AIDS versus Rotterdam: A Cox Nonnested Test with Parametric Bootstrap

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Abstract

A Cox nonnested test with parametric bootstrap is developed to select between the linearized version of the First Difference Almost Ideal Demand System (FDAIDS) and the Rotterdam model. The Cox test with parametric bootstrap is expected to be more powerful than the various orthodox tests used in past research. The new approach is then used for U. S. meat demand (beef, pork, and chicken) and compared to results obtained with an orthodox test. The orthodox test gives inconsistent results depending on the inclusion or exclusion of fish and the time period covered. In contrast, under the same varied conditions, the Cox test with parametric bootstrap consistently indicates that the Rotterdam model is preferred to the FDAIDS.

Keywords: First Difference Almost Ideal Demand System, meat demand, nonnested hypotheses, parametric bootstrap, Rotterdam model.

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Introduction

Functional form is an important issue in empirical production and consumption studies. Different functional forms often result in very different elasticity estimates. The two most commonly used models in demand analysis are the Almost Ideal Demand System (AIDS) and the Rotterdam model. Most researchers arbitrarily pick one model or the other. The two models are nonnested and recent interest has focused on developing proper nonnested tests of the two demand systems.

Two prominent studies have presented techniques to select between the AIDS and the Rotterdam demand systems (Alston and Chalfant; LaFrance). Alston and Chalfant used a compound-model approach to select between the First Difference AIDS (FDAIDS) and the Rotterdam models, using U.S. meat demand data (beef, pork, chicken, and fish). They found support for the Rotterdam model. However, LaFrance pointed out that Alston and Chalfant's least squares approach is biased and inconsistent because of endogeneity. Using the same data, he conducted both a Lagrange multiplier test and a likelihood ratio test and failed to reject either demand system. Compound model approaches typically have correct asymptotic size, but low power (Pesaran). Thus, the failure to reject either null hypothesis may simply be the result of using a test with low power[1]. Most of the previous nonnested tests have been developed for models that have the same dependent variables (e.g. Pesaran). Coulibaly and Brorsen show that a Cox's nonnested test based on the parametric bootstrap has high power, is relatively easy to use, and is applicable to any model that can be simulated. The approach appears promising as a method for selecting among functional forms in demand systems.

In this paper, a Cox nonnested test with parametric bootstrap is developed to test FDAIDS vs. Rotterdam demand systems. The test is then used to determine whether the Rotterdam or the FDAIDS is preferred for U.S. meat demand. A difficulty in using the parametric bootstrap is in simulating quantities from the Rotterdam model. The approach eventually adopted is based on a Taylor's series expansion similar to Kastens' and Brester's approach.

Tomek's suggestions on how to make research more cumulative are followed. Tomek suggests using both the data and methods from past research. That way it can be determined whether differences in results are due to different data or different methods. LaFrance's 1967-1988 data[2] set on U. S. meat demand includes four commodities beef, pork, chicken, and fish. The updated data have a 1970-1997 time span, come from a different source and do not include fish[3]. For the purpose of better comparison, the analysis in this study is applied to LaFrance's data set with and without fish, as well as to the updated data set.

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[1] Note that the papers by LaFrance and by Alston and Chalfant are misnamed. The lambdas in Alston and Chalfant are not silent and the lambdas in Lafrance do not bleat.

[2] In fact, the data used by LaFrance are the same as Alston and Chalfant

[3] According to Nick Piggott and Derrell S. Peel, the fish data are not reliable (personal communication). Piggot is a professor at North Carolina State University. Peel is a professor from the Agricultural Extension Service at Oklahoma State University and provides the updated data set.

Nonnested Hypothesis Tests

Nonnested hypothesis tests select between two regression models where one model cannot be written as a special case of the other. In such a case, the models themselves are said to be nonnested. Suppose we have two nonnested models A and B with the same set of explanatory variables to choose from using the same set of data. To test that model A is the true model, the nonnested hypotheses for the two models can be written in the following general form:

(1) $$H_0 \ : f_{it}(y_{it}) = X_t^{'}\beta_{0i} + u_{0it}$$ model A

(2) $$H_1 \ : \ g_{it}(y_{it}) = X_t^{'}\beta_{1i} + u_{1it}$$ model B

where $i = 1, \ldots, n$ meaning there are n goods and thus, n equations. Observations are indexed with $t = 1, \ldots, T$. The variable y_{it} is quantity of the i^{th} good for period t, $X_t^{'}$ is a vector of explanatory variables, β_{0i} and β_{1i} are parameter vectors under the null and alternative hypotheses, and u_{0it} and u_{1it} are vectors of error terms under the null and alternative hypotheses. The two approaches considered to select between nonnested hypotheses are the orthodox test and the Cox test.

