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# A Method to Address the Effectiveness of the SIC Code for Selecting Comparable Firms

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To find peer firms is very important in several situations, for example in equity valuation for publicly traded firms, as well as for not publicly traded ones. Very often the pay of a chief executive officer (CEO) is set at the basis of a peer compensation group. Financial policies are often driven by a response to peers. It is a very common approach to use industry membership given by the SEC (United States Security and Exchange Commission) SIC (Standard Industrial Classification) code to form peer groups. In the paper the effectiveness of the SIC code for selecting comparable firms is evaluated through nonparametric testing for difference in firm financial ratios.

**Keywords:** financial ratios, SIC code, peer firms, comparable firms, multivariate nonparametric testing.

## 1 Introduction

The SIC (Standard Industrial Classification) code is a four digit code used by the United States Security and Exchange Commission (SEC) to classify industries. Very commonly, industry membership given by the SIC code is used to form peer groups. The rationale is that firms in the same industry are expected to be similar in terms of risk and growth, and tend to use similar accounting methods. To find peer firms is very important in several situations, for example in equity valuation for publicly traded firms using financial ratios (Liu et al., 2002), as well as for not publicly traded ones. In fact there exist situations in which a business should be valued without referring to a market value, examples are the

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valuation of spinoffs and of privately held businesses for the purpose of estate or divorce settlements, for setting the initial public offering (IPO) price or for further venture capital financing (Kim and Ritter, 1999). In such situations, a common practice of investment bankers is to use market ratios of a peer group. Faulkender and Yang (2010) emphasized the use of relative performance evaluation to set chief executive officer (CEO) pay and that companies with the same two or three digit SIC code are the ones most likely to be chosen for the peer compensation group. This practice has spread particularly after a compensation transparency rule issued by the SEC in 2006 according to which firms engaged in any benchmarking of compensation must identify the benchmark and, if possible, its components (see also Black et al. (2011) and the references therein). In general, corporate policies are affected by peer firms. In particular, Leary and Roberts (2010) considered financial policy and showed that financial policies are often driven by a response to peers. This is particularly true for smaller, more financially constrained firms with lower paid and less experienced CEOs.

Henschke and Homburg (2009) underlined that financial ratios may vary significantly when employing different peer groups and then may be manipulated so that, for example, an IPO looks like cheap. They suggest to use financial ratios rather than industry membership for selecting peers that correspond to the target firm as far as risk, cash flow (profitability) and growth potential are concerned. This is the same point of view of Damodaran (2006). Kim and Ritter (1999) and Liu et al. (2002) caution against the potential arbitrarity of classification based on the SIC code. Bhojraj and Lee (2002) find that using industry SIC code to find comparable firms performs poorly in predicting $EV/S$ (enterprise value to sales) and $P/B$ (price to book value) ratio and suggest to select the peers on the basis of risk, profitability and growth. Alford (1992) studies the effect of the selection of peers on the accuracy of the $P/E$ (price to earnings) ratio valuation method and concludes that industry membership or a combination of risk and earnings growth are effective criteria.

The literature review shows that the problem of finding peers of a target firm is very important and that there are different ways to address it. In this paper we would like to evaluate the effectiveness of the SIC code for selecting comparable firms through nonparametric testing for difference in firm financial ratios. In Section 2 we present the methods. In Section 3 we apply the methods to a real data set. Section 4 concludes the paper with discussion.

## 2 The methods

The values of firms should be standardized in some way to be compared. It is common to standardize the values relative to the earnings, book value or revenues of the firm (Damodaran, 2006). The idea is to express the value of an asset relative to the earnings that asset generates, or to look at the ratio between the price of a stock and the book value of equity of that stock as a measure of over or under valuation. Both earnings and book value being accounting measures, are affected by accounting choices. Revenues are less affected by accounting choices and then ratios based on revenues can be used as an alternative to earnings and book value based ratios. Unfortunately, as Damodaran (2006) underlines, the literature is not clear on what ratios are preferable. Theoretically, the values of a firm depend on three quantities: cash flow generation, expected growth of these cash flows and the risk associated to them. These quantities are the determinant of all the ratios. Ratios of a target firm are compared to ratios of comparable firms in order to determine the relative under or over valuation of the target firm with respect to its comparable firms. Following the point of view of the determinants of value, a comparable firm or peer is a firm with similar cash flows, growth potential and risk. Damodaran (2006) emphasizes that this definition of peer is not related to the industry to which a firm belongs. As discussed in the introduction, it is common to select peers at the basis of industry (defined by the SIC code) because it is assumed that firms in the same industry are similar in terms of the determinants of value. Statistically, this may be viewed as a hypothesis testing problem.

