Confidence Sets for Asset Correlation

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February, 2007

Abstract

This paper addresses the estimation of confidence sets for asset correlation for credit risk assessment using rating transition data. Research on the estimation of asset correlation with rating transition data has focused on the point estimation of the correlation without giving any consideration with respect to the uncertainty around this point estimators. We obtain for both approaches, Standard Transition Matrix (STRM) and Directional Transition Matrix (DRTM), confidence intervals for the pairwise asset correlations. In both cases it is a regularity to find that the inferior bounds are most of the time negative while the superior bounds are most of the time positive, implying that most of the correlations are not significantly different from zero.

1 Introduction

The assessment of the credit risk of a financial institution requires a portfolio analysis due to the fact that it is necessary to consider simultaneously all of the institutions credit related instruments across a pool of obligors. This portfolio analysis requires an explicit consideration of the relationship between the obligors/issuer[1] risk and exposure, this is where default dependence between issuers becomes important.

There are numerous articles both in the professional and academic literature that have dealt with the estimation of the correlation structure within the portfolio; specifically in determining the asset correlation between the issuers[2]. Within this literature we find two competing approaches. The first approach defines a structural relation between a latent variable (the asset values of the

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[1]Although the focus on client/issuer is restrictive and it could be more general to consider a portfolio of all credit instruments, the focus of the paper is on the the diversification effects across groups of client/issuer types and not on particular instruments.

[2]As pointed out by McNeil, Frey and Nyfeler (2001), concentrating on the correlation estimates is not enough since the aggregate portfolio loss distribution is often very sensitive to the exact nature of the multivariate distribution used to estimate the joint default probability.

firm) that determines the dynamics of the rating transitions and the probability of default. Since there is a structural model that links the evolution of the latent variable and the probability of default, for estimation purposes we consider this type of approach as parametric (see Gordy and Heitfield (2002), Demey, Jouanin, Roget and Roncalli, Schonbucher (2000)). A second approach uses the directly observed data of rating transitions and defaults to tabulate the univariate and bivariate rating transitions and default probabilities; for estimation purposes we consider this method as non-parametric (see Akhavein, Kocagil and Neugebauer (2005), Fu et al. (2004), Servigny and Renault (2003)). Naturally both approaches have their strengths and weakness that should be dully noted.

The aim of this article is to concentrate on the direct/non-parametric approach for estimating asset correlation, review the two methods to derive the transition matrices (standard and directional) and estimate confidence sets for asset correlation to determine the amount of uncertainty around the point estimators. Most professional practitioners that work with the direct/non-parametric approach have concentrated on the point estimation of asset correlation without taking a proper analysis of the uncertainty around the estimators.

We obtain for both approaches, Standard Transition Matrix (STRM) and Directional Transition Matrix (DRTM), confidence intervals for the pairwise asset correlations. In both cases, it is a regularity to find that the inferior bounds are most of the time negative while the superior bounds are most of the time positive, implying that most of the correlations are not significantly different from zero.

The outline of the paper is as follows in: Section 2 reviews and compares the two approaches for obtaining asset correlations (parametric vs non-parametric). Section 3 focuses on the direct/non-parametric approach and its two main ramifications: standard transition matrices and directional transition matrices. Section 4 describes the dataset and comments on some data issues that are common in working with the institutional rating data. Section 5 describes the asset correlation estimation results following the two approaches considered in section 3. Section 6 gives a brief description and results of the bootstrap technique used to obtain the confidence sets and Section 7 concludes the paper.

2 Review of the methods to estimate asset or default correlation

Credit risk analysis is primarily concerned with the shape of the loss distribution for a portfolio of assets. Particularly, more concern with the tails of the distribution is given when determining the adequate amount of capital an institution must put aside to cover its operations. With this in mind, correlation measurement has gained importance for professional practitioners as well as academics in the field of risk management. Changes in the correlation between assets transfers some of the risk from the mean toward the tail of the loss distribution; for example an increase in the correlation between assets fattens the tail of the loss distribution and therefore requires a greater amount of capital set aside to cover the possible losses born out of the underlying assets.

In the credit risk literature the most frequently used methods to estimate asset/default correlation can be considered for estimation purposes as parametric and non-parametric. It is more common to make the characterization out of the difference in the data, whether the data used is based on historical rating and default data or the data is equity information[3]. However, this differentiation might not be the most appropriate both theoretically and empirically. Theoretically it is possible to embed a credit migration model (like Creditmetrics) as a structural firm value model (see Gordy (1998)). Empirically the factor type models used with equity data to disentangle the systematic and idiosyncratic risk from the latent variable which represents the returns on an obligor/issuer assets, have been also applied on rating data (see Gordy and Heitfield (2002), Demey, Jouanin, Roget and Roncalli).

The most common industry type of factor-based regression models use equity prices (J.P. Morgan and Co (1997), Servigny and Renault (2003)) or a relation between equity returns and liabilities (see Fu et al. (2004)) as proxies for the asset values of the firms. Equity correlations are considered as proxies for asset correlations. In Creditmetrics (1997) equity return correlations are used as proxies of asset return correlations; the method relies in producing correlation estimates between sector/country indexes, that are then mapped onto the obligors by industry participation. Other more academic approaches to the factor models use method of moments or maximum likelihood type estimation techniques (see Gordy and Heitfield (2002), Demey, Jouanin, Roget and Roncalli).

The direct observations in the rating changes including the migration from the non-default states to default are used to draw inference with respect to the asset/default correlations between obligors. With the direct observation of rating migrations it is possible to determine both individual and joint transition probabilities between grades (Aaa, Aa, A, Baa,...), without any precise structural assumptions. This non-parametric type estimators of the transitions probabilities are then used directly to infer asset correlations from the rating movements (upgrade, downgrade, no-movement) under the Directional Transition Matrix approach. It is also possible to use the individual and joint transition probabilities from the non-default grades to the default grade to estimate default correlations across groups of issuers (industries and/or countries). After the default correlation are estimated, a copula (in most cases the Gaussian copula) is used to map the asset correlations from the individual and joint default probabilities.

When comparing the parametric vs the non-parametric approach it is common to find the following appreciations (Akhavein, Kocagil and Neugebauer

[3]Credit spread data is sometimes considered; however, this data contains additional information that is difficult to disentangle from the information that the spread contains with respect to the creditworthiness of an obligor/issuers. Comparing this property of spread data to equity and rating data, makes the former less likely to be used when the other data is available.

(2005), Fu et al. (2004), McNeil, Frey and Embrechts (2005)):

- Default events, although very direct in terms of capturing correlations between obligors, are also very rare, sometimes null for the investment grades (Aaa,Aa,A,Baa). Therefore it is very difficult to draw inference across some issuer groups. Sometimes, aggregations are required, at the cost of loosing the more granular information, in order to obtain a default observation within a particular group.
- Although equity information is more widely available for publicly traded obligors (complete granularity) it is an indirect way of capturing the correlation between obligors. Movements in equity prices contain additional information that will affect any inference on the creditworthiness of the underlying obligor, information that most likely bears little resemblance with changes on the default probabilities of the obligors.

3 Credit Migration Approach to estimating asset or default correlation

The credit migration approach uses historical credit rating information to determine the probability of migrating between non-default states and from these states to the default state, for a given time horizon. The historical information can be collected from the internal rating information of the financial institutions, however since this information is in most cases private most of the literature on the subject uses the rating information provided by major rating companies such as Moody's, Standard & Poor's or Fitch. Most rating systems assign a letter rating to a particular obligor/issuer. The ordered rating system considers each rating category as representing a homogeneous groups of issuers that share the same credit quality. Where quality can be considered as informative with respect to the creditworthiness of the issuer and its relative distance to default. From the historical information, particularly the number of issuers (from a sector or country) migrating from a given rating category to some other rating category, within a predefined time horizon, it is possible to obtain the transition probabilities. Transition probabilities are typically presented in the form of a rating transition probability matrix; an example using Moody's data for the banking sector is presented in Table 1.

The number of states considered for this Markov type transition matrix is determined by the number of rating, sometimes aggregating over some of the original groups considered by the rating agencies. In the paper we work with two migration based methods. The first method we denoted as the standard transition matrix method because the states in the transition matrix capture the broad rating categories used by Moody's. The second method we denote as directional transition matrix because it aggregates over the rating categories and considered only three directional states (upgrade, downgrade, no movement). However this differentiation is oversimplified since their main difference is in

ratings	Aaa	Aa	A	Baa	Ba	B	Caa-C	Default	WR
Aaa	0,901	0,078	0,002	0,000	0,000	0,000	0,000	0,000	0,019
Aa	0,009	0,904	0,067	0,002	0,000	0,000	0,000	0,000	0,018
A	0,001	0,025	0,907	0,041	0,004	0,001	0,000	0,000	0,022
Baa	0,002	0,005	0,130	0,762	0,054	0,010	0,008	0,001	0,028
Ba	0,000	0,000	0,015	0,078	0,787	0,050	0,010	0,007	0,052
B	0,000	0,000	0,002	0,020	0,157	0,613	0,053	0,080	0,075
Caa-C	0,000	0,000	0,000	0,000	0,071	0,035	0,396	0,358	0,140

Table 1: One year rating transition individual probability matrix corresponding to the Moody's data from 1970 to 2005, for industries of sector "Banks", using a time average estimator

the way to infer asset correlation from the transition matrix. Both methods will be more throughly explained in the following subsections.

3.1 Standard transition matrix method: STRM

The Standard transition matrix method considers straight migrations between the broad ratings to estimate the transition probabilities. In the literature one find two approaches; although we only use the most common cohort (multinomial) approach, we mentioned the duration or hazard rate approach in order to illustrate the main downside of the method we use for estimating the transition matrices. It is also relevant to mention that the cohort approach is used generally when the objective is to estimate asset/default correlation (Akhavein, Kocagil and Neugebauer (2005), Fu et al. (2004), Servigny and Renault (2003)), whereas the duration/hazard rate approach is used when the objective is the transition matrix itself (Skodeberg and Lando (2002), Schuermann and Jafry (2004), Christensen, Hansen and Lando (2004)).

In the cohort approach, the individual (only considering one grade at a time) transition probability from grade i to j over an horizon T(say a year) is given by:

$$p_i^j = \frac{N_{i,j}}{N_i} \tag{1}$$

where N_i is the number of issuers in rating category i at the beginning of the year and $N_{i,j}$ migrated to grade j by year-end. If a transition from i to j does not occur during the given period then the corresponding estimate is 0.

The duration or hazard approach uses a continuous time setup to capture the transition intensities which will allow not only to capture the directly observable default events (rare events) but also to take into account the indirect default possibilities, in the estimation of the transition probabilities (most important in our case the transition to the default state). In a continuous time data it is possible to think a transition as a time to event problem. The benefit is that the measure takes into account censoring (when we do not know what happens to the obligator after the relevant time window closes) and truncation (when obligator only enters the sample if they survived long enough). Under the assumption of time homogeneity in the Markov process, transitions probabilities can be described by a generator or intensity matrix (this is the equivalent of the transition matrix in a continuous time process)[4]. A maximum likelihood estimator for the individual transition probability from grade i to j over a horizon T is given by:

$$p_i^j = \frac{N_{i,j}(T)}{\int_0^T Y_i(s)ds} \tag{2}$$

where $Y_i(s)$ is the number of firms with rating i at time s and $N_{i,j}$ is the total number of transitions from i to j ($i \neq j$). The denominator is the effective time that an obligator spend in state i within a year (say we use monthly data, the obligator has one rating assigned per month). As pointed out by Skodeberg and Lando (2002) the gains of this estimator are the following:

- It is possible to obtain non-zero estimates for probabilities of events which the cohort/multinomial method estimate as 0. The continuous-time estimator captures indirect defaults, defaults that happen through a sequence of downgrades.
- It is possible to obtain estimates for the generator matrix for transitions probabilities for arbitrary time horizons.
- The estimator uses all available data in the information set by using information up until the date of a withdrawal rating and by including information of an obligator even when it enters a new state. In the cohort/multinomial method we do not distinguish the exact date within the year that a firm changed its rating.