Orthodox Test

The orthodox test is based on a supermodel obtained by forming a linear combination of the two models in the null and alternative hypotheses. For models A and B in equations (1) and (2), the supermodel can be written in the following way:

(3) $$(1-\lambda) f_{it}(y_{it}) + \lambda g_{it}(y_{it}) = X_t^{'}\beta_i + u_{it}$$

$$\beta_i = (1-\lambda)\beta_{0i} + \lambda\beta_{1i}$$

$$u_{it} = (1-\lambda)u_{oit} + \lambda u_{1it}$$

where $i = 1, \ldots, n$ and $t = 1, \ldots, T$. The parameter λ linearly combines the two models. All other elements are as defined above.

Testing that model A is the true model is equivalent to testing that the parameter λ is equal to zero. On the other hand, testing that model B is the true model corresponds to a test of λ equal to 1. Since the model is nonlinear in the parameters, a likelihood ratio test is used to test the null hypotheses. Greene argues that the orthodox test does not really distinguish between the null and the alternative hypotheses, but rather distinguishes between the alternative and a hybrid model. This is because the supermodel uses a combination of the parameters from the two models that is not captured in the F test.

Cox Test and Parametric Bootstrap

The Cox test in its generic version proposed by D. R. Cox is based on the log-likelihood ratio of two models under consideration. In our example of the two models A and B, the log-likelihood ratio statistic under the null hypothesis can be computed as the difference between the log likelihood values of models A and B. In general, the Cox test statistic has the following representation in testing the null hypothesis H_0 against H_1.

(4) $$T_0 = L_{01} - E_0(L_{01}),$$

where $L_{01} = L_0(\hat{\theta}_0) - L_1(\hat{\theta}_1)$ is the difference in estimated maximum log-likelihoods under H_0 and H_1. $E_0(L_{01})$ is the expected value of L_{01} under H_0, and $\hat{\theta}_0$ and $\hat{\theta}_1$ are the maximum likelihood parameter estimates of the null and the alternative models, respectively. T_0 is asymptotically distributed with mean zero and variance v_0^2 under H_0 (Cox, 1962). Similarly, the test statistic for testing H_1 against H_0 would be $T_1 = L_{10} - E_1(L_{10})$.

The difficulty in implementing the Cox test resides in obtaining analytical formulas for $E_0(L_{01})$ and v_0^2. Pesaran derived analytical results for the linear regression models with the same dependent variable. Both Pesaran and Deaton and Pesaran and Pesaran have developed a version of the Cox test with transformed dependent variables such as needed for testing linear versus log-linear models. However, their test statistics have incorrect size in small samples.

Coulibaly and Brorsen (1999) have shown that a Cox test associated with a parametric bootstrap approach gives a test statistic with correct size and high power, even in small samples. The test statistic is the likelihood ratio of the two models and the parametric bootstrap is used to estimate its distribution under the null. With the parametric bootstrap, Monte Carlo samples are generated using the parameters estimated under the null hypothesis. Samples are generated with the same number of observations as the original data. The hypothesis test is performed by computing a p-value, which is the percentage of simulated likelihood ratio statistics that are less than the likelihood ratio computed from the actual data. This p-value is calculated using the actual and the generated data and in the following way (Coulibaly and Brorsen, 1999):

$$\text{(5)} \qquad \text{p} - \text{value} = \frac{\left(numb\left[L_0(\hat{\theta}_{0j}, y_j) - L_1(\hat{\theta}_{1j}, y_j) \le L_{01} \right] + 1 \right)}{N+1},$$

where *numb*[ ] stands for the number realizations for which the specified relationship is true, *N* is the number of realizations, L_{01} is the actual value of the likelihood function under the null and alternative hypotheses, $L_0(.)$ and L_1 (.) are the values of the log-likelihood function with the generated data under the null and the alternative hypotheses, respectively. The one is added to the numerator and denominator as a small sample correction. This p-value estimates the area to the left of the Cox test statistic L_{01}. A small area indicates that the statistic is far from the mean according to H_0, so we can reject the null hypothesis. In other words, a small p-value indicates rejection of the null hypothesis.