To keep things simple, firstly consider only one ratio $X$ and two industries. Let $\underline{X}_1 = (X_{11}, ..., X_{1n_1})$ and $\underline{X}_2 = (X_{22}, ..., X_{2n_2})$ denote the ratios of the first and second industry. We would like to test the hypothesis that the two industries have equal mean ratio against the two sided alternative that mean ratios are unequal, in symbols we test

$$H_0 : \mu_1 = \mu_2 \text{ against } H_1 : \mu_1 \neq \mu_2. \tag{1}$$

We assume that data are homoscedastic under $H_0$ (ie we assume exchangeability with respect to industries), but not under $H_1$. This is a Beherens-Fisher problem. We address this problem nonparametrically, within the permutation testing framework because it has several points of strength.

1. The classical parametric framework cannot be considered because $\underline{X}_1$ and $\underline{X}_2$ are not random samples and therefore classical/unconditional population inference on $H_0$ and $H_1$ cannot be drawn. On the contrary, the permutation framework is justified because we may assume that under the null hypothesis of no difference due to industry, the observed datum may be indifferently assigned to either industry 1 or industry 2 and therefore conditional (on the observed data) inference can be drawn (Pesarin and Salmaso, 2010). Note that rarely in practice we have random sampling, because real samples are often obtained by selection biased procedures, even in most experimental problem and clinical trials where usually non random samples (eg the patients present in a hospital that suffer of a disease) are randomly assigned to the various treatments (Ludbrook and Dudley, 1998; Marozzi, 2002). Therefore unconditional inferences associated with parametric tests, being based on random sampling, often cannot be drawn in practice.

2. Another important advantage is that within the permutation testing approach there exist tests that do not require the existence of mean values nor variances, nor the homoscedasticity under the alternative hypothesis (provided that the cumulative distribution functions do not cross each other). For example Marozzi (2003), Marozzi (2004a), Marozzi (2004b) and Marozzi (2007) proposed tests for location that are exact, unbiased and consistent for Cauchy or Student's $t$ with 2 df.

3. Financial ratios are not normally distributed because most of them cannot be negative numbers but can be very large positive numbers. Damodaran (2006) notes that the distribution of a ratio depends on the distribution of its numerator and denominator. Barnes (1982) and Barnes (1987) emphasized that if the numerator and denominator are not proportional then the distribution of the ratio is skewed. Non normality due to skewness and heavy tails was noted by many early empirical studies, see Bedingfield et al. (1985), Bird and McHugh (1977), Boughen and Drury (1980), Deakin (1976), Horrigan (1968), Mecimore (1968), O'Connor (1968) and Ricketts and Stover (1978). Deakin (1976) noted that square root and logarithmic transformations tend to produce normality. Another suggestion is to remove outliers. However, Ezzamel et al. (1987) found that after removing the outliers many ratio distributions are still non normal.

4. Permutation testing allows to address quite easily the multivariate problem that arises when two or more ratios are considered.

5. Permutation testing allows to address quite easily the multiplicity problem that also arises when two or more ratios are considered.

Note that in practice, it is very common to consider more than one ratio when valuing a firm and that the ratios are very likely to be dependent. It is important to emphasize that to address the problem at hand we cannot assume multivariate normality, random sampling nor homoscedasticity also in the alternative hypothesis. Without these stringent assumptions traditional parametric methods cannot be used (Pesarin and Salmaso, 2010).

Let $\underline{X} = (\underline{X}_1, \underline{X}_2) = (X_{11}, ..., X_{1n_1}, X_{21}, ..., X_{2n_2}) = (X_1, ..., X_{n_1}, X_{n_1+1}, ..., X_n)$ be the pooled sample and $n = \sum_{k=1}^{K} n_k$, $K = 2$. Let $(u_1^*, ..., u_n^*)$ be a random permutation of $(1, ..., n)$, then $\underline{X}^* = (\underline{X}_1^*, \underline{X}_2^*) = (X_{u_1^*}, ..., X_{u_n^*}) = (X_1^*, ..., X_n^*)$ is a random permutation of $\underline{X}$. Let $\overline{X}_1^*$ and $\overline{X}_2^*$ denote the mean of $\underline{X}_1^*$ and $\underline{X}_2^*$ respectively, and $S_k^{*2} = \frac{1}{n_k-1}\sum_{i=1}^{n_k}(X_i^* - \overline{X}_k^*)^2$, $k = 1, 2$.

To test (1) we use the permutation Welch test, which is based on

$$T^* = T(\underline{X}_1^*, \underline{X}_2^*) = \frac{\overline{X}_1^* - \overline{X}_2^*}{\sqrt{\frac{S_1^{*2}}{n_1} + \frac{S_2^{*2}}{n_2}}}.$$

The p-value of the test is estimated by taking a random sample of $B$ permutations as

$$L_T(T_0) = \frac{1}{B}\left[\sum_{b=1}^{B} I(T_b^* \leq -|T_0|) + \sum_{b=1}^{B} I(T_b^* \geq |T_0|)\right],$$

where $T_0 = T(\underline{X}_1, \underline{X}_2)$ is the observed value of $T^*$, $T_b^*$ is the value of $T^*$ in the $b$th permutation $b = 1, ..., B$ and $I(.)$ is the indicator function. $H_0$ is rejected at the $\alpha$ nominal significance level if $L_T(T_0) \leq \alpha$. The literature shows that $B = 1000$ random permutations are enough for a good p-value estimate (Marozzi, 2004c). Note that the inference on $H_0$ is respect to the permutation space conditional on $\underline{X}$ and it is not a traditional inference that relies on a population model. Note that the permutation Welch test can be appropriate when the exchangeability cannot be assumed, by providing for an asymptotically exact solution.

