On the Ranking Uncertainty of Labor Market Wage Gaps

William C. Horrace
University of Arizona
Department of Economics
PO Box 210108
Tucson, AZ 85721
whorrace@u.arizona.edu

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Abstract: This paper uses multiple comparison methods to perform inference on labor market wage gap estimates from a regression model of wage determination. The regression decomposes a sample of workers' wages into a human capital component and a gender specific component; the gender component is called the gender differential or wage gap and is sometimes interpreted as a measure of sexual discrimination. Using data on fourteen industry classifications (e.g. retail sales, agriculture), a new *relative* estimator of the wage gap is calculated for each industry. The industries are then ranked based on the magnitude of these estimators, and inference experiments are performed using "multiple comparisons with the best" and "multiple comparisons with a control". The inference indicates that differences in gender discrimination across industry classifications is statistically insignificant at the 95% confidence level and that previous studies which have failed to perform inference on gender wage gap order statistics may be misleading.

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1. Introduction.

There is a considerable body of economic literature devoted to estimation of labor market wage discrimination by gender, race and ethnicity. For a good survey see Gunderson (1989). The general idea is to decompose a sample of individuals' wages into 1) a human capital component and 2) a gender, race or ethnicity component using some form of regression analysis and then to test the statistical significance of the latter component. The latter component is typically referred to as the "wage gap" or sometimes the "wage differential" and is often interpreted as a measure of discrimination.

Often in these studies interest centers on computing a wage gap for each of several different employment classifications (e.g. occupational types, industry types or employment locality) and ranking them to determine which employment classifications possess the largest or smallest wage gaps. For instance, Geisler (1997) ranks the gender wage gap for academics in four different occupational classes: assistant professor, associate professor, full professor and administrator. Kidd and Shannon (1996) rank the gender wage gaps across Australia and Canada. Fields and Wolff (1995) rank the gender wage gap across 14 industry classes such as public utilities, retail trade and agriculture. These types of studies have an obvious policy implication: *if one can generate a ranking of the wage gaps for different employment classifications, and those wage gaps can be interpreted as discrimination, then those classifications with the largest gaps should be the focus of any policy aimed at decreasing employment discrimination, or perhaps those classifications with the smallest gaps should serve as model classifications to which other classifications can strive.* For instance, Fields and Wolf (1995) show that the retail trade and non-durable goods manufacturing industries possess the largest gender wage gap. This may suggest that these industries be the focus of investigation for equal opportunity compliance.

Since the measured wage gaps are sample estimates of population parameters they are subject to the usual estimation variance or noise. When one is interested in the ranking of wage gaps across employment classifications, one must be aware *that the sample rankings of the estimates are contaminated with this noise and may not be indicative of the true ranking of the population parameters.* Subsequently, this "ranking uncertainty" can lead to incorrect assessment of those employment classifications with the largest or smallest gap. Unfortunately, economic wage studies have heretofore not taken this uncertainty into account. Indeed, the economics discipline has had a preoccupation with test of statistical significance over tests of relative magnitude.[1]

[1] For a good introduction to this debate, see McCloskey (1998).

This paper attempts to fill this void by using the theories of *multiple comparisons with the best* (MCB) and *multiple comparisons with a control* (MCC) to perform inference on gender wage gaps across fourteen industry classifications in the United States.[2] The data are a sample of 52,870 workers from the March 1998 Current Population Survey compiled by the Bureau of Labor Statistics. The data indicate that differences in the gender wage gap across industries are not significant, suggesting that the rank statistics reported in previous wage discrimination studies may not be as reliable as is often thought. In the course of the analysis it is argued that previously used estimators of the gender wage gap across industries are flawed, and a new estimator is introduced which lends itself quite nicely to multiple comparisons inference. The paper is organized as follows. The next section provides the analytical framework. Section 3 discusses inference. Section 4 introduces the data and the results. Section 5 concludes.

