THE EFFECT OF INCREASING RIVER FLOW VARIABILITY ON DATA SHARING IN THE CONTEXT OF INTERNATIONAL AGREEMENTS: AN EMPIRICAL ANALYSIS

Student: Michele Quaranta Vogliotti (2633012)

Supervisor: Professor Erik Ansink

Abstract: *The aim of this study is to examine the relationship between river flow variability and data sharing type and frequency categories included in treaties regulating transboundary rivers. We used ordinal categories extrapolated from Gerlak et al. (2011) as data sharing indicators, and coefficient of variation of precipitation data from Dinar et al. (2015) as river flow variability estimator. Besides, control variables exploited in related literature are tested as well. Several econometric techniques have been used, including ordered logit and ordinary least squares models. Overall, we find a U-shaped relationship between river flow variability and data sharing type, and an inverted U-shaped function relating river flow variability and data sharing frequency categories.*

1. Introduction & Research Motivations

Rivers cover a large extent of the emerged lands on Earth. To give an idea, HydroRIVERS (https://hydrosheds.org/page/hydrorivers), a database which provides data of all global rivers meeting certain minimum criteria, embodies a total of 8.5 million singular river reaches with an average length of 4.2 kilometers. Some of these freshwater streams are transboundary rivers, namely rivers which cross the border between two different countries. The longest and most important are Nile, Mekong, Niger, Indus, Brahmaputra, Danube, Euphrates, Ganges, Zambezi and Colorado, but the total number is much higher, about 265 international watersheds (Hamner and Wolf, 1998). Bangladesh alone has 57 major rivers entering its boundaries from India and Myanmar, as reported in Afroz and Rahman (2013). The hydrologic, economic and political consequences of rivers which flow in more than one country are huge and difficult to manage. Freshwater streams may be a source of wealth, as long as they provide water, hydroelectric energy and sediment, but they might also cause catastrophes such as floods. Since two or more countries are involved, a fair distribution of all these potential benefits and losses seems hard to determine, implement and check. In consideration of that, numerous multi-later treaties have been signed with the objective of regulating transboundary water flows. According to Hamner and Wolf (1998), 3600 water-related agreements have been enforced from organized political bodies since A.D. 805. Such agreements should work as a governance tool, given the existence of incentives for countries to cheat. In fact, Gerlak et al. (2011) research sustains that countries may obtain the benefits of unilateral exploitation while dividing the costs, in terms of either degraded water quality or reduced water quantity. This hypothesis becomes an empirical evidence in several studies, such as Dinar et al. (2010), Dinar et al. (2011) and Dinar et al. (2015). The incentive to cheat is practically translated into less treaty formation or cooperation associated with higher variability of river flows. The explanation is the following: as water flow variability within a river increases (consequently to more precipitation, or dry periods), it is easier for countries to deviate from standards defined into agreements, enabling them to steal water or to obtain free hydroelectric energy at the expenses of the other riparians. This particular insight is deduced by the functional form of the relationship between river flow variability and treaty cooperation or formation, which is hump-shaped, meaning that more variability initially leads to more collaboration between countries over the common resource, but then, as flow variability passes a certain threshold, higher variability is associated with less cooperation or treaty formation. River flow variability is expected to increase in the future consequently to climate change, which will have an impact on precipitation patterns, as the authors point out in Dinar et al. (2010) research. It is worth then to deeper analyze the relation which ties transboundary river agreements and variations in river water flows, and the present study adopts an approach that, to our knowledge, has been tested only once before. In fact, we rely on Van de Poll (2016) analysis and methodology to examine a specific aspect of treaties regulating transboundary rivers, namely the quality and sharing frequency of data about water flows which should be shared among riparians according to the enforced agreement. With countries forced to share better quality data more often, it should be much more difficult for them to cheat by unilateral exploitation. Moreover, the Global Environment Facility's (GEF) International Waters Program considers data and information sharing as the starting point for reaching cooperation and joint management of shared waters (Gerlak et al., 2011). In addiction to considering data sharing type and frequency rather than treaty formation or cooperation as fundamental aspects of agreements, the other peculiarity of Van de Poll (2016) research which we embody in the present analysis is the use of river flow variability as explanatory variable, rather than a simple control. This means that we are going to investigate the direct causal effect of a change in river flow variability on the type and sharing frequency of freshwater data, whereas using water variability as control implies its exploitation only in function of another relationship of interest. The main objective of the present study is to examine the relationship between river flow variability and data sharing type and frequency, in order to assess findings from Van de Poll (2016) and other related analyses. Specifically, we are going to test the hypothesis that more variability causes less data sharing, namely worse quality data shared less often, which is in line with the aforementioned assumptions regarding incentives to cheat. In fact, increasing river flow variability associated with less data sharing is a tempting combination for countries willing to cheat. If data will confirm this theory, it appears clear the need for better defined and more effective criteria concerning data sharing rules within agreements regulating transboundary rivers.

2. Data & Variables

The dataset used in the present analysis is the result of a merging operation that unifies Gerlak et al. (2011) database with Dinar et al. (2015) one. These two datasets rely in turn on the same database, namely the Transboundary Freshwater Dispute Database (TFDD), which contains information concerning more than 400 international freshwater-related agreements stipulated between 1820 and 2007 (Wolf et al., 2016). Gerlak et al. (2011) analysis embodies data about information sharing type and frequency (the two dependent variables of the present study) for treaties signed in the period 1900-2000. Dinar et al. (2015) research includes precipitation variability per river basin, which is a measure of river variability used in other related studies such as Dinar et al. (2010) and Dinar et al. (2011), and it works as explanatory variable within this framework. After a meticulous check for correspondences and the correction of all discrepancies, Gerlak et al. (2011) and Dinar et al. (2015) datasets were joined by the common variable 'document name', which briefly describes each treaty considered in the datasets. The result of this operation is a table with 135 observations regarding 123 different country dyads, since some state couples are included in different treaties or present distinct precipitation variability values. Of these 135 total observations, 84 concerns country dyads sharing at least one border, while 51 are about states which do not share any border. This divergence will be further exploited in order to implement a robustness check in the result section. Although the same two datasets were merged within Van de Poll (2016), there are some data differences between the two analyses that are worth to be mentioned. Firstly, here we were able to obtain some more observations (135 compared to 100), and this probably depends on merging operations based on different criteria. We joined Gerlak et al. (2011) and Dinar et al. (2015) datasets by document name variable since it contains a short description of each treaty, and it was easy to check for correspondences. Secondly, the present study does not include any treaty with data sharing type and frequency having 0 as value (0 means 'no information sharing' in both data sharing type and frequency), whereas the previous analysis contains a consistent number of them (62 observations in either data sharing type and sharing frequency). The latter discrepancy happens since all the seven treaties which present 'no information sharing' values in Gerlak et al. dataset are not reported in Dinar et al. dataset, hence they are excluded from the resulting final dataset which considers only common observations. The following tables (1 and 2) show the rearranged categories of data sharing type and frequency and their respective original codes in Gerlak et al. research, as well as (table 3 and 4) frequencies of both sharing type and frequency categories within the dataset used in the present analysis. In their work, Gerlak et al. (2011) read and examined 287 fresh-water related agreements, looking for "reference to data and information exchange or presence of mechanisms likely to enable data and information exchange". It can be noticed from table 1 that *hydrologic data* and *hydrologic information* belong to two different categories. Indeed, *data* are defined from the authors as "hard" numbers associated to water, i.e. levels of water quality or rates of river flow; while *information* refers to a more general and qualitative knowledge exchange, i.e. potential solutions for a flood obtained through hard data analysis. The frequency with which data and information ought to be shared is categorized into four classes, which are well explained in table 2.