Selecting between the AIDS and the Rotterdam Models for U. S. Meat Demand

The Selected Models

Previous studies by AC and LaFrance used orthodox tests to select between the AIDS and the Rotterdam models for U. S. meat demand. For the Rotterdam, AC present two alternative models with seasonal dummy variables. One uses the Divisia volume index as real income, and the other uses deflated expenditures (with the Stone index). They show that these two specifications give nearly the same parameter estimates. For the AIDS model, AC use four alternative specifications of the first-difference model (this model can also be in non-difference form) with seasonal dummy variables. Parameter estimates for these four specifications are the same. For the purpose of this study, and following AC, the standard specifications for each model are models II and VI for the Rotterdam and AIDS respectively. These two models are also considered in LaFrance's paper.[4] The first-difference linearized version of the AIDS model with quarterly seasonal dummies and real expenditure variables (using the Stone index) presented as AC's model VI is:

$$(6) \qquad \Delta s_i = \tau_i + \sum_{k=1}^{4} \theta_{ik} D_k + \sum_{j=1}^{n} \gamma_{ij} \Delta \ln p_j + \beta_i [\Delta \ln x - \Delta \ln P], \qquad i = 1, \ldots, n$$

In this model, s denotes budget share, D_k's are quarterly seasonal dummy variables, p_j is price of good *j*, *x* is the total expenditure on the *n* goods, $\tau, \theta, \gamma, \beta$ are parameters, Δ is a first-difference operator, and *P* is the Stone index.

The Rotterdam model II with real expenditure variable computed with the average budget share between two time periods in the index has the following specification in AC's paper:

$$(7) \qquad \bar{s}_i \, \Delta \ln y_i = \tau_i + \sum_{k=1}^{4} \theta_{ik} D_k + \sum_{j=1}^{4} \gamma_{ij} \Delta \ln p_j + \beta_i \left[\Delta \ln x - \sum_{j=1}^{4} \bar{s}_j \Delta \ln p_j \right],$$

where $\bar{s}_j$ is the average budget share of good *j* (four goods are considered), y denotes quantity, and all the other variables are defined as above. The term in brackets is real expenditure.

Orthodox Tests and Selection between the AIDS and Rotterdam

The two major studies by AC and LaFrance are based on orthodox tests, with a difference in estimation methods and in the representation of the compound model equation. While AC adopt a least squares approach that does not account for endogeneity, LaFrance uses full information maximum likelihood to address the bias and inconsistency

[4] LaFrance's paper is a comment on AC's paper. These two papers use the same data and the same AIDS

associated with AC's least squares test. AC present two compound models; one to test the Rotterdam model in equation (7) against an approximate FDAIDS while the other is used to test the linearized version of the first differences AIDS (FDAIDS) in equation (6) against an approximate Rotterdam,. AC's compound models are:

(8) $$(1-\lambda)\bar{s}_i \Delta \ln y_i + \lambda \, \Delta \, s_i = \tau_i + \sum_{k=1}^{4} \theta_{ik} D_k + \sum_{j=1}^{4} \gamma_{ij} \Delta \ln p_j + \beta_i \left\{ \Delta \ln x - \sum_{j=1}^{4} \bar{s}_j \Delta \ln p_j \right\}$$

(9) $$(1-\lambda')\Delta \, s_i + \lambda' \, \bar{s}_i \Delta \ln y_i = \tau_i + \sum_{k=1}^{3} \theta_{ik} D_k + \sum_{j=1}^{4} \gamma_{ij} \Delta \ln p_j + \beta_i \{ \Delta \ln x - \Delta \ln P \},$$

where P is the Stone index, and all other elements are defined as previously. Equation (8) compounds AC's Rotterdam II with their FDAIDS IV, which is an approximation to the FDAIDS. This approximation leads to both models having a common right hand side, and thus, the convex combination is only applied to the left had side or dependent variables. In this compound model, testing $\lambda = 0$ is equivalent to testing that the Rotterdam model is the true model. Equation (9) compounds AC's FDAIDS VI with their approximate Rotterdam; again, this allows combining only the left hand side of both models. Testing $\lambda' = 0$ corresponds to testing that FDAIDS is the true model.

