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Benchmarking New Statistical Techniques in Ratio-Based Modelling of Corporate Collapse

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Up until 1979, Multiple Discriminant Analysis (MDA) was the primary multivariate methodological approaches to ratio-based modelling of corporate collapse. However, as new statistical tools became available, researchers started testing them with the primary objective of deriving models that would at least do as good a job as MDA, but that rely on fewer assumptions. Regardless of which methodological approach was chosen, most were compared to MDA. This paper analyses 84 studies on ratio based modelling of corporate collapse over the period 1968 to 2004. The results indicate that when MDA was not the primary methodology it was the benchmark of choice for comparison; thereby, demonstrating its importance as a foundation multivariate methodological approach in signalling corporate collapse.

Field of research: Finance.

1. Introduction

The year 1968 saw a major methodological shift from univariate to multivariate ratio-based modelling of corporate collapse (Altman, 1968). What facilitated this shift was the introduction of a new statistical tool called Multiple Discriminant Analysis (MDA) (Huber, 1964; Lachenbruch, 1967; Walter, 1959). With very little happening on the statistical front, MDA became the standard methodological approach for signalling corporate collapse for almost one and a half decades. (Altman, 1968; Altman, 1973; Altman et al., 1977; Altman and Levallee, 1980; Blum, 1974; Dambolena and Khoury, 1980; Deakin, 1972; Edmister, 1972; Elam, 1975; Ketz, 1978; Norton and Smith, 1979; Sharma and Mahajan, 1980)

However, with the introduction of new statistical tools, researchers became pre-occupied with testing new methodological approaches for signalling corporate collapse. Among the ratio-based approaches were Logit analysis (Ohlson, 1980), Neural Network analysis (Coats and Fant, 1993), Probit analysis (Gentry et al., 1985), ID3 (Kim and McLeod Jr., 1999), Recursive Partitioning Algorithm (Frydman et al., 1985), Rough Sets analysis (Dimitras et al., 1999), Decomposition analysis (Walker et al., 1979), Going Concern Advisor (Lenard et al., 1998), Koundinya and Puri judgmental approach (Clark et al., 1997), Tabu Search (Drezner et al., 2001) and Mixed Logit analysis (Jones and Hensher, 2004).

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Therefore, it is apparent that statistical developments were causing methodological shifts in modelling corporate collapse. The whole exercise was primarily aimed at developing models that would generate predictive accuracies that are at least as good as MDA (particularly with respect to reducing Type I error, which is classifying a collapsed company as non-collapsed), but that rely on fewer assumptions.

The first section of this paper provides a brief overview of MDA and its underlying assumptions. The second section discusses the various methodological approaches that followed MDA and how they fared against it. The third section specifies the methodology used in order to facilitate the empirical evidence presented in the fourth section. The fifth section draws on these findings to bring this paper to a conclusion, thereby emphasize the importance of MDA as a foundation multivariate methodological approach in signalling corporate collapse.

2. Literature review

2.1 Brief overview of MDA and its underlying assumptions

MDA is a statistical approach for determining the group with which a unit is identified (Huberty, 1994). In the context of corporate collapse, there are two groups: collapsed companies and non-collapsed companies. MDA attempts to classify a company into one of these two groups based on a set of predictor variables. The predictor variables in this case are financial ratios. The classification process is based on a decision rule, which is primarily a linear function of financial ratios. The researcher might start with a large number of financial ratios, but not all would necessarily be included in the final model. MDA selects those financial ratios that can best discriminate between collapsed and non-collapsed companies. Calculating a linear combination *score* does this. Companies that have a linear combination score, which is less than a cut-off score, will be classified as collapsed, and companies that have a score, which is greater than a cut-off score, will be classified as non-collapsed. The cut-off score is such that it minimizes the overall misclassification. In other words, it minimizes total error, but not necessarily Type I error.

The assumptions underlying the proper use of MDA include: distribution of the variables, dispersion matrices of the sample groups, interpretation of the significance of individual variables, dimension reduction, definition of groups, selection of prior probabilities and samples and assessment of classification error rates. The next section demonstrates how the development of new multivariate statistical tools led to their application in modelling corporate collapse, particularly when they rely on fewer assumptions and at the same time are at least as accurate as MDA in signalling collapse.

