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Profitability Differences: Persistency and Determinants as Revealed in a Dynamic Panel Approach*

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1. Motivation and structure of the paper

The explanation of differences in the profitability of firms and industries is a seminal topic in industrial organisation. Myriads of papers are available on the cross-section relation between concentration and profits, and then followed by papers exploring the time series approach. The critique on the cross-section approach focuses on the lack of a structural model, on ignoring disequilibria and on the use of accounting profit and cost data. The time series studies infer market power from a supply relation and a demand equation suffer from economic and econometric identification problems and focus on very narrow markets (Aiginger, Brandner, Wüger, 1995).

Our alternative is to apply panel analysis on a set of 3-digit industries from 1982 to 1988. The 3-digit industries are still more aggregated than the markets that the industrial organisation expert would ideally like to analyse. Some problems of both approaches can be solved by a panel data analysis. In particular there are two specific advantages for explaining profitability differences: first, the panel approach allows for correction of latent variables, and secondly, it enables us to exploit simultaneously cross-section and time-series information to get more accurate parameter estimates. Furthermore, profits are known to be persistent over time and the usually tested economic determinants can explain only a small part of the actual variance of profits. Since actual profit data usually do not reflect equilibrium profits, we specifically concentrate on dynamic models, which can incorporate disequilibria.

Despite the growing popularity of panel data, there are not many studies in which the profitability of firms is investigated into by a thorough panel data approach. To our knowledge the first study estimating fixed effects models in industrial organisation was Domowitz, Hubbard and Peterson

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(1986); Mueller (1986) and Coate (1989, 1991) were among the first to estimate dynamic price cost margin equations. Recent contributions using a dynamic panel approach came from Conyon and Machin (1991), Haskel and Martin (1992), Machin and van Reenen (1994) and Haskel and Martin (1994). However, in screening Martin (1993) or Hay and Morris (1991) as two leading industrial organisation textbooks with empirical orientation and Hsiao (1986), Mátyás and Silvestre (1992) and Baltagi (1995) as three books on panel research, none of these books offers a comprehensive application of panel research technique on a core industrial organisation question.[1]

We have structured the paper as follows. Section 2 reviews the most popular hypotheses about the economic determinants of profits, and then inserts these hypotheses into an econometric model which specifies three static and three dynamic panel models. Section 3 outlines the data and variables. Sections 4 and 5 form the core of the paper presenting panel results first for static models (section 4) and then for dynamic models (section 5). In the final section, we sum up the findings and stress their limitations.

2. The economic determinants of profitability

The literature on the economic determinants of profitability is quite large and diverse. It provides many hypotheses and a set of stylised facts. Previous results from Austrian firm and industry data (Aiginger, 1994A, 1994B) help us further to screen the hypotheses for the data set we use.

The older literature stressed the relationship between profits and concentration or market shares. The empirical literature found that the explanatory power of these and other economic determinants was rather limited. The econometrically most important "determinants" of current profits are past profits and the capital sales ratio. Both cannot be viewed as final determinants, but the first reflects sluggish adjustment of profits to changes in the environment, entry barriers and limits for capital mobility across industries. The second may be considered as a determinant of profits, but to some degree it is also a method to correct for the fact that the left hand side profit variable is measured as often gross profits. Supergames stress that the feasibility of collusion increased with market growth and with the stability of demand (Aiginger 1994B, Aiginger, Pfaffermayr 1996). We add these vari-

[1] Manfred Neumann reported in a private conversation with the first author of this paper, that he applied panel technique to the profit concentration question, that the fixed effects model was superior to the random effects model and that the sign of the concentration rate depends on the model chosen. This conversation and Neumann's critique of an older draft of this paper were stimulating for the origin and content of this paper.

ables and a variable on the openness of markets (which could signal entry barriers) to a tentative set of candidates to represent economic determinants of profitability.

More formally, let us begin with the standard Cowling and Waterson (1976) equation which states that the industry price cost margin is positively related to market concentration and then add our additional explanatory variable as the economic determinants of the otherwise unspecified conjectural variation parameter (see Dockner 1992, Cabral 1995, Aiginger, Pfaffermayr 1996). The Cowling-Waterson Model for gross margins reads, prior to adding the structure for the conjectural variation parameter, as follows (we are skipping the time and the industry index):

$$GPCM = \sum_{i=j}^{n} \frac{p - s_j c_j}{p} = \frac{a + (1-\alpha)H}{\epsilon} + \bar{\theta}\frac{p^k K}{pQ}$$

where s_j refers to the market share of firm j, α denotes the conjectural elasticity and H the Herfindahl index of concentration. The last term on the right hand side refers to capital intensity with $\bar{\theta}$ as weighted average of the firm's user cost of capital (Martin, 1993).

The dependant variable is the gross profit sales ratio $GPCMS_{it}$, where i indicates the three digit industry (from *1* to *97*) and t indicates time (from 1982-88). If we allow for the persistency of profit differences over time and insert our determinants for the conjectural variation parameter we get the following empirical model (with indication of the expected sign of the coefficient):

$$GPCMS_{it} = \beta_o + \gamma GPCMS_{it-1} + \mathbf{x}_{it}^{'}\boldsymbol{\beta}_l + \bar{\mathbf{x}}_i^{'}\boldsymbol{\beta}_2 + \mu_i + \lambda_i + \epsilon_{it}$$

$\mathbf{x}_{it} = (CR_{it}^{+}, CRS_{it}^{+}, EXP_{it}^{-}, GR_{it}^{+}, SG_{it}^{-})$ is the vector of economic determinants for profits as are listed in the parenthesis. $\bar{\mathbf{x}}$ represents the industry means for these variables and $\epsilon_{it} \approx N(0, \sigma^2)$. μ_i, λ_t are either fixed or random industry and time effects with mean zero and the variances σ_μ^2 and σ_λ^2, respectively. We have estimated the following panel models and tested them against each other.

