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ORIGINAL ARTICLE

Biospheric values as predictor of climate change risk perception: A multinational investigation

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Abstract
Climate change is one of the big challenges of our time. A better understanding of how individuals form their evaluation of the risk related to climate change seems to be key to win broad support for climate change mitigation efforts. Extant research indicates that biospheric values (BV) are an important antecedent of individuals' perception of the risk and consequences related to climate change. However, risk perception scholars have only recently started to study how BV relate to individuals' climate change risk perception (CCRP) and much is still to be learned about this relationship. The present study contributes to this growing literature by studying the BV–CCRP relationship in a multinational context. The results suggest that the BV – CCRP relationship varies in strength between different countries. These differences can be explained in part by societies' cultural leanings (i.e., individualism vs. collectivism) and societies' wealth. The present research adds to our understanding of why individuals in different countries perceive climate change related risk differently and how this perception is shaped differently by biospheric values in different countries. In this way, the findings help to build a more nuanced theory of how CCRP are formed. The presented results also have implications for policymakers and NGOs who wish to increase individuals' engagement with climate change and its consequences in different populations. In particular, the findings suggests that it might be necessary to use different strategies in different societies to achieve a greater awareness of climate change related risks.

KEYWORDS
biospheric values, climate change risk perception, culture, GDP, individualism

1