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# Inter–industry financial ratio comparison of Japanese and Chinese firms using a permutation based nonparametric method

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Inter-industry comparison of financial ratios of publicly traded Japanese and Chinese firms is assessed. This issue is very important because Japan and China have respectively the world's second and third largest economy, the trade volume between them is very large and many investors are searching for Japanese and Chinese investment opportunities. The most familiar methods for comparing financial ratios are multivariate analysis of variance and multiple discriminant analysis. However, these methods have many shortcomings. We use a permutation based nonparametric method that does not require any stringent assumptions and that is particularly suitable for financial data because it is very robust against skewness and heavy tailness, takes into account the possible difference in variability as well as the dependence among the financial ratios. Data about the most familiar valuation ratios have been analyzed. It is found that industry sectors of Japanese firms are generally more different than those of Chinese firms. In general, with few exceptions, the difference between industry sectors is large. The most different financial ratio is the price to sale ratio and the least different one is the price to earnings ratio for both Chinese and Japanese firms.

**keywords:** Nonparametric Methods, Permutation p–values, Finance, Valuation Ratios.

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# 1 Introduction

China and Japan have respectively the world's second and third largest economy after the USA and therefore are the two largest economies of Asia. They are respectively the world's largest and second largest holder of foreign currency reserves. They run a trade surplus since exports are larger than imports. At the end of 2011, China and Japan signed an agreement to encourage direct trading of the yen and the yuan bypassing the US dollar with the aim at reducing currency risks and trading costs for companies (Fujioka, 2011). This agreement is central because the trade volume between China and Japan is very large. China is the largest trading partner of Japan. In 2002 China outperformed the USA to become the largest source of imports to Japan. In 2009 China outperformed the USA in exports from Japan (The Statistics Bureau of Japan, 2011). Japan is one of the most important import/export partner of China (National Bureau of Statistics of China, 2012). These are a few of the many reasons for which it is interesting to compare Japan and China. The focus of the paper is on comparing publicly traded firm valuation ratios. This is an interesting issue because many investors are searching for Chinese and Japanese investment opportunities. Knowing how valuation ratios of Chinese and Japanese firms compare would be helpful to investors in decision making. It is important to note that Chinese firms are valued markedly above Japanese firms as far as the most familiar valuation ratios are considered. This is generally true for all industry sectors. Wang (2012) emphasized that Chinese firms are overvalued because the state is the main shareholder of many of them. Since Chinese and Japanese firms are valued very differently, we compare industry valuation ratios among Chinese and among Japanese firms. In Section 2, we discuss the shortcomings of the most familiar methods for comparing firm financial ratios. In Section 3, we describe an alternative method for comparing firm financial ratios that does not require any stringent assumptions. Data analysis is carried out in Section 4. Section 5 concludes the paper with some remarks and directions for future research.

# 2 Shortcomings of the most familiar methods for financial ratio comparison

Multivariate analysis of variance (MANOVA) and multiple discriminant analysis (MDA) are the most commonly used methods for comparing firm financial ratios (Meric et al., 2008). Many finance scholars use these methods for inferential purposes without checking wether underlying assumptions are fulfilled or not. This is a very important issue because typical financial data do fulfill neither MANOVA nor MDA assumptions.

The assumptions behind MANOVA are (Bray and Maxwell, 1985)

- units are randomly sampled from the populations of interest;
- observations are independent of one another;
- the dependent variables have a multivariate normal distribution within each group. Even if, strictly speaking, univariate normality is necessary but not sufficient for

multivariate normality, in practice this assumption is often lowered to univariate normality of each dependent variable;

- the groups have a common within–group population variance/covariance matrix. This assumption is twofold: the homogeneity of variance assumption should be met for each financial ratio; the correlation between any two financial ratios must be the same in the two groups.

It is implausible that all these assumptions are fulfilled in practice. MANOVA is not robust to violations of one or both of the first two assumptions. Without outliers, departures from multivariate normality generally have slight effects on the type-one error rate of the test but may reduce its power. In the presence of outliers, MANOVA is not robust for purposes of hypothesis testing. A possible solution to this problem is to transform the data to achieve approximate normality and/or remove the outliers. Violations of the assumption on variances have adverse effects on the robustness of MANOVA in particular when the sample sizes are unequal. When the sample sizes are equal, unless they are small or the number of financial ratios is large or the difference in variance/covariance matrices is quite large, the MANOVA tests tend to be robust. It is important to limit the number of financial ratios because the power of MANOVA tests tends to decrease as the number of variables increases (unless the sample sizes increase as well). A recent paper that used MANOVA for comparing the financial characteristics of US and Japanese electric and electrical equipment manufacturing firms is Meric et al. (2008). They consider liquidity, turnover, leverage and profitability ratios. As confirmed by the first author of the paper (personal communication), inferential conclusions are drawn from the data using traditional MANOVA tests and computing the corresponding p–values even if the assumptions underlying MANOVA are not met. More precisely, the samples were not random because they included all firms for which data were available. Moreover, the financial ratios have non normal distribution and the homogeneity of variances has not been checked. Therefore the data do not meet the formal requirements of standard MANOVA testing and the results should be looked at as approximations to give a general idea about country ratio comparisons. It is suggested, if large samples were available, to use the factor scores of the principal component analysis on the financial ratios. However, it should be noted that principal components are guaranteed to be normally distributed if the data set is jointly normally distributed (Jolliffe, 2002). Therefore the use of MANOVA inferential procedures with principal components is not a solution (unless the sample sizes are large).