(1) static, fixed industry and time effects: μ_i, λ_t fixed and $\gamma = 0, \boldsymbol{\beta}_2$, not estimable

(2) static, random industry and time effects (Mundlak formulation): μ_i, λ_t random and $\gamma = 0, \boldsymbol{\beta}_2 \neq \mathbf{0}$

(3) static, fixed effects like (1) with *CR* instrumented

(4) dynamic, random industry and time effects (Mundlak formulation): μ_i, λ_t, random $\gamma \neq 0, \boldsymbol{\beta}_2 \neq \mathbf{0}$

(5) dynamic, orthogonal deviations with fixed time effects: λ_t fixed and $\gamma \neq 0, \boldsymbol{\beta}_2$, sweeps out

(6) dynamic, orthogonal deviations like (5) with *CR* instrumented

We will refer to each of the panel models as well as to the exact formulation and test of the hypotheses stated in (1) to (6) in more detail in the course of discussing the estimation results.

3. The data and the variables

We have a panel of 97 three digit industries for Austria covering the period 1982-88. After eliminating outliers our final panel has 88 industries. We use gross profits as the dependent variable (see the appendix for the formula used). As the concentration ratio we take the share of the largest four firms in employment of an industry as approximation since the Herfindahl index is not available. We have census data about concentration for 1978, 1983 and 1988 and for the years in between we have interpolated linearly. We corrected the concentration ratio for import competition using the technique proposed in Salinger 1990 (see appendix).

The capital sales ratio is constructed as investment divided into sales. This variable is needed as a control variable since we use gross profits (Martin, 1993, p. 499-500), but it may also indicate that capital intensive industries face higher entry barriers and need higher profits (because they face a higher risk, golden rules purport certain relations of own assets to fixed capital). Controlling for market-openness is an essential point in studies on industry profitability. Since we have corrected the concentration ratio by the import/sales ratio in order to account for competition from abroad, we have also included the export sales ratio. This variable should indicate whether foreign markets are more competitive as compared to the home market. We know, however, that the sign could be ambiguous since exports could also be a performance proxy. As an indicator of market growth we have taken the two years average of sales. Note, that this measure varies across industries and over time. Our variable about instability of demand is unsatisfactory. Ideally this measure should capture the uncertainty of the market or the unpredictability of demand (which would decrease collusion in supergame models, see Aiginger 1994B). We constructed the variable as the deviation of the two years average industry growth from median sales growth of the whole sample. This variable also varies across industries and over time. However, it only reflects average uncertainty in one period, so that systematic cross-sectional differences in the risk are poorly captured. In essence, it measures the deviation of industry specific demand growth from overall industry growth. So it accounts for industry-specific cyclical factors. Aggregated over time it could be a measure of riskness.

The sample is affected by outliers. We have excluded industries with the most implausible values as documented in the appendix. We checked furthermore as to whether the exclusion is justified on statistical grounds using the outlier procedures of Belsley, Kuh and Welsch (1980). Outliers which refer to only one or two periods have been controlled by the inclusion of outlier dummies. Furthermore, we have excluded variables without fluctuation over time. In principle, we could include these variables by estimating random effects models. However, as it turns out (see below), that these models are strongly rejected by the data. To keep things comparable we have restricted ourselves to the most important variables which vary across industries and over time. Therefore, we do not consider measures of product differentiation, a proxy for nationalised industries, the beta coefficient, a measure for economies of scale, since all of them do not have enough time variation. For other variables (like growth and volatility) we construct variables with a time variation that are somewhat different from the cross section study in Aiginger (1994A).

In summary, we estimate the standard Cowling-Waterson equation which is augmented by a market growth variable and a proxy for industry specific demand uncertainty. To account and to test for long run persistence of profits, we consider a partial adjustment process and include lagged profits on the right hand side. Note, that our approach differs from previous studies which consider industry- or firm-specific adjustment parameters (e.g. Mueller 1986, Geroski, Jacquemin, 1988). We follow Haskel, and Martin (1994), Coynon and Machin (1991) and in assuming a constant speed of adjustment across industries, but we also try to sort out persistent long run differences in profits by additionally controlling for fixed (i.e. persistent) industry effects.[2]

4. Static models with panel data techniques

We estimated three static models with industry and time effects. Panel model 1 is the usual fixed effects estimator with μ_i capturing fixed persistent industry effects and λ_t fixed time effects. Both, industry and time effects are highly significant. According to the test statistics in Table 2 we can

[2] This should highlight two sources of persistence over time: The autocorrelation (within industries) should indicate the degree of state dependence whereas industry effects provide evidence on the heterogeneity of industries.

firmly reject the hypothesis $H_o : \mu_i = 0, H_o : \lambda_t = 0, \mu_i \neq 0$ as well as $H_o : \mu_i = 0, \lambda_t = 0$, respectively. Particularly, the industry effects have proved to be quite strong, which may reveal the presence of large unobserved entry barriers (in panel model 1 the fixed industry effects increase the R^2 to 0.74). The large impact of industry effects is accomplished by the rejection of the random effects model in favour of the fixed effects model suggested by the Hausman-test in Table 2 (i.e. the test of panel model 2 with $\boldsymbol{\beta}_2 = \mathbf{0}$ with null hypothesis μ_i, λ_t, random against panel model 1 as $H_1 : \mu_i, \lambda_t$ fixed). This is based on the idea that the random effects estimator is consistent and efficient under H_o but biased under H_1. In contrast, the fixed effects estimator is consistent under both hypotheses. Another test of the random vs. fixed effects estimator is to use a random effects model (panel model 2) and to test whether the industry means are correlated with the random effects, which is the main assumption of the random effects estimator (i.e. $H_o : \boldsymbol{\beta}_2 = \mathbf{0}$ vs. $H_1 : \boldsymbol{\beta}_2 \neq \mathbf{0}$). This approach is known as the Mundlak formulation (Mundlak, 1978) which augments the random effects model by the industry means of all dependent variables. As Hsiao (1986) and Baltagi (1995) point out, the significance of the corresponding parameters implies that the most critical assumption of the random effects model – the independence of the right hand side variables and the random effects – does not hold true. The random effects model is then rejected in favour of the fixed effects model. Furthermore, Baltagi (1995, p. 117) mentions that a test on $\boldsymbol{\beta}_2 = \mathbf{0}$ basically reproduces the Hausman-test described above and shows that in case of rejection the random effects estimator coincides with the fixed estimator. The t-tests on Table 2 also reject the random effects model on these grounds. Another important element of the Mundlak formulation lies in the break up of the impact of the right hand side variables in two parts, within industry and between industry variation, which is informative in its own right. Here the most interesting result concerns the concentration ratio with a significant positive impact on profits within industries and a negative, although not significant, sign of average industry concentration (between variation). The time invariant average concentration ratio may thus reflect structural information like technology, economies of scale etc.

