Accounting and Economic Rates of Return: A Dynamic Econometric Investigation

Rodrigo M. Zeidan*
Marcelo Resende**

Abstract

Many studies have questioned empirical utilization of accounting data, as internal rates of return would be more consistent with the relevant economic concept. The paper investigates the dynamic relationships between different measures of accounting rates of return (ARRs) and an estimated internal rate of return (IRR). In contrast with the prevailing case-study investigations, we consider a panel for quoted Brazilian firms in the manufacturing industry for the 1988-3/2003-2 period. Granger causality tests are considered and the results indicate a bi-directional causality pattern when ROA (Net Profits/Total Assets) is considered as the accounting measure. This seems to indicate that there is some validity in using accounting rates of return in certain economic settings, especially when long time series are considered.

Keywords: accounting rates of return; internal rate of return; Granger causality; panel data.

JEL codes: M21; M41.

Resumo

Vários estudos questionam a utilização de dados contábeis para análise econômica. O presente artigo investiga a possível relação de longo prazo, dinâmica, entre diferentes medidas contábeis e uma estimada taxa interna de retorno para empresas brasileiras do setor de transformação no período de 1998 a 2003. Foram executados testes de causalidade de Granger e os resultados indicaram uma relação bi-direcional entre a TIR estimada e ROA (Retorno sobre Ativo Total). Isso indica que parece existir alguma validade em se utilizar dados contábeis para análises econômicas em cenários com séries de longo prazo.

Palavras-chave: taxas contábeis de retorno; taxa interna de retorno; causalidade de Granger; dados de painel.
1. Introduction

The search for the best financial performance measure is an open question in the finance literature, with a plethora of different measures having surfaced to try to yield the best answer to this pressing problem. Measures like Q-tobin’s (for more, see Wernerfelt and Montgomery (1988)), Economic Value Added (EVA) and Refined Economic Value Added (REVA) (Bacidore et al., 1997), alongside the usual accounting and economic measures like return over assets, net present value and internal rate of return are all attempts at giving good information on firm performance.

There are many approaches to try to answer questions relative to measuring firm performance, and one with a particular interesting history involves the differences between economic and accounting rates of return. Seminal papers date back to Solomon (1966), Kay (1976), Fisher and McGowan (1983) and Salamon (1985). The main conclusion is that there are differences between accounting and economics definition and the measurement of rates of return. The differences arise from many sources – important ones include, but are not limited to: advertising and research and development are considered investment from an economic viewpoint, but both are costs or expenses in financial statements; and accounting depreciation is arbitrary, be it straight-line depreciation or reducing balance methods.

Since then, many papers have dealt with empirical measures of economic and accounting rates of return (see e.g., Verma (1990), Bosch (1989), Chang et al. (1994), Baber and Kang (1996), Kelly (1996a,b), Feenstra and Wang (2000), Taylor (1999) and Salvary (2005)). Some of these studies used the differences between accounting and economic rates of return as a route towards the measurement of the real economic rate of return whereas others investigated the relationship between them.

Disenchantment with the utilization of accounting rates of return for economic analysis became evident with the emergence of the New Empirical Industrial Organization (NEIO), that proposed indirect strategies of identifying market conduct without the need of marginal cost observability (see Bresnahan (1989) for an early account of the literature). Nevertheless, the use of improved rates of return remains relevant in different contexts as, for example, in the case of regulatory schemes that rely heavily on accounting data such as cost-plus and earnings sharing regimes.

The economic role of accounting data is still unresolved. For instance, Ball (2008) posits many different open questions in this line of research. The main motivation of the paper is to abandon the usual short-term concerns on the differences between accounting and economic measures of return and focus on the long-term relationship between these measures. The idea is that for economic analysis, especially market regulation, long-term concerns are more relevant than short-term ones, like market valuation. Instead of focusing on short-terms concerns, by shifting the focus to the long-term relationship between economic and accounting data one can conclude by the validity of using accounting measures in economic analysis. If the differences between accounting and economic measures prevail in the
long-run, efficiency in market regulation can be improved by focusing solely on accounting information for long-run strategies instead of the implementation of highly complex schemes to measure the return of regulated firms.