In general, the industries to be compared are $K \geq 2$ and the system of hypotheses is

$$H_0 : \mu_1 = ... = \mu_k \text{ vs } H_1 : \mu_k \neq \mu_{k'} \text{ for at least one couple with } k, k' = 1, ..., K \text{ and } k \neq k'. \tag{2}$$

In the multisample case we have $\underline{X} = (\underline{X}_1, ..., \underline{X}_K) = (X_{11}, ..., X_{1n_1}, ..., X_{K1}, ..., X_{Kn_K}) = (X_1, ..., X_n)$ and $\underline{X}^* = (\underline{X}_1^*, ..., \underline{X}_K^*)$. To test (2) we use the multisample permutation version of the Welch test which is based on

$$U^* = U(\underline{X}_1^*, ..., \underline{X}_K^*) = \frac{\sum_{k=1}^K w_k^* (\overline{X}_k^* - \overline{X}^*)^2/(K-1)}{1 + [2(K-2)/(K^2-1)] \sum_{k=1}^K h_k^*},$$

where $w_k^* = n_k/S_k^{*2}$, $\overline{X}^* = \frac{\sum_{k=1}^K w_k^* \overline{X}_k^*}{\sum_{k=1}^K w_k^*}$, $h_k^* = \left(1 - \frac{w_k^*}{\sum_{k=1}^K w_k^*}\right)^2 /(n_k - 1)$. $H_0 : \mu_1 = ... = \mu_k$ is rejected at the $\alpha$ significance level if $L_U(U_0) \leq \alpha$ where $L_U(U_0) = \frac{1}{B}\sum_{b=1}^B I(U_b^* \geq U_0)$. Note that for $K = 2$ the $U^*$ statistic is permutationally equivalent to the $T^*$ statistic.

We address now the multivariate case because it is much more realistic to consider a set of $P \geq 2$ financial ratios ${}_1X, ..., {}_PX$ rather than only one in valuing firms. Consider the problem of comparing $K \geq 2$ industries, ie the multisample situation. The data set is

$$\underline{\underline{X}} = \begin{bmatrix} {}_1\underline{X}_1 & \cdots & {}_1\underline{X}_K \\ \vdots & \cdots & \vdots \\ {}_P\underline{X}_1 & \cdots & {}_P\underline{X}_K \end{bmatrix} = \begin{bmatrix} {}_1X_{11} & \cdots & {}_1X_{1n_1} & \cdots & {}_1X_{K1} & \cdots & {}_1X_{Kn_K} \\ \vdots & \cdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ {}_PX_{11} & \cdots & {}_PX_{1n_1} & \cdots & {}_PX_{K1} & \cdots & {}_PX_{Kn_K} \end{bmatrix} =$$

$$= \begin{bmatrix} {}_1X_1 & \cdots & {}_1X_{n_1} & \cdots & {}_1X_{n_1+...+n_{K-1}+1} & \cdots & {}_1X_n \\ \vdots & \cdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ {}_PX_1 & \cdots & {}_PX_{n_1} & \cdots & {}_PX_{n_1+...+n_{K-1}+1} & \cdots & {}_PX_n \end{bmatrix} = \begin{bmatrix} {}_1\underline{X} \\ \vdots \\ {}_P\underline{X} \end{bmatrix}$$

where ${}_pX_{ij}$ denotes the financial ratio ${}_pX$ $(p = 1, ..., P)$ of firm $i$ $(i = 1, ..., n_k)$ of industry $k$ $(k = 1, .., K)$. We would like to test

$$H_0 : \bigcap_{p=1}^{P} ({}_p\mu_1 = ... = {}_p\mu_k) \text{ against } H_1 = \{H_0 \text{ not true}\}. \tag{3}$$

For the reasons discussed earlier in this section, there are no parametric solution to this problem, while it is natural to address it within the nonparametric combination (NPC) of dependent tests theory (Pesarin and Salmaso, 2010) because we can break down the multivariate problem in $P$ univariate problems: testing ${}_pH_0 : {}_p\mu_1 = ... = {}_p\mu_k$ against ${}_pH_1 : {}_p\mu_k \neq {}_p\mu_{k'}$ for at least one couple with $k, k' = 1, ..., K$ and $k \neq k'$, each of which is related to a single financial ratio and that is addressed through the $U^*$ test. Note that $H_0 : \bigcap_{p=1}^{P} {}_pH_0$, ie the multivariate null hypothesis, is true if all the univariate null hypotheses are jointly true. Note that the multivariate null hypothesis implies the exchangeability of the observations and then it can be tested through a permutation procedure obtained by nonparametric combination of the dependent univariate tests. A central feature of this procedure is that the underlying dependence among the univariate tests is nonparametrically captured by the combining procedure and then no specific assumptions on the dependence structure among the univariate tests are required.