In contrast to previous cross-section estimates in panel model 1 and 2 the investment sales ratio is insignificant and the exports sales ratio turns out to be significantly positive (note both are reflecting within variation). This latter finding is not in line with the commonly held view taken in cross section studies that export markets are more competitive, it may be interpreted as the mix of two effects. First, it mirrors deviations of industry demand in foreign markets from domestic demand. Secondly, it captures the effect that industries which are ceteris paribus gaining competitiveness in the world markets exhibit higher exports and thus higher profits. Looking at the

Table 1: **Panel Estimation Results, 88 Industries, 1982-1988**
(coefficients in the first line, t-values in the second line)[a)]

	$GPCMS_{-1}$	CR	CSR	EXP	GR	SG	CRM	$CSRM$	$EXPM$	GRM	SGM	R^2	σ	σ_α [b)]	σ_t [c)]
(1) static fixed effects	–	0.03	-0.01	2.91	2.11	-0.62	–	–	–	–	–	0.77	2.33	–	–
CR exogenous	–	1.40	-0.22	2.37**)	2.24**)	-0.79	–	–	–	–	–				
(2) static random effects	–	0.03	-0.01	2.29	2.11	-0.61	-0.04	0.85	-4.29	-2.39	-5.79	0.34	2.34	3.10	1.42
CR exogenous	–	2.08**)	-0.34	3.52**)	3.31**)	-1.13	-1.75*)	6.52**)	-2.77**)	-0.33	-0.96				
(3) static fixed effects	–	0.17	-0.01	4.26	1.58	-0.55	–	–	–	–	–	0.78	2.31	–	–
CR instrumented [d)]	–	3.23**)	-0.21	3.26**)	1.65*)	-0.69	–	–	–	–	–				
(4) dynamic random e.	0.63	0.02	-0.02	2.31	1.24	-0.18	-0.03	0.37	-2.82	-1.15	-1.87	0.67	2.53	0.75	1.34
CR exogenous [e)]	22.08**)	1.05	-0.48	1.88*)	1.30	-0.23	-1.10	5.56**)	-2.14**)	-0.45	-0.87				
(5) dynamic orth. dev.	0.09	-0.02	-0.01	0.62	1.38	0.30	–	–	–	–	–	0.88	2.38	–	–
CR exogenous [f)]	6.68**)	-2.41**)	-0.62	0.87	4.42**)	0.96	–	–	–	–	–				
(6) dynamic orth. dev.	0.14	0.04	-0.01	1.36	0.96	0.52	–	–	–	–	–	0.88	2.37	–	–
CR instrumented [g)]	9.89**)	4.03**)	-0.31	2.51**)	3.63**)	1.75*)	–	–	–	–	–				

*) Significant at 10%
**) Significant at 5%
a) Outlier dummies, industry effects, time effects and constants are suppressed.
b) Standard deviation of industry effects.
c) Standard deviation of time effects.
d) *CR* instrumented by energy intensity, employment per firm, openness and all exogenous right-hand side variables including fixed industry and time effects.
e) Dynamic random effects with fixed starting values fixed, ($GPCMS_o$); Hsiao, 1986, p. 79.
f) All variables transformed to orthogonal deviations; *CR* instrumented by lagged levels only; see Arellano, Bond (1991).
g) All variables transformed to orthogonal deviations; *CR* instrumented by lagged levels, CR_{-1} and the instruments used in d); Arellano, Bond (1991)

Table 2: **Tests of the Panel Specifications**

	normal residuals J.-B. [a]	Ramsey-RESET-Test [b]	Fixed vs. random e. [c]	Indepen-dent v. [d]	No ind. e.	No fixed time e. [g]	No random time+ind. E. [h]	H.-W. [i]	Sargan [j]	Serial correlation 2.0. [k]
(1) static fixed effects CR exogenous	0.30	0.10	49.58**)	12.96**)	731.74**), e)	20.02**)	–	–	–	–
(2) static random effects CR exogenous	0.28	0.03	–	–	622.06**), f)	–	622.08**)	–	–	–
(3) static fixed effects CR instrumented	0.30	0.14	–	21.86**)	731.74**), e)	20.02**)	–	16.99**)	–	–
(4) dynamic random e. CR exogenous	0.49	5.60**)	–	–	0.13 f)	-1.84	–	–	–	
(5) dynamic orth. dev. CR exogenous	–	–	–	26.21**)	–	47.98**)	–	–	59.80	1.11
(6) dynamic orth. dev. CR instrumented	–	–	–	35.55**)	–	51.19**)	–	–	62.12	0.75

*) Significant at 10%
**) Significant at 5%
a) Jarque-Bera-test on normality: χ^2 (2)
b) Ramsey-Reset test: t-statistic of predicted GPCM squared
c) Hausman-test: χ^2 (11)
d) Likelihood ratio test (Wald Test for panel model 5 and 6) for: χ^2 (5)
e) Likelihood ratio test: χ^2 (87)
f) Lagrange multiplier test: χ^2 (2)
g) Likelihood ratio test: χ^2 (7)
h) Lagrange multipiler test: χ^2 (87)
i) Hausman-Wu-test on exogeneity of: χ^2 (1); Greene (1993)
j) Sargan test of overidentifying restrictions (GMM-estimation): χ^2 (54); Arellano, Bond (1991)
k) Robust test of second order serial correlation: N(0,1); Arellano, Bond (1991)

Mundlak specification in panel model 2, indicates that the industry averages of these two variables (reflecting between variation in this case) show the expected sign with CSR significant positive and EXP significant negative. It confirms previous cross section estimation results for Austrian data (Aiginger, 1995A) which by definition also relies exclusively on between industry variation.

