Chapter 9

Patterns of Persistence of Abnormal Returns: A Finite Mixture Distribution Approach

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9.1 INTRODUCTION

Abnormal returns, that is, profits well above or below the competitive or equilibrium level, have been studied extensively in strategic management research. They are usually interpreted as a measure of the relative ability of firms to avoid competitive forces and achieve sustained competitive advantage.

Numerous theories in strategic management research and in related fields, such as industrial organization economics and organizational ecology, have proposed alternative explanations of the dynamical behavior of abnormal returns. For example, Neoclassical Economics (Arrow & Hahn, 1971) and the Austrian School of Economics (Jacobson, 1992) predict that abnormal returns are transitory and they vanish when markets reach an equilibrium, or when factors such as imitation, substitution, and innovation erode or supersede all sources of competitive advantage. In contrast, other theoretical approaches including industrial organization economics (Bain, 1956) and the resource-based view of the firm (Barney, 1991; Wernerfelt, 1984) propose the existence
of industry- and firm-specific factors that sustain competitive advantages and superior economic performance over time.

Differences in predictions are related not only to the persistence, but also to the presence of groups of firms that exhibit different patterns of abnormal returns, and to firms’ characteristics in each group. For example, theoretical approaches such as industrial organization economics (Bain, 1956; Caves & Porter, 1977) and strategic group theory (Hunt, 1972; Porter, 1979) predict the existence of stable groups of firms that exhibit extremely abnormal returns due to entry and mobility barriers, respectively, whereas the Austrian School of Economics predicts turnover in the membership of firms in the high-performer group (Wiggings & Ruefli, 2002). Regarding the firms’ characteristics, organizational ecology predicts stability of both high and low performers due to inertia that is greater for larger and older firms. However, resource-based theorists emphasize the stability of only high-performing firms with valuable, rare, imperfectly imitable, and nonsubstitutable resources (Barney, 1991; McGahan & Porter, 2003).

In summary, theoretical approaches differ in how abnormal returns evolve and in the type of firms that follow each path. The study of the patterns of evolution of abnormal returns can thus provide important insights into the relevance of predictions of theories in strategic management; further, it can also help in understanding the relationship between competitive advantage and abnormal returns.

With the exception of Mueller (1986) and the so-called persistence of profit line of research (Connolly & Schwartz, 1985; Geroski & Jacquemin, 1988; Odagiri & Yamawaki, 1986; Schohl, 1990), less attention has been paid to the dynamics of abnormal returns. In a regression-based time-series study, Mueller (1986, 1990) found evidence that abnormal profits vanish because profits tend to converge toward the mean. He found that high-performing firms tended to have a slower rate of convergence than did low performers.

More recently, the dynamics of abnormal returns has received additional attention. Using panel data of American corporations from 1981 through 1994, McGahan and Porter (1999) found differences in the persistence of industry, corporate-parent, and business-level effects, where the transient industry effect was more persistent than business-segment and corporate-parent transient effects. Based on these results, they highlight the importance of the industry in the dynamic behavior of abnormal returns. In a later study, McGahan and Porter (2003) explored the patterns in the emergence and sustainability of abnormal returns in high- and low-performer firms. They found evidence of differences in both, emergence and sustainability, across two groups of firms. For example, they found that low performance arises from business-specific factors, whereas for high performers, both industry and business-line factors are important. Wiggings and Ruefli (2002) also reported empirical evidence of
the dynamics of above-normal returns in a sample of 40 industries. They found that at least one firm achieved 10 or more years of persistent superior economic performance in every industry, that large firms are more likely to achieve persistent superior performance, and that industry membership and market share were not always significant factors in persistent superior performance.

The present study continues the research on the dynamics of abnormal returns. The chapter has three objectives; (a) to establish the existence of alternative forms of how abnormal returns evolve, and to estimate the percentage of firms whose abnormal returns follow each path; (b) to describe each pattern of evolution and its implications for the predictions of alternative theoretical approaches; (c) to describe the characteristics of firms that form each group.

Two assumptions characterize our approach. First, we assume the existence of dynamic heterogeneity in abnormal returns; that is, the evolution of abnormal returns follows alternative paths. This assumption is in accord with previous empirical studies (Mueller, 1986; Odagiri & Yamawaki, 1986; Schohl, 1990), which, for example, found that high-performing firms exhibit a slower convergence of abnormal returns than did firms that obtain normal returns. The main implication of this assumption is that the evolution of firms’ abnormal returns varies, not only across firms, corporations, and industries, as Waring (1996) and McGahan and Porter (1999) among others have reported, but also in the way they evolve. Under dynamic heterogeneity, time is an important dimension and is introduced into the study of abnormal returns as an additional source of variation. The second assumption is that the dynamic heterogeneity is latent or unobserved, that is, it is not possible to know a priori which path best describes the evolution of abnormal returns for each firm. In our approach, we assign firms into groups not with certainty, but based on the probability of belonging of each firm to a group.

We investigated the dynamical behavior of abnormal returns on 5,000 Spanish firms in a 6-year period. We fit first a dynamic panel data model that decomposes abnormal returns into three components; static or permanent, transient, and firm-year specific. Each component corresponds to a different evolution of abnormal returns. In the second stage, we adopt a finite mixture approach to uncover various alternative paths of abnormal returns (classes) that compose the data set, obtaining for each firm its probability of belonging to each class.

Our research shares some of the assumptions of previous studies. We recognize that abnormal returns vary substantially across firms over time; that abnormal returns at any point in time provide only a snapshot of the type and the sustainability of competitive advantage; and that differences in abnormal returns can be studied in greater detail in longitudinal studies, in which abnormal returns are recorded over an extended period of time. But our research differs from previous work in three aspects. First, our objective is to explain
how abnormal returns evolve over time, taking into account unobserved
dynamic heterogeneity. Second, we employ a different statistical method, relying
on multivariate normal mixture models. The finite mixture approach is ade-
quate when the studied population (Spanish firms) comprises a small number
of groups (patterns) with a relatively homogeneous distributions. As we do not
assume that the abnormal returns of all the firms follow the same path, nor do
we assign firms to classes based on the firms’ levels of performance, our ap-
proach prevents bias that can arise in the analysis with an a priori classification
of firms into groups. Finally, previous research is based mainly on data from
the United States. and other large economies (Japan, U.K., Germany, Canada,
etc.), so it will be interesting to investigate persistence in another country and
compare our results with previous research.

