THE PERSISTENCE OF ABNORMAL RETURNS AT INDUSTRY AND FIRM LEVELS: EVIDENCE FROM SPAIN

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We apply structural equation models to longitudinal data on profits of firms within industries to study the persistence of abnormal returns. We obtain a two-way variance decomposition for abnormal returns: at firm vs. industry levels, and at permanent vs. transitory components. This decomposition enables us to assess the relative importance of the fundamental components of abnormal returns discussed in the literature. The method is applied to a panel of 5,000 Spanish firms observed over the period 1995–2000. We conclude that: (a) there are significant and permanent differences between profit rates at both industry and firm levels; (b) variation of abnormal returns at firm level is greater than at industry level; and (c) firm and industry levels do not differ significantly regarding rates of convergence of abnormal returns. Copyright © 2007 John Wiley & Sons, Ltd.

INTRODUCTION

Empirical data show that, at a given point in time, profit rates differ widely across firms and industries, with some firms showing what is called ‘abnormal returns,’ that is, profits that deviate significantly from the mean or equilibrium level (Jacobson, 1988). This empirical fact gives rise to certain basic questions. Will these deviations from the equilibrium profit rate disappear over time; i.e., are these differences ‘permanent’ or merely ‘transitory’? Do these differences arise at industry or at firm level? What are the relative magnitudes of these components of abnormal returns? Two main research directions can be distinguished in the literature on these questions.

One line focuses on identifying the level of analysis—whether it be firm (or business unit), corporation or industry—where differences in profits arise (Schmalensee, 1985; Rumelt, 1991; Wernerfelt and Montgomery, 1988; Roquebert, Phillips, and Westfall, 1996; Powell, 1996; Mauri and Michaels, 1998; McGahan and Porter, 1997; Brush, Bromiley, and Hendrickx, 1999; Bowman and Helfat, 2001; Spanos, Zaralis, and Lioukas, 2004). Findings from this research show: (a) a wide consensus regarding the existence of significant firm and industry effects (Bowman and Helfat, 2001; McGahan and Porter, 2002); (b) firm effects to be greater than effects from industry (see, e.g., Rumelt, 1991; Roquebert et al., 1996; McGahan and Porter, 1997); and (c) the existence of a significant time dependence on these effects (Rumelt, 1991; McGahan and Porter, 1997; Chang and Singh, 2000).

A second line of research focuses on the time dependency of profit rates and, specifically, on the convergence process of firm–profit differences.
toward a long-run equilibrium value (e.g., Connolly and Schwartz, 1985; Mueller, 1986, 1990a; Odagiri and Yamawaki, 1986; Jacobson, 1988; Schohl, 1990; Ghemawat, 1991; Jacobson and Hansen, 2001; Furman and McGahan, 2002). Their findings can be summarized as follows: there is a convergence process toward the mean profit rate (see, e.g., Mueller, 1986; Jacobson, 1988); and the convergence process is incomplete, because it does not lead to an equalization of firm–profit rates in the long run (Connolly and Schwartz, 1985; Ghemawat, 1991).

The above research uses variance component analysis and nested ANOVA models to disentangle the different sources of profitability, or the time-series models to study the evolution of profit rate differences over time. However, later studies (Cubbin and Geroski, 1987; Waring, 1996; McGahan and Porter, 1999, 2003) focused on the change of abnormal returns over time at firm and industry levels, thus bringing together the two analysis perspectives (McGahan and Porter, 2003). In addition, some authors have recently recommended that variance decomposition should pay more attention to the time dimension of the abnormal returns (see Bowman and Helfat, 2001; Adner and Helfat, 2003).

The first author to claim the importance of the industry effect in the study of persistence was Waring (1996), who argued that estimates of persistence that do not take into account industry heterogeneity can be misleading. He found that estimated industry persistence rates differ substantially, ranging from nearly zero to complete convergence in 1 year. Pursuing Waring’s (1996) approach, McGahan and Porter (1999) achieve the decomposition of abnormal returns into year, industry, corporate parent, and business segment components, with a ‘time-incremental’ component modeled as an autoregressive process. They concluded that changes in industry structure have a more persistent impact on profitability than changes in firm structure. More recently, McGahan and Porter (2003) studied the influence of the entire (i.e., fixed and incremental) industry, corporate and business-specific effects on the emergence and the sustainability of abnormal returns, finding that differences exist in the size of these effects.

The above findings were obtained from databases from the United States and other large economies, including the United Kingdom, Japan, Canada, Germany, and France (see Mueller, 1990b). It should be interesting to see whether these general findings also hold in medium- or small-size economies. The scant research comparing persistence rates across countries (see Odagiri and Yamawaki, 1990) finds important differences across countries in the extent to which profit differences persists. Different variables such as import penetration, tariff levels, and industry concentration (Geroski and Mueller, 1990), which represent the relative competitiveness of these countries in the international markets, have been proposed as a possible explanation of the observed differences across countries.

Although Spain has experienced rapid economic growth since it joined the European Union (EU) in 1986, the competitive landscape in which its firms have been immersed during the second half of the 1990s differs from that of the large economies mentioned above. Spain during the 1995–2000 period is an example of a medium-sized economy that may yield interesting information regarding these research questions. To our knowledge, the persistence of abnormal returns at firm and industry levels in Spain has not been studied in the past.

The statistical approach used in Waring (1996) and McGahan and Porter (1999) suffers from certain difficulties regarding the decomposition of abnormal returns on its basic constituents. Specifically, the decomposition is dependent on a specific ordering of the subtraction of effects; moreover, no inference statistics such as standard errors for assessing the magnitudes of these components are available. Using the same model as in Waring and McGahan and Porter, in the present paper we propose a new method based on structural equation models for a variance decomposition of abnormal returns into time, firm and industry components. The method provides a variety of statistics for carrying out inferences regarding the magnitude of these components. Like McGahan and Porter (2003), we analyze the entire influence in abnormal returns of industry and firms, distinguishing the influence arising from transient and permanent components. In contrast with the (fixed effects) variance decomposition approach, our method uses a variance component specification in which abnormal returns are decomposed into random effects associated to time, industry, and firm-by-year components. We apply this method to a Spanish database of the 5,000 larger firms observed over the period 1995–2000, and
compare our results with those obtained using other methods.