The growth of demand, forms an important determinant of profits. It is significant (but not the industry average) in both panel models (1 and 2). This is in line with game theoretical models, especially supergames which predict a higher potential for collusion in growing markets (Aiginger, 1994A, 1994B). Collusion in a growing market is more likely to be sustainable, because a growing market puts more weight on future collusive profits. These have to be weighted against short run gains from defection combined with the losses in the following periods due to punishment. The risk-variable is insignificant. Note, however, that our indicator may be a poor one, since it measures one period deviations of industry demand from aggregate industry demand. The usual indicators (Martin, 1993) do not vary across time and therefore, have not been utilised in this setting.

From both a theoretical, as well as, an empirical point of view, the main problem with the standard specification of profit equations is the possible endogeneity of concentration. Theory suggests that there may be a significant feedback from high profitability in an industry to concentration, as the entry of new firms may be encouraged or highly profitable firms may hold higher market shares. As Clarke and Davies (1982) have stated price cost margins may be positively related to market shares but not caused by it. They are jointly determined by demand conditions, costs and the remaining exogenous parameters of the model. Empirically, this produces a simultaneity bias. It is this point which makes cross section estimates so difficult to interpret. One way out is to estimate the profit equation as an equilibrium relationship which is part of a larger system. We take a limited information approach and use proper instruments in a 2SLS-procedure. This is the most promising way to overcome this problem of interpretation and estimation given the data at hand which do not allow to set-up a full system. Since the random effects estimator has been rejected in favour of the fixed effects estimator in our first naive approach of panel model 1 and 2 (which takes concentration exogenously), we use the Covariance-2SLS estimator (a within estimator) of Krishnakumar (1992). This estimation proceeds in two steps. In the first step the endogenous right hand side variables are regressed on all exogenous variables plus further exogenous determinants of market structure as well as on fixed time and industry-effects. The second stage includes the predicted endogenous variables of the first stage along with the remaining exogenous variables and fixed time and industry effects. This estimator is consistent and asymptotically efficient as Krishnakumar (1992) has demonstrated.

For the instrumentation of concentration, exogenous variables which describe the structure of the industry and the conditions of entry (Table 2) are needed. Our preferred instrumentation is by energy intensity, average firms size and market openness[3]. Unfortunately other instruments like advertising intensity are not available. However, the estimation results of the first stage show that concentration is predicted quite well with energy intensity and openness significantly negative, firms size and export share significantly positive, very strong fixed effects and less pronounced, insignificant time effects[4]. Panel model 3, gives the expected significant positive estimate for the impact of concentration on profit. All other exogenous variables remain grossly unaffected. The Hausman-Wu-test[5] in Table 2 confirms this finding and strongly rejects the hypothesis of an exogenous concentration ratio. The main conclusion that can be drawn, is that proper instrumentation is even more important in panel models due to the presence of fixed industry effects.

In general, the high explanatory power of the fixed industry effects, from an economic point of view, is not particularly appealing. It suggests that profit (and also concentration) are relatively stable over time and presumably determined by stable features of the market, especially by entry barriers. Usually these characteristics remain unobserved. However, the fixed effects estimator controls for these structural time invariant characteristics by fixed industry effects and the statistics show that these are important. Yet, what we can learn from our data is not as much, as the high coefficient of determination suggests, since we do not get much information on the proper determinants of inter-industry variation of profits. The remaining estimated parameters for the proper economic explanatory variables reflect exclusively within industry variation. Consequently, they should be interpreted differently from the cross section results above. The correct interpre-

[3] Openness of the market is measured by the sum of imports and exports divided into sales. More details on the definition of the instruments can be found in the appendix.

[4] In the first stage CRC is regressed on all exogenous variables and the additional instruments leading to the following estimation results (outlierdummies are skipped, t-statistics in the second row)

EN	SIZE*100	OPEN	CSR	EXQ	GA	SG	R^2	σ	fixed ind. e.	fixed time e.
-1.4	-2.8	-12.3	-0.1	10.4	-1.1	-0.3	0.96	4.3	78.07**	0.7
-6.3**	3.3**	-6.8**	-0.7	2.9**	-0.6	-0.2			(87,517)	(6,510)

[5] This test is also based on the Hausman-principle. Under the null (concentration is exogenous) both the LSDV-fixed effects estimator and the COV2SLS estimator are consistent but under the alternative LSDV is inconsistent.

tation is as follows: given the fixed interindustry differences of profitability, to what extent an increase in a right hand side variable does affect profits? This effect is common to all industries by the pooling assumption.

5. Dynamic models with panel data techniques

The static cross-sectional price cost margin equations have to be interpreted as a long run equilibrium relationship. Two arguments have raised serious doubts about this interpretation and suggest the usage of an explicit dynamic model. First, the authors from Brozen (1971) to Schmalensee (1989) argue that cross section data may reflect a disequilibrium situation and if so, we cannot distinguish it from the long run equilibrium assumed in the static approach. A dynamic partial adjustment model, however, does this job as pointed out by Mueller (1986), Geroski and Jacquemin (1988), Coate (1989, 1991), Haskel and Martin (1994). In a partial adjustment model we can estimate both the impact of market structure and other structural variables on long run profits, as well as, the adjustment dynamics. Note, however, that the early studies did not rely on dynamic panel estimation methods, but estimated the partial adjustment parameter for each industry separately and then calculated the average adjustment speed. The second problem pointed out by Baumol et al. (1982) refers to the dependence of market performance on potential entry which remains unobservable. The long run profit level of an industry reflects this fact and the partial adjustment model can control for it in a proper way.