Within the multivariate problem, permutation of individual firm data should be considered: to obtain a random permutation $\underline{\underline{X}}^*$ of $\underline{\underline{X}}$, randomly permute the order of the columns of $\underline{\underline{\mathrm{X}}}$

$$\underline{\underline{X}}^* = \begin{bmatrix} {}_1\underline{X}_1^* & \cdots & {}_1\underline{X}_K^* \\ \vdots & \cdots & \vdots \\ {}_P\underline{X}_1^* & \cdots & {}_P\underline{X}_K^* \end{bmatrix}$$

and therefore all the underlying dependence relations between the financial ratios are preserved. Each row of $\underline{\underline{X}}^*$ (ie each ${}_pH_0$) is analyzed with ${}_pU^*({}_p\underline{X}_1^*, .., {}_p\underline{X}_K^*)$. The statistic for testing the multivariate null hypothesis is obtained by combining the p-values $L_{{}_pU}({}_pU_0)$, which are one to one decreasingly related with the observed values ${}_pU_0$, $p = 1, ..., P$, as

$$V_b^* = -2\sum_{p=1}^{P} \ln(L_{{}_pU}({}_pU_b^*)),$$

whose observed value is $V_0 = -2\sum_{p=1}^{P} \ln(L_{{}_pU}({}_pU_0))$, where ${}_pU_b^*$ denote the $b$th permutation value of the ${}_pU^* = U^*({}_p\underline{X}_1^*, ..., {}_p\underline{X}_K^*)$ statistic, $b = 1, ..., B$. The multivariate null hypothesis is rejected if $L_V(V_0) = \frac{1}{B}\sum_{b=1}^{B} I(V_b^* \geq V_0) \leq \alpha$. Note that to estimate the permutation distribution of the $V^*$ statistic we use the permutation distributions of the ${}_pU^*$ statistics.

The multivariate test is obtained applying the Fisher combining function to the univariate p-values. We choose this function because it shows an intermediate behavior with respect to the Tippett one (preferable when only one or a few among the financial ratios are expected to be significantly different between the industries) and the Liptak one (preferable when almost all of the financial ratios are expected to be significantly different between the industries). See Pesarin and Salmaso (2010) for more details on the choice of the combining function.

The combination procedure starts with a set of univariate tests, each appropriate for a financial ratio, and jointly analyzes them looking for inference on the global null hypothesis. Multiple comparison procedures start with a global (in our case: multivariate) test and look for significant univariate tests. It is important to note that the multivariate test provides weak FWER (Family Wise Error Rate) control of the multiplicity in testing for the global null hypothesis Pesarin and Salmaso (2010). However, the univariate tests have to be adjusted for multiplicity to draw marginal inference on each financial ratio.

Within the NPC framework, it is rather easy to perform closed testing using a modified $MinP$ Bonferroni-Holm procedure. The steps of the original procedure are:

1. sort the raw p-values increasingly: $L_{(1)}U \leq ... \leq L_{(P)}U$;
2. compute $\tilde{L}_{(1)}U = PL_{(1)}U$; if $\tilde{L}_{(1)}U > \alpha$ then all the partial null hypotheses are accepted and the procedure stops; if $\tilde{L}_{(1)}U \leq \alpha$ then $H_{0(1)}$ is rejected and the procedure continues;
3. compute $\tilde{L}_{(j)}U = \max((P-p+1)L_{(p)}U, \tilde{L}_{(p-1)}U))$ for $p = 2$; if $\tilde{L}_{(2)}U > \alpha$ then $H_{0(2)}, ..., H_{0(P)}$ are accepted and the procedure stops; if $\tilde{L}_{(2)}U \leq \alpha$ then $H_{0(2)}$ is rejected and the procedure continues for $p = 3, ..., P$.

Unfortunately this procedure is very conservative. The modified procedure is more powerful while retaining FWER control. In the modified procedure the observed minimum significant test p-value $MinP_0$ is compared with the $\alpha$ quantile of the $MinP$ permutation distribution under the null hypothesis rather than comparing it to $\alpha/P$ (Pesarin and Salmaso, 2010). This corresponds to compute the p-value $\sum_{b=1}^{B} I(MinP_b^* \leq MinP_0)/B$ where $MinP_1^*, ..., MinP_B^*$ is the permutation distribution of the minimum p-value $MinP$ under the null hypothesis.

