the smallest size class moves towards the highest size class in the next period is equal to 14%. This informal desription does not suggest convergence. This hypothesis is confirmed by the ergodic distribution.

	0.322	0.698	1.157	1.911	8.640
1 (199)	0.47	0.26	0.13	0.10	0.05
2 (196)	0.24	0.35	0.19	0.14	0.08
3 (191)	0.12	0.19	0.35	0.25	0.09
4 (200)	0.04	0.09	0.22	0.34	0.29
5 (189)	0.04	0.09	0.06	0.18	0.63
Ergodic	0.163	0.187	0.180	0.204	0.266

Table 5: Average first order Markov transition matrix for return on investment (NACE 483)

	0.413	0.912	1.329	1.881	10.301
1 (317)	0.43	0.20	0.12	0.11	0.14
2 (293)	0.23	0.29	0.26	0.12	0.09
3 (298)	0.15	0.25	0.26	0.22	0.11
4 (302)	0.15	0.16	0.20	0.25	0.25
5 (306)	0.08	0.09	0.13	0.21	0.48
Ergodic	0.209	0.197	0.192	0.182	0.221

Table 6: Average first oder Markov transition matrix for return on investment (NACE 7232)

The convergence statistics of the equity debt ratio are presented in Table 7 and Table 8. This ratio clearly shows the highest persistence in the different size classes considered. This conclusion corresponds to the existing literature, where this ratio seems to be more expensive to adjust. It is important to note that this does not mean that the equity debt ratio shows convergence towards the mean. Consider the ergodic distribution for both industries selected. These distributions tend toward uniform distributions. They certainly do not show a mass point in the third class.

	0.426	0.780	1.264	2.202	46.962
1 (190)	0.72	0.15	0.03	0.09	0.01
2 (208)	0.17	0.47	0.23	0.11	0.02
3 (194)	0.07	0.23	0.45	0.24	0.02
4 (187)	0.04	0.04	0.20	0.54	0.18
5 (203)	0.04	0.07	0.02	0.15	0.72
Ergodic	0.219	0.185	0.179	0.237	0.180

Table 7: Average first oder Markov transition matrix for equity debt (NACE 483)

	0.419	0.773	1.315	2.413	172.993
1 (307)	0.63	0.21	0.08	0.05	0.03
2 (294)	0.23	0.54	0.17	0.04	0.02
3 (321)	0.06	0.20	0.57	0.15	0.03
4 (301)	0.03	0.03	0.17	0.55	0.21
5 (300)	0.03	0.02	0.07	0.19	0.69
Ergodic	0.199	0.208	0.222	0.189	0.182

Table 8: Average first oder Markov transition matrix for equity debt (NACE 7232)

Tables 9 and 10 show the results for the sales to total assets ratio. Again similar conclusions hold. The ergodic distribution in Tble 9 shows a bimodal distribution with a peak at the second size class and one at the largest and Table 10 shows that the ergodic distribution has a peak at the smallest and one at the largest category.

	0.887	1.132	1.370	1.699	7.751
1 (180)	0.56	0.22	0.08	0.07	0.07
2 (181)	0.18	0.51	0.21	0.06	0.04
3 (176)	0.06	0.20	0.39	0.27	0.07
4 (170)	0.04	0.14	0.11	0.46	0.26
5 (200)	0.09	0.09	0.05	0.17	0.61
Ergodic	0.179	0.241	0.161	0.199	0.221

Table 9: Average first order Markov transition matrix for sales to total assets (NACE 483)

	0.781	1.012	1.219	1.523	5.433
1 (249)	0.67	0.19	0.04	0.04	0.06
2 (265)	0.21	0.43	0.24	0.07	0.05
3 (249)	0.08	0.24	0.40	0.24	0.04
4 (255)	0.07	0.08	0.24	0.36	0.24
5 (263)	0.10	0.03	0.10	0.19	0.58
Ergodic	0.261	0.203	0.191	0.163	0.176

Table 10: Average first order Markov transition matrix for sales to total assets (NACE 7232)

The average transition matrix and ergodic distribution for the sales to inventory ratio are shown in Table 11 and Table 12. The results are similar as the other ratios and thus the interpretation can be self-explanatory.

	0.781	1.024	1.308	1.848	2336.38
1 (171)	0.63	0.22	0.06	0.05	0.05
2 (192)	0.25	0.40	0.21	0.08	0.06
3 (172)	0.12	0.28	0.37	0.19	0.05
4 (177)	0.11	0.07	0.24	0.46	0.11
5 (175)	0.05	0.03	0.02	0.14	0.75
Ergodic	0.265	0.202	0.163	0.165	0.204

Table 11: Average first order Markov transition matrix for sales to inventory (NACE 483)

	0.419	0.911	1.611	3.798	332.933
1 (175)	0.64	0.22	0.04	0.08	0.02
2 (186)	0.19	0.51	0.18	0.04	0.08
3 (168)	0.04	0.32	0.45	0.14	0.06
4 (195)	0.05	0.09	0.21	0.50	0.15
5 (172)	0.06	0.10	0.07	0.14	0.63
Ergodic	0.215	0.275	0.187	0.156	0.168

Table 12: Average first order Markov transition matrix for sales to inventory (NACE 7232)

The above results demonstrate that when the dynamic evolution of the cross-section distribution is explicitly taken into account no convergence towards the industry average financial ratio occurs. Note that the transition probabilities show a rich underlying dynamics of intra-distribution mobility and this is so for all financial ratios considered in this study. Moreover, there are some similarities between the different ratios for the various industries. In particular, in most cases there is higher persistency in the smallest and in the largest category. Furthermore, there is no off-diagonal element in the transition matrices that is equal to zero. This means that firms are "jumping" around and not only to the neighbouring size class, but also to more distant categories. This intra-distribution mobility goes in both directions, though not symmetrically.

These results have important implications for the adjustment literature of financial ratios. It suggests that firms remain in the same size class with temporary jumps to higher or lower size classes. It also suggests that the study of adjustment processes should take into account the entire dynamic evolution of the cross-section distribution of financial ratios. Whether these results will hold for other sectors and other countries (including a longer time frame) remains an open question.

IV. Conclusions

This study introduces a non-parametric approach to test the convergence hypothesis of financial ratios. In practical ratio analysis optimal industry targets are assumed to exist. Existing literature uses partial adjustment models to study adjustment dynamics, keeping as a maintained assumption that convergence exists. An important problem in these models is Galton's fallacy of regression towards the mean. Therefore, we investigated first the assumption of convergence, using a non- parametric methodology to test the convergence of financial ratios.

The results demonstrate that, contrary to the models used in the existing literature, we find no convergence towards the industry average for financial ratios in the industries considered. Ergodic distributions indeed tend towards uniform distributions with weak bimodal tendency. There is on average more persistency in the smallest and the largest size classes. Furthermore there is substantial intra-distribution mobility. Further study using longer time series in this area is necessary and will provide supplementary insights in the dynamics of financial ratios.

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