RESEARCH QUESTIONS

This section describes various research questions concerned with persistence of abnormal returns, at firm and industry levels.

Permanent differences

Conventional microeconomic theory assumes that, in the long run, abnormal returns disappear under the pressure of competitive forces. This corresponds to the belief that there are no systematic or permanent differences among firms or industries for abnormal returns; that is, the observed differences of abnormal returns are only a transitory phenomenon that vanishes completely when short-run rents are eroded by the competitive process. The eventual equalization of profits in the long run should arise both at firm and at industry levels. Our research question is whether there is complete convergence of abnormal returns toward the mean, both at firm and industry levels.

Persistence

The issue of the speed of convergence of abnormal returns to zero, or to some mean value, is referred to in the literature as the ‘persistence’ of abnormal returns (Mueller, 1986, 1990a; Odagiri and Yamawaki, 1986). Previous research has established the existence of persistence at industry level (e.g., Coate, 1989, 1991; Waring, 1996; Mueller and Raunig, 1999), and at firm level (e.g., Mueller, 1977, 1986; Schwalbach, Grasshoff, and Mahmoud, 1989; Ghemawat, 1991; Jacobson, 1988; Roberts, 1999, 2001). McGahan and Porter (1999) concluded that industry effects are more persistent than firm effects. Thus, a research question is whether convergence of abnormal returns is faster at industry than at firm level.

Industry vs. firm effects

So far we have considered only the presence of a permanent component and the amount of persistence, both at firm and industry levels. We have not yet considered the relative importance of industry vs. firm effects in terms of the magnitude of their variances. Previous empirical analyses have shown the existence of both industry and firm effects. Although there are differences across studies in the relative size of these effects, the predominant conclusion is that variation at firm level is greater than at industry level (Rumelt, 1991; Roquebert et al., 1996; Mauri and Michaels, 1998; McGahan and Porter, 1997, 2002). We therefore expect profit differences within industries to be greater than across industries.

THE MODEL

We apply a dynamic model for panel data to examine the persistence of abnormal returns. This is Anderson and Hsiao’s state dependence model (1982), and Kenny and Zautra’s trait-state-error model (1985, 2001). The model can be traced back to Goodrich and Caines (1979). Below, this model is extended to two-level data. The model decomposes firms’ abnormal returns into a static (permanent), a dynamic (transitory), and an unexplained (error-term) component:

\[ Y_{it} = \lambda_t P_t + A_{it} + U_{it}, \quad t = 1, 2, \ldots, T \]

\[ A_{it+1} = \beta A_{it} + D_{it}, \quad t = 1, 2, \ldots, T - 1 \]  

(1)

where subscripts \( i \) and \( t \) denote firm \((i = 1, 2, \ldots, n)\) and time, respectively.

The variables (varying across firms) involved in the equations are: \( Y_t \), the abnormal return at time \( t \) (difference of the firms’ profit in year \( t \) from the overall mean of the firms’ profit in that year); \( P_t \), the static or permanent component; \( A_{it} \), the autoregressive component at time \( t \); \( U_{it} \), idiosyncratic (unexplained) firm-by-year component at time \( t \); and \( D_{it} \), a disturbance component of the dynamic autoregressive part of the model at time \( t \).\(^1\) We assume \( U_{it} \) to be uncorrelated with \( P_t \) and \( A_{it} \); and \( D_{it} \) to be uncorrelated with \( A_{it} \) and with each other. The model allows for possible correlation between \( P \) and \( A_1 \) (thus introducing possible correlation between permanent and temporary components). Variables \( U_{it} \) and \( D_{it} \) are assumed to be centered and

\(^1\) We do not include an intercept term, since we take \( Y_t \) to be the firm’s profit in deviations from the mean of profits for the given year. In this way, we separate industry and firm-specific components from total profitability (Waring, 1996; McGahan and Porter, 1997), thus removing the cyclical component of profitability change (Mueller, 1986).
uncorrelated with each other. Here \( \lambda_i \) denotes the factor loading of variable \( Y_i \) on \( P_i \), and \( \beta_i \) is the so-called autoregressive parameter, possibly varying across time. Without loss of generality, we assign a unit of measurement to the (latent) random component \( P_i \) by setting \( \lambda_1 = 1 \). Before proceeding with estimation, we describe in more detail the substantive meaning of each of the model’s components.

**Permanent component, \( P \)**

This represents the stable part of abnormal returns, with random variation across firms, that does not vary over time. It accounts for long-run or sustainable differences across firms within the period of observation. As argued in earlier studies (e.g., Mueller, 1986, 1990a; Geroski 1990; Waring, 1996; McGahan and Porter, 1997), such a permanent component may account for industry-stable structural characteristics (economies of scale, entry barriers, product differentiation, etc.) and permanent firm-specific rents (that is, differences between firms in the configuration of activities and organizational processes, in managerial competence, in resource endowment, etc.). When other factors are constant, the magnitude of the variance of this component is likely to decrease with the length of the panel.

**Temporary (autoregressive) component, \( A_t \)**

This reflects the part of the firm’s profit rate that changes over time. It can be interpreted as short-run rents\(^2\) that are eroded by the competitive process. Its variance depends on the size and frequency to which these short-run rents are generated (i.e., the propensity of firms to innovate; see Roberts, 1999, 2001), and the extent to which short-run rents are asynchronous across firms (Neseroade, 1991).

Following previous work (Jacobson, 1988; Mueller, 1986, Geroski and Jacquemin, 1988; Cubbin and Geroski, 1987, 1990; Geroski, 1990, Maruyama and Odagiri, 2002), \( A_t \) is assumed to follow a first-order autoregressive process, AR(1). This AR(1) structure implies that short-run rents converge to a mean value (equilibrium rate of return), with the speed of this convergence determined by the autoregressive parameter \( \beta_i \) (maximum speed corresponding to \( \beta_i = 0 \)). Our model easily extends to a more general AR structure; though, for the sake of parsimony and following previous research (e.g., Mueller, 1986; Jacobson, 1988; McGahan and Porter, 1997), here we adhere to the restricted specification of an AR of order one.