2.2 Methodological approaches that followed MDA and how they fared against it

2.2.1 Logit analysis

Logit analysis was among the first methodological approaches to take over MDA in deriving ratio-based models for signalling corporate collapse (Ohlson, 1980). Logit analysis avoids a number of problems that are associated with MDA. First, it avoids the statistical requirement imposed by MDA on the distributional properties of the predictor variables, that is, the financial ratios. Specifically, this refers to two properties: that the variances of the financial ratios are equal for both groups of collapsed and non-collapsed companies, and that the financial ratios are normally distributed. Second, unlike MDA, the output of logit analysis is not a *score* that has little intuitive interpretive value. Instead, it is a probability, that is, a number between 0 and 1. A value close to 0 indicates a low probability of collapse and a number close to 1 indicates a high probability of collapse.

The final logit model in Ohlsen (1980) was derived from a sample of 105 collapsed and 2058 non-collapsed companies, and was based on 5 financial ratios. These ratios were collected over a 7-year period. The model generated a predictive accuracy of just over 96%. This was indeed a strong result, which spurred more interest in using logit analysis to signal corporate collapse.

2.2.2 Neural Network analysis

Neural Network (NN) analysis relaxes a number of the assumptions that existed under MDA. In addition to the assumptions regarding multivariate normality, the equality of group variances and the linear structure of the MDA model, NN analysis attempts to address the assumption in relation to the independence of the financial ratios. (Coats and Fant, 1993, p. 144)

The results in Coats and Fant (1993) indicate that the NN-based corporate collapse prediction model performed better than the MDA-based model the farther the data was from ‘y_0’, where ‘y_0’ denotes the year in which collapse occurred. Moreover, NN analysis generated a lower occurrence of a Type I error than MDA.

2.2.3 Probit analysis

As a multivariate methodological approach to ratio-based prediction of corporate collapse, probit analysis is considered closely related to logit analysis. As a matter of fact some even regarded the two approaches as an inseparable combination (Gritta et al., 2000). As a result, the literature did not make much use of probit analysis. Instead, the preference was to use logit analysis. Therefore, the fact that probit analysis was considered as a variant to logit analysis, coupled with the fact that it was not portrayed in the literature as a promising methodological alternative does not warrant discussing it further.

2.2.4 The ID3 approach

The ID3 approach is a procedure for classifying patterns that have common attributes. Classification is based on a decision tree, which is generated through a process of learning. This inductive learning method derives from information theory; specifically, it is based on a concept called entropy, which could be defined as the information content in a message. As such the ID3 approach is not subject to the assumptions under MDA. (Fisher and McKusick, 1989; Mitchie, 1987; Quinlan, 1979; Shannon, 1948)

The results in Kim and McLeod Jr. (1999) indicate that the overall predictive power of the ID3-based model that they derived was 76.4% compared to 74.8% for the MDA-based model. This is a marginal improvement over MDA.

2.2.5 Recursive Partitioning Algorithm

In essence, Recursive Partitioning Algorithm (RPA) is a non-parametric technique based on pattern recognition. It requires four inputs. In the context of ratio-based models for signaling corporate collapse, these four inputs translate to the following: first, a data sample consisting of financial ratios; second, two groups: one for collapsed companies and one for non-collapsed companies; third, determination of the percentages of collapsed and non-collapsed companies in the chosen data sample; and finally the cost of misclassifying a collapsed company, that is the occurrence of Type I error. Given those four input variables, RPA then generates a model in the form of a binary classification tree. Like the ID3 approach, RPA is not subject to the assumptions under MDA.

In modelling corporate collapse, at times RPA outperformed MDA, whereas at other time MDA outperformed RPA (Frydman et al., 1985). Such inconsistency in the results was most probably the reason behind the unpopularity of RPA as a suitable tool for signalling collapse.

2.2.6 Rough Sets analysis

Rough Sets (RS) analysis was put forward as an approach to handling imperfect data (Pawlak, 1982). It relies on *decision rules.* In the context of ratio-based models for signaling corporate collapse, a decision rule is whether to classify a particular company as collapsed or non-collapsed.