9.2 MODEL
We use a dynamic model for panel data to examine the pattern of evolution
of abnormal returns. This is Anderson and Hsiao’s state-dependence model
(1982), and Kenny and Zautra’s trait-state-error model (1985, 2001). We ex-
tend the latter to mixture analysis in the next section.

The model decomposes firms’ abnormal profits into a static, a dynamic,
and an error term component,

\[ Y_{it} = \lambda_t P_t + A_{it} + U_{it} \]  
\[ A_{it+1} = \beta_t A_{it} + D_{it}, \]

where \( Y_{it} \) is the mean deviation of profit rate of firm \( i \) at time \( t \) (\( Y_{it} \) is the dif-
ference of the firms’ profit rates in year \( t \) minus the overall mean of the firms’
profit rates in that year). \( P_{it} \) is the static or permanent component, and its
variance captures long-run or sustainable differences across firms (i.e., the dif-
ferences that persist in a period longer than the length of the series). \( A_{it} \) is the
dynamic or transient component. Its variance captures short-run or nonsustain-
able rents that disappear over time as a result of the competitive process. As in
previous studies (Geroski & Jacquemin, 1988; Jacobson, 1988; McGahan &
Porter, 1999; Mueller, 1986), \( A_{it} \) is assumed to follow a first-order autoregres-
sive process, AR(1). Component \( U_{it} \) is an idiosyncratic, unexplained, firm-by-
year component. It encompasses all the specific and unstable circumstances
that affect a firm’s profit rate in one specific year, as well as measurement error
(Benston, 1985; Demsetz, 1979; Fisher & McGowan, 1983). Finally, \( D_{it} \) is the
disturbance component of the dynamic autoregressive part of the model. Here
\( U_{it} \) and \( D_{it} \) are centered random variables, assumed to be independent across \( i \)
and \( t \), \( \lambda_t \) denotes the factor loading associated with the permanent component,
and \( \beta_t \) is the so-called autoregressive parameter.
To better represent the nature of the model, Figure 9–1 shows a path diagram representation of the model, a representation used often in structural equation modeling (SEM).

![Path diagram](https://example.com/path.png)

Figure 9–1. Path-diagram representation of the model.

Observable variables are represented in squares, while latent variables are shown in circles. An arrow leading from the predictor to the dependent variable indicates a loading or a regression effect. In the graph, the values of the loadings and regression effects are represented by the $1$s and the $\beta$s respectively. Disturbance and error terms in the regression equations are represented by $D_t$s and $U_t$s respectively, the sub-index indicating the time point. This path diagram shows that the variance of firms’ profit rates ($Y_{it}$) is decomposed into the “permanent” component ($P$) that exerts a (static) effect on $Y_{it}$, the “temporary” components ($A_{it}$) that have an autoregressive structure, and the “unexplained firm-by-year component” ($U_{it}$). These three components are assumed to be uncorrelated with different structures of correlations over time. The absolute value of the first-order autoregressive parameter $\beta$ indicates a “memory effect” ($\beta = 0$, zero memory) of the time-dependent component of abnormal returns.

The model also assumes a stationary dynamic component. This implies that the autoregressive parameters ($\beta_t$), the variances of the disturbance terms ($D_{it}$), and the loadings $\lambda_t$ are equal across $t$. For the model to be identified, we need to fix one of the loading parameters $\lambda_t$; all the loadings are set to 1. 

These conditions imply that

$$\text{Var} (A_{it}) = \text{Var} (A_{it-1}),$$  \hspace{1cm} (3)

---

$^1$This is a more restricted version of the model than is strictly needed, because identification is attained by just setting one of the $\lambda_t$ to 1.
and hence
\[
\text{Var}(A_{it}) = \frac{\text{Var}(D_{it})}{1 - \beta^2}.
\] (4)

This equality constrains the variance of the transient component on the first year, the variance of \(A_{i1}\). It is easy to derive the identities
\[
\text{Var}(Y_{it}) = \lambda^2 \text{Var}(P_t) + \frac{\text{Var}(D_{it})}{1 - \beta^2} + \text{Var}(U_{it})
\] (5)
\[
\text{Cov}(Y_{it}, Y_{is}) = \lambda_t \lambda_s \text{Var}(P_t) + \text{Cov}(A_{it}, A_{is}), \quad t \neq s,
\] (6)

and
\[
\text{Cov}(A_{it}, A_{is}) = \beta^{t-s} \text{Var}(A_{it}).
\] (7)

Equation 4 is used to assign the value of the parameter variance of \(A_{it}\) at the initial condition \(t = 1\).

By the stationarity assumption, \(\beta\) is smaller than one in absolute value, hence the correlation among \(A_{it}\) and \(A_{is}\) decreases to zero when the time distance \(|t - s|\) increases. From Equations 6 and 7, it follows that different parameters of the model produce different variances and covariances of observed variables; hence the model is identified.