**Unexplained firm-by-year component, \( U_{i_t} \)**

This component accounts for the portion of a firm’s profit variance that correlates neither across time nor across firms. It is a ‘shock’ for each year with random variation across firms. It encompasses all the specific circumstances that are not stable, but that affect a firm’s profit rate in a given year (such as extraordinary profits or losses due to breakdowns, damage, etc.). Our model allows variation of the variance of \( U_{i_t} \) across time (heteroskedasticity) to account for unequal impact of these ‘shocks’ over the years. The \( U_{i_t} \) also encompass measurement error that accounting conventions could introduce in the measurement of abnormal returns (see, e.g., Demsetz, 1979; Fisher and McGowan, 1983; Benston, 1985).

**Estimation and parameter restrictions**

The above model can be fitted using standard structural equation model (SEM) methodology. The model we posited in Equation 1, which specifies a linear relationship among the different components of abnormal returns, including errors and disturbance terms, represents a special case of the general linear latent variable model. In Appendix 1, we provide details of this general model (see also the LISREL model of Jöreskog and Sörbom, 1996). See Satorra (2002) for a general technical description of the methods used in fitting general latent variable models, and Muthén and Satorra (1995) for technical details regarding the extension of linear latent variable models to two levels, as seen below.

Different degrees of parameter restrictions can be imposed on the model. We consider first a model that restricts \( \beta_i \) and the variances of \( D_t \) not to vary across time. This restriction imposes stationarity on the dynamic component of abnormal returns (not, however, on the observed variables, since the variances of \( U_{i_t} \) are allowed to vary with
t). We will also restrict to zero the possible correlation between the permanent and transitory components. With these restrictions, the model achieves a simple variance decomposition of the abnormal returns into its various components. We will relax any of these restrictions if the goodness-of-fit test of the model, and other statistics for testing sets of restrictions, indicate the need to do so. In other words, we start with a parsimonious model that provides simple interpretation, and relax restrictions on this model when necessary. Under this specification, the parameters of our model are the regression coefficient \( \beta \), and the variances \( V_p, V_A, V_D \), and \( V_{U_t} \) of the respective random components \( P, A, D \), and \( U_t \).

Our approach differs from precedents in the literature (Waring, 1996; McGahan and Porter, 1999, 2003) but is based on similar hierarchical models. We fit the single- and two-level model with temporal dependency by maximum likelihood (ML), and estimate variances of temporary and permanent components at firm and industry levels. The strength of the method is that these variances, and the autoregressive coefficient \( \beta \) of temporal dependency, are parameters with direct substantive interpretation. Standard errors, chi-square goodness-of-fit test statistics, and tests for specific set of restrictions are available. When standard assumptions such as normality hold, our analysis is efficient and provides correct inferences. A possible limitation of our approach is the distributional assumption of the various sources of variation. The extent of the distortion in the analysis due to departure from the distributional assumptions is an issue that could be pursued in further research.4

The methods we use are fundamentally different from Ruefli and Wiggins (2003). We do not have to cluster the observations and therefore avoid losing any information by categorizing the data, and sidestep the ambiguities of the clustering algorithms. Our approach should help to clarify some of the controversial issues in the literature on business performance (see McGahan and Porter, 2005), by providing a general framework in which methods and assumptions can be assessed more clearly.5

### Variation at firm and industry levels

We recognize a hierarchical or two-level structure in the formation of abnormal returns, so that if \( Y_{ijt} \) denotes the abnormal return of firm \( i (i = 1, 2, \ldots, n_i) \) of industry \( j (j = 1, 2, \ldots, J) \) at time \( t (t = 1, \ldots, T) \), we let \( Y_{ijt} = Y_{ijt}^{Firm} + Y_{ijt}^{Industry} \), with \( Y_{ijt}^{Firm} \) and \( Y_{ijt}^{Industry} \) being the respective (latent) firm and industry components of abnormal returns.6 Model 1 is now applied to each of these two components, obtaining the following two-level model specification:

\[
Y_{ijt} = \lambda_{1t} P_{ij} + A_{ijt} + \lambda_{Ft} F_{ijt} + A_{Fijt} + U_{ijt}, \\
A_{F(i+1)} = \beta_F A_{Fit} + D_{Fit}, \\
A_{I(i+1)} = \beta_I A_{ijt} + D_{ijt} \tag{2}
\]

where the components \( P, A, U, \) and \( D \) have the same interpretation as earlier, with subscripts \( F \) and \( I \) denoting, respectively, firm and industry levels. The same Model 1 was applied to both levels, except that the firm-by-year component \( U_{ijt} \) was absent at the industry level.7 If information on diversification of firms were available, the second level would be defined as the ‘interaction’ of corporation and industry (corporation \( \times \) industry); a third level could be introduced if we wanted to separate the effects of corporation (alternatively, industry) from the interaction effect. The details of such a three-level model go beyond the initial purpose of this work, particularly because the Spanish database we intend to analyze lacks information on firm diversification.8

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3 This strategy aims for parsimony, or simple models, rather than models that have an excess of parameters and thus are more prone to capitalizing on chance.

4 Results of Satorra (2002) applied to the one-level model of the present paper establish robustness of ML regarding inferences on \( \beta \), and consistency of the parameter estimates despite non-normality.

5 For a similar parametric approach as in this paper, but allowing for latent heterogeneity (latent groups), see Bou and Satorra (2007).

6 We use the term firm and industry effect to refer to the variation of firm profit rates within industry and across industry, respectively.

7 Previous analysis including \( U_{ijt} \) also at the industry level led to small values for the variance of these components; moreover, we even found improper estimates (negative variances) for some of the \( U_{ijt} \). This was taken as an indication that our model would have an excess of parameters if we included this component at industry level.

