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SPECIFICATION OF A MODEL TO MEASURE - THE VALUE OF TRAVEL TIME SAVINGS FROM BINOMIAL DATA

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SPECIFICATION OF A MODEL TO MEASURE

THE VALUE OF TRAVEL TIME SAVINGS FROM BINOMIAL DATA[1]

Mogens Fosgerau

Danmarks TransportForskning

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Using nonparametric methods, the paper examines the specification of a model to evaluate the distribution of willingness-to-pay (WTP) for travel time savings from binomial choice data from a simple time-cost trading experiment involving four public transport modes. A formulation in preference space in terms of constant marginal utilities is rejected in favor of a formulation in log(WTP) space for each mode. Results further indicate that the log(WTP) distribution can be decomposed into an independent random variable and a linear index shifting the location of the log(WTP) distribution, which is useful for parametric modeling. The index strongly indicates that small time savings are valued less than large time savings for all four modes in this experimental choice situation. The sign for journey duration varies significantly between modes, which could be due to self-selection into modes.

Keywords: Willingness-to-pay, WTP, value of travel time savings, nonparametric, semiparametric, local logit

JEL codes: C14, C25, R41

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[1] I thank Ninette Pilegaard for comments.

1 INTRODUCTION

This paper performs an econometric analysis of the value of public transport travel time savings using various nonparametric and semiparametric techniques permitting the identification of effects that are otherwise hard to discern. A particular strength of the techniques is that they allow one to visually inspect various distributions and relationships. These techniques are applied in parallel analyses of binary stated choice data relating to four different public transport modes.

The paper finds first that the conventional formulation of the binary logit model in terms of constant marginal utilities of time and cost is misspecified with the current data for all four modes. Instead a simple formulation in terms of willingness-to-pay (WTP) is proposed, which fits the data. Second, it is found that a model whereby the WTP depends on the log of the size of the time saving offered and also on travel time gives a good representation of the data. These findings are robust as they emerge within a semiparametric model with weak assumptions on the stochastic terms of the model and under various specifications of the systematic variation in WTP.

The formulation in terms of random WTP lends itself naturally to an interpretation of random variability as preference variation. Specification of models in WTP space and interpretation of random variation as preference variation is the norm in environmental economics (Hanemann & Kanninen, 1998), whereas the tradition in the transport economics literature has been to interpret random variation as noise (Gunn, 2000). The issue of whether to specify a discrete choice model in preference space or in WTP space is discussed by Train & Weeks (2004), who find with their data that mixed logit models that use convenient (normal, lognormal) distributions for the coefficients in preference space fit the data better than similar models in WTP space, but that the models in preference space give less reasonable distributions for the WTP. They call for alternative distributional assumptions that either fit the data better in WTP space or imply more reasonable

distributions of WTP when applied in preference space. This paper achieves this aim by applying nonparametric distributions of random variability.

The layout of the paper is as follows. Section 2 sets out some models and the econometric methodology, section 3 presents the data, the econometric analysis is carried out in section 4 while section 5 concludes by discussing the findings made.

2 METHODOLOGY

Much research has been devoted to the WTP for travel time savings as they usually constitute the main benefit of transport infrastructure investment (Hensher, 2001, Mackie et al., 2001). The micro-economic formulation of the theory of the value of travel time savings was fundamentally formulated by Becker (1965), Johnson (1966), Oort (1969) and DeSerpa (1971). Jara-Diaz (2000) provides a review. The estimation of the WTP for travel time savings is reviewed in Hensher (2001) and Gunn (2000). Here we shall employ a different perspective on the problem.

2.1 Some different models

We will be concerned with models for binary choices where the alternatives are characterized by time and monetary cost only. Denote the time difference by Δt and the cost difference by Δc. Alternatives are rearranged such that $\Delta c < 0 < \Delta t$. The time and cost variables are observed together with the choice y, which is 1 if the cheap and slow alternative is chosen.

Assuming random utility maximization we have $y=1\{\Delta U>0\}$. The data provide information about $P(y=1|\Delta c, \Delta t)$. There are different ways in which a model may be specified, Table 1 shows some polar cases. They are distinguished first by the interpretation of random variability. At one extreme individuals are seen as identical and all variability is due to optimization errors. At the other

extreme all variability is interpreted as variation in preferences. The second distinction is between formulating the model in utility space in terms of marginal utilities of time and cost and formulating the model in WTP space in terms of a willingness to pay for time. The models are identical when no assumptions are made concerning the distribution of the error terms. They become different when assumptions about independence are made.

The first model (a.) specifies marginal utilities of time and cost, α, β, and an additive error. This is the binary logit model when ε is logistic and independent of $(\Delta t, \Delta c)$. When also α, β are stochastic it is the mixed binary logit model. With fixed parameters and independent error, a quantile in this model is given by $P(y=1)=q$ *iff* $\Delta c = -F_{\varepsilon}^{-1}(1-q)/\beta - (\alpha/\beta)\Delta t$, assuming $\beta \neq 0$. Thus, quantiles are parallel in $(\Delta t, \Delta c)$-space. The spacing between quantiles depends on the distribution of ε.

Models (a.) and (b.) are equivalent when $\beta \neq 0$ and fixed. Models (c.) and (d.) are similarly equivalent with $w=-\alpha/\beta$.

The quantiles in model (d.) are given by $P(y=1)=q$ *iff* $\Delta c = -\Delta t\, F_w^{-1}(q)$, assuming w is independent of Δt, Δc. Thus quantiles in this model fan out from the origin in $(\Delta t, \Delta c)$-space. Define $v = -\Delta c/\Delta t$ such that $y = 1\{w<v\}$. Then quantiles depend only on v if w is independent of Δt and Δc.

Table 1. Some different models

	Model	Assumptions
a. Pure optimization error, utility space	$y = 1\{\alpha \Delta t + \beta \Delta c + \varepsilon > 0\}$	α, β fixed
b. Pure optimization error, WTP space	$y = 1\{w\Delta t + \Delta c + \varepsilon < 0\}$	w fixed
c. Pure preference variation, utility space	$y = 1\{\alpha \Delta t + \beta \Delta c > 0\}$	α, β stochastic
d. Pure preference variation, WTP space	$y=1\{w\Delta t + \Delta c < 0\}$	w stochastic

2.2 Econometric technique

Härdle (1990), Horowitz (1998), Pagan & Ullah (1999) and Yatchew (2003) are general references to nonparametric and semiparametric modeling. Here we shall make extensive use of the local logit model using locally weighted maximum quasi-likelihood as discussed in Fan, Heckman & Wand (1995). At each point *x*, a logit model is estimated by maximizing the quasi-loglikelihood function given in (1) with local weights $K_h(x_i - x)$, where K_h is a multidimensional kernel with bandwidth *h*, x_i are the observations in the sample and *P()* is the logistic distribution. Then $P(\alpha_x)$ is an estimate of *P(y|x)*. We use the triangular product kernel with the same bandwidth in all directions. The computation of confidence intervals is given in Fan, Heckman & Wand (1995).

$$\boldsymbol{L}_x = \sum_i \boldsymbol{K}_h(\boldsymbol{x}_i - \boldsymbol{x})[\boldsymbol{y}_i \log \boldsymbol{P}(\alpha_x + \beta_x(\boldsymbol{x}_i - \boldsymbol{x})) + (1 - \boldsymbol{y}_i)\log(1 - \boldsymbol{P}(\alpha_x + \beta_x(\boldsymbol{x}_i - \boldsymbol{x})))] \qquad (1)$$

The use of a local logit model may reduce bias compared to local constant regression, and hence allows for use of a larger bandwidth since the logit model conforms with the binary response data: the estimate is always a probability. When the bandwidth becomes large the model approaches the conventional logit model. Thus the optimal bandwidth will tend to be high when the logit model is a good approximation to the data. This means that the optimal bandwidth can be fairly high in comparison to a local constant regression.

We shall also estimate parameters δ in the model $E(y|v,x)=F(\log(v)-\delta x)$, where *F* is an unknown distribution. This is accomplished by means of the Klein & Spady (1993) estimator. It is implemented with a normal density kernel and no trimming is applied.

The Zheng (1996) test is used to test restrictions of the form $E(y|v,x) = E(y|g(v,x))$, where *g* is a known function. The Zheng test is a test of functional form against a general nonparametric

alternative, the Zheng test statistic is distributed as standard normal under the null hypothesis and diverges to infinity under the alternative.

The Klein-Spady estimator and the Zheng test are both based on local constant regression, whereas the local logit regression fits a local curve. The bias is larger in the local constant regression, wherefore the bandwidth is reduced relative to the bandwidth chosen for the local logit model. The normal density kernel is also rescaled such that it is comparable to the triangular kernel (Härdle, 1990).

Estimation is carried out in Ox (Doornik, 2002).

3 DATA

The data origin from the Danish value of time study conducted for the Danish Ministry of Transport and Energy. The questionnaire design is discussed in Burge et al. (2004). For this paper we use binary stated choice data from a simple within-mode experiment, where respondents chose between alternatives varying only by within mode travel time and cost.