Category by Gerlak et al., (2011)	Explanation	New category
1a, 1b, 1c	Hydrologic Data	3
2a, 2b, 2c, 4, 4a, 4b, 4c	Hydrologic information ; Research, investigations and assessments	2
5	Unspecified (general reports)	1

Table 1 Classification of data sharing type

Category by Gerlak et al., (2011)	Explanation	New category
1	Regular sharing	4
2	Event-triggered	3
3	On request, as needed	2
4	Unclear	1

Table 2 Classification of data sharing frequency

Data sharing type category	**Frequency** (N = 135)
3	41.48 % (56)
2	24.44 % (33)
1	34.07 % (46)

Table 3 Frequency of data sharing type categories

Data sharing frequency category	**Frequency** (N = 135)
4	31.11 % (42)
3	2.96 % (4)
2	33.33 % (45)
1	32.59 % (44)

Table 4 Frequency of data sharing frequency categories

In order to implement and analyze the effect of including control variables already examined within related literature, this study relies on different data sources. In regard of number of disputes between country dyads, data are obtained from Dyadic Inter-State War Dataset (v3.1), developed within the Correlates of War Project. It consists of dyadic records of interstate wars during the period 1816-2010, with a dyad-year unit of analysis. Since data sharing may be considered as one of the several aspects determining overall relations between riparian countries, it is logical to assume that the militarized history among dyads of states does matter. In fact, it appears straightforward that riparians which experienced a consistent number of disputes are expected to have a worsen relationship between them, compared to countries with a less belligerent past. A better overall relation is likely to be translated into more transparency about data sharing, which means better quality data shared more often. Thus, it seems reasonable to add number of disputes occurred among country dyads as control variable within our framework. In Dinar et al. (2011) and (2015) analyses, the same variable is implemented, although with a different time coverage (all disputes occurred between 1816 and 2001). Concerning the perceived corruption measure, Corruption Perception Index 2018 values are exploited. Each country receives a score, going from 0 (maximum level of perceived corruption) to 100 (minimum level of perceived corruption). Countries with low levels of perceived corruption (high CPI scores) should not be reluctant to share high quality data on a regular basis, whereas the opposite is expected for states with high perceived corruption (low CPI scores). Hence this index functions as control, partly replicating what the authors did in Dinar et al. (2011), where they computed a 7-year (1998-2004) average of CPI score for each country (we used 2018 values to capture recent trends). Trade data are obtained from UN Comtrade Database. Import and export records for the period between 2012 and 2018 (re-Import and re-Export are not considered for simplification) are expressed in current US$ value for each country dyad. Trade might be thought as the economic transposition of cooperation between countries (i.e., riparians which appear more cooperative among each other are likely to trade more, since there are probably less tariffs and commercial obstacles). As already mentioned, data sharing is a facet of the general relationship connecting two riparian states, therefore it seems reasonable to embody a trade measure as control variable in our framework which aims at estimating data sharing type and frequency. An analogous approach is used in Dinar et al. (2015), where trade importance between country dyads works as control in their estimates of treaty effectiveness. Finally, Gross Domestic Product (GDP) for countries in all dyads within the period 2012-2018 is deduced from the World Bank database, and is also expressed in current US$. GDP values are used to create an indicator of economic power asymmetry, considering that in dyads with significant unbalance of power there should be an incentive (especially for the stronger country, for which it might be easier to cheat) to share lower quality data less often. This is the reason for the inclusion of power asymmetry as control variable, and it was already done is related studies such as Dinar et al. (2010), (2011) and (2015). The majority of these data sources are the same as the other similar analyses mentioned so far. Remarkably, an important assumption which justifies the use of recent CPI, trade and GDP data associated with treaties that have been signed in various past time periods ought to be explicitly reported. Specifically, we assume that if a treaty is still regulating transboundary rivers' data sharing among riparians nowadays, it must be certainly influenced by economic and political dynamics (trade, power and perceived corruption) which are occurring at the present time, otherwise the treaty would have been modified or dissolved. As final note, averages of 2012-2018 period for trade and GDP were considered instead of single year values, with the objective to obtain less non-specified values as possible (not all the countries included in the dyads have available data).

With these information, various operations were performed for obtaining the control variables included in the extended model, and they are reported in detail within the following subsections.

Militarized disputes

This measure is directly built from Dyadic Militarized Interstate Disputes (MID) dataset (v3.1), which followed a first attempt using the Directed Dyadic Interstate War dataset. The reason behind this switch was to obtain less observations with non-specified values. After re-grouping disputes in the original MID dataset by the country dyads included in the data-frame 'Dinar & Gerlak' and by the dispute-code which assigns unique values to different militarized disputes, it was possible to calculate the total number of disputes occurred between country dyads during the considered time period. We did not assume that dyads presenting a non-specified value have experienced no conflict at all during the considered period, since the majority of countries reporting such value are African states, thus it is probably difficult to obtain reliable records from those areas. Theoretically, number of disputes should have a negative impact on both data sharing type and frequency, since we expect that riparians which have fought a lot are less willing to cooperate between each other, hence more reluctant to regularly share good quality data.

Corruption Perception Index

Aiming for a proxy of corruption level in a country, the present analysis exploits the Corruption Perception Index (CPI), which is an indicator deduced from expert assessments and national opinion surveys. Although it is recognized that national surveys submitted to the population are likely to suffer from self-perception bias, this study relies on the fact that CPI is a well-known and widely used measure of perceived levels of public sector corruption. Moreover, there are practically no incentives for a normal citizen to declare an inflated or deflated level of perceived corruption in his own state. Therefore the only measurement issue is that the quantification of corruption level is a subjective operation. This means that two individuals can hypothetically perceive the same level of corruption within the same state, yet they assign completely different scores (the score may range between 0 and 100). Regarding this concern, it might be said that the score is computed also through expert assessments, which should reflect a more harmonized scale of values. The scores recorded in 2018 have been attached to 'Dinar & Gerlak' dataset, in order to obtain two variables: CPI 2018 score of country 1 in the dyad, and CPI 2018 score of country 2 in the dyad. The impact of CPI score on data sharing might be positive, but also negative: it is likely that countries where low internal corruption is experienced do not cheat in international treaties either, but it is not straightforward.

Trade Importance

Trade importance variable is implemented by combining trade data with GDP values. For the period 2012-2018, the average of trade volume is calculated as the sum of import and export of all kind of commodities between each country dyad, divided by the number of years for which data are available. Such value expresses trade occurring exclusively and directly between the two states which form the dyad. In order to examine the weight of trade between a couple of countries with respect to their economies, or in other words trade importance, trade volume must be considered taking into account GDP values. In fact, studying trade volume in relation to the total dimension of the economy is necessary to obtain proportional result (i.e., two small states might present the same trade importance as two big countries). GDP averages for the period 2012-2018 were accordingly computed. The final value for each dyad is obtained applying the following formula:

$$\frac{import\ 2012\_2018_{i,j} + \ export\ 2012\_2018_{i,j}}{GDP\ 2012\_2018_{i} + \ GDP\ 2012\_2018_{j}}$$

with i,j representing state dyads. The expected effect of trade importance on data sharing is positive: countries which trade more should have incentives to share their data, since they might create synergies over the common water source as well.

Power Asymmetry

The last control variable considered is a proxy for power asymmetry between the two states in the same dyad. It is obtained through the ratio of the two average 2012-2018 GDP values, with the higher value always being the numerator. This is done because the resulting power asymmetry indicator presents higher values the greater the power disparity among the two countries. It ought to be recognized that summarizing the power a specific country has only in its GDP value might be seen as an excessive simplification. On the other hand, it is undeniable that bigger economies have stronger military power or greater influence on global markets, both factors which reflect higher level of power with respect to other countries. Power asymmetry control variable is expected to present negative sign, given that in dyads where there is a strong power unbalance, it should be easier for the most powerful country to cheat by unregularly sharing low quality data.