The major assumptions of MDA are (Klecka, 1980)

- data are random samples;
- each variable is normally distributed;
- sample sizes should not be grossly different and should be at least five times the number of variables;
- the group population variance/covariance matrices should be approximately equal.

The very familiar paper of Altman (1968) about bankruptcy prediction applying MDA to a set of financial ratios does not assess the possible non normal distribution of the data nor the possible difference in variance/covariance matrices. Moreover, as noted also by Deakin (1972) the data were not random samples. Therefore, since the assumptions of MDA were not met in practice nor checked, the conclusion of Altman (1968) should be considered descriptive rather than inferential. Deakin (1972) used MDA for addressing the same problem but cared for considering random samples of firms and the effect on the results of departures from both the normal and the variance/covariance assumptions. As unique shortcoming, this paper does not meet the assumption that sample sizes should be al least five times the number of financial ratios because it considered sample sizes of 32 firms and 14 financial ratios. Another paper that does not meet this assumption is for example Meric et al. (2007) which considered sample sizes from 24 to 30 firms and 9 financial ratios. Dambolena and Khoury (1980) presented a model on corporate failure that uses MDA on financial ratios measuring profitability, activity and turnover, liquidity, indebtedness. They follow a descriptive point of view without drawing any inferential conclusions from the data. In the finance literature, there are many other papers that are not as correct as Dambolena and Khoury (1980). For example, Bhunia and Sarkar (2011); Edmister (1972); Ray (2011); Stevens (1973); Zhang et al. (2010) used MDA to analyze data that do not meet one, some or all assumptions required by the method. Note also that non random samples are very often considered also in situations that despite not involving MDA or MANOVA involve hypothesis testing, see for example Sudarsanam and Taffler (1995).

In finance, the problem of analyzing data that do not meet the assumptions of MANOVA and MDA is severe. The typical data source is a database of publicly traded firms. All the firms that have no missing data are generally considered, there is no random sampling. Another important issue is the highly skewness and heavy tailness of financial ratios. Financial ratios are not normally distributed because most of them are restricted from taking on values below zero but can be very large positive values (Damodaran, 2006). 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); Ricketts and Stover (1978). Deakin (1976) suggested square root and logarithmic transformations for normal approximation. Another suggestion is to remove outliers. However, Ezzamel et al. (1987) found that after removing outliers many financial ratio distributions remain non normal.

The permutation/resampling framework can be used to analyze non random samples of firms because we may assume that under the null hypothesis of no difference due to grouping, the observed datum may be indifferently assigned to either group 1 or group 2 (i.e. the exchangeability assumption under the null hypothesis holds) and therefore conditional (on the observed data) inference can be drawn (Pesarin and Salmaso, 2010). Random samples are rare even in most experimental problems and clinical trials (Ludbrook and Dudley, 1998; Marozzi, 2015). Therefore unconditional inferences associated with parametric tests, being based on random sampling, often cannot be drawn in practice. Finance researchers and practitioners should pay much more attention on the assumptions required by MANOVA and MDA to draw inferential conclusions from the data. In the next section, we consider a much more robust alternative to MANOVA when addressing the problem of financial ratio comparison.

## 3 A robust method for financial ratio comparison

The comparison of financial ratios of different groups of firms is useful to predict company distress and bankruptcy (see the references given in the previous section). The comparison is also important to identify the different characteristics of taken-over and non-taken-over companies (Rege, 1984); the different characteristics of companies which go public through stock market quotation (Hutchinson et al., 1988); and the different characteristics of firms in different countries (Meric et al., 2008). We consider a method proposed by Marozzi (2014a) that follows a descriptive point of view and then no particular assumptions are required. As discussed in the previous section, for drawing inference using MANOVA and MDA the basic assumptions are: random sampling, (multivariate) normal distribution and homogeneity of variance/covariance. The method does not require the first two assumptions and it is devised to explicitly consider the possible difference in variances. It is a sort of measure of difference between groups of firms which takes also into account the dependence among the financial ratios.

Let $\{{}_lX_{ij}; i = 1, 2; j = 1, ..., n_i; l = 1, ..., L\}$ be the data set, where ${}_lX_{ij}$ denotes the value of financial ratio $l$ for firm $j$ of group $i$, $n = n_1+n_2$. We say that the two groups are not different so far as ${}_lX$ is concerned if both means $M({}_lX_i)$ and variances $VAR({}_lX_i)$ of ${}_lX$ in the two groups are equal. To measure the difference between groups when $M({}_lX_1) \neq M({}_lX_2)$ and/or $VAR({}_lX_1) \neq VAR({}_lX_2)$ compute

$${}_lC = C({}_l\underline{X}_1, {}_l\underline{X}_2) = C({}_lU, {}_lV) = {}_lU^2 + {}_lV^2 - 2\rho_l U_l V,$$

where ${}_l\underline{X}_i$ denotes the vector of ${}_lX$ values for the $i$-th group,

$${}_lU = U({}_l\underline{R}_1) = \frac{6\sum_{i=1}^{n_1} {}_lR_{1i}^2 - n_1(n+1)(2n+1)}{\sqrt{n_1 n_2 (n+1)(2n+1)(8n+11)/5}},$$

$${}_lV = V({}_l\underline{R}_1) = \frac{6\sum_{i=1}^{n_1} (n+1-{}_lR_{1i})^2 - n_1(n+1)(2n+1)}{\sqrt{n_1 n_2 (n+1)(2n+1)(8n+11)/5}},$$