2. Analytical Framework.

Interest centers on measuring the wage gap between males and females for J industries. Consider a sample of field data of size N. An extremely common specification, primarily due to Oaxaca (1972), is to split the sample into F females and M males and estimate the following equations:

(1) $$y_i = \alpha^f + \mathrm{x}_i\theta^f + \sum_{j=2}^{J}\beta_j^f d_{ij} + \varepsilon_i^f \qquad i = 1, \ldots F.$$

$$y_i = \alpha^m + \mathrm{x}_i\theta^m + \sum_{j=2}^{J}\beta_j^m d_{ij} + \varepsilon_i^m \qquad i = 1, \ldots M,$$

Where:

$y_i > 0$ is ln(hourly wage) for the i^{th} individual

$d_{ij} = 1$ if i^{th} individual is in the j^{th} industry , 0 otherwise.

$\mathbf{x}_i$ = a $(k\times1)$ vector of other demographic variables that explains y_i (e.g. education)

ε^f_i and ε^m_i are *iid*, zero-mean constant variance random variables.

α^f, α^m, β^f_j and β^m_j ; $j = 2, \ldots, J$ are scalar parameters for estimation.

θ^f and θ^m are $(k\times1)$ parameter vectors for estimation.

[2] MCB are due to Hsu (1981, 1984) and Edwards and Hsu (1983), while MCC are due to Dunnett (1955). Modifications to basic procedures are to numerous to name here. A good survey and textbook treatment is provided in Hsu (1996).

Notice that the *omitted reference group* in the J industries is the first industry (j = 1). This implies the restriction $\beta^f{}_1 = \beta^m{}_1 = 0$. Estimation of equation 2 usually proceeds as ordinary least squares, producing unbiased estimates: $\hat{\alpha}^f$, $\hat{\alpha}^m$, $\hat{\theta}^f$, $\hat{\theta}^m$ $\hat{\beta}^f_j$ and $\hat{\beta}^m_j$. Based on these results, a common specification for the gender wage gap in industry j is:

(2) $\hat{g}_j = (\hat{\alpha}^f - \hat{\alpha}^m) + (\hat{\beta}^f_j - \hat{\beta}^m_j)$, j = 1, …, J,

with the restriction $\hat{\beta}^f_1 = \hat{\beta}^m_1 = 0$. According to Fields and Wolff (1995) this estimator is intended to capture the difference in wages in industry j through $(\hat{\beta}^f_j - \hat{\beta}^m_j)$, while controlling for the omitted reference industry through $(\hat{\alpha}^f - \hat{\alpha}^m)$. The gender wage gap estimates are then reported in an order statistic, and claims are made as to which industries possess the largest and smallest wage gap.

Unfortunately, these types of analyses are flawed. First, the estimator of equation 2 is unreliable, because it is not invariant to selection of omitted reference groups for other indicator variables that may be contained in the vector x_i. That is, if x_i contains binary (indicatory variables) such as:

x_{i1} = 1, if individual i is married; x_{i1} = 0, if individual i is unmarried,

then selection of the omitted group for x_{i1} (in this case: “unmarried”) affects the magnitude (and the standard error) of the intercept estimates, $\hat{\alpha}^f$ and $\hat{\alpha}^m$. This, in turn, will affect the magnitude and standard error of $\hat{g}_j$ in equation 2. Selection of omitted reference groups is *purely arbitrary*. For this reason $\hat{g}_j$ is unreliable. An alternative estimator that *is* invariant to omitted reference group selection is proposed below. Second, inference on the order statistic is never performed. This is the primary goal of this empirical study. Multiple comparison procedures are used to infer that at any reasonable confidence level these types of wage gap order statistics are insignificant.

The propose gender wage gap estimator is the *relative* distance measure:

(3) $\hat{\gamma}_j = \max_{n=1,\ldots,J} \hat{g}_n - \hat{g}_j$, j = 1, …, J,

which sweeps out the effects of *all* omitted reference groups and is therefore unaffected by their selection. Additionally, this is a “comparison with the best” estimator that immediately lends itself to multiple comparisons inference. Notice that, while this estimator gives us no sense of the absolute magnitude of the individual gender wage gaps, it does imply the convenient normalization,

$\exp(-\hat{\gamma}_j) \in [0,1]$, so that gender wage gaps can be expressed as percentages relative to the largest in the sample.

3. Inference.

If we are interested in testing whether a single industry or a subset of industries have the largest gender gap, then we are testing a multiple hypothesis with is amenable to MCB analysis. The advantages of multiple hypothesis testing, such as MCB, over customary homogeneity tests, such as *F* tests, have been well documented in the literature. These advantages were first recognized by Bahadur (1950). This section is dedicated to detailing MCB in the context of wage gap estimation.