Returning to the cohort approach, we now consider the joint (two obligators) transition probability from some initial rating to other rating. In this case, we need to consider some multinomial estimator that takes into account all the possible joint migration possibilities over a given horizon. Servigny and Renault (2003) considered the following cases required to cover all possible combinations of joint migrations for two obligators:

1. Migrations from the same starting rating i to the same rating k, denoted as $T_{i,k}$: If we recall that for a group of N_i elements, it is possible to create $N_i(N_i-1)/2$ different pairs, then the joint probability of migration (for a given time horizon, say a year) can be estimates as follows:

$$p_i^k = \frac{T_{i,k}(T_{i,k}-1)}{N_i(N_i-1)} \tag{3}$$

   The problem with the estimator above as mentioned by Servigny and Renault (2003) is that it can generate spurious negative correlation (when

[4] A more through explanation is found in Skodeberg and Lando (2002).

there are zero migrations from i to k). To solve this problem Servigny and Renault (2003) proposes the following estimator:

$$p_i^k = \frac{T_{i,k}^2}{N_i^2} \tag{4}$$

2. Migrations from the same starting rating i to different ratings k and l, denoted as $T_{i,k}$ and $T_{i,l}$: Using the same logic as before (following Lucas (2005))the joint probability of migration (for a given time horizon, say a year) can be estimates as follows:

$$p_{i,i}^{k,l} = \frac{T_{i,k}T_{i,l}}{N_i^2} \tag{5}$$

3. Migrations from different ratings i and j to different ratings k and l, denoted as $T_{i,k}$ and $T_{j,l}$: Using the same logic as before the joint probability of migration (for a given time horizon, say a year) can be estimates as follows:

$$p_{i,j}^{k,l} = \frac{T_{i,k}T_{j,l}}{N_iN_j} \tag{6}$$

In order to estimate the overall (through the sample) transition probabilities, given that there are approximately 20 to 30 years of disposable data, it is common to estimate simple or weighted time averages (weighted by the number of observations in the year) over the individual and joint transition matrices. This estimator assumes stationarity of the model over time, since the default event is considered as independent across the years in order to compounded the multinomial yearly estimates into this time averaged estimator[5]. This approach (time average estimator) is also considered in the literature as a through-the-cycle transition probability estimate, since out of the company rating data it is possible to construct this matrices from the 1970's. If the time horizon is yearly this gives about 35 of such matrices. When averaging across the matrices the time span covers multiple business cycles so in average it is considered in the literature that this overall matrix captures average economic conditions. Although it is also possible, and it is probably more accurate in terms of the assumption of stationarity, to nest the years according to some reference cycle indicator. This would allow risk managers to build interesting scenarios for their risk models, such as considering a *stressed* matrix estimated so as to capture the transitions probabilities observed just before and during a recession.

The empirical counterparts of the simple or weighted time average estimators of the joint transition probabilities, as mentioned in Gagliardini and Gourieroux (2005), are consistent estimators of the joint migration probabilities and migration correlation (in our case default correlation) as both the cross-section[6]

[5]This independence assumption can be considered as weak since economic cycles could induce serial dependence.

[6]By cross-section data we mean the information across the different obligors/issuers, in this particular phrase that would mean the number of issuers considered

and time dimensions tend to infinity. Whereas, if only the cross-section data is used, it is not possible to estimate consistently the migration correlations. Using a Monte-Carlo exercise the authors analyse the finite sample properties (1000 firms and 20 years) of the cross-section and the average estimators. They find that in the estimation of the joint probabilities both seem unbiased but the time average estimator features better accuracy than the pure cross-section estimator. On the other hand they also find that the theoretical inconsistency of the pure cross-section estimator could have serious consequences for any time averaged estimator of the migration correlation, with small finite time dimension. Their simulation results suggest some overall underestimation of the migration correlation.

In Table 2 we present an estimated joint bivariate probability matrix build by grouping the 9 broad Moody's ratings into investment grade, non-investment grade and default as the relevant states in the transition matrix. It is very important to recall that this joint transition probability estimates are obtained using the time average estimator mentioned before, averaging over the one year transition matrices from 1970 to 2005. The matrix is bivariate since it considers the information of the Banking and Diversified Financial sector. An interpretation of this matrix is the following: there is 0.004 probability that a company of sector "Banking" and a company of sector "Diversified Financials", both starting at a Non-investment grade rating, will after one year, end up both in default, and 0.011 that both types will end up with an investment grade rating.

Issuer 1	T(1)	IG	IG	IG	NIG	NIG	NIG	D	D	D
T(0)	Issuer 2	IG	NIG	D	IG	NIG	D	IG	NIG	D
IG	IG	0,995	0,002	0,000	0,002	0,000	0,000	0,000	0,000	0,000
IG	NIG	0,064	0,857	0,067	0,001	0,010	0,001	0,000	0,000	0,000
IG	D	0,000	0,000	0,988	0,000	0,000	0,012	0,000	0,000	0,000
NIG	IG	0,079	0,001	0,000	0,881	0,014	0,000	0,025	0,000	0,000
NIG	NIG	0,011	0,017	0,001	0,013	0,934	0,015	0,001	0,004	0,004
NIG	D	0,000	0,000	0,082	0,000	0,000	0,897	0,000	0,000	0,021
D	IG	0,000	0,000	0,000	0,000	0,000	0,000	0,984	0,015	0,000
D	NIG	0,000	0,000	0,000	0,000	0,000	0,000	0,060	0,871	0,069
D	D	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1,000

Table 2: One year rating transition joint probability matrix corresponding to the Moody's data from 1970 to 2005, for industries of sectors "Banks" and "Diversified Financials", using the time average estimator

The estimation of the individual p_i^k and joint $p_{i,j}^{k,l}$ transition probabilities can be considered as a first step toward estimating asset correlations. In the second step we use these probabilities to estimate default or asset correlation.

The estimator of the linear default correlation $\rho_{i,j}^{D,D}$ is defined as follows:

$$\rho_{1,i;2,j}^{D,D} = \frac{p_{1,i;2,j}^{D,D} - p_{1,i}^{D} p_{2,j}^{D}}{\sqrt{p_{1,i}^{D}(1-p_{1,i}^{D}) p_{2,j}^{D}(1-p_{2,j}^{D})}}, i,j \in \{IG, NIG\} \tag{7}$$

Where $p_{1,i}^{D}$ and $p_{2,j}^{D}$ is taken to be the individual transition probability from state i or j to the default state D, for issuer 1 and 2, respectably. $p_{1,i;2,j}^{D,D}$ is the joint transition probability that issuer 1 and issuer 2 migrate at the same time from state i and j, respectably, to the default state D. Both the individual and joint transition probabilities are estimates using the time average estimator mentioned before. To estimate asset correlations from the issuers' 1 and 2 individual and joint transition probabilities, we must make a distributional assumption on the bivariate distribution, to relate the transition probabilities with the *implied* asset correlation $\rho_{1,i;2,j}^{A}$. In the estimation we use a bivariate gaussian copula as follows: Let x_1 and x_2 denote the return on the asset values[7] of issuers 1 and 2.

$$p_{1,i;2,j}^{D,D} = \int_{-\infty}^{\phi^{-1}(p_{1,i}^{D})} \int_{-\infty}^{\phi^{-1}(p_{2,j}^{D})} \frac{1}{2\pi\sqrt{1-(\rho_{1,i;2,j}^{A})^2}} \exp\left\{ \frac{1}{2(1-(\rho_{1,i;2,j}^{A})^2)} \left[x_1^2 - 2\rho_{1,i;2,j}^{A} x_1 x_2 + x_2^2 \right] \right\} dx_1 x_2, i,j \in \{IG, NIG\} \tag{8}$$

With the individual and joint transition probabilities for issuer 1 and 2 estimated using the time average estimator it is possible to derive an *implied* asset correlation; using a grid search procedure to find the possible values[8] that satisfy equation 8 and the following restriction on asset correlation$-1 \leq \rho_{1,i;2,j}^{A} \leq 1$.

3.2 Directional transition matrix method: DRTM

The STRM, as presented in the previous section, can be considered as default driven since it only takes into account transitions from one non-default state to the default state (only concentrates in the last column of Table 2); therefore it only uses a handful of observations available from the historical rating data. On the other hand, a directional rating transition matrix (DRTM) is formed by considering three movements or states: upgrade (U), downgrade (D) and no movement (N), hence there is a substantial increase in the number of useful historical rating data with respect to the STRM method.

In order to construct the DRTM, we need to consider, for all possible pairs of obligors, the movements each year, and compute the number of joint movements after T years for those pairs. The DRTM corresponding to the Moody's data from 1970 to 2005, for industries of sector "Automobiles" and industries of sector "Capital goods" is shown in Table 3, with $T = 1$. An interpretation of

[7] We assume that the return on the asset values have a standard normal distribution.

[8] This procedure does no guarantee a unique value of the asset correlation, therefore we could have more than one possible value for the asset correlation that satisfies our system. When we estimate the *implied* asset correlations we checked for this non uniqueness problem, by changing the direction of the grid search, and we found that for the tolerance criterion used in the grid search (1e-5) most of the pairwise *implied* asset correlations were indeed unique.

		Capital goods		
		downgrade	no movement	upgrade
Automobiles	downgrade	0.0106	0.0894	0.003
	no movement	0.0786	0.765	0.0236
	upgrade	0.0022	0.0268	0.0009

Table 3: DRTM corresponding to the Moody's data from 1970 to 2005, for industries of sector "Automobiles" and industries of sector "Capital goods", with $T = 1$.

this matrix is the following: there is 0.0009 probability that a company of sector "Automobiles" and a company of sector "Capital goods" will, after 1 year, end up with a better rating than their initial rating, and 0.0106 that the companies in those sectors will both face a downgrade after 1 year.

The DRTM represents a bivariate empirical distribution. The underlying random variables (formed by the possible pairs of U, D and N) are ordinal. Therefore, a measure of the correlation can be obtained by the "Kendall τ" association estimator, which is a nonparametric estimator. In classical bivariate analysis, the notion underlying the use of Kendall τ is very intuitive: if we observe two variables (x, y), and arrange the x values in ascending order, the extend to which the y values depart from the increasing order indicates the lack of positive association between x and y. In this view, we need to consider how many concordant pairs and discordant pairs can be obtained from the bivariate data. A concordant pair, here, is represented by two cells of the DRTM for which, once the arguments for the set of industry of the first sector are arranged in ascending order, the arguments of the set of the second sector are also in ascending order. An example of concordant pairs is therefore (D, N) and (N, U). Similarly, we define discordant pairs as two cells of the DRTM for which, once the arguments for the set of industry of the first sector are arranged in ascending order, the arguments of the set of the second sector are also in descending order. An example of discordant pairs is therefore (D, U) and (N, N). We also define "Ties in X" as pairs for which the arguments of the industries of the first sector are constants, as for example (D, U) and (D, N); "Ties in Y" are defined accordingly. Denoting C the number of concordant pairs, D, the number of discordant pairs, Tx the number of ties in X, and Ty the number of ties in Y, Kendall τ is defined as

$$\tau = \frac{C - D}{\sqrt{C + D + Tx}\sqrt{C + D + Ty}}.$$

The asset correlation is then obtained from the relationship, for elliptical distribution, between linear correlation and Kendall τ (Greiner's equality).

$$\rho = \sin\left(\frac{\pi\tau}{2}\right).$$

The asset correlation computed on the DRTM in Table 3 is 0.0211.

3.3 Comparison of the methods

Both the STRM and DRTM methods use rating information to infer asset correlation across pairs of obligors. For a group of industries and/or companies it is possible to estimate a pairwise matrix that in the diagonal capture the intra correlation between the firms belonging to a particular group and out of the diagonal (the matrix is symmetric) capture the inter correlation across groups of firms.