${}_l\underline{R}_1 = ({}_lR_{11}, ..., {}_lR_{1n_1})$, ${}_lR_{1i}$ denotes the rank of ${}_lX_{1i}$ in the pooled sample

$${}_l\underline{X} = ({}_l\underline{X}_1, {}_l\underline{X}_2) = ({}_lX_{11}, ..., {}_lX_{1n_1}, {}_lX_{21}, ..., {}_lX_{2n_2}) = ({}_lX_1, ..., {}_lX_{n_1}, {}_lX_{n_1+1}, ..., {}_lX_n)$$

and

$$\rho = cor({}_lU, {}_lV) = -\frac{30n + 14n^2 + 19}{(8n+11)(2n+1)}.$$

The ${}_lU$ and ${}_lV$ statistics are respectively the standardized sum of squared ranks and squared contrary ranks of the first group. Note that the ${}_lC$ statistic is a combination of ${}_lU$ and ${}_lV$ taking into account their negative correlation $\rho$. When there is no difference between the groups so far as ${}_lX$ is concerned $M({}_lU) = M({}_lV) = 0$, $VAR({}_lU) = VAR({}_lV) = 1$ and $({}_lU, {}_lV)$ is centered on $(0,0)$, whereas it is not when the two groups have different means and/or variances of ${}_lX$, see Cucconi (1968) and Marozzi (2009). Therefore ${}_lC$ increases as the difference between groups increases.

The ${}_lC$ statistic is normalized to lay between 0 and 1 in order to compare the grade of difference between various financial ratios. Marozzi (2014a) proposed a resampling based algorithm to do so:

1. randomly permute ${}_l\underline{X}$ obtaining

$$ {}^1_l\underline{X}^* = ({}^1_l\underline{X}^*_1, {}^1_l\underline{X}^*_2) = ({}_lX_{u^*_1}, ..., {}_lX_{u^*_n}) = ({}_lX^*_1, ..., {}_lX^*_n) $$

   where $(u^*_1, ..., u^*_n)$ is a random permutation of $(1, ..., n)$ and ${}^1_l\underline{X}^*_i$ denotes the first permutation of ${}_l\underline{X}_i$, $i = 1, 2$;

2. compute the first permutation value of ${}_lC$ as

$$ {}^1_lC^* = C({}^1_l\underline{X}^*_1, {}^1_l\underline{X}^*_2) = C({}^1_lU^*, {}^1_lV^*) = ({}^1_lU^*)^2 + ({}^1_lV^*)^2 - 2\rho {}^1_lU^* {}^1_lV^* $$

   where ${}^1_lU^* = U({}^1_l\underline{R}^*_1)$, ${}^1_lV^* = V({}^1_l\underline{R}^*_1)$ and ${}^1_l\underline{R}^*_1$ contains the ranks of the ${}^1_l\underline{X}^*_1$ elements;

3. repeat step 1 and step 2 for $B - 1$ times, where $B = \frac{n!}{n_1! n_2!}$, by considering all the possible random permutations of $(1, ..., n)$ and then obtain ${}^b_lC^*$, $b = 2, ..., B$. Note that $B$ is not $n!$ because the $C$ statistic does not depend on the order of the firms within the groups;

4. compute

$$ {}_l\tilde{C} = \frac{B - \sum_{b=1}^{B} I({}^b_lC^* \geq {}^0_lC)}{B} $$

   where ${}^0_lC = C({}_l\underline{X}_1, {}_l\underline{X}_2)$ is the observed value of ${}_lC$, ie the ${}_lC$ statistic computed on the original (non permuted) data;

5. repeat steps 1 to 4 for $l = 1, ..., L$. Note that the $B$ permutations of $(1, ..., n)$ must be considered in the same order for all ${}_lX$.

The normalized statistic ${}_l\tilde{C}$ lays between 0 (when there is no difference in ${}_lX$ between the groups of firms) and 1 (when the difference reaches the maximum value among all possible permutation values of the ${}_lC$ statistic). Therefore ${}_1\tilde{C}, ..., {}_L\tilde{C}$ are useful to find out which are the most (or least) different financial ratios. It is important to emphasize that ${}_l\tilde{C}$ may be seen as the complement to 1 of the permutation p-value of the test for the location-scale problem based on the ${}_lC$ statistic. The ${}_lC$ statistic is a monotone function of a test statistic proposed by Cucconi (1968) for jointly detecting location and scale differences. The corresponding test has been further studied by Marozzi (2009) that showed that it maintains its size very close to the nominal significance level and is more powerful than the most familiar test for the location–scale problem. It should be noted that the ${}_lC$ statistic is particularly suitable for analyzing financial data because the corresponding test is very robust against highly skewness and heavy tailness and more powerful than the Kolmogorov–Smirnov and Cramer–Von Mises tests when the distributions under comparison may differ also in shape.