3.1 *Multiple Comparisons with a Control*

Let the covariance structure of the $\hat{g}_j$ be given by the covariance matrix estimate $\hat{\Omega}$ with typical element $\hat{\omega}_{st} = Cov(\hat{g}_s, \hat{g}_t)$ $s,t = 1, \ldots, J$. Let the k^{th} industry be regarded as a control. Then (1-α)×100% simultaneous confidence intervals on all distance from the control are given by:

(4) $\{L^k_j, U^k_j\}$ $\qquad j = 1, ..., k\text{-}1, k\text{+}1, ..., J.$

$$L^k_j = \hat{g}_k - \hat{g}_j - T^{\alpha}_{J-1,\nu,\hat{\Omega}} (\hat{\omega}_{kk} + \hat{\omega}_{jj} - 2\hat{\omega}_{jk})^{1/2}$$

$$U^k_j = \hat{g}_k - \hat{g}_j + T^{\alpha}_{J-1,\nu,\hat{\Omega}} (\hat{\omega}_{kk} + \hat{\omega}_{jj} - 2\hat{\omega}_{jk})^{1/2}$$

Where $T^{\alpha}_{J-1,\nu,\hat{\Omega}}$ is the upper (1-α)×100% percentage point of a (*J*-1)-variate Student's t-distribution with ν degrees of freedom and covariance structure $\hat{\Omega}$. Equation 4 is called "multiple comparisons with a control" (see Dunnett (1955)) and is a standard result in the multiple comparisons literature. If the k^{th} industry is known *a priori* to have the largest wage gap, then these are also confidence intervals for all distances from the industry with the largest wage gap, the population equivalent of $\hat{\gamma}_j$. The critical value, $T^{\alpha}_{J-1,\nu,\hat{\Omega}}$, is problematic because it cannot be tabulated for the general covariance structure, $\hat{\Omega}$. Additionally, even if it is calculated numerically for a particular value of the covariance, it will be random, since it is based on $\hat{\Omega}$, a finite sample estimate of some unknown covariance Ω. This has negative implications for inference precision and "replication of field experiments". However, the sample that we have is very large (57,870 observations), so this should improve the precision of $\hat{\Omega}$. Also, replication of field experiments is less important in economics than in some of the natural science disciplines, so for the purposes of the current study the random value $T^{\alpha}_{J-1,\nu,\hat{\Omega}}$ is reasonable. Indeed, since $T^{\alpha}_{J-1,\nu,\hat{\Omega}}$ is random anyway, a *simulated* critical value is used with a simulation sample size of 100,000.

3.2 *A Special Case*

When $\theta^f = \theta^m = 0$ in equation 1, $\hat{\Omega}$ is a diagonal matrix, because the d_{ij} are orthogonal by construction. In this case $\hat{\omega}_{st} = 0$ for all $s \neq t$, and the $\hat{g}_j$ are orthogonal. Then the MCC parameters of interest are said to be *equicorrelated* with common correlation coefficient $\rho = 0.5$. This allows the MCC critical value to tabulated. See Dunnett and Sobel (1954, 1955), Cornish (1954) and most recently Bechhofer and Dunnett (1986). Otherwise, the calculation of the critical value can be cumbersome for large values of *J*. While the assumption of $\theta^f = \theta^m = 0$ for gender wage gap estimates seems impractical, this may not be the case for applications in other fields. The orthogonality condition created by this simplification has, to this author's knowledge, gone unnoticed. Therefore, it is mentioned here for its computational parsimony in other applications where MCC or MCB of regression parameters is desired.