The STRM greatest downside is in its focus in default events, which historically can be considered as rare events, especially if we want to estimate a default probability and correlation in the highest (investment type) grades. Since there are few default observations for these particular groups it is difficult to make reliable inference. The fact that we consider only the transition to default in the STRM means that we are not using all the transition information (just focusing on the most critical of transitions, but also most obscure, see next section on the data issues). The DRTM disregards the information on the initial rating states (9 broad rating categories) since it considers only the 3 mentioned states (upgrade, downgrade, no-movement). This approach captures the co-movements born out of all transition events, not only default. However, it is not without downside since by disregarding the initial grades it makes an assumption of homogeneity over all transitions which might not be realistic (a downgrade from Aa to B is not the same than a downgrade from B to Default). A possible improvement on the properties of both method would make the STRM consider not only transitions to default as informative with respect to asset correlation. On the other hand it is possible to adapt DRTM so as to not disregard the information on the initial ratings. However these two suggestions are not the object of the present paper. Empirically in Akhavein, Kocagil and Neugebauer (2005), they find that DRTM estimates of asset correlation (using a common database) are significantly lower in comparison to the asset correlation estimates of STRM and an equity based method develop by Fitch[9]. They mentioned that the DRTM's low asset correlation estimates may be disregarded on the grounds that regulators might not find these levels conservative enough or credit analysis might feel more comfortable with higher estimates.

4 The data

The data used is Moody's database on issuer/obligator senior rating, which contains information on 44,547 rating actions affecting 11,295 corporate and financial institutions during the period 1970 to 2005. During this period Moody's contains 9 broad ratings (Aaa, Aa,..) for the period 1970 to 1982 and 18 alphanumeric ratings (Aaa, Aa1, Aa2,..) from 1983 onwards. For consistency across the sample we transform all the data into the 9 broad ratings.

Although Moody's does not have an explicit default state it does have flag variable within the database that determines when an institution can be con-

[9]Fitch's Vector Model 2.0.

sidered in default or close to it. Since there are different definition of default (missed or delayed disbursement of interest and/or principal, Bankruptcy, A distressed exchange, among others) Moody's keeps rating the issuer according to their rating grades. In our database we transform this flag variable into a new default state irrespective of the fact that Moody's still gives a broad grade; using this default flag we get 1400 issuers that at some point in time go into default.

In our database we consider default as an absorbing state, so the first time one fall in default, one stay in this state. In Christensen, Hansen and Lando (2004) using Moodys data (but at a lower frequency, daily and only for the US) they look at each of the default cases and create new issuers if there is a rating upgrade after a default or if there are two default dates that are identifiable independent. They also correct the ratings leading to default that can actually be considered in default already. Our approach could seem arbitrary since we find that there are some 40 issuers that display multiple defaults but only consider their last date of default. However, when we looked closely at these 40 cases (where we found multiple default dates) we found that is was difficult to consider that the information between default was identifiably independent so as to consider two issuers; our appreciation was that most of these issuers looked more like a slow dying patient than a resurrection.

Another important data issues mentioned in the literature is the withdrawn ratings (WR). Ratings may be withdrawn among other reasons because the issuer has bought the principal or stopped paying the rating agencies for their rating services (reasons that may not be included on the databases). In Christensen, Hansen and Lando (2004), WR are not relevant if they are in between two ratings (they are replaced by one of the boundary observed ratings). If a WR is observed as a last observation they remove the issuer (right censored). In Schuermann and Jafry (2004) they mentioned that considering withdrawn ratings or not rated as not informative is common in the literature. In Bangia et al. (2002), they also consider them as non informative and mentioned that it has become an industry standard to gradually eliminate companies whose ratings are withdrawn. Following industry standards we consider WR's as non informative and gradually eliminate the issuers.

5 Estimation of Asset Correlation

For the estimation of the asset correlation using both rating transition "model free" approaches STRM and DRTM we first used the industrial classifier to group the issuers into 20 activity sectors and according to country of origin we make 6 world regions, table 4.

The asset correlation is estimated for every sector and/or region pair for a total of 351 pairs. The estimation was done in some cases separately for the investment (IG) and non-investments grade rating groups (NIG) [10].

[10] Following Moody's the investment grades are: Aaa, Aa, A, Baa ; leaving the non-investment grades: Ba, B, Caa, Ca, C.

We use this investment/non-investment grade separation because we consider it to be the most general organization of the 9 original broad grades (and the default state) that allows us to get better estimates of asset correlation in the STRM approach. To understand this point it is important to recall that in the STRM approach it is necessary to determine the starting rating for the pair of issuers, whereas the informative ending rating is the default state for the pair of issuers. This means that, under the STRM approach, we consider two situations in estimating the point estimation and the confidence sets: first joint migrations of the pair of issuers starting (both issuers) from an investment grade and second starting (both issuers) from a non-investment grade and ending in default (both issuers). The estimators used by STRM (defined in subsection 3.1) depend crucially on the definition of the starting rating.

The most extensive approach would be to map the transition of each broad rating into the default state, however trying to report on the complete results of this exercise would turn out to be too lengthly; instead what we do is regroup these broad ratings into a larger rating class.

The largest of these possible classes is to consider the non-default and default class and to apply the estimators into the transition between these classes. This approach turn out to be too thick since the asset correlation estimates were severely affected by the few or null observations of default in the highest rating classes. What happen was that since the investment grades do not show any history of defaults they reduced significantly the transition probability to the default state, because they inflated the denominator in the individual and joint transition probability estimators.

These results lead us to consider the estimation of separate matrices for the investment (IG) and non-investments grade rating groups (NIG). At the end we only report on the latter because the fact that we are looking at the highest rating grades where defaults are rare or null in most cases will imply that there is perfect ($\rho^A_{a,IG;b,IG} = -0.99 \forall a, b \in \{sectors\&regions\}$) negative asset correlation between the sectors or regions considered. This strong and most likely incorrect appreciation is the result of using this default only event approach. Our appreciation is that this method is not able to use the rating information to make adequate inference on asset correlation at the highest grading category.

For the DRTM approach the investment/non-investment grade separation is not necessary since the starting and ending rating of the issuer is non-informative in this method (only the direction of the rating change is informative). The point estimation of the matrices and the confidence sets that will be presented, following the DRTM approach, are based on the information that considers all the broad 9 grades information without using the separation, we will only resort to the separation in order to *comparable* between both methods (STRM vs DRTM).

The results are presented in matrices, the diagonal reflects the intra-sector/country effects whereas the out-off the diagonal elements reflect the inter-sector/country effects; since the matrices are symmetric we only present the upper triangular elements. The last line of the tables shows the average inter-correlation across sectors and regions for the particular column sector or region.

Table 5 presents the estimation of the intra and the inter correlation after one year for the NIG group, when the estimation is based on the STRM method. All the correlations (intra and inter) are found to be positive. It is difficult to make an interpretation of the pairwise asset correlation estimates that result form this "model free default event" method. The advantage of the method is that you can obtain a pairwise asset correlation for any group (sector, rating or country); however its dependence on default events restrict the mesaurability of the event in some of these groups. Furthermore, since it is model free it is hard to disentangle systematic and idiosyncratic elements that allow you to give precise meaning to the correlation structure. As found generally in the literature (Fu et al. (2004), Servigny and Renault (2003)) we find that average inter-correlation are in most cases lower than intra-correlation (diagonal elements). We find that asset correlation between sector is non-negative and that it is between 15 and 35 percent with an average of 21 percent; this average is a bit higher than what is found in the literature, that is 13 to 16 percent (Akhavein, Kocagil and Neugebauer (2005)). In the region estimates we also find non-negative inter-correlation. The region results by looking at both the intra and inter correlation seem to characterize well (at least rank wise) the patterns of regional exposure. For example, there is an overall greater exposure of all regions and sectors toward Africa and the Middle East (the average inter-correlation is the highest 0.56).

Table 9 and 13 presents the estimation of the intra and the inter correlation after one year, considering transitions between all broad ratings and the non-investment grade group, respectably; when the estimation is based on the DRTM method. Almost all the intra correlations are found to be positive, while the inter correlations are sometimes negative. The values are in all cases relatively close to zero.

In this case it is also difficult to make an interpretation of the pairwise asset correlation estimates that result form this "model free transition event" method. This method has the same flexibility as the STRM in allowing you to obtain a pairwise asset correlation for any group (sector, rating or country) and additionally it overcomes the measurability problems of the STRM by using all the transition information available (not only default). We find that asset correlation between sector, using all broad ratings (non-investment grade group), is non-negative and between 0 and 4 percent (0 and 7 percent for NIG) with an average of 2 percent (4 percent); this average is close to what is found in the literature 3 to 4.5 percent (Akhavein, Kocagil and Neugebauer (2005), Fu et al. (2004))[11]. We also find by comparing the DRTM vs STRM asset correlation estimates that the former are significantly lower, this is also common in the literature; and this observation has lead to cast some doubt on the DRTM approach (Akhavein, Kocagil and Neugebauer (2005)); by argumenting that they are so low so as to be accepted by any regulator. We do not share this view since the methods draw inference from two different events (default and transition)

[11] A survey of the literature on asset correlation by Chernih, Vanduffel and Henrard (2006) find that in general most studies yield correlation estimates in the range of approximately 1 to 10 percent

in order to obtain an implied asset correlation; therefore it is difficult to make an absolute appreciation of the level differences between the estimated asset correlation.

6 Confidence Sets

We obtain confidence region by using the bootstrap method, Efron and Tibshirani(1994). The fundamental idea of this method is that we can obtain an estimate of the dispersion of an estimator by re sampling the data. Starting from a dataset of n observations, we can create $nsim$ new samples by selecting n data with replacement in the initial dataset. The 95th upper and lower quantile of the estimates computed from the $nsim = 1000$ samples are then used for creating confidence sets. Another purpose of the bootstrap method is to proceed to a bias correction for the estimator[12].

Table 6, 7 and 8 present the superior bounds, bias corrected estimates and the inferior bounds of the confidence set following the STRM (only for NIG category), respectably. With the bias corrected estimates we find that asset correlation between sector is non-negative and that it is between 10 and 31 percent with an average of 16 percent. The inferior bounds are most of the time negative while the superior bounds are most of the time positive, implying hat the correlations are not significantly different from zero. Example of significantly positive correlation is between sector "Diversified Financial" and sector "Capital Goods".

Table 11 presents the bootstrap estimates of the intra and the inter correlations following the DRTM. Table 10 and 12 present the superior bounds and the inferior bounds of the confidence set. The inferior bounds are most of the time negative while the superior bounds are most of the time positive, implying hat the correlations are not significantly different from zero. Example of significantly positive correlation is between sector "Diversified Financial" and sector "Capital Goods". An example of a significantly negative correlation is between sector "Banks" and sectors "Materials". The same comments hold when considering the non investment grades only, as can be seen in Tables 14, 15, and 16.

7 Conclusions

In this paper we estimate and compare the asset correlations using the "model free" rating based methods which we denote as STRM and DRTM. There are

[12]Since the purpose of the bootstrap is to establish the variability of a given estimator (e.g. its bias, its variance, its distribution). In particular we can obtain an expression for the bias of the estimator that can be used to obtain the bias corrected bounds and point estimate. However, the correction applied can lead to asset correlation greater than one (or lower than -1), this happens because the uncorrected asset correlation estimates are close or are exactly at 0.99 or -0.99 and if the bias correction obtained by the bootstrap is negative in the first case and positive in the second case, then the corrected estimates will be grater then 1 or lower than -1, respectably. It is not often that this happens.

two significant methodological differences between the methods: the first is the STRM is a default event approach while the DRTM considers all possible transitions (not just default); the second is that the STRM uses a bivariate gaussian copula to derive the implied pairwise asset correlation from the bivariate and individual default (transition) probabilities while the DRTM uses as measure of the asset correlation the "Kendall τ" association estimator. The estimator used by the DRTM method is a robust estimator for linear correlation for elliptically distributed data (Lindskog, McNeil, Schmock(2004)); this property makes this estimator more general then estimator used in the STRM where we had to make a rigid assumption on the normality of the asset return process. The use of all of the rating transition information by the DRTM method permits the estimation of asset correlation in the highest ratings where default in rare or inexistent and where the STRM cannot make any relevant inference.