Univariate analysis of financial ratios may be misleading, for example a fictitious firm with a poor profitability ratio might be regarded as potential distress if one does not look to its good liquidity ratio. Therefore several financial ratios should be combined for a complete picture of the firm. The need for a combination of the various financial ratio measures of difference naturally arises and can be assessed using the following algorithm (Marozzi, 2014a):

1. compute the observed value of the combined $C$ statistic as

$$ {}^{0}MC = \sum_{l=1}^{L} \ln \left( \frac{1}{1 - {}^{0}_{l}\tilde{C}} \right) $$

   where ${}^{0}_{l}\tilde{C} = {}_{l}\tilde{C}$;

2. compute the first permutation value of the combined $C$ statistic as

$$ {}^{1}MC^{*} = \sum_{l=1}^{L} \ln \left( \frac{1}{1 - {}^{1}_{l}\tilde{C}^{*}} \right) $$

   where

$$ {}^{1}_{l}\tilde{C}^{*} = \frac{B - \sum_{b=1}^{B} I\left({}^{b}_{l}C^{*} \geq {}^{1}_{l}C^{*}\right)}{B}; $$

3. repeat step 2 for the other $B-1$ permutations of $(1, ..., n)$;

4. compute the normalized combined $C$ statistic as

$$ \widetilde{MC} = \frac{B - \sum_{b=1}^{B} I\left({}^{b}MC^{*} \geq {}^{0}MC\right)}{B}. $$

It is very important to underline that the combination procedure is devised just to take into account the dependence among the financial ratios, therefore $\widetilde{MC}$ is a normalized measure of difference between the groups of firms which simultaneously considers all the financial ratios as well as their underlying dependence relations.

# 4 Inter–industry comparison of Chinese and Japanese firms

In this section, the measure of difference presented in Section 3 is used for an inter–industry comparison of the financial ratios of Chinese and Japanese publicly traded firms. In general, ratios measuring profitability, liquidity, solvency, leverage and activity are considered to assess the financial strength (or weakness) of a firm. Chen and Shimerda (1981) and Hossari and Rahman (2005) reviewed the literature finding 41 and 48 ratios, respectively, to be used in practice. Unfortunately, there is no clear indications on which are the most or least important financial ratios. Marozzi (2012) proposed a quick and simple method for selecting financial ratios according to their relevance in ranking a group of firms. A similar method has been successfully used also to analyze social variables Marozzi (2014b). In this paper we consider valuation ratios. In particular, we consider the following ratios, which are very popular in practice (Damodaran, 2006)

- ${}_1X = P/E =$ price to earnings ratio $= \frac{\text{market capitalization}}{\text{net income}}$. It represents the market capitalization of a firm as a multiple of its net income. It shows how much investors are willing to pay per unit of earnings. Firms trading at high $P/E$ are expected to show higher earnings growth in the future compared to firms with lower $P/E$, for this reason the former ones are more expensive than the latter ones.

- ${}_2X = P/B =$ price to book equity ratio $= \frac{\text{market capitalization}}{\text{current book value of equity}}$. It represents the market capitalization of a firm as a multiple of its book value of equity. It shows how much investors are willing to pay per unit of book value of equity. Firms trading at high $P/B$ are expected to create in the future more value from their assets than those firms trading at lower $P/B$.

- ${}_3X = P/S =$ price to sales ratio $= \frac{\text{market capitalization}}{\text{revenues}}$. It represents the market capitalization of a firm as a multiple of its revenues. Firms trading at high $P/S$ are expected to show higher revenues growth in the future compared to firms with lower $P/S$.

- ${}_4X = EV/EBITDA =$ enterprise value to $EBITDA$ ratio $= \frac{\text{enterprise value}}{EBITDA}$, where the enterprise value is the market value of debt and equity of a firm net of cash and $EBITDA$ stands for earnings before interest, taxes, depreciation and amortization. ${}_4X$ represents the enterprise value of a firm as a multiple of its $EBITDA$. It shows how much a potential bidder is willing to pay to acquire the firm, including its debt position, per unit of $EBITDA$. Firms trading at high $EV/EBITDA$ are expected to improve their $EBITDA$ in the future more than firms trading at lower $EV/EBITDA$.

- ${}_5X = EV/C =$ enterprise value to capital ratio $= \frac{\text{enterprise value}}{\text{current invested capital}}$. It represents the enterprise value of a firm as a multiple of its invested capital. It shows how much a potential bidder is willing to pay to acquire the firm, including its debt position, per unit of invested capital. Firms trading at high $EV/C$ are expected to improve their investing projects in the future (i.e. to be wealth creating firms) more than firms trading at lower $EV/C$.

- ${}_6X = EV/S =$ enterprise value to sales ratio $= \frac{\text{enterprise value}}{\text{revenues}}$. It represents the enterprise value of a firm as a multiple of its revenues. It shows how much a potential bidder is willing to pay to acquire the firm, including its debt position, per unit of revenues. Firms trading at high $EV/S$ are expected to increase their revenues in the future more than firms trading at lower $EV/S$.

The initial data sets have been downloaded from Damodaran Online website at

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

The data sets consist of financial data of several thousands of Japanese and Chinese publicly traded firms, updated on January 1, 2010, 2011 and 2012. Many firms have missing or negative values and then it is not possible to compute the corresponding financial ratio, and many ratios are extremely large, usually due to very small denominators. For these reasons the initial data sets have been pre-processed according to general practice (see eg MacKay and Phillips (2005); Bhojraj and Lee (2002)). More precisely we excluded

- any firm with missing or negative financial data necessary to compute the financial ratios of interest;
- any firm with a capitalization less than 100 millions USD;
- any firm with data necessary to compute the financial ratios of interest not lying within the 1st and 99th percentile of data distribution.

The aim of the selection is to obtain a data set of "regular" firms, ie firms suitable to be analyzed with valuation ratios. The last step of data pre-processing is the computation of 2010-11-12 average financial ratios which are far less influenced by temporary or extraordinary circumstances than single year financial ratios. Note that a limitation of Marozzi (2014a) was to consider only one year financial ratios. We consider industry sectors whose number of firms after the initial selection and before three years averaging is greater than or equal to 29. There is no theoretical motivation for this cut–off point. The practical motivation is to exclude industry sectors that have few firms after three–year averaging, see Table 1. Here, we are not interested in the effectiveness of industry sector classification, this problem has been addressed elsewhere, see Marozzi (2013).