Dimitras et al. (1999) were the first to use RS analysis in modelling corporate collapse Overall, the classification accuracy of their RS-based corporate collapse prediction model stood at 71.1% when tested on data 1 year prior to collapse, and 55.3% when tested on data 2 and 3 years prior to collapse. On the other hand, the MDA-based model delivered an overall classification accuracy of 60.5% when tested on data 1 year prior to collapse, 55.3% when tested on data 2 years prior to collapse, and 57.9% when tested on data 3 years prior to collapse.

2.2.7 Decomposition analysis

Decomposition analysis is “an efficient and convenient device for identifying whether significant change in financial statement constructs has occurred, and where most of the change is located.” (Walker et al., 1979) In order to compute decomposition measures, two balance sheets at two different points in time are required. Financial ratios are then calculated from each balance sheet, and the results are compared. As such, the approach is seemingly straightforward and relaxes the assumptions under MDA. However, Walker et al. (1979) have clearly stated that decomposition analysis has little use when it comes to initial investigations of the financial standing of corporations. They only recommended decomposition analysis as an adjunct to MDA. As a result, the literature did not seem to make much use of decomposition analysis.

2.2.8 The Going Concern Advisor

The Going Concern Advisor (GCA) integrates qualitative aspects into the quantitative-based MDA model for signaling corporate collapse. These qualitative aspects represent opinions of auditors regarding the financial health of their client companies. These auditors’ opinions are then incorporated into the MDA-based corporate collapse prediction model as predictor variables, in addition to the financial ratios. As such, the GCA is primarily an MDA approach. Therefore, like MDA, the GCA approach relies on similar assumptions. (Lenard et al., 1998) The GCA-based model in Lenard et al. (1998) delivered an overall predictive power of 96.2% compared to 94.2% for the MDA-based model.

2.2.9 The Koundinya and Puri judgmental approach

In addition to financial ratios, the Koundinya and Puri (K&P) approach incorporates judgmental factors in modelling corporate collapse. Sorting the ratios into various levels of risk does this. Specifically, three levels of risk are defined in the K&P process: high, medium and low. These three levels of risk are based on some financial factors. Among the most notable factors are a company’s liquidity position, earning power, asset utilization and financial flexibility (Saaty, 1977; Saaty and Kerns, 1985). Deciding on what constitutes a high, medium or low level of risk is based on the researcher’s judgment (Koundinya and Puri, 1991; Koundinya and Puri, 1992).

The results in Clark et al. (1997), which is the only study that used the K&P approach for signaling corporate collapse, indicated that there was a dramatic improvement in the predictive power of a K&P-based model compared to an MDA-based counterpart. This was particularly true with respect to reducing Type I error. Using the K&P approach, Type 1 error ranged from 0% to 29% over a 5-year period prior to collapse. These results compare to a range of 86% to 100% when using MDA. Despite such strong results in favor of the K&P approach, it did not spur more interest amongst researcher to apply it in signalling corporate collapse. The reason could be attributed to the fact that it relies heavily on subjective elements when it comes to model derivation. This is evident from the fact that the researcher’s judgment plays a dominant role.

2.2.10 Tabu search

In the context of ratio-based modelling of corporate collapse, tabu search increases the number of possible combinations of financial ratios in the model derivation process. Therefore with tabu search, it is implied that some methodological approach is used in deriving the model. The preferred approach is MDA (Drezner et al., 1999; Drezner et al., 2001). As such tabu search relies on the same assumptions that MDA relies on. Nevertheless, the fact that tabu search relies on MDA indicates that MDA is still the prominent benchmark even at the turn of the millennium.

The results in Drezner et al. (2001) indicated that the procedure improves the power of the corporate collapse prediction model. When applied to a sample of 185 collapsed and 185 non-collapsed companies, the predictive accuracy of the MDA-based model increased from 60.5% (without using tabu search) to 66.5% (using tabu search). Similar results could be observed concerning the occurrence of Type I error, which dropped from 62.2% to 57.3% when tabu search was applied.

2.2.11 Mixed Logit analysis

Mixedl Logit (ML) analysis is a refinement on logit analysis, which was discussed earlier in this section of the paper. As such, ML analysis supplants, rather than replaces, logit analysis. The main improvement is that ML-based models include a number of additional parameters that capture observed and unobserved variations both within and between elements in the data sample. (Louviere et al., 2000; Train, 2003)

In the context of modelling corporate collapse, observed variations relate to differences in the financial ratios among companies in the data sample, whereas unobserved variations relate to behavioral information embedded in the data set of financial ratios (Jones and Hensher, 2004). Moreover, ML analysis relaxes the assumption of multivariate normality of the financial ratios, which is a pre-requisite under MDA (Hensher and Greene, 2003).