Some summary statistics for the data are given in Table 2. We use data for four different modes. Bus, Metro, S-train and train. The Metro is a new facility mainly going through central Copenhagen, while the S-train is a regional rail service in the Greater Copenhagen area. The bus and train modes cover the whole country. Trips by Metro and S-train are generally brief with an average main mode journey time (*jtime*) of 16 minutes and 22 minutes respectively. Trips by bus are longer with an average duration of 33 minutes while trips by train are longest with an average duration of 80 minutes. Travel time and cost are varied in the experiment around a current trip with

a minimum time difference of 3 minutes and an implicit price of time ranging between 2 and 200 DKK/hour.[2]

Table 2 Descriptive statistics

	Bus			Metro			S-train			Train		
	min	max	mean	min	max	mean	min	max	mean	min	max	mean
Δc, min.	-50	-0.5	-6.27	-50	-0.5	-4.33	-50	-0.5	-5.03	-200	-0.5	-12.3
Δt, DKK	3	60	7.11	3	15	4.77	3	20	5.55	3	60	12.7
v = -Δc/Δt, DKK/min.	0.05	3.35	0.79	0.05	3.35	0.83	0.05	3.35	0.82	0.05	3.35	0.82
jtime, min.	5	240	33.3	5	45	15.9	5	60	22.0	10	460	79.9
No of obs.			9308			3442			3428			7222

4 ECONOMETRIC ANALYSIS

4.1 Local logit in preference space

We begin the econometric analysis by estimating a local logit model using a conventional formulation in preference space where responses are explained by the difference in cost and the difference in travel time and local parameters may be interpreted as marginal utilities of time and cost. No assumptions are imposed except for those required by the nonparametric local logit regression. The results for the four modes are shown in Figure 1. The range on the axes in the figures is the same as the range of data. Several findings emerge, common to all modes.

First, the estimated densities show that the data are concentrated around small values of Δt and Δc. Second, from the estimated regression surfaces we note that the quantiles generally have a positive slope, which corresponds to a positive value of time: Starting from a point in $(\Delta t, \Delta c)$-space, when

[2] The currency is Danish kroner, 1 EUR = 7.45 DKK.

the time difference increases also the cost difference must increase in order to maintain a constant probability. This is reassuring, but of course not so surprising. Third, there seems to be a tendency for the slopes to increase as the time savings gets larger. Thus the WTP distribution may not be independent of the size of the time saving.

Finally, the quantiles are clearly not parallel, as they would be in model (a.) with independent errors and constant marginal utilities, or specifically as they would be in the binary logit model.[3] It rather seems as if the quantiles fan out from the origin as they would in model (d.) with independent errors. It thus seems that preference variation dominates optimization errors and that this is consistent across modes.

4.2 Local logit in WTP space

These observations motivate some transformation of the space of independent variables. First, define $v = -\Delta c/\Delta t$ as the cost per minute in the presented trade-off. This corresponds to model (d.). Second, transform the variables v and Δt to logs in order to obtain a more even coverage of space.

Then a local logit regression is performed on $(log(\Delta t), log(v))$. The bandwidths shown in Table 3 are selected by cross-validation (Härdle, 1990).

Table 3 Bandwidths

	Bus	Metro	S-train	Train
λ	0.48	0.52	0.52	0.36

[3] Fosgerau (2005b) also rejected the logit model using a similar model on data for car drivers.

The results from this local logit regression are shown in figure 2. As intended, the densities of *(log(Δt), log(v))* now show a much more uniform coverage of space. Second, the quantiles seem to be roughly parallel. They do however seem to depend on *log(Δt)*, so we do not have independence between *w* and *Δt* in model (d.): The WTP per minute depends on the size of the time saving.

This observation leads us to elaborate the specification of model (d.) by the following model, whereby

$$y=1\{\log(w) < \log(v)\} \text{ and } \log(w) = \gamma \log(\Delta t) + u, \quad (2)$$

and *u* is independent of *(v,Δt)* with unknown distribution. Thus the distribution of *u* is taken as fixed and the location of *log(w)* is shifted linearly by *log(Δt)*. We expect to find a positive parameter for *log(Δt)* corresponding to a positive slope of quantiles in figure 2. The parameters γ are estimated using Klein-Spady. The Zheng test statistic is applied to test the restriction of model (2) against the general model *P(y=1|log(v),log(Δt))*. Results are shown in Table 4.

Table 4. Estimation results

	Bus	Metro	S-train	Train
γ, log(Δt)	0.30842 (10.19)	0.17231 (2.29)	0.27651 (4.67)	0.49295 (19.47)
Zheng statistic	-0.01	0.02	-1.37	1.69

t-statistics in parentheses

The Zheng test accepts the linear restriction in all cases. The estimated slopes are all positive and significant. It thus seems that model (d.) is the more adequate model for the data after allowing for dependence of *w* on *Δt*.

4.3 Introducing journey time

Looking at the magnitudes of the slopes estimated in Table 4, it seems some systematic variation might still be present. The slope is largest for train, which also has the longest journey times; bus

has both the second largest journey time and slope parameter. It is also the case that the size of the time saving presented is the choice situation is partly determined by the journey time, since the design sets time savings by relative variations around the actual journey and journey times cannot be negative.

Therefore we expand the model by including the variable *jtime* for travel time in the main mode. We specify the model

$$log(w) = \gamma\, log(\Delta t) + \eta log(jtime) + u \qquad (3)$$

and estimate the parameters using Klein-Spady and test the restriction with the Zheng test. The results are shown in Table 5.

Table 5 Estimation results

	Bus	Metro	S-train	Train
γ, log(Δt)	0.31798 (7.90)	0.31682 (4.10)	0.3643 (5.34)	0.30681 (9.70)
η, log(jtime)	-1.93E-02 (-0.54)	-0.27277 (-4.87)	-0.26835 (-4.09)	0.29537 (9.00)
Zheng statistic	1.85	-0.64	2.31	1.29

t-statistics in parentheses

The coefficient for *log(Δt)* is always positive and significant and the estimates are now very similar across modes in contrast to the model without *jtime*.

The sign of the coefficient for journey time varies significantly between modes. It is significantly negative for metro and S-train, which have short trips on average, and significantly positive for train, which is a more comfortable mode and has longer trips on average.

The Zheng test now accepts the semiparametric model except for S-train. The rejection for S-train is not strong, but indicates that the relationship is not exactly linear or that independence of *u* and *(log(Δt),jtime)* does not hold.

Local logit regressions of y on $(\log(jtime), \log(v)-\gamma\log(\Delta t))$ are performed with results shown in Figure 3. The slopes estimated in Table 5 are also in evidence in the figure. Independence of u and the index implies that the quantiles should be parallel in Figure 3, which they seem to be. Thus the assumption of independence is a fair approximation to the data.

4.4 Introducing more covariates

The conclusions of the previous section are checked by adding a number of variables to the model. Define the model

$$\log(w) = \delta x + u \text{ and } y = 1\{\log(w)<\log(v)\}. \quad (4)$$

Descriptive statistics for the variables are provided in Table 6. The variable *Sex* is 1 for females and 0 otherwise; *income* is after-tax personal annual income; *inc1* is a dummy for the lowest income group (<100,000 DKK/year); *inc NA* is a dummy for missing income information; *Commute* is 1 when the travel purpose is commuting; *Passengers* is 1 when there is at least one accompanying person on the trip. Note that *log(income)* and *age* have been demeaned before input to the estimation procedure.

Table 6. Descriptive statistics for covariates

	Bus	Metro	S-train	Train
log(Δt)	1.722	1.4722	1.5729	2.1758
log(jtime)	3.1995	2.6153	2.9662	4.008
Sex	0.61603	0.53167	0.57176	0.55234
log(income)	11.621	11.774	11.863	11.725
inc1	0.24667	0.19262	0.15169	0.22002
inc NA	0.0896	0.052586	0.044049	0.065633
Commute	0.25301	0.25015	0.27392	0.21711
Passengers	0.2225	0.30767	0.28471	0.28081
Age	38.318	36.503	40.679	38.234

The coefficients in Table 7 are estimated using Klein-Spady. The coefficients for *log(Δt)* and *log(jtime)* are much the same as before. The coefficients to *log(jtime)* have become somewhat smaller in absolute value compared to model (3), indicating that the inclusion of other variables accounts for some of this effect. Furthermore, we notice that income has a strong influence on the location of the WTP distribution with a significantly positive coefficient in all cases. Women have lower WTP than men with similar values of the coefficients for all modes, the coefficients are however only significant for bus and train. The travel purpose dummy for commuters is only significant for Metro. The presence of accompanying persons has no detectable influence on WTP.

