Are specific meta-models a solution for transfer reliability? An application on recreation

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Abstract

At this point state of the art on transfer method seems to show meta-models as a promising way in environmental valuation process by transfer but needing improvements. Moreover creating specific databases for meta-models is very time-consuming. The question asked here is: can we make reliable meta-models for transfer from existing environmental economic databases? The main databases around the world were reviewed and it appeared some improvements in what and how to code primary study information were needed to make potentially reliable meta-models. Then a meta-analysis on recreation was specially achieved to evaluate transfer reliability and to make judgment on global versus specific meta-models. This meta-analysis is based on a modified version of Kaval and Loomis' database (2003), the only one public and actually designed for potential reliable meta-modeling. In particular, model robustness was shown, and use-specific models and method-specific models did not yield better results than global model. A significant income effect was shown but taking it into consideration did not improve significantly transfer valuation. Global model transfer estimations were statistically proved unbiased but imprecise. So meta-model transfers should not yet be used for one particular application system (policy site). More research is needed on meta-models.

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1. Introduction

Non-marketable goods need to be valued in particular for present environmental policy developments or ex post policy evaluations. To answer this demand economists have built different valuation methods (contingent valuation, travel cost method) whose implementing is still long and costly. That is why a systematic use of these methods appears to be non reasonable. In case of modest recurrent issues an economical alternative, the transfer method, can be interesting. It consists in reusing for an application system (policy site) results from previous similar studies of reference systems (study sites).

In this view decision-making authorities have set up tools improving transfer use and making it easier. Since about ten years we have witnessed in particular the creation and development of environmental economic databases which are not simple listings of primary studies existing on a given subject. These databases synthesize some key transfer information, for example characteristics of the valued good, of the concerned population or of the used valuation method. Then asking databases on given criteria basis allows a fast reference study selection for transfer. Another point to consider is the potential of meta-analysis offered by these databases. The long, costly and fastidious work of gathering and coding study information into a database in order to make a meta-analysis is potentially already done.

Meta-model transfers have been said a promising transfer way because they can theoretically take into account good, population and methodology valuation attributes. This contribution explores first the issue on meta-model construction with existing databases. Second it presents use-specific and method-specific meta-models and a more global meta-model based on a modified version of Rosenberger and Loomis' database (2001), updated by Kaval and Loomis (2003). Model robustness is shown between original database and its update, and a special attention is paid to income effect. Third meta-model transfer reliability (validity and accuracy) is analyzed with specific versus global meta-model comparisons.

2. Meta-analyses and environmental economic databases

A meta-analysis is heard here as a statistical synthesis of subject-related primary studies. Gathering and coding studies allow to build and estimate models which explain result variability observed in these studies. These meta-models could be further applied to application systems within a transfer process. But databases recording and coding studies are first needed. Creating a specific database for a meta-model is very time-consuming, so an alternative is using existing environmental economic databases. Can we make reliable meta-models for transfer from them?

We can presently account for a dozen of public environmental economic databases in the world. The best known is *Environmental Valuation Reference Inventory*™ (EVRI), but we can quote for instance *Envalue*, *Sportfishing Values Database* (SVD), *Beneficial Use Values Database* (BUVD), *Recreation Use Values Database* (RUVD), *Ecosystem Services Database* (ESD), *Non-Market Values Portal* (NMVP), *Review of Externality Data* (RED), *ValueBase*^{SWE}, or *Environmental Benefit and Damage Valuation* (EBDV). Main characteristics of theirs are shown in Table 1: references, provider, subject, geographic covering, and number of primary studies and valuations included. The databases have been here ranked in descending number of primary studies. All these databases except RED are provided by only one specific country (USA, Australia, Canada, France or Sweden). Little international cooperation has been developed so far. Moreover most databases limit geographic covering to their providing country. Few notable exceptions are EVRI and Envalue which actually extend their covering to the world. To go further, some databases are very subject-specific, for instance SVD concerns only US fishing, whereas some others are much wider: EVRI and Envalue deal with environment and health goods everywhere in the world. In terms of studies included, it is not surprising that the more general databases (EVRI and Envalue) reference the more primary studies.

Table 1 : Environmental Economic Databases

Database	Author references	Provider	Subject	Countries	Studies	Valuations
EVRI	De Civita *et al.* (1998)	Canada	Environment, health	World	1028*	n.c.
Envalue	James *et al.* (2004)	Australia	Environment, health	World	387*	n.c.
RUVD	Kaval and Loomis (2003)	USA	Recreation	USA**	209	1239
ESD	Villa *et al.* (2002)	USA	Ecosystem	World	146	429
NMVP	Kildow *et al.* (2004)	USA	Ocean	World	143	n.c.
BUVD	Lew *et al.* (2001)	USA	Water	USA	128	2034
SVD	Boyle *et al.* (1998)	USA	Fishing	USA	109	3104
RED	European Commission (2003)	E.U	Externality	E.U	96	n.c
ValueBase	Sundberg and Söderqvist (2004)	Sweden	Environment, health	Sweden	96	410
EBDV	Amigues *et al.* (2005)	France	Water	France	25	74

* potential duplicates included;
** 5 studies are from Canada;
n.c. : not communicated.

All these databases are transfer-oriented in the sense they were created to encourage transfer. All are distributed on Internet with their own website (cf. references). This medium allows easy up-date, fast data access, and user interactivity. If databases are quite similar in the core, their thematic (subject and location), appearance, architecture and data processing vary quite a lot from each other.

Searchable databases (BUVD, EBDV, Envalue, ESD, EVRI, NMVP, RED, SVD) allow a fast reference study selection for transfer by asking them on criteria such as valued use type, geographic location, and valuation method. Note that ESD and NMVP which are just simple searchable study listings will not be explored further. Searchable databases give opportunities to make value or function transfers. But in the present state of our knowledge, this kind of public tool cannot allow to achieve meta-analysis because information is not displayed as a usable meta-analysis table. Information is shared out in complex related tables, which offers many possibilities in terms of searching and pre-selecting. Nevertheless every display needs a preprogrammed request to gather pieces of information spread along the tables. And no searchable database does not still propose an adapted request for a meta-analysis table-like display.

At the opposite non-searchable databases (ValueBase, RUVD) do not allow an easy search for reference studies, but they take advantage of their simple display in one unique table which can be easily transformed in a meta-analysis table. Assuming n valuations in the non-searchable database, E and Y n–length vectors of, respectively, environmental change to be valued and related valuation, G the $(n \times g)$ related matrix of good attributes, S the $(n \times s)$ related matrix of substitute attributes, C the $(n \times c)$ related matrix of consumption attributes, P the $(n \times p)$ related matrix of population characteristics, M the $(n \times m)$ related matrix of valuation methodology attributes, ε an error term and f a function, we can estimate a meta-model of basic form:

$$Y = f(E, G, S, C, P, M) + \varepsilon \tag{1}$$

In terms of architecture every database has its own data organization. But information storage follow a shared principle: data for each referenced study are coded in raw fields, hold in one table for non-searchable databases, or generally distributed in several tables with multiple connections for searchable databases. In the latter information is presented to the user in synthesized fields whose number ranges from 20 to 50 with a median point around thirty (e.g. 18 for BUVD, 27 for Envalue, 29 for EBDV, 31 for EVRI, 48 for SVD). Information is not synthesized and remains displayed in raw fields in the former; were it synthesized we would find again the previous range (e.g. 27 for ValueBase, 60 for RUVD).

Through databases some fields seem to be never omitted: valued good type with its location and valuation, valuation method and study references. An environmental good valuation is indeed location-specific and method-specific, and a transfer valuation should not be considered as serious without getting back to the primary study sources. Other contents are sometimes filled in and concern survey methodology, site attributes, and population characteristics. A summary is often given. Table 2 shows how information details are displayed through databases. Column 2, 3, and 4, indicate, respectively, if values were relatively homogenous (vs. values were just reported like in the primary studies), if valued uses were rigorously classified (e.g. fishing, purification), and if use-related resources were rigorously classified (e.g. water, wetland). Column 5, 6, and 7, qualify, respectively, good, population, and method characterization. Last column show if a summary is available. We have to note databases give, all in all, the same basic information; but some databases relatively code a few pieces of information in fields and let the user find some key information in the sum-up. This is a key point because the summing-up information is generally unusable for asking process and need an entire recoding for meta-analysis.