The estimated pairwise asset inter-correlation obtained is close to the average between sector correlation found in the relevant literature. By comparing both methods we also confirm that the asset correlation estimated by the DTRM is significantly lower than the asset correlation implied by STRM, however we believe that this cannot be considered as an issue to cast some doubt on the usefulness of the DRTM method, especially when we have mentioned the gains in generality obtained from using the estimator associated with the method and the possibility of using more information (not only concentrate on defaults).

Using both approaches STRM and DRTM we obtain confidence intervals for the pairwise asset correlations. In both cases it is a regularity to find that the inferior bounds are most of the time negative while the superior bounds are most of the time positive, implying that most of the correlations are not significantly different from zero.

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Sector or Region	Abbreviations
Automobiles and Components	AUT
Banks	BAN
Capital Goods	KGO
Commercial Services and Supplies	CSS
Consumer Durables and Apparel	CDA
Diversified Financials	DVF
Food and Drug Retailing	FDR
Food Beverage and Tobacco	FBT
Health Care Equipment and Services	HLT
Hotels Restaurants and Leisure	HRL
Insurance	INS
Materials	MAT
Media	MED
Real Estate	RST
Retailing	RET
Semiconductors and Semiconductor Equipment	SEM
Technology Hardware and Equipment	TEC
Telecommunication Services	TEL
Transportation	TRA
Utilities	UTL
EU	EUC
Europe Non EU	NEU
North America	NOA
Central and South America	SCA
Asia and Oceania	AOC
Africa and Middele East	AFM

Table 4: Sectors and Region codes

	AUT	BAN	KGO	CSS	CDA	DVF	FDR	FBT	HLT	HRL	INS	MAT	MED	RST	RET	SEM	TEC	TEL	TRA	UTL	EUC	NEU	NOA	SCA	AOC	AFM
AUT	0,29	0,23	0,23	0,24	0,39	0,3	0,23	0,17	0,17	0,24	0,28	0,25	0,15	0,14	0,14	0,19	0,14	0,65	0,19	0,09	0,29	0,29	0,13	0,24	0,4	0,58
BAN	0	0,39	0,33	0,11	0,15	0,19	0,17	0,21	0,11	0,17	0,15	0,24	0,2	0,17	0,11	0,29	0,14	0,29	0,14	0,13	0,29	0,31	0,22	0,27	0,3	0,53
KGO	0	0	0,34	0,33	0,4	0,26	0,23	0,25	0,21	0,27	0,35	0,27	0,19	0,19	0,16	0,25	0,2	0,48	0,22	0,14	0,32	0,31	0,14	0,24	0,15	0,58
CSS	0	0	0	0,28	0,27	0,23	0,19	0,21	0,19	0,19	0,29	0,23	0,16	0,14	0,13	0,18	0,16	0,38	0,2	0,12	0,29	0,28	0,1	0,25	0,07	0,57
CDA	0	0	0	0	0,39	0,26	0,17	0,2	0,15	0,2	0,29	0,19	0,14	0,11	0,11	0,25	0,13	0,44	0,17	0,07	0,3	0,38	0,06	0,3	0,2	0,81
DVF	0	0	0	0	0	0,23	0,15	0,26	0,21	0,2	0,33	0,14	0,15	0,17	0,15	0,18	0,16	0,37	0,19	0,17	0,24	0,44	0,02	0,2	0,21	0,92
FDR	0	0	0	0	0	0	0,19	0,2	0,2	0,16	0,27	0,21	0,16	0,19	0,15	0,19	0,18	0,25	0,15	0,13	0,21	0,24	0,09	0,18	0,1	0,61
FBT	0	0	0	0	0	0	0	0,26	0,18	0,14	0,36	0,24	0,16	0,15	0,12	0,15	0,16	0,39	0,2	0,15	0,29	0,26	0,14	0,21	0,12	0,51
HLT	0	0	0	0	0	0	0	0	0,23	0,12	0,26	0,24	0,14	0,12	0,14	0,13	0,15	0,33	0,18	0,12	0,26	0,19	0,13	0,22	0,07	0,52
HRL	0	0	0	0	0	0	0	0	0	0,24	0,13	0,22	0,12	0,12	0,14	0,17	0,15	0,39	0,16	0,13	0,25	0,23	0,14	0,19	0,22	0,55
INS	0	0	0	0	0	0	0	0	0	0	0,42	0,33	0,24	0,16	0,17	0,23	0,24	0,61	0,28	0,16	0,36	0,28	0,19	0,34	0,15	0,47
MAT	0	0	0	0	0	0	0	0	0	0	0	0,23	0,22	0,29	0,23	0,27	0,28	0,18	0,19	0,28	0,24	0,28	0,12	0,18	0,14	0,66
MED	0	0	0	0	0	0	0	0	0	0	0	0	0,19	0,18	0,13	0,29	0,17	0,25	0,15	0,16	0,22	0,21	0,14	0,2	0,04	0,51
RST	0	0	0	0	0	0	0	0	0	0	0	0	0	0,19	0,14	0,16	0,19	0,29	0,16	0,14	0,24	0,16	0,21	0,2	0,12	0,39
RET	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,16	0,14	0,16	0,27	0,16	0,13	0,22	0,15	0,15	0,15	0,1	0,47
SEM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,36	0,16	0,25	0,11	0,11	0,26	0,3	0,19	0,29	0,14	0,63
TEC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,2	0,28	0,17	0,17	0,23	0,05	0,2	0,16	0,08	0,4
TEL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,55	0,27	0,24	0,49	0,69	0,01	0,34	0,82	0,99
TRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,2	0,17	0,26	0,28	0,09	0,18	0,08	0,61
UTL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,27	0,25	0,13	0,3	0,15	0,05	0,38
EUC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,3	0,3	0,11	0,23	0,22	0,52
NEU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,26	0,12	0,22	0,66	0,29
NOA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,11	0,1	0,12	0,34
SCA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,25	0,25	0,45
AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,66	0,82
AFM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,34
inter	0,25	0,22	0,27	0,22	0,25	0,24	0,20	0,22	0,19	0,20	0,28	0,24	0,19	0,18	0,16	0,22	0,18	0,40	0,20	0,16	0,28	0,28	0,14	0,23	0,23	0,56

Table 5: STRM: Non-Investment Grade NIG

	AUT	BAN	KGO	CSS	CDA	DVF	FDR	FBT	HLT	HRL	INS	MAT	MED	RST	RET	SEM	TEC	TEL	TRA	UTL	EUC	NEU	NOA	SCA	AOC	AFM
AUT	0,4	0,36	0,29	0,33	0,6	0,41	0,31	0,2	0,2	0,35	0,37	0,37	0,21	0,2	0,19	0,32	0,19	0,91	0,23	0,13	0,38	0,43	0,23	0,32	0,66	0,88
BAN	0	0,57	0,54	0,15	0,21	0,25	0,21	0,32	0,17	0,22	0,23	0,31	0,27	0,21	0,12	0,46	0,15	0,34	0,16	0,13	0,4	0,54	0,29	0,39	0,44	0,86
KGO	0	0	0,39	0,45	0,59	0,33	0,31	0,29	0,26	0,38	0,43	0,38	0,25	0,25	0,21	0,39	0,26	0,65	0,26	0,17	0,41	0,37	0,25	0,32	0,21	0,79
CSS	0	0	0	0,34	0,34	0,3	0,25	0,26	0,22	0,26	0,35	0,33	0,21	0,19	0,16	0,28	0,22	0,49	0,24	0,17	0,36	0,35	0,19	0,33	0,13	0,83
CDA	0	0	0	0	0,52	0,33	0,23	0,23	0,16	0,29	0,34	0,29	0,2	0,16	0,14	0,45	0,18	0,55	0,2	0,11	0,39	0,53	0,15	0,41	0,32	1,26
DVF	0	0	0	0	0	0,28	0,19	0,32	0,27	0,23	0,43	0,2	0,2	0,21	0,18	0,27	0,2	0,46	0,22	0,21	0,3	0,61	0,09	0,24	0,28	1,35
FDR	0	0	0	0	0	0	0,21	0,27	0,25	0,2	0,36	0,25	0,19	0,22	0,17	0,25	0,21	0,33	0,17	0,15	0,24	0,34	0,13	0,21	0,13	0,88
FBT	0	0	0	0	0	0	0	0,29	0,23	0,17	0,49	0,34	0,21	0,19	0,14	0,24	0,21	0,5	0,24	0,21	0,35	0,31	0,24	0,27	0,19	0,7
HLT	0	0	0	0	0	0	0	0	0,26	0,14	0,32	0,33	0,19	0,14	0,16	0,18	0,19	0,43	0,21	0,16	0,33	0,22	0,22	0,3	0,13	0,72
HRL	0	0	0	0	0	0	0	0	0	0,32	0,19	0,29	0,14	0,15	0,17	0,26	0,18	0,51	0,18	0,15	0,31	0,34	0,22	0,24	0,32	0,84
INS	0	0	0	0	0	0	0	0	0	0	0,49	0,47	0,35	0,23	0,23	0,36	0,35	0,82	0,35	0,24	0,48	0,33	0,32	0,48	0,27	0,68
MAT	0	0	0	0	0	0	0	0	0	0	0	0,27	0,27	0,36	0,29	0,32	0,34	0,26	0,25	0,34	0,3	0,41	0,14	0,23	0,18	0,96
MED	0	0	0	0	0	0	0	0	0	0	0	0	0,23	0,22	0,16	0,44	0,2	0,31	0,18	0,19	0,27	0,31	0,19	0,25	0,06	0,76
RST	0	0	0	0	0	0	0	0	0	0	0	0	0	0,23	0,17	0,2	0,22	0,37	0,18	0,16	0,29	0,23	0,27	0,24	0,17	0,58
RET	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,17	0,19	0,19	0,35	0,18	0,15	0,25	0,21	0,21	0,18	0,14	0,65
SEM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,56	0,19	0,32	0,14	0,13	0,33	0,53	0,25	0,42	0,24	1,04
TEC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,23	0,37	0,19	0,19	0,27	0,17	0,25	0,2	0,1	0,5
TEL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,71	0,34	0,3	0,64	0,95	0,08	0,43	1,36	1,23
TRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,21	0,19	0,29	0,36	0,15	0,21	0,11	0,85
UTL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,3	0,29	0,2	0,37	0,17	0,05	0,56
EUC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,36	0,41	0,16	0,28	0,32	0,76
NEU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,3	0,24	0,32	1,14	0,43
NOA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,12	0,15	0,19	0,56
SCA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,32	0,38	0,71
AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1,04	1,34
AFM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1,67
inter	0,36	0,31	0,36	0,30	0,35	0,32	0,26	0,28	0,25	0,27	0,38	0,33	0,25	0,23	0,21	0,33	0,23	0,53	0,24	0,20	0,35	0,41	0,22	0,31	0,35	0,83