It is important to emphasize that different combining functions (as defined by Pesarin and Salmaso (2010) p. 128–134) are asymptotically equivalent in the alternative, but for finite sample sizes, they may give slightly different p-values. To eliminate the influence of the combining function on the multivariate p-value, an iterated combination procedure may be adopted, that is to compute $C > 1$ multivariate p-values using different combining functions:

$$^{1}V_b^* = \psi_1(L_{1}U({}_1U_b^*), ..., L_{P}U({}_PU_b^*)), ...,^{C} V_b^* = \psi_C(L_{1}U({}_1U_b^*), ..., L_{P}U({}_PU_b^*)),$$

with $b = 1, ...B$, and then combine these p-values by means on one combining function:

$$W_b^* = \psi_c(L_{1}V({}_1V_b^*), ..., L_{C}V({}_CV_b^*)),$$

with $b = 1, ...B$, and $c \in \{1, ..., C\}$. The resulting p-value $L_W(W_0) = \frac{1}{B}\sum_{b=1}^{B} I(W_b^* \geq W_0)$ where $W_0 = \psi_c(L_{1}V({}_1V_0), ..., L_{C}V({}_CV_0))$ is the observed value of the $W^*$ statistic, is almost invariant with respect to the choice of the latter combining function (Pesarin and Salmaso (2010) p. 133).

An important feature of NPC is that it is quite simple to perform weighted testing by assigning different weights ${}_p\omega \geq 0$ to the univariate tests leading to the following multivariate weighted test statistic

$$\hat{V}^* = -2\sum_{p=1}^{P} {}_p\omega \ln(L_{p}U({}_pU^*)).$$

Weighted testing is useful when the practitioner prefers to assign different degrees of importance to the financial ratios. It should be noted that weighted testing is practically impossible to be performed within the parametric framework, especially if one follows the likelihood ratio principle (Pesarin and Salmaso, 2010). In the next section we do not adopt weighted testing because it is not clear to us which financial ratios are less or more important for the purpose of our study of assessing the effectiveness of the SIC code. In other situations, like when one would like to compare US and UE firms belonging to a specific industry, it may be of interest for example to assign more importance to the $EV/EBITDA$ (where $EBITDA$ stands for earning before interest, taxes, depreciation and amortization) ratio when comparing heavy infrastructure firms or to the $P/B$ ratio when comparing financial service firms.

## 3 Assessing the effectiveness of the SIC code

In this section we use the methods described in the previous section to assess the effectiveness of the SIC code for selecting comparable firms. It should be noted that in the literature two digit to four digit SIC codes are used, for example Bhojraj and Lee (2002) use the two digit SIC code, Faulkender and Yang (2010) and Black et al. (2011) use both the two and three digit SIC code; Alford (1992) uses the three digit SIC code, Kim and Ritter (1999) and Henschke and Homburg (2009) use the four digit SIC code. We focus on the four and three digit SIC code because classifications based on the two digit SIC code are too wide. More precisely, we would like to compare industries with different four digit SIC code but same three digit SIC code in order to evaluate if the groups of companies that share the same three digit but have different four digit code are comparable as far as several financial ratios are considered. Our point of view is that comparable firms should be selected on the basis of profitability, growth and risk characteristics that theoretically should drive a particular valuation ratio. Authors like Damodaran (2006) and Bhojraj and Lee (2002) have the same point of view. To this aim we select $K = 6$ financial ratios following the suggestions of Damodaran (2006).

- ${}_1X = P/B =$ price to book equity ratio $= \frac{\text{market capitalization}}{\text{current book value of equity}}$. The fundamental determinants of the $P/B$ ratio are the expected growth rate in earnings per share, the payout, the risk and the return on equity.

- ${}_2X = P/S =$ price to sales ratio $= \frac{\text{market capitalization}}{\text{revenues}}$. The fundamental determinants of the $P/S$ ratio are the expected growth rate in earnings per share, the payout, the risk and the net margin.

- ${}_3X = P/E =$ price to earnings ratio $= \frac{\text{market capitalization}}{\text{net income}}$. The fundamental determinants of the $P/E$ ratio are the expected growth rate in earnings per share, the payout and the risk.

- ${}_4X = EV/EBITDA =$ enterprise value to EBITDA ratio $= \frac{\text{enterprise value}}{\text{EBITDA}}$, where the enterprise value is the market value of debt and equity of a firm net of cash. The fundamental determinants of the $EV/EBITDA$ ratio are the expected growth rate in earnings per share, the reinvestment rate, the risk, the return on invested capital and the tax rate.

- ${}_5X = EV/C$ = enterprise value to capital ratio $= \frac{\text{enterprise value}}{\text{current invested capital}}$. The fundamental determinants of the $EV/C$ ratio are the expected growth rate in earnings per share, the reinvestment rate, the risk and the return of capital.
- ${}_6X = EV/S$ = enterprise value to sales ratio $= \frac{\text{enterprise value}}{\text{revenues}}$. The fundamental determinants of the $EV/S$ ratio are the expected growth rate in earnings per share, the reinvestment rate, the risk and the operating margin.