Table 2: Displayed Field Characteristics in Databases

Database	Value H.	Use C.	Resource C.	Good	Population	Method	Sum-up
BUVD	No	Yes	No	Absent	Absent	Very imprecise	No
EBDV	No	Yes(1)	Yes	Absent	Absent	Imprecise	Long(2)
Envalue	Yes	No	Yes	Absent	Absent(3)	Precise	Short
EVRI	No	Yes	Yes	Absent	Absent(3)	Precise	Medium
RUVD	Yes	Yes	Yes	Incomplete	Precise	Very precise	No
SVD	Yes	Yes	Yes	Incomplete	Precise	Very precise	Short
ValueBase	No	No	Yes	Absent	Absent	Precise	Medium

H.: homogeneity;
C.: classification;
(1) Only two distinct uses;
(2) Moreover most primary study manuscripts are available;
(3) Existing but unfilled field.

As can be observed in Table 2, SVD and RUVD yield the best data process (data included in database, sum-up excluded) because these databases get the best results compared to the expected ideal answers. Then come EVRI and Envalue, next EBDV, and lastly ValueBase and BUVD. If we add summing-up information, it generally appears databases (except BUVD) answer study references, valuations and method valuation characteristics, superficially deal with good attributes, and very poorly, if not at all, touch on population attributes.

A point of interest is data quality: exactness, accuracy and homogeneity. Data exactness was not here considered because of excessive time needed to verify databases versus original manuscripts. At this point only RUVD can be said to show some inexactnesses (judgment relies on its use for meta-analysis presented further in the paper). Data accuracy is quite acceptable in most cases (Envalue, EVRI, RUVD, and SVD), even though some databases are less accurate (BUVD, EBDV, and ValueBase). On the other hand data homogeneity varies quite much within and among databases. If we focus on fields of good valuation and attributes, and of methodology attributes, we can say these fields remain quite homogenous through database for RUVD and SVD, less homogenous for EBDV and EVRI and still less for the others. All in all, data quality seems to be heterogeneous for all databases except SVD since at least for each of these databases one of the three criteria above is not reached.

To conclude about environmental economic databases, if their raw materials are quite equivalent from each other, information coding and displaying vary among them, which has two consequences. First in most cases databases cannot communicate each other. In a transfer perspective this implies to query not one but several databases, given that databases are not exhaustive and their thematic partially recover themselves. Second different presentations and running require user's investment for controlling all databases. Furthermore number of primary studies included is relatively low. Carson (2003) references more than five thousand environmental contingent valuations in the world up to 2001 whereas the biggest database (EVRI) hardly treats one thousand environmental studies in 2005, all valuation methods together. A certain lack of international cooperation until now must be pointed out, which could partly explain this fact. In the future scarce human and financial means should be shared among countries to reach an exhaustive and global point of view rather than dissipated inefficiently at national levels. Global environmental economic network setting-up is going in the right direction.

In a meta-model perspective we can say the main databases around the world cannot be yet used for meta-analysis. First there is often a practical infeasibility (display default), which nevertheless could be repaired. Second data heterogeneity would oblige an important data processing work. But a more profound problem would have still remained: the lack of good and population attributes in the databases, which is in part a primary study reporting default. Without such variables meta-model reliability will be limited, which is found in literature (Engel, 2002 ; Santos, 2001). Some improvements are needed in coding (data homogeneity, good and population attributes) and displaying (data synthesis) the databases to make potentially reliable meta-models, but it could not be sufficient without basically a good primary study reporting. This point has to be enlightened for future studies, and a new study should not be carried through without thinking of its secondary (transfer) potential use.

3. Use-specific and method-specific meta-models versus global meta-model

Data

Recreation Use Values Database (RUVD), already quoted above, is Rosenberger and Loomis' database (2001), updated by Kaval and Loomis (2003), and is the only one public and actually designed for potentially reliable meta-modeling. Moreover it is a research database, whose analysis has already shown some results presented further, and consequently data processing should be limited to some extents. That explains the choice of this existing database as a starting point of the contribution.

RUVD synthesizes 209 transfer-usable recreation valuation studies (travel cost and contingent valuations) from 1967 to 2003 in the USA (five studies took place in Canada and gave 9 values) and codes 1239 values. More than thirty valued recreation types are covered, such as hunting, fishing, wildlife viewing, hiking, biking, skiing, boating, and swimming. The database is a result of successive updates, with Kaval and Loomis' one as the fifth. Research work on it produced many contributions. Recent works have shown a global meta-model gives in some extents better results than regional meta-models (Rosenberger and Loomis, 2000). Shrestha and Loommis (2001 ; 2003) test the same models out of sample in other countries and in the USA. Results are not discouraging and confirm the global meta-model superiority in the US applications. Nevertheless used sample sizes are too small to conclude on either meta-model transfer validity or invalidity (statistical bias question).

Data were here based on RUVD last version (Kaval and Loomis, 2003). Since some mistakes and unclear variable specifications appeared in the database, a fastidious work of checking was carried through, and comparisons of database vs. original (primary study manuscript) data were made whenever a suspicion existed (if manuscript available). At this step RUVD can be said to contain some inexactnesses. Over this review process which led changes in the initial database, some valuations in referenced studies were added (13 values) or removed (39 values) based on primary study manuscripts, 28 studies (55 values) were excluded by lack of key information, and one omitted important study (U.S. Department of the Interior *et al.*, 2002 ; Aiken and Pullis La Rouche, 2003) was added (200 values in all). Thus final meta-analysis database (MAD) used in this contribution contained 1358 values of 182 studies. However as RUVD values added by Kaval and Loomis (2003) appeared less reliable than those previously coming from Rosenberger and Loomis (2001), I chose to base meta-models as well as transfer valuation reliability analysis on the first part of MAD (710 values of 135 studies), which is in fact a corrected version of Rosenberger and Loomis' database, and to test robustness of these meta-models in using all MAD (1358 values of 182 studies), which represent a corrected version of Kaval and Loomis' database. MAD last part though corrected is indeed suspected still to contain some mistakes.

In the paper we are proposing (i) to improve the previous global meta-model (Rosenberger and Loomis, 2001) based on a modified database and with considering some omitted variables like income, (ii) to take advantage of the last update and use it to test model robustness between corrected Rosenberger and Loomis' database and corrected Kaval and Loomis' one, (iii) to make up use-specific and method-specific meta-models and compare with the global one, and (iv) to test in-sample meta-model transfer validity and accuracy on large sample size, but with a systematic model re-estimation for every transfer valuation by leaving aside the study for which we want to apply the meta-model.

Model

As noticed earlier by Rosenberger and Loomis (2000), homoskedasticity assumption had to be rejected, but panel modeling in many forms did not give significant improvements. So we here estimated ordinary least squares models with HC3 MacKinnon and White's correction (1985) for consistent covariance estimates, also called jackknife heteroskedasticity-consistent covariance matrix. This correction was preferred to the basic White's heteroskedastic correction (1980) since the former was proved by MacKinnon and White (1985) and Chesher and Jewitt (1987), or more recently by Long and Ervin (2000) and Davidson and Flachaire(2001), to work always better, especially in small samples (n ≤ 250). This modeling seems the more robust in spite of failure in OLS assumptions (e.g. valuation independence, even in a same study, which is obviously false). The meta-model functional form is linear in the dependant variable which is the individual consumer surplus per day in 2003 dollars (using implicit price deflator). Most explanatory variables are dummy binary variables. A few quantitative variables were considered; they are either discrete (trend, number of activities offered by the site, sample size), or positively continue (average income, average education, average age, average sex, average group size). All quantitative variables are used in a linear form because logarithmic transformations did not improve results. So meta-analysis models are of a basic linear form without interactions, which writes in a matrix shape:

$$(2) \qquad Y = \beta x + \varepsilon$$

where Y is the dependant variable matrix, β is the parameter vector to be estimated (all models have a constant term), x is the explanatory (independent) variable matrix, and ε is an error matrix term with mean zero and x-conditionally covariance matrix $\Omega \neq \sigma_{\varepsilon}^{2} I_d$ with I_d the identity matrix.