### 9.2.1 A Finite Mixture Model

In this section, we extend the previous model by allowing for several distinct patterns of evolution of abnormal returns. The finite mixture approach is suitable when the studied population is comprised of a small number of groups or classes with relatively homogeneous distributions within the classes and the groups into which a firm belongs is not known (see, e.g., Muthén, 2002). The objective is to carry out inferences accounting for such unobserved heterogeneity and, ultimately, to classify individuals (firms) into groups. To do this, mixture models incorporate a latent categorical variable with \(K\) classes, with the unknown marginal (unconditional) probability of membership \(\pi_k\) of a firm to be in latent class \(k\). Conditional on the individuals being in class \(k\) (\(k = 1, \ldots, K\)), the \(T\)-dimensional \((T\) is the number of time points) vector \(z\) of observed (mean centered) profit rates is assumed to be normally distributed with a mean vector \(\mu_k\) and a covariance matrix \(\Sigma_k\). Such a mean vector and covariance matrix are, as in a typical SEM analysis, functions of a vector of parameters \(\theta_k\), according to the dynamic model specification of the previous section. That is, we have \(z \sim \mathcal{N}(\mu_k, \Sigma_k)\), with \(\mu_k = \mu_k(\theta_k)\) and \(\Sigma_k = \Sigma_k(\theta_k)\), \(\theta_k\) being a vector of parameters that collects the regression coefficients, loading parameters, and the variances and covariances of stochastic components of the model. Given observed data \((z_1, \ldots, z_n)\), the log-likelihood function to be
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maximized is

\[ \log \ell = \sum_{i=1}^{n} \log \left( \sum_{k=1}^{K} \pi_{ik} f_{k}(z_i | \vartheta_k) \right) \]  \hspace{1cm} (8)

where \( f_{k} \) is the density function of \( N(\mu_k, \Sigma_k) \). We define the parameter vector

\( \psi = (\pi, \vartheta)^t \), where \( \pi = (\pi_1, \ldots, \pi_K) \) is the vector of mixing proportions (i.e., the probabilities of class membership) and \( \vartheta \) is a vector that collects all the distinct elements of the class-specific \( \vartheta_k \). In this approach, we allow parameters of the model to vary across latent classes. So, we consider a specific structure of the mean and the variance and covariance matrix in each class; each class has a characteristic pattern of evolution of abnormal returns. Estimation of the model is carried out using the approach made explicit in Muthén (2002) and implemented in the software Mplus of Muthén and Muthén (2004); (see also McLachlan & Peel, 2000).

9.3 PATTERNS OF THE DYNAMICS OF ABNORMAL RETURNS

The decomposition of abnormal returns into permanent, temporary, and unexplained components introduces the time dimension into the analysis and allows alternative patterns of evolution to be formulated. Each pattern is a particular case of the model of the previous section where different components are absent. Firms whose abnormal returns follow a similar pattern are assigned to the same class. In this section, we introduce the alternative paths that firms can follow, and discuss the implications of each path for the efficiency of the competitive process and the sustainability of firms’ abnormal returns. Next, we propose various models with a different number of classes as alternative hypotheses about the evolution of abnormal returns.

In the simplest pattern of evolution, abnormal returns are completely random, that is, they correlate neither across time nor across firms. This corresponds to no systematic differences between firms for abnormal returns and no time dependence. In this pattern, abnormal returns (and the potential sources that generate them) are eroded instantly or over a period shorter than the time sequence of the observations. Firms’ competitive advantages are not sustainable and markets are always in equilibrium. The model that represents this path constrains the variance of the permanent and temporary components to be zero, as the firm-by-year component is the only one in the model (\( Y_{it} = U_{it} \)). The evolution of abnormal returns has the properties of a random shock model, where abnormal returns fluctuate around zero, and the variance of \( U_{it} \) determines the size of the heterogeneity in profit rates.

Abnormal returns evolve in a different way if we assume that firms’ profit differences vanish completely, but only after some time. This occurs, for example, when abnormal returns are the result of long-lived assets with appro-
piable values (Barney, 1991; Williams, 1992), when there are impediments to imitation as isolation mechanism (Rumelt, 1984), or when the structure of the industry may promote persistence (Bain, 1956). Such a pattern of evolution, consistent with the empirical research in persistence of profit research line, is also a particular case of the model of the previous section. As profit differences are only transitory, the permanent component is absent, var(\(P\)) = 0. In this case, the time dependence of the abnormal returns can be modeled as a first-order autoregressive process, AR(1). The speed of convergence (i.e., the sustainability of abnormal returns) is governed by the value of the autoregressive parameter (\(\beta\)). The higher the \(\beta\), the more persistent the abnormal returns will be, and consequently, the lower the efficiency of the competitive process.\(^2\)

An entirely different pattern of evolution of abnormal returns arises when the differences in profit rates are completely static, and do not vanish. In this case, abnormal returns persist, and firms that are more (less) profitable at the beginning of the period remains more (less) profitable at the end (i.e., abnormal returns are stable). This pattern of evolution is possible, for example, when the sources that sustain profit differences are not eroded by competitive forces, or the processes of imitation are not effective against them, at least, in the period of study. Winter (1987) focused on this type of rents and exemplifies this situation when there are Ricardian rents generated by an asset with fixed supply because replication and imitation processes are not effective.

In terms of the model in the previous section, this pattern of evolution implies that the autoregressive coefficient (\(\beta\)) and the variance of the disturbance term (\(D_{it}\)) of the dynamic part of the model are zero. Thus the evolution of abnormal returns has the properties of a static process (\(Y_{it} = P_{it} + U_{it}\)).

Finally, firms’ abnormal returns can follow a combination of the previous patterns of evolution if we assume that they are partly permanent and partly transient. In this pattern, all the components of the model in the previous section are different from zero, and the same conclusions made earlier can be applied in the portion of abnormal returns that follow each path.

Having introduced the alternative patterns of evolution, various models with different number of classes are proposed. Table 9–1 shows the alternative hypotheses of the number of latent classes that we have considered, and the dynamics of abnormal returns in each class. Model 0 is the base model and assumes the same pattern of evolution of abnormal returns for all firms (i.e., there is no latent dynamic heterogeneity). It corresponds to a single-class model with abnormal returns formed by the three components of the model (\(P\), \(A\), and \(U\)). Both models 1 and 2 assume the existence of two classes,

\(^2\)Abnormal returns converge toward the mean when \(0 < \beta < 1\). We do not consider values of \(\beta\) out of this range because it is not in accordance with economic theory, and because of previous evidence of convergence of abnormal profits.
but in class 1 of Model 1 abnormal returns are static, whereas in class 1 of Model 2 they are partly permanent and partly transient. In Model 3, there are three classes; partly permanent and partly transient, permanent, and transient. Finally, Model 4 introduces a fourth class of firms with completely random abnormal returns.