3.3 *Multiple Comparisons with the Best*

When the industry with the largest wage gap is unknown MCB theory can be employed. When MCC intervals on $k \in [1, \ldots, J]$ exist, then $(1-\alpha)\times 100\%$ simultaneous confidence intervals on all distance from the largest wage gap are given by:

(5) $$L_j = 0 \qquad \zeta = \{j\}$$
$$L_j = \max(\min_{k\in\zeta} L_j^k, 0) \quad \zeta \neq \{j\}$$
$$U_j = \max(\max_{k\neq j} U_j^k, 0).$$

Where $\zeta = \{k: U_j^k \geq 0 \text{ for } j \in [1, ..., k-1, k+1, ..., J]\}$. For a proof see Edwards and Hsu (1983). To implement this result construct MCC intervals using each of the $\hat{g}_k$ as the control. If any of the $\hat{g}_k$ have all positive upper bounds, then the index, *k*, of that parameter is in the set ζ. The set ζ is the usual Gupta (1956, 1965) subset. It consists of the indices of all industries that may have the largest wage gap at the $(1-\alpha)\times 100\%$ confidence level. The magnitude of the difference between the parameter values of the largest and smallest elements of ζ, $\max_{i\in\zeta}\hat{g}_i$ - $\min_{i\in\zeta}\hat{g}_i$, represents ranking uncertainty or, more specifically, uncertainty over which of the J industries truly has the largest gap. If ζ consists of a single element, then $\max_{i\in\zeta}\hat{g}_i$ - $\min_{i\in\zeta}\hat{g}_i = 0$; the estimation was accurate enough to produce a single largest wage gap; and the sample ranking should be believed. Also these MCB intervals reduce to the MCC intervals of the last section. If ζ consists of several elements, then there may be several classifications with the largest gap, and the accuracy of the sample rankings should be questioned.

4. Data and Results.

The data is drawn from the March 1998 Current Population Survey (CPS). Covariates were selected to follow Fields and Wolff (1995). The data are summarized below. y_i is the logarithm of hourly wage of individual i; The demographic vector x_i was:

$$x_i = [EDUC_i, EXP_i, (EXP_i)^2, URBAN_i, SMSA_i, REGION_i, MARRIED_i, RACE_i, OCCUP_i],$$

where $EDUC_i$ = years of schooling of individual i; EXP_i = years of work experience of individual i; $URBAN_i$ = a dummy variable for urban residence (central city versus other); $SMSA_i$ = the size of the population of residence; $REGION_{is}$ = a set of 3 dummy variables for 4 region of country (Northeast, South and West); $MARRIED_i$ = a dummy variable for marital status of individual i; $RACE_i$ = a dummy variable for race (white versus non-white); and $OCCUP_{is}$ = a set of 12 dummy variables for 13 one-digit occupation. Notice that x_i includes binary variables with omitted reference groups, so the estimator $\hat{g}_j$ will be unreliable. The following observations were excluded from the data set: those individuals who did not work last week, those whose estimated hourly wage was outside the range \$1 to \$250, those who were employed on a farm, those who were employed in the armed forces, those who were under age 16 and those who reported self-employed unincorporated business income. The resulting sample size was 52,870 individuals, of which F = 25,444 individuals were female. The J = 14 industries used in the analysis and the frequency of males and females in each industry are reported in Table 1.

The OLS regressions of equation 1 were estimated and the gender wage gaps calculated. Order statistics are reported in Table 2. The Agriculture-forestry-fisheries industry has the largest gender wage gap, $\hat{g}_j$, while the Finance-insurance-real estate industry had the smallest. Almost all of the gaps are positive, erroneously implying that all the industries are discriminatory towards males. The reader is reminded that the measure $\hat{g}_j$ is not invariant to selection of omitted reference groups and should not be trusted. The relative measure $\hat{\gamma}_j$ and the normalized measure $\exp(-\hat{\gamma}_j)$ are also reported in Table 2. The normalized results are convenient. For example, the wage gap in the Retail trade industry is 92.7% of that in the Agriculture-forestry-fisheries industry. The rest of the results will be couched in terms of the normalized estimator. The reported rankings differ from those reported by Fields and Wolff (1995) who performed a similar study, but used the 1988 CPS data set. They do, however, rank the Agriculture-forestry-fisheries industry as having the largest wage gap. One explanation for the ranking differences reported here and in Fields and Wolff (1995) may be that the studies used different samples at different points in time (a decade apart). Another, and more important, explanation for the differences in the rankings is that the magnitude of the ranking uncertainty of both studies may be large, so minor differences in the samples could produce large differences in the wage gap rankings. This ranking uncertainty can be inferred with MCB analysis.

