ON THE INTERPRETATION AND ESTIMATION OF THE MARKET MODEL R-SQUARE

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Abstract: The R-square of the market model is largely employed in finance and accounting studies as a measure of stock price informational efficiency. Individual firms R-squares are usually aggregated at the country-level by using the individual firm total risk over the country total risk as weighting factor. This paper shows how to interpret the country-level R-square as a Chisini mean of the firm-specific R-squares and under what conditions it may be related to the R-square of a Seemingly Unrelated Regression (SUR) model. In particular we show that for the latter a necessary constrain is that returns must be centered on zero, which appears to be in this context not only a common practice but also a methodological assumption.

Keywords: R-square, market model, informational efficiency, SUR model, Chisini mean.

1. Introduction

The R-square of the market model is largely employed in finance and accounting studies as a metric of stock price informational efficiency. The earliest studies that use the R-square as a measure of price efficiency are Morck et al.’s analysis at the country level [12] and Durnev et al.’s analysis [4] at the firm level. The authors investigate stock returns synchronicity in emerging and developed economies based on a sample of bi-weekly stock returns for 15,920 firms spanning 40 countries. [12] define the country-level R² as:

\[ R_j^2 = \frac{\sum_i R_{i,j}^2 \cdot \frac{SST_{i,j}}{\sum_i SST_{i,j}}}{\sum_i SST_{i,j}} \]  \hspace{1cm} (1)

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On the interpretation and estimation of the market model R-square

where $SST_{i,j}$ is the sum of squared total variations for stock $i$ in country $j$ and $R^2_{i,j} = SSR_{i,j}/SST_{i,j}$ measures the proportion of the variation in the bi-weekly returns of stock $i$ in country $j$ explained by variations in country $j$’s market return.

Following [12], a large body of research uses the R-square as an indicator of price efficiency. A non exhaustive list of studies that employ the R-square includes [1], [2], [3], [4], [5], [8], [9], [10], [13], [14], [15], [16].

Since (1) is a weighted average of the individual stocks R-squares, it must itself be considered as an R-square. However, the weights in (1) are neither frequencies nor probabilities. Consequently, the interpretation of (1) as a coefficient of determination (i.e., as a measure of the fit of a model) must be appropriately justified and a natural question arises: does it exist a model whose R-square is equal to (1)? In this paper we address two strictly related issues: first, how to interpret the country-level R-square defined in (1) and, second, how to obtain (1) as the R-square of a regression model.

The issues we address in this paper are important both to interpret the country-level R-square in an appropriate way and to specify under what conditions (1) may be considered as an average of the R-squares of the stocks traded in a market.

2. Preliminary empirical evidence

In this Section we present some preliminary evidence about the market model $R^2$ estimated for the US market\(^1\). Specifically, our sample includes all the stocks traded on the NYSE and the NASDAQ markets. We also include dead stocks. For each common stock trading in the company’s home market we collected from Thomson Reuters Datastream (TRD) the daily total return index ($RI$ is the variable name – also known as datatype – in TRD), the daily adjusted price ($P$) and the market capitalization ($MV$). The sampling frequency is weekly. The data span from January 1995 through December 2011. Table 1 reports, for each year, the number of stocks and the average market capitalization for the two markets. We construct, for each year, 5 size-sorted portfolios based on the quintiles of market capitalization at the end of the previous year. Results in Table 1 are reported for both the full sample and the 5 size-sorted portfolios.

For each stock $i$ and each period $t$ of weekly data we run a market model regression:

$$r_{i,t} = \alpha_i + \beta_i \cdot r_{m,t} + \epsilon_{i,t}$$  \hspace{1cm} (2)

where $r_{i,t}$ is the return for stock $i$ at time $t$; $r_{m,t}$ is the return for the stock market at time $t$; $\epsilon_{i,t}$ is the residual. This procedure produces yearly estimates for market model parameters and R-square. By using (1) the stocks R-squares have been aggregated.

\(^1\) For a more comprehensive study and details about the use of R-square as price inefficiency measure see Bramante et al. (2012)
In Table 2 we report, for each market, the mean and the median of the yearly estimates of the R-square for both the full sample and the 5 size-sorted portfolios. Looking at size-sorted portfolios, both the average and the median R-squares are strictly increasing in firm size.