### TABLE 9–1

Description of Alternative Models with Their Associated Number of Free Parameters and Values of the Goodness of Fit Index BIC

<table>
<thead>
<tr>
<th>Model</th>
<th>Class</th>
<th>No. parameters</th>
<th>BIC*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>P A U</td>
<td>9</td>
<td>207.26</td>
</tr>
<tr>
<td>1</td>
<td>P U</td>
<td>29</td>
<td>188.83</td>
</tr>
<tr>
<td>2</td>
<td>P A U</td>
<td>32</td>
<td>188.36</td>
</tr>
<tr>
<td>3</td>
<td>P A U</td>
<td>46</td>
<td>184.71</td>
</tr>
<tr>
<td>4</td>
<td>P A U</td>
<td>59</td>
<td>184.42</td>
</tr>
</tbody>
</table>

* \( \times 10^3 \)

** P = Permanent, A = Autoregressive, U = Unexplained

Our objective is to find subgroups of firms whose abnormal returns follow a similar path. Because we do not know a priori how many different groups of firms there are, and which path best describes each group, we first choose the number of different paths (classes) by assessing the goodness of fit of various different models; see the goodness of fit value BIC (to be described below) shown in the last column of Table 9–1. Once we have chosen the number of latent classes, we fit the corresponding finite mixture model by maximum likelihood. At the end, we assign firms to classes based on the probability of class membership arising from the mixture analysis.

### 9.4 DATA AND ESTIMATION

The database is composed of 5,000 large Spanish firms, belonging to all sectors of the economy excluding financial and public companies. For each firm, financial data was collected for the 1995–2000 period. The dataset contained information about return on assets (ROA), sales, assets, and a four-digit standard industrial classification (SIC) code that characterizes industry membership. Our initial database contains 30,000 records, six annual records for each of the 5000 firms.

Like other databases usually used in previous studies in persistence (e.g., Compustat, FCT, Fortune 500, etc.), our database presents several advantages.
First, it captures a large portion of Spanish economy, including all sectors (agriculture and mining, manufacturing, wholesale and retail trade, transportation, lodging, entertainment, and other services) except for financial and government sectors. Second, our sample contains time series over the 6 years allowing for studying the dynamic behavior of profit rates over time, and separating the static, transient, and year-specific effects. Finally, it covers only large Spanish firms, although, compared with other databases, such as Compustat, or Fortune 500, the average size of the Spanish firm is smaller than for the American firms. The average firm in our database has assets of 62.9 million euros, with annual sales of 64.8 million euros.

A plot of the profiles of ROA for a sample of 15 firms is shown in Figure 9–2. In this plot we see a wide fluctuation of the profits across the years within each firm. This variation is what we want to model using a finite mixture model approach.

![Profiles of a sample of 15 firms](image)

Figure 9–2. Profiles of ROA for a random sample of 15 firms.

9.4.1 Variables

Accounting return data was used in the analysis. As in previous studies (McGahan & Porter, 1999, 2003; Wiggins & Ruefli, 2002), we used 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 recorded annually from 1995 to 2000. By subtracting ROA from its annual
mean we constructed the observed variable $Y_{it}$, where the indices $i$ and $t$ denote firm and time, respectively. Annual sales, firm size (measured as firms’ total assets), and industry membership was used to describe the classes emerging from the analysis.

9.4.2 Estimation

Estimation was conducted using structural equation model methodology. SEM permits a suitable approximation for most research designs for longitudinal data, as we can easily formulate relationships between latent variables, rather than directly between their fallible measures. In fact, within SEM, permanent and temporary components are modeled as latent factors, and the portion of the total variance accounted for by the different latent variables. Standard software can be used for fitting models within the SEM approach. However, when we turn to the mixture analysis, we found Mplus (Muthén & Muthén, 2004) to be the most suitable software. Mplus uses maximum likelihood (ML) estimation employing the EM algorithm (Muthén & Muthén, 2004).

9.5 RESULTS

9.5.1 Heterogeneity in the Evolution of Abnormal Returns

We fit first the conventional model in which all firms have the same pattern of evolution of abnormal returns (Model 0 in Table 9–1). We found a significant chi-square goodness-of-fit value of $\chi^2_{12} = 62.878$, $p \leq 0.05$, indicating a poor fit. It may be interpreted as evidence of heterogeneity in the evolution of abnormal returns that the single-class model does not capture. To improve the fit, we fit the models 1 to 4 of Table 9–1, that assume several groups of firms with distinct patterns of persistence.

9.5.2 Number of Classes

In finite mixture analysis, the number of classes is typically assessed by goodness-of-fit indices such as the Bayesian information criterion (BIC; Schwartz, 1978) or the Akaike information criterion (AIC; Akaike, 1974). The recommendation is to choose a model with the smallest AIC or BIC. Here we use BIC. In our context, we have that $\text{BIC} = 2\log L - q\log n$, where $L$ is the likelihood, $q$ is the number of parameters in the model, and $n$ is the number of firms.

In the last column of Table 9–1 we see the BIC values for models with different number of latent classes. The model with four classes yield the smallest BIC value; therefore, we choose the four-class model (Model 4 in Table 9–1) as our final model.
9.5.3 Description of Classes

Having assessed the number of classes, a description of the dynamics of the
abnormal returns in each class is in order. This involves examination of the
size of the components of the variances of abnormal returns as well as the ROA
average within each latent class. Estimated parameters with standard errors for
the four classes are shown in Table 9–2. Note that the covariance structure and
the size of the components of variance vary among latent classes.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Class 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Var(P)</td>
<td>5.45</td>
<td>550.477</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.78)</td>
<td>(108.52)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>β</td>
<td>0.67</td>
<td>0.83</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.01)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Var(D)</td>
<td>3.48</td>
<td>23.28</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.37)</td>
<td>(1.83)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Var(A)</td>
<td>6.26</td>
<td>74.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Var(U)</td>
<td>0.60</td>
<td>642.66</td>
<td>5.23</td>
<td>142.56</td>
</tr>
</tbody>
</table>

Both classes 1 and 3 have a significant autoregressive component $\beta$ (0.67
and 0.83, respectively), and their variances of the temporary components are
also significant. Moreover, in class 1 the variance of the permanent component,
Var(P), is also significant. It accounts for a higher proportion of variance than
the transient component. These results indicate that, although abnormal returns
persist in both classes, they evolve differently in them. In class 3, abnormal
returns disappear completely over the 6 years, whereas in class 1, a significant
proportion is permanent, and does not vanish completely over the observation
time. The differences between classes 1 and 3 are analyzed in greater detail in
the discussion section.