The investigation of the relationship between accounting and economic rates of return and therefore the contribution of the present paper can be also motivated in at least two levels:¹

a) Studies that attempt to assess differences between accounting rates of return (ARRs) and economic measures of return such as internal rates of return (IRRs) are either purely theoretical (Kay, 1976, Salamon, 1985, Feenstra and Wang, 2000) or based on case studies (Fisher and McGowan, 1983, Taylor, 1999). Salamon (1988) did a cross-section study, but we propose a systematic approach using panel data for quoted Brazilian industrial firms.

b) The conditional IRRs (Salamon, 1985) are conceptually a good proxy of the unobserved real economic rate of return. We consider a Granger causality test to verify if there is informational content between ARRs and IRRs. Robust results would indicate that ARRs are a good proxy for the conditional IRRs and thus to the unobserved real economic rate of return. ARRs and IRRs could present a co-movement in the long-run because the sources of the difference between them could be negligible in the long-run, hence ARRs would yield sufficient information on the underlying IRRs in a Granger test setting. The main hypothesis is to test this assumption, i.e., if ARRs Granger cause the IRRs.²

The Granger causality test has already been used successfully in the context of Brazilian financial reports by Costa Jr. et al. (2007). In their paper the author found marginal evidence that accounting returns cause stock returns.

The paper is organized as follows. Section 2 introduces the conceptual aspects related to the calculation of the conditional IRRs necessary for the test, and the set of accounting rates of return to be considered. Section 3 presents the data construction procedures and the results for the Granger causality tests. Section 4 brings some final comments.

2. Accounting and Economic Rates of Return: Conceptual Aspects

2.1 The conditional IRRs

The main problem when trying to establish the long term relationship between accounting rates of return (ARRs) and the internal rate of return (IRR) is arriving

¹An additional gap in the literature concerns the empirical behavior of improved rates of return that attempt to proxy the internal rate of return in the context of structure-conduct-performance models. In fact, well established robust results prevail in the case of accounting rates of return [see Schmalensee (1989)].

²For non-stationary variables an ideal setting would be to test for co-integration. Since ARRs and IRRs are stationary, the Granger causality test is suited to analyze a possible long-term relationship between the variables.
at the correct IRR to compare to the ARRs. Letting $Y_n$ be the revenue stream and $I_n$ the investment, the IRR of a project is defined as the rate $r$ that solves:

$$Y_0 - I_0 + \frac{Y_1 - I_1}{1 + r} + \ldots + \frac{Y_n - I_n}{(1 + r)^n} = 0$$

(1)

The IRR is then the rate that equals the present value of the investment with the cash flow that it generates, thus turning the present value of the investment zero. It is the change in the present value of the investment that can be considered as the economic depreciation (Schmalensee, 1989) since depreciation distributes the value of investment over time. Thus the IRR can be considered a good proxy for the real unobserved economic return, since a project would only be viable if its IRR would be higher than a control parameter – usually the cost of capital.

Although conceptually easy to follow, empirical measurement of the IRR is not simple to do. Three are the main reasons:

- Equation 1 is a $n$-polynomial with $n$ possible solutions. Thus for non-conventional cash flows there would be multiple IRRs with no possible way to determine which one would be the proxy for the economic rate of return (Ross et al., 1998);
- Investment projects with the same IRR may not be interchangeable since investment decisions consider other aspects such as uncertainty or the need for initial investment. Thus a project that needs less investment should be preferable to a project with the same IRR but higher initial investment;
- Financial reports have many idiosyncrasies and it is difficult to retrieve which information is essential to build $Y_n$ and $I_n$.

Different approaches have been built to analyze the different behaviors of economic and accounting rates of return, always with the goal of determining if accounting rates of return are a good surrogate to economic rates of return. Particularly interesting approaches can be found in Baber and Kang (1996) – they find that accounting rates of return are higher than their implied internal rates of return for the US pharmaceutical industry, and Kelly (1996a,b), where the author finds that the ARR is an unreliable substitute for the IRR, using 44 Australian corporations between 1968 and 1990. Following previous work, we investigate the relationship between the ARR and IRR by trying, first, to develop a reliable IRR surrogate.