Next, MCB analysis of equation 5 was performed to assess the variability or uncertainty of all differences with the largest wage gap. The fourteen MCC critical values for the MCB inference were simulated using the GAUSS programming language per the algorithm presented in Horrace (1998) but with a general covariance structure for $\hat{\Omega}$. Simulation sample size was set to 100,000. Since the sample sizes (*F* and *M*) and degrees of freedom were large, multivariate normal critical values were used instead of Student's t. The simulation algorithm was tested against numerically calculated tables in Odeh (1982) and produced results that were accurate to two decimal places. The fourteen critical values ranged from 2.43 to 2.88.

MCB results are in Table 3 and are expressed in terms of the normalized percentage wage gap, $\exp(-\gamma_j)$. The cardinality of the Gupta subset was thirteen (all of the industries except the Finance-insurance-real estate industry). All the MCB upper bounds were 100%, implying that all fourteen industries may have the largest gender wage gap at the 95% level. Also, the intervals are extremely wide with much overlap. Based on these results it can be concluded that the order statistic is meaningless at the 95% level. These may be surprising results given the large sample sizes in the study, however it just underscores the importance of performing some form of inference when order statistics are reported. Three sources of uncertainty contribute to the width of the MCB intervals: 1) uncertainty of which industry has the largest wage gap; 2) the multiplicity of the confidence statement (the fact that fourteen simultaneous comparisons are being made); and 3) the usual sampling noise. Experiments were conducted to unravel the three sources of uncertainty in the MCB intervals.

First it was assumed that the Agriculture-forestry-fisheries industry possessed the largest wage gap so as to remove this first source of uncertainty. As stated earlier, in this case the MCB intervals reduce to the MCC intervals of equation 2, with the Agriculture-forestry-fisheries industry as the control and with the upper bound restricted less than or equal to 100%. These results are reported in Table 5. The salient feature of this analysis is that the intervals are now less wide as compared to the MCB intervals (as expected), however the intervals are still contain 100%, so it remains impossible to infer anything about the order statistic. One can conclude that the MCB intervals are not wide because of uncertainty over the largest gap. Next, the sources of MCB interval width were further decomposed by controlling for both the uncertainty of the industry with the largest gap *and* the multiplicity of the probability statement. This amounted to constructing marginal (non-simultaneous) confidence intervals for the wage gap percentages for each industry with the Agriculture-forestry-fisheries industry assumed largest. These were the usual univariate confidence intervals: the parameter estimate plus or minus the product of a critical value (1.96) and a standard error. Upper bounds were restricted to be less than or equal to 100% since the Agriculture-forestry-fisheries industry is assumed *a priori* to possess the largest $\hat{g}_j$. The intervals are contained in Table 5. Again the intervals are fairly wide with much overlap, so one can conclude that the major source of uncertainty in this analysis is the usual sampling variability and not necessarily the uncertainty over the best or the multiplicity of the probability statement. There is just too much noise for the rankings to be believed. Therefore, studies such as Fields and Wolff need to incorporate similar MCB analyses to assess the statistical validity of their reported rank statistics.

5. Conclusions.

This empirical study indicates that ranking uncertainty in wage gap estimates is large and that what are thought to be "explained" differences in wage gaps across industries is no more than statistical noise. The implication is that wage discrimination may not exist in a statistical sense within any particular sample, and that perhaps other sources of employment discrimination should be the focus of subsequent studies. There is a growing body of discrimination literature that examines the distribution of males and females across classifications (industries, occupations and promotional levels) and attempts to explain discrimination, not in terms of wage differentials, but in terms of differentials in access to the various classification for men and women. The present study seems to support such approaches.

The study also uses simulated critical values for an economic field study to overcome the difficulties inherent in numerical calculation of multivariate critical values with unwieldy covariance structures. Indeed, economic studies can involve extremely large sample size and very large numbers of treatments, so numerical calculation of critical values may be prohibitive. The disadvantages (and perhaps the dangers) of using random critical values in some studies (such as drug trials) is obvious, but it is unclear that these problems exist for economic field data studies such as that presented here.

Finally, it is intriguing to speculate on other applications of simultaneous inference in economics. For instance one might use MCB to compare income growth rates across countries. Perhaps MCB could be used to quantify the uncertainty of rank statistics of the eigen value estimates of cointegration vectors in macroeconomic systems of equations. These and other ideas are currently being pursued by the author.