8 The presence of a corporate effect when it is ignored can distort the analysis in a specific way. Essentially, such effects would induce correlation among firms within the same industry (as they belong to the same corporation), as well as some dependence among industries (for sharing corporations), thus violating the

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Parameters and research questions

The research questions described above can now be expressed in terms of parameters of the model. First, violation of equalization of profits in the long run (as assumed by conventional microeconomic theory) corresponds to positive variance of the permanent component (that is, \( V_p > 0 \)), at firm, industry or both levels. Second, the speed of convergence is characterized by the magnitude of the autoregressive coefficients at firm and industry levels, \( \beta_F \) and \( \beta_I \), respectively, being the convergence faster at industry than at firm level when \( \beta_I > \beta_F \). And third, profit differences within industries will be greater than across industries when the sum of the variances of \( P, A_r \), and \( U_i \) is greater at firm level than at industry level, in each year.

DATABASE, VARIABLES, AND STATISTICS

Database

We analyze a widely recognized Spanish database of firms compiled by the Spanish business newspaper *La Gaceta de los Negocios* (Cabza, 2002). This database contains information on the 5,000 largest Spanish firms belonging to all sectors of the economy (agriculture, mining, manufacturing, wholesale and retail trade, transportation, lodging, entertainment, and other services) except for financial and government sectors. For each firm, it provides financial data for the 1995–2000 period, including information about return on assets (ROA), sales, assets, and four-digit SIC codes that identify industry classification. Complete information is available for all firms and all the years; that is, there are no entrants or exiters in the panel. Only 1.4 percent of the firms in this database are publicly traded. The data set thus include 30,000 records of 5,000 firms in 342 four-digit SIC industries, with 59 industries comprising just one firm (and an average of 14.6 firms per industry).\(^9\) Table 1 offers a description of this dataset regarding distribution of firms in different sectors.

No information on the level of diversification of the represented firms is available in our dataset. In fact, each firm is located in just one industry. Hence, even though some firms are involved in more than one industry, only one of them (the dominant) is recorded. To compensate for this lack of information, a complementary analysis is carried out below to investigate the potential impact of diversification on our main results (see Table 7).

As in previous studies (Schmalensee, 1985; Rumelt, 1991; Roquebert et al., 1996; Mauri and Michaels, 1998; McGahan and Porter, 1997), we use ROA as the measure of business performance. This variable was constructed by dividing the annual income (before extraordinary items) by the total assets. ROA was measured on a yearly basis from 1995 to 2000. We constructed the manifest values \( Y_{ijt} \) by subtracting ROA from its mean-year value.

Table 2 shows information on the sample mean (second column), standard deviations (third column), and correlations (columns 4–9) of firms’

\(^9\) To avoid any bias in the sample, we do not drop the industries with only one firm (equivalent to a monopoly); though, of course, these firms are not expected to add information regarding the separation of industry and firm effects. We retain these firms since we are interested in analyzing not only intra-industry variation, but also to explain the variability at the single (firm) level. Below, we comment on results obtained when we exclude these firms from the sample.

<table>
<thead>
<tr>
<th>First digit</th>
<th>Sector</th>
<th>No. of represented firms</th>
<th>No. of represented 4-digit SICs</th>
<th>Aver. ROA</th>
<th>Aver. assets</th>
<th>Aver. sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>0,1</td>
<td>Agriculture</td>
<td>464</td>
<td>36</td>
<td>5.56</td>
<td>48,347</td>
<td>36,678</td>
</tr>
<tr>
<td></td>
<td>Mining</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Construction</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2,3</td>
<td>Manufacturing</td>
<td>2361</td>
<td>200</td>
<td>8.97</td>
<td>50,061</td>
<td>64,814</td>
</tr>
<tr>
<td></td>
<td>Transportation</td>
<td>261</td>
<td>15</td>
<td>6.29</td>
<td>402,497</td>
<td>151,145</td>
</tr>
<tr>
<td></td>
<td>Communication</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Wholesale</td>
<td>1531</td>
<td>52</td>
<td>6.94</td>
<td>28,768</td>
<td>60,404</td>
</tr>
<tr>
<td></td>
<td>Retail trade</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7,8</td>
<td>Services</td>
<td>383</td>
<td>39</td>
<td>7.57</td>
<td>54,922</td>
<td>40,951</td>
</tr>
</tbody>
</table>

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Table 2. Means, standard deviations and correlations for ROA

<table>
<thead>
<tr>
<th>ROA</th>
<th>Mean</th>
<th>S.D.</th>
<th>Correlations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>95</td>
</tr>
<tr>
<td>1995</td>
<td>7.640</td>
<td>9.732</td>
<td>1.00</td>
</tr>
<tr>
<td>1996</td>
<td>7.457</td>
<td>9.389</td>
<td>0.661</td>
</tr>
<tr>
<td>1997</td>
<td>7.638</td>
<td>9.494</td>
<td>0.532</td>
</tr>
<tr>
<td>1998</td>
<td>7.908</td>
<td>10.665</td>
<td>0.392</td>
</tr>
<tr>
<td>1999</td>
<td>7.966</td>
<td>9.689</td>
<td>0.394</td>
</tr>
<tr>
<td>2000</td>
<td>7.863</td>
<td>10.456</td>
<td>0.336</td>
</tr>
</tbody>
</table>

ROA over the 6 years. For example, 0.392 is the correlation between the ROA of years 1995 and 1998, across the 5,000 firms. As expected, we see that correlations of ROA for adjacent years are greater than for years far apart. There is no clear upward or downward trend in either the means or the variances across the years.

Model fitting in the single- and two-level specifications was carried out using the Mplus (Muthén and Muthén, 1998) SEM software. Details of the fitting functions for the two-level analysis are given in Appendix 2. For the single-level analysis, we used the aggregate estimation approach of Muthén and Satorra (1995), which protects the inferences from the effects of clustering of firms within industries.

RESULTS

In this section, we present the main results of the analysis; first, single-level estimation, followed by two-level estimation. Our findings are confined to the economic context of the Spanish firms. We have no basis to claim that these might apply in other countries, and/or other time periods.

Single-level estimation

Parameter estimates, standard errors, and confidence intervals (CI) for the single-level analysis are shown in Table 3. The variances of the permanent and transitory components, as well as the common variance of disturbance terms $D_i$, deviate significantly from zero. This, however, is not the case for the variances of the unexplained firm-by-year components $U_i$, except for the first year, in which we see the corresponding CI is truncated at zero. In fact, some of the estimates of these variances are high but so are the corresponding standard errors. This leads to uncertainty on the size of this component for some years. Table 3 also shows the estimate of 0.63 for the ‘persistence’ parameter $\beta$, and it deviates significantly both from 0 and 1. Overall, these results provide evidence for the presence of a permanent component of abnormal return, as well as a transitory component with high persistence.