In class 2, abnormal returns are static (i.e., complete persistence), because
no transient components are allowed. Table 9–2 shows that the permanent
component has an extremely high variance (Var (P) = 550.48) indicating that
firms in this class present stable high or low profitability. In class 2, we also
see a very large variance for the atemporal component $U$ (Var (U) = 142.56),
indicating that in this class, profit rates fluctuate around zero with a high vari-
ability. The high variability across firms in classes 2 and 4 indicates that those
firms are highly unstable in profitability, so they are firms of high risk. Fi-
nally, class 4 comprises firms whose abnormal returns are random. The only
restriction that we have introduced in this class is that the variance of the firm-
by-year specific component is constant across years to ensure that the process is stationary. We comment more about this in the discussion section.

9.5.4 Proportion of Firms in each Class

Table 9–3 shows the estimated number and proportions of firms in each of the four classes of Model 4. Classes 1 and 3 account for 90% of firms (39% and 51% respectively), representing the most common patterns of evolution. Classes 2 and 4 represent only 4% and 6% of the firms respectively, and they represent atypical patterns of the evolution of abnormal returns. In fact, these are patterns that depart markedly from the assumptions of the economic theory and from the previous empirical studies. We see that the firms in these minority classes have unusual extreme variances on the components of $P$ and $U$. Later on we discuss the parameter estimates of the model of each of the four classes.

<table>
<thead>
<tr>
<th>Class</th>
<th>Count</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1969</td>
<td>39</td>
</tr>
<tr>
<td>2</td>
<td>174</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>2541</td>
<td>51</td>
</tr>
<tr>
<td>4</td>
<td>316</td>
<td>6</td>
</tr>
<tr>
<td>Total</td>
<td>5000</td>
<td>100</td>
</tr>
</tbody>
</table>

TABLE 9–4

The Average Probability of Belonging to the Classes for the Firms Classified in Each of the Four Classes (rows)

<table>
<thead>
<tr>
<th>Class</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.903</td>
<td>0.000</td>
<td>0.096</td>
<td>0.000</td>
</tr>
<tr>
<td>2</td>
<td>0.000</td>
<td>0.912</td>
<td>0.029</td>
<td>0.060</td>
</tr>
<tr>
<td>3</td>
<td>0.057</td>
<td>0.003</td>
<td>0.909</td>
<td>0.031</td>
</tr>
<tr>
<td>4</td>
<td>0.000</td>
<td>0.074</td>
<td>0.104</td>
<td>0.822</td>
</tr>
</tbody>
</table>

Using the firms’ posterior probabilities to belong to the different classes, we assign firms to the class with highest posterior probability. Table 9–4 shows the average probability to belong to each of the classes 1 to 4 (columns) for the firms that were classified in class 1 to 4 (the rows). Note that these average probabilities are relatively high, ranging from 0.822 to 0.912, indicating the suitability of the four-class solution.
9.5.5 Variance Decomposition

The decomposition of variance of abnormal returns by year for the four classes is given in Table 9–5. In class 1, temporary and permanent components represent 39% and 56% of the variance of abnormal returns, respectively. This means that more than half of the abnormal returns in firms in class 1 remains stable. In class 3, the autoregressive component of abnormal returns represents more than 86% of the variance of abnormal returns. Finally, 50% of the abnormal returns in class 2 are permanent, whereas in class 4 all abnormal returns are obviously random.

Table 9–5 also shows the means of the abnormal returns for each class, as estimated by the model. A comparison of the average of ROA shows differences in their evolution by classes. Class 1 shows low ROA averages ranging from 6.2 to 5.2%, with a trend of slowing decrease. Firms in class 3 achieve higher average profitability than class 1 and an upward trend. In this class, ROA ranges around 9.5%.

9.5.6 Characteristics of the Firms by Classes

To further characterize the four derived classes, Table 9–6 presents additional information about annual sales and assets by class and by year. As shown in Table 9–6, firms in four groups differ in their size. Classes 1 and 3 are formed by larger firms, with sales and assets significantly higher (almost twice), than the other two groups. Classes 1 and 3 also have differences between them. Firms in class 1 have average assets higher than class 3 (70.1 and 61.9 respectively), where as the average in sales in class 3 is 4.2 million euros higher than in class 1 (69.2 and 64.9 respectively). There are also differences in the evolution of sales and assets between groups. In all classes, sales and assets increase, but their rates of growth differ. Class 4 has the higher growth rate in assets, followed by classes 3, 2, and 1 in that order; and class 2 has the higher growth rate in sales, followed by class 4, 3, and 1. So, among the two most common patterns of abnormal returns, firms in class 3 not only are more profitable, but also have a higher growth rate in sales and in assets.