Econometric strategy

The ultimate goal of the present analysis is to estimate the relationship between type and frequency of data sharing concerning transboundary rivers and water streams variability. In order to do that, two different regressions with two distinct dependent variables -sharing type and sharing frequency- are examined, and they empirically test the following framework:

$$sharing\ type = C + \alpha\ (CV\ Precipitation) + \beta\ (Control\ variables) + \varepsilon$$

$$sharing\ frequency = C + \alpha\ (CV\ Precipitation) + \beta\ (Control\ variables) + \varepsilon \qquad ,$$

where *sharing type* and *sharing frequency* indicate type of data sharing and frequency of data sharing respectively, α is the coefficient of CV (coefficient of variation) of precipitation, the variable which measures river variability, β represents the coefficient of control variables and ε is the error term. Firstly, all models are going to be tested using ordered logit technique, due to the fact that both dependent variable, data sharing type and frequency, are ordinal (they may be ranked in ascending or descending order) categories. Secondly, within the robustness check section, ordinary least squares (OLS) estimation method is implemented, as long as this approach has been employed in Dinar et al. (2015) as well. Indeed, although recognizing that dependent variables examined in the present study and Dinar et al. (2015) are formally different (the one used in their framework is a numeric score for treaty effectiveness with greater values meaning more effective treaties), there is one analogy which makes OLS worth to try. Namely, within this research, higher categories of *sharing type* and *sharing frequency* translate into better quality data shared more often, and treaty effectiveness might be seen as partially determined by the quality and the frequency of data shared among riparians. Importantly, ordered logit is useful to study the magnitude and the sign of each variable coefficient, but no causal effect may be inferred, whereas OLS allow us to interpret explanatory variable coefficient as the numeric representation of the causal effect on the dependent variable. Endogeneity is not expected to be an issue in our estimated models, since we aim at investigating the effect of river variability on data sharing, and CV precipitation should be a representative estimator of water-stream flow variations, thus not correlated with the error term. Additionally, the incorporation of other potential determinants of data sharing type and frequency as control variables lowers the risk of omitted-variable bias.

Besides, the main reason of including control variables within a model is to better isolate the relationship between the dependent variable and the explanatory one (in this case, CV precipitation), by 'absorbing' the effect of other factors influencing the dependent variable (*sharing* *type* and *sharing frequency*). One of the main issues when using control variables is the so defined 'bad control problem': it occurs if both the dependent variable and the control variable are potential outcomes of the explanatory variable or, in other words, if control variables are not pre-determined. Since none of the control variables considered in this study (number of disputes, CPI score, trade importance and power asymmetry) are direct outcomes of river variability, this should be enough to say that 'bad control problem' does not subsist in this context.

Another reason of concern when incorporating control variables in a model is that for each additional regressor included, model fitting measure such as R-squared will automatically increase, no matter if the newly considered variable is not significant at all. A potential solution is to check how adjusted R-squared, rather than R-squared, varies over distinct models with different number of regressors. Besides that, CV precipitation will be regressed with various combinations of control variables[1], aiming for a better understanding of which additional regressors improve the most estimates of the relationship of interest between type and frequency of data sharing and river variability. The only exception will occur for number of militarized disputes variable: since it has a significant number of non-specified values, it will be examined only singularly with CV precipitation, and excluded from more comprehensive models.

[1] Including CV precipitation squared, in order to examine a potential non-linear relationship between river variability and data sharing type and frequency.

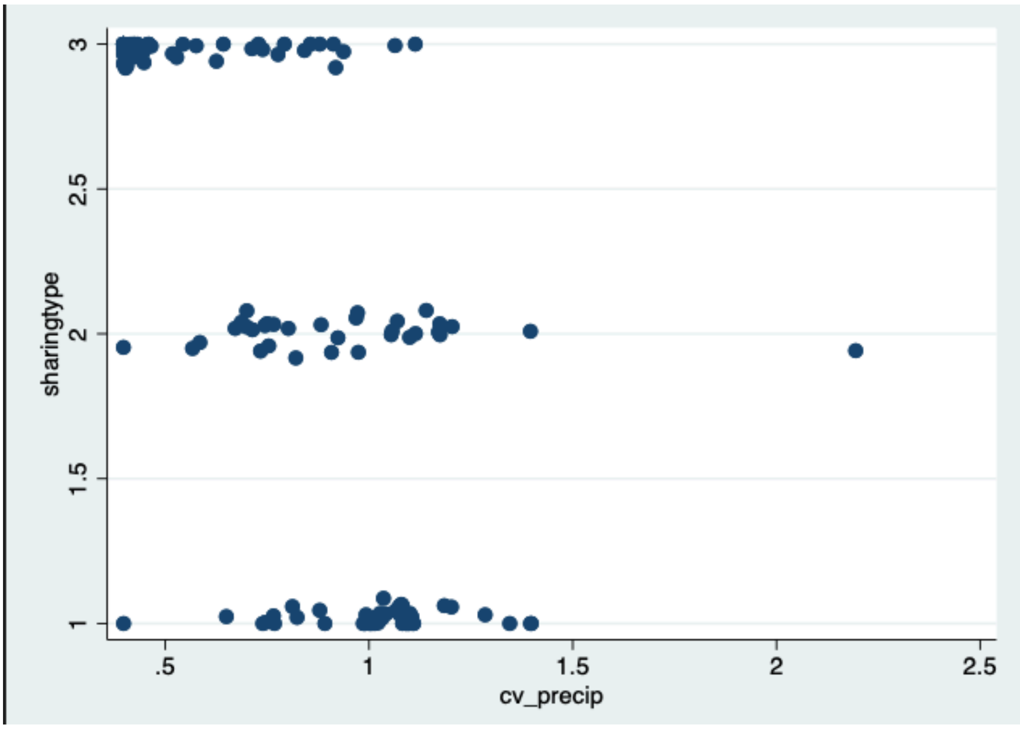
3. Results

Within this section, the results of each model are presented and discussed. First all the models having data sharing type as dependent variable are displayed, while the next subsection will include all models where data sharing frequency functions as dependent variable. In both cases, the models gradually include and test additional control variables, and the last two combinations are the most comprehensive. Table 5 reports summary statistics of all the variables analyzed within the models:

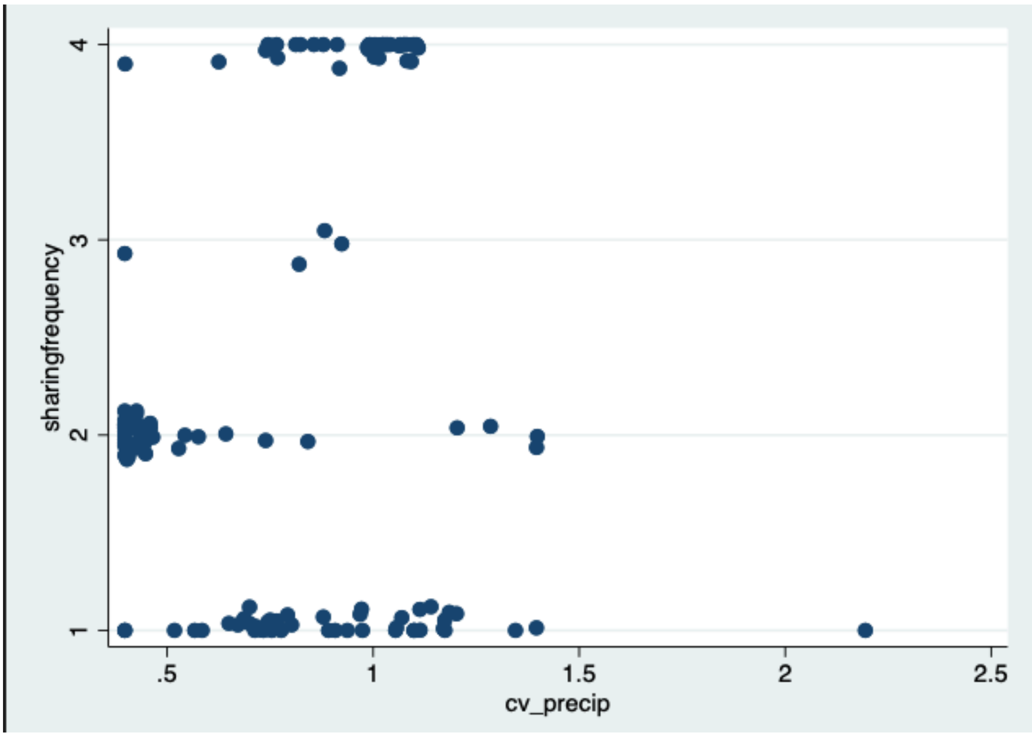
Variable	Observations	Mean	Standard dev.	Min	Max
Type of data sharing	135	2.074074	0.8692906	1	3
Frequency of data sharing	135	2.325926	1.226752	1	4
River variability	135	0.796351	0.3184327	0.3972326	2.202437
Squared River variability	135	0.7348232	0.5853111	0.1577937	4.850727
Militarized disputes	64	6.328125	7.592926	1	40
CPI Score 2018 Country1	133	42.75188	16.98012	18	85
CPI Score 2018 Country2	133	38.15038	14.4885	13	85
Trade importance	125	0.0065502	0.0087053	9.49e-06	0.0475601
Power asymmetry	130	35.74731	139.8797	1.006187	904.8937

Table 5 Summary statistics

Within the two following graphs, CV precipitation is plotted against data sharing type and frequency categories, respectively. At a first glance, the relationship depicted in the first scatterplot appears somewhat negative, whereas from the second graph the situation seems a bit more noisy.