The traditional method to address our problem would be MANOVA, but several assumptions for it are not fulfilled in the data. First, samples are non random. Secondly, many financial ratios remain highly skewed and/or heavy tailed after data pre–processing, which includes also three–year averaging. Thirdly, homogeneity of variance/covariance between groups is generally not fulfilled, see Tables 2 and 3. Therefore it is suggested to use the method described in the previous section. It does not require random sampling because it is a descriptive method. It is robust against skewness and heavy tailness, takes explicitly into account the difference in variability as well as in central tendency between groups, and the dependence relations among financial ratios. We compute the non combined (univariate) $\tilde{C}$ and the combined (multivariate) $\widetilde{MC}$ normalized measure of difference between industry sectors of Japanese and Chinese firms. Tables 4 and 5 display the results (computed with $B = 20000$). To understand which

Table 1: Sample sizes of the industry sectors of interest.

| Industry sector | Label | Japan | China |
|---|---|---|---|
| Autoparts | 1 | 26 | 24 |
| Chemical (specialty) | 2 | 35 | 34 |
| Electronics | 3 | 22 | 19 |
| Engineering | 4 | 37 | 25 |
| Food processing | 5 | 49 | 28 |
| Machinery | 6 | 42 | 23 |
| Pharma & drugs | 7 | 23 | 67 |
| Retail (distributors) | 8 | 33 | 28 |

sectors the results refer to, look at sector label in Table 1, so for example the row headed by 32 refers to the comparison between electronics (label 3) and chemical (specialty) (label 2) sectors.

By looking at inner columns of Tables 4 and 5 it is possible to grade the difference in each financial ratio and find out which are the most (or least) different financial ratios as far as mean and variability are concerned. Table 6 displays some descriptive statistics for $\tilde{C}$ and $\widetilde{MC}$ and shows that considering the mean across all inter–industry comparisons, the ranking of financial ratios from the most to the least different one is $P/S$, $EV/S$, $EV/C$, $EV/EBITDA$, $P/B$ and $P/E$ for Japanese firms and $P/S$, $EV/S$, $EV/C$, $P/B$, $EV/EBITDA$ and $P/E$ for Chinese firms. By considering the median we obtain the same rankings. It is interesting to note that the rankings of financial ratios for Japanese and Chinese firms are very similar. In both cases, the most different financial ratio is $P/S$ and the least different is $P/E$. It is interesting to note also that $\tilde{C}$s of Japanese financial ratios are always larger than $\tilde{C}$s for the corresponding Chinese financial ratios.

By looking at $\widetilde{MC}$ values in Tables 4 and 5 we can find out which are the most (or least) different couples of industry sectors as far as $P/E$, $P/B$, $P/S$, $EV/EBITDA$, $EV/C$ and $EV/S$ are simultaneously considered. First, it is interesting to note that industry sectors of Japanese firms are generally more different than those of Chinese firms. Inter–industry comparison for Japanese firms gives rise to a combined difference that is 1 (ie maximum) in 20 out of 28 comparisons and greater than or equal to .95 in 26 cases; in only one case the difference is less than .5. Inter-industry comparison for Chinese firms gives rise to a combined difference that is 1 in 10 cases, greater than or equal to .95 in 17 cases and less than .9 in 9 cases. Paired comparisons between Japanese and Chinese couples of industry sectors show that in 8 cases the difference between Japanese firms exceeds the corresponding difference between Chinese firms by more than .1 and in only one case the difference between Chinese firms exceeds the corresponding difference between Japanese firms by more than .1. In the remaining cases the difference between combined difference lays between $-.1$ and .1. In general, with few exceptions like machinery/electronics Japanese comparison and pharma & drugs/machinery Chinese

Table 2: Financial ratio descriptive statistics for Japanese firms.