The explanatory variables are related to the good attributes (use, resource and a few site characteristics), population attributes (income, age, sex, education, and group size), and methodological attributes (valuation method, survey characteristics, modeling specification); and a composite variable, the trend, takes into account time variations in demand (consumer preferences) and supply (site offers) as well as valuation methodology evolution. A presentation of all significant variables is given in Table 3. Some remarks are needed. First some qualitative variables are not always filled in (*Dispers*, *Rosclass*, *Resident*, *Expert*, *Sitequal*, *Lfunct*, *Rfunct*, *Multsite*, *Modeling*, *Survey*, and *Sampfram*). An *unknown* modality was added, which then transformed all binary variables (*Dispers*, *Resident*, *Expert*, *Sitequal*, and *Multsite*) into three-modality nominal variables, and got one more modality for the others (*Rosclass*, *Lfunct*, *Rfunct*, *Modeling*, *Survey*, and *Sampfram*). For instance, *Dispers* (site dispersion) could be *dispersed*, *not dispersed*, or *unknown*. In addition other qualitative variables are also naturally multi-modality variables (*Activity*[1], *Resource*, *Location*, *Method*, *Payvhcle*, and *Perunit*). In all cases, multi-modality variables were decomposed in as many dummy binary variables as modalities so that modality mean effects could be estimated. For example, *Dispers* was coded in three dummy variables: *Disper* (1 if dispersed), *Ndisper* (1 if not dispersed) and *DisperNC* (1 if site dispersion unknown). Note that *Method* is first decomposed in stated / revealed preferences (coded by *CVM*), then in type for each one (coded by CVMtype and TCMtype).

Second a multi-modality variable can be either nominal and then modalities are exclusive each other so the sum of all dummy modality variables equals one, or can be composite and modalities are not exclusive so the sum of all dummy modality variables can be different to one. In the first case, there are no interactions, and one modality effect cannot be estimated (only n–1 linearly independent dummy variables), and is put in the constant term. That concerns *Activity*, *Resource*, *Disper*, *Rosclass*, *Resident*, *Expert*, *Method*, *Sitequal*, *Lfunct*, *Rfunct*, *Multsite*, *Modeling*, and *Perunit*. The *unknown* option was given the preference for the omitted category, and it could be chosen for all except *Method* (zonal travel cost), and *Perunit* (unit day value). In the second case, several modalities can exist at the same time so interactions among modalities are possible, and all modality effects can be estimated.

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[1] Note that *Activity* already has its own *unknown* category, called *other recreation*, and which gathers undefined and obscure recreation activities.

Payvhcle, *Location*, *Survey*, and *Sampfram* are concerned. For simplification's sake it is assumed that the whole variable effect is equal to the mean of all modality variable effects. For instance, was a survey partly administrated by telephone and mail, the whole *Survey* effect was equal to one half phone modality effect plus one half mail modality effect. So no interactions were here considered and binary modality variables were transformed in discrete ones so their sum would get back to one. In those conditions only n–1 linearly independent modality variables could be estimated. *Unknown* option was the omitted category for *Survey* and *Sampfram*, payments other than trip cost, entrance fee or license, and annual pass, for *Payvhcle*, and US nation-wide valuations for *Location*.

Third as population attributes are very sparsely filled in, I coded a fixed mean effect for unfilled studies (unknown population values) and a quantitative effect for filled studies (known population values). Let V a quantitative population variable which has an E_V effect (E_{Vi} for unfilled study, and E_{Vu} for filled study), it gives:

$$(3) \qquad E_V = \begin{cases} E_{V_u} = \beta_m \times 1 = \beta_V V_m & \text{for unfilled study} \\ E_{V_i} = \beta_V V & \text{for filled study} \end{cases}$$

where β_m and β_V are estimated parameters and V_m is a virtual mean value for V.

In modeling the fixed effect is put in the constant, so that actually estimated mean effect $E_{V'}$ equals:

$$(4) \qquad E_{V'} = \begin{cases} 0 & \text{for unfilled study} \\ E_{V_i} - E_{V_u} = -\beta_m + \beta_V V & \text{for filled study} \end{cases}$$

Thus incompletely filled quantitative variable effect is here modeled by a slope term plus an intercept term (equal to $-\beta_m$), and concerns, besides quantitative population attributes, cost of time and cost of mile in travel cost valuations. This modeling allows variation when data are available around a fixed population attribute effect. Moreover dividing the opposite of intercept term –(–β_m) by slope term β_V gets back to V_m for further verifications (Is this virtual mean value in the range of observed values?).

Table 3: Description of Variable Meta-analysis

Variable type	Variable	Significant effects for multi-modality variable	Description of variable modality or variable
CONSTANT	CONSTANT	—	Model constant term
GOOD	ACTIVITY	CAMPING	1 if camping
		PICNIC	1 if picnic
		SWIM	1 if swimming
		SISEE	1 if sightseeing
		OFFRDVCL	1 if off road vehicle
		BOAT	1 if boating (float or motor boating)
		HIKE	1 if hiking
		SKI	1 if skiing (cross-country or downhill skiing)
		BGHUNT	1 if big game hunting
		SMHUNT	1 if small game hunting
		WATFOWL	1 if waterfowl hunting
		FISH	1 if fishing
		WLVIEW	1 if wildlife viewing
		GENRECR	1 if general recreation (composite of activities)
	RESOURCE	FOREST	1 if forest
		LAKE	1 if lake
		RIVER	1 if river
		SEA	1 if sea (estuary, bay, Atlantic, Gulf of Mexico, or Pacific)
	DISPERS	DISPER	1 if dispersed site
	PUBLIC	—	1 if public ownership of recreation site
	NUMACT	—	Number of different recreation good offers
	EXISTING	—	1 if good valuation in existing conditions
	FEDAG	—	1 if federal agency administered (Forest Service, National Park Service, Fish and Wildlife Service, and Bureau of Land Management)
	WILDER	—	1 if wilderness area
	STPARFOR	—	1 if state park or state forest
	ROSCLASS	ROS2	1 if Recreation Opportunity Spectrum class 2 (Semi-primitive non-motorized area)
	LOCATION	IM	1 if Intermountain
		PC	1 if Pacific Coast
		SE	1 if South-Eastern
		NE	1 if North-Eastern
		ALASKA	1 if Alaska
		Canada	1 if Canada
	GRLAKES	—	1 if Great Lakes
	MULSTATE	—	1 if multi-state valuation
POPULATION	INCOME	INC03INT	1 if filled income (Income intercept term)
		INC03SLP	Income (Income slope term), 0 if unfilled
	RESIDENT	RESID	1 if resident
	EXPERT	EXPUSE	1 if expert user
METHODOLOGY	CVM	—	1 if contingent valuation
	SUBS	—	1 if substitutes included
	M/ULTSITE	MULT	1 if multi-site valuation
	MODELING	OLS	1 if ordinary least squares model
		LOGIT	1 if logit model
		COUNT	1 if count data model (Poisson, negative binomial)
		EQOTHER	1 if neither ordinary least squares, neither tobit, neither logit, neither probit, nor count data model
	SURVEY	MAILSVY	1 if mail survey

		PHONESVY	1 if phone survey
		INPERSON	1 if onsite survey
	SAMPFRAM	USERLIST	1 if user list sample selection
	PERUNIT	TRIP	1 if per trip original value
		YEAR	1 if per year original value
CVM-specific	CVMTYPE	DCCVM	1 if dichotomous choice in CVM
		ITBID	1 if iterative bidding in CVM
	PAYVHCLE	TRIPCOST	1 if trip cost payment vehicle in CVM
		FEE	1 if entrance fee or license payment vehicle in CVM
TCM-specific	TCMTYPE	INDIVID	1 if individual TCM
		RUM	1 if random utility model TCM
	TCTIME	—	1 if cost of time included in TCM
	COSTMILE	MIL03INT	1 if filled cost of mile (Cost of mile intercept term)
		MIL03SLP	Cost of mile (Cost of mile slope term), 0 if unfilled
	SITEQUAL	SITEQ	1 if site quality included in TCM
	LFUNCT	YLIN	1 if left-hand linear form in TCM
	RFUNCT	XLIN	1 if right-hand linear form in TCM
MIXED VARIABLE	TREND	—	Collecting year (1=1967)

— without purpose;
CVM: contingent valuation method;
TCM: travel cost method.

Twelve meta-models were estimated from MAD first part: a global one which included all values, five activity-specific ones which were HUNT (all values of big game, small game and waterfowl hunting), BGHUNT (all values of big game hunting), WATFOWL (all values of waterfowl hunting), FISH (all values of fishing), and WILDVIEW (all values of wildlife viewing), and six method-specific ones which were CVM (all values of contingent valuations), OE (all values of open-ended contingent valuations), DC (all values of dichotomous choice contingent valuations), TCM (all values of travel cost valuations), ZONAL (all values of zonal travel cost valuations), and INDIVID (all values of individual travel cost valuations). The choice of methods and activities for, respectively, method-specific and activity-specific meta-models was based on model ability to be estimated with a sufficient large sub-sample available from MAD first part. For example, a RUM (all values of random utility model travel cost valuations) or a CAMP (all values of camping valuations) meta-model could not be estimated for lack of values.