Salamon (1982, 1985) and Taylor (1999) tried to estimate the IRR by using Ijiri’s (1978) concept of Cash Recovery Rate (1978) to measure an indirect economic rate of return. We will follow those works and arrive at a IRR indirectly through the cash recovery rate (CRR), which has the advantage of being a cash flow concept instead of a balance sheet concept.

The concept of the CRR was first developed by Ijiri (1978) as an alternative to the conventional ARRs. The rationale was that since the ARR did not measure
cash flows in the economic sense, having a measure of how the firms recover past investments would be complementary to the regular information presented in financial reports. Focusing on cash flows, the CRR then shows the pattern of recoveries from a firm and is defined as:

\[ \text{CRR} = \frac{\text{INCBD} + \text{INTERP} - \Delta \text{LTASS} + \Delta \text{TASS} - \text{DEPR}}{\text{TASS}} \]  

(2)

with INCBD being income from operations; INTERP interest expenses; \( \Delta \text{LTASS} \) book-value of long-term assets disposed; DEPR depreciation; TASS the average total asset of the period considered. The numerator represents the firm’s flow of recoveries, while the denominator is a stock variable. Taylor (1999) includes research and development and advertisement in the CRR to allow for better recovery estimates to the pharmaceutical industry that was being studied. Since R&D and advertisement expenditures are not always published in financial reports, in this paper we considered mature manufacturing industrial sectors to calculate CRRs and conditional IRRs – examples of those sectors are steel, pulp, mining, fertilizers mechanical and electrical machines, etc. The choice was as ample as possible, considering any quoted company that did not operate in industrial sectors with high R&D and advertisement expenditures.

The idea behind the CRR is then to present a cash flow measure that is easier to calculate and is derived solely from financial reports. The usual cash flow measures, like net present value, IRR, and discounted payback, are hard to derive for a whole firm. The CRR would be an approximation of an economic rate of return and would have the advantage of looking at data for more than one period, instead of the usual static accounting measures. Salamon (1982, 1985) showed that under some circumstances the CRR could be a proxy for the IRR of a firm, and thus estimates the relationship between the CRR and IRR. The relationship between CRR and IRR can be derived because both are cash-flow methods that use similar information to achieve the firm’s rate of return. The main hypothesis that allows the estimation is that the firm is a collection of similar projects, and with this it can be established that:

\[ \text{CRR} = g \left[ \frac{1}{(1 + g)^n - 1} \right] \left[ \frac{(1 + g)^n - b^n}{(1 + g - b)} \right] \left[ \frac{(1 + r)^n (1 + r - b)}{(1 + r)^n - b^n} \right] \]  

(3)

with \( g \) a constant that represents the growth of a firm’s investment over time; \( n \) the life-time of the representative project of the firm; \( b \) a cash flow linear profile that shows if recoveries for the firm’s investments increase, decrease, or are constant over time; \( r \) the IRR of the typical project of the firm. The cash-flow pattern, \( b \), is crucial to estimation of equation 3. If \( Y_0, Y_1, ..., Y_n \) is the cash-flow of a representative project of the firm, with \( Y_0 < 0 \) and \( Y_1, ..., Y_n > 0 \), then \( b \) is such that \( Y_i = b^{i-1}Y_1 \), for \( i = 1, ..., n \). Thus the cash-flow profile \( b \) relates past and
future cash flows. If $b < 1$ ($> 1$), the cash flow diminishes (grows) exponentially. If $b = 1$, the recovery process is constant. Salamon (1985) argued that $b$ could be estimated using information on past recoveries for the firms, but used ad hoc profiles of 0.8; 1.0; 1.1; and a random value between (0.8;1.1), arriving then at four conditional IRRs. We follow Salamon’s argument that $b$ can be estimated and provide it in the next section.