LaFrance conducted an orthodox test based on a likelihood ratio for selecting between the AIDS and the Rotterdam, based on a compound model like the one presented in equation (3); i.e., one that combines all aspects of the two models. This compound model is presented below:

(10) $$\begin{aligned}(1-\lambda)\bar{s}_i \Delta \ln y_i + \lambda \Delta s_i &= \tau_i + \sum_{j=1}^{4} \theta_{ij} D_j + \sum_{j=1}^{4} \gamma_{ij} \Delta \ln p_j + \\ &+ (1-\lambda)\beta_{i0}(\Delta \ln x - \sum_{j=1}^{4} \bar{s}_j \Delta \ln p_j) + \lambda \beta_{i1}(\Delta \ln x - P)\end{aligned}$$

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and Rotterdam models.

where all the elements are defined as previously.

Using a likelihood ratio test on LaFrance's compound model (with restrictions imposed) to select between the two models in equations (6) and (7) is a better approach than performing the same likelihood ratio test with AC's adjusted compound model in equations (8) and (9). This is because the compound model by LaFrance takes into account both, the AIDS and Rotterdam model's expenditure terms, whereas AC's models approximate these variables.

The estimable version of equation (10) for meat demand is:

$$
\begin{aligned}
u_{it} = {} & (1-\lambda)\frac{1}{2}\left[\left(\frac{p_{it}}{x_t}\right)y_{it} + s_{i\,t-1}\right]\log\left(\frac{y_{it}}{y_{i\,t-1}}\right) + \lambda\left[\left(\frac{p_{it}}{x_t}\right)y_{it} - s_{i\,t-1}\right] \\
& - \tau_i - \sum_{j=1}^{3}\theta_{ij}\left(D_{jt} - D_{4t}\right) - \sum_{j=1}^{3}\gamma_{i,j}\log\left(\frac{p_{jt}p_{4\,t-1}}{p_{j\,t-1}p_{4t}}\right) \\
& - \beta_{i0}(1-\lambda)\left\{\log\left(\frac{x_t}{x_{t-1}}\right) - \frac{1}{2}\sum_{j=1}^{3}\left[\left(\frac{p_{jt}}{x_t}\right)y_{jt} + s_{j\,t-1}\right]\log\left(\frac{p_{jt}p_{4\,t-1}}{p_{jt-1}p_{4t}}\right) - \log\left(\frac{p_{4t}}{p_{4\,t-1}}\right)\right\} \\
& - \beta_{i1}\lambda\left\{\log\left(\frac{x_t}{x_{t-1}}\right) - \sum_{j=1}^{3}\left(\frac{p_{jt}}{x_t}\right)y_{jt}\log\left(\frac{p_{jt}}{p_{4t}}\right) + \sum_{j=1}^{3}s_{j\,t-1}\log\left(\frac{p_{j\,t-1}}{p_{4\,t-1}}\right) - \log\left(\frac{p_{4t}}{p_{4\,t-1}}\right)\right\}
\end{aligned}
\tag{11}
$$

for i = 1, 2, 3 meat commodities and t = 1, …, T observations. Here u_i is assumed to be *i.i.d.* $N(0, \Sigma)$, and so that symmetry holds, we take $\gamma_{ij} = \gamma_{ji}$ for all $i \neq j$. Homogeneity and adding-up are embedded in the system of equations. All other elements are defined in previous sections. The parameters in this equation can be determined by maximum likelihood estimation. From AC's perspective, a test of one model against the other could be conducted, based on the value of the parameter λ. In LaFrance's view, "a likelihood ratio test should be used to discriminate between the two competing models, rather than simply examining the t-ratio for the estimated lambda".

Using a t-test or a likelihood ratio test on a compound model to select between the two models does not eliminate the fact that the test performed is an orthodox test. Orthodox tests have correct size when the number of non-overlapping variables is greater than one but low power. Such a drawback can be resolved by using a Cox test with parametric bootstrap to choose between the two models.