Table 7. Parameter estimates

	Bus	Metro	S-train	Train
log(Δt)	**0.343 (8.71)**	**0.327 (4.00)**	**0.363 (5.01)**	**0.288 (8.73)**
log(jtime)	-0.050 (-1.45)	**-0.259 (-4.36)**	**-0.212 (-3.02)**	**0.255 (7.44)**
sex	**-0.090 (-2.09)**	-0.053 (-0.88)	-0.115 (-1.72)	**-0.124 (-2.72)**
inc	**0.451 (6.54)**	**0.514 (5.58)**	**0.802 (7.80)**	**0.700 (9.07)**
inc1	**0.274 (2.69)**	0.273 (1.88)	**0.774 (4.58)**	**0.776 (6.97)**
inc na	-0.076 (-0.94)	0.083 (0.60)	0.197 (1.24)	0.057 (0.64)
commute	0.041 (0.78)	**0.388 (4.99)**	0.002 (0.02)	-0.056 (-0.93)
passengers	0.019 (0.36)	0.088 (1.26)	0.030 (0.39)	0.025 (0.48)
age	-0.001 (-0.50)	-0.006 (-1.66)	**-0.014 (-4.58)**	0.003 (1.44)
agesq/100	**-0.032 (-3.78)**	-0.016 (-0.99)	0.006 (0.39)	**-0.078 (-7.14)**

t-statistics in parentheses

This model is tested twice by the Zheng test. First for the hypothesis that E(y|v,δx) = E(y|log(v)-δx) with δ taken as the parameter estimates in Table 7. This is accepted for all four modes. This says that conditional on the definition of the index δx, we can accept model 4, whereby log WTP is equal to the index plus an independent error. Second, the Zheng test is applied for the hypothesis that E(y|v,log(Δt),log(jtime),δx) = E(y|log(v)-δx). In this case the test rejects the hypothesis for all modes. This indicates that there is scope for elaborating the model, for example with higher order terms and interactions between the independent variables. That is not required for the purpose of this paper.

Table 8. Zheng test statistics

	Bus	Metro	S-train	Train
E(y|v,δx) = E(y|log(v)-δx)	-0.09	1.13	-0.24	-0.43
E(y|v,log(Δt),log(jtime),δx) = E(y|log(v)-δx)	6.66	3.70	4.32	4.13

5 DISCUSSION

We shall discuss the findings of the paper, first the findings concerning model specification and then the findings related to WTP for travel time savings.

The analysis has presented some fairly clear findings concerning model specification; all subject to the qualification that they apply, strictly, only to the current data. It is of interest to test whether they apply also to other datasets. First of all, models with fixed parameters in preference space and an independent error fit the data quite badly, this includes specifically the logit model in preference space. Formulating a model in WTP space and interpreting random variation as preference variation leads to a very simple model enabling the estimation of a number of effects that would otherwise have been hard to discern. Transforming the model to WTP space enables us to accept the index assumption that $log(w) = \delta x + u$ where u is an independent random variable. This leaves little potential for models including more heterogeneity such as the mixed binomial logit model.

The semiparametric model is perfectly capable of predicting choices. If desired it is possible to replace the nonparametric distribution of the error term with a parametric distribution. Fosgerau (2005) presents a methodology for fitting a parametric distribution to the nonparametric distribution of u for the purpose of estimating the mean WTP, $E(w)$.

We have found that preference variation seems to be the main source of variation in the data, but it can be expected that optimization errors also play a role. It would be ideal to be able to distinguish preference variation and optimization errors in a nonparametric way not relying on strong prior assumptions. As noted by Lewbel et al. (2002), it is however also a hard problem. An estimator of the two distributions is conceivable using a panel data specification not unlike the mixed binary logit model, but with seminonparametric distributions (Pagan & Ulla, 1999) of both errors and WTP.

It is a firm conclusion that the distribution of WTP is shifted up by increasing the size of the time saving. This presents a problem for the use of the estimated WTP for project evaluation, which requires a single price of time for consistency. Otherwise splitting a project into smaller projects each with smaller time savings could yield different results from treating the project as a whole. So some interpretation of the estimation results is required in order to derive values for application in practical cost-benefit analysis. The subject of small travel time savings in project evaluation is discussed in Welch & Williams (1997) and Mackie et al. (2001).

Using similar data, Hultkrantz & Mortazawi (2001) find also that small travel time savings are valued less than large. The effect has also been found in the UK (Bates & Whelan, 2001) and the Netherlands. Hultkrantz & Mortazawi argue mainly in favor of an explanation in terms of decision costs whereby the effort in deciding whether a given time saving is worth the cost may outweigh the potential gain. This effect could be interpreted as a short-term phenomenon, perhaps relating to the fixed schedule of respondents in the short term, or even as an artifact of the experimental choice situation, neither is relevant for project evaluation. If, on the other hand, the effect is thought to persist in real choices, then there should be significant consequences for evaluation of projects involving many small time savings. Given that household have many ways of adapting to changed travel times in the long term, one may lean toward the first interpretation of the small travel time savings effect. Then the value of travel time savings should be corrected for the effect before application in cost-benefit analysis. The effect does however not seem to level off at larger time savings, which could be a source of some uneasiness.

The coefficient to log(jtime) varies between modes in a way that seems to be systematic and related to the relative comfort of the modes. It is negative for Metro and S-train, insignificant for bus, but positive for train. Fosgerau (2005a) estimated a positive coefficient for log(jtime) in a similar model for a dataset consisting of car drivers. A common intuition is that the WTP for time savings is lower

in a comfortable mode where one can work or enjoy a private space. But it does not seem reasonable that this effect should diminish for longer journeys; one would expect the opposite. There is however another potential explanation, also related to comfort. According to this explanation, people could be self-selecting into modes according to their WTP and the strength of the self-selection could increase with the length of trip. Our model controls for observable characteristics so consider as an example a population of travelers that are identical except for the WTP for travel time, which has a random distribution from our point of view. For short trips they may all have similar probabilities of choosing the different modes. But for longer trips it seems likely that those with a high WTP tend to choose the more comfortable modes, while those with lower WTP choose the cheaper and less comfortable modes. This effect could produce the observed relation between coefficients.

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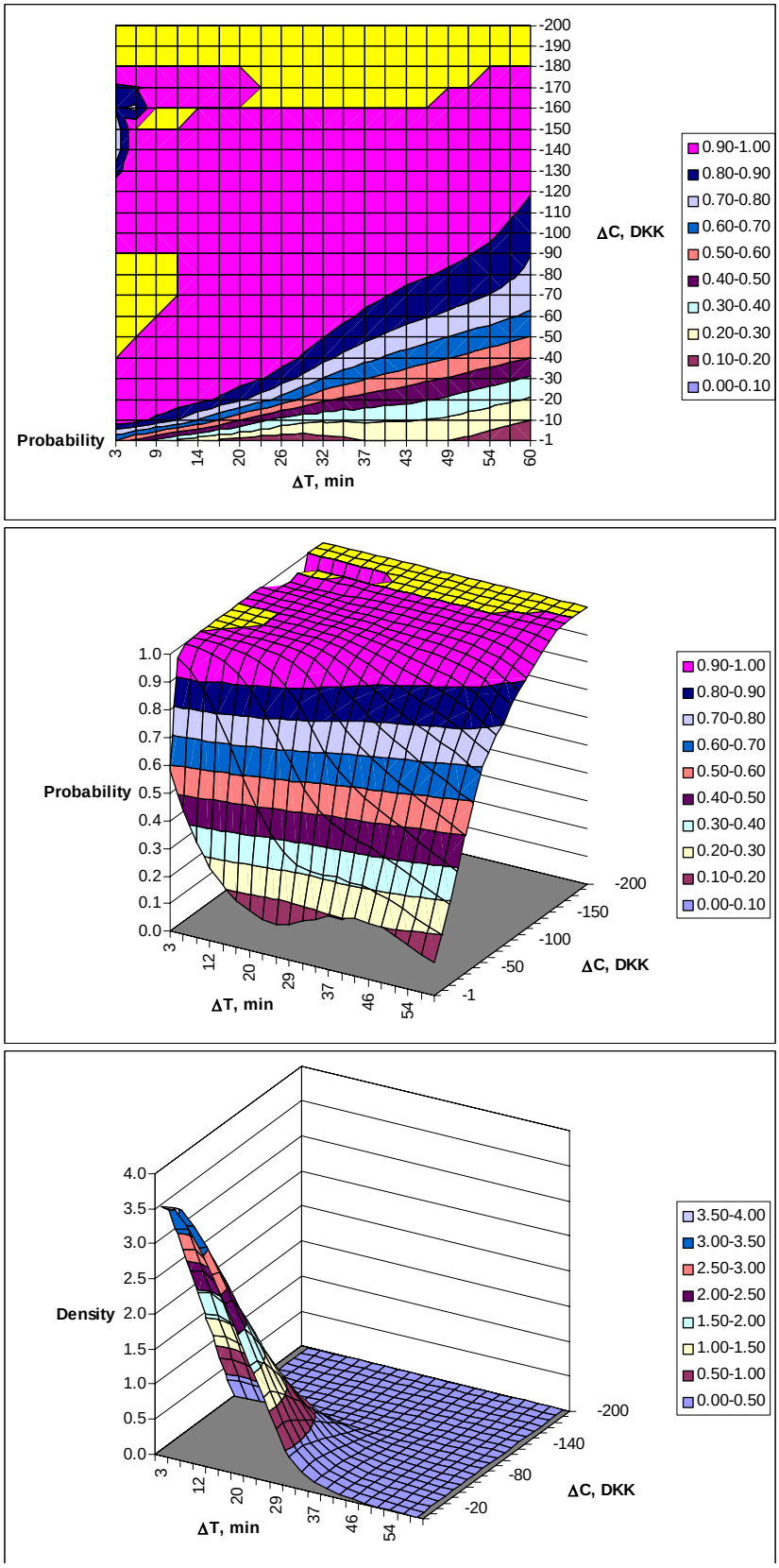
Probability
ΔT, min
ΔC, DKK
0.90-1.00
0.80-0.90
0.70-0.80
0.60-0.70
0.50-0.60
0.40-0.50
0.30-0.40
0.20-0.30
0.10-0.20
0.00-0.10
Probability
ΔT, min
ΔC, DKK
0.90-1.00
0.80-0.90
0.70-0.80
0.60-0.70
0.50-0.60
0.40-0.50
0.30-0.40
0.20-0.30
0.10-0.20
0.00-0.10
Density
ΔT, min
ΔC, DKK
3.50-4.00
3.00-3.50
2.50-3.00
2.00-2.50
1.50-2.00
1.00-1.50
0.50-1.00
0.00-0.50