Equation 3 presents some strong assumptions: each firm is a collection of projects with similar IRRs, life-times, and cash-flow patterns; and the rate of investment growth of the firm is linear. These assumptions are needed to make calculations possible – for instance, a linear cash-flow pattern is needed to avoid multiple IRRs for each firm. A particular important critique to the concept of the CRR can be found in Brief (1985), where the author argues that the CRR as a predictive measure is ineffectual due to the problem of predicting future cash flows. Here we can safely ignore this critique because we are dealing with ex-post cash flows, and future cash flows are represented in the cash-flow profile. We are not particularly interested in finding a completely accurate proxy to the IRR, but build measures that share information content with the IRR in a way that is possible to derive a causality test.

Taylor (1999) derives a cash-flow profile for pharmaceutical firms based on the concept of summation point. The rationale is that investment processes are not perfectly perceived by financial reports since said processes take place over more than a year. The idea behind the summation point is to define at which point the firm starts to recover the investment necessary to construct its cash-flow profile. For the pharmaceutical industry the number found by Taylor (1999) is 5 years – thus recoveries of a typical project begin at the start of the 5th year of the investment process. The main problem with this approach is that it requires too much industry-specific information, which is untenable in the context of the panel data approach for testing Granger causality in this paper. Instead of using ad hoc cash-flow profiles as in Salamon (1985) we will follow the author’s suggestion and construct a firm-specific cash-flow profile to achieve a conditional IRR to use in the causality test and to avoid the fact that if there is no recovery a conditional IRR can not be estimated. The cash-flow profiles will then use past firm-specific information. The rationale is that if investments are growing more than recoveries then recoveries will need to grow more rapidly in the future for the firm to recover its investment, and thus will have an increasing ($> 1$) cash-flow profile. On the other hand, if recoveries are much larger than investments firms should have a declining cash-flow profile. Using the numerator of (3) as recoveries, the firm-specific cash-flow profile is presently defined as:

\[ Y_n - I_n \]

One important observation is that if the growth of investment is greater than the recoveries calculation of the IRR is impossible (Salamon, 1988). This is straightforward, since any calculation in finance requires negative and positive values for present and future values – and if recovery is never greater, then all $Y_n - I_n$ will be negative and thus will be impossible to derive a $r$ that solves (1).
Expression 4 defines $b$ as a relationship between the past growth of investments and recoveries. The cash-flow pattern $b$ found in (4) is crucial to finding the IRR since economic return depends on how firms recover their investments. All information for (4) is present on financial reports and the following simplifying assumptions are made to make it possible to empirically estimate (4): once estimated, $b$ does not change over the period analyzed – this assumption is necessary and is not as strong as in Salamon (1985), since we are estimating it from firm-specific data and consider information on the whole investment and recovery period; also, $b$ is time-invariant: it depends not only on the ex-post future financial data but it has to be the same when backtracked to past investments, since we assume that the firms were operating before the first quarter of the analyzed period, and will continue to operate after that. In other words, since (4) depends on information like total assets and change in investments, variables that predate the period 0 of our analysis, $b$ has to be time consistent.

We do not treat the firm as beginning to operate on the first period and ending at the last period of our analysis. The result is a firm-specific cash-flow pattern, which allows the IRR ($r$) being estimated by solving (3). We take:

$$W = \frac{CRR}{\left(\frac{g}{(1 + g)^n - 1}\right) \left(\frac{(1 + g)^n - b^n}{(1 + g - b)}\right)}$$  \hspace{1cm} (5)$$

Substituting (5) into (3) implies that solving (3) in terms of $r$ is:

$$r = \sqrt{\frac{-b^nW}{(1 + r - b - W) - 1}}$$ \hspace{1cm} (6)$$

Equation (6) then yields the estimated IRR dependent on the estimated $b$. The information necessary to solve (6) is: $b$, $g$, and the CRR, and after estimating $b$ we have all three. To solve it we initially took $r = 0$ and iterated (6) to arrive at single conditional IRRs.