The only identifiable study that applies ML analysis to modelling corporate collapse is Jones and Hensher (2004). However, the authors therein did not compare their results to MDA; instead they compared them to a logit-based model. This is because logit is the basis for ML analysis. Although the Jones and Hensher (2004) study was lacking in this respect, it nevertheless confirmed that researchers are still pre-occupied with exploring new statistical tools that could be applied to signalling corporate collapse.

Having discussed the relationship between statistical developments and methodological shifts in modelling corporate collapse, it is imperative to draw on empirical evidence in order to support what has been discussed so far. However, before doing so, it is necessary to set out the methodology used in the analysis.

3. Methodology

The methodology is exploratory in nature and relies on a systematic analysis of 84 refereed studies on ratio-based modelling of corporate collapse between 1968 and 2004.

In order to facilitate the analysis, relevant information is presented in Table 1, which contains two identical pairs of columns. The first column in each pair is a list of studies that used ratio-based multivariate approaches for signalling corporate collapse and the second column is a list of the specific methodological approach/approaches used in the corresponding studies.

The following acronyms are used to distinguish between the various methodological approaches:

MDA: stands for Multiple Discriminant Analysis.
Logit: stands for Logit analysis.
NN: stands for Neural Network analysis.
Probit: stands for Probit analysis.
ID3: stands for ID3 analysis.
RPA: stands for Recursive Partitioning Algorithm.
RS: stands for Rough Sets analysis.
DM: stands for Decomposition analysis.
GCA: stands for Going Concern Advisor.
KP: stands for Koundinya and Puri judgmental approach.
TS: stands for Tabu Search.
ML: stands for Mixed Logit analysis.

Whenever any of these acronyms appears in parentheses in Table 1, this means that the corresponding methodological approach was used as a benchmark (as opposed to the primary methodology) in the corresponding study.

The role of a benchmark methodology is to enable comparison of the performance of the primary approach used in signalling collapse.

Table 1 - Summary of the various multivariate methodological approaches in ratio-based models for signalling corporate collapse across 84 studies (1968 - 2004)