| Industry sector | Statistic | $P/E$ | $P/B$ | $P/S$ | $EV/EBITDA$ | $EV/C$ | $EV/S$ |
|---|---|---|---|---|---|---|---|
| Autoparts | Mean | 32.62 | 0.97 | 0.52 | 4.03 | 0.92 | 0.51 |
| | SD | 39.55 | 0.41 | 0.24 | 1.61 | 0.36 | 0.27 |
| | Skewness | 16.66 | 3.96 | 4.03 | -0.72 | -0.81 | 2.08 |
| | Kurtosis | 3.84 | 1.54 | 1.93 | 0.30 | 0.00 | 1.36 |
| Chemical (specialty) | Mean | 48.67 | 0.96 | 0.75 | 5.99 | 0.95 | 0.73 |
| | SD | 121.18 | 0.36 | 0.40 | 2.06 | 0.42 | 0.35 |
| | Skewness | 33.09 | -0.30 | 2.44 | 0.37 | 1.46 | 1.36 |
| | Kurtosis | 5.69 | 0.55 | 1.43 | 0.46 | 0.71 | 1.14 |
| Electronics | Mean | 29.42 | 1.19 | 1.55 | 7.13 | 1.25 | 1.36 |
| | SD | 23.73 | 0.47 | 1.59 | 3.39 | 0.59 | 1.52 |
| | Skewness | 10.40 | 1.25 | 9.50 | 1.12 | 1.36 | 11.82 |
| | Kurtosis | 2.91 | 1.02 | 2.79 | 0.88 | 1.01 | 3.12 |
| Engineering | Mean | 16.68 | 0.68 | 0.36 | 6.64 | 0.68 | 0.32 |
| | SD | 8.81 | 0.29 | 0.22 | 5.54 | 0.37 | 0.19 |
| | Skewness | 2.73 | 4.48 | 4.29 | 7.52 | 8.18 | 3.07 |
| | Kurtosis | 1.57 | 1.94 | 1.98 | 2.58 | 2.45 | 1.74 |
| Food processing | Mean | 32.59 | 0.95 | 0.50 | 7.23 | 0.95 | 0.52 |
| | SD | 27.56 | 0.37 | 0.37 | 3.18 | 0.32 | 0.32 |
| | Skewness | 15.15 | 6.48 | 7.09 | 0.45 | 2.12 | 4.87 |
| | Kurtosis | 3.39 | 2.07 | 2.25 | 1.01 | 1.11 | 1.94 |
| Machinery | Mean | 36.10 | 1.11 | 1.21 | 8.39 | 1.18 | 1.08 |
| | SD | 26.51 | 0.52 | 1.17 | 4.00 | 0.81 | 0.93 |
| | Skewness | 5.03 | 2.44 | 14.17 | 0.36 | 16.47 | 9.64 |
| | Kurtosis | 2.12 | 1.48 | 3.26 | 0.89 | 3.51 | 2.66 |
| Pharma & drugs | Mean | 23.55 | 1.43 | 1.74 | 9.12 | 1.50 | 1.74 |
| | SD | 8.94 | 0.44 | 0.65 | 3.15 | 0.46 | 0.62 |
| | Skewness | 0.40 | -0.91 | 0.69 | 3.10 | -0.80 | 0.28 |
| | Kurtosis | 1.18 | 0.36 | 0.58 | 1.77 | 0.19 | 0.65 |
| Retail (distributors) | Mean | 17.68 | 0.77 | 0.28 | 8.23 | 0.83 | 0.36 |
| | SD | 11.90 | 0.29 | 0.35 | 4.15 | 0.33 | 0.41 |
| | Skewness | 2.25 | 7.66 | 8.83 | -0.39 | 13.20 | 3.61 |
| | Kurtosis | 1.59 | 2.10 | 2.80 | 0.72 | 2.91 | 2.09 |

comparison, the difference between industry sectors is large.

To find evidence whether our method is robust against skewness and heavy tailness, we log transformed the data and repeated the analysis. It is important to note that the

Table 3: Financial ratio descriptive statistics for Chinese firms.

| Industry sector | Statistic | $P/E$ | $P/B$ | $P/S$ | $EV/EBITDA$ | $EV/C$ | $EV/S$ |
|---|---|---|---|---|---|---|---|
| Autoparts | Mean | 82.74 | 4.38 | 4.39 | 42.52 | 3.93 | 4.48 |
| | SD | 83.41 | 2.16 | 4.39 | 51.80 | 2.21 | 4.10 |
| | Skewness | 5.38 | 4.23 | 9.21 | 9.84 | 2.22 | 7.11 |
| | Kurtosis | 2.35 | 1.85 | 2.85 | 2.91 | 1.68 | 2.53 |
| Chemical (specialty) | Mean | 78.64 | 4.23 | 3.80 | 27.82 | 4.28 | 4.04 |
| | SD | 95.49 | 2.43 | 2.64 | 18.56 | 3.07 | 2.50 |
| | Skewness | 12.62 | 1.84 | 1.81 | 1.45 | 0.58 | 2.32 |
| | Kurtosis | 3.29 | 1.56 | 1.45 | 1.45 | 1.26 | 1.50 |
| Electronics | Mean | 80.98 | 6.15 | 8.58 | 43.92 | 8.27 | 8.25 |
| | SD | 49.03 | 2.51 | 4.72 | 12.84 | 6.16 | 4.34 |
| | Skewness | 4.72 | 1.44 | 1.02 | 0.26 | 5.30 | 1.09 |
| | Kurtosis | 2.26 | 1.00 | 1.04 | -0.13 | 2.18 | 0.96 |
| Engineering | Mean | 90.10 | 4.17 | 2.67 | 38.73 | 4.68 | 3.08 |
| | SD | 101.12 | 2.64 | 2.28 | 31.42 | 6.84 | 2.46 |
| | Skewness | 9.07 | 6.32 | 1.72 | 7.08 | 17.24 | 1.01 |
| | Kurtosis | 2.91 | 2.34 | 1.50 | 2.42 | 3.98 | 1.38 |
| Food processing | Mean | 53.00 | 5.62 | 4.51 | 31.49 | 6.73 | 4.67 |
| | SD | 28.64 | 5.03 | 3.96 | 19.29 | 8.62 | 3.98 |
| | Skewness | 0.16 | 8.41 | 3.15 | 4.62 | 10.50 | 2.55 |
| | Kurtosis | 0.76 | 2.51 | 1.64 | 1.61 | 3.00 | 1.54 |
| Machinery | Mean | 85.47 | 5.31 | 6.29 | 54.26 | 5.54 | 6.33 |
| | SD | 61.25 | 3.29 | 4.00 | 62.70 | 3.48 | 3.86 |
| | Skewness | 4.68 | 4.69 | 1.74 | 15.89 | 0.62 | 2.34 |
| | Kurtosis | 2.01 | 2.06 | 1.12 | 3.78 | 1.09 | 1.32 |
| Pharma & drugs | Mean | 62.46 | 5.78 | 6.97 | 38.33 | 6.75 | 6.90 |
| | SD | 31.81 | 2.57 | 5.54 | 22.52 | 4.49 | 5.36 |
| | Skewness | 1.41 | -0.12 | 6.56 | 2.90 | 1.83 | 6.19 |
| | Kurtosis | 0.92 | 0.76 | 2.17 | 1.45 | 1.54 | 2.12 |
| Retail (distributors) | Mean | 67.80 | 3.04 | 1.85 | 53.95 | 2.70 | 2.02 |
| | SD | 58.60 | 1.11 | 1.85 | 47.87 | 1.72 | 2.02 |
| | Skewness | 2.62 | 3.85 | 0.38 | 4.27 | 14.71 | 1.94 |
| | Kurtosis | 1.67 | 1.26 | 1.30 | 1.91 | 3.39 | 1.59 |