The chi-square goodness-of-fit test statistic also shown in Table 3 does not reject the restrictions implied by the model (note the high $p$-value of this model test). This confirms that there is no need to relax the parameter restrictions of our initial model, such as the equality of the $\beta$, coefficients across time, the equality of the variances of $D_i$, nor the uncorrelation between $P$ and the $A_i$.

From the estimates of the variances obtained in this analysis, we can easily derive a variance decomposition of the abnormal returns. By averaging the contribution of the $U_i$ component across years, we obtain the following variance decomposition (in percent): 58, 29, and 13 for the
temporary, permanent, and unexplained components, respectively. In particular, transitory abnormal returns account for twice the variance of the permanent component.

Two-level estimation

As in the single-level analysis, we first fit the two-level model we posited in Equation 2 with \( \beta \) and variances of \( D \), constrained to be equal across time. Further, we add the restriction of the equality of \( \beta \) across levels. Table 4 provides the estimates, standard errors, and CI for the parameters of this two-level model, and the chi-square goodness-of-fit test statistics. The variance of the permanent component deviates significantly from zero, both at firm and industry levels. This means that permanent differences in profit rates exist at both levels. The estimates of the variances of the industry- and firm-permanent components are 22.91 and 5.35, respectively, suggesting that permanent differences in Spain are about four times greater within industries than across industries. As in single-level analysis, the 95 percent confidence intervals for the variances of the unexplained firm-by-year component, variances of \( U \), are generally very wide and have a coverage that contain the value zero, except for the first year. The chi-square goodness-of-fit test (\( \chi^2 = 25.747 \), associated to 29 degrees of freedom) shows a \( p \)-value far above any standard significance level (e.g., 5%). This indicates a good fit, with no reason to reject the restrictions implied by the initial model posited, including the equality of \( \beta \) across levels.

By comparing these results with the single-level analysis, we see that the magnitude of the variances of the permanent and transitory components have now been decomposed into firm and industry levels. For example, the sum of the variances of the permanent component at firm and industry level (22.91 and 5.35, respectively), shown in Table 4, roughly equals the variance of the permanent component (28.33) shown in Table 3. The same occurs for the variance of the transitory component and that of the disturbance term \( D \). The variance of the firm transitory component (54.81) is much greater than the industry transitory component (2.69). These results indicate that in Spain (and for the period of observation considered) short-run rents rise primarily at firm level. Finally, the autoregressive coefficient is estimated at 0.64, with a standard error that attests that it deviates significantly from both 0 and 1 (see the corresponding CI). This indicates that profits decay slowly toward the sample mean (i.e., to the equilibrium level) both at firm and industry levels, and at the same rate at both levels. The restriction of equality of industry and firm autoregressive parameters is not rejected by the data, as indicated by the chi-square goodness-of-fit test.

From these estimates we derive Table 5, where we see the percentage of the total variance of temporary and permanent components that are assigned to the two components. We see that firm variation is much greater than industry variation, both for permanent or temporary components, as well as for the total (sum of the two components). When adding the two levels (firm and industry) the

<table>
<thead>
<tr>
<th>Par.</th>
<th>Level one (firms)</th>
<th>Level two (industries)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Est.</td>
<td>S.E.</td>
</tr>
<tr>
<td>( \beta )</td>
<td>0.64</td>
<td>0.04</td>
</tr>
<tr>
<td>( V_2 )</td>
<td>22.91</td>
<td>3.47</td>
</tr>
<tr>
<td>( V_1 )</td>
<td>54.81</td>
<td>5.44</td>
</tr>
<tr>
<td>( V_0 )</td>
<td>32.64</td>
<td>4.97</td>
</tr>
<tr>
<td>( V_{11} )</td>
<td>14.26</td>
<td>3.46</td>
</tr>
<tr>
<td>( V_{12} )</td>
<td>4.09</td>
<td>3.24</td>
</tr>
<tr>
<td>( V_{13} )</td>
<td>4.60</td>
<td>5.01</td>
</tr>
<tr>
<td>( V_{14} )</td>
<td>25.44</td>
<td>16.45</td>
</tr>
<tr>
<td>( V_{15} )</td>
<td>6.37</td>
<td>4.93</td>
</tr>
<tr>
<td>( V_{16} )</td>
<td>22.45</td>
<td>15.82</td>
</tr>
</tbody>
</table>

Goodness-of-fit model test: \( \chi^2 = 25.74 \), d.f. = 29 (\( p \)-value = 0.64)

a These are 95% confidence intervals, truncated at zero in the case of estimates of variances.

b Parameter absent in the model.
The value of the permanent component \( P \) can be estimated for each of the firms and industries represented in the sample. With our approach, the estimates of \( P \) are firm specific (a different value for each firm, and for each industry), obtained as regression factor score estimates of \( P \), for both levels. Since we declare \( P \) to be random, such estimates are Bayes (in fact, Stein) type, in contrast to the estimates that would arise if a fixed-effect specification was used. The estimates of \( P \) enable us to identify firms with extreme high or low performance at the permanent level, once the industry effect on that firm has been discounted.\(^{11}\)

### Persistence

A relevant question raised in this paper refers to persistence. Our model estimates the persistence parameter \( \beta \) as 0.64, a common value for both levels. This estimate deviates significantly both from 0 and 1. This indicates that short-run rents converge to the sample mean, but the process of convergence is slow. This concurs with other research on profit persistence by, for example, Mueller (1977, 1986), Jacobson (1988), and McGahan and Porter (1997). In our Spanish context, we have no evidence to reject the hypothesis that the speed of convergence is the same at firm and industry levels. This contrasts with the finding of McGahan and Porter (1999), who report different speeds of convergence for firm and industry levels.\(^{12}\)

### Firm vs. industry

The sources of abnormal returns are important in strategic management research. If permanent and temporary differences arise mainly at industry level, barriers to entry may be a plausible explanation, and rents earned by successful firms can be regarded as monopoly rents. On the other hand,

\(^{11}\) For example, among the highest values of \( P \) for industries, we find the industries ‘Newspapers publishing and printing,’ ‘Coin-operated amusement devices,’ and ‘Pesticides and agricultural chemicals,’ while among the lowest we find ‘Television broadcasting stations,’ ‘Department stores,’ ‘Travel agencies,’ and ‘Ship building and repairing.’