Results

Meta-model regression results based on the first part of MAD are shown in Table 4. Each presented model is the result of optimization process in which more than 145 mean effects were considered and dropped one after another step by step based on MacKinnon and White's pseudo t-values (1985) of coefficient estimates. All variable coefficients are statistically significant at the 0.3 level. Most of them are statistically significant at the classical 0.05 level, but some which seemed to be interesting were conserved until the 0.3 statistical level (which is the limit where coefficient estimate becomes lower than heteroskedasticity-consistent covariance standard error of the coefficient). In the following, some comparisons will be made with Rosenberger and Loomis (2000) abbreviated in RL, and Walsh *et al.* (1992) abbreviated in WJM, since both studies were also based on RUVD of their time.

Global mean value of consumer surplus is \$39.60 and standard deviation equals \$29.86. In terms of adjusted R^2, the global meta-model has a 0.29 value, which is between 0.26 of RL's and 0.36 of WJM's. Adjusted R^2 range for activity-specific meta-models from 0.22 for WILDVIEW to 0.75 for WATFOWL, and 0.3 (TCM) to 0.61 (DC) for method-specific meta-models. Adjusted R^2 of RL's four regional-specific meta-models ranging from 0.28 to 0.66, and WJM's two method-specific meta-models ranging from 0.39 to 0.44, are slightly more tightened. As will be shown, most coefficients have here the expected sign (whenever a sign can be assumed).

Eight of the twelve meta-models have a statistically significant (0.1 level) constant term: only one (OE) among them is negative whereas the other seven (GLOBAL, HUNT, FISH, CVM, OE, DC, ZONAL, INDIVID) are positive. This agrees with previous results: in WJM all three model constants were significantly positive whereas only two in five were significantly positive for RL.

The different activity variable modalities have a quite wide range of effect. Depending on the meta-model some of them remain significant and not mandatory in the same direction from one model to another. Thus camping, picnicking, sightseeing, hiking, fishing, and wildlife viewing, were shown to have a mitigated effect through meta-models with a shifting significant sign. On the other hand significant sign of swimming, off road vehicle, skiing, small game hunting, and general recreation effects, appeared always to be negative. And boating, big game hunting, and waterfowl hunting, had always their significant sign as positive. The other activities (biking, snowmobiling, horseback riding, and rock climbing) had no effect in any investigated meta-model (global and method-specific). We have to note largely sampled recreations are the most present across models (5 out of 8 models possible for big game and waterfowl hunting, and 4 out of 7 for fishing). These results are quite different from RL but are closer to WJM. For instance big game and waterfowl hunting have always a significant sign as positive in WJM, which is not the case in RL (sometimes significantly positive, sometimes significantly negative).

Resource effect depends on the resource type supporting the activity. Forest and lake have a significant negative influence on value, whereas river and sea have a significant positive one. Almost all these effects only appeared significant in global and method-specific meta-models. Resource effect insignificance in activity-specific meta-models may result from the fact resource type is in general related to the activity opportunities. So in activity-specific models a resource type effect could not be apparent because of too much correlation with the constant term or too few occurrences to get a real signification. In WJM theses effect were not considered. RL's lake effect is similar, but their forest and river effects are not stable and then diverge from here.

Relative to other good attributes, the dispersion of the recreation site and number of activities which site offers has a significantly negative influence on value in meta-models.

More the site dispersed and multi-activity, lowest recreation valued. The significant negative sign of existing effect (good valued at existing conditions) in global meta-model seems to confirm people tend to give more value to hypothetical goods (idealized goods?) than real ones. Federal registered goods are of relative good quality so that effect could be expected positive. But in meta-models federal registered effect appeared to be significantly negative (as in RL but unlike in WJM). That has to be connected with the fact US people generally pay to access a federal registered good, and this fee is likely integrated in (taken away from) benefit value.

An important combined effect is the regional effect. Good location is indeed very often related to population location since in many cases the good population is quite local. So regional effect covers both good (e.g. good availability) and population (e.g. income) aspects, although it was thought here to be dependant more of good attributes. Location was spilled into six North-American geographic areas (plus a specific one for US nation-wide valuations, which is the omitted category). The five US areas are well represented in MAD, and their effects appear in many of the twelve meta-models. Globally Intermountain (Montana, Idaho, Wyoming, Colorado, Arizona, New Mexico, Nevada, and Utah) and Alaska have a positive effect, Pacific Coast (California, Oregon, Washington), US South-Eastern, and US North-Eastern, have a negative one (still more in Great Lakes region). No clear effect appeared for Canada, but it not surprising given the few of Canadian values included. So US regional effect appeared quite stable (signs did not change) and could be ranked by decreasing effect in comparing relatively each other: Alaska, Intermountain, Eastern (South and North), and finally Pacific Coast.

Few population attributes were significant but it can be mainly attributed to the widely incomplete raw material for theses variables. A significant positive effect for expert user could be shown in OE (also positive but not significant in INDIVID). The income slope term (similar to a marginal income effect) has an expected significant positive sign in GLOBAL and CVM, the two biggest meta-models in terms of values (and thus in filled incomes). Lack of information certainly prevents income effect to reveal significant in the other meta-models. Estimated income marginal effect values for individual consumer surplus per day in $ 2003, which are around $1.7 / $1 000 of income (0.17 % of income), should be interpreted with caution because of multi-collinearities among effect variables and mixing of quantitative and qualitative effect variables. If we pay attention to income effect, we can see that the mean effect put in the constant (for unfilled studies) would correspond to a $27 856 mean income (46.77 / 0.001679) for global meta-model, and to a $27 681 mean income (48.83 / 0.001764) in CVM, which are in the range of observed income ($12 622-$64 340).

In respect with methodological attributes, stated preferences effect has a significant negative sign in almost all meta-models (5 in 6). That, though conflicting with theory, has already found in WJM and RL, and was also reported in other papers (Carson *et al.*, 1996 ; Gen, 2004). The hypothetical bias could partly explain this empirical fact. Moreover dichotomous choice seems to increase CVM values compared to the other experimental modes (open-ended, payment card, and iterative bidding) based on global and activity-specific meta-models. But this assumption could not be shown as true in CVM, the more seemingly adapted meta-model to analyze this question. In TCM, individual technique is shown to increase values; RUM technique might do the opposite.

Inclusion of substitutes has the expected negative sign in 5 out of 12 meta-models (as in WJM and RL). Modeling effect is sparsely significant and not in a clear direction. Mail survey has a significantly positive effect in 5 meta-models and a negative one in 2 cases. Seemingly positive effect of mail survey would also be found in RL. A significantly negative per trip original values effect was globally revealed. Per trip original values would be lower than those per day. The opposite was found in RL.

In stated preferences attributes trip cost payment vehicle increases significantly values. Fee entrance / license payment vehicle seems to have the same effect. As regards revealed preferences attributes inclusion of cost of time in travel cost could not be proved having a positive effect on value. WJM showed this expected effect, but RL did not. However the mechanically positive effect of cost of mile was shown here in TCM and ZONAL. In the same way as income we can calculate the virtual cost of mile for unfilled studies, equal to \$0.58/mile (44.86 / 77.204) for TCM and \$0.49/mile (32.28 / 65.876) for ZONAL, and which is realistic compared to the observed range (observed range: \$0.12-\$0.88/mile).

Lastly trend has an expected positive sign in half meta-models (positive effect was also shown in RL). Benefit values are then greater in real terms (inflation effect has excluded in normalizing all values in \$ 2003) over time. What can result in increased benefits? Valuation methodology evolution could be one of the reasons. For example there is a learning process for population to control stated valuation methods, and first fears can disappear over time associated with increased values. However stated preferences meta-models tend to have no trend effects unlike revealed preferences meta-models (methods in which there cannot be learning process). Moreover nothing allows to support researcher modeling evolved with an increase in values. Thus methodological reasons have to be rejected at this point. The main three other explanations of increasing in people valuation are consumer preferences changing in favor of environmental activities, increase in consumer financial resource, and quantitative and qualitative improvements in environmental goods. The first one is supported by population growing awareness of environment value since the seventies in the USA. The second assumption is based on perpetual US wealth increase, which leads American people to be richer. Theses demand aspects represent the main signification of trend in stated preferences. However only DC showed a significantly positive effect (CVM and OE did not), so these two first assumptions could be somehow secondary in value increase. The third assumption is supported by growing environmental regulation with a better protection (and thus resulting in better quality sites) since also the seventies in the USA, and the growing role played by federal services in supplying quality environmental goods such as Forest Service, National Park Service, Fish and Wildlife Service, and Bureau of Land Management. It appears as the author's preferred assumption on significantly positive effect of trend.