data, even after the exclusion of firms with extreme ratios and three–year averaging, show highly skewness and/or heavy tailness for several ratios/industry sectors for both Chinese and Japanese firms, see Tables 2 and 3. The repetition of the analysis gave

Table 4: Inter-industry normalized difference of Japanese firms, industry sector labels are reported in Table 1.

| Sectors | $P/E$ | $P/B$ | $P/S$ | $EV/EBITDA$ | $EV/C$ | $EV/S$ | Combined |
|---|---|---|---|---|---|---|---|
| 21 | 0.190 | 0.004 | 0.983 | 0.998 | 0.002 | 0.980 | 0.970 |
| 31 | 0.247 | 0.808 | 1.000 | 0.999 | 0.862 | 0.999 | 1.000 |
| 41 | 0.972 | 0.996 | 1.000 | 0.968 | 0.989 | 0.995 | 1.000 |
| 51 | 0.659 | 0.674 | 0.994 | 1.000 | 0.867 | 0.007 | 0.999 |
| 61 | 0.887 | 0.433 | 1.000 | 1.000 | 0.496 | 0.998 | 1.000 |
| 71 | 0.985 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| 81 | 0.965 | 0.966 | 1.000 | 1.000 | 0.993 | 1.000 | 1.000 |
| 32 | 0.019 | 0.836 | 0.995 | 0.962 | 0.848 | 0.991 | 0.980 |
| 42 | 0.997 | 0.999 | 1.000 | 0.901 | 0.998 | 1.000 | 1.000 |
| 52 | 0.343 | 0.728 | 0.999 | 0.790 | 0.738 | 0.994 | 0.984 |
| 62 | 0.692 | 0.458 | 0.964 | 0.984 | 0.475 | 0.946 | 0.941 |
| 72 | 0.956 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| 82 | 0.996 | 0.967 | 1.000 | 0.991 | 0.966 | 1.000 | 1.000 |
| 43 | 0.989 | 1.000 | 1.000 | 0.712 | 1.000 | 1.000 | 1.000 |
| 53 | 0.184 | 0.981 | 1.000 | 0.423 | 0.993 | 1.000 | 0.999 |
| 63 | 0.538 | 0.348 | 0.523 | 0.464 | 0.391 | 0.474 | 0.328 |
| 73 | 0.860 | 0.770 | 0.994 | 0.963 | 0.878 | 0.998 | 0.993 |
| 83 | 0.981 | 1.000 | 1.000 | 0.312 | 1.000 | 1.000 | 1.000 |
| 54 | 1.000 | 1.000 | 0.888 | 0.983 | 1.000 | 0.999 | 1.000 |
| 64 | 1.000 | 1.000 | 1.000 | 0.993 | 1.000 | 1.000 | 1.000 |
| 74 | 0.999 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| 84 | 0.549 | 0.959 | 1.000 | 0.958 | 0.997 | 0.998 | 1.000 |
| 65 | 0.366 | 0.788 | 1.000 | 0.621 | 0.909 | 1.000 | 1.000 |
| 75 | 0.917 | 1.000 | 1.000 | 0.997 | 1.000 | 1.000 | 1.000 |
| 85 | 1.000 | 0.960 | 1.000 | 0.760 | 0.881 | 1.000 | 1.000 |
| 76 | 0.963 | 0.994 | 0.999 | 0.996 | 0.996 | 1.000 | 1.000 |
| 86 | 1.000 | 0.998 | 1.000 | 0.131 | 0.988 | 1.000 | 1.000 |
| 87 | 1.000 | 1.000 | 1.000 | 0.986 | 1.000 | 1.000 | 1.000 |

almost the same results as before. This finding of robustness evidence confirms previous findings (Marozzi, 2009, 2014a).

## 5 Conclusion

Inter–industry comparison of financial ratios of publicly traded Chinese and Japanese firms has been addressed using a nonparametric permutation based method that does not suffer of the drawbacks of classical methods like MANOVA when applied to financial

Table 5: Inter-industry normalized difference of Chinese firms, industry sector labels are reported in Table 1.