Damodaran (2006) emphasizes that there have been relatively few studies that compare the efficacy of the financial ratios and notes that the usage of them varies widely across industries with the $EV/EBITDA$ ratio commonly used for valuing heavy infrastructure firms (like the telecommunication ones) and the $P/B$ ratio for financial service firms. $P/E$ and $EV/EBITDA$ ratios are the most frequently used by the research arms of investment banks. Kim and Ritter (1999), Liu et al. (2002) and Lie and Lie (2002) suggest the forecasted earnings per share to best explain pricing differences and emphasize that earnings ratios are better than book value ratios or sales ratios. If the aim of the study was to rank firms at the basis of the most important financial ratios discarding the less important ones, a very simple method proposed by Marozzi (2009) and Marozzi (2012) in another context may be used. We do not use this method because the aim of our study is different.

We analyze a data set downloaded from Damodaran Online website at

`http://pages.stern.nyu.edu/~adamodar`

about all 5928 publicly traded US firms (source: Value Line) updated on January 1, 2011. For each firm there are 74 variables, including the SIC code and all the financial data necessary to compute the six ratios we would like to study. Many ratios can be extreme, usually due to very small denominators, many firms may have missing or negative values, therefore according to general practice (see eg MacKay and Phillips (2005), Bhojraj and Lee (2002), Henschke and Homburg (2009)) before analyzing the data we cleaned them by dropping any firms with missing or negative data needed for computing the $P/E$, $P/B$, $P/S$, $EV/EBITDA$, $EV/C$ and $EV/S$ ratios. We also eliminate firms with a market capitalization less than 100 millions USD. In addition we eliminate firms with data necessary for computing the six ratios not lying within the 1st and 99th percentile of the datum distribution. The number of remaining firms is 1784. The aim was to construct a data set for which we can use ratios for valuation and then we dropped firms with financial ratios indicating extreme situations and then non comparable to others firms in the data set.

Table 1 reports the industries that we compare for assessing the effectiveness of the SIC code for selecting comparable firms. The data set contains other industries with same three digit SIC code but different four digit SIC code but they are not analyzed because of very small sample sizes (eg SIC code 3311 - Steel (General) with 6 firms and

Table 1: Industries to be analyzed.

| Sic code | Industry name | # of firms |
|---|---|---|
| 2810 | Chemical (Basic) | 12 |
| 2813 | Chemical (Diversified) | 19 |
| 2830 | Biotechnology | 13 |
| 2834 | Drug | 49 |
| 3670 | Electronics | 42 |
| 3674 | Semiconductor | 34 |
| 4810 | Telecom. Utility | 10 |
| 4811 | Telecom. Equipment | 26 |
| 4920 | Natural Gas Utility | 18 |
| 4929 | Natural Gas (Div.) | 15 |
| 7370 | Internet | 24 |
| 7372 | E-Commerce | 17 |
| 7375 | Healthcare Information | 13 |

3312 - Steel (Integrated) with 2 firms) or because of too unbalanced sample sizes (eg SIC code 4911 - Electrical Utility (Central) with 42 firms, 4913 - Electrical Utility (West) with 13 firms and 4914 - Utility (Foreign) with 3 firms).

Table 2 displays that many data are highly skewed and heavy tailed, and therefore we log transform them to reduce skewness and kurtosis before applying the methods of the previous section.

Table 3 displays the results of the application of tests $T^*$, $U^*$ and $V^*$ (with $B = 20000$) to compare the industries of Table 1. Large p-values of the multivariate test are evidence in favor of the null hypothesis of no significant differences between the industries with same three digit SIC code but different four digit SIC code as far as the $P/E$, $P/B$, $P/S$, $EV/EBITDA$, $EV/C$ and $EV/S$ ratios are concerned, whereas small p-values (ie less than or equal to $\alpha = .05$) are evidence in favor of the presence of differences in one, some or all the financial ratios. The adjusted univariate p-values allow to make inference on the univariate null hypothesis that concerns each financial ratio, with FWER multiplicity control, and to understand which financial ratio(s) is(are) more responsible for the possible presence of differences between industries. Before discussing the results, note that since the multivariate p-value is the nonparametric combination of the univariate p-values, it provides inference on the null hypothesis of no significant difference according to all the financial ratios jointly considered by nonparametrically taking into account the dependence relations between the financial ratios and without the necessity of formalizing these relations. The adjusted for multiplicity univariate p-values are useful for marginal inference on each financial ratio.