The dynamic panel model cannot be estimated by the usual fixed effects estimator. Hsiao (1986) notes two problems: The first problem concerns the assumptions about the starting values of the dynamic process. He shows that the estimation procedure has to be different for distinct assumptions on the starting values of the process (i.e. fixed starting values, random starting values or starting values explained by an empirical model). The consistency of the estimator also depends on these assumptions. Secondly, he demonstrates that the fixed effects estimator of the parameter of the lagged endogenous variables will be biased downwards (of order $1/T$) in a sample with a small number of time periods even in a large cross-section, leading to erroneous calculations of the long-run effects. The OLS-estimator, on the contrary, tends to be biased upwards, especially in samples that cover a short time period. This also holds true for the random effects estimator if the random effects are correlated with industry means of the right hand side variables. Using the Mundlak formulation of the random effects model one gets consistent estimates with appropriate assumptions on the starting value (Hsiao, 1986; Baltagi, 1995). For the random effects estimator the assumption on the starting values (fixed or random, explained by an empirical model) is particularly important since it implies different likelihood estimators (Hsiao, 1986).

Arellano and Bond (1988, 1991)[6] made clear that both problems can be overcome by proper instrumentation of the lagged endogenous variables using the two-step generalised-method of moments-estimator proposed by Hansen (1982). They suggest to transform the model into first differences or orthogonal deviations in order to sweep out industry effects and to use the levels of the endogenous variables lagged twice and higher as additional instruments. In the absence of second order serial correlation, these will be uncorrelated with the residuals, but correlated with the endogenous variables lagged once. Therefore, the levels of the endogenous variables with lag higher than two form proper instruments. This is true for both transformations (Arellano and Bover, 1995). Furthermore, it can be shown that due to the transformation in first differences or orthogonal deviations and the instrumentation, the estimated parameters are independent of the starting values (Hsiao, 1986).

For the empirical analysis, the data were transformed to orthogonal deviations as proposed by Arellano and Bover (1995). This transformation calculates the deviations of each data point from its future mean:

$$y_{it}^{*} = \left[y_{it} - \sum_{j=1}^{T} \frac{y_{it} + j}{T - t} \right] \sqrt{\frac{T - t}{T - t + 1}} \qquad t = 1, \ldots, T - 1; y_{it} = GPCM_{it}, CRC_{it}, CSR_{it}, \ldots$$

The great advantage of this transformation is that it generates independent or orthogonal residuals if the untransformed residuals are independent, whereas first differences would lead to negative first order serial correlation. In addition, industry-specific fixed effects are eliminated. Variables lacking variation across industries are not removed by this transformation as can be seen from (5). We thus include fixed time effects in the model. In addition, Arellano and Bond (1988, 1991) propose to estimate heteroscedasticity-consistent standard errors of the parameters based on the procedure of White (19820). This allows arbitrary correlation between the error terms within an industry but independence between industries and gives an asymptotically efficient GMM-estimator (see appendix).

We report the estimation results of three dynamic models, panel model 4 to 6. First, we have taken the concentration ratio exogenously and estimated a dynamic random effects model with exogenous starting values in the Mundlak formulation (panel model 4) with the assumption of fixed starting values. The estimation results of the independent variables are in line with the

6 Confer the appendix for more detail of the estimation procedure.

static ones. The main difference lies in the variance of the random industry effects which is now considerably lower and insignificant according to the Lagrange multiplier-test (μ, λ random, $H_o : \mu = 0$ as well as $H_o :\ \mu = 0$, $\lambda = 0$) in Table 3. The speed of adjustment parameter (γ) is highly significant and with 0.37 comparable in value to other studies (Müller, 1986; Jacquemin, Geroski, 1988; Coate, 1989, 1991). The persistence of profit is a very important aspect also from an empirical point of view. However, since lagged profits carry time invariant structural information, this result has to be interpreted with care. It mainly reflects the industry variability of the deterministic starting values (i.e. the time invariant heterogeneity of industries) as becomes clear from the decrease in the variance of random industry effects as compared to panel model 2. Furthermore, the RESET-test points to misspecification. The two dimensions of long run persistence, heterogeneity and state dependence thus cannot be disentangled properly by this model.

The picture changes if we consider the 2- stage GMM-estimates of panel model 5 and 6 (Arellano and Bond, 1988, 1991) with lagged profits and concentration rate instrumented by lagged levels (panel model 5). The estimated speed of adjustment is now much higher, 0.86. So when controlling for the starting values by proper instrumentation the estimated average persistence of profits is considerably lower than those reported in the literature. This mirrors the importance of fixed long-run interindustry profit differentials, as found in the static estimates of the static fixed effects model and it turns out that within industries, profits exhibit rather large time variation with low persistence (interpreted as state dependence). We thus conclude, that the main source of persistence lies in the heterogeneity of industries which is constant over time. State dependence, in contrast is by far less pronounced, although the test of the dynamic model against the static model (i.e. $H_o : \gamma = 0$) is firmly rejected. According to this finding there is quick adjustment to the long run profits within industries. Long run profits, however, remain different over time as found in the static estimates. So profitability differences are not dampened out over time, again pointing to a limited role of capital mobility, as well as, to high entry barriers. Both remain unobserved, however. In addition, we have found a positive impact of the concentration ratio on profits, but only significantly positive if it is properly instrumented (using the same set of instruments as in the static model as well as the lagged concentration rate (panel model 6)). The positive impact of market growth and exports is also confirmed at high levels of significance as in the static models, whereas the risk variable is found significantly positive. This may be interpreted by standard mean-variance arguments (measured profits need to be higher for greater risk), but remind that demand risk may be measured inadequately.

6. Conclusions

Explaining the behaviour of profits over time and across industries is an important economic question. Profits are very volatile and differ dramatically across industries and firms. Industrial Organisation has focused for a long time on the cross section approach, then on time series models for very narrowly defined industries. Panel analysis allows for the combination of some advantages of both approaches. The panel data approach makes use of variation across time and industries, so that relatively short time series can lead to reliable coefficients. It allows to correct for latent variables, and it allows to estimate cross section relationships even if sluggish adjustment of profits takes place. Panel techniques became popular after the time in which the profit concentration relation had been investigated into most intensively. Therefore, there are rather few papers which attack this old question with this (relatively) new technique. We specifically focus on dynamic panel models, since we do not believe that reported profits represent equilibrium values.