\(^{12}\) This could be just a lack of power of our database to disentangle such differences, or the consequence of actual equality (very small differences) of the speed of convergence at firm and industry levels. A power analysis could be carried out to investigate this issue.

---

**Table 5. Industry and firm variance decomposition of ROA (in %)**

<table>
<thead>
<tr>
<th>Components</th>
<th>Permanent</th>
<th>Temporary</th>
<th>Un-explained*</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm</td>
<td>23.22</td>
<td>55.54</td>
<td>13.09</td>
<td>91.85</td>
</tr>
<tr>
<td>Industry</td>
<td>5.42</td>
<td>2.73</td>
<td>0</td>
<td>8.15</td>
</tr>
<tr>
<td>Total</td>
<td>28.64</td>
<td>58.27</td>
<td>13.09</td>
<td>1</td>
</tr>
</tbody>
</table>

* Average across the years.
if differences arise principally at firm level, differences reflect heterogeneity between firms due to variation in resource endowment or superior efficiency of more profitable firms.

For the Spanish firms, the results in Table 5 show that permanent and temporary abnormal returns arise mainly at firm level. Firm effects are estimated to be more than 10 times greater than industry effects. These results are partly consonant with those obtained by Rumelt (1991), Roque- bert et al. (1996), and McGahan and Porter (1997, 2002) using classical variance and covariance component techniques and a wider data context and different time frame. They also coincide with those of Brush et al. (1999), who used a simultaneous equation model approach.\(^\text{13}\)

Note also that the relative magnitude of the transitory and permanent components reverse when we go from industry to firm level, with the transitory component being greater at firm than at industry level. This could be interpreted as saying that, for a given firm, the industry effect contributes more to the permanent than to the transitory component. In contrast, for a given industry, the firm effect contributes more to the transitory component than to the permanent one.

We would like to stress that despite the small values of the variances of industry level components, compared with the variances at firm levels, our analysis shows that these variances deviate significantly from zero.

**Comparison with the Method in McGahan and Porter (1999)**

In this section we now examine how our results would differ if we applied a more classical estimation approach, such as that of McGahan and Porter (1999) (M&P). To do this, we need to consider the two orderings of subtraction (M&P(a) and M&P(b)) implicit in M&P. Our results must also be expressed in terms of averages of the deviations from the median in absolute value, to agree with the format in M&P.\(^\text{14}\) Table 6 shows the results of the various methods. The first row in the table shows the results of our method (see Table 4) expressed as averages of the absolute of the results from the median, while rows 2 and 3 present the equivalent results using M&P(a) and M&P(b). The table shows that (at least for this dataset) the results by the new method stand in between the values obtained by M&P(a) and M&P(b). Since McGahan and Porter (1999) suggest that their results should be interpreted as bounds on the size of the effects, and our method provides results that are within these bounds, we conclude that in terms of estimates there is a high degree of agreement between ours and M&P’s method. Our approach, however, provides a set of statistics for carrying out inferences which are not available in M&P’s method.

**Effects of diversification**

As commented on above, our database does not contain information on diversification of firms. This could introduce a distortion in the analysis, especially in the interpretation of the results obtained at industry level, since the industry effect may be confounded with the corporate effect. To explore this, we used information external to the database in order to be able to classify the firms into two groups: those that, in addition to the primary SIC code, reported one or more secondary SIC codes; and the rest. Thus, using the reporting of a secondary SIC code as a proxy for diversification, we defined two groups of firms: ‘diversified’ firms (1,539) and ‘non-diversified’ firms (3,461). We then applied the two-level analysis to each of the groups separately, in order to assess whether there was any variation in the results across the two groups. If we observed no substantial change in results across groups, nor with the results of the total sample of 5,000 firms, we would interpret it as an indication that our analysis is not affected by the lack of information on diversification of firms.

**Table 6. Comparison of different estimation methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Effects</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Year</td>
<td>Industry</td>
</tr>
<tr>
<td>New method</td>
<td>0.102</td>
<td>2.151</td>
</tr>
<tr>
<td>M&amp;P(a)</td>
<td>0.102</td>
<td>3.507</td>
</tr>
<tr>
<td>M&amp;P(b)</td>
<td>0.102</td>
<td>2.069</td>
</tr>
</tbody>
</table>

\(^1\) The three methods use the same formula for this column.
firms. Table 7 shows the results of these two additional analyses. To expedite the comparison with the overall sample results, the table also shows the results of the two-level analysis for the 5,000 firms from Table 4.

Table 7 shows that the results at the firm level are basically identical across analyses. That is, the various estimates obtained when analyzing the whole sample, or the subsamples of ‘diversified’ and ‘non-diversified’ firms separately, are nearly the same. We therefore tend to believe that no difference in results at the firm level would arise if information on diversification of firms were incorporated into our analysis. This, however, does not apply to the results at the industry level. In this case, the magnitude of the persistence parameter estimate $\hat{\beta}$ differs only slightly across the analyses; however, the variance of the permanent component for nondiversified firms is much greater than for diversified firms or the overall sample. In addition, the estimates of the variance of the transitory components at industry level in both subsamples (diversified and nondiversified) show a very large standard error and do not deviate significantly from zero. Further, the goodness-of-fit test shows a good fit in the case of the nondiversified firms, but a very poor fit in the case of diversified firms. We have no explanation as to why such differences arise, though it seems that the corporate effect, ignored in the analysis, has a potential for distorting the conclusions at the industry level, specifically on the magnitude of the variance of $A_t$, the dynamic part of the abnormal return. The lack of fit for the nondiversified firms is likely to be due to positive intra-class correlation among firms (as well as among industries) introduced by the corporate effect that our analysis ignores. Clarifying this issue however, is beyond the scope of this paper, as we would need information not provided by our database. We believe, however, that such a complementary analysis supports the conjecture that large parts of the analysis (results at firm level, as well as the results on persistence at industry level) would be unaffected if we added information on diversification of firms, in the case that it were available. At the same time, this complementary analysis tells us that caution should be exercised when interpreting results on the magnitude of transitory components at industry level.