Graph 1 Scatterplot of CV Precipitation against data sharing type



Graph 2 Scatterplot of CV Precipitation against data sharing frequency

Table 6 shows the results of the models estimating the relationship between CV precipitation and data sharing type. Model 1.1 is the starting point: CV precipitation is the only variable which is regressed, therefore this framework tests a linear relationship without any additional control. Yet, we can notice that something is already going on in the data, even within this reduced and simple model.

Variables, sharing type as dependent	**Model 1.1 (only CV Precipitation)**	**Model 1.2 (Non-linear)**	**Model 1.3 (N° of disputes)**	**Model 1.4 (CPI Country 1)**	**Model 1.5 (CPI Country 2)**	**Model 1.6 (Trade importance)**	**Model 1.7 (Power Asymmetry)**
CV Precipitation	-5.96*** (0.8197551)	-15.52*** (2.40072)	-9.71*** (2.901794)	-14.35*** (2.507517)	-16.84*** (2.692447)	-15.86*** (2.852149)	-16.65*** (2.891957)
CV Precipitation squared		5.24*** (1.049209)	2.99** (1.213407)	4.83*** (1.083056)	5.68*** (1.136506)	5.291066*** (1.177377)	5.59*** (1.197388)
N° of disputes			0.029 (0.0343314)				
CPI Score country 1				0.039** (0.0155347)		0.040** (0.0185903)	0.046*** (0.0175524)
CPI Score country 2					0.011 (0.0165462)	-0.0004 (0.0190274)	-0.0015 (0.0177509)
Trade Importance						6.2266 (33.89194)	
Power Asymmetry							0.00105 (0.010971)
Observations	135	135	64	133	133	125	130
Pseudo R-squared	0.2715	0.3374	0.1797	0.3554	0.3722	0.3916	0.4052
Log Likelihood	-105.84408	-96.27498	-56.4477	-92.50353	-89.641059	-81.227656	-83.049626

*Table 6 Ordered logit, data sharing type as dependent variable. Standard errors are in brackets. * = p-value less than 0.1 ; ** = p-value less than 0.05 ; *** = p-value less than 0.01*

In fact, the coefficient of CV precipitation is significant and it has negative sign, confirming the hypothesis that higher river variability leads to lower categories of data sharing type. Going further with the analysis, a new insight comes out from model 1.2, where a non-linear relationship between CV precipitation and data sharing type is examined. In order to perform such a test, the variable CV precipitation squared has been incorporated into the model. It can be noticed that the latter is also significant, it increases the magnitude of CV precipitation quite considerably and, most importantly, it has positive sign. This means that rather than an inverted U-shaped relationship between river variability and data sharing type, the present analysis predicts a U-shaped relationship occurring between these two variables.

Since such a functional form is in contrast with previous research (Van de Poll, 2016), this specific point will be further analyzed within the robustness check section. For now, it ought to be noticed that CV precipitation squared has a highly significant coefficient, and the framework tested with model 1.2 fits better the data, compared to its linear version in model 1.1 (pseudo R-squared goes from 0.2715 to 0.3374). Therefore, CV precipitation will be maintained even in the following specifications which consider the other control variables, constructed from external data sources. The first one to be tested is number of militarized disputes, for the aforementioned reason of having only 64 available observations. As expected, model 1.3 offers the worse performance so far, although the heavily reduced number of observations makes difficult to properly compare it with the other frameworks. Nevertheless, the coefficients of CV precipitation and CV precipitation squared remain significant at 5 % level and 10 % level respectively, and they both slightly decrease in magnitude compared to model 1.2. Pseudo R-squared has the lowest value between all the seven models displayed in table 6 (0.1797). The insight coming from model 1.3 is twofold: number of militarized disputes does not improve our understanding of the relationship between river variability and data sharing type, and the non-linear functional form appears to resist even with poor performance controls. In light of these considerations, number of disputes will be excluded from the remaining models within table 6. Model 1.4 and model 1.5 are somewhat similar, since they both test the effect of CPI country scores (one country at time in order to understand the separated effects). Pseudo R-squared is slightly higher in model 1.5 (0.3722) than in model 1.4 (0.3554). Both coefficients are small and positive, and the effect of these controls on CV precipitation coefficient and CV precipitation squared coefficient is distinct in the two models. Indeed, in model 1.4 the magnitude of either CV precipitation coefficient and CV precipitation squared coefficient is a bit lower compared to model 1.2 (from -15.52 to -14.35 for CV precipitation, from 5.24 to 4.83 for CV precipitation squared). Contrarily, in model 1.5 the coefficients are slightly higher in comparison with model 1.2 (from -15.52 to -16.84, and from 5.24 to 5.68). Acknowledging that model 1.4 includes a significant control with smaller pseudo R-squared, whereas model 1.5 presents an insignificant coefficient for CPI score with higher pseudo R-squared, it seems a logical compromise to include CPI scores for the two countries of each dyad in the next models. Model 1.6 embodies trade importance as control variable, in addition to CPI score of country 1 and CPI score of country 2. CV precipitation and CV precipitation squared are still significant and the magnitude of their coefficients is somewhat between model 1.4 and 1.5 (actually very close to model 1.2). The pseudo R-squared of model 1.6 is 0.3916, which is the highest R-squared value of the models discussed so far. Since trade importance resulted insignificant in model 1.6, and to avoid endogeneity issues with the inclusion of the last control variable power asymmetry (trade importance might be endogenously determined by economic power asymmetry, and viceversa), this control is excluded from the last model presented in this subsection. In model 1.7 the performance of the control variable power asymmetry is tested, and CPI scores of the two countries are included as well. CV precipitation and CV precipitation squared stay significant at 1 % level, and the magnitude of their coefficients is almost the same as in model 1.5. The pseudo R-squared of model 1.7 is 0.4052, slightly higher than model 1.6.

In this subsection, results of all models having data sharing frequency as dependent variable are reported and discussed. All frameworks are essentially the same as in the previous subsection, with a different dependent variable, therefore we will not explain anymore the reasons behind each model. Rather, the focus of this paragraph consists of noticing similarities and differences between the results in table 7 (data sharing frequency as dependent variable) and the ones in table 6.

Variables, sharing freq. as dependent	**Model 2.1 (only CV Precipitation)**	**Model 2.2 (Non-linear)**	**Model 2.3 (N° of disputes)**	**Model 2.4 (CPI Country 1)**	**Model 2.5 (CPI Country 2)**	**Model 2.6 (Trade importance)**	**Model 2.7 (Power Asymmetry)**
CV Precipitation	0.3995 (0.4939433)	4.518417* (2.663409)	4.414349 (4.064021)	2.490576 (2.489164)	3.951364 (2.684649)	1.908987 (2.542549)	2.668484 (2.556636)
CV Precipitation squared		-2.462986 (1.645813)	-2.807396 (2.42714)	-1.683711 (1.461976)	-2.258576 (1.631119)	-1.50655 (1.479986)	-1.791477 (1.48903)
N° of disputes			0.031 (0.0313053)				
CPI Score country 1				-0.02617** (0.0109352)		-0.024850** (0.0116959)	-0.0236112* (0.011305)
CPI Score country 2					-0.010202 (0.012266)	-0.0132702 (0.0132778)	-0.087688 (0.012688)
Trade Importance						-5.694617 (20.0673)	
Power Asymmetry							-0.004075** (0.0020515)
Observations	135	135	64	133	133	125	130
Pseudo R-squared	0.002	0.015	0.0275	0.0326	0.0165	0.0365	0.0562
Log Likelihood	-161.54894	-159.46518	-77.762206	-154.39989	-156.9792	-144.72932	-147.30364

*Table 7 Ordered logit, data sharing frequency as dependent variable. Standard errors are in brackets. * = p-value less than 0.1 ; ** = p-value less than 0.05 ; *** = p-value less than 0.01*