2.2 Accounting rates of returns

There is no assumption on the preferential ARR for trying to establish the long-term relationship between ARRs and IRRs. As table 1 indicates, the ARRs can be categorized as measures of return on total assets, return on equity, profit margin, and total asset turnover. There are three measures of profit in Brazilian financial reports: gross profit, earnings before interest, taxes, depreciation and amortization (EBITDA), and net profit.
Table 1
Different accounting rates of return (ARRs)

<table>
<thead>
<tr>
<th>Return on Assets (ROA)</th>
<th>Profit Margin (Gross and Net)</th>
<th>Return on Equity (ROE)</th>
<th>Total Asset Turnover</th>
</tr>
</thead>
<tbody>
<tr>
<td>TASS</td>
<td>INCBD</td>
<td>Equity</td>
<td>TASS</td>
</tr>
<tr>
<td>How much profit per $100 of investment</td>
<td>How much profit per $100 of income</td>
<td>How much profit per $100 of proprietary investment</td>
<td>How much sales per $100 of firm’s structure</td>
</tr>
</tbody>
</table>

Of the three classes, return over equities and assets are the classes that best represent economic return, due to investors focusing on the profitability of the assets of the firm or their holdings – equities. As the numerator, we use net profits, since it is the profit measure most akin to economic rationale. In their seminal study, Fisher and McGowan (1983) used ROA measures, while Long and Ravenscraft (1984) argued that Fisher and McGowan (1983) erred for not using profit margins, which is more commonly used. To prevent any such problems, no a priori ARR is considered the best one to compare it to the IRRs estimated, and therefore the Granger causality tests, later implemented, will use both ROA and ROE. Thus two ARRs were used for comparison with the conditional IRRs:

- ROA – Net Profits/Total Assets;
- ROE – Net Profits/Equities.

3. Empirical Analysis

3.1 Data construction

Data was obtained from Economatica – quarterly financial reports for quoted companies from 1988 to 2003. The final data comprised a balanced panel that run from the third quarter of 1988 through the second quarter of 2003, a total of 60 observations. The total number of selected firms was 93 and, as previously observed, only industrial firms from mature, low R&D and advertising sectors were chosen, to avoid some of the biggest discrepancies between ARRs and IRRs.

Regarding the average for the entire period, the ROA for the selected firms was -1.9%, ROE was -6.7% and the estimated IRR was -1.5%. All averages are slightly negative, with many quarters of negative values. This is interesting and corroborates the view of the two lost decades of the 80’s and 90’s in Brazil.

R&D is not a significant source of concern for discrepancies between ARRs and IRRs for Brazilian firms, since the average expenditure of R&D in Brazil is 0.4% of GDP, compared to the 2% of GDP in most industrialized countries (Rocha and Ferreira, 2001).

Although this makes for a biased comparison between ARRs and IRRs, it could be justified for being the first exploratory test between its long run relationship. Also, it allows for a better control of the test, since if for the selected industrial firms no relationship were to be found this could be extended to the more intensive in R&D and advertising expenses’ firms.

Just as a comparison, for the same period the average ROA for the American manufacturing sector was 4.7%, profit margin 4.5%, and return on equities 11.9% (Bureau of the Census, “Quarterly Financial Report for Manufacturing, Mining, and Trade Corporations” – 2004).
I presents some interesting information on this, showing that volatility on ROE is much bigger than the other measures, and that all measures are stationary.

![Figure 1](image)

**Figure 1**
ROA, ROE and estimated IRR for selected Brazilian companies

### 3.2 Causality analysis

A panel data causality test between the estimated conditional IRRs and selected ARRs is used to explore the long-term relationship between economic and accounting measures of return, trying to measure informational content between the variables. The usefulness of the test is due to the fact that even if the two forms of measurement present clear differences, they could reveal the same information if a long period is considered. Since a major critique of accounting measures of return is that they do not represent economic reality, if in the long run there is no persistent bias the comparison between accounting and economic rates of return should yield no difference.

The paper will consider relationships between pairs of rates of return. However, unlike the usual time series setting for testing causality, we face a data set with a panel structure that should be fully explored.