Finally, Table 9–7 shows the percent of firms in each class, grouped by one-digit SIC code. Class 1 contains relatively more transportation and communications firms (SIC = 4), and wholesale and retail trade firms (SIC = 5), whereas class 3 has comparatively more manufacturing firms (SIC = 2 and 3). Classes 2 and 4 cover a low percentage of firms in all industries, except for service firms (SIC = 7 and 8) that with both classes 16.5% are assigned to them. In general, there is no clear correspondence between the industry classification
Patterns of Persistence of Abnormal Returns

### TABLE 9–5

Estimated Mean and Variance Decomposition (in %) for Each of the Four Latent Classes

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean (s.e.)</th>
<th>Temporary</th>
<th>Permanent</th>
<th>Unexplained</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Class 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ROA 95</td>
<td>6.216 (0.15)</td>
<td>45.50</td>
<td>39.89</td>
<td>14.62</td>
</tr>
<tr>
<td>ROA 96</td>
<td>5.699 (0.14)</td>
<td>35.81</td>
<td>56.52</td>
<td>7.66</td>
</tr>
<tr>
<td>ROA 97</td>
<td>5.375 (0.14)</td>
<td>37.64</td>
<td>59.41</td>
<td>2.96</td>
</tr>
<tr>
<td>ROA 98</td>
<td>5.382 (0.16)</td>
<td>38.41</td>
<td>60.63</td>
<td>0.96</td>
</tr>
<tr>
<td>ROA 99</td>
<td>5.381 (0.17)</td>
<td>38.32</td>
<td>60.48</td>
<td>1.20</td>
</tr>
<tr>
<td>ROA 00</td>
<td>5.234 (0.16)</td>
<td>37.52</td>
<td>59.21</td>
<td>3.27</td>
</tr>
<tr>
<td><strong>Average %</strong></td>
<td>38.87</td>
<td>56.02</td>
<td>5.11</td>
<td></td>
</tr>
<tr>
<td><strong>Class 2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ROA 95</td>
<td>3.950 (2.53)</td>
<td>0.00</td>
<td>53.44</td>
<td>46.56</td>
</tr>
<tr>
<td>ROA 96</td>
<td>4.865 (2.65)</td>
<td>0.00</td>
<td>67.62</td>
<td>32.38</td>
</tr>
<tr>
<td>ROA 97</td>
<td>5.807 (2.87)</td>
<td>0.00</td>
<td>61.53</td>
<td>38.47</td>
</tr>
<tr>
<td>ROA 98</td>
<td>6.835 (3.73)</td>
<td>0.00</td>
<td>36.64</td>
<td>63.36</td>
</tr>
<tr>
<td>ROA 99</td>
<td>7.136 (2.92)</td>
<td>0.00</td>
<td>45.29</td>
<td>54.71</td>
</tr>
<tr>
<td>ROA 00</td>
<td>8.915 (3.09)</td>
<td>0.00</td>
<td>32.34</td>
<td>67.66</td>
</tr>
<tr>
<td><strong>Average %</strong></td>
<td>0.00</td>
<td>49.48</td>
<td>50.52</td>
<td></td>
</tr>
<tr>
<td><strong>Class 3</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ROA 95</td>
<td>9.074 (0.21)</td>
<td>84.65</td>
<td>0.00</td>
<td>15.35</td>
</tr>
<tr>
<td>ROA 96</td>
<td>8.970 (0.22)</td>
<td>79.95</td>
<td>0.00</td>
<td>20.05</td>
</tr>
<tr>
<td>ROA 97</td>
<td>9.356 (0.24)</td>
<td>89.33</td>
<td>0.00</td>
<td>10.67</td>
</tr>
<tr>
<td>ROA 98</td>
<td>10.073 (0.25)</td>
<td>89.31</td>
<td>0.00</td>
<td>10.69</td>
</tr>
<tr>
<td>ROA 99</td>
<td>10.124 (0.25)</td>
<td>89.35</td>
<td>0.00</td>
<td>10.65</td>
</tr>
<tr>
<td>ROA 00</td>
<td>9.570 (0.24)</td>
<td>86.07</td>
<td>0.00</td>
<td>13.93</td>
</tr>
<tr>
<td><strong>Average %</strong></td>
<td>86.44</td>
<td>0.00</td>
<td>13.56</td>
<td></td>
</tr>
<tr>
<td><strong>Class 4</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ROA 95</td>
<td>7.025 (1.19)</td>
<td>0.00</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>ROA 96</td>
<td>7.673 (1.11)</td>
<td>0.00</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>ROA 97</td>
<td>8.926 (1.21)</td>
<td>0.00</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>ROA 98</td>
<td>6.837 (1.39)</td>
<td>0.00</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>ROA 99</td>
<td>7.176 (1.23)</td>
<td>0.00</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>ROA 00</td>
<td>9.947 (1.12)</td>
<td>0.00</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td><strong>Average %</strong></td>
<td>0.00</td>
<td>0.00</td>
<td>100.00</td>
<td></td>
</tr>
</tbody>
</table>
TABLE 9–6
Estimated Means of Annual Sales and Total Assets for the Firms Classified in Each of the Four Classes (all annual figures are in 10^6 euros)

<table>
<thead>
<tr>
<th>Class</th>
<th>Year</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total Assets</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1995</td>
<td>54.613</td>
<td>30.298</td>
<td>44.712</td>
<td>19.425</td>
<td>46.853</td>
</tr>
<tr>
<td></td>
<td>1996</td>
<td>59.795</td>
<td>34.110</td>
<td>50.138</td>
<td>22.918</td>
<td>52.022</td>
</tr>
<tr>
<td></td>
<td>1997</td>
<td>64.109</td>
<td>37.671</td>
<td>54.939</td>
<td>28.059</td>
<td>56.606</td>
</tr>
<tr>
<td></td>
<td>1998</td>
<td>71.003</td>
<td>48.276</td>
<td>61.689</td>
<td>29.213</td>
<td>63.228</td>
</tr>
<tr>
<td></td>
<td>1999</td>
<td>79.923</td>
<td>55.270</td>
<td>72.614</td>
<td>34.897</td>
<td>72.928</td>
</tr>
<tr>
<td></td>
<td>2000</td>
<td>90.923</td>
<td>58.366</td>
<td>87.525</td>
<td>42.506</td>
<td>85.479</td>
</tr>
<tr>
<td>Average*</td>
<td>70.061</td>
<td>43.998</td>
<td>61.936</td>
<td>29.503</td>
<td>62.853</td>
<td></td>
</tr>
<tr>
<td>Growth**</td>
<td>66.48</td>
<td>92.64</td>
<td>95.75</td>
<td>118.81</td>
<td>82.44</td>
<td></td>
</tr>
<tr>
<td>Annual Sales</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1995</td>
<td>50.836</td>
<td>28.594</td>
<td>52.258</td>
<td>29.705</td>
<td>49.720</td>
<td></td>
</tr>
<tr>
<td>1996</td>
<td>54.898</td>
<td>30.559</td>
<td>57.929</td>
<td>30.541</td>
<td>54.320</td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td>60.812</td>
<td>31.978</td>
<td>65.624</td>
<td>35.797</td>
<td>60.961</td>
<td></td>
</tr>
<tr>
<td>1998</td>
<td>67.268</td>
<td>37.011</td>
<td>71.478</td>
<td>36.625</td>
<td>66.761</td>
<td></td>
</tr>
<tr>
<td>1999</td>
<td>72.897</td>
<td>46.782</td>
<td>78.225</td>
<td>40.342</td>
<td>72.976</td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>82.973</td>
<td>54.594</td>
<td>89.455</td>
<td>51.672</td>
<td>83.636</td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>64.947</td>
<td>38.253</td>
<td>69.161</td>
<td>37.447</td>
<td>64.729</td>
<td></td>
</tr>
<tr>
<td>Growth</td>
<td>63.22</td>
<td>90.92</td>
<td>71.18</td>
<td>73.95</td>
<td>68.21</td>
<td></td>
</tr>
</tbody>
</table>