| Sectors | $P/E$ | $P/B$ | $P/S$ | $EV/EBITDA$ | $EV/C$ | $EV/S$ | Combined |
|---|---|---|---|---|---|---|---|
| 21 | 0.538 | 0.607 | 0.299 | 0.452 | 0.927 | 0.071 | 0.528 |
| 31 | 0.993 | 0.969 | 0.999 | 1.000 | 1.000 | 0.998 | 1.000 |
| 41 | 0.154 | 0.605 | 0.958 | 0.742 | 0.932 | 0.961 | 0.925 |
| 51 | 0.533 | 0.920 | 0.730 | 0.694 | 0.935 | 0.652 | 0.850 |
| 61 | 0.781 | 0.485 | 0.958 | 0.995 | 0.904 | 0.958 | 0.975 |
| 71 | 0.576 | 0.976 | 0.998 | 0.970 | 1.000 | 0.997 | 0.999 |
| 81 | 0.644 | 0.988 | 1.000 | 0.858 | 0.974 | 1.000 | 1.000 |
| 32 | 0.999 | 0.993 | 1.000 | 0.999 | 0.999 | 1.000 | 1.000 |
| 42 | 0.318 | 0.051 | 0.974 | 0.744 | 0.385 | 0.981 | 0.872 |
| 52 | 0.296 | 0.854 | 0.806 | 0.489 | 0.636 | 0.894 | 0.757 |
| 62 | 0.941 | 0.859 | 0.985 | 0.992 | 0.725 | 0.978 | 0.986 |
| 72 | 0.898 | 0.999 | 1.000 | 0.979 | 1.000 | 0.995 | 1.000 |
| 82 | 0.079 | 0.857 | 1.000 | 0.980 | 0.907 | 1.000 | 1.000 |
| 43 | 0.957 | 0.996 | 1.000 | 0.975 | 1.000 | 1.000 | 1.000 |
| 53 | 0.976 | 0.958 | 0.996 | 0.992 | 0.996 | 0.992 | 0.998 |
| 63 | 0.677 | 0.797 | 0.760 | 0.891 | 0.820 | 0.646 | 0.833 |
| 73 | 0.840 | 0.235 | 0.879 | 0.955 | 0.494 | 0.823 | 0.865 |
| 83 | 0.997 | 1.000 | 1.000 | 0.996 | 1.000 | 1.000 | 1.000 |
| 54 | 0.853 | 0.905 | 0.874 | 0.145 | 0.796 | 0.742 | 0.845 |
| 64 | 0.658 | 0.873 | 0.999 | 0.843 | 0.914 | 0.998 | 0.993 |
| 74 | 0.868 | 1.000 | 1.000 | 0.372 | 1.000 | 1.000 | 1.000 |
| 84 | 0.296 | 0.668 | 0.926 | 0.450 | 0.356 | 0.978 | 0.834 |
| 65 | 0.935 | 0.829 | 0.845 | 0.808 | 0.738 | 0.898 | 0.905 |
| 75 | 0.632 | 0.982 | 0.986 | 0.629 | 0.999 | 0.981 | 0.994 |
| 85 | 0.563 | 1.000 | 0.996 | 0.846 | 0.999 | 0.996 | 0.999 |
| 76 | 0.518 | 0.663 | 0.088 | 0.454 | 0.624 | 0.196 | 0.297 |
| 86 | 0.978 | 1.000 | 1.000 | 0.850 | 1.000 | 1.000 | 1.000 |
| 87 | 0.965 | 1.000 | 1.000 | 0.782 | 1.000 | 1.000 | 1.000 |

data. Data about the most familiar valuation ratios have been analyzed. It is found that industry sectors of Japanese firms are generally more different than those of Chinese firms. In general, with few exceptions, the difference between industry sectors is large. The most different financial ratio is the price to sale ratio and the least different one is the price to earnings ratio for both Chinese and Japanese firms. It is found that industry sectors of Japanese firms are generally more different than those of Chinese firms. Our findings confirm that the method is very robust against highly skewness and heavy tailness and takes into account the possible difference in variability as well as the

Table 6: Descriptive statistics of $\tilde{C}$ and $\widetilde{MC}$.

| | China | | | | |
|---|---|---|---|---|---|
| | Mean | Median | SD | Min | Max |
| $P/E$ | 0.695 | 0.729 | 0.272 | 0.079 | 0.999 |
| $P/B$ | 0.824 | 0.912 | 0.238 | 0.051 | 1.000 |
| $P/S$ | 0.895 | 0.991 | 0.211 | 0.088 | 1.000 |
| $EV/EBITDA$ | 0.781 | 0.848 | 0.232 | 0.145 | 1.000 |
| $EV/C$ | 0.859 | 0.934 | 0.192 | 0.356 | 1.000 |
| $EV/S$ | 0.883 | 0.987 | 0.231 | 0.071 | 1.000 |
| Combined | 0.909 | 0.993 | 0.158 | 0.297 | 1.000 |
| | Japan | | | | |
| | Mean | Median | SD | Min | Max |
| $P/E$ | 0.759 | 0.959 | 0.312 | 0.019 | 1.000 |
| $P/B$ | 0.845 | 0.974 | 0.247 | 0.004 | 1.000 |
| $P/S$ | 0.976 | 1.000 | 0.090 | 0.523 | 1.000 |
| $EV/EBITDA$ | 0.853 | 0.984 | 0.238 | 0.131 | 1.000 |
| $EV/C$ | 0.867 | 0.991 | 0.236 | 0.002 | 1.000 |
| $EV/S$ | 0.942 | 1.000 | 0.205 | 0.007 | 1.000 |
| Combined | 0.971 | 1.000 | 0.124 | 0.328 | 1.000 |

dependence among the financial ratios. The $\tilde{C}$ statistic has two main limitations in case the groups are found to be different: (i) the $\tilde{C}$ statistic is not useful to investigate the specific direction where a detected difference occurs because it has a squared form, and (ii) it is not possible to understand whether the difference is due to the location effect, or the variability effect, or both, because the $\tilde{C}$ statistic assesses location and variability effects simultaneously. A possible direction of future research may be a post-hoc analysis, in the light of Section 3.2 of Mukherjee and Marozzi (2016). Another possible direction of future research might be the consideration also of the distribution shape aspect when comparing groups of firms.

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