The focus of the paper will be on tests for Granger causality. The concept is largely widespread since Granger (1969). Let $x$ and $y$ denote two stationary stochastic processes, $x$ is said to Granger cause $y$ if the inclusion of past values of $x$ help to explain $y$ by reducing the variance of the prediction error, that is:

$$\sigma^2(y_t, y_{t-1}, ..., x_{t-1}, \ldots) < \sigma^2(y_t, y_{t-1}, \ldots)$$

$x$ is said to ‘Granger cause’ $Y$ ($X \Rightarrow Y$ but not $Y \Rightarrow X$) if and only if $

\sigma^2(Y_t|Y, X) < \sigma^2(Y_t|Y)$ where $Y$ and $X$ denote information on past realizations of the two stochastic processes. Bidirectional causality would, of course, arise when causality prevails in both directions. In summary, Granger causality arises when past realizations of $X$ improve the prediction of $Y$ and in that sense usual empirical implementations rely on joint statistical tests of lagged coefficients of the regressors. Assessments of Granger causality are now widespread in the case
of time series but are becoming increasingly common in the context of panel data models. Microeconomic applications include Rouvinen (2002) that investigates causality between R&D and productivity and Banerjee (2003) who explores causal patterns between incentive regulation and service-quality in U.S. telecommunications. This latter work takes advantage of a GMM efficient estimator for dynamic panels. Traditional panel data estimators will lead to well-known biases in a dynamic setting (for an overview of consistent and efficient estimators for dynamic panel data see Bond (2002) and Baltagi (2005)) and therefore some basic discussion is warranted.

A simple dynamic panel model is given by:

$$y_{it} = \alpha y_{i,t-1} + \beta x_{it} + \mu_i + v_{it}$$  \hspace{1cm} (7)

The model could also include time effects ($\lambda_t$) that would capture non-observed heterogeneities that only depend on the time period and typically are considered by means of period dummy variables. The lagged dependent variable induces significant biases in traditional panel data estimators and therefore Arellano and Bond (1991) have suggested a consistent and efficient estimator for short panels based on the first difference of the dynamic model. The estimator is generalized method of moment estimator that uses orthogonality conditions on the appropriate instruments and the error (henceforth GMM-DIF). The first differencing of expression (1) would lead to:

$$\Delta y_{it} = \alpha \Delta y_{i,t-1} + \beta \Delta x_{it} + \Delta v_{it}$$  \hspace{1cm} (8)

The lag structure of the equation in differences follow the choice of lag structure for the equation in levels. The first-differencing transformation therefore wipes out the fixed effect. Suitable instruments for $\Delta y_{i,t-1}$, in terms of lagged dependent variable in levels, become increasingly available starting with $y_{i1}$ at $T = 3$, $y_{i1}$ and $y_{i2}$ at $T = 4$ up to $y_{i1},..., y_{i,T-2}$ for $T$. The other elements of the instrument matrix will reflect the assumptions regarding the additional regressors $x_{it}$. If they are assumed to be strictly exogenous (uncorrelated with past, current and future errors) the variables can be readily used as instruments whereas in the case of endogeneity, an instrumenting procedure with lagged variables in levels that is analogous to the previous procedure would be implemented. The validity of the instruments is important for the consistency of the GMM-DIF estimator. Sargan’s test for overidentifying restrictions in terms of the joint significance of the instruments in excess to the minimum necessary for identification is distributed as a chi-square with the number of degrees of freedom given by the difference between the number of instruments and the number of endogenous variables, under the null hypothesis. Moreover, even in the absence of serial correlation for the model in levels, the first-differencing procedure would induce first-order serial correlation but not second-order serial correlation. Tests for AR(1) and AR(2) errors were suggested by AB and the latter is important to assure adequate properties to the estimator. Under the null hypothesis of no serial correlation, the test statistics
would follow a standard normal distribution. The estimation is carried out later in this section and considers the widespread two-step GMM procedure that can be more efficient in a heteroscedastic context.