Considering all meta-models the most often significant effects are in respect with proportion stated preferences (negative sign), big game hunting (positive sign), waterfowl hunting (positive sign), constant term (positive sign), fish (rather positive sign), mail survey (positive sign), trend (positive sign), inclusion of substitutes (negative sign), per trip original values (negative sign), and Pacific Coast (negative sign).

Global meta-model robustness has been shown between MAD first part (710 values) and whole MAD (1358 values). Almost all coefficients still keep the same sign and remain significant (meta-models based on whole MAD are not here presented for an obvious space saving, but can be obtained upon request from the author). Most effect values do not change in important proportion. And models have not been said statistically[2] different.

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[2] Testing process has, however, to be refined.

Table 4: Optimized Global, Activity-specific, and Method-specific, Meta-model Regression Results

Variable	GLOBAL	HUNT	BGHUNT	WATFOWL	FISH	WILDVIEW	CVM	OE	DC	TCM	ZONAL	INDIVID
CONSTANT	43.63 **	56.69 *	14.59	1.30	74.30 **	-40.61	38.56 **	-97.37 **	55.12 **	31.51	47.37 †	79.82 **
	(10.56)	(23.59)	(28.69)	(37.68)	(11.73)	(35.12)	(10.15)	(34.36)	(14.55)	(27.33)	(24.38)	(16.95)
CAMPING								15.42 †		16.13	-21.09 *	
								(9.00)		(12.89)	(8.56)	
PICNIC										16.60		
										(16.35)		
SWIM	-16.35											-39.15 *
	(10.12)											(15.34)
SISEE	14.43						-28.53 **			30.78 *		
	(11.39)						(8.24)			(15.36)		
OFFRDVCL	-26.46 *											
	(10.39)											
BOAT										30.29 *		
										(13.34)		
HIKE							-19.77					
							(12.60)					
SKI	-12.00 †						-21.93 †					
	(6.72)						(12.60)					
BGHUNT	19.41 **							12.37 **	24.90 **	15.68 †	26.51 **	
	(3.84)							(2.99)	(3.93)	(8.36)	(9.69)	
SMHUNT							-16.48 *			20.39		
							(7.47)			(17.31)		
WATFOWL	13.52 **	10.78						5.94 †	71.61 **		42.13	
	(4.98)	(7.44)						(3.57)	(20.06)		(35.89)	
FISH	8.60 *						-8.30 **		-34.79	26.31 **		
	(4.02)						(3.02)		(25.35)	(9.76)		
WLVIEW							-19.01 **	14.49 **				
							(3.27)	(2.81)				
GENRECR							-38.40 **					
							(9.45)					
FOREST									-38.89 **		-24.04 *	
									(11.41)		(10.26)	
LAKE	-6.22						-31.08 **			-20.56 *		
	(5.28)						(8.38)			(10.22)		
RIVER	34.33 **				32.58 **		20.61		53.66 *	34.36 *	32.75 †	41.94 †
	(9.69)				(11.70)		(12.85)		(27.05)	(14.95	(18.51)	(23.89)
SEA	22.37 †				32.37					64.97 †		
	(13.49)				(22.54)					(33.74)		
ROS2		14.58 †										
		(7.99)										
FEDAG	-5.79						-10.23 **					
	(3.86)						(3.83)					
WILDER											60.22	
											(54.80)	

Variable	GLOBAL	HUNT	BGHUNT	WATFOWL	FISH	WILDVIEW	CVM	OE	DC	TCM	ZONAL	INDIVID
STPARFOR	-23.74 **											
	(7.78)											
DISPER	-15.81 **	-17.75										-22.14 *
	(4.58)	(15.42)										(10.02)
PUBLIC										30.39 *		
										(14.68)		
NUMACT		-1.189 †			-2.239		-4.912 **					
		(0.671)			(1.851)		(1.725)					
EXISTING	-12.30 *		-18.88									
	(5.72)		(15.18)									
IM	4.99 †		7.21			6.86 †	2.53		11.57 *	8.34		
	(2.74)		(7.10)			(4.03)	(2.53)		(4.72)	(7.60)		
PC	-6.27	-15.53 *			-32.33 *			3.61	8.51	-12.73	-22.72 †	-39.04 *
	(4.25)	(7.76)			(13.67)			(2.46)	(5.50)	(9.84)	(12.35)	(15.72)
SE		-8.63 **	-4.22									-31.49 *
		(2.80)	(3.14)									(13.37)
NE					-17.81 *		-3.60 †				-13.44	
					(6.82)		(1.98)				(9.18)	
GRLAKES										-46.41 **		
										(16.19)		
ALASKA	9.47		16.40				16.78 **					
	(6.48)		(12.82)				(5.85)					
CANADA			25.94							-31.16		
			(26.10)							(23.56)		
MULSTATE	-26.41 **		-47.83 **		-80.84 *			59.63 **		-22.84 *	-22.29	
	(8.80)		(16.20)		(34.50)			(22.37)		(10.80)	(20.23)	
TREND	1.113 †	3.069 **	3.518 **	3.169		4.344 **		2.253 *		0.887	3.538 **	
	(0.583)	(0.557)	(1.123)	(2.068)		(1.665)		(0.985)		(0.787)	(0.946)	
INC03INT	-46.77 †						-48.83 **					
	(24.92)						(17.37)					
INC03SLP	0.001679 **						0.001764 **					
	(0.000583)						(0.000398)					
RESID					-11.06							
					(8.50)							
EXPUSE								31.43 *				37.44
								(14.64)				(29.06)
CVM	-36.93 **	-80.39 **	-51.32 **	-76.45 **	-78.21 **	-51.46						
	(11.57)	(17.30)	(14.98)	(21.02)	(25.01)	(36.35)						
DCCVM	20.05 **	32.95 **	27.87	28.84								
	(5.60)	(7.26)	(18.52)	(17.96)								
ITBID		36.48 **										
		(11.42)										
INDIVID					-10.57					14.14 †		
					(9.04)					(7.90)		
RUM										-34.31		
										(20.82)		
TRIPCOST	20.40 *			35.04 **	33.95		17.37 **	33.18 †	35.41 **			
	(10.01)			(12.29)	(23.92)		(6.45)	(17.93)	(10.17)			

Variable	GLOBAL	HUNT	BGHUNT	WATFOWL	FISH	WILDVIEW	CVM	OE	DC	TCM	ZONAL	INDIVID
FEE	11.73							44.84 *				
	(11.42)							(22.13)				
SUBS	-12.09 †	-26.37 **	-18.37	-74.55 **	-9.24					-13.92 †		-35.50 *
	(6.42)	(9.84)	(15.12)	(23.43)	(7.96)					(7.60)		(14.07)
SITEQ				31.19								
				(23.75)								
TCTIME										15.79		
										(10.78)		
MIL03INT										-44.86 **	-32.28 †	
										(14.38)	(17.66)	
MIL03SLP										77.204 †	65.876	
										(41.517)	(48.939)	
MULT								38.20 **	26.81 †	-27.44 **	-16.51	
								(10.17)	(14.30)	(9.74)	(11.60)	
OLS		-31.98 *					10.48			-11.83	-16.90	
		(14.11)					(9.09)			(10.41)	(12.73)	
LOGIT							14.65 †					
							(7.85)					
COUNT	40.12 **										-67.88	
	(9.93)										(50.92)	
EQOTHER		-27.27 *										
		(11.91)										
YLIN	15.48 †		37.02								34.24 *	
	(8.52)		(24.69)								(15.79)	
XLIN											-24.35 **	53.48 **
											(9.27	(16.89)
MAILSVY		39.34 **	36.39 **	60.58 **		34.35 *	-16.21 †	33.37 **	-49.05 **	15.42		-21.38
		(6.83)	(9.66)	(16.74)		(15.19)	(8.44)	(9.48)	(13.79)	(10.57)		(19.98)
PHONESVY	-16.57 **					39.85 *	-13.26					
	(5.37)					(16.54)	(8.27)					
INPERSON					63.77 *						-43.99 **	
					(29.37)						(13.75	
USERLIST										34.19 †		80.35 *
										(17.45)		(30.74)
TRIP		-22.81 *	-28.33 *				21.10 **		-19.85 †	-21.65 **		-26.20
		(9.64)	(12.81)				(4.07)		(11.46)	(7.44)		(17.86)
YEAR							25.56 **		-17.62			
							(5.25)		(11.12)			
n (studies)	709 (135)	255 (45)	177 (35)	59 (13)	121 (39)	158 (16)	448 (62)	248 (25)	125 (21)	263 (91)	135 (49)	108 (35)
Adjusted R^2	0.29	0.48	0.38	0.75	0.51	0.22	0.46	0.37	0.61	0.30	0.60	0.31
F-statistics	11.19	16.69	9.25	25.22	11.49	9.64	17.77	13.02	15.81	5.00	12.47	5.44
(degrees of freedom)	(29, 679)	(15, 239)	(13, 163)	(7, 51)	(12, 108)	(5, 152)	(23, 424)	(12, 235)	(13, 111	(28, 234)	(18, 116)	(11, 96)

Dependant variable is consumer surplus per person per day in 2003 dollars using implicit price deflator.
Standard error in parentheses is corrected for heteroskedasticity using MacKinnon and White's correction (1985).
Statistical signification level of coefficient estimate is given based on pseudo t-value: † 0.1 level, * 0.05 level, and ** 0.01 level. All estimates are 0.3 level.