Cox Test and Parametric Bootstrap with AIDS and Rotterdam

Using the Cox nonnested test with the parametric bootstrap for selecting between the AIDS and the Rotterdam models requires the following steps: 1) Estimate the two models under consideration using the actual data set. 2) Based on the likelihood values of the two estimated models, compute the actual likelihood ratio of the two models. 3) Assuming the null hypothesis model, estimate a distribution function for the original data and, based on it, generate a large number of data sets of the same size. 4) Re-estimate the two models for each of the generated samples. 5) Compute the simulated log-likelihood ratio for each simulated data set, and 6) compare the true and simulated log-likelihood ratios to compute the p-value presented in equation (5). The calculation of the p-value is done first by letting one of the two models (say FDAIDS) represent the null hypothesis, and second under the assumption that the other model (say the Rotterdam) represents the null hypothesis.

Parametric Bootstrap and Difficulties in Data Generation

The data that must be generated in the context of the FDAIDS and Rotterdam models are quantity data. However, as seen above, quantity is not explicit in the left-hand side of both the AIDS and the Rotterdam when the two models are estimated.

The approach used requires predicted quantities. However, it is difficult to simulate data from the Rotterdam model. “Since the Rotterdam involves a nonlinear transformation of quantity on the left-hand side, predicted or expected quantities are not immediately derived by taking the inverse functional transformation of the model-predicted left-hand side ”(Kastens and Brester p. 303, 1996). Kastens and Brester proposed a method for obtaining the expected quantities from the Rotterdam model using the predicted left-hand side (*predLHS*) and a second-order Taylor series expansion of the dependent variable. We start with the predicted equation of the Rotterdam model:

(12) $$E\left(\tfrac{1}{2}(s+s_{t-1})(\ln y-\ln y_{t-1})\right)=X_t^{'}\hat{\beta}_1=predLHS\,,$$

where the variables s and y without subscript are current budget shares and current quantities. The dependent variable or term within the expectation operator can be approximated by a second-order Taylor series expansion around y_0, the expected value of y. Then, the expected value of this approximation can be used to approximate (12) as follows:

$$f(y)=\tfrac{1}{2}(\tfrac{p}{x}y+s_{t-1})(\ln y-\ln y_{t-1})$$

$$f(y)\approx f(y_0)+f'(y_0)(y-y_0)+0.5*f''(y_0)(y-y_0)^2$$

(13) $$predLHS=E(f(y))\approx f(y_0)+f''(y_0)E(y-y_0)^2\,,$$

where sample variance of y is used to estimate $E(y - y_0)^2$. Thus, we can solve for y in equation 13 and have an approximation for the predicted quantity. Predicted quantities for the AIDS model as proposed by Kastens and Brester are obtained as follows:

$$y_o = \frac{[\Pr edLHS + y_{t-1}]}{P} x \tag{14}$$

In the current study, we use these approximation methods to simulate quantity for the Rotterdam and the FDAIDS models, respectively.

AIDS and Rotterdam Likelihood Functions

To use the Cox statistics the likelihood functions of both the AIDS and the Rotterdam models must be converted to the same units. The dependent variables in the FDAIDS model are budget share differences or budget shares, depending on whether the model is presented in difference form or not. In the Rotterdam model the dependent variables are log–quantity-differences multiplied by average expenditure shares. The log-likelihood functions for the dependent variables in both models are transformed to log likelihoods of quantity by adding a Jacobian term. Then, the transformed values are compared.

Meat Demand Data

AC and LaFrance used data on U. S. demand and prices of beef, pork, chicken, and fish to select between the AIDS and the Rotterdam. The data used in their studies are quarterly per capita consumption and retail prices of beef, chicken, pork, and fish in the United States, for the years 1967-1988.

We use the same data used by AC and LaFrance, and a different set of updated quarterly data on beef, pork and chicken. Since the latter data does not include fish (because of the poor quality of the U. S. fish data), for comparison purposes, we also run both the orthodox and the Cox tests with parametric bootstrap on AC and LaFrance's data set without fish. Such an approach allows identifying the effect on the model choice results of difference in method, difference in data, and difference in both data and method, as recommended by Tomek. Conducting the orthodox test or the parametric bootstrap requires parameters estimation.