Table 1. Sample Descriptive Statistics.

<table>
<thead>
<tr>
<th>Year</th>
<th>United States - NYSE</th>
<th></th>
<th>United States - NASDAQ</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Stock</td>
<td>Sample</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>1995</td>
<td>2,025</td>
<td>2,501</td>
<td>77</td>
<td>249</td>
</tr>
<tr>
<td>1996</td>
<td>1,928</td>
<td>3,210</td>
<td>119</td>
<td>366</td>
</tr>
<tr>
<td>1997</td>
<td>2,051</td>
<td>5,883</td>
<td>180</td>
<td>412</td>
</tr>
<tr>
<td>1998</td>
<td>2,051</td>
<td>4,710</td>
<td>98</td>
<td>324</td>
</tr>
<tr>
<td>1999</td>
<td>2,020</td>
<td>5,298</td>
<td>88</td>
<td>301</td>
</tr>
<tr>
<td>2000</td>
<td>1,906</td>
<td>5,672</td>
<td>82</td>
<td>302</td>
</tr>
<tr>
<td>2001</td>
<td>1,800</td>
<td>5,548</td>
<td>99</td>
<td>366</td>
</tr>
<tr>
<td>2002</td>
<td>1,814</td>
<td>4,462</td>
<td>95</td>
<td>381</td>
</tr>
<tr>
<td>2003</td>
<td>1,820</td>
<td>5,465</td>
<td>127</td>
<td>485</td>
</tr>
<tr>
<td>2004</td>
<td>1,798</td>
<td>6,274</td>
<td>160</td>
<td>633</td>
</tr>
<tr>
<td>2005</td>
<td>1,802</td>
<td>6,651</td>
<td>166</td>
<td>678</td>
</tr>
<tr>
<td>2006</td>
<td>1,765</td>
<td>7,032</td>
<td>213</td>
<td>823</td>
</tr>
<tr>
<td>2007</td>
<td>1,707</td>
<td>8,091</td>
<td>222</td>
<td>798</td>
</tr>
<tr>
<td>2008</td>
<td>1,590</td>
<td>4,084</td>
<td>95</td>
<td>374</td>
</tr>
<tr>
<td>2009</td>
<td>1,666</td>
<td>6,216</td>
<td>164</td>
<td>608</td>
</tr>
<tr>
<td>2010</td>
<td>1,649</td>
<td>7,204</td>
<td>223</td>
<td>777</td>
</tr>
<tr>
<td>2011</td>
<td>1,638</td>
<td>6,976</td>
<td>201</td>
<td>693</td>
</tr>
</tbody>
</table>

Table 2. $R^2$ by Market Capitalization in 5-size sorted portfolios.

<table>
<thead>
<tr>
<th>R² United States</th>
<th>NYSE</th>
<th>NASDAQ</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>Full Sample</td>
<td>0.222</td>
<td>0.203</td>
</tr>
<tr>
<td>Size Sorted Portfolios</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 (Smallest)</td>
<td>0.121</td>
<td>0.096</td>
</tr>
<tr>
<td>2</td>
<td>0.194</td>
<td>0.183</td>
</tr>
<tr>
<td>3</td>
<td>0.234</td>
<td>0.227</td>
</tr>
<tr>
<td>4</td>
<td>0.260</td>
<td>0.254</td>
</tr>
<tr>
<td>5 (Largest)</td>
<td>0.301</td>
<td>0.293</td>
</tr>
</tbody>
</table>

To investigate the intertemporal behaviour of the size effect, the two graphs of Figure 1 provide, for each market, a representation of the time series dynamics of the R-squares over the entire sample period for the 5 size-sorted portfolios, while the mean and the median of the whole markets are in Table 3.
The R-square increases with market capitalization. The difference in R-squares across size-sorted portfolios increases over time in our sample period for the US markets. For the NYSE, in 1995, the average R-square for the 5th quintile (largest stocks) was 12% and for the 1st quintile (smallest) was 3%; in 2011, the average R-square for the 5th quintile was 53% and for the 1st quintile was 30%. Consequently, the difference in R-squares between top and bottom quintiles increased from 27 to 41 percentage points.