Our calculations show an important impact of the proper instrumentation of the concentration rate, allowing for fixed effects, and allowing a dynamic adjustment of profits. From the economic point of view the results are somewhat disappointing. The explanation of profits by fixed effects and sluggish adjustment is support for the persistency of profit difference hypothesis but it is not really satisfactory. Among the proper economic variables, the market growth variable and the market stability of markets increase profits. We prefer to interpret this as sluggish entry or with growth being favourable to some degree of collusion (as it could be modelled in supergames). We know from other investigations that the total impact of other variables (like product differentiation, economies of scale) is not too large. In this study these other variables could not be tested since they did not have enough time variation.

We conclude that the advantages offered by the panel data approach are specifically important for the study of profitability. Profits vary a lot over time and across industries, so that – as expected – concentration is only one aspect and it is not exogenous. Latent variables seem to be present and the coefficients of economic explanatory variables can be relied on only if we allow for fixed effects and if we instrument concentration. We have shown this for a panel of 3-digit industries and we will extend the research to firm data. Schmalensee (1989) encouraged further research with cross section data in an environment increasingly hostile to this approach and, calling for the extensive testing of the robustness of the results (calculating different test statistics, testing functional forms etc.). Instrumenting the variables which are supposed to be endogenous, exploiting the panel structure of the data and modelling a dynamic adjustment process are three necessary elements of this robustness test.

References

Aiginger, K., The Usefulness of Supergames in Explaining Profitability Differences in an Industry Panel, mimeo, 1994A.

– The Usefulness of Oligopoly Models for Explaining Firm Differences in Profitability, WIFO Working Paper, 1994B.

– The Use of Game Theoretical Models for Empirical Research, Working Paper, University of Linz, 1995.

– Testing Cournot Models with Firm and Industry Data, Small Business Economics, 8, 1996, pp. 365-378.

Aiginger, K., *Brandner,* P., *Wüger,* M.: Measuring Market Power for some Industrial Sectors in Austria, Applied Economics 27(4), 1995, pp. 369-376.

Aiginger, K., *Pfaffermayr,* M., CV-models, Supergames and the Determinants of Profit Margins in a Firm Panel, WIFO, mimeo, 1996.

Arellano, M., *Bond,* S., Dynamic Panel Data Estimation Using DPD – a Guide for Users, IFS-Working Paper, 88/15, 1988.

– Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations, Review of Economic Studies, 58, 1991, pp. 277-297.

Arellano, M., *Bover,* O., Another Look at the Instrumental Variable Estimation of Eerror Component Models, Journal of Econometrics, 68, 1995, pp. 29-51.

Bain, J. S., Relation of Profit Rate on Industry Concentration: American Manufacturing, 1936-1940, Quarterly Journal of Economics, 65, 1951, pp. 293-324.

– Barriers to New Competition, Harvard Press, Cambridge, 1956.

Baltagi, B. H., The Econometrics of Panel Data, John Wiley & Sons, Chichester, New York, 1995.

Baumol, W. J., *Panzar,* J. C., *Willig,* R., Contestable Markets and the Theory of Industrial Structure, New York, Harcourt Brace Jovanowich, 1982.

Belsley, D. A., *Kuh,* E., *Welsch,* R. E., Regression Diagnostics, Identifying Influential data and Sources of Collinearity, John Wiley & Sons, New York, 1980.

Bothwell, J., *Keeler,* T. E., Profits, Market Structure and Portfolio risk. in Masson, R. T., Qualls, D. P. (eds), Essays in Industrial Organization in Honour of J. S. Bain, Cambridge MA, Ballinger, pp. 71-88.

Bresnahan, T. F., Empirical Studies of Industries with Market Power, in Schmalensee, R., Willig, R. D. (eds.), Handbook of Industrial Organization, Elsevier Publishers, Amsterdam, New York, 1989.

Cabral, L. M. B., 1995 Conjectural Variations as a Reduced Form, Economics Letters, 49, 1995, pp. 397-402.

Clarke, R., *Davies,* St., Market Structure and Price Cost Margins, Economica, 49, 1982, pp. 227-287.

Coate, M. B., The Dynamics of Price-Cost Margins in Concentrated Industries, Applied Economics, 21(2), 1989, pp. 261-272.

– The Effect of Dynamic Competition on Price-Cost Margins, Applied Economics, 23(6), 1991, pp. 1065-1076.

Conyon, M., Machin, Profit Margins in UK Manufacturing, Journal of Industrial Economics, 29(4), 1991, pp. 369-382.

Cowling, K., Waterson, M., Price Cost Margins and Market Structure, Economica, 38, 1976, pp. 378-394.

Davidson, R., *MacKinnon,* J. G., Estimation and Inference in Econometrics, Oxford University Press, New York, Oxford, 1993.

Demsetz, H., Industry Structure, Market Rivalry, and Public Policy, Journal of Law and Economics, 16, 1973, pp. 1-10.

– Two Systems of Belief about Monopoly, in Goldschmid, H. J., Mann, H. M., Weston, J. F. (eds.), Industrial concentration: The new learning, Boston, Little Brown, 1974.

Dixit, A. K., The Role of Investment in Entry Deterrence, Economic Journal, 90, 1980, pp. 95-106.

Dockner, E. J., A Dynamic Theory of Conjectural Variations, Journal of Industrial Economics, 40(4),1992, pp. 377-395.

Domowitz, I., *Hubbard,* G. R., *Petersen,* B. C., The Intertemporal stability of the Concentration-Margins Relationship, Journal of Industrial Economics, 35(1), 1986, pp. 13-34.

Fisher, F. M., On the Misuse of Profit Sales Ratios to Infer Monopoly Power, Rand Journal of Economics, 18, 1987, pp. 384-396.

Fisher, F. M, *Gowan,* J. J., On the Misuse of Accounting Rates of Return to Infer Monopoly Profits, American Economic Review, 73 (1), 1983, pp. 82-97.

Gale, B. T., Market Share and the Rate of Return, Review of Economics and Statistics, 54, 1972, pp. 421-423.

Gale, B. T., *Branch,* B. S., Concentration versus Market Share, Antitrust Bulletin, 1982, pp. 83-106.

Geroski, P. A., Specification and Testing the Profits – Concentration Relationship: Some Experiments for the U.K., Economica, 48, 1981, pp. 279-288.