Table 6: Confidence Sets: STRM, Upper Bound NIG

	AUT	BAN	KGO	CSS	CDA	DVF	FDR	FBT	HLT	HRL	INS	MAT	MED	RST	RET	SEM	TEC	TEL	TRA	UTL	EUC	NEU	NOA	SCA	AOC	AFM
AUT	0,19	0,14	0,18	0,17	0,33	0,23	0,18	0,1	0,11	0,13	0,17	0,25	0,11	0,1	0,09	0,13	0,11	0,6	0,13	0,03	0,24	0,2	0,13	0,2	0,3	0,55
BAN	0	0,33	0,28	0,03	0,06	0,11	0,11	0,13	0,04	0,07	0,04	0,22	0,13	0,11	0,04	0,23	0,08	0,23	0,08	0,07	0,23	0,24	0,21	0,21	0,21	0,47
KGO	0	0	0,29	0,28	0,34	0,21	0,19	0,21	0,18	0,2	0,28	0,28	0,17	0,16	0,12	0,21	0,18	0,46	0,18	0,1	0,3	0,26	0,15	0,22	0,04	0,57
CSS	0	0	0	0,2	0,2	0,19	0,15	0,16	0,14	0,14	0,19	0,22	0,13	0,11	0,08	0,12	0,12	0,35	0,15	0,09	0,26	0,22	0,1	0,21	-0,03	0,53
CDA	0	0	0	0	0,29	0,18	0,11	0,11	0,06	0,11	0,16	0,18	0,1	0,06	0,04	0,21	0,07	0,37	0,1	0,02	0,25	0,3	0,05	0,25	0,07	0,85
DVF	0	0	0	0	0	0,13	0,12	0,22	0,17	0,1	0,25	0,13	0,12	0,14	0,11	0,13	0,13	0,3	0,15	0,13	0,18	0,32	0,02	0,15	0,04	0,99
FDR	0	0	0	0	0	0	0,13	0,16	0,15	0,1	0,2	0,19	0,12	0,15	0,1	0,14	0,14	0,23	0,12	0,1	0,18	0,19	0,08	0,14	0,01	0,61
FBT	0	0	0	0	0	0	0	0,17	0,14	0,06	0,27	0,24	0,13	0,12	0,08	0,1	0,13	0,37	0,16	0,11	0,25	0,19	0,15	0,18	0,02	0,46
HLT	0	0	0	0	0	0	0	0	0,16	0,05	0,18	0,23	0,11	0,08	0,1	0,06	0,12	0,3	0,14	0,08	0,23	0,13	0,12	0,19	-0,01	0,51
HRL	0	0	0	0	0	0	0	0	0	0,12	0,02	0,2	0,07	0,07	0,08	0,1	0,09	0,31	0,1	0,07	0,18	0,13	0,13	0,13	0,06	0,5
INS	0	0	0	0	0	0	0	0	0	0	0,31	0,3	0,18	0,08	0,09	0,14	0,16	0,54	0,2	0,1	0,31	0,19	0,17	0,29	0,02	0,41
MAT	0	0	0	0	0	0	0	0	0	0	0	0,22	0,21	0,28	0,22	0,23	0,27	0,19	0,18	0,26	0,24	0,28	0,12	0,17	0,08	0,72
MED	0	0	0	0	0	0	0	0	0	0	0	0	0,15	0,16	0,1	0,26	0,15	0,23	0,12	0,13	0,2	0,18	0,13	0,18	-0,04	0,53
RST	0	0	0	0	0	0	0	0	0	0	0	0	0	0,14	0,1	0,11	0,16	0,27	0,12	0,09	0,21	0,12	0,2	0,17	0,05	0,38
RET	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,09	0,08	0,13	0,25	0,12	0,08	0,18	0,09	0,14	0,11	0,02	0,46
SEM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,33	0,11	0,2	0,07	0,07	0,23	0,27	0,18	0,25	0,06	0,67
TEC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,16	0,27	0,14	0,13	0,2	0,02	0,19	0,13	0	0,36
TEL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,53	0,24	0,22	0,48	0,66	0,02	0,31	0,91	1,01
TRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,13	0,13	0,22	0,22	0,09	0,15	-0,02	0,59
UTL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,22	0,22	0,08	0,29	0,11	-0,04	0,37
EUC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,28	0,29	0,11	0,21	0,17	0,46
NEU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,2	0,12	0,21	0,61	0,19
NOA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,11	0,09	0,11	0,3
SCA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,23	0,19	0,4
AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,6	0,79
AFM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,43
inter	0,20	0,15	0,23	0,17	0,18	0,19	0,16	0,17	0,14	0,13	0,20	0,24	0,16	0,14	0,12	0,17	0,14	0,37	0,16	0,12	0,24	0,23	0,13	0,19	0,15	0,55

Table 7: Confidence Sets: STRM, Bias Corrected Estimates NIG

	AUT	BAN	KGO	CSS	CDA	DVF	FDR	FBT	HLT	HRL	INS	MAT	MED	RST	RET	SEM	TEC	TEL	TRA	UTL	EUC	NEU	NOA	SCA	AOC	AFM
AUT	-0,21	-0,2	0,04	-0,18	-0,02	-0,08	-0,04	-0,04	-0	-0,25	-0,14	0,11	-0,01	-0,02	-0,04	-0,28	0	0,31	-0,01	-0,08	0,06	-0,25	0,01	0,04	-0,15	0,17
BAN	0	0,05	-0,04	-0,21	-0,22	-0,16	-0,05	-0,24	-0,18	-0,24	-0,31	0,13	-0,2	-0,06	-0,12	-0,08	-0,03	-0	-0,03	0	0,01	-0,12	0,12	-0,04	-0,05	0,07
KGO	0	0	0,16	-0,05	0,02	0,05	0,03	0,1	0,09	-0,16	0,07	0,16	0,07	0,07	0,01	-0,19	0,1	0,19	0,07	0,01	0,19	0,12	0,04	0,11	-0,25	0,24
CSS	0	0	0	-0,04	-0,03	0,04	-0,01	0	0,03	-0,07	-0,04	0,11	0,03	0,01	-0,03	-0,23	-0,02	0,18	0,04	-0,01	0,14	-0,01	-0,01	0,06	-0,26	0,15
CDA	0	0	0	0	-0,01	-0,02	-0,09	-0,11	-0,09	-0,15	-0,1	0,04	-0,03	-0,04	-0,11	-0,14	-0,11	0,1	-0,01	-0,1	0,11	-0,06	-0,07	0,08	-0,27	0,63
DVF	0	0	0	0	0	-0,19	0,03	0,1	0,03	-0,13	-0,02	0,07	0,03	0,05	0,01	-0,06	0,05	-0,01	0,06	0,05	-0,07	-0,11	-0,05	0,01	-0,49	0,85
FDR	0	0	0	0	0	0	-0,02	-0,02	-0,01	-0,09	-0,02	0,1	-0,02	0,05	-0,01	-0,11	0,03	0,1	0,05	0,04	0,1	-0,03	0,02	-0	-0,17	0,23
FBT	0	0	0	0	0	0	0	0,03	0,05	-0,14	-0,01	0,12	0,03	0,04	-0,02	-0,28	0,06	0,21	0,06	0,02	0,14	-0,02	0,04	0,07	-0,21	0,03
HLT	0	0	0	0	0	0	0	0	0,04	-0,08	0	0,12	0,02	0	0,02	-0,26	0,04	0,14	0,05	-0,01	0,12	-0,02	0,01	0,07	-0,18	0,27
HRL	0	0	0	0	0	0	0	0	0	-0,19	-0,23	0,09	-0,04	-0,03	-0,07	-0,27	-0,09	-0,04	-0,02	-0,01	-0,03	-0,22	0,02	-0	-0,44	0,11
INS	0	0	0	0	0	0	0	0	0	0	0,09	0,06	-0,06	-0,13	-0,1	-0,2	-0,14	0,23	-0,03	-0,09	0,06	-0,02	-0,04	0,04	-0,33	0,08
MAT	0	0	0	0	0	0	0	0	0	0	0	0,16	0,14	0,2	0,14	0,06	0,19	0,13	0,11	0,17	0,17	0,09	0,08	0,11	-0,13	0,52
MED	0	0	0	0	0	0	0	0	0	0	0	0	0,06	0,08	0,02	-0,02	0,09	0,14	0,06	0,07	0,12	0,03	0,06	0,1	-0,18	0,32
RST	0	0	0	0	0	0	0	0	0	0	0	0	0	0,04	0,01	-0,12	0,1	0,17	0,05	0,03	0,12	-0,03	0,12	0,08	-0,1	0,19
RET	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,04	-0,18	0,03	0,13	0,04	0	0,08	-0,08	0,06	0,02	-0,15	0,24
SEM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,01	-0,03	-0,13	-0,02	0	0,08	-0,11	0,09	-0	-0,19	0,27
TEC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,07	0,14	0,07	0,08	0,13	-0,13	0,11	0,06	-0,13	0,22
TEL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,37	0,14	0,11	0,31	0,39	-0,04	0,08	0,69	0,99
TRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,03	0,06	0,13	0,02	0,02	0,06	-0,21	0,23
UTL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,13	0,14	-0,08	0,21	0,04	-0,15	0,2
EUC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,18	0,13	0,05	0,14	-0,11	0,05
NEU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,06	-0,03	0,07	0,34	-0,14
NOA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,09	0,02	-0,01	0,05
SCA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,14	-0,23	0,03
AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,42	0,65
AFM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,01
inter	-0,04	-0,09	0,04	-0,01	-0,03	0,01	0,00	0,00	0,01	-0,10	-0,06	0,12	0,03	0,03	0,00	-0,10	0,03	0,19	0,04	0,03	0,09	-0,01	0,04	0,04	-0,11	0,27

Table 8: Confidence Sets: STRM, Lower Bound NIG

	AUT	BAN	KGO	CSS	CDA	DVF	FDR	FBT	HLT	HRL	INS	MAT	MED	RST	RET	SEM	TEC	TEL	TRA	UTL	EUC	NEU	NOA	SCA	AOC	AFM
AUT	0,036	-0,007	0,021	0,010	0,035	-0,003	0,009	0,002	-0,004	0,007	-0,004	0,014	0,012	0,003	0,021	0,019	-0,004	0,007	0,016	-0,003	0,001	-0,025	0,008	0,013	-0,004	-0,073
BAN	0	0,028	-0,004	-0,017	-0,016	0,016	-0,012	-0,002	0,013	0,002	0,002	-0,009	-0,005	-0,010	-0,018	0,004	0,009	0,017	-0,013	0,003	-0,002	0,049	-0,006	0,009	0,036	0,008
KGO	0	0	0,054	0,069	0,036	0,034	0,040	0,040	0,019	0,055	0,016	0,058	0,027	0,035	0,030	0,061	0,004	0,060	0,048	0,032	0,026	0,009	0,030	0,073	0,037	-0,013
CSS	0	0	0	0,046	0,005	0,016	0,032	0,035	0,046	0,047	0,007	0,040	0,003	0,044	0,015	0,031	0,008	0,008	0,018	0,018	0,002	0,008	0,020	0,047	0,009	-0,023
CDA	0	0	0	0	0,039	0,004	0,012	0,013	-0,034	-0,001	0,006	0,027	0,030	0,008	0,026	0,032	-0,022	0,042	0,033	0,005	0,010	-0,044	0,015	0,017	-0,012	-0,082
DVF	0	0	0	0	0	0,033	0,013	0,024	0,003	0,027	0,025	0,024	0,021	0,012	-0,005	0,040	-0,001	0,058	0,016	0,039	0,025	0,011	0,018	0,059	0,043	-0,013
FDR	0	0	0	0	0	0	0,027	0,022	0,007	0,029	0,019	0,031	0,018	0,023	0,019	0,032	-0,008	0,037	0,031	0,025	0,013	-0,025	0,019	0,043	-0,003	-0,017
FBT	0	0	0	0	0	0	0	0,025	0,021	0,032	0,017	0,030	0,021	0,020	0,013	0,039	0,001	0,047	0,026	0,032	0,015	0,008	0,022	0,057	0,018	-0,003
HLT	0	0	0	0	0	0	0	0	0,029	0,026	-0,007	0,001	-0,029	0,010	-0,009	-0,001	0,030	-0,037	0,014	0,005	-0,001	0,034	0,001	0,006	0,033	0,039
HRL	0	0	0	0	0	0	0	0	0	0,055	0,010	0,035	0,012	0,025	0,017	0,039	0,012	0,033	0,021	0,034	0,020	0,019	0,021	0,064	0,029	0,019
INS	0	0	0	0	0	0	0	0	0	0	0,018	0,018	0,032	0,019	-0,006	0,036	-0,015	0,060	0,022	0,044	0,026	-0,040	0,021	0,049	-0,003	-0,042
MAT	0	0	0	0	0	0	0	0	0	0	0	0,035	0,027	0,026	0,022	0,044	-0,003	0,046	0,035	0,026	0,018	-0,009	0,020	0,048	0,012	-0,015
MED	0	0	0	0	0	0	0	0	0	0	0	0	0,028	0,013	0,012	0,040	-0,017	0,060	0,027	0,032	0,021	-0,030	0,021	0,043	-0,001	-0,048
RST	0	0	0	0	0	0	0	0	0	0	0	0	0	0,026	0,015	0,026	-0,001	0,028	0,018	0,017	0,009	-0,015	0,017	0,034	-0,004	-0,007
RET	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,024	0,018	-0,003	0,011	0,022	-0,003	0,000	-0,029	0,010	0,017	-0,017	-0,009
SEM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,033	-0,009	0,074	0,042	0,046	0,034	-0,012	0,030	0,073	0,026	-0,037
TEC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,037	-0,015	-0,010	-0,008	-0,007	0,014	-0,004	0,010	0,023	0,040
TEL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,045	0,057	0,074	0,056	-0,022	0,037	0,067	0,040	-0,028
TRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,034	0,032	0,016	-0,027	0,023	0,048	0,007	-0,031
UTL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,030	0,031	-0,008	0,021	0,074	0,015	-0,036
EUC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,022	0,001	0,017	0,053	0,027	-0,013
NEU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,045	0,000	0,020	0,082	0,047
NOA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,006	0,044	0,009	-0,019
SCA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,045	0,028	-0,001
AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,048	0,040
AFM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,045
inter	0,00	0,00	0,03	0,02	0,01	0,02	0,02	0,02	0,01	0,03	0,01	0,02	0,01	0,01	0,01	0,03	0,00	0,03	0,02	0,02	0,02	0,00	0,02	0,04	0,02	-0,01