* Average across the six years
** Growth over six years (in %)

by first digit of SIC, 3 and the derived four-class typology based on the pattern of evolution of abnormal returns.

9.6 DISCUSSION AND CONCLUSIONS

This paper explores the patterns of evolution of abnormal returns allowing for the presence of several groups of firms that present specific dynamical behavior of ROA. Each group (or class) represents a particular case of the more general model for the persistence of abnormal returns (Bou & Satorra, in press) that decomposes the variance of abnormal returns into three components with different correlation structures over time; static, dynamic or changing, and an

3The same results are obtained when a more detailed industry classification is used (e.g., four-digit SIC code).
TABLE 9–7
For Each of the First Digit SIC Code This Table Shows the % of Firms Classified to Each of the Four Latent Classes (with last column being the number of firms)

<table>
<thead>
<tr>
<th>Digit</th>
<th>Sector</th>
<th>Class</th>
<th>Class</th>
<th>Class</th>
<th>Class</th>
<th># firms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Agriculture</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>461</td>
</tr>
<tr>
<td>0,1</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>34.08</td>
<td>2.45</td>
<td>59.22</td>
<td>4.25</td>
<td>2,327</td>
</tr>
<tr>
<td>4</td>
<td>Transportation</td>
<td>44.62</td>
<td>5.38</td>
<td>45.38</td>
<td>4.62</td>
<td>260</td>
</tr>
<tr>
<td>5</td>
<td>Wholesale</td>
<td>49.11</td>
<td>2.56</td>
<td>42.68</td>
<td>5.65</td>
<td>1523</td>
</tr>
<tr>
<td>7,8</td>
<td>Retail Trade</td>
<td>31.73</td>
<td>8.53</td>
<td>51.73</td>
<td>8.00</td>
<td>375</td>
</tr>
<tr>
<td></td>
<td>Services</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. SIC code was not available for 54 firms.

unexplained firm-by-year specific component. The evolution of ROA in each group is characterized by the size of these three components.

In the most common pattern of evolution, class 3 (51% of firms), abnormal returns are modeled as an AR(1) process. In this class, abnormal returns persist some time, but disappear progressively. This pattern of evolution is consistent with many of the previous empirical work in the “persistence of profit” literature, such as Mueller (1986, 1990), Jacobson (1988), McGahan and Porter (1997) and Jacobson and Hansen (2001) among others. Using time-series methodology, these authors have modeled persistence of profits as an AR(1) process, and have demonstrated that profits do not vanish quickly, but persist over time. The estimated autoregressive coefficient ($\beta = 0.83$) indicates high persistence, because only 20% of abnormal returns dissipate per year. This autoregressive coefficient is in line with those obtained in previous work in other countries (see Jacobson, 1988, for the U.S. and Odagiri & Yamawaki, 1990, for an international comparison).

A related pattern of evolution is suggested by class 1 that comprises transient, but also permanent differences in abnormal returns. Results for Spanish firms show that in this class, roughly 40% of abnormal returns converge to the mean following an AR(1) process with $\beta = 0.67$. In comparison with class 3, the process of convergence is quicker (less persistence), as indicated by the lower level of the autoregressive coefficient. In turn, the variance of the temporary differences is almost 10 times lower than in class 3 (3.9% and 31.75%, respectively) indicating that this class is formed by very homogeneous firms. As the variance of the transient component captures the size of the nonsus-
tiable differences, the previous results indicate that firms in class 3 have a
greater ability to generate short-run or nonsustainable rents that take longer to
vanish than in class 1.

Class 1 also takes account of permanent differences among firms; 56% of
the total variance of abnormal returns remain constant in the 6-year period of
study. The stability of abnormal returns reveals that competitive forces cannot
erode the potential sources of competitive advantages, whichever they are, that
generate these abnormal returns, at least during the period of study. Consequently, firms in this class exhibit different levels of profitability measured by
the individual score obtained in the permanent component, and maintain the
profit differential over time. Firms that are more (less) profitable at the begin-
ing of the period remain more (less) profitable at the end, at least in the
portion of variance of abnormal returns that is static.

Classes 1 and 3 also differ in their profit rates, as well as in their growth
rates. Firms in class 3 have a high average of ROA (9.5%) and an upward trend,
whereas class 1 is formed by less profitable firms (ROA average = 5.5%), with
a slight downward trend. In turn, although assets and sales average growth
in both classes, firms in class 3 have a comparatively faster growth in two
magnitudes, especially in assets with a difference of almost 30 points over the
6-year period of study. Firms in class 3 are thus not only more profitable, but
also have a faster growth than firms in class 1. As a consequence, the gap in
sales between the two groups increases to 6.5 million euros in 2000, whereas
difference in total assets decreases to 3.4 million euros.