Figure 1: Bus

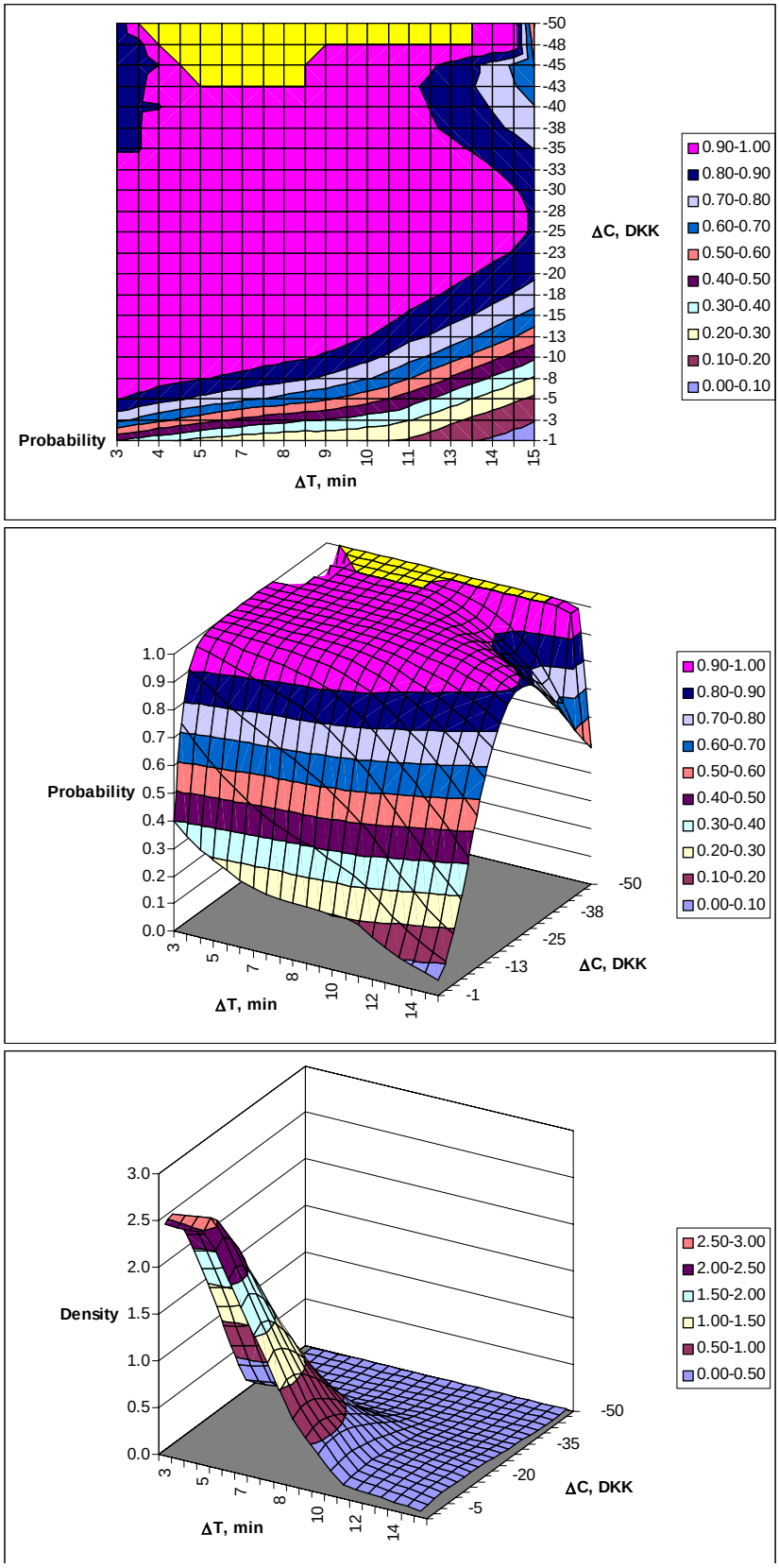
Probability
ΔT, min
ΔC, DKK
0.90-1.00
0.80-0.90
0.70-0.80
0.60-0.70
0.50-0.60
0.40-0.50
0.30-0.40
0.20-0.30
0.10-0.20
0.00-0.10
Probability
ΔT, min
ΔC, DKK
0.90-1.00
0.80-0.90
0.70-0.80
0.60-0.70
0.50-0.60
0.40-0.50
0.30-0.40
0.20-0.30
0.10-0.20
0.00-0.10
Density
ΔT, min
ΔC, DKK
2.50-3.00
2.00-2.50
1.50-2.00
1.00-1.50
0.50-1.00
0.00-0.50