Study	Method	Study	Method
(Altman, 1968)	MDA	(Koh and Killough, 1990)	MDA
(Deakin, 1972)	MDA	(Skogsvik, 1990)	Probit
(Edmister, 1972)	MDA	(Flagg and Giroux, 1991)	Logit
(Altman, 1973)	MDA	(Koh, 1991)	Probit
(Blum, 1974)	MDA	(Laitinen, 1991)	MDA
(Elam, 1975)	MDA	(Aly et al., 1992)	Logit(MDA)
(Altman et al., 1977)	MDA	(Bahnson and Bartley, 1992)	Logit
(Ketz, 1978)	MDA	(Baldwin and Glezen, 1992)	MDA
(Norton and Smith, 1979)	MDA	(Coats and Fant, 1993)	NN(MDA)
(Walker et al., 1979)	DM	(Fletcher and Goss, 1993)	NN(Logit)
(Altman and Levallee, 1980)	MDA	(Johnsen and Melicher, 1994)	Logit
(Dambolena and Khoury, 1980)	MDA	(Platt et al., 1994)	Logit
(Ohlson, 1980)	Logit	(Poston and Harmon, 1994)	MDA
(Sharma and Mahajan, 1980)	MDA	(Sheppard and Fraser, 1994)	Logit
(Castagna and Matolcsy, 1981)	MDA	(Ward, 1994)	Logit
(Taffler, 1982)	MDA	(Wilson and Sharda, 1994)	NN(MDA)
(El-Hennawy and Morris, 1983)	MDA	(Boritz et al., 1995)	NN(MDA/Logit/Probit)
(Hamer, 1983)	Logit(MDA)	(Lacher et al., 1995)	NN(MDA)
(Taffler, 1983)	MDA	(Wilson et al., 1995)	NN(Logit)
(Izan, 1984)	MDA	(Hill and Perry, 1996)	Logit
(Lincoln, 1984)	MDA	(Lee et al., 1996)	NN/ID3(MDA)
(Micha, 1984)	MDA	(Clark et al., 1997)	KP(MDA)
(Takahashi and Kurokawa, 1984)	MDA	(Lenard et al., 1998)	GCA(MDA)
(Zmijewski, 1984)	Probit	(McGurr and Devaney, 1998)	MDA
(Casey and Bartczak, 1985)	Logit(MDA)	(Richardson et al., 1998)	Logit
(Frydman et al., 1985)	RPA(MDA)	(Dimitras et al., 1999)	RS(MDA/Logit)
(Gentry et al., 1985)	Logit/Probit(MDA)	(Kim and McLeod Jr., 1999)	NN/ID3(MDA/Logit)
(Levitan and Knoblett, 1985)	MDA	(Kyung et al., 1999)	NN(MDA)
(Zavgren, 1985)	Logit	(Laitinen and Kankaanpaa, 1999)	NN/RPA/(MDA/Logit)
(Keasey and Watson, 1986)	MDA	(Lennox, 1999)	Logit/Probit(MDA)
(Lawrence and Bear, 1986)	MDA	(Bongini et al., 2000)	Probit
(Lo, 1986)	Logit(MDA)	(Gritta et al., 2000)	NN(MDA)
(Betts and Belhoul, 1987)	MDA	(Laitinen and Laitinen, 2000)	Logit
(Gombola et al., 1987)	MDA	(Zapranis and Ginoglou, 2000)	NN(MDA)
(Karels and Prakash, 1987)	MDA	(Beynon and Peel, 2001)	VPRS(MDA/Logit)
(Keasey and Watson, 1987)	Logit	(Drezner et al., 2001)	TS(MDA)
(Lau, 1987)	Logit(MDA)	(Lin and McClean, 2001)	NN(MDA/Logit)
(Peel and Peel, 1987)	Logit(MDA)	(Ginoglou et al., 2002)	Logit/Probit(MDA)
(Dambolena and Shulman, 1988)	Logit	(Darayseh et al., 2003)	Logit
(Barniv and Raveh, 1989)	Logit/Probit(MDA)	(Charitou et al., 2004)	NN(Logit)
(Hopwood et al., 1989)	Logit	(Jones and Hensher, 2004)	ML(Logit)
(Gilbert et al., 1990)	Logit	(Neophytou and Molinero, 2004)	Logit

4. Findings

4.1 MDA: the dominant primary methodological approach in the early state of the literature

Table 2 provides a summary of the number of studies using Multiple Discriminant Analysis (MDA) as the primary methodological approach during the period 1968 to 2004. The results are based on the data presented in Table 1. Two sub-periods are evident: prior to 1979 and subsequent to 1979. These sub-periods are listed in the first column of Table 2. The reason why 1979 is chosen as the dividing point is because it signifies the year in which a new methodological approach other than MDA was used for the first time in modelling corporate collapse. This approach is decomposition analysis, which was used in Walker et al. (1979). The second column in Table 2 provides the number of studies using MDA as the primary approach corresponding to each sub-period. The third column expresses those numbers as percentages based on the total number of studies in each sub-period.

Table 2 - Summary of the number of studies using MDA as the primary methodological approach in modelling corporate collapse by sub-period (1968 - 2004)

Sub-Period	Number of studies using MDA as the primary methodological approach	Percentage of studies using MDA as the primary methodological approach
Prior to 1979	9	100% (n=9)
Subsequent to 1979	22	29% (n=75)

The second row of the second column in Table 2 indicates that 9 studies used MDA as the primary methodological approach prior to 1979 (that is, between 1968 and 1979). Moreover, during this sub-period, a total of 9 studies on ratio-based modelling of corporate collapse could be identified (this corresponds to ‘n=9’ in the second row of the last column in the table). Hence, all studies in this sub-period used MDA as the primary approach. This translates to a hit rate of 100% (shown in the second row of the last column in the table).

Similarly, the third row of the second column in Table 2 indicates that 22 studies used MDA as the primary methodological approach subsequent to 1979 (that is, between 1979 and 2004). Moreover, during this sub-period, a total of 75 studies on ratio-based modelling of corporate collapse could be identified (this corresponds to ‘n=75’ in the third row of the last column in the table). In other words, 22 out of 75 studies in this sub-period used MDA as the primary approach, which translates to a hit rate of 29% (shown in the third row of the last column in the table).