These differences suggest that in the more profitable group of firms and
with a faster growth, differences across firms in abnormal returns are transi-
tory and based on the successive introduction of short-run rents. Although the
objective of this chapter is not to directly contrast the alternative theoretical
predictions about differences in abnormal returns, some preliminary insights
can be advanced. Our results suggest that firm profit rates are more related
to the generation of short-run rents (as in class 3), than to the sustainability
of the present rents, and are more consistent with the Schumpeterian and ef-
ficiency point of view that supports that persistence is related to the ability of
firms to introduce innovations continually (Roberts, 1999; 2001) in a process
of creative destruction (Schumpeter, 1934).

As a whole, 90% of Spanish firms in our sample can be classified into
classes 1 and 3. Both classes denote persistence in abnormal returns, but they
differ in the path that their abnormal returns follow and in their level of prof-
itability and growth. Firms in class 1 have a stable firm-specific component,
whereas in class 3, all abnormal returns vanish. As different classes are formed
based on their path of abnormal returns, differences in profit rates and growth
across classes show that profitability depends, at least partially, on the dynamic
behavior of abnormal returns.
Mixture analysis allows identifying two additional paths in abnormal returns, as classes 2 and 4 show. They are the extreme cases in the continuum of no persistence and complete persistence, and are paths that are followed by only a few firms. Class 2 is characterized by the stability of abnormal returns and by the high within-class variability, that is, large differences in profit rates across firms that do not vanish over time. Consequently, firms that persistently achieve very high or low profit rates have high probabilities to follow the path described by class 2. In our sample, only 174 firms (4% ) follow this path, indicating that this is a path that departs from the classical assumptions of the economic theory and from the previous empirical studies in profit persistence.

On the other hand, class 4 (316 firms, 6% of the sample) highlights completely different dynamics of abnormal returns. This class contains firms that have highly unstable ROA across the years, thus highly unpredictable profits. Besides, the high variance means that profit rates fluctuate around zero with a high variability. In this class, firms that obtain returns above the norm are not capable to sustain it, and abnormal returns are eroded instantaneously (or over a shorter term than the time sequence of the observations). This dynamic behavior is in accordance with predictions arising from neoclassical economics and the work of Austrian School of Economics that predict that factors such as imitation, entry, or substitution prevent abnormal returns from persisting (Wiggins & Ruefli, 2002).

From a methodological point of view, it is interesting to note the importance of classes 2 and 4 in our analysis. Although these classes are not common paths (10% of firms), they group firms whose dynamics of the abnormal returns departs markedly from the regular paths of the majority of firms. Traditionally these firms are considered “outliers” that have to be excluded to avoid their influence on the results, or because they cause problems of nonnormality that impede the application of statistical analysis based on normality. Nevertheless, there are no clear criteria to determine outliers, which introduce some degree of arbitrariness in the research. In the sustainability of abnormal returns analysis, the problem of outliers has compelled some researchers to avoid the use of autoregressive models because this technique is based on measures of central tendency (Wiggins & Ruefli, 2002, p. 89) that do not allow disentangling outliers from regular firms.

Instead of excluding outliers from the analysis, or to avoid the use of autoregressive models, our mixture analysis approach encompasses the presence of “outlier” firms. We treat outliers as groups of firms with a singular pattern of behavior of abnormal returns. We thus adopt a different perspective than do Wiggins and Ruefli (2002), considering the existence of outliers and in turn using autoregressive models to model persistence as the previous literature does. That is, in our sample of Spanish firms, classes 2 and 4 are outliers,
with a pattern of evolution of abnormal returns that differ from the regular paths represented by classes 1 and 3.

Mixture models are a suitable approach to longitudinal studies in which heterogeneity is present and it is assumed that a finite number of subpopulations have different associations among the time points, with the dynamic of the abnormal returns being different in each subpopulation or (latent) classes. Figure 9–3 shows the profiles of ROA for 20 firms simulated from the different classes estimated by the fitted model. In this figure, we can see how classes 1 and 3 have stable patterns of evolution, whereas classes 2 and 4—the outlier groups—have highly unstable ROA across years.

![Figure 9–3](image)

Figure 9–3. For each of the classes 1 to 4, we plot the profiles of 20 firms simulated from the fitted model.

Our approach of finite mixture models also represents an alternative to standard cluster analysis, because the posterior probability of membership of a firm in a class can be used to assign latent class membership. In addition, mixture analysis offers a clear advantage over the traditional K-MEANS cluster
analysis, because we have better inference tools for assessing the appropriate number of classes. Further, our approach permits the formation of groups based on a priori defined structure of variance and covariance that, as in this case, reflect a specific pattern of evolution of abnormal returns. Our approach is more in line with recent empirical work, such as that of McGahan and Porter (2003). In our study of the emergence and sustainability of the abnormal returns, groups of firms are formed based on their dynamic behavior, instead of the more traditional group formation based on cluster analysis using data only at the beginning of the period studied (see among others, for example, Mueller, 1986; Odagiri & Yamawaki, 1986; Schohl, 1990), or the industry classification (Wiggings & Ruefli, 2002). In the case of Spanish firms, there is a lack of correspondence between the four derived classes and the first-digit SIC code. These results suggest that the identification of patterns of persistence of abnormal returns is best captured by decomposing abnormal returns into the static and dynamic components, and that the industry classification cannot capture the unobserved dynamic heterogeneity in the sample, because the firms in each industry follow different patterns of evolution.

This chapter can be extended in a number of ways. Explanatory variables can provide additional insights into the patterns of evolution of abnormal returns. Further research could be done on assessing the role of independent variables such as resources, capabilities, and other variables usually used in this literature, in explaining the pattern of variation of abnormal returns. The present modeling approach could also be applied to sample data from other countries, where a different mix of firms in each class can be found. Differences across countries should offer additional insights about the persistence of abnormal returns and the “efficiency” of the competitive markets.

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