Table 9: DRTM: All

	AUT	BAN	KGO	CSS	CDA	DVF	FDR	FBT	HLT	HRL	INS	MAT	MED	RST	RET	SEM	TEC	TEL	TRA	UTL	EUC	NEU	NOA	SCA	AOC	AFM
AUT	0,042	0,011	0,054	0,052	0,070	0,018	0,028	0,027	0,036	0,037	0,018	0,034	0,034	0,021	0,044	0,042	0,018	0,037	0,036	0,017	0,017	0,022	0,020	0,048	0,034	0,010
BAN	0	0,032	0,014	0,002	0,005	0,025	0,001	0,010	0,032	0,017	0,013	-0,001	0,006	0,000	-0,004	0,015	0,017	0,032	0,000	0,011	0,006	0,077	0,000	0,028	0,047	0,052
KGO	0	0	0,070	0,106	0,080	0,055	0,060	0,068	0,062	0,086	0,044	0,075	0,052	0,056	0,056	0,088	0,023	0,094	0,071	0,057	0,043	0,060	0,042	0,106	0,066	0,052
CSS	0	0	0	0,058	0,042	0,040	0,059	0,068	0,091	0,086	0,037	0,065	0,034	0,068	0,045	0,062	0,033	0,043	0,047	0,044	0,020	0,062	0,034	0,087	0,044	0,048
CDA	0	0	0	0	0,049	0,031	0,037	0,042	0,016	0,035	0,040	0,051	0,057	0,032	0,052	0,065	0,005	0,089	0,060	0,037	0,032	0,003	0,030	0,063	0,021	0,004
DVF	0	0	0	0	0	0,039	0,026	0,039	0,024	0,048	0,041	0,034	0,035	0,024	0,012	0,054	0,012	0,077	0,030	0,051	0,033	0,044	0,025	0,078	0,058	0,046
FDR	0	0	0	0	0	0	0,032	0,040	0,035	0,044	0,038	0,042	0,033	0,036	0,035	0,047	0,007	0,057	0,045	0,040	0,024	0,014	0,026	0,066	0,014	0,041
FBT	0	0	0	0	0	0	0	0,031	0,051	0,052	0,036	0,046	0,038	0,037	0,032	0,060	0,014	0,075	0,045	0,047	0,027	0,039	0,032	0,083	0,035	0,052
HLT	0	0	0	0	0	0	0	0	0,037	0,061	0,020	0,026	0,001	0,036	0,022	0,031	0,051	-0,002	0,044	0,029	0,017	0,079	0,015	0,046	0,067	0,097
HRL	0	0	0	0	0	0	0	0	0	0,071	0,035	0,052	0,035	0,042	0,040	0,064	0,030	0,067	0,042	0,056	0,033	0,058	0,030	0,095	0,057	0,082
INS	0	0	0	0	0	0	0	0	0	0	0,021	0,033	0,051	0,035	0,016	0,056	0,002	0,088	0,041	0,062	0,039	-0,007	0,030	0,076	0,016	0,023
MAT	0	0	0	0	0	0	0	0	0	0	0	0,040	0,042	0,037	0,038	0,057	0,010	0,061	0,047	0,036	0,026	0,023	0,025	0,069	0,026	0,035
MED	0	0	0	0	0	0	0	0	0	0	0	0	0,034	0,029	0,030	0,058	-0,001	0,083	0,044	0,046	0,031	0,009	0,029	0,066	0,017	0,009
RST	0	0	0	0	0	0	0	0	0	0	0	0	0	0,031	0,030	0,043	0,013	0,050	0,032	0,032	0,020	0,015	0,024	0,057	0,013	0,039
RET	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,028	0,041	0,013	0,040	0,040	0,017	0,011	0,008	0,019	0,045	0,007	0,045
SEM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,040	0,007	0,096	0,059	0,062	0,045	0,025	0,037	0,099	0,042	0,025
TEC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,045	0,008	0,007	0,006	0,003	0,036	0,004	0,031	0,040	0,064
TEL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,054	0,079	0,092	0,072	0,025	0,046	0,098	0,060	0,061
TRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,041	0,047	0,027	0,015	0,030	0,074	0,027	0,028
UTL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,036	0,040	0,024	0,027	0,097	0,028	0,036
EUC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,025	0,028	0,021	0,069	0,036	0,035
NEU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,058	0,019	0,055	0,111	0,088
NOA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,007	0,056	0,014	0,012
SCA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,053	0,046	0,059
AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,054	0,088
AFM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,062
inter	0,03	0,02	0,06	0,05	0,04	0,04	0,04	0,04	0,04	0,05	0,04	0,04	0,03	0,03	0,03	0,05	0,02	0,06	0,04	0,04	0,03	0,04	0,03	0,07	0,04	0,05

Table 10: Confidence Sets: DRTM, Upper Bound All

	AUT	BAN	KGO	CSS	CDA	DVF	FDR	FBT	HLT	HRL	INS	MAT	MED	RST	RET	SEM	TEC	TEL	TRA	UTL	EUC	NEU	NOA	SCA	AOC	AFM
AUT	0,023	-0,007	0,021	0,010	0,035	-0,002	0,009	0,002	-0,005	0,007	-0,004	0,014	0,012	0,003	0,021	0,019	-0,004	0,007	0,016	-0,003	0,002	-0,026	0,008	0,013	-0,004	-0,076
BAN	0	0,027	-0,004	-0,017	-0,016	0,016	-0,012	-0,001	0,013	0,002	0,002	-0,009	-0,005	-0,010	-0,018	0,004	0,009	0,017	-0,012	0,003	-0,002	0,049	-0,006	0,009	0,036	0,007
KGO	0	0	0,040	0,069	0,036	0,035	0,040	0,041	0,020	0,055	0,016	0,057	0,026	0,035	0,030	0,061	0,004	0,060	0,048	0,032	0,026	0,010	0,030	0,072	0,038	-0,013
CSS	0	0	0	0,030	0,005	0,017	0,032	0,036	0,047	0,047	0,007	0,041	0,003	0,044	0,015	0,031	0,008	0,007	0,018	0,018	0,002	0,008	0,020	0,047	0,009	-0,024
CDA	0	0	0	0	0,018	0,002	0,012	0,012	-0,034	-0,002	0,006	0,026	0,030	0,007	0,026	0,031	-0,022	0,041	0,033	0,004	0,010	-0,044	0,014	0,016	-0,013	-0,086
DVF	0	0	0	0	0	0,030	0,014	0,024	0,003	0,028	0,025	0,024	0,021	0,012	-0,005	0,040	-0,001	0,058	0,016	0,039	0,025	0,011	0,018	0,059	0,043	-0,014
FDR	0	0	0	0	0	0	0,023	0,022	0,007	0,028	0,019	0,031	0,019	0,023	0,019	0,032	-0,008	0,037	0,031	0,026	0,014	-0,025	0,020	0,043	-0,003	-0,018
FBT	0	0	0	0	0	0	0	0,017	0,022	0,031	0,017	0,030	0,021	0,020	0,012	0,039	0,000	0,048	0,026	0,032	0,014	0,008	0,021	0,056	0,018	-0,004
HLT	0	0	0	0	0	0	0	0	0,019	0,025	-0,007	0,001	-0,029	0,010	-0,010	-0,001	0,030	-0,036	0,014	0,005	-0,001	0,032	0,001	0,006	0,032	0,040
HRL	0	0	0	0	0	0	0	0	0	0,043	0,010	0,034	0,012	0,024	0,017	0,039	0,011	0,033	0,021	0,034	0,019	0,019	0,020	0,064	0,029	0,020
INS	0	0	0	0	0	0	0	0	0	0	0,012	0,018	0,032	0,019	-0,005	0,036	-0,014	0,060	0,022	0,044	0,026	-0,040	0,021	0,049	-0,003	-0,044
MAT	0	0	0	0	0	0	0	0	0	0	0	0,033	0,027	0,026	0,022	0,044	-0,003	0,046	0,035	0,026	0,018	-0,009	0,020	0,048	0,012	-0,016
MED	0	0	0	0	0	0	0	0	0	0	0	0	0,023	0,013	0,012	0,040	-0,017	0,061	0,027	0,032	0,021	-0,030	0,021	0,043	-0,002	-0,051
RST	0	0	0	0	0	0	0	0	0	0	0	0	0	0,021	0,014	0,026	-0,001	0,028	0,018	0,017	0,009	-0,016	0,017	0,034	-0,004	-0,008
RET	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,016	0,019	-0,003	0,011	0,023	-0,002	0,000	-0,029	0,010	0,018	-0,017	-0,012
SEM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,029	-0,008	0,074	0,043	0,046	0,034	-0,012	0,030	0,073	0,026	-0,040
TEC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,033	-0,015	-0,010	-0,008	-0,007	0,013	-0,005	0,009	0,024	0,032
TEL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,040	0,057	0,074	0,056	-0,022	0,037	0,067	0,040	-0,029
TRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,028	0,032	0,016	-0,026	0,023	0,048	0,007	-0,032
UTL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,028	0,031	-0,008	0,021	0,075	0,014	-0,037
EUC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,021	0,001	0,017	0,053	0,027	-0,012
NEU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,037	0,000	0,020	0,083	0,046
NOA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,006	0,044	0,009	-0,020
SCA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,041	0,028	-0,001
AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,046	0,038
AFM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,017
inter	0,00	0,00	0,03	0,02	0,01	0,02	0,02	0,02	0,01	0,03	0,01	0,02	0,01	0,01	0,01	0,03	0,00	0,03	0,02	0,02	0,02	0,00	0,02	0,04	0,02	-0,01