4. Meta-model transfer reliability

We here understand reliability as the combination of validity and accuracy (Genty, 2004). Assuming V_t the value with model transfer valuation and V_0 the value directly obtained (original value), we can define the transfer error *Err* in two ways:

$$(5) \qquad \begin{aligned} &\text{Absolute error: } Err = V_t - V_0 \\ &\text{Relative error: } Err = \frac{V_t - V_0}{V_0} \end{aligned}$$

The transfer validity is the absence of measure statistical bias, or a null transfer error expected value, which can be written:

$$(6) \qquad \mathrm{E}(Err) = 0$$

The transfer accuracy is related to transfer error variance. Smaller the latter is, more accurate the transfer valuation is. Let transfer error the sum of a systematic error or bias (b) and a centered random error (ε), reliability can be analyzed as following:

$$(7) \qquad \begin{aligned} &Err = b + \varepsilon \quad \text{where } \mathrm{E}(\varepsilon)=0 \\ &\text{Reliability}\begin{cases} \text{Validity} \Leftrightarrow \mathrm{E}(Err) = b = 0 \\ \text{Accuracy} \Leftrightarrow \mathrm{V}(Err) = \mathrm{V}(\varepsilon) \text{ small} \end{cases} \end{aligned}$$

If transfer is reliable, absolute error should be distributed as a normal distribution $\mathrm{N}(0, \sigma_1)$ with σ_1 small, and relative error should be distributed as a log-normal distribution $\mathrm{LN}(-1, 0, \sigma_2)$[3] where first value is the threshold parameter (values range from -1 to $+\infty$), second value is the scale parameter, and third value is the shape parameter which is to be small. The second proposal (relative error) is equivalent to the logarithm of the ratio of transfer valuation and original valuation is distributed as a normal distribution $\mathrm{N}(0, \sigma_2)$ with σ_2 small, which will be used for relative error analysis instead.

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[3] Expected value of this log-normal distribution is $\exp(\sigma_2^2/2) - 1$, and its variance is $\exp(\sigma_2^2/)\ (\exp(\sigma_2^2/) - 1)$.

Here I want to test meta-model transfer reliability. Each meta-model (12 in all) for each study was re-estimated with leaving aside the study for which I wanted to apply the meta-model. Then meta-model was applied to value goods of the left aside study, and both absolute and relative transfer errors (difference between meta-model valuation and original valuation) were calculated. In those conditions, meta-model variable selection is not independent from the study for which meta-model is applied (selection optimization takes into account all studies together), but meta-model estimation is independent from it. So it near approaches an out of sample meta-model transfer test. Both absolute and relative transfer error distribution for each meta-model were lastly analyzed, in particular their expected values and standard errors. Asked questions are:

$$
\begin{aligned}
&(V_t - V_0) \sim \mathrm{N}(0,\sigma_1) \text{ with } \sigma_1 \text{ small?} \\
&\ln\left(\frac{V_t}{V_0}\right) \sim \mathrm{N}(0,\sigma_2) \text{ with } \sigma_2 \text{ small?}
\end{aligned}
\tag{8}
$$

Only main highlights will be shown here. Expected value of each error was tested to be different from zero. Test results are presented in Table 5 for absolute errors and in Table 6 for relative errors. Nine of 12 expected values for absolute errors and 5 of 12 expected values for relative errors are not statistically different from zero at the classical 0.05 level. Thus in most cases absolute error appeared unbiased, which is not the case for relative error. In absolute term global meta-model is not biased, and only HUNT, WATFOWL, and DC, were proved to be biased. We have to note absolute error is here more meaningful since there are some very small original valuations (from \$1 to \$5), which implies a small and acceptable error in absolute term (a few dollars) can become tremendous in relative term. This fact tends to bias the relative error to the right (in a positive way). So in the following results on relative error are to be interpreted with caution.

As regards accuracy results are not good. Absolute transfer error standard errors are not small and comparable in value to sample mean consumer surplus value ($39.6). They range indeed from 19.48 for WILDVIEW to 51.52 for INDIVID. Relative transfer error standard errors are even worse. Inclusion or exclusion of income effect does not change prediction quality.

Figure 1 and Figure 2 show absolute error distribution for all meta-models, and Figure 3 and Figure 4 show relative error distribution for all meta-models. A normal distribution was adjusted for each error distribution based on Kolmogorov-Smirnov's test, Cramer-von Mises' test and Anderson-Darling's test. Globally the normal adjustment worked quite well, but normal distribution appeared zero mean in both errors only for revealed preferences meta-models (TCM, ZONAL, and INDIVID). Moreover WILDVIEW normal distribution is zero mean for absolute error, and FISH and OE ones are zero mean for relative error. These results complete previous ones. Revealed preferences meta-models and WILVIEW are confirmed to be unbiased, and HUNT, WATFOWL, and DC, are confirmed to be biased, though HUNT bias appeared limited (bias signification test was at the very limit of the 0.01 level, and bias in adjustment is $6). However the five others meta-models (GLOBAL, BGHUNT, FISH, CVM, and OE) have to be questioned about their bias. No clear answer could be given, because results seem to be contradictory with previous ones on expected value tests (expected value not statistically different from zero but a best adjustment with a non zero mean distribution). All in all if bias were present, it would be very limited for all of five and would not get over a $5 bias as show adjustments. In conclusion all meta-models except WATFOWL and DC can be said to be unbiased or limited biased.

To compare global and specific meta-models, I selected global absolute error sub-samples corresponding to specific valuations for which specific meta-model could apply. For instance, HUNT can apply only to hunting valuation. So global meta-model absolute transfer error related to hunting valuations will be selected (HUNT-global), which will allow comparing global versus specific error for hunting. Basic comparisons between global and specific meta-model show no big differences in terms of validity and accuracy. Standard errors are quite equivalent between global and specific meta-models. Global vs. specific bias indications based on expected value tests show no difference for BGHUNT, FISH, WILDVIEW, TCM, and ZONAL (unbiased), and WATFOWL (biased) sub-samples. At the opposite HUNT-specific and DC-specific were shown biased at 0.01 level whereas HUNT-global and DC-global were not, and CVM-global, OE-global, and INDIVID-global were significantly biased though specific ones were not. Besides valuations from both meta-modeling are statistically equivalent at 0.01 level for all except FISH, OE, DC, and INDIVID. So transfer performance are quite similar between global and specific meta-models, and specific meta-models can be said at that point not to significantly improve global meta-model transfer results. More insights would be, however, needed.

Table 5: Absolute Transfer Error Test for Global, Activity-specific, and Method-specific Meta-model

Meta-model	Sample size	Mean	Standard Error	t-value	P-value	
GLOBAL	709	0.48	33.88	0.37	0.71	
HUNT	255	5.17	31.28	2.64	0.01	**
BGHUNT	177	2.46	29.41	1.11	0.27	
WATFOWL	59	16.00	26.40	4.66	0.00	**
FISH	121	-2.46	30.84	-0.88	0.38	
WILDVIEW	158	0.42	19.48	0.27	0.79	
CVM	448	1.77	21.17	1.77	0.08	
OE	248	2.95	23.72	1.96	0.05	
DC	125	27.25	30.52	9.98	0.00	**
TCM	263	-4.33	49.68	-1.41	0.16	
ZONAL	135	-0.13	30.76	-0.05	0.96	
INDIVID	108	-0.80	51.52	-0.16	0.87	

* statistically significant at 0.05 level, ** statistically significant at 0.01.