Table 2: Data skewness and kurtosis.

| Industry Name | SIC Code | | $P/B$ | $P/S$ | $PE$ | $EV/EBITDA$ | $EV/C$ | $EV/S$ |
|---|---|---|---|---|---|---|---|---|
| Chemical (Basic) | 2810 | Skewness | 1.81 | 2.08 | 0.04 | 2.77 | 1.86 | 2.47 |
| | | Kurtosis | 4.07 | 5.04 | -1.51 | 8.55 | 4.72 | 7.07 |
| Chemical (Diversified) | 2813 | Skewness | 2.03 | 3.14 | 2.20 | 1.51 | 1.31 | 3.33 |
| | | Kurtosis | 6.14 | 11.66 | 4.04 | 2.50 | 1.89 | 12.84 |
| Biotechnology | 2830 | Skewness | 0.87 | 1.09 | 3.32 | 2.03 | 1.71 | 1.25 |
| | | Kurtosis | 1.07 | 1.56 | 11.52 | 6.10 | 1.79 | 2.44 |
| Drug | 2834 | Skewness | 2.00 | 1.89 | 5.34 | 1.65 | 2.38 | 1.67 |
| | | Kurtosis | 4.35 | 5.13 | 33.16 | 3.87 | 5.84 | 3.84 |
| Electronics | 3670 | Skewness | 3.44 | 1.90 | 3.64 | 1.93 | 2.25 | 2.36 |
| | | Kurtosis | 15.85 | 3.46 | 15.23 | 3.63 | 5.59 | 6.74 |
| Semiconductor | 3674 | Skewness | 2.56 | 0.85 | 0.55 | 1.20 | 2.98 | 0.82 |
| | | Kurtosis | 8.91 | 0.59 | -0.31 | 1.05 | 12.56 | 0.36 |
| Telecom. Utility | 4810 | Skewness | 0.89 | 1.13 | 2.91 | 2.66 | 1.73 | 0.08 |
| | | Kurtosis | 0.90 | 1.91 | 8.82 | 7.63 | 3.71 | -1.12 |
| Telecom. Equipment | 4811 | Skewness | 0.73 | 0.98 | 2.95 | 1.18 | 1.06 | 1.06 |
| | | Kurtosis | 0.14 | 0.43 | 10.59 | 0.64 | 0.11 | -0.02 |
| Natural Gas Utility | 4920 | Skewness | 3.04 | 1.89 | 3.12 | 1.01 | 1.13 | 1.19 |
| | | Kurtosis | 9.56 | 4.54 | 11.82 | 0.18 | 0.81 | 2.15 |
| Natural Gas (Div.) | 4929 | Skewness | 1.03 | 0.36 | 1.02 | 1.24 | 1.57 | 0.01 |
| | | Kurtosis | 0.81 | -1.08 | 0.61 | 1.69 | 2.37 | -1.27 |
| Internet | 7370 | Skewness | 2.38 | 1.18 | 2.04 | 1.21 | 1.33 | 1.46 |
| | | Kurtosis | 7.09 | 0.93 | 4.85 | 1.13 | 1.38 | 1.57 |
| E-Commerce | 7372 | Skewness | 0.66 | 0.83 | 1.99 | 0.44 | 2.22 | 0.65 |
| | | Kurtosis | 0.25 | -0.18 | 3.60 | -0.64 | 5.37 | -0.58 |
| Healthcare Information | 7375 | Skewness | 1.71 | 0.42 | 1.44 | 1.01 | 1.61 | 0.55 |
| | | Kurtosis | 3.67 | -0.15 | 0.90 | 0.21 | 2.09 | -0.11 |

Table 3 shows that the comparison between the Chemical (Basic) - 2810 SIC code and Chemical (Diversified) - 2813 SIC code industry leads to non significant difference in the financial ratios and then the use of the three digit 281 SIC code is justified. Instead the results do not justify the use of 367 (Electronics - Semiconductor industry), 283 (Biotechnology - Drug), 481 (Telecom Utility and Equipment), 492 (Natural Gas) and 737 (Internet - E Commerce - Healthcare Information) three digit SIC codes in classifying industries because the industries are significantly different in the financial ratios. In these cases it is preferable to use the four digit SIC code and then the practitioners are suggested to pay attention when using three digit or even two digit SIC code to identify the peers of a target firm as it happens often in practice (see Bhojraj and Lee (2002), Faulkender and Yang (2010), Black et al. (2011) and Deakin (1976)).

From the univariate (marginal) point of view, it is interesting to note that the most responsible financial ratios in indicating the presence of significant difference between industries are the $P/S$, $EV/C$ and $EV/S$ for the Electronics - Semiconductor comparison, the $P/S$ and the $EV/S$ for both the Biotechnology - Drug and the Natural Gas Utility - Natural Gas Diversified comparisons, the $EV/EBITDA$ for the Telecom Utility - Telecom Equipment comparison.

The results of the comparison between 7370, 7372, and 7375 SIC code industries worth a special comment because at first sight it may look surprising that the multivariate p-value is less than $\alpha$ while the univariate p-values are not. The reason is that the multivariate p-value is the nonparametric combination of the unadjusted univariate p-values whose three out of six are less than $\alpha$ (.019, .032 and .043 for $P/B$, $EV/EBITDA$ and $EV/S$ respectively).