– Competition and Innovation, Report prepared for the EC Commission, Brussels, 1987.

– In Pursuit of Monopoly Power, Journal of Applied Econometrics, 3, 1988, pp. 107-23.

Geroski, P. A, *Jacquemin,* A., The Persistence of Profits: a European Comparison, Economic Journal, 98, 1988, pp. 375-389.

Greene, W. H., Econometric Analysis, Macmillan, New York, 1993.

Häckner, J., Collusive Pricing in Markets for Vertically Differentiated Products, International Journal of Industrial Oorganization, 12, 2, 1994, pp. 141-296.

Hansen, L. P., 1982, Large Sample Properties of Generalized Method of Moment estimators, Econometrica 50, 1029-1054.

Haskel, J., *Martin,* Ch., Margins, Concentration, Unions and the Business Cycle, Theory and Evidence for Britain, International Journal of Industrial Organization, 41(1), 1992, pp. 611-632.

– Capacity and Competition: Empirical Evidence on UK panel data, Journal of Industrial Economics, 42(1), 1994, pp. 23-44.

Haskel, J., *Scaramozzino,* P., Do other Firms Matter in Oligopolies forthcoming in Journal of Industrial Economics, 1996.

Hay, D. A., *Morris,* D. J., Industrial Economics and Organization, Oxford, Oxford University Press, 1991.

Hendry, D. F., Dynamic Econometrics, Oxford, Oxford University Press, 1995.

Hsiao, C., Analysis of Panel Data, Cambridge University Press, 1986.

Krishnakumar, J., Simultaneous Equations, in Mátyás, L., Sevestre, P. (eds.), The Econometrics of Panel data, Handbook of Theory and Applications, Kluwer, 1992.

Machin, S., *van Reenen,* J., Profit Margins and the Business Cycle: Evidence from UK Manufacturing Firms, Journal of Industrial Economics, 41(1), 1993, pp. 29-50.

Martin, St., Advanced Industrial Economics, Blackwell 1993.

Mátyás, L., *Sevestre,* P. (eds.), The Econometrics of Panel Data, Handbook of Theory and Applications, Kluwer, 1992.

Mueller, D. C., Profits in the Long Run, Cambridge, Cambridge University Press, 1986.

Mundlak, Y., On Pooling Time Series and Cross Section Data, Econometrica, 46, 1978, pp. 69-85.

Neumann, M., *Böbel,* I., *Haid,* A., Profitability, Risk and Market Structure in West German industries, Journal of Industrial Economics, 27 (3), 1979, pp. 227-42.

Neumann, M., *Haid,* A., Concentration and Economic Performance, in Schwalbach, J. (ed.), Industry structure and performance, WZB Edition Sigma, Berlin, 1985.

Salinger, M., The Concentration-Margins Relationship Reconsidered, in Brookings Papers: Microeconomics, 1990, pp. 287-321.

Schmalensee, R., Interindustry Studies of Structure and Performance, in Schmalensee, R., Willig, R. D. (eds.), Handbook of Industrial Organization, Elsevier Publishers, Amsterdam, New York, 1989.

Shapiro, C., Theory of Oligopoly Behaviour, in Schmalensee, R., Willig, R.D., Handbook of Industrial Organization, Elsevier Publishers, Amsterdam, New York, 1989.

Sutton, J., Explaining Everything, Explaining Nothing, European Economic Review, 34, 1990, pp. 505-512.

– Sunk Costs and Market Structure, MIT Press, Cambridge, London, 1992.

Tirole, J., The Theory of Industrial Organization, MIT Press, Cambridge, London, 1989.

Waterson, M., Price Cost Margin and Successive Market Power, Quarterly Journal of Economics, 94, 1980, pp. 135-150.

– Product Differentiation and Profitability: an Asymmetric Model, Journal of Industrial Economics, 39, 1990, pp. 113-130.

White, H., 1982, Maximum Likelihood Estimation of Misspecified Models, Econometrica 50, p. 1-25.

Appendix 1

Sources and variables

Sources:	Austrian Statistical Office Census (Nichtlandwirtschaftliche Bereichszählung), 1983, 1988; BZ Annual Industrie- and Gewerbestatistik, 1980-88; ISGS Audoclassis (trade and production statistics); Audo WIFO-database (Traude Novak)

Manufacturing industries:

3-digit-level No 311-594 (excluding 328 tabacco, 343 furrier, 473 calcium and phosphates, 477 magnesite, 478 cement, 544 paper, print and office machines, 558 repair shops, 591 optical instruments, 594 watches and jewellery)

Period:	1980-1988
Country:	Austria

We excluded industries with obvious measurement errors namely with

(i) negative GPCMS for more than 2 periods

(ii) export shares above 200% (obviously a mismatch of trade and industry data)

(iii) growth higher than 100%.

For industries with outliers according to this definition in one or two periods we included outlier-dummies.

Variables:

GPCM:	Gross Price Cost Margin (sales as denominator) = 100.(Sales – Payroll – Material)/Sales, ISGS
CRH:	employment share of the largest four firms 1988 (criterion for ranking value added), BZ available for 1978, 1983 and, 1988; values in between have been linearly interpolated. In order to control for import penetration we corrected by (1-IMP) with IMP=Imports/(domestic sales + imports), see Salinger (1990)
CSR:	investment/sales 1988, BZ
EXP:	export/sales, Audo
GR:	annual average growth of nominal production, 2 year-moving average, Audo
SD:	deviation of GR from median industry growth, Audo
EN:	share of energy cost in total costs, ISGA
SIZE	average number of employees per firm
OPEN	(export + imports)/sales, Audo

Appendix 2

An overview of the Arrelano-Bond Procedure for the Estimation of Dynamic panels

Arrelano and Bond (1991) show that the bias of the lagged dependent variable in a dynamic panel model can be corrected by instrumenting with lagged levels. To illustrate this, assume the most simple model without exogenous variables in first differences:

(i) $$\Delta y_{it} = \alpha \Delta y_{it-1} + \Delta v_{it} \qquad i = 1, \dots, N;\ t = 2, \dots, T;\ \Delta v_{i1} = v_{i1}$$