Table 11: Confidence Sets: DRTM, Bias Corrected Estimates All

	AUT	BAN	KGO	CSS	CDA	DVF	FDR	FBT	HLT	HRL	INS	MAT	MED	RST	RET	SEM	TEC	TEL	TRA	UTL	EUC	NEU	NOA	SCA	AOC	AFM
AUT	0,002	-0,024	-0,015	-0,034	0,001	-0,022	-0,011	-0,024	-0,048	-0,027	-0,026	-0,007	-0,009	-0,017	-0,003	-0,006	-0,026	-0,024	-0,006	-0,023	-0,015	-0,071	-0,005	-0,023	-0,039	-0,151
BAN	0	0,022	-0,022	-0,036	-0,037	0,007	-0,024	-0,012	-0,005	-0,013	-0,008	-0,017	-0,016	-0,020	-0,030	-0,006	0,002	0,003	-0,024	-0,005	-0,010	0,022	-0,011	-0,010	0,026	-0,039
KGO	0	0	0,002	0,025	-0,006	0,014	0,018	0,015	-0,023	0,021	-0,013	0,039	-0,001	0,014	0,000	0,035	-0,017	0,029	0,025	0,007	0,007	-0,036	0,019	0,032	0,009	-0,074
CSS	0	0	0	-0,005	-0,034	-0,009	0,007	0,004	0,002	0,003	-0,022	0,017	-0,026	0,021	-0,014	0,000	-0,017	-0,029	-0,009	-0,010	-0,017	-0,046	0,006	0,005	-0,024	-0,092
CDA	0	0	0	0	-0,022	-0,028	-0,014	-0,019	-0,079	-0,039	-0,030	-0,001	0,001	-0,022	-0,006	-0,006	-0,048	-0,010	0,004	-0,030	-0,015	-0,086	-0,004	-0,031	-0,047	-0,175
DVF	0	0	0	0	0	0,020	0,001	0,007	-0,020	0,007	0,008	0,014	0,007	-0,002	-0,020	0,025	-0,013	0,037	0,001	0,026	0,015	-0,020	0,012	0,039	0,027	-0,064
FDR	0	0	0	0	0	0	0,011	0,004	-0,022	0,010	0,001	0,019	0,004	0,009	0,001	0,015	-0,022	0,017	0,017	0,011	0,003	-0,055	0,011	0,019	-0,019	-0,064
FBT	0	0	0	0	0	0	0	0,001	-0,008	0,008	-0,003	0,013	0,003	0,002	-0,008	0,016	-0,013	0,022	0,007	0,014	0,002	-0,021	0,012	0,030	0,000	-0,050
HLT	0	0	0	0	0	0	0	0	-0,007	-0,016	-0,034	-0,023	-0,058	-0,016	-0,043	-0,030	0,009	-0,070	-0,015	-0,019	-0,018	-0,018	-0,014	-0,032	0,000	-0,018
HRL	0	0	0	0	0	0	0	0	0	0,010	-0,015	0,016	-0,010	0,004	-0,007	0,014	-0,009	0,001	-0,001	0,012	0,005	-0,017	0,009	0,033	0,001	-0,030
INS	0	0	0	0	0	0	0	0	0	0	0,000	0,003	0,012	0,000	-0,025	0,014	-0,029	0,031	0,002	0,024	0,013	-0,071	0,012	0,023	-0,023	-0,100
MAT	0	0	0	0	0	0	0	0	0	0	0	0,026	0,013	0,015	0,006	0,031	-0,016	0,032	0,021	0,015	0,010	-0,038	0,015	0,027	-0,002	-0,060
MED	0	0	0	0	0	0	0	0	0	0	0	0	0,010	-0,003	-0,008	0,021	-0,031	0,036	0,011	0,015	0,010	-0,060	0,012	0,018	-0,020	-0,106
RST	0	0	0	0	0	0	0	0	0	0	0	0	0	0,010	-0,002	0,011	-0,014	0,006	0,003	0,002	-0,001	-0,045	0,010	0,011	-0,021	-0,049
RET	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,001	-0,001	-0,018	-0,015	0,005	-0,022	-0,013	-0,064	0,000	-0,013	-0,039	-0,069
SEM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,016	-0,024	0,051	0,025	0,029	0,022	-0,049	0,023	0,046	0,010	-0,097
TEC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,019	-0,035	-0,024	-0,021	-0,017	-0,009	-0,013	-0,012	0,007	-0,008
TEL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,021	0,036	0,055	0,040	-0,065	0,026	0,037	0,019	-0,109
TRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,013	0,016	0,004	-0,061	0,015	0,022	-0,013	-0,088
UTL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,019	0,021	-0,040	0,015	0,051	0,000	-0,099
EUC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,017	-0,021	0,013	0,038	0,018	-0,050
NEU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,011	-0,017	-0,013	0,055	0,002
NOA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,005	0,032	0,003	-0,045
SCA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,027	0,010	-0,058
AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,036	-0,012
AFM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,049
inter	-0,03	-0,01	0,00	-0,01	-0,03	0,00	0,00	0,00	-0,02	0,00	-0,01	0,01	-0,01	0,00	-0,02	0,01	-0,02	0,00	0,00	0,00	0,00	-0,03	0,01	0,01	0,00	-0,07

Table 12: Confidence Sets: DRTM, Lower Bound All

	AUT	BAN	KGO	CSS	CDA	DVF	FDR	FBT	HLT	HRL	INS	MAT	MED	RST	RET	SEM	TEC	TEL	TRA	UTL	EUC	NEU	NOA	SCA	AOC	AFM
AUT	0,006	-0,011	0,056	0,025	0,025	0,002	0,014	0,002	0,008	0,020	-0,001	0,035	0,016	0,013	0,032	0,034	0,004	0,012	0,038	0,027	0,019	-0,005	0,023	0,014	0,020	-0,048
BAN	0	0,029	0,003	0,008	-0,016	0,022	-0,011	0,001	0,001	0,008	0,010	-0,001	0,006	-0,001	-0,012	0,016	0,011	0,021	-0,015	0,029	0,020	0,107	-0,002	0,014	0,058	0,023
KGO	0	0	0,135	0,121	0,046	0,069	0,062	0,071	0,045	0,080	0,061	0,113	0,061	0,059	0,046	0,089	0,043	0,101	0,077	0,093	0,096	0,072	0,074	0,075	0,057	0,011
CSS	0	0	0	0,115	0,015	0,068	0,057	0,089	0,079	0,086	0,119	0,080	0,045	0,054	0,025	0,068	0,044	0,026	0,057	0,098	0,045	0,091	0,066	0,072	0,001	0,005
CDA	0	0	0	0	-0,014	0,014	0,005	0,014	-0,017	0,004	-0,003	0,031	0,025	0,019	0,012	0,026	-0,021	0,044	0,027	0,011	0,022	-0,068	0,019	0,022	0,001	-0,060
DVF	0	0	0	0	0	0,056	0,033	0,041	0,023	0,042	0,061	0,054	0,039	0,027	0,000	0,064	0,016	0,086	0,030	0,062	0,064	0,043	0,040	0,071	0,045	0,015
FDR	0	0	0	0	0	0	0,029	0,037	0,034	0,045	0,057	0,049	0,035	0,032	0,022	0,044	0,015	0,046	0,044	0,046	0,040	-0,001	0,040	0,044	-0,010	0,030
FBT	0	0	0	0	0	0	0	0,030	0,053	0,048	0,064	0,051	0,029	0,044	0,017	0,041	0,025	0,028	0,021	0,048	0,030	0,045	0,042	0,045	-0,011	0,030
HLT	0	0	0	0	0	0	0	0	0,086	0,052	0,088	0,030	0,002	0,025	0,022	0,024	0,050	-0,037	0,022	0,044	0,004	0,117	0,029	0,017	-0,009	0,065
HRL	0	0	0	0	0	0	0	0	0	0,053	0,048	0,063	0,030	0,031	0,032	0,056	0,043	0,032	0,038	0,083	0,044	0,098	0,047	0,068	0,015	0,040
INS	0	0	0	0	0	0	0	0	0	0	0,051	0,049	0,043	0,039	0,005	0,054	0,036	0,041	0,040	0,057	0,046	0,069	0,049	0,063	-0,010	0,017
MAT	0	0	0	0	0	0	0	0	0	0	0	0,079	0,055	0,048	0,034	0,071	0,021	0,084	0,066	0,074	0,064	0,011	0,056	0,059	0,008	0,018
MED	0	0	0	0	0	0	0	0	0	0	0	0	0,045	0,035	0,016	0,059	0,001	0,086	0,052	0,056	0,055	-0,016	0,042	0,064	0,017	-0,006
RST	0	0	0	0	0	0	0	0	0	0	0	0	0	0,021	0,022	0,036	0,014	0,045	0,032	0,035	0,037	0,016	0,036	0,037	0,000	0,015
RET	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,017	0,021	0,015	0,005	0,029	0,028	0,017	0,017	0,024	0,016	-0,004	0,022
SEM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,079	0,013	0,100	0,057	0,082	0,077	0,024	0,052	0,085	0,043	-0,005
TEC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,021	-0,010	0,004	0,034	0,009	0,073	0,017	0,014	0,023	0,060
TEL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,187	0,062	0,057	0,114	-0,080	0,049	0,085	0,077	0,005
TRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,053	0,064	0,042	-0,034	0,047	0,063	0,001	-0,050
UTL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,105	0,057	0,099	0,055	0,086	0,043	0,012
EUC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,084	-0,010	0,055	0,078	0,065	0,010
NEU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,256	0,042	0,015	0,149	0,147
NOA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,034	0,057	0,021	-0,008
SCA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,087	0,028	0,004
AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,112	0,014
AFM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,038
inter	0,02	0,01	0,07	0,06	0,01	0,04	0,03	0,04	0,03	0,05	0,04	0,05	0,03	0,03	0,02	0,05	0,02	0,04	0,03	0,06	0,04	0,04	0,04	0,05	0,03	0,01

Table 13: DRTM: Non-Investment Grade NIG

	AUT	BAN	KGO	CSS	CDA	DVF	FDR	FBT	HLT	HRL	INS	MAT	MED	RST	RET	SEM	TEC	TEL	TRA	UTL	EUC	NEU	NOA	SCA	AOC	AFM
AUT	0,023	0,031	0,124	0,090	0,080	0,052	0,051	0,053	0,061	0,079	0,068	0,083	0,058	0,055	0,078	0,083	0,043	0,077	0,082	0,094	0,071	0,094	0,060	0,072	0,072	0,082
BAN	0	0,042	0,048	0,049	0,022	0,051	0,014	0,031	0,037	0,033	0,055	0,030	0,032	0,024	0,018	0,047	0,034	0,063	0,022	0,059	0,054	0,171	0,020	0,049	0,091	0,099
KGO	0	0	0,180	0,194	0,117	0,115	0,102	0,128	0,112	0,130	0,138	0,149	0,104	0,098	0,093	0,133	0,086	0,171	0,122	0,142	0,144	0,194	0,100	0,129	0,111	0,109
CSS	0	0	0	0,164	0,081	0,117	0,098	0,151	0,144	0,140	0,227	0,123	0,095	0,090	0,069	0,120	0,084	0,093	0,108	0,162	0,097	0,200	0,094	0,122	0,056	0,134
CDA	0	0	0	0	-0,008	0,067	0,047	0,067	0,046	0,062	0,059	0,080	0,069	0,058	0,059	0,081	0,023	0,127	0,072	0,065	0,080	0,025	0,053	0,083	0,051	0,075
DVF	0	0	0	0	0	0,079	0,059	0,086	0,067	0,077	0,122	0,082	0,068	0,052	0,033	0,096	0,046	0,135	0,067	0,097	0,105	0,143	0,057	0,105	0,084	0,130
FDR	0	0	0	0	0	0	0,041	0,074	0,069	0,070	0,112	0,072	0,057	0,053	0,047	0,069	0,038	0,083	0,070	0,074	0,066	0,070	0,057	0,073	0,022	0,101
FBT	0	0	0	0	0	0	0	0,055	0,101	0,091	0,137	0,090	0,067	0,075	0,050	0,088	0,056	0,096	0,068	0,096	0,077	0,131	0,071	0,096	0,035	0,117
HLT	0	0	0	0	0	0	0	0	0,118	0,098	0,157	0,071	0,038	0,059	0,056	0,066	0,082	0,023	0,072	0,094	0,052	0,209	0,055	0,062	0,044	0,133
HRL	0	0	0	0	0	0	0	0	0	0,077	0,104	0,090	0,059	0,056	0,066	0,092	0,071	0,084	0,074	0,120	0,080	0,179	0,065	0,101	0,055	0,101
INS	0	0	0	0	0	0	0	0	0	0	0,113	0,099	0,095	0,089	0,055	0,109	0,086	0,123	0,107	0,109	0,102	0,172	0,092	0,129	0,064	0,186
MAT	0	0	0	0	0	0	0	0	0	0	0	0,099	0,082	0,072	0,063	0,094	0,050	0,116	0,091	0,097	0,093	0,090	0,067	0,090	0,037	0,079
MED	0	0	0	0	0	0	0	0	0	0	0	0	0,063	0,058	0,044	0,086	0,030	0,124	0,080	0,086	0,085	0,055	0,061	0,095	0,046	0,072
RST	0	0	0	0	0	0	0	0	0	0	0	0	0	0,031	0,046	0,064	0,038	0,093	0,059	0,061	0,067	0,086	0,053	0,069	0,032	0,080
RET	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,027	0,054	0,041	0,051	0,064	0,065	0,055	0,093	0,045	0,049	0,034	0,083
SEM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,102	0,041	0,142	0,090	0,113	0,110	0,103	0,068	0,120	0,073	0,078
TEC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,033	0,034	0,033	0,060	0,042	0,154	0,037	0,046	0,060	0,147
TEL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,240	0,111	0,097	0,163	0,021	0,070	0,137	0,119	0,139
TRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,071	0,098	0,080	0,064	0,066	0,100	0,042	0,056
UTL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,136	0,092	0,177	0,071	0,122	0,074	0,086
EUC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,119	0,078	0,071	0,115	0,096	0,109
NEU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,385	0,083	0,082	0,215	0,259
NOA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,039	0,076	0,035	0,029
SCA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,118	0,056	0,086
AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,152	0,100
AFM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,097
inter	0,07	0,05	0,12	0,12	0,07	0,08	0,07	0,09	0,08	0,09	0,11	0,08	0,07	0,06	0,06	0,09	0,06	0,10	0,08	0,10	0,09	0,13	0,06	0,09	0,07	0,11