Model 2.1 already points out two important differences compared to model 1.1: the coefficient of CV precipitation is positive instead of negative, and it is not significant. Additionally, pseudo R-squared value of model 2.1 is significantly lower than R-squared value of model 1.1 (0.02 compared to 0.2715). Model 2.2 tests the non-linear relationship between river variability and data sharing frequency, but in this case the inclusion of CV precipitation squared actually worsens the model performance compared to framework 2.1 (pseudo R-squared decreases from 0.02 to 0.015). Beyond that, the coefficient of CV precipitation squared is not significant and it has negative sign. The coefficient of CV precipitation has greater magnitude in model 2.2 than in 2.1, it is still positive and it becomes significant. For the sake of comparison with the models presented in the previous subsection, CV precipitation squared will be maintained even in the following models, in spite of its insignificance. Model 2.3 tests the effect of controlling for number of militarized disputes. Pseudo R-squared is higher in model 2.3 than in model 2.1, but this might simply reflect the fact that model

2.3 considers more variables than 2.1, which anyway are not significant. Model 2.4 embodies CPI score of country 1, but CV precipitation and CV precipitation squared coefficients are not significant in this framework either, and they maintain the same signs as previous models in table 7. Their magnitude is slightly lower in model 2.4 than in frameworks 2.2 and 2.3. Pseudo R-squared gently increases from 0.0275 in model 2.3 to 0.0326 in model 2.4. Moving to model 2.5, even here CV precipitation and CV precipitation squared are insignificant and with positive and negative sign respectively, additionally pseudo R-squared value is pretty low (0.0165). Model 2.6 tests the effect of adding trade importance as control, and the coefficients of CV precipitation and CV precipitation squared are the same as the other models of table 7 concerning significance and signs, but they show the lowest magnitude since model 2.2. Pseudo R-squared value is the highest so far (0.0365). Finally, model 2.7 as well does not improve our estimation of the relationship between data sharing frequency and river variability: both coefficients of CV precipitation and CV precipitation squared are insignificant. Pseudo R-squared is 0.0562, which is the highest of pseudo R-squared values in table 7.

Marginal effects

Since coefficients from ordered logit models do not have a straightforward interpretation (only their magnitude and sign are indicative), it is usual to compute marginal effects of the explanatory variables. These might be seen as the effect of a change in the independent variable on the dependent variable, measured through the probability that the variation within the right side of the equation will lead to a certain outcome in the left side. In our case, we have different categories of data sharing type and frequency as potential results, therefore we obtain distinct probabilities for each of the various categories. Marginal effects of CV precipitation and CV precipitation squared are displayed for both dependent variables, data sharing type and frequency, in table 8 and 9 respectively. To give an example, we may examine the diverse values which occur between CV precipitation and data sharing type in table 8. When a treaty shows the value of one in data sharing type category (data are general reports), a one unit increase in CV precipitation is expected to rise the category of data sharing type by two classes, thus from general reports to hydrologic data. This is in contrast with the insights coming from model 1.1 and 1.2, where the coefficient of CV precipitation is negative, pointing out a negative relationship between river variability and data sharing type. Nevertheless, by widening our focus on the other two categories of data sharing type, it may be actually noticed that in both cases the marginal effect of CV precipitation has negative sign. When a treaty presents 'three' as data sharing type category (hydrologic data), a one unit increase of CV precipitation leads to a decrease between one and two categories of data sharing type. Hence, it can be deduced that for two out of three potential outcomes of data sharing type, the marginal effects of CV precipitation confirm what the ordered logit estimates already suggested, namely the negative impact of increasing river variability on data sharing type categories. The same may be said in regards of CV precipitation squared, since the marginal effect for category 'one' is negative, whilst for the other two categories it has positive sign. When data sharing frequency is considered as dependent variable, there are four possible outcomes instead of three, but for the rest, the general behavior of marginal effects is similar to the previous case. In fact, for both CV precipitation and CV precipitation squared, the marginal effects change signs across the different categories of data sharing frequency. Specifically, CV precipitation shows negative marginal effects for categories 'one' and 'two', and positive ones for categories 'three' and 'four'. Contrarily, CV precipitation squared presents positive marginal effects for categories 'one' and 'two', while they are negative for categories 'three' and 'four'. As for data sharing type, marginal effects of the highest categories of data sharing frequency (i.e., ‘three’ and ‘four’) report the same signs of the respective coefficients of CV precipitation and CV precipitation squared within the ordered logit models 2.1 and 2.2, namely positive and negative. The general conclusion which might be drawn from this examination of the marginal effects of CV precipitation and CV precipitation squared is that the impact of a change in river variability on data sharing type and frequency categories changes a lot across distinct moments of the distribution of the dependent variable. Depending on the actual category of data sharing type or frequency which is assigned to a treaty, a variation in CV precipitation may have opposite effects, increasing or decreasing data sharing type or frequency categories.

Explanatory variable	**Data type category**	**Marginal effect**
CV Precipitation	**1**	2.20
	2	-0.52
	3	-1.68
CV Precipitation squared	**1**	-0.74
	2	0.17
	3	0.56

Table 8 Marginal effects with data sharing type as dependent variable.

Explanatory variable	**Sharing frequency category**	**Marginal effect**
CV Precipitation	**1**	-0.93
	2	-0.08
	3	0.04
	4	0.97
CV Precipitation squared	**1**	0.51
	2	0.04
	3	-0.02
	4	-0.53

Table 9 Marginal effects with data sharing frequency as dependent variable.

4. Robustness checks

In this section, various strategies will be adopted in order to better understand whether the models discussed in the previous paragraphs are reliable, and to deeper investigate the U-shaped relationship that we found between river variability and data sharing type. The starting approach consists of excluding from our analysis dyads of countries which do not share any border, but obviously do share a freshwater stream. By focusing only on riparian states which are actual 'neighbors', the analysis narrows down to a subsample that is expected to reflect situations in which river variability has a slightly lower influence on data sharing standards. This is because it should be easier to check for discrepancies between what is reported from a certain country and actual river flows when states are neighbors. As a consequence, river variability should work less as an incentive to cheat within this particular context. After dropping all observations which involve not-neighbor dyads, we are left with 84 observations, and results of the various regressions tested are displayed in table 10 for frameworks having data sharing type as dependent variable, and in table 11 for models with data sharing frequency as dependent variable.

Variables, sharing type as dependent	**Model 3.1 (only CV Precipitation)**	**Model 3.2 (Non-linear)**	**Model 3.3 (N° of disputes)**	**Model 3.4 (CPI Country 1)**	**Model 3.5 (CPI Country 2)**	**Model 3.6 (Trade importance)**	**Model 3.7 (Power Asymmetry)**
CV Precipitation	-3.88*** (0.8817694)	-10.99*** (2.581166)	-9.18*** (3.035623)	-10.05*** (2.659145)	-12.57*** (2.915708)	-11.69*** (3.011344)	-12.98*** (2.930016)
CV Precipitation squared		3.60*** (1.096362)	2.76** (1.253403)	3.29*** (1.121008)	4.13*** (1.193683)	3.785604*** (1.216614)	4.25*** (1.195335)
N° of disputes			0.034 (0.0349631)				
CPI Score country 1				0.0222925 (0.01701)			
CPI Score country 2					0.010 (0.0169322)		
Trade Importance						39.30738 (30.11275)	
Power Asymmetry							0.0005678 (0.0010659)
Observations	84	84	59	82	82	77	79
Pseudo R-squared	0.1371	0.1870	0.1631	0.1851	0.2277	0.2274	0.2215
Log Likelihood	-79.415766	-74.824125	-53.374669	-73.342755	-69.282489	-65.075314	-67.380667

*Table 10 Ordered logit with common border countries only, data sharing type as dependent variable. Standard errors are in brackets. * = p-value less than 0.1 ; ** = p-value less than 0.05 ; *** = p-value less than 0.01*