The data used for the test is a panel of ROA and ROE for each firm and each quarter from the 1998-2003 period, measured against each IRR estimated for each firm for the same period. The idea is to test for Granger causality of ROA and ROE against IRR. Tables 2-4 summarize the corresponding results. The results were obtained for the two-step GMM-DIF estimator by means of the software DPD 1.21 that runs in the platform Ox 3.0\(^7\)

<table>
<thead>
<tr>
<th>Table 2</th>
<th>Causality analysis IRR → ARR: results from GMM-DIF estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ROA</td>
</tr>
<tr>
<td>Regressor</td>
<td>coeff</td>
</tr>
<tr>
<td>(\Delta IRR_{-1})</td>
<td>0.922</td>
</tr>
<tr>
<td>(\Delta IRR_{-2})</td>
<td>0.044</td>
</tr>
<tr>
<td>(\Delta IRR_{-3})</td>
<td>-</td>
</tr>
<tr>
<td>(\Delta IRR_{-4})</td>
<td>-</td>
</tr>
<tr>
<td>(\Delta ARR_{-1})</td>
<td>-0.003</td>
</tr>
<tr>
<td>(\Delta ARR_{-2})</td>
<td>0.001</td>
</tr>
<tr>
<td>(\Delta ARR_{-3})</td>
<td>-</td>
</tr>
<tr>
<td>(\Delta ARR_{-4})</td>
<td>-</td>
</tr>
<tr>
<td>Constant</td>
<td>0.000</td>
</tr>
<tr>
<td>Sargan test</td>
<td>85.14</td>
</tr>
<tr>
<td>AR(1) test</td>
<td>-4.839</td>
</tr>
<tr>
<td>AR(2) test</td>
<td>-1.096</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Causality analysis ARR → IRR: results from GMM-DIF estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ROA</td>
</tr>
<tr>
<td>Regressor</td>
<td>coeff</td>
</tr>
<tr>
<td>(\Delta ARR_{-1})</td>
<td>0.519</td>
</tr>
<tr>
<td>(\Delta ARR_{-2})</td>
<td>0.519</td>
</tr>
<tr>
<td>(\Delta ARR_{-3})</td>
<td>0.518</td>
</tr>
<tr>
<td>(\Delta IRR_{-1})</td>
<td>0.943</td>
</tr>
<tr>
<td>(\Delta IRR_{-2})</td>
<td>0.459</td>
</tr>
<tr>
<td>(\Delta IRR_{-3})</td>
<td>0.486</td>
</tr>
<tr>
<td>Constant</td>
<td>0.002</td>
</tr>
<tr>
<td>Sargan test</td>
<td>84.72</td>
</tr>
<tr>
<td>AR(1) test</td>
<td>-1.099</td>
</tr>
<tr>
<td>AR(2) test</td>
<td>1.029</td>
</tr>
</tbody>
</table>

\(^7\)Small sample corrections for the standard errors were implemented as advanced by Windmeijer (2005).
Zeidan, R., Resende, M.

Table 4
Joint significance tests

<table>
<thead>
<tr>
<th>Test</th>
<th>ROA→ARR</th>
<th>ROE→ARR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Chi-sq</td>
<td>p-value</td>
</tr>
<tr>
<td>overall significance</td>
<td>1384</td>
<td>0.000</td>
</tr>
<tr>
<td>lag p coefficients</td>
<td>14.593</td>
<td>0.001</td>
</tr>
<tr>
<td>IRR→ARR</td>
<td>15.627</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>overall significance</td>
<td>9793</td>
<td>0.000</td>
</tr>
<tr>
<td>lag p coefficients</td>
<td>8887.77</td>
<td>0.000</td>
</tr>
<tr>
<td>ARRO→IRR</td>
<td>7.293</td>
<td>0.063</td>
</tr>
</tbody>
</table>

In order to assure consistency properties to the estimators, we need to conduct diagnosis tests for the validity of the instruments and for the presence of second-order serial correlation. The lag structure was explored in the range of \( p = 1, \ldots, 4 \). We chose a parsimonious set of instruments with the involved accounting and economic rates of return instrumented with lagged variables from \( t - 2 \) up to \( t - 4 \). Sargan’s test for overidentifying restrictions was satisfactory so that we cannot reject the null hypothesis. Moreover, the tests for AR(2) errors favor the absence of serial correlation.