**CONCLUSION AND FURTHER RESEARCH**

Using a Spanish database, we achieved a two-way variance decomposition of abnormal returns at firm and industry levels, and at permanent and temporary components. We confirmed the presence in Spain of permanent and temporary differences between profit rates, both at industry and firm levels, and that permanent and temporary differences are greater at firm than at industry levels. These results are in accord with findings based on more general databases and larger economies. In contrast, we found no evidence in Spain that industry and firm deviations converge to the norm at different rates, and we found that at firm level the
transitory component of variance dominates the permanent component, whereas at industry level
the reverse is the case.

Our analysis confirms for Spain the resource-
based and efficiency views asserting that vari-
ation at firm level is greater than at industry
level. We interpret the presence of a permanent
component, both at firm and industry levels, as
a lack of efficiency of the markets in Spain,
or that abnormal returns cannot be eroded by
competitive imitation. We argue that such ineffi-
ciency is more severe at the industry than at
the firm level, since our estimates of the rel-
ative magnitudes of the permanent component
are larger for the industry than for the firm
level. These findings are consistent with the view
that industry structure affects the performance
by impeding the imitation by rivals and new
entrants.

Analysis of the Spanish database demonstrates
various aspects of the flexibility of our approach.
Several opportunities for further research arise.
First, our method with a three-level model applied
to a dataset with information on corporate lev-
els (such as the Compustat database) could dis-
entangle industry and corporate levels of varia-
tion.

Next, various interpretations for the presence of
the permanent component have been proposed in
the literature on strategic management. Such inter-
pretations can be tested by introducing covariates
at the industry and firm levels. Covariates could
affect permanent, transient, or both components.
This is an important issue since previous research
has recognized that the variables that affect per-
manent components are different from those that
affect transient components. Such an extension to
be pursued using an appropriate database could
shed interesting information on the sources of
abnormal returns and their persistence.

Further, the database we analyzed has data for
all the years within the period of observation.
There are no late entries or early exits in the panel.
Our approach also applies when the periods of
observation vary across firms (either because of
missing data because of births/deaths of the firms).
This imbalance of the panel could have been dealt
with routinely by either multiple-group analysis
for the sets of firms within patterns of dates of
observation, or by applying missing data methods
(years not present for the firm would be treated
as missing data). In the latter option, ML could
accommodate some degree of nonignorability of
the mechanism of entering and exiting the panel.
ML estimation with missing data and multiple
group analysis are standard features of the software
of structural equation analysis employed in the
present work.

Finally, our analysis of the Spanish data found
some differences in the magnitude of the compo-
ments of abnormal returns, when compared to
the findings in other economies. It would be of
interest to explore these differences further by
using a wider range of national economies, so that
we could assess the key variables accounting for
differences among the countries. This could be
accomplished using the same approach with stan-
dard multiple-group features of structural equation
models, which permit direct assessment of differ-
ences across countries as groups.

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Persistence of abnormal returns


J. C. Bou and A. Satorra


APPENDIX 1: STRUCTURAL EQUATIONS AND MOMENT STRUCTURES

General linear latent variable model

A widely used formulation of the general model in SEM is the following (e.g., Jöreskog and Sörbom, 1996):

\[ y = \Lambda \eta + \varepsilon \text{ and } \eta = B \eta + \zeta \]

where \( y \) is the vector of manifest variables, \( \Lambda \) and \( B \) are coefficient matrices and \( \eta, \varepsilon \) are vector variables, with some of the components being non-observable (matrix \( I - B \) is assumed to be non-singular). The variables \( \varepsilon \) and \( \zeta \) have respective variance matrices \( \Psi \) and \( \Phi \). In a specific model, the matrices \( \Lambda, B, \Psi \) and \( \Phi \) are expressed as continuously differentiable matrix-valued functions of a vector of parameters \( \vartheta \). This model specification implies the following structure for the variance and covariance matrix \( \Sigma \) of \( y \):

\[ \Sigma = \Lambda (I - B)^{-1} \Phi (I - B, \omega)^{-1} \Lambda' + \Psi \]

Thus, each model implies a specific variance and covariance structure \( \Sigma = \Sigma(\vartheta) \) for \( \Sigma \). If the model is identified (i.e., in \( \Sigma = \Sigma(\vartheta) \), different \( \vartheta \) produce different \( \Sigma \) ) estimation proceeds by fitting \( \Sigma = \Sigma(\vartheta) \) to the sample variance covariance matrix \( S \) of \( y \), with the fitting function \( F = F(S, \Sigma) \) based on ML or other generalized method of moment estimators. The difference between the number of distinct elements in \( \Sigma \) and the number of parameters is called the degrees of freedom (d.f.) of the model. This is the number of independent restrictions (nonnegative, for an identified model) the covariance structure \( \Sigma = \Sigma(\vartheta) \) imposes on \( \Sigma \). This set of restrictions is the basis of a chi-square goodness-of-fit test used to assess the validity of the model.

This set-up encompasses a wide family of models, such as the classical simultaneous equation model, factor analysis, regression with errors, in variables, etc. This general model also encompasses the model we posited in Equation 1. In this case, \( y \) is the vector of abnormal returns observed over the \( T \) periods, \( y' = (Y_1, Y_2, \ldots, Y_T) \), and the random components \( P, A_1, D_1, \) and \( U_t \) are specific components of the random vectors \( \varepsilon \) and \( \zeta \). In this formulation, the coefficients \( \beta_t \) are elements of the parameter matrix \( B \), and the variances of the variables \( P, A_1, D_1, \) and \( U_t \) correspond to the diagonal elements of matrices \( \Phi \) and \( \Psi \). The parameter expressing the possible correlation between \( P \) and \( A_1 \) can be represented by a specific nondiagonal element of \( \Phi \).