Variables, sharing freq. as dependent	Model 4.1 (only CV Precipitation)	Model 4.2 (Non-linear)	Model 4.3 (N° of disputes)	Model 4.4 (CPI Country 1)	Model 4.5 (CPI Country 2)	Model 4.6 (Trade importance)	Model 4.7 (Power Asymmetry)
CV Precipitation	-0.1143809 (0.6115301)	3.465794 (3.119297)	4.533801 (4.059314)	1.674726 (2.984383)	2.145162 (2.99141)	1.399945 (2.946945)	2.522581 (3.254706)
CV Precipitation squared		-1.995504 (1.807724)	-2.725993 (2.357773)	-1.342229 (1.662416)	-1.48155 (1.683405)	-1.231601 (1.624403)	-1.791227 (1.850905)
N° of disputes			0.0283711 (0.0310754)				
CPI Score country 1				-0.028545* (0.0149815)		-0.0300579* (0.0176058)	-0.028796* (0.015368)
CPI Score country 2					-0.019733 (0.0146435)		
Trade Importance						7.806133 (24.705)	
Power Asymmetry							-0.0067359 (0.0062601)
Observations	84	84	59	82	82	77	79
Pseudo R-squared	0.0002	0.0102	0.0260	0.0286	0.0190	0.0264	0.0603
Log Likelihood	-101.56794	-100.5501	-71.85315	-96.999264	-97.963407	-92.444988	-91.280478

*Table 11 Ordered logit with common border countries only, data sharing frequency as dependent variable. Standard errors are in brackets. * = p-value less than 0.1 ; ** = p-value less than 0.05 ; *** = p-value less than 0.01*

Regarding both table 10 and 11, the general situation about significance and signs of CV precipitation and CV precipitation squared is basically the same as table 6 and 7 respectively. In fact, river variability shows a significant U-shaped relationship with data sharing type in all the specifications considered in table 10. Contrarily, CV precipitation and CV precipitation squared have no significant impact on data sharing frequency within all frameworks displayed in table 11. Focusing on control variables, somewhat different emerges from this first robustness check: looking at table 10, not a single control variable (excluded CV precipitation squared) has a significant impact. For this reason, they are all considered separately in each model. The framework which shows the higher pseudo R-squared value is model 3.5 (0.2277). Moving to table 11, CPI score country 1 variable is the only significant one (at 10 % level) within all models in which is considered, and consequently is tested also with other control variables. The specification with the highest pseudo R-squared value in table 11 is model 4.7 (0.0603).

Table 12 and table 13 display the results of all models processed through OLS regressions, rather than ordered logit. Table 12 contains frameworks having data sharing type as dependent variable, while table 13 embodies specifications with data sharing frequency on the left side of the equation. The advantage of OLS is the easy interpretation of the coefficients: for example, in model 5.1, one unit increase of CV precipitation corresponds to 1.85 decrease in data sharing type category, which might be rounded to 2 since data type categories are coded with integer numbers. Therefore, our model predicts that countries pass from exchanging hydrological data to share unspecified general reports if CV precipitation increases by one unit. If a model includes both CV precipitation and CV precipitation squared as framework 5.2, assuming a non-linear relationship between river variability and data sharing type, the coefficients have to be summed up in order to estimate the total impact of a change in CV precipitation. Taking coefficients in model 5.2, one unit increase of CV precipitation is equal to (-4.42) + 1.46, namely a 2.96 decrease in data sharing type category (rounded to 3 also in this case). We assume that within this particular model, one unit increase of CV precipitation leads from hydrological data sharing to no data sharing at all.

Variables, sharing type as dependent	**Model 5.1 (only CV Precipitation)**	**Model 5.2 (Non-linear)**	**Model 5.3 (N° of disputes)**	**Model 5.4 (CPI Country 1)**	**Model 5.5 (CPI Country 2)**	**Model 5.6 (Trade importance)**	**Model 5.7 (Power Asymmetry)**
CV Precipitation	-1.85*** (0.1740586)	-4.42*** (0.556428)	-3.15*** (0.9030554)	-3.95*** (0.6037781)	-4.49*** (0.5602677)	-4.02*** (0.5991854)	-4.07*** (0.5909298)
CV Precipitation squared		1.46*** (0.302719)	0.924** (0.4323682)	1.29*** (0.3133743)	1.48*** (0.2972516)	1.30*** (0.3075159)	1.32*** (0.303702)
N° of disputes			0.014 (0.0122)				
CPI Score country 1				0.0068* (0.0035357)		0.00621 (0.0037596)	0.0075** (0.0035186)
CPI Score country 2					0.0024 (0.0037259)	0.00004 (0.0041632)	0.0011 (0.0037984)
Trade Importance						6.276103 (6.796316)	
Power Asymmetry							0.00033 (0.0003565)
Observations	135	135	64	133	133	125	130
Adj. R-squared	0.4552	0.5335	0.2854	0.5379	0.5689	0.5718	0.5832

*Table 12 OLS, data sharing type as dependent variable. Standard errors are in brackets. * = p-value less than 0.1 ; ** = p-value less than 0.05 ; *** = p-value less than 0.01*

The remaining frameworks in table 12 maintain the same signs for both CV precipitation and CV precipitation squared coefficients, and also their magnitude does not change that much across models. Widening the perspective on table 12, it can be noticed that there are minimal differences in the performance of control variables, compared to the respective ordered logit frameworks in table 6. Even in this case, the specification presenting the highest adjusted R-squared value is model 5.7, which considers CPI scores of both countries and power asymmetry variable. Therefore, OLS regressions for the models having data sharing type as dependent variable confirm the kind of relationship that it has been found using ordered logit technique, and it will be further investigated in the last robustness check. On the other hand, as table 13 shows, OLS methodology evidently improves the significance of CV precipitation and CV precipitation squared related to data sharing frequency.

Variables, sharing freq. as dependent	Model 6.1 (only CV Precipitation)	Model 6.2 (Non-linear)	Model 6.3 (N° of disputes)	Model 6.4 (CPI Country 1)	Model 6.5 (CPI Country 2)	Model 6.6 (Trade importance)	Model 6.7 (Power Asymmetry)
CV Precipitation	0.6896** (0.3286561)	3.5805*** (1.108914)	2.6586* (1.538563)	2.270695* (1.185811)	3.23*** (1.163182)	1.9375 (1.209389)	2.3707* (1.196583)
CV Precipitation squared		-1.6431*** (0.603293)	-1.4174* (0.7366388)	-1.178124* (0.6154625)	- 1.52594** (0.617129)	-1.068478* (0.6206864)	-1.22676** (0.6149711)
N° of disputes			0.0261 (0.0207856)				
CPI Score country 1				-0.01821** (0.006944)		-0.016927** (0.0075884)	-0.01654** (0.0071248)
CPI Score country 2					-0.006128 (0.007735)	-0.0054106 (0.0084029)	-0.002742 (0.0076914)
Trade Importance						-2.267877 (13.7176)	
Power Asymmetry							-0.00174** (0.0007219)
Observations	135	135	64	133	133	125	130
Adj. R-squared	0.02	0.069	0.02	0.1045	0.061	0.0849	0.1267

*Table 13 OLS, data sharing frequency as dependent variable. Standard errors are in brackets. * = p-value less than 0.1 ; ** = p-value less than 0.05 ; *** = p-value less than 0.01*

In fact, they are significant through all the models considered, while in table 7, where ordered logit is used, CV precipitation is significant only in framework 2.2. The non-linear relationship hypothesis improves the estimation, since adjusted R-squared increases from 0.02 to 0.069, and the inverted U-shaped relationship holds in all specifications, with CV precipitation being positive and CV precipitation squared negative. Focusing on coefficients interpretation, we can exploit model 6.2 as example: if CV precipitation increases by one unit, data sharing frequency category should increase by two categories (3.58 – 1.64 = 1.94), so a treaty would pass from data sharing as needed to regular data sharing. When including control variables, the magnitude of both CV precipitation and CV precipitation squared is generally slightly lower compared to model 6.2. The final model 6.7 is the one which fits better the data in this context as well (adjusted R-squared is 0.1267).

As last robustness check, the relationship occurring between river variability and data sharing type is analyzed more in detail, in the light of the fact that the present analysis finds opposite results compared with previous similar research (Van de Poll, 2016), using either ordered logit and OLS techniques. In order to implement this specific focus, four dummy variables are created for different ranges of CV precipitation value. Particularly, the first bin contains all CV precipitation values less than 0.5, the second bin ranges from 0.5 to 1, the third one from 1 to 1.5 and the last bin goes from 1.5 to 2.5. The constructed dummies are equal to one when the respective CV precipitation value is included within the specific bin, and they are zero otherwise. This dummy approach is expected to be helpful in better understanding the impact of specific quantiles of the distribution of CV precipitation variable on data sharing type. Both ordered logit and OLS frameworks are used to test this simple model, aiming at finding potential differences in the results depending on the econometric approach. The outcomes are displayed in table 14.