Next, rather than focusing on the analysis of specific coefficients, we consider Wald-type joint significance tests as reported in table 4. The overall significance for all the coefficients (except the constant) holds in all cases. As for the lag choice, we relied on the joint significance of the coefficients of the highest lag. When one considers ROA as the accounting measure, that criterion favored a lag of 2 in the case of the analysis for IRR → ARR and a lag of 3 in the case of the ARR → IRR analysis. For ROE, on the other hand, the lags for the referred analyses were given by 4 and 2 respectively. Only the estimates for the chosen lag are reported for conciseness.

Having verified those preliminary aspects, we can proceed with the causality tests. The joint tests detects no relevant pattern when ROE is involved and when one considers ROA as the accounting measure there is some evidence of bi-directional causality if we consider a 6% significance level in one of the regressions.

The main result therefore indicates that AARs can possess relevant informational content with respect to IRRs.

4. Final Considerations

Many papers deal with differences between accounting and economic rates of return (e.g. Fisher and McGowan (1983) and Salamon (1985) among others). The goal of the paper was to delve into the subject to verify whether within a dynamic structure of analysis the differences between accounting and economic rates of return are so important to render accounting rates of return irrelevant for economic modeling. The paper contrasts with the previous literature by exploring the panel
structure of the data set comprising different sectors and therefore departing from the previously adopted case-study or purely theoretical framework. In particular, we attempt to verify if accounting rates of return could be salvaged on the grounds of being leading indicators for internal rates of return or vice-versa.

The main difficulty was estimating the IRRs, that requires strong assumptions for being constructed. In order to undertake the investigation, we considered a dynamic panel data approach with a GMM estimator for testing Granger causality. The motivation was to detect eventual informational content between series of internal rates of return and accounting rates of return so as to discern differences between the series and infer possible implications towards economic modeling.

The results did not present completely clear cut patterns for both accounting measures. But a bidirectional causality pattern is suggestive and indicates that ARRs can possess important information content with respect to IRRs when at least ROA is chosen as the accounting measure.

The tendency in studies of market power assessment is to bypass the use of accounting data by considering indirect methods of conduct measurement based in oligopoly models but the present evidence also indicates that accounting measures should not be totally discarded in some contexts. This study provides an initial exploratory analysis on the connection between ARRs and IRRs, but it would be interesting to investigate short-run co-movements between those variables by testing for the presence of common cycles. In that case, however, the analysis would need to be carried out in a firm-by-firm basis as panel methods are not developed in that context.

References


Zeidan, R., Resende, M.


Appendix

We want to solve (3) in terms of \( r \), and \( g \), \( b \), and \( n \) are given:

\[
CRR = g/[(1 + g)^n - 1] \left[ \frac{(1 + g)^n - b^n}{(1 + g - b)} \right] \frac{(1 + r)^n(1 + r - b)}{(1 + r)^n - b^n}
\]

We take:

\[
W = \frac{CRR}{g/[(1 + g)^n - 1] \left[ \frac{(1 + g)^n - b^n}{(1 + g - b)} \right]}
\]

which gives:

\[
W = \frac{(1 + g)^n(1 + r - b)}{(1 + r)^n - b^n} \rightarrow W(1 + r)^n - Wb^n = (1 + r)^n(1 + r - b)
\]

Dividing it by \((1 + r)^n\):

\[
\frac{W(1 + r)^n}{(1 + r)^n} - \frac{Wb^n}{(1 + r)^n} = (1 + r - b) \rightarrow \frac{Wb^n}{1 + r)^n} = 1 + r - b - W
\]

Rearranging it:

\[
1 + r)^n = \frac{-Wb^n}{1 + r - b - W}
\]

which finally gives:

\[
r = \sqrt[1 + r - b - W]{\frac{-b^nW}{1 + r - b - W}} - 1
\]

which is equation (6).