Fig 1: Metro

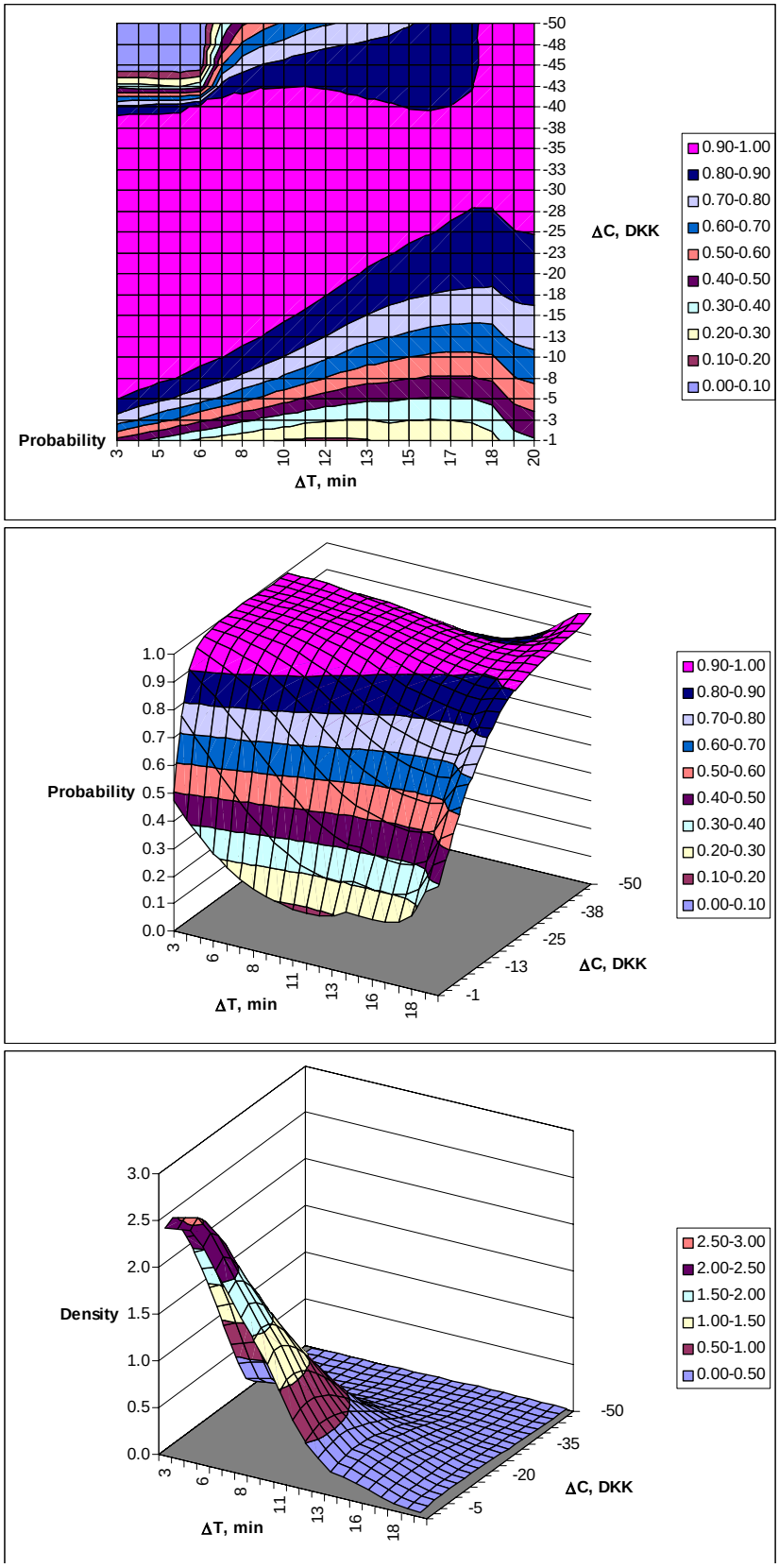

Figure 1: S-train

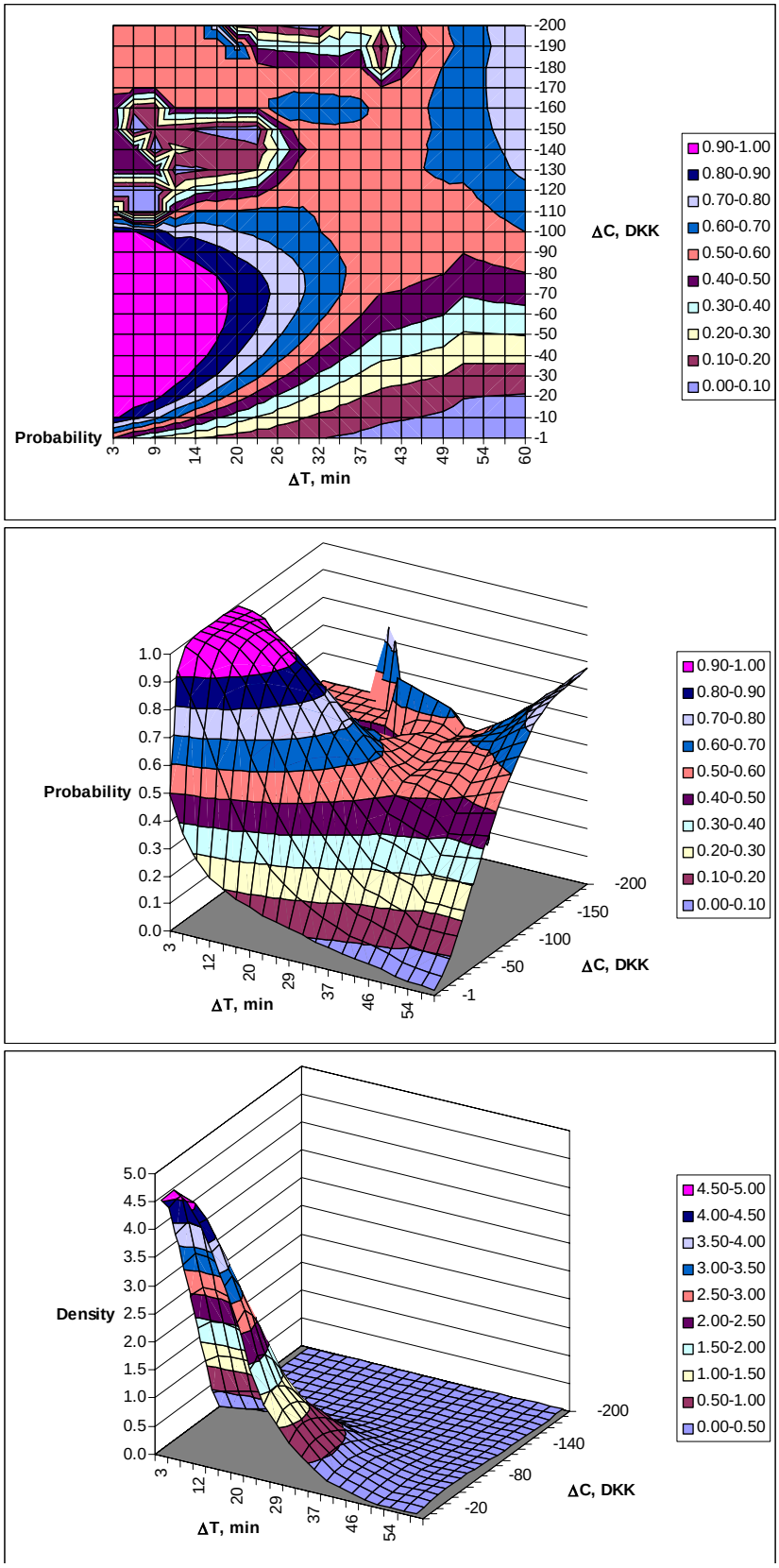

Figure 1: Train

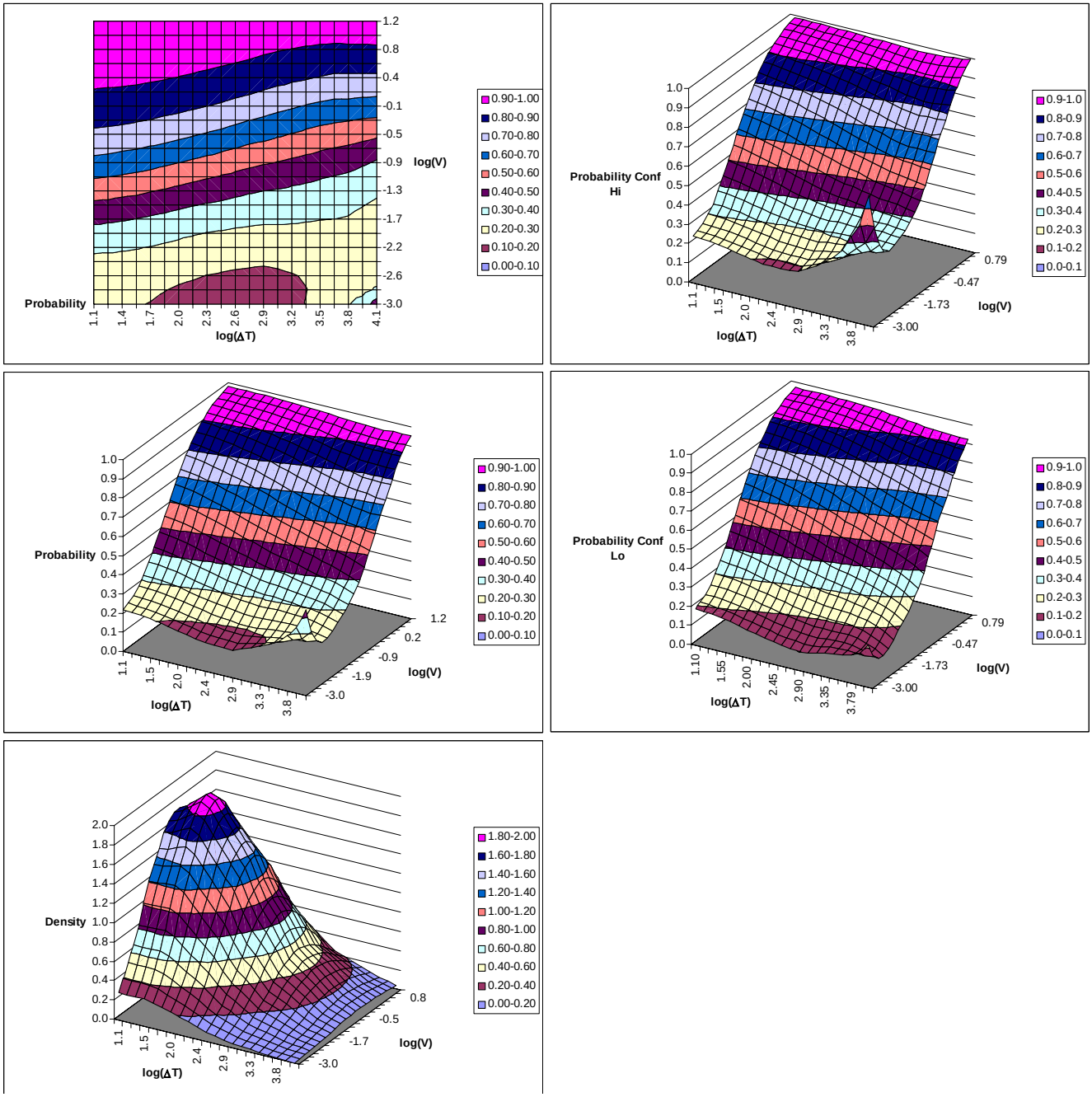
Probability
log(ΔT)
log(V)
0.90-1.00
0.80-0.90
0.70-0.80
0.60-0.70
0.50-0.60
0.40-0.50
0.30-0.40
0.20-0.30
0.10-0.20
0.00-0.10
Probability Conf Hi
0.9-1.0
0.8-0.9
0.7-0.8
0.6-0.7
0.5-0.6
0.4-0.5
0.3-0.4
0.2-0.3
0.1-0.2
0.0-0.1
Probability Conf Lo
Density
1.80-2.00
1.60-1.80
1.40-1.60
1.20-1.40
1.00-1.20
0.80-1.00
0.60-0.80
0.40-0.60
0.20-0.40
0.00-0.20