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Table 1. Industry Frequencies

INDUSTRY	**Female**	**Male**	**Total**
Agriculture, Forestry & Fisheries	104	189	293
Mining	49	303	352
Construction	303	2629	2932
Durables Manufacturing	1471	3857	5328
Non-Durables Manufacturing	1401	2141	3542
Transportation & Communication	1181	2705	3886
Wholesale Trade	586	1401	1987
Retail Trade	4602	4428	9030
Finance, Insurance & Real Estate	2210	1393	3603
Business & Repair Service	1141	2007	3148
Personal Services	1192	513	1705
Entertainment	427	434	861
Professional & Related Services	9569	3948	13517
Public Administration	1208	1478	2686
Total	25444	27426	52870

Table 2. Order Statistics

INDUSTRY	$\hat{g}_j$	$\hat{\gamma}_j$	$\exp(-\hat{\gamma}_j)$
Agriculture, Forestry & Fisheries	0.144	0.000	1.000
Personal Services	0.138	0.007	0.993
Wholesale Trade	0.137	0.007	0.993
Business & Repair Service	0.100	0.044	0.957
Mining	0.089	0.055	0.946
Transportation & Communication	0.083	0.061	0.941
Professional & Related Services	0.074	0.070	0.932
Retail Trade	0.069	0.075	0.927
Entertainment	0.068	0.076	0.927
Public Administration	0.066	0.078	0.925
Construction	0.052	0.093	0.912
Durables Manufacturing	0.034	0.111	0.895
Non-Durables Manufacturing	0.019	0.125	0.882
Finance, Insurance & Real Estate	-0.014	0.158	0.854

Table 3. 95% MCB Confidence Interval

INDUSTRY	$\exp(-\hat{\gamma}_j)$	L_j	U_j
Agriculture, Forestry & Fisheries	1.000	0.740	1.000
Personal Services	0.993	0.789	1.000
Wholesale Trade	0.993	0.727	1.000
Business & Repair Service	0.957	0.765	1.000
Mining	0.946	0.757	1.000
Transportation & Communication	0.941	0.745	1.000
Professional & Related Services	0.932	0.745	1.000
Retail Trade	0.927	0.744	1.000
Entertainment	0.927	0.733	1.000
Public Administration	0.925	0.738	1.000
Construction	0.912	0.731	1.000
Durables Manufacturing	0.895	0.715	1.000
Non-Durables Manufacturing	0.882	0.694	1.000
Finance, Insurance & Real Estate	0.854	0.682	1.000

Table 4. 95% MCC Confidence Interval

INDUSTRY	$\exp(-\hat{\gamma}_j)$	L_j	U_j
Agriculture, Forestry & Fisheries	1.000	1.000	1.000
Personal Services	0.993	0.792	1.000
Wholesale Trade	0.993	0.727	1.000
Business & Repair Service	0.957	0.769	1.000
Mining	0.946	0.759	1.000
Transportation & Communication	0.941	0.747	1.000
Professional & Related Services	0.932	0.747	1.000
Retail Trade	0.927	0.747	1.000
Entertainment	0.927	0.735	1.000
Public Administration	0.925	0.741	1.000
Construction	0.912	0.734	1.000
Durables Manufacturing	0.895	0.718	1.000
Non-Durables Manufacturing	0.882	0.696	1.000
Finance, Insurance & Real Estate	0.854	0.685	1.000

Table 5. 95% Per Comparison Confidence Interval

INDUSTRY	$\exp(-\hat{\gamma}_j)$	L_j	U_j
Agriculture, Forestry & Fisheries	1.000	1.000	1.000
Personal Services	0.993	0.829	1.000
Wholesale Trade	0.993	0.774	1.000
Business & Repair Service	0.957	0.803	1.000
Mining	0.946	0.794	1.000
Transportation & Communication	0.941	0.783	1.000
Professional & Related Services	0.932	0.782	1.000
Retail Trade	0.927	0.781	1.000
Entertainment	0.927	0.770	1.000
Public Administration	0.925	0.775	1.000
Construction	0.912	0.767	1.000
Durables Manufacturing	0.895	0.751	1.000
Non-Durables Manufacturing	0.882	0.731	1.000
Finance, Insurance & Real Estate	0.854	0.716	1.000