This study has some limitations. In primis, we analyze a data set that we cleaned from those firms assumed to not be properly valuable using ratios. Therefore the results are limited for example to firms with positive earnings and reasonable financial ratios. In secundis, the inferential conclusions have to be interpreted noting that they are not classical inferences based on a parametric population model, but conditional nonparametric inferences drawn from non random samples. It is important to emphasize that unless one randomly samples firms from a publicly traded population of firms (finite population sampling), as apparently very few have explicitly done within the studies cited here, we always have non random samples at our disposal, and the inferences should be drawn with very special care. In our opinion this central question is generally not properly nor clearly addressed in large part of the financial literature (as in Hall et al. (2004), Royer (1991) and Bancel and Mittoo (2004)). More specifically, for example Alford (1992), Raya (2008), MacKay and Phillips (2005) and Nissim and Penman (2001) analyzed non random samples by performing hypothesis testing and commented the inferences as were drawn by random samples.

# 4 Conclusion

A method to address the effectiveness of the SIC code for selecting comparable firms has been proposed. The method is based on nonparametric testing for difference in firm financial ratios. The classical parametric framework cannot be considered because the samples are not random samples. Note that we have not to assume the homoscedasticity under the alternative hypothesis (provided that the cumulative distribution functions do not cross each other) nor multivariate normality nor independence between the financial ratios. This is very important since financial ratios are generally highly skewed, heavy tailed and dependent. The method provides also FWER multiplicity control. An application to a data set of US publicly traded firms has been presented. Industries with different four digit SIC code but same three digit SIC code have been compared in order to evaluate if the groups of companies that share the same three digit but have different

Table 3: Industry comparison multivariate and adjusted for multiplicity univariate p-values (pv).

| | | | |
|---|---|---|---|
| Industry - SIC code | | Industry - SIC code | |
| Chemical (Basic) - 2810 | Multiv. pv | Biotechnology - 2830 | Multiv. pv |
| Chemical (Divers.) - 2813 | 0.134 | Drug - 2834 | 0.008 |
| Financial ratio | Adj. univ. pv | Financial ratio | Adj. univ. pv |
| $P/B$ | 0.400 | $P/B$ | 0.191 |
| $P/S$ | 0.400 | $P/S$ | 0.017 |
| $P/E$ | 0.494 | $P/E$ | 0.666 |
| $EV/EBITDA$ | 0.262 | $EV/EBITDA$ | 0.209 |
| $EV/C$ | 0.283 | $EV/C$ | 0.184 |
| $EV/S$ | 0.494 | $EV/S$ | 0.029 |
| Industry - SIC code | | Industry - SIC code | |
| Telecom. Utility - 4810 | Multiv. pv | Electronics - 3670 | Multiv. pv |
| Telecom. Equip. - 4811 | 0.023 | Semiconductor - 3674 | 0.001 |
| Financial ratio | Adj. univ. pv | Financial ratio | Adj. univ. pv |
| $P/B$ | 0.449 | $P/B$ | 0.068 |
| $P/S$ | 0.359 | $P/S$ | 0.000 |
| $P/E$ | 0.399 | $P/E$ | 0.523 |
| $EV/EBITDA$ | 0.011 | $EV/EBITDA$ | 0.523 |
| $EV/C$ | 0.060 | $EV/C$ | 0.019 |
| $EV/S$ | 0.399 | $EV/S$ | 0.001 |
| | | Industry - SIC code | |
| Industry - SIC code | | Internet - 7370 | |
| Natural Gas Utility - 4920 | Multiv. pv | E-Commerce - 7372 | Multiv. pv |
| Natural Gas (Div.) - 4929 | 0.000 | Healthcare Info. -7375 | 0.026 |
| Financial ratio | Adj. univ. pv | Financial ratio | Adj. univ. pv |
| $P/B$ | 0.707 | $P/B$ | 0.077 |
| $P/S$ | 0.000 | $P/S$ | 0.218 |
| $P/E$ | 0.664 | $P/E$ | 0.218 |
| $EV/EBITDA$ | 0.707 | $EV/EBITDA$ | 0.114 |
| $EV/C$ | 0.300 | $EV/C$ | 0.218 |
| $EV/S$ | 0.000 | $EV/S$ | 0.129 |

four digit code are comparable as far as the $P/E$, $P/B$, $P/S$, $EV/EBITDA$, $EV/C$ and $EV/S$ ratios are considered. The results show that the use of the 281 (Chemical) three digit SIC code (obtained by merging the 2810 (Chemical (Basic)) and 2813 (Chemical (Diversified)) four digit SIC codes) is justified, whereas the use of 367 (Electronics - Semiconductor industry), 283 (Biotechnology - Drug), 481 (Telecom Utility and Equipment), 492 (Natural Gas) and 737 (Internet - E Commerce - Healthcare Information) three digit SIC codes is not justified. In these cases it is preferable to use the four digit SIC code and then we suggest the practitioners to pay attention when using three digit or even two digit SIC code to identify the peers of a target firm as it happens often in practice (see Bhojraj and Lee (2002), Faulkender and Yang (2010), Black et al. (2011) and Alford (1992)).

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