Figure 2: Bus

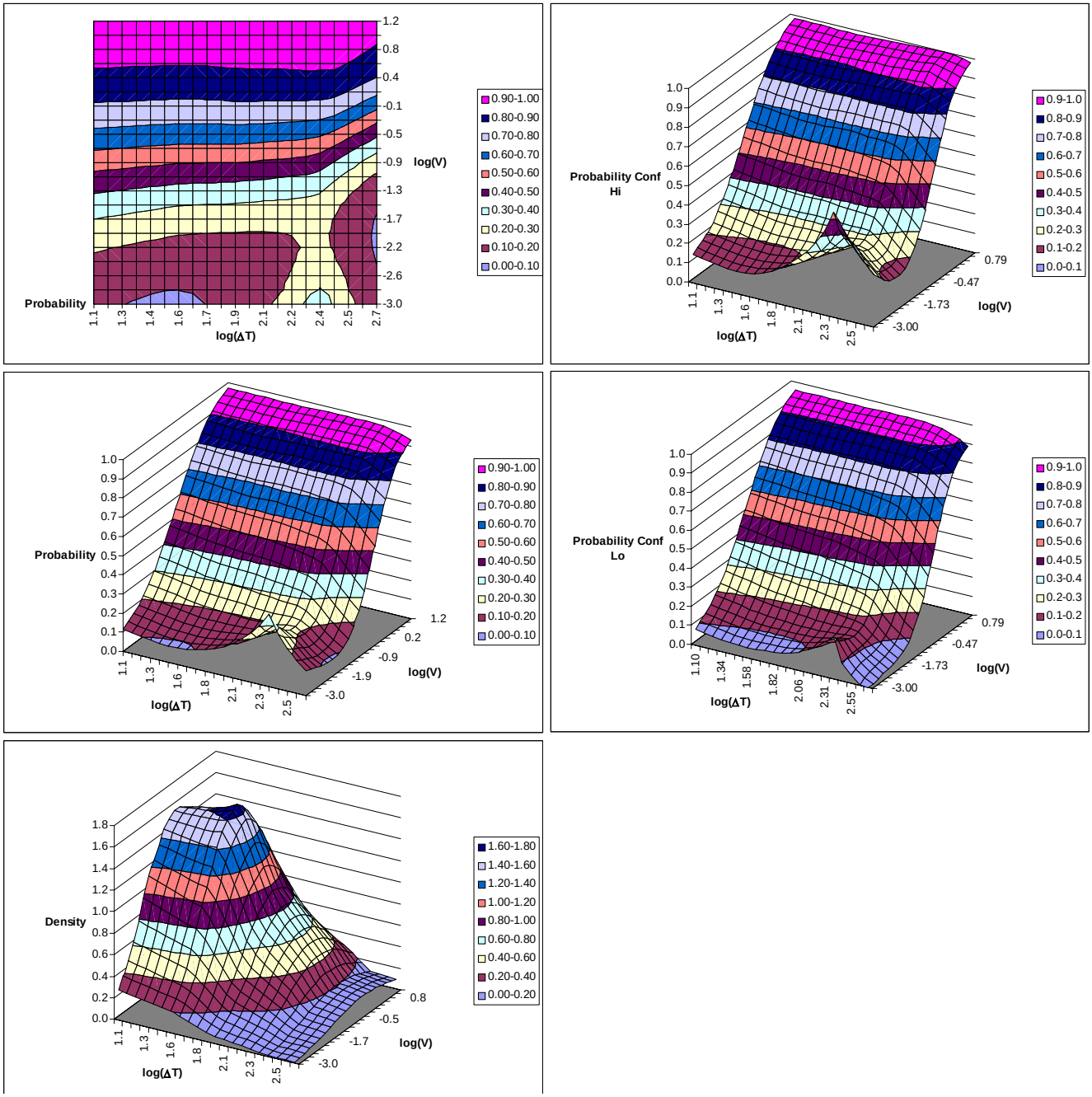

Figure 2: Metro

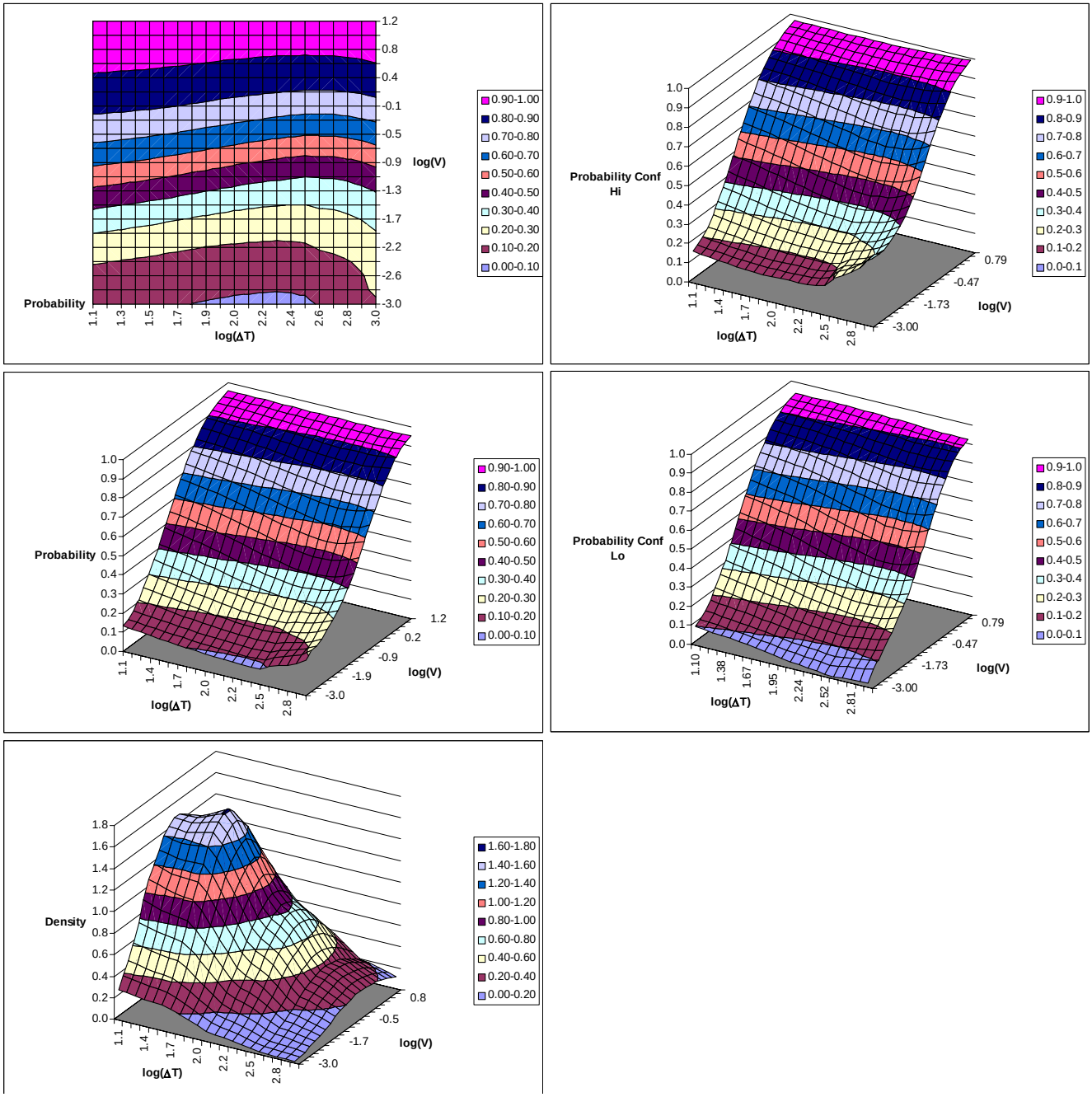

Figure 2: S-train

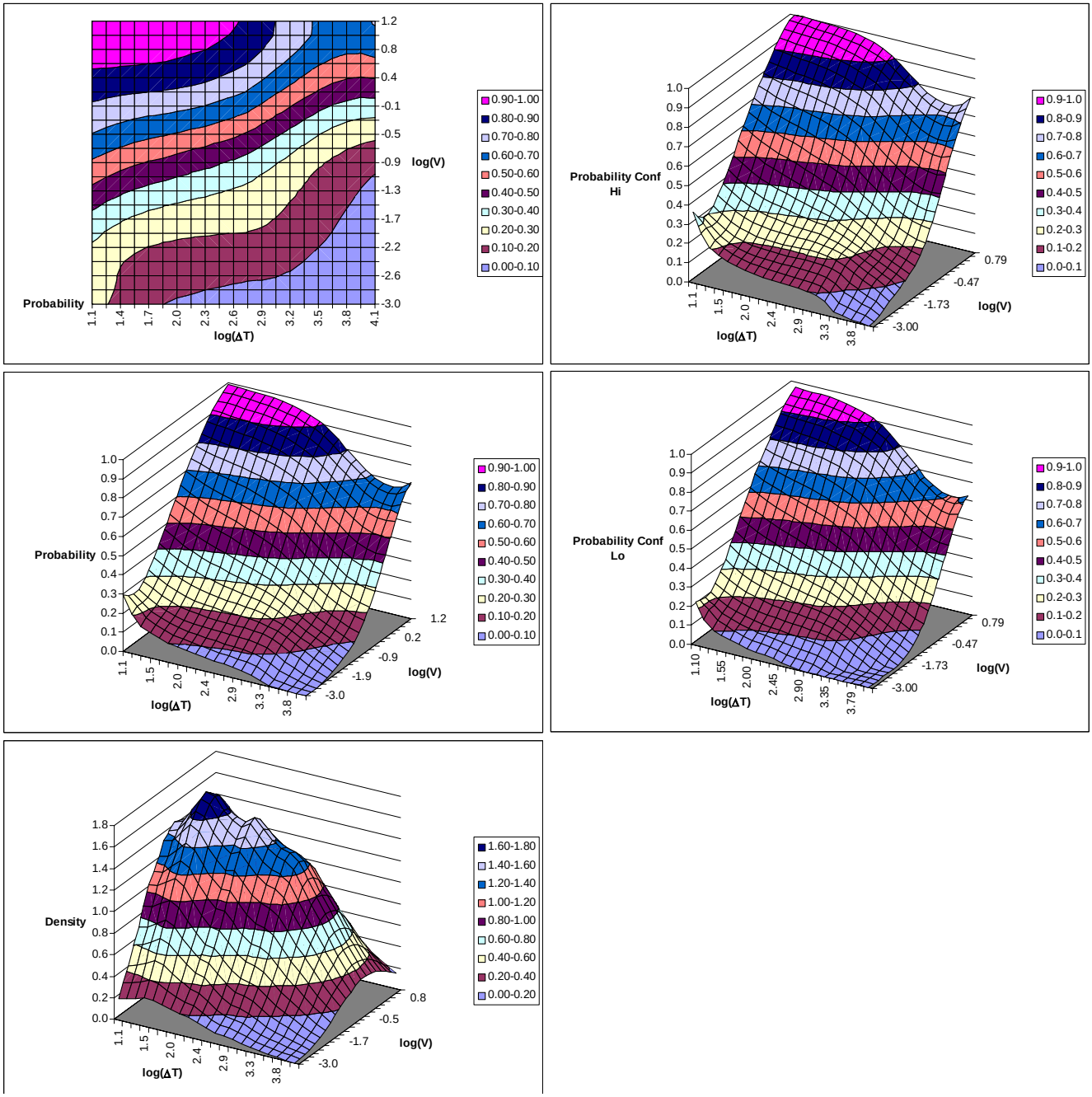

Figure 2: Train

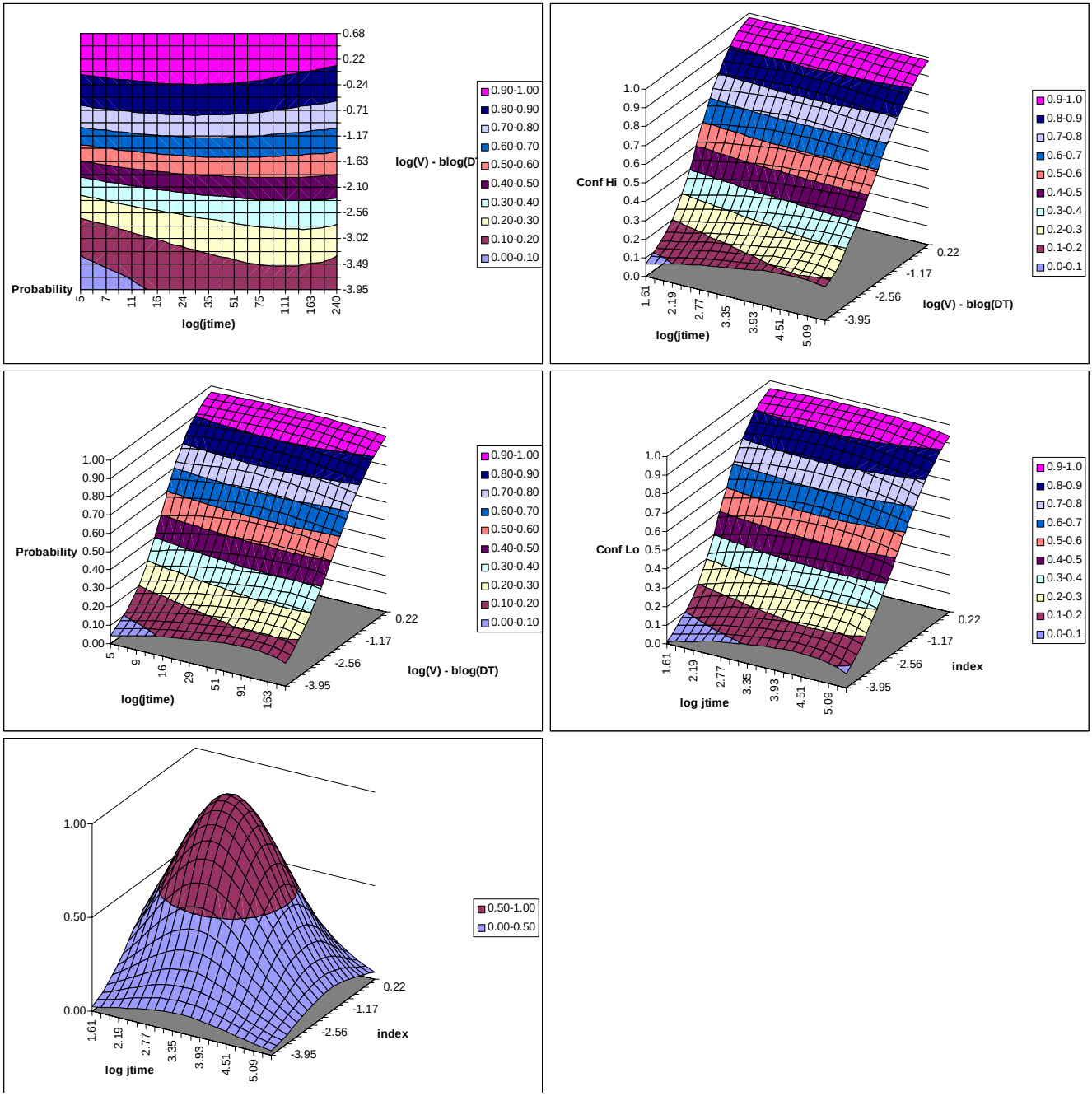
Probability
log(jtime)
log(V) - blog(D
0.68
0.22
-0.24
-0.71
-1.17
-1.63
-2.10
-2.56
-3.02
-3.49
-3.95
5 7 11 16 24 35 51 75 111 163 240
0.90-1.00
0.80-0.90
0.70-0.80
0.60-0.70
0.50-0.60
0.40-0.50
0.30-0.40
0.20-0.30
0.10-0.20
0.00-0.10
Conf Hi
log(jtime)
log(V) - blog(DT)
1.61 2.19 2.77 3.35 3.93 4.51 5.09
0.22 -1.17 -2.56 -3.95
0.9-1.0
0.8-0.9
0.7-0.8
0.6-0.7
0.5-0.6
0.4-0.5
0.3-0.4
0.2-0.3
0.1-0.2
0.0-0.1
Probability
log(jtime)
log(V) - blog(DT)
5 9 16 29 51 91 163
Conf Lo
log jtime
index
0.50-1.00
0.00-0.50

Figure 3: Bus

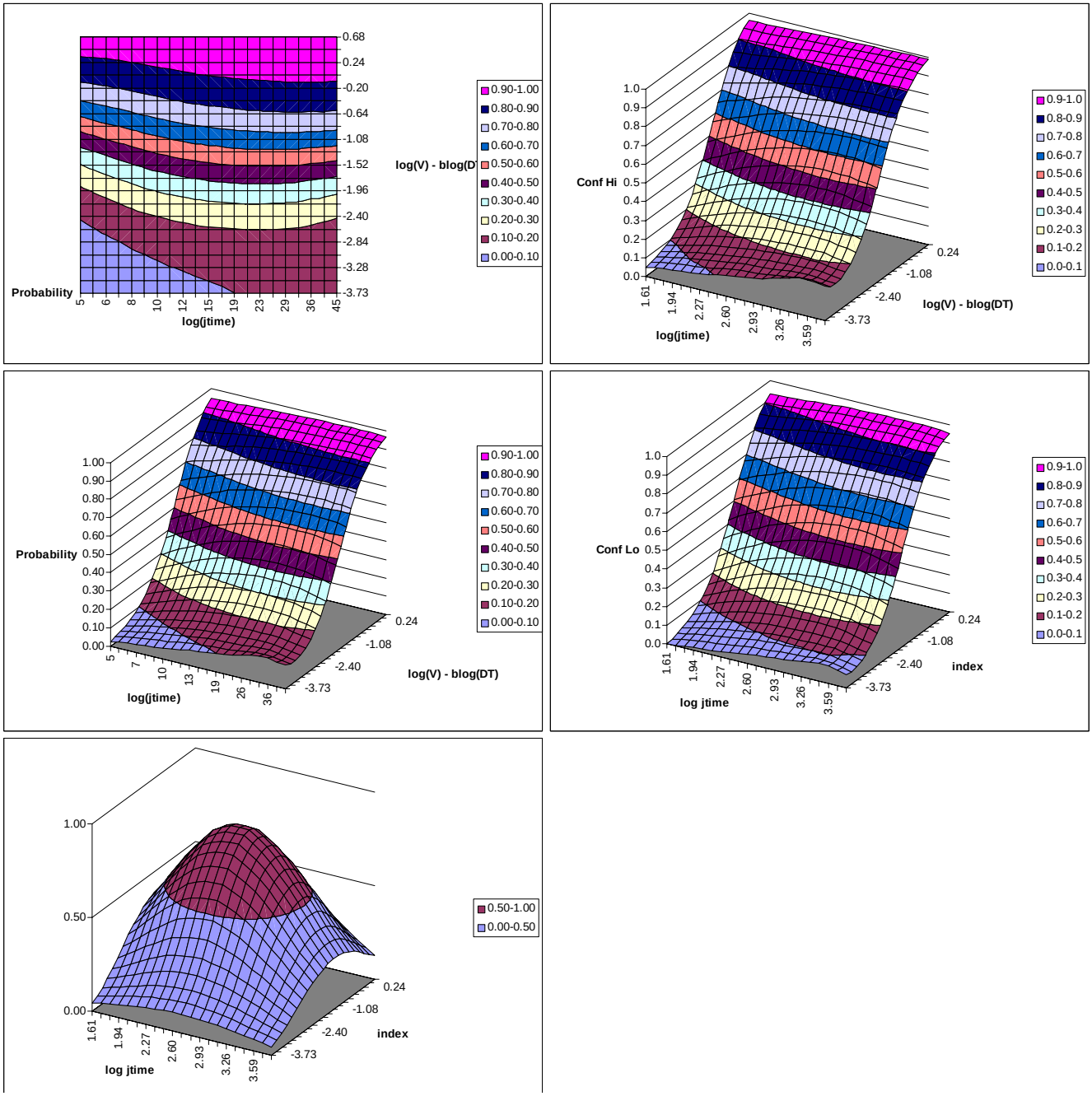

Figure 3: Metro

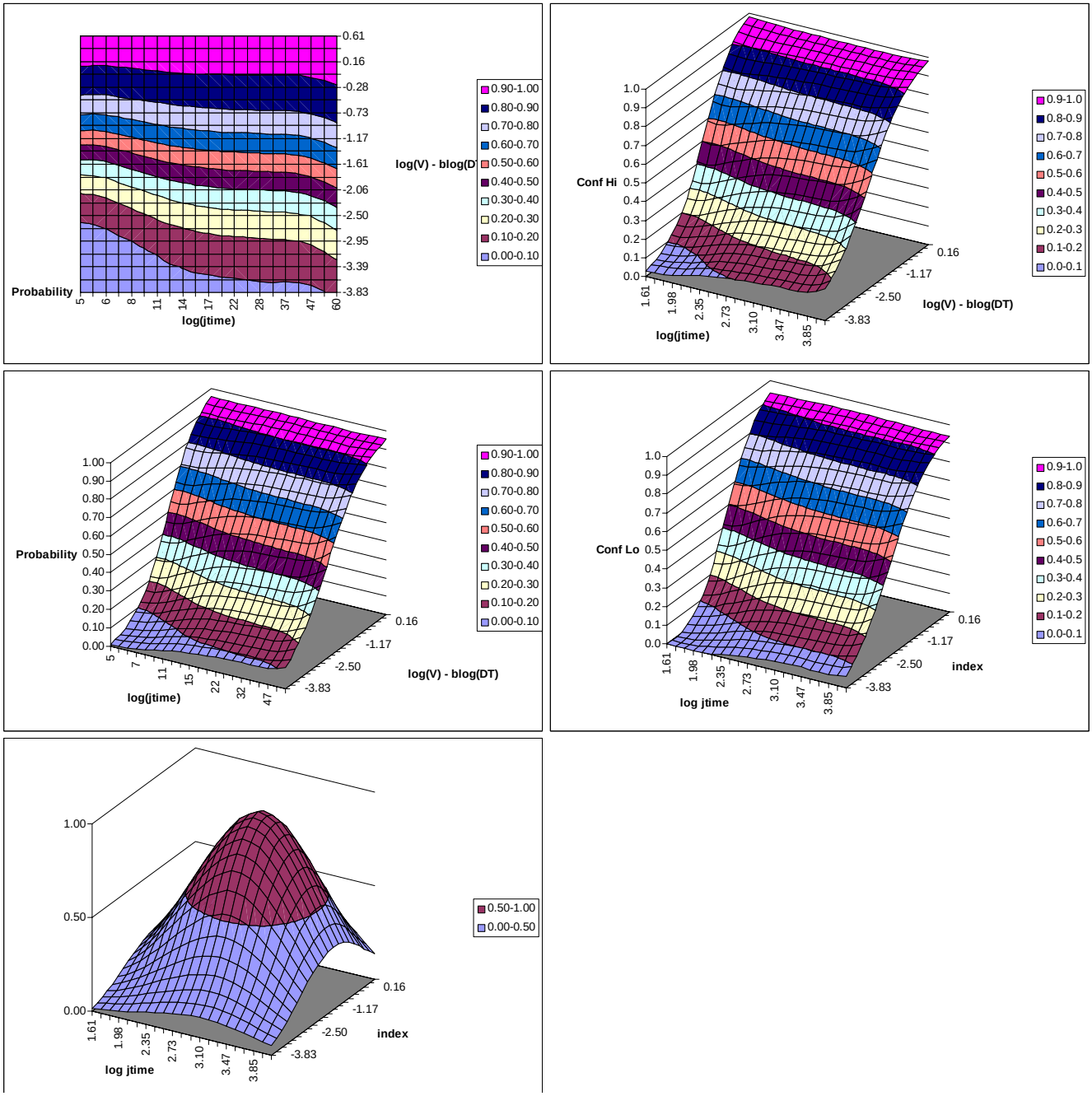

Figure 3: S-train

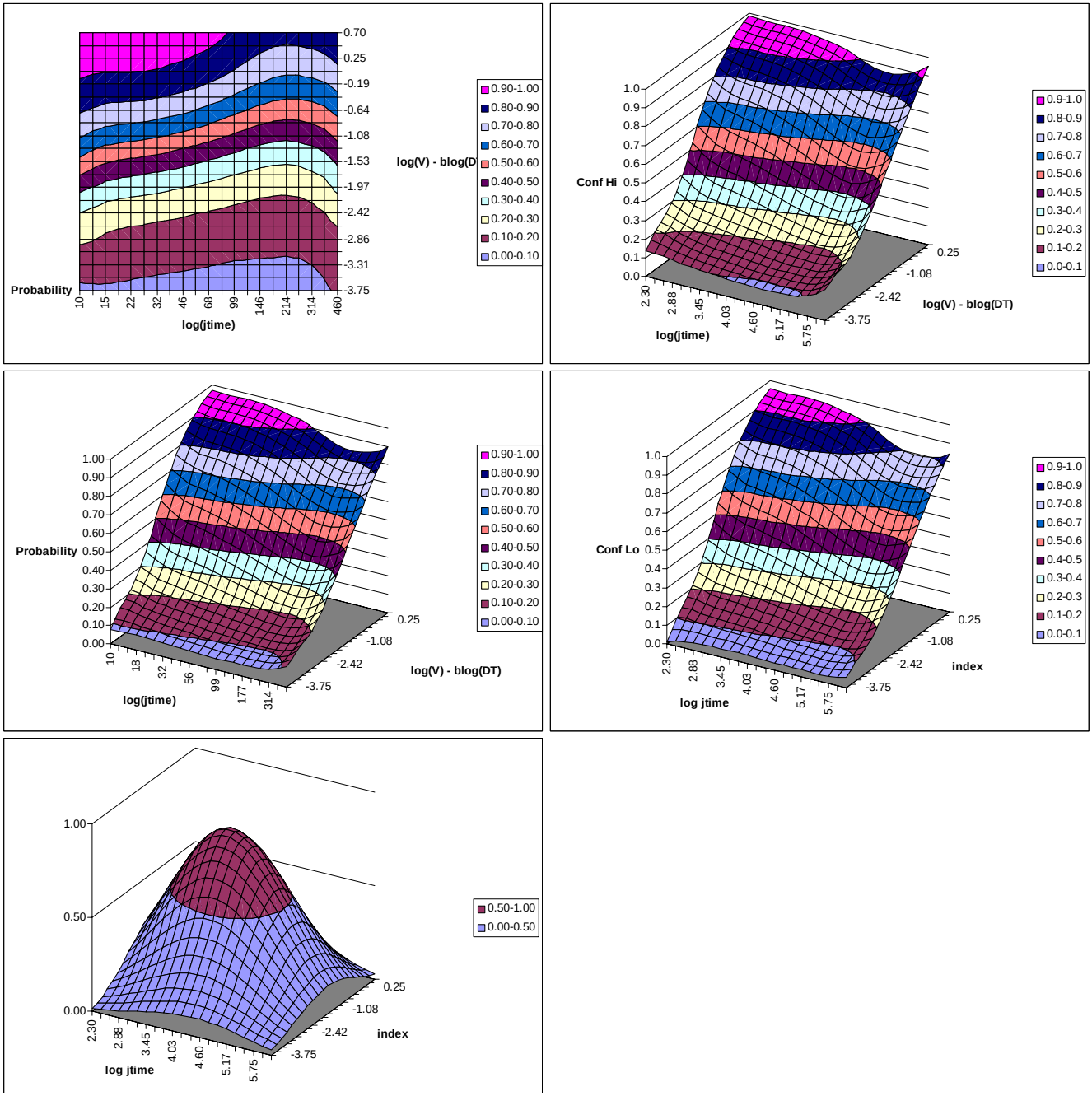

Figure 3: Train