Table 6: Relative Transfer Error[4] Test for Global, Activity-specific, and Method-specific Meta-model

Meta-model	Sample size	Mean	Standard Error	t-value	P-value	
GLOBAL	709	0.19	0.87	5.89	0.00	**
HUNT	255	0.17	0.80	3.31	0.00	**
BGHUNT	177	0.08	0.83	1.24	0.22	
WATFOWL	59	0.56	0.81	5.31	0.00	**
FISH	121	-0.43	1.48	-3.17	0.00	**
WILDVIEW	158	0.08	0.53	1.81	0.07	
CVM	448	0.12	0.67	3.86	0.00	**
OE	248	0.11	0.77	2.18	0.03	*
DC	125	0.43	0.59	8.19	0.00	**
TCM	263	-0.08	1.48	-0.92	0.36	
ZONAL	135	-0.15	1.25	-1.41	0.16	
INDIVID	108	0.12	1.18	1.04	0.30	

* statistically significant at 0.05 level, ** statistically significant at 0.01.

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[4] Logarithm of the ratio of transfer valuation and original valuation.

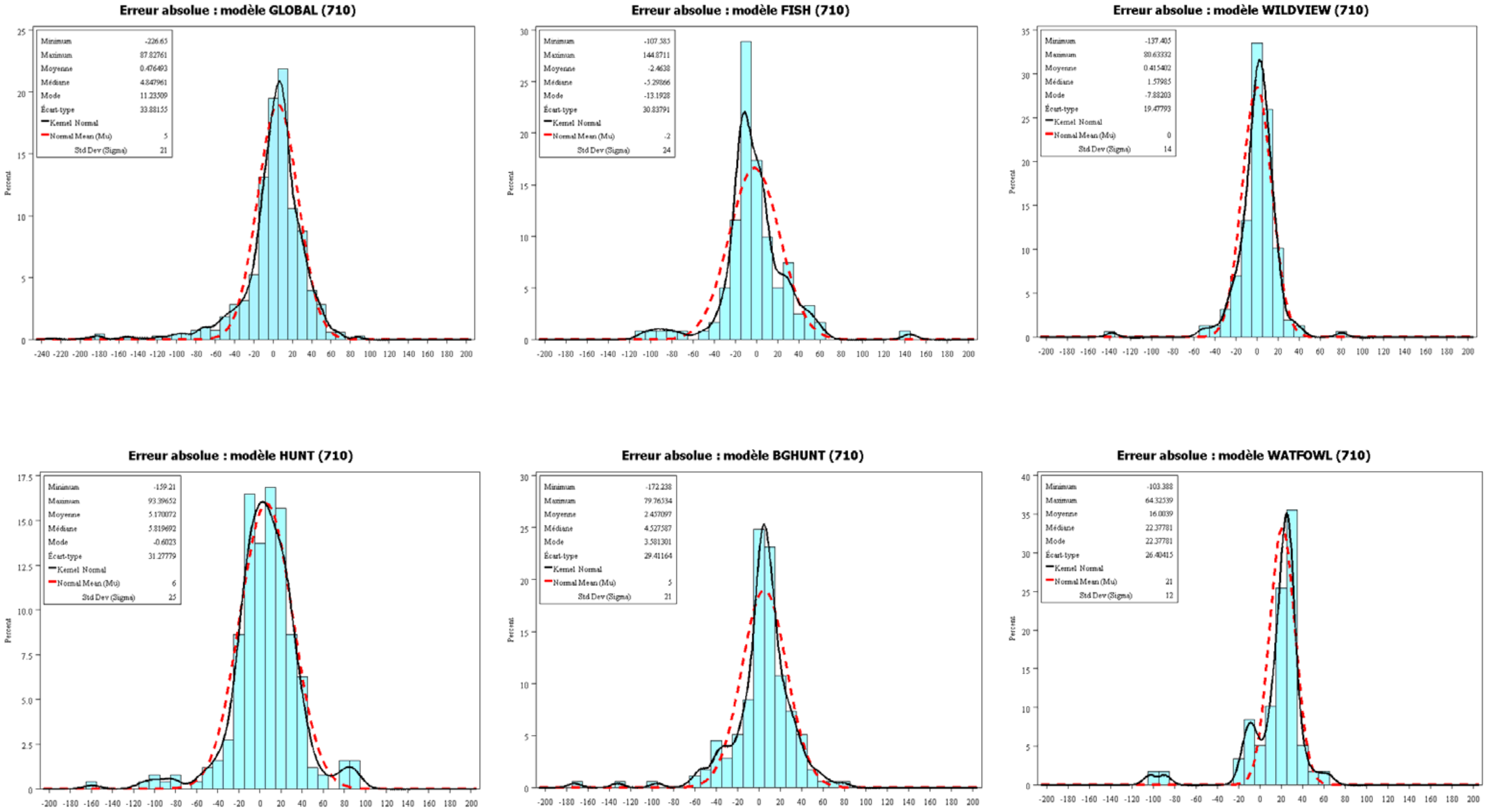

Figure 1: Absolute Transfer Error Distribution for Global and Activity-specific Meta-models