3. The Country-Level R-Square as a Chisini mean

Since we are interested in studying the country-level $R^2$ and not in the comparison across countries, for the sake of simplicity, we drop the subscript $j$ and rewrite (1) as follows:

$$R^2 = \frac{\sum_i R^2_i \cdot \sigma^2_i}{\sum_i \sigma^2_i} = \frac{\sum_i \sigma^2_i}{\sum_i \sigma^2_i}$$

where, $\sigma^2_i = SSR_i/T$, $\sigma^2_i = SST_i/T$, and $T$ is the length of the available time horizon. Since $R^2$ may be read as the ratio of two variables, alike most of balance or economic indexes or in physics e.g. speed, in this Section we propose an interpretation of (3) based on the Chisini
approach to compute a mean (see, e.g. [6]). The intuition behind this method is explained as follows. In general, consider the variables $Y, X_1, X_2, \ldots, X_h, \ldots, X_q$ and the associated sample set $y_i, x_{i1}, x_{i2}, \ldots, x_{ih}, \ldots, x_{iq}$ for $i=1, 2, \ldots, n$. Suppose that a function $f(\cdot)$ exists such that $Y = f(X_1, X_2, \ldots, X_h, \ldots, X_q)$. We may write:

$$\sum_i y_i = \sum_i f(x_{i1}, x_{i2}, \ldots, x_{ih}, \ldots, x_{iq})$$

Consider the variable $X_h$, for $1\leq h\leq q$ and let $\overline{x}_h$ be a scalar which maps $\{x_{1h}, x_{2h}, \ldots, x_{nh}\} \rightarrow \mathbb{R}^1$. For example, $\overline{x}_h$ may be the average of $X_h$. If:

$$\sum_i f(x_{i1}, x_{i2}, \ldots, x_{ih}, \ldots, x_{iq}) = \sum_i f(x_{i1}, x_{i2}, \ldots, \overline{x}_h, \ldots, x_{iq}) \quad (4)$$

holds, then $\overline{x}_h$ is the Chisini mean of the variable $X_h$. The solution $\overline{x}_h$ has the usual properties of an average operator, plus the one of keeping invariant the quantity $\sum_i y_i$. Equation (4) is indeed known as the invariance requirement. If we estimate the R-squares of individual stocks in a country and we wish to use the country-level R-square computed as in (3) as a price efficiency measure, equation (3) may be considered as the solution of a problem like (4) by supposing to keep invariant either:

a) the country systematic risk, computed as the sum of the variances explained by the market model estimated for all the stocks in the country (i.e., $\sum_i \sigma_i^2$),

or

b) the country total risk, computed as the sum of the overall stock return variances\(^2\) (i.e., $\sum_i \sigma_i^2$).

If a) holds, using the Chisini approach and the fact that $\overline{\sigma}_i^2 = \sigma_i^2 \cdot R_i^2$, we may write:

$$\sum_i \sigma_i^2 = \sum_i \sigma_i^2 \cdot R_i^2 \quad \text{Apply Chisini} \quad \Rightarrow \quad \sum_i \sigma_i^2 \cdot R_i^2 = \sum_i \sigma_i^2 \cdot R_i^2 \quad \Rightarrow \quad R^2 = \frac{\sum_i \sigma_i^2 \cdot R_i^2}{\sum_i \sigma_i^2} \quad (5)$$

If b) holds, using again the Chisini approach and the fact that $\sigma_i^2 = \frac{\overline{\sigma}_i^2}{R_i^2}$, we have:

$$\sum_i \sigma_i^2 = \sum_i \frac{\sigma_i^2}{R_i^2} \quad \text{Apply Chisini} \quad \Rightarrow \quad \sum_i \frac{\sigma_i^2}{R_i^2} = \sum_i \frac{\sigma_i^2}{R_i^2} \quad \Rightarrow \quad R^2 = \frac{\sum_i \sigma_i^2}{\sum_i \sigma_i^2} \quad (6)$$

which may be interpreted as the harmonic mean of the $R^2$s with weights given by the variances explained by the market model.