Nowadays, maximum likelihood (ML) estimation of this general model is an easy task for practitioners with the use of standard SEM software such as

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as LISREL of Jöreskog and Sörbom (1996), Mplus of Muthén and Muthén (1998), EQS of Bentler (1995), and the procedure CALIS in SAS (1990), among others. See, for example, Satorra (2002) for further discussion on statistical inference in this general setup of linear latent variable models.

**Restricted model**

Of particular relevance in the present paper is Model 1, with the restrictions that $\beta_i$ and the variances of $D_i$ do not vary across time. We develop the specific variance and covariance structure underlying this model. In practice, however, we carry the analysis using the general linear latent variable model.

From Equation 1 and the stated assumptions, we obtain

$$\text{var}(A_{t+1} + 1) = \text{var}(A_t), \ t = 1, 2, \ldots, T - 1$$

so that

$$\text{var}(A_t) = \frac{\text{var}(D_t)}{1 - \beta^2}, \ t = 1, 2, \ldots, T$$

(4)

Hence the variances and covariances of manifest variables can be expressed as

$$\text{var}(Y_t) = \lambda_t^2 \text{var}(P) + \frac{\text{var}(D_t)}{1 - \beta^2} + \text{var}(U_t)$$

(5)

$$\text{cov}(Y_t, Y_{t'}) = \lambda_t \lambda_{t'} \text{var}(P) + \text{cov}(A_t, A_{t'}), \ t \neq t'$$

(6)

Also

$$\text{cov}(A_t, A_{t'}) = \beta^{\mid t - t'\mid} \text{var}(A_t)$$

(7)

and, since a proper solution is attained only when $|\beta| < 1$ (see Equation 4), the correlation between $A_t$ and $A_{t'}$ will decrease with increasing time distance $|t - t'|$.

Equations 5 and 6 show that the variances and covariances of abnormal returns are functions of the variances of $P$, $A_t$, $U_t$, and the parameters $\lambda_t$ and $\beta$.

---

**APPENDIX 2: LIKELIHOOD FOR THE TWO-LEVEL MODEL**

This appendix provides the expressions for the fitting function of the ML analysis of the two-level model, as well as for the (pseudo)-likelihood fitting function used in obtaining the (MUML) estimates. For SEM analysis of single-level multiple-group data, the reader is referred to Satorra (1993, 2002).

For a $p$-variate (centered) vector $z_{ig}$ of observed variables we consider the following two-level model:

$$z_{ig} = v_g + w_{ig}, \quad i = 1, \ldots, n_g, \quad g = 1, 2, \ldots G$$

(8)

where $w$ and $v$ are, respectively, first- and second-level random components, with expectations $E(w_{ig}) = E(v_g) = 0$, with $w_{ig}$ independent of $v_g$. These components are assumed to have finite variance matrices $\Sigma_w$ and $\Sigma_v$, respectively. In our paper, $z$ corresponds to the vector of observed abnormal returns for firm $i$ of industry $g$, and $v$ and $w$ correspond to the respective industry- and firm-level contributions of abnormal returns. For a given model, $\Sigma_v = \Sigma_v(\vartheta)$ and $\Sigma_w = \Sigma_w(\vartheta)$ are specific functions of a common vector $\vartheta$ of parameters.

Apart from a constant that is irrelevant for optimization, minus twice the log-likelihood function (see Muthén and Satorra, 1995: 292–303) is

$$f = (n - G) \left[ \text{tr} \left\{ \Sigma_w^{-1} S_w \right\} + \ln |\Sigma_w| \right]$$

$$+ \sum_{g=1}^{G} \left[ \text{tr} \left\{ (n_g \Sigma_v + \Sigma_w)^{-1} n_g \bar{z}_{ig} \bar{z}_{ig}' \right\} \right]$$

$$+ \ln |n_g \Sigma_v + \Sigma_w|$$

where

$$S_w = (n - G)^{-1} \sum_{g=1}^{G} n_g \sum_{i=1}^{n_g} (z_{ig} - z_{ig}) (z_{ig} - z_{ig})'$$

is the within-group sample variance matrix, $n = \sum_{g=1}^{G} n_g$ is the total sample size, and $z_{ig} = n_g^{-1} \sum_{i=1}^{n_g} z_{ig}$ is the mean vector of group $g$. We require the between-group sample variance matrix

$$S_B = (G - 1)^{-1} \sum_{g=1}^{G} n_g (z_{ig} - \bar{z}) (z_{ig} - \bar{z})'$$

---

Note that Equation 4 imposes a nonlinear constraint on the variance of the transitory component on the first wave.
where $\bar{z}$ is the overall mean. When $n_g = c \left( = \frac{n}{G} \right)$ for all $g$, the balanced case, we have

$$f = (n - G) \left( \text{tr} \{ \Sigma_w^{-1} S_w \} + \ln |\Sigma_w| \right)$$
$$+ G \left( \text{tr} \{ c(\Sigma_v + \Sigma_w)^{-1} S_B \} \right)$$
$$+ \ln |c \Sigma_v + \Sigma_w|$$

so, ML estimation corresponds to minimizing

$$F = (n - G) \left( \text{tr} \{ \Sigma_w^{-1} S_w \} + \ln |\Sigma_w| \right)$$
$$- \ln |S_w| - p \right) + G \left( \text{tr} \{ c(\Sigma_v + \Sigma_w)^{-1} S_B \} \right)$$
$$+ \ln |c \Sigma_v + \Sigma_w| - \ln |S_B| - p$$

where offset terms have been added to ensure that the minimum of $F$ corresponds to the usual chi-square goodness-of-fit test statistic. Thus, for balanced data, ML can be carried out using standard software for two-group SEM analysis.

In the MUML approach (Muthén, 1994), we minimize the fitting function $F$ using

$$c = \frac{n^2 - \sum_{g=1}^{G} n_g^2}{n(G - 1)}$$

when the data are unbalanced. For balanced data, MUML coincides with exact ML estimation. Experience with MUML shows that even for unbalanced data the estimates, standard errors, and chi-square values are very close to those obtained using ML. We have checked that this applies with our data as well. We decided to report the results given by MUML, given the quality of such estimates and their easy access via the multiple-group options of SEM software.