Dummies	**Ordered Logit**	**OLS**
Bin 1	3.87** (1.751901)	0.92 (0.5855043)
Bin 2	0.44 (1.611184)	0.17 (0.5843896)
Bin 3	-2.00 (1.624747)	-0.69 (0.5840088)
Bin 4	omitted	omitted
Pseudo/Adj. R-squared	0.36	0.56

Table 14 Dummy approach results, first version

It can be noticed that the fourth bin is omitted from both models, and this happens since N-1 (in this case, three) dummies have to be incorporated within a regression. Additionally, the last bin only contains one observation, therefore it should not be very representative. Only one coefficient is significant (bin 1 in ordered logit specification), thus it is not possible to draw reliable conclusions based on this dummy approach framework. Nevertheless, the only significant coefficient is positive, which means the more river variability, the higher category of data sharing type. The coefficients of the third bin have a negative sign, and this might lead to think about an inverted U-shaped relationship, although for the hypothesis to be confirmed, we would need significant outcomes. We also present a slight variation of this dummy approach, where only three bins are implemented, with the objective of distributing CV precipitation observations more evenly. Specifically, bin 1 contains all the 39 observations where CV precipitation is smaller than 0.5, bin 2 embodies 46 observations for which the value of CV precipitation ranges between 0.5 and 1, and bin 3 contains all the remaining 50 observations. The results are reported in table 15.

Dummies	**Ordered Logit**	**OLS**
Bin 1	3.15***(0.4377847)	1.19***(0.1157555)
Bin 2	omitted	omitted
Bin 3	omitted	omitted
Pseudo/Adj. R-squared	0.23	0.44

Table 15 Dummy approach results, second version

Here two bins are omitted, one because of the previously explained reason (N-1 dummies ought to be included), and the other one due to collinearity, thus our purpose of investigating the effect of a change in river variability on data sharing type for different values of CV precipitation cannot be achieved within this specific framework. Nonetheless, coefficients for bin 1 in both ordered logit and OLS specifications confirm what we already found by dividing CV precipitation observations into four bins: the impact of an alteration of river variability on data sharing type categories is positive and significant.

5. Discussion

Within this section, the results presented in previous paragraphs are discussed and connected with findings from previous research. Due to heterogeneous outcomes obtained from the two different specifications of the dependent variable, data sharing type and frequency, they will be first reviewed separately, and then considerations concerning data sharing in general will occur. Probably the most controversial insight emerging from the present analysis is the relationship between river variability and data sharing type, since we found exactly opposite results in terms of signs compared to the previous research by Van de Poll (2016). Indeed, CV precipitation is negative in our framework and positive in Van de Poll's one, while CV precipitation squared is positive here and negative in the other analysis. Additionally, the non-linear functional form fits better the data using either ordered logit and OLS (CV precipitation squared coefficient is significant and R-squared increases) compared to a simple linear relationship in both our context and Van de Poll's. Acknowledging the differences in the data of the two analyses, it is anyway worth to deeper examine this fundamental discrepancy. Although so far only this study and Van de Poll's one have explicitly investigated the connection between data type and sharing frequency categories and river variability, several other frameworks have inspected how river flows variations affect treaties regulating transboundary freshwater streams. Particularly, Van de Poll links her results about the hump-shaped relationship occurring between CV precipitation and data sharing type with findings from Dinar et al. (2010), which actually found an inverted U-shaped relationship between treaty cooperation and water variability. We believe that two main arguments make this connection of results somewhat weak. Even though it might be argued that treaty cooperation means higher quality data shared more often, it should not be neglected that data sharing type is only one of the two aspects which influences treaties quality in our assumed framework. Secondly, Dinar et al. (2010) exploit number of treaties signed between river riparians and a dichotomous indicator treaty/no treaty as dependent variables, which are totally different measures compared to data sharing categories used in the present study and Van de Poll's one. Hence, we suggest an alternative explanation concerning the non-linear relationship between CV precipitation and data sharing type that is in line with our outcomes. Specifically, when river variability increases within a relatively low range of values, there are incentives to cheat and so lower categories of data sharing type are experienced. Nonetheless, above a certain point, river variability might become unsustainable for both countries within a dyad, therefore higher CV precipitation leads to higher categories of data sharing type. This might reflect a situation where the benefits of cooperation overcome the benefits of cheating, i.e. predicted losses caused by floods are higher than expected gains from stolen water. As pointed out in Dinar et al. (2010), higher river variability has both positive and negative impacts on treaty stability, which is at least partially determined by data sharing practices. Hence, we might extend this insight, and deduce that higher values of CV precipitation may have either positive and negative effects on data sharing standards. The results from robustness checks ought to be incorporated in this discussion though, since they reveal more nuances regarding the non-linear functional form assumption. In fact, while the non-linear model performs better than the linear one even using OLS specification and the signs are the same as in ordered logit frameworks, the overall impact of CV precipitation and CV precipitation squared, given by the sum of their two coefficients, is negative. Moreover, the examination of the marginal effects of CV precipitation on data sharing type points out that negative signs occur in two data sharing type categories out of three. Furthermore, when CV precipitation is plotted against data sharing type categories, it can be noticed that a negative relationship appears in a quite clear way. Finally, the coefficient of CV precipitation is negative and significant even in linear models. All these considerations might be translated into the following: if a non-linear U-shaped relationship occurs between river variability and data sharing type, the downturn side of the curve should represent the majority of the observations. On the other hand, the dummy variables approach which we used as last robustness check leads to positive and significant coefficients for all the observations having a CV precipitation value lower than 0.5. This last contrasting outcome makes difficult to conclude something definitive concerning the relationship between river variability and data sharing type of the treaties considered in the present study. Focusing on the performance of the various models, frameworks 1.7 and 5.7 are the ones which show the best results in terms of explanatory variables significance and R-squared value (no specification in table 8 is improved from control variables inclusion). Overall, CPI score of country 1 is the only control variable that is found to be significant across the majority of the models, and it does not change neither the signs nor the range of magnitude of CV precipitation and CV precipitation squared coefficients. Additionally, the coefficient of country 1 CPI score is positive as in Dinar et al. (2011), but its magnitude is slightly lower compared to their study. Another difference is that in their framework, the authors find significant coefficients for CPI scores of both countries, whereas here only CPI score of country 1 is significant in almost each specification. Regarding the control variable 'number of disputes', our results are analogous to findings from Dinar et al. (2011), Stinnett and Tir (2009) and Tir and Ackerman (2009), but not with outcomes from Dinar et al. (2015). Particularly, we find insignificant coefficients in all the frameworks where number of disputes is included as in the previous cited researches, while in Dinar et al. (2015), the authors obtain significant and negative coefficients for the militarized history indicator. Moving to trade importance, the present analysis finds insignificant coefficients for this control variable in all the specifications, as in one of the six models implemented within Dinar et al. (2015) paper. When data sharing type is considered as dependent variable, power asymmetry control results insignificant in all the models, as in Dinar et al. (2011), Dinar et al. (2015) and Stinnett and Tir (2009).