Although both approaches simplify into (3), there are important differences in the interpretation of the country-level measure. According to (5) (i.e., if a) holds), we place greater weight on the R-squares that are associated with highly volatile stocks, holding constant the country systematic risk. This weighting scheme facilitates the decomposition of stock returns variation in a market-

\(^2\) Other papers in this area also refer to this quantity as “total variance of returns” or “squared total variations” or “total sum of squares”.
wide component and a firm-specific component (see, e.g., [12]). According to (6) (i.e., if b) holds), we keep invariant the country total risk and we weight individual stocks on the basis of their proportion of total risk explained by the market model.

The main difference between (5) and (6) is that in (5) the overall country systematic risk is held constant and, consequently, stock-by-stock models are implicitly assumed to be estimated. By contrast, (6) holds constant the overall country total risk and, to guarantee the equivalence in (3), assumes that a model exists such that the country systematic risk is equal to $\sigma_i^2$.

In the next Section we further investigate the above interpretations, looking for the conditions such that, given a model that simultaneously estimates the market model in (1) for all the stocks traded in a country, its R-square is (3).

4. The Country-Level R-Square and the corresponding Market Model

The most common model used to jointly study the multivariate responses (stock returns) as a function of one only explanatory variable (market returns) is the Seemingly Unrelated Regression (SUR) model. Focusing on that model, we need to satisfy the following two conditions: first, when a SUR have explained variance equal to $\sum \sigma_i^2$ and, second when its R-square equals to (3). We emphasize that in this paper our aim is not to make inference on the model parameters or on the model itself, which are topics already well addressed in the financial econometrics literature, but only to study under which conditions a multivariate response model satisfies the previous requirements.

We will make use of the following notation:

- $I_k$ is the identity matrix of dimension $k \times k$ and $1$ is a $T \times 1$ vector of ones, otherwise specified in the text;
- $r_m$ is the $T \times 1$ vector of market returns and $r_{m,t}$ for $t=1,2,\ldots,T$ is the market return at time $t$;
- $R_p$ is a $T \times k$ matrix with the $i$-th column, $r_i$, representing the $T \times 1$ vector of returns of the $i$-th stock, and $r_{i,t}$ is the return at time $t$;
- $\mu_p$ and $\mu_m$ are, respectively, the mean vector of the stocks and the mean of the market;
- $\beta$ is a vector of parameters;
- $\text{vec}(\cdot)$ and $\otimes$ are, respectively, the “vec” and the Kronecker matrix operators.

Conditionally to $r_m$, the standard univariate market model in (2) has the following multivariate representation:

$$\text{vec}(R_p) = (I_k \otimes [1 \ r_m])\beta + \text{vec}(E_p)$$ (7)

Let $SST_R$ be the sum of squared total variations for $\text{vec}(R_p)$, i.e. $SST_R = \sum_t SST_t$. To show that (7) is the model whose R-square is (3), we start by checking whether $SST_R$ is equal to the denominator of the country-level R-square. For a generic vector $Q$, let $\text{dev}(Q) = Q'Q$ and let $1_T$ be a vector of $T \times k$ ones. We may write:
\[ SST_R = dev(vec(R_p)) - Tk \left( (1'_k 1_Tk)^{-1} 1'_k vec(R_p) \right)^2 \]

where according to the definition of market return the last term equals to \( Tk(\mu_m)^2 \). The denominator of the country-level R-square is:

\[ T \sum_i \sigma_i^2 = dev(vec(R_p)) - T(\mu'_p \mu_p) \]

From (8) and (9) it follows that \( SST_R \) will be equal to \( T \sum \sigma_i^2 \) if:

\[ Tk(\mu_m)^2 = T(\mu'_p \mu_p) \]

This condition is generally not satisfied and it may hold – for example – when \( \mu_i = \mu_m \ \forall i \). To guarantee the equivalence of (8) and (9) a solution is by centring returns on zero. From these preliminaries to show that (7) is the model whose R-square is (3), we need to verify whether the variance explained by (7) equals to \( T \sum \sigma_i^2 \). This will be true if the \( i \)-th term in \( \hat{\beta} \), i.e. the estimate of \( \beta \), corresponds to the estimate of the slope coefficient of the univariate market model (2) for the \( i \)-th stock. The parameters in (2) are usually estimated by OLS in the classical Gaussian linear model framework. This implies that the residuals are supposed to be homoschedastic and spherical. Since model (7) aggregates the \( k \) models in (2) for \( i=1,\ldots,k \), to be coherent with the previous assumption and introducing cross-correlation among stocks we have to assume that:

\[ E[vec(E_p)vec(E_p)'] = V_p = E[E'_p E_p] \otimes I_k := \Sigma_p \otimes I_T . \]

where \( \Sigma_p \) is the variance covariance matrix of the errors. Estimating by GLS, since regressors in (7) are the same for all the equations, by Kruskal’s theorem we know that OLS and GLS estimators are the same:

\[
\begin{align*}
\hat{\beta} &= \left( (I'_k \otimes r'_m)(\Sigma_p^{-1} \otimes I_T)(I_k \otimes r_m) \right)^{-1}(I'_k \otimes r'_m)(\Sigma_p^{-1} \otimes I_T) vec(R_p) \\
&= (\Sigma_p \Sigma_p^{-1} \otimes (r_m r_m)^{-1} I'_k \otimes r'_m)^{-1}(I'_k \Sigma_p^{-1} \otimes r_m r_m I_T) vec(R_p) \\
&= (\Sigma_p \Sigma_p^{-1} \otimes (r_m r_m)^{-1} r'_m)^{-1} vec(R_p) \\
&= (\sigma_m)^{-1} \text{Cov}(R_p, r_m)
\end{align*}
\]

3 The de-meaning procedure does not bias the estimate of \( R^2 \)

4 The choice to center return on zero has been shown to be relevant to guarantee equivalence of (8) and (9). By contrary it is well known that the Frish-Waugh-Lovell theorem [11] states that centring returns on zero is equivalent to the projection of the sample space onto the orthogonal complement of \( (I_k - 1_k (1_k 1_k)^{-1} 1'_k) \), where \( 1_k \) is a vector of length \( k \). Then the estimates of the betas in (10) do not change.
where Cov(·) is the column vector of covariances across the k stocks and the market returns. Hence 
\[ \text{dev} \left( \mathbf{I}_k \cdot \mathbf{r}_m \right) \hat{\beta} = T \sum \frac{\text{Cov}(r_i, r_m)^2}{\sigma_m^2} = T \sum_i \hat{\sigma}_i^2. \] Had we assumed more generally:

\[ E[\text{vec}(\mathbf{E}_p)\text{vec}(\mathbf{E}_p)^T] := \mathbf{V}_p \]  \hspace{1cm} (11)

i.e. introducing also cross-dependencies within stocks, we could not have found the equivalence. This implies that, under assumption (11), the \( R^2 \) will not be equal to (3).

We close this section with some comments on the equivalence \( \sum_{i} \sigma_i^2 = T \sigma^2 \). From that we may argue that \( \sum_{i} \sigma_i^2 \) refers to the variance of mixture of uncorrelated variables (i.e. returns). Since the covariances are not included, we must suppose that either the variables at the denominator of (3) are cross-sectionally uncorrelated or, less commonly, a transformation (i.e. by principal components) has been adopted to make stock returns uncorrelated. We have shown that a SUR model matches this condition centring returns on zero. Even assuming the existence of cross-correlations in (10) they vanish in the computation of R-square (but obviously (10) plays a role if we were dealing with inferential issues): on one side this is coherent with the denominator of (3) on the other it is in contradiction with the assumption (10). To include the covariances among stocks, we may set up an alternative formulation of the market model by considering stocks within a portfolio. By gathering stock returns in \( \mathbf{r}_p = \mathbf{r}_1 + \cdots + \mathbf{r}_k \) we should study the model:\n
\[ \mathbf{r}_p = [1 \mathbf{r}_m] \hat{\beta}_p + \mathbf{e}_p \text{ with } E[\mathbf{e}_p \mathbf{e}_p^T] = \text{diag}(\mathbf{\Sigma}_p) \] \hspace{1cm} (12)

where, using assumptions in (10), the \( ii \)-th element of the diagonal matrix \( \text{diag}(\mathbf{\Sigma}_p) \) is equal to \( 1^T \mathbf{\Sigma}_p 1 \), i.e. the sum of all the elements in the matrix \( \mathbf{\Sigma}_p \). \( \hat{\beta}_p \) is estimated by GLS. The denominator of the R-square of (12) equals to \( \text{Var}(\mathbf{r}_p) = \sum \sigma_i^2 + 2 \sum_{i<j} \text{Cov}(r_i, r_j) \). Since:

\[ \hat{\beta}_p = \left( [1 \mathbf{r}_m]' \text{diag}((\mathbf{\Sigma}_p))^{-1} [1 \mathbf{r}_m] \right)^{-1} [1 \mathbf{r}_m]' \text{diag}((\mathbf{\Sigma}_p))^{-1} \mathbf{r}_p \]
\[ = ([1 \mathbf{r}_m]' [1 \mathbf{r}_m])^{-1} [1 \mathbf{r}_m]' (\mathbf{r}_1 + \cdots + \mathbf{r}_k) \]
\[ = \hat{\beta}_1 + \hat{\beta}_2 + \cdots + \hat{\beta}_k \]

where \( \hat{\beta}_i = [\hat{\alpha}_i \hat{\beta}_i]' \) is the OLS estimate of the parameters in (2), we have:

\[ \text{Var}(\hat{\mathbf{r}}_p) = \hat{\beta}_p' ([1 \mathbf{r}_m]' [1 \mathbf{r}_m]) \hat{\beta}_p \]
\[ = \sum i \hat{\beta}_i' ([1 \mathbf{r}_m]' [1 \mathbf{r}_m]) \hat{\beta}_i + 2 \sum_{i<j} \hat{\beta}_i' ([1 \mathbf{r}_m]' [1 \mathbf{r}_m]) \hat{\beta}_j \]
\[ = \sum \sigma_i^2 + 2 \sum_{i<j} \text{Cov}(\hat{r}_i, \hat{r}_j) \]

Finally the R-square of model (12) is:

---

5 For the rest of the paper centering returns on zero is not a compulsory condition.
\[ R^2_{[12]} = \frac{\sum \sigma_i^2 + 2 \sum_{i<j} \text{Cov}(\hat{r}_i, \hat{r}_j)}{\sum \sigma_i^2 + 2 \sum_{i<j} \text{Cov}(r_i, r_j)} = \frac{R^2 + 2 \sum_{i<j} \text{Cov}(\hat{r}_i, \hat{r}_j) / \sum \sigma_i^2}{1 + 2 \sum_{i<j} \text{Cov}(r_i, r_j) / \sum \sigma_i^2} \]

which is clearly a function of (3), corrected for the cross-correlation among stocks without having constrained mean returns on zero. Considering that using (2) and the properties of OLS, stock returns can be thought of the sum of fitted values plus the residuals we have

\[
\text{Cov}(\hat{r}_i, \hat{r}_j) = \text{Cov}([1 \ r_m] \beta_i, [1 \ r_m] \beta_j) = E(\beta_i'[1 \ r_m]'[1 \ r_m] \beta_j) - E(1'[1 \ r_m] \beta_i)E(1'[1 \ r_m] \beta_j)
\]

\[
\text{Cov}(r_i, r_j) = \text{Cov}([1 \ r_m] \beta_i + \epsilon_i, [1 \ r_m] \beta_j + \epsilon_j) = E(\beta_i'[1 \ r_m]'[1 \ r_m] \beta_j) + E(\beta_j'[1 \ r_m]' \epsilon_i) + E(\epsilon'_i \epsilon_i) - E(1'[1 \ r_m] \beta_i)E(1'[1 \ r_m] \beta_j)
\]

Then we expect \( \text{Cov}(\hat{r}_i, \hat{r}_j) < \text{Cov}(r_i, r_j) \) and \( R^2_{[12]} < R^2 \).

5. Conclusion

This paper shows that the country-level R-square, computed using the individual firm total risk as weighting factor, can be interpreted as a Chisini mean of the individual firms R-squares in two ways. In the first way, the weight is the proportion of firm total risk over country total risk and the mean is computed to hold constant the country systematic risk. In the second way, the weight is the proportion of firm systematic risk over country systematic risk and the mean is computed to hold constant the country total risk. Only the second way allows the country-level R-square to be interpreted as the coefficient of determination of a unique model to be estimated jointly considering all the stocks traded in a country. Specifically, we show that the country-level R-square can be obtained, through the estimation of a Seemingly Unrelated Regressions (SUR) model even assuming correlation across stocks and by centering returns on zero.

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References


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