For the i-th industry (y_{it-2}) is a proper instrument since

(ii.1) $$E[\Delta v_{it} y_{it-2}] = E\left[(v_{it} - v_{it-1})\left(\sum_{j=1}^{t-2} \alpha^{j-1} v_{it-j-1} + \alpha^{t-2} y_{i0}\right)\right] = 0$$

(ii.2) $$E[\Delta v_{it} y_{it-2}] = E\left[(v_{it} - v_{it-1}) y_{it-2}\right] \neq 0$$

Obviously the same holds true $y_{it-2}, y_{it-3}, \dots$. The optimal instrumentation uses all lagged levels available (Arrelano, 1988, Arrelano and Bond, 1991) so that the matrix of instruments possesses the following form:

(iii) $$z = \left[Z_1', \dots, Z_N'\right] \quad \text{with} \quad Z_i = \begin{bmatrix} y_{i1} & 0 & 0 & & 0 & 0 & & 0 \\ 0 & y_{i1} & y_{i2} & & 0 & 0 & & 0 \\ & . & . & & & & & \\ . & . & . & & . & . & & . \\ 0 & 0 & 0 & & y_{i1} & y_{i2} & & y_{iT-2} \end{bmatrix}$$

The estimation employs the GMM-procedure which is based on the fact that the instrumentation proposes restrictions on the moments of the endogenous variable. (Greene, 1993, p. 370-381, Davidson and MacKinnon, 1993, p. 620). It can be demonstrated that the usage of the empirical moments leads to a proper estimator. In our case it must hold that:

(iv) $$\sum_{i=1}^{N} Z_i'({}_i - \alpha \Delta y_{i,-1}) = 0 \quad \text{with} \quad \Delta y_i = [\Delta y_{i2}, \dots, \Delta y_{iT}] \quad \text{und} \quad \Delta y_{i,-1} = [\Delta y_{i1}, \dots, \Delta y_{iT-1}]$$

Since (iv) usually is overidentified the following quadratic form with weighting matrix A_N is minimised:

$$(\Delta y - \alpha \Delta y_{-1}) Z A_N Z' (\Delta y - \alpha \Delta y_{-1})$$

leading to the GMM-estimator (H is again a weighting matrix):

$$\hat{\alpha} = \left[\left(\sum_{i=1}^{N} \Delta y_{i,-1}^{'} Z_i\right) A_N \left(\sum_{i=1}^{N} Z_i^{'} \Delta y_{i,-1}\right)\right]^{-1} \left(\sum_{i=1}^{N} \Delta y_{i,-1}^{'} Z_i\right) A_N \left(\sum_{i=1}^{N} Z_i \Delta y\right). \qquad \text{with}$$

$$A_N = \frac{1}{N}\left(\sum_{i=1}^{N} Z_i^{'} H Z_i\right)^{-1}$$

Greene (1993) and Davidson and MacKinnon (1993) mention the following characteristics of this estimator:

(1) If the number of instruments is equal to the number of variables (iv) can be solved directly. In particular if it is the only instrument and all variables are first differences or orthogonal deviations (or more general inclusive the industry mean corrected right hand side variables) then (vi) is a within estimator (Arrelano, Bond, 1988, p. 4, Hsiao, 1986, p. 13).

(2) For each weighting matrix H (vi) is consistent and asymptotic normal (Davidson and MacKinnon, 1993, Theorem 17.1 and 17.2).

(3) It can be shown (Hansen, 1982; Greene, 1993; Davidson and MacKinnon, 1993, Theorem 17.3) that the GMM-estimator is asymptotically efficient if H is chosen in such a way that corresponds to the asymptotic variance-covariance matrix of (iv), i.e.

(vii) $$A_N^{-1} = as.Var\left[z^{'}(y - \alpha y_{-1})\right] = as.Var[Z^{'}\epsilon] = Z^{'}\Omega Z$$

where Ω denotes variance-covariance matrix of Δv_{it}. Following the procedure of White (1982) in the second step, (vi) is estimated with estimated weights $\hat{A}_N$. This implies that there can be any form of heteroscedasticity within an industry. However, between industries the errors are assumed to be independent from each other.

(4) The estimation results depend heavily on two assumptions: First it is has to be tested as to whether the overidentifying restrictions indeed hold so that the estimation results are compatible with the moment-restrictions in (iv). Secondly, the instrumentation with lagged levels twice is only valid if there is no second order autocorrelation in the error-term. For both hypotheses Arrelano and Bond (1991) provide diagnostic tests. The test statistic for overindentification is asymptotically distributed as χ^2 with the degrees of freedom equal to the number of overidentifiying restrictions and that for first and second order serial correlation are asymptotically standard normal.

(5) Linear restriction on the right hand side variables can be tested by the usual Wald-Tests (Davidson and MacKinnon, 1993).

Zusammenfassung

Wir untersuchen die Unterschiede in der Profitabilität von Industrien in einem dynamischen Panelansatz. Die ökonomische Erklärung beginnt mit der traditionellen Hypothese, daß Anbieterkonzentration die Gewinne erhöht. Diese Grundhypothese wird um zwei Implikationen der Superspielliteratur ergänzt, nämlich, daß die Möglichkeit zur Kollision mit dem Branchenwachstum und der Stabilität der Nachfrage steigt. Als strukturelle Erklärungsvariable kommen Kapitalintensität, Marktoffenheit und random und fixed effects hinzu, wobei drei statische und drei dynamische Panelmodelle geschätzt werden. Es zeigt sich eine erhebliche Persistenz der Gewinnunterschiede über die Zeit; nur ein Teil davon kann durch die von der ökonomischen Theorie vorgeschlagenen Determinanten erklärt werden.

Abstract

In a panel approach we have investigated the differences in profitability of industries. The economic hypotheses used for the explanation are that concentration and/or market shares are positively related to profitability, and the supergame implications that growth and stability of demand facilitate collusion. We have added structural controls for capital intensity and openness of markets and estimate fixed, as well as, random effects in three static and three dynamic panel models. The results show a pronounced persistence of profit differences, where some part of these differences can be explained by the economic hypotheses supplied by the theory.

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