Overall, the results in Table 2 indicate that MDA was the dominant primary methodological approach in the early state of the literature, specifically prior to 1979.

4.2 MDA: the dominant benchmark methodological approach in the later state of the literature

Based on the data presented in Table 1, Figure 1 depicts the usage rates of the various benchmark methodologies during the entire period 1968 to 2004.

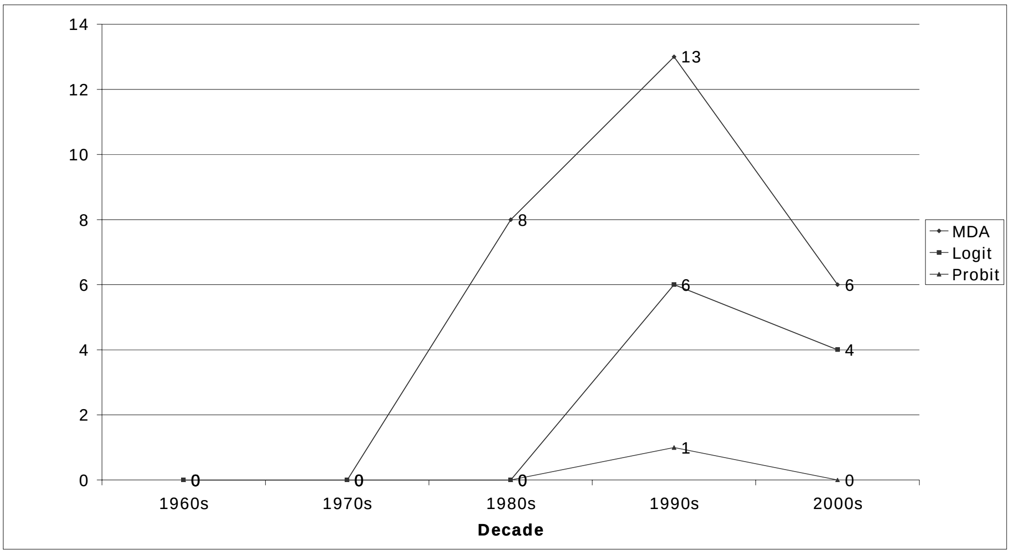

Figure 1 - Comparative analysis of the frequency of usage of the three primary benchmark multivariate methodological approaches for modelling corporate collapse by decade (1968 - 2004)

The results in Figure 1 indicate that during the period 1968 to 2004, a total of three methodological approaches were used as benchmarks for comparison. These are MDA, logit analysis and probit analysis. The figure indicates that no benchmarks were used during the first two decades (1960s and 1970s). This is evident from having all three lines (corresponding to the three approaches) in the figure running along the x-axis during these two decades. However, the situation changed from the 1980s onwards. Evidence of usage of benchmark methodologies is observed during this period. All three lines corresponding to the three benchmark approaches rise above the x-axis with the exception of that corresponding to probit analysis, which registered activity during the 1990s only. The main feature of Figure 1 is the prominence of MDA as the preferred benchmark. This is evident from its line being above all the others in the figure, particularly in the later state of the literature.

5. Conclusion

This paper discussed how statistical developments were causing methodological shifts in modelling corporate collapse. The whole exercise was aimed at developing models that would generate predictive accuracies that are at least as good as MDA and that preferably rely on fewer assumptions.

After a brief overview of MDA and its underlying assumptions, this paper identified a variety of techniques used in modeling corporate collapse. Using a systematic analytic exploratory methodology, empirical evidence demonstrated that MDA is the most prominent methodological approach when it comes to modelling corporate collapse. Specifically, the results indicated that during the early state of the literature 100% of studies adopted MDA as the primary tool for modelling corporate collapse. However, as researchers started using new methodological approaches, the usage rate of MDA as the primary tool dropped to 29%. However, MDA did not lose prominence. Researchers turned to MDA once again, but this time as the preferred benchmark methodology, where 87% of studies that used some sort of benchmark chose MDA. This puts MDA comfortably ahead of the other two benchmarks, which are logit and probit analysis.

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