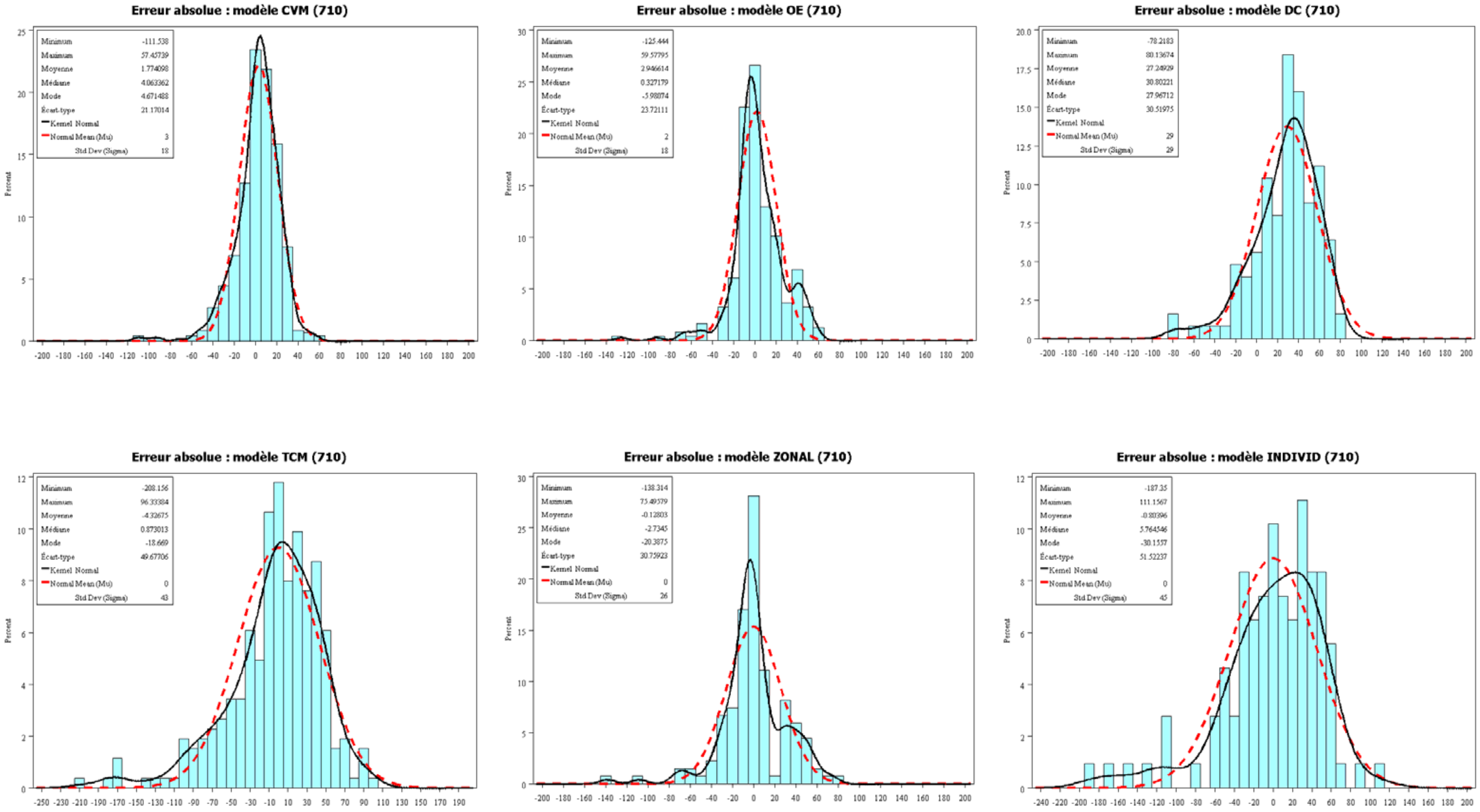

Figure 2: Absolute Transfer Error Distribution for Method-specific Meta-models

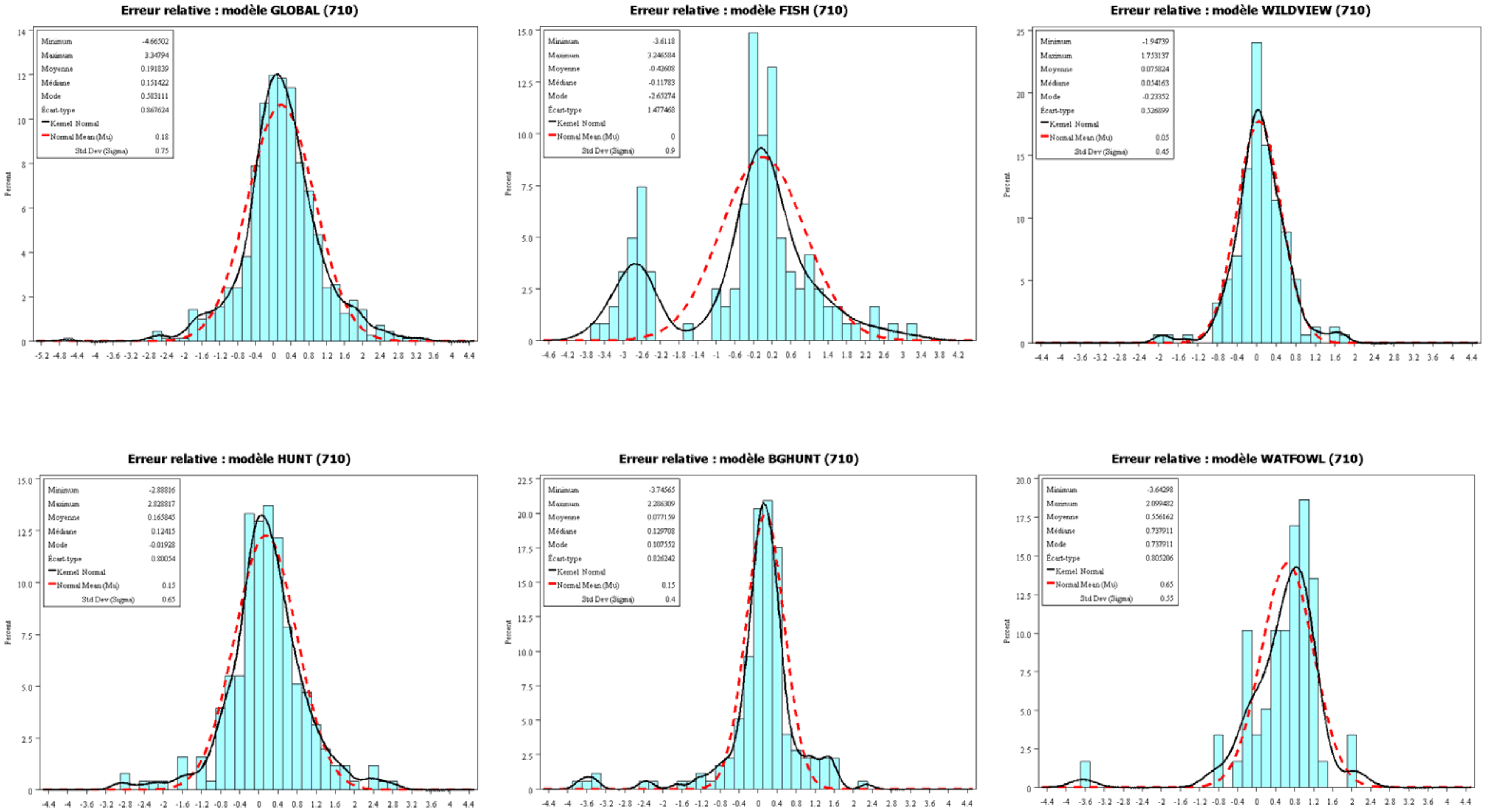

Figure 3: Relative Transfer Error Distribution for Global and Activity-specific Meta-models

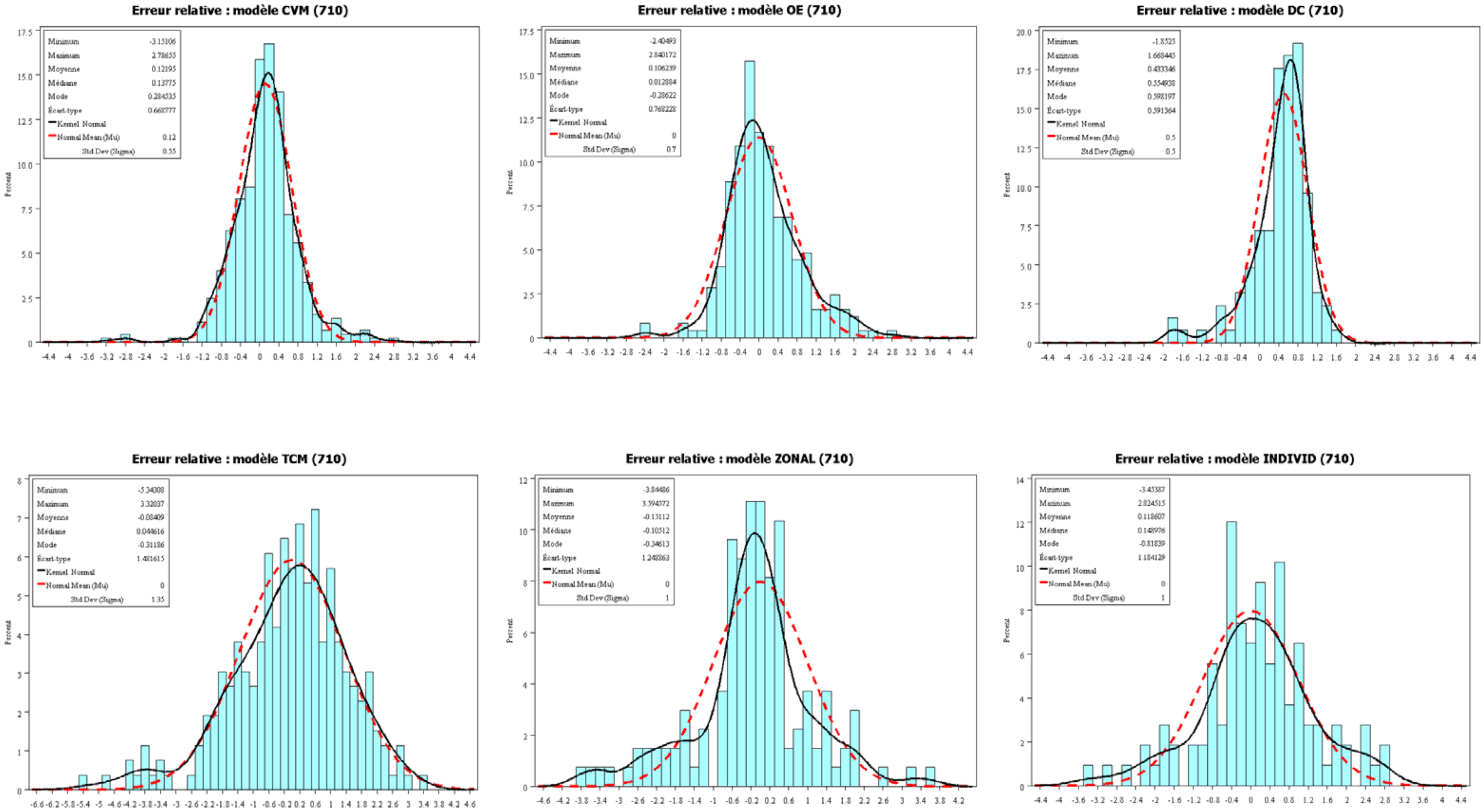

Figure 4: Relative Transfer Error Distribution for Method-specific Meta-models

5. Findings conclusion

As meta-models appeared promising transfer valuation, and creating a specific database for meta-model is very time-consuming, I asked here if we could make potential reliable meta-models for transfer from existing environmental economic databases. The answer is rather negative and databases need some improvements in what and how it has to be coded. Then a meta-analysis on recreation has been specially achieved to evaluate transfer reliability and to make judgment on global versus specific meta-models. In particular, global meta-model robustness has been shown and use-specific and method-specific models do not yield better results than global model. Besides, a significant income effect has been shown but taking it into consideration has not improved significantly transfer valuation. Lastly global model transfer estimations have been shown unbiased but imprecise. So meta-model transfers should not be used at this point for one particular application system (policy site). More research is, however, needed on meta-models.

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