Estimation Methods

The Model Procedure (PROC MODEL) in SAS with the option full information maximum likelihood (FIML) and iterated seemingly unrelated regressions (ITSUR) are used to conduct the orthodox test on the data. The Interactive Matrix Language Procedure (PROC IML) in SAS with the Seemingly Unrelated Regression (SUR) estimation method is used to implement the Cox test with parametric bootstrap. The estimation methods incorporate the homogeneity, symmetry, and adding-up restrictions.

Results

Different results are obtained when the orthodox test is performed on different data sets with both estimation methods. With the 1967-1988 data including fish we are able to replicate AC's results using ITSUR instead of SUR. Using AC's compound model to test AIDS VI versus the (almost) Rotterdam II, we obtain 0.3579 as an estimate for λ, as compared to LaFrance's 0.36 (with SUR) and AC's 0.35997. However FIML yields an estimate of -0.034. We also estimated λ using the compound model by LaFrance. We obtained 0.059 as compared to his 0.0558 when prices were means scaled, but the value of the log-likelihood function was estimated at 116.29 as compared to his 68.6028. Not mean scaling prices for the full model introduced convergence problems in the estimation. However, when *no* mean scaling was performed on prices and λ was set to one (in order to estimate the Rotterdam II), we could almost match the value for the log-likelihood function (we obtained 68.544 as compared to LaFrance's 68.5439). Thus, the orthodox test gives inconsistent results.

The Cox test with parametric bootstrap selects the Rotterdam model (regardless of prices being mean scaled) for all data sets (Table 1). In all the cases, a small p-value indicates a rejection of the null and a large p-value indicates a failure to reject the null.

This study gives additional evidence of the high power of the Cox test, as compared to an orthodox test. An orthodox test on the compound model, as recommended by LaFrance for U. S. meat demand, is likely to generate unreliable test results, given that it introduces nuisance parameters under the null hypotheses. Indeed, under each null hypothesis corresponding to an appropriate restriction on the parameter lambda (i.e. lambda = 0, or 1), the real expenditures parameters of the alternative model become nuisance parameters that cannot be estimated when in compound model. In the presence of nuisance parameters, the distribution of the likelihood ratio test statistics is unknown. It is no longer chi-square under the null.

Conclusions

This study develops a Cox nonnested test with parametric bootstrap and uses it to select between the FDAIDS and the Rotterdam models for U. S. meat demand. Unlike the orthodox test, the Cox test with parametric bootstrap yields results that do not vary with differences in data sets.

There is a disadvantage in using a convex combination in the orthodox test to select between the two competing FDAIDS and Rotterdam models. Under the null hypothesis, the convex combination introduces nuisance parameters corresponding to the real expenditure parameters of the alternative model. In the presence of nuisance parameters, the distribution of the likelihood ratio test statistics is no longer chi-square under the null. It is unknown and can be estimated using Monte Carlo methods.

The Cox test with parametric bootstrap approach developed in this study does not suffer from any lack of generality. It can easily be used to test any functional form, for instance, a double-log demand model, the Almost Ideal Demand System in levels, the Rotterdam and the AIDS with different expenditure deflators.

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Table 1 Cox Test with Parametric Bootstrap Using Seemingly Unrelated Regression (SUR) as Estimation Method.

			LaFrance's 1967-88 Data with fish	LaFrance's 1967-88 Data w/o fish	Updated Data w/o fish, 1970-97
Log-likelihood values (LLV) for true data		FDAIDS	1136.994	713.763	845.597
		Rotterdam	1126.368	701.777	826.576
		difference	-10.626	11.986	19.021
Average LLV for randomly generated data	H_0: FDAIDS	FDAIDS	987.751	605.660	714.671
		Rotterdam	988.087	610.344	707.582
		difference	-0.336	-4.684	7.088
	H_0: Rotterdam	FDAIDS	993.513	612.674	718.748
		Rotterdam	1000.185	621.831	725.795
		difference	-6.672	-9.158	-7.047
Estimated p-values	Test for:	FDAIDS	0.002	0.004	0.001
		Rotterdam	0.938	0.875	0.998
	Conclude:		Reject FDAIDS	Reject FDAIDS	Reject FDAIDS