The outcomes when data sharing frequency is used as dependent variable draw a different picture. In fact, the first difference compared to data sharing type frameworks is that in model 2.1, where just CV precipitation is considered, its coefficient is small, positive and not significant. This means that whereas between river variability and data sharing type both a linear and a non-linear relationship were found to be significant, in the present context the former does not occur. The situation changes as CV precipitation squared is included, since CV precipitation coefficient becomes significant and remains positive, while the squared term is not significant and negative. Therefore, ordered logit estimation does not predict a non-linear relationship either between river variability and data sharing frequency. Rather, CV precipitation squared functions as good control for CV precipitation, pointing out a positive impact of water-stream variability on data sharing frequency, i.e. when CV precipitation increases, data are shared more often. All the other models in table 7 do not exhibit any significant coefficient, which might lead to think that CV precipitation squared is not such a robust control. When only countries which share at least one border are included in the dataset, we found no significant relationship existing between river variability and data sharing type. Nevertheless, the last robustness check, where OLS is used in spite of ordered logit, is the only section of this analysis which finds the same results as in Van de Poll research. In fact, a hump-shaped relationship between river variability and data sharing frequency appears, and it is significant across all the models in table 13. The non-linear functional form fits better the data, since adjusted R-squared increases from model 6.1 and CV precipitation turns from 5 % into 1 % level of significance. Moreover, the two coefficients of river variability reach their highest level of significance (both at 1 % level) when no additional control variable is considered, although the model with greatest adjusted R-squared value is specification 6.7 (0.1267). The inverted U-shaped relation has the following meaning: data are shared more often when river variability increases, but only up to a certain level of CV precipitation, after which frequency categories decrease as river variability raises. This is exactly the opposite compared to what we found about the estimated impact of CV precipitation on data sharing type, and weighing the two different effects against each other might result in an interesting broader perspective. In the context of data sharing frequency, OLS estimates suggest that after a certain level of river variability, benefits from cheating outweigh benefits from cooperation. Yet, as it was already pointed out in the results section, the overall impact of river variability on data sharing frequency when summing up the two coefficients of CV precipitation and CV precipitation squared is positive in all OLS frameworks. The concrete translation is that higher river variability leads country to share data more frequently. Hence, a general conclusion is that when CV precipitation increases, data sharing type and data sharing frequency variables take opposite paths. A confirmation comes from Spearman's rank-order correlation coefficient, which takes a value of -0.2935, meaning that the two independent variables are negatively and significantly (1 % level) correlated. The interpretation might be the following: as river variability increases, for a country it could be easier to cheat about the actual river flow by adjusting the two data sharing parameters of the treaty (data sharing type and frequency) in opposite ways. In fact, it is more likely to detect a state which cheats if it suddenly starts to share poor quality data less often, rather than more detailed data shared less often, or less precise information shared more regularly. The negative value of the Spearman's rank-order correlation coefficient is in contrast with what is found in Van de Poll's study (a positive and significant value), pointing out even further fundamental differences in the data between the present study and Van de Poll (2016) research. As in the models where data sharing type is the dependent variable, CPI score of country 1 is the control variable which performs better in terms of significance through all the specifications where data sharing frequency is the dependent variable. Nonetheless, when the latter appears on the left side of the equation, country 1 CPI score coefficient is negative rather than positive, as some governance quality and democracy indicators analyzed in Dinar et al. (2010). Both number of disputes and trade importance control variables are insignificant in all the models where data sharing frequency is the dependent variable, as well as specifications with data sharing type being the dependent variable. Regarding power asymmetry, models 2.7 and 6.7 present significant and negative coefficients, as in Dinar et al. (2010) and Tir and Ackerman (2009).

6. Conclusions

The main hypothesis which we tested in the present framework is the negative impact of increasing river flow variability on data sharing type and frequency categories embodied within agreements regulating transboundary rivers. A more nuanced picture comes out from the data. In fact, various econometric techniques have led to contrasting outcomes, and the two distinct dependent variables, data sharing type and frequency, were found to behave differently. This is a fundamental discrepancy between the results of the present study and the ones from Van de Poll (2016), where the impact of increasing river flow variability assumes a hump-shaped functional form on both data sharing type and frequency. We consider our variegate outcomes as more realistic, since it appears more difficult for countries to cheat by deviating from data sharing type and frequency standards contemporaneously, without being detected. Estimates from ordered logit models having data sharing type as dependent variable point out a significant U-shaped relationship with river flow variability. Nevertheless, results from OLS predict an overall negative impact of increasing river flow variability on data sharing type categories, when summing up the coefficients of CV precipitation and CV precipitation squared. Lastly, the dummy approach examined in the robustness check section presents only one significant coefficient, and it is positive. Hence, we might conclude that in our data, a U-shaped relationship occurs between river flow variability and data sharing type categories, where the negative part of the function seems to embody the majority of the observations. This partly confirms the initial hypothesis that increasing river flow variability has a negative effect on data sharing type. The situation completely changes when data sharing frequency enters the framework as dependent variable. In this particular context, only OLS models embodying even non-sharing border country dyads estimate a significant non-linear functional form between river flow variability and data sharing frequency. Specifically, a hump-shaped relationship is found, even though the sum of CV precipitation and CV precipitation squared coefficients is positive in all the models. Contrarily to specifications examining data sharing type, here most of the observations appears to be represented by the positive part of the function. The initial hypothesis is partially confirmed also when data sharing frequency is considered as dependent variable. In fact, after an initial positive impact, increasing river flow variability has then a negative effect on data sharing frequency. To sum up, river flow variability is found to have a U-shaped relationship with data sharing type, and an inverted U-shaped relationship with data sharing frequency. After the threshold where the two functions reverse their paths, it seems easier for countries to cheat by sharing data less often, rather than by lowering the quality of the data. Either the function which relates river flow variability with data sharing type and the one that associates river flow variability with data sharing frequency have moments where increasing variability leads to higher categories of data sharing type or frequency. This insight may be in line with the concept of “hydro-cooperation” as developed by Hamner and Wolf (1998), who identify collaboration between riparians over a common water source as an historical trend. Nonetheless, there are also moments in both functions where increasing river flow variability negatively affects data sharing type or frequency. Therefore, we want to point out policy recommendations with the aim of disincentivizing countries from cheating behaviors associated with less data sharing. Particularly, it seems necessary to better standardize treaties governing transboundary rivers and information sharing rules, since from the data, it appears that countries have room and incentives to cheat, exploiting deviations from at least one of the two parameters, data sharing type and frequency. These standards should guarantee that good quality data are shared regularly, in order to make more difficult for countries to adjust the two parameters, data sharing type and frequency, in opposite directions. Further research could consider the implementation of a unique data sharing indicator that embodies both data type and sharing frequency characteristics, with the objective of assessing which one of the two opposite effects caused by increasing river flow variability overcomes the other. Additionally, the dataset which the present analysis relies upon might be enlarged, considering more treaties regulating transboundary rivers than the ones that we extrapolated from Gerlak et al. (2011).

References

- *Afroz, R. and Rahman, M., (2013). Transboundary River Water for Ganges and Teesta Rivers in Bangladesh: An Assessment. Global Science and Technology Journal, [online] Vol. 1, pp.Pp.100-111. Available at: <https://www.researchgate.net/profile/Rounak_Afroz/publication/278037218_Transboundary_River_Water_for_Ganges_and_Teesta_Rivers_in_Bangladesh_An_Assessment/links/557b2aeb08aeb61eae21c717/Transboundary-River-Water-for-Ganges-and-Teesta-Rivers-in-Bangladesh-An-Assessment.pdf>*
- *Dinar, A., Blankespoor, B., Dinar, S. and Kurukulasuriya, P. (2010). Does precipitation and runoff variability affect treaty cooperation between states sharing international bilateral rivers?. Ecological Economics, 69(12), pp.2568-2581.*
- *Dinar, S., Dinar, A. and Kurukulasuriya, P. (2011). Scarcity and Cooperation along International Rivers: An Empirical Assessment of Bilateral Treaties1. International Studies Quarterly, 55(3), pp. 809-833.*
- *Dinar, S., Katz, D., De Stefano, L. and Blankespoor, B. (2015). Climate change, conflict, and cooperation: Global analysis of the effectiveness of international river treaties in addressing water variability. Political Geography, 45, pp.55-66.*
- *Gerlak, A., Lautze, J. and Giordano, M., (2010). Water resources data and information exchange in transboundary water treaties. International Environmental Agreements: Politics, Law and Economics, 11(2), pp.179-199.*
- *Hamner, J., & Wolf, A. (1998). Patterns in international water resource treaties: the Transboundary Freshwater Dispute Database. Colorado Journal of International Environmental Law and Policy, 1997 Yearbook*
- *Tir, J. and Stinnett, D. (2009). The Institutionalization of River Treaties. International Negotiation, 14(2), pp.229-251.*
- *Tir, J. and Ackerman, J., (2009). Politics of Formalized River Cooperation. Journal of Peace Research, 46(5), pp.623-640.*
- *Van de Poll, F., (2016), Dare to share: information sharing in transboundary river basins, VU University Amsterdam bachelor thesis*