Table 14: Confidence Sets: DRTM, Upper Bound NIG

	AUT	BAN	KGO	CSS	CDA	DVF	FDR	FBT	HLT	HRL	INS	MAT	MED	RST	RET	SEM	TEC	TEL	TRA	UTL	EUC	NEU	NOA	SCA	AOC	AFM
AUT	-0,039	-0,010	0,056	0,025	0,025	0,003	0,014	0,002	0,007	0,022	-0,001	0,036	0,017	0,014	0,032	0,035	0,004	0,012	0,039	0,027	0,020	-0,003	0,023	0,015	0,019	-0,047
BAN	0	0,018	0,003	0,009	-0,017	0,022	-0,011	0,001	0,000	0,007	0,010	0,000	0,007	-0,001	-0,012	0,017	0,011	0,021	-0,014	0,029	0,019	0,110	-0,002	0,013	0,058	0,020
KGO	0	0	0,102	0,122	0,044	0,068	0,062	0,072	0,046	0,080	0,063	0,112	0,061	0,059	0,046	0,089	0,043	0,100	0,078	0,093	0,097	0,073	0,074	0,075	0,057	0,015
CSS	0	0	0	0,083	0,014	0,069	0,058	0,090	0,081	0,086	0,119	0,082	0,046	0,055	0,026	0,069	0,045	0,026	0,058	0,101	0,045	0,091	0,065	0,072	0,000	0,009
CDA	0	0	0	0	-0,068	0,011	0,003	0,012	-0,019	0,002	-0,006	0,029	0,024	0,017	0,012	0,023	-0,022	0,040	0,026	0,009	0,020	-0,067	0,018	0,019	0,000	-0,065
DVF	0	0	0	0	0	0,038	0,033	0,042	0,022	0,043	0,061	0,055	0,040	0,027	0,000	0,065	0,016	0,086	0,031	0,063	0,064	0,043	0,039	0,071	0,044	0,017
FDR	0	0	0	0	0	0	0,015	0,037	0,034	0,045	0,057	0,049	0,035	0,032	0,022	0,044	0,015	0,045	0,044	0,046	0,040	0,000	0,040	0,044	-0,009	0,028
FBT	0	0	0	0	0	0	0	-0,004	0,053	0,048	0,065	0,051	0,030	0,044	0,016	0,041	0,025	0,030	0,021	0,047	0,030	0,046	0,042	0,045	-0,011	0,028
HLT	0	0	0	0	0	0	0	0	0,052	0,052	0,087	0,030	0,002	0,025	0,021	0,024	0,050	-0,037	0,022	0,044	0,004	0,118	0,028	0,017	-0,011	0,066
HRL	0	0	0	0	0	0	0	0	0	0,029	0,048	0,063	0,030	0,030	0,032	0,055	0,044	0,032	0,038	0,082	0,043	0,100	0,047	0,068	0,013	0,040
INS	0	0	0	0	0	0	0	0	0	0	-0,039	0,050	0,043	0,041	0,006	0,053	0,038	0,038	0,042	0,058	0,046	0,072	0,048	0,063	-0,010	0,017
MAT	0	0	0	0	0	0	0	0	0	0	0	0,074	0,055	0,048	0,033	0,071	0,022	0,083	0,065	0,074	0,064	0,014	0,056	0,059	0,007	0,017
MED	0	0	0	0	0	0	0	0	0	0	0	0	0,033	0,035	0,016	0,059	0,002	0,085	0,052	0,056	0,055	-0,016	0,043	0,064	0,016	-0,011
RST	0	0	0	0	0	0	0	0	0	0	0	0	0	0,004	0,022	0,035	0,014	0,045	0,032	0,035	0,036	0,017	0,036	0,036	0,000	0,013
RET	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,005	0,022	0,016	0,006	0,030	0,028	0,017	0,019	0,024	0,017	-0,004	0,019
SEM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,067	0,013	0,100	0,057	0,082	0,077	0,026	0,052	0,085	0,043	-0,008
TEC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,006	-0,011	0,003	0,034	0,009	0,073	0,017	0,014	0,023	0,059
TEL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,174	0,062	0,058	0,114	-0,077	0,049	0,085	0,077	0,006
TRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,033	0,064	0,040	-0,032	0,047	0,063	-0,001	-0,055
UTL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,093	0,057	0,102	0,055	0,087	0,042	0,010
EUC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,076	-0,010	0,055	0,079	0,066	0,008
NEU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,230	0,043	0,015	0,151	0,146
NOA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,033	0,056	0,020	-0,009
SCA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,079	0,028	0,003
AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,103	0,011
AFM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,080
inter	0,02	0,01	0,07	0,06	0,01	0,04	0,03	0,04	0,03	0,05	0,04	0,05	0,03	0,03	0,02	0,05	0,02	0,04	0,03	0,06	0,04	0,04	0,04	0,05	0,03	0,01

Table 15: Confidence Sets: DRTM, Bias Corrected Estimates NIG

	AUT	BAN	KGO	CSS	CDA	DVF	FDR	FBT	HLT	HRL	INS	MAT	MED	RST	RET	SEM	TEC	TEL	TRA	UTL	EUC	NEU	NOA	SCA	AOC	AFM
AUT	-0,125	-0,048	-0,026	-0,051	-0,027	-0,048	-0,028	-0,052	-0,058	-0,046	-0,070	-0,014	-0,025	-0,031	-0,016	-0,017	-0,033	-0,061	-0,014	-0,040	-0,035	-0,095	-0,012	-0,044	-0,039	-0,155
BAN	0	-0,015	-0,044	-0,033	-0,054	-0,008	-0,033	-0,030	-0,034	-0,020	-0,032	-0,029	-0,019	-0,024	-0,037	-0,012	-0,011	-0,017	-0,047	0,001	-0,011	0,042	-0,021	-0,021	0,023	-0,066
KGO	0	0	-0,001	0,047	-0,040	0,022	0,021	0,010	-0,025	0,028	-0,018	0,074	0,017	0,015	-0,007	0,046	0,001	0,031	0,029	0,040	0,042	-0,041	0,049	0,016	-0,001	-0,069
CSS	0	0	0	-0,027	-0,056	0,023	0,015	0,019	0,016	0,026	0,009	0,040	0,002	0,015	-0,023	0,018	0,001	-0,046	0,008	0,034	-0,007	-0,024	0,038	0,017	-0,059	-0,096
CDA	0	0	0	0	-0,160	-0,055	-0,042	-0,046	-0,086	-0,057	-0,087	-0,023	-0,024	-0,025	-0,038	-0,041	-0,064	-0,059	-0,022	-0,048	-0,043	-0,157	-0,021	-0,052	-0,047	-0,191
DVF	0	0	0	0	0	-0,014	0,009	-0,003	-0,026	0,006	-0,008	0,029	0,011	0,000	-0,032	0,029	-0,013	0,038	-0,005	0,025	0,021	-0,045	0,022	0,035	0,001	-0,072
FDR	0	0	0	0	0	0	-0,016	-0,002	-0,003	0,016	0,005	0,023	0,011	0,009	-0,002	0,016	-0,010	0,006	0,017	0,015	0,009	-0,060	0,021	0,016	-0,038	-0,035
FBT	0	0	0	0	0	0	0	-0,085	-0,003	0,004	-0,019	0,014	-0,013	0,012	-0,021	-0,006	-0,010	-0,040	-0,027	-0,002	-0,018	-0,034	0,010	-0,007	-0,051	-0,045
HLT	0	0	0	0	0	0	0	0	-0,025	0,000	0,009	-0,010	-0,039	-0,011	-0,017	-0,020	0,013	-0,097	-0,030	-0,010	-0,044	0,021	0,003	-0,029	-0,064	-0,006
HRL	0	0	0	0	0	0	0	0	0	-0,032	-0,015	0,034	-0,001	0,003	-0,002	0,018	0,015	-0,015	0,001	0,041	0,004	0,022	0,028	0,032	-0,030	-0,015
INS	0	0	0	0	0	0	0	0	0	0	-0,245	0,003	-0,011	-0,013	-0,046	-0,007	-0,013	-0,051	-0,020	-0,002	-0,016	-0,017	0,012	-0,012	-0,075	-0,106
MAT	0	0	0	0	0	0	0	0	0	0	0	0,048	0,029	0,024	0,002	0,049	-0,006	0,051	0,040	0,049	0,034	-0,051	0,044	0,026	-0,022	-0,043
MED	0	0	0	0	0	0	0	0	0	0	0	0	-0,008	0,010	-0,012	0,030	-0,024	0,043	0,022	0,025	0,023	-0,077	0,024	0,032	-0,011	-0,092
RST	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,034	-0,005	0,007	-0,011	-0,004	0,004	0,006	0,001	-0,043	0,021	0,003	-0,035	-0,050
RET	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,049	-0,010	-0,011	-0,042	-0,006	-0,008	-0,022	-0,055	0,002	-0,017	-0,043	-0,040
SEM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,025	-0,013	0,056	0,024	0,050	0,040	-0,037	0,037	0,048	0,016	-0,081
TEC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,029	-0,052	-0,030	0,005	-0,025	-0,011	-0,001	-0,015	-0,013	-0,006
TEL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,101	0,015	0,021	0,067	-0,180	0,029	0,034	0,032	-0,097
TRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,010	0,026	0,001	-0,116	0,028	0,026	-0,040	-0,159
UTL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,042	0,022	0,026	0,039	0,055	0,006	-0,062
EUC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,026	-0,087	0,039	0,041	0,034	-0,073
NEU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,064	0,007	-0,041	0,089	0,028
NOA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,028	0,037	0,007	-0,051
SCA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,029	0,000	-0,080
AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,050	-0,075
AFM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,367
inter	-0,04	-0,02	0,01	0,00	-0,06	0,00	0,00	-0,01	-0,02	0,00	-0,02	0,01	0,00	0,00	-0,02	0,01	-0,01	-0,01	-0,01	0,01	0,00	-0,04	0,02	0,00	-0,02	-0,07

Table 16: Confidence Sets: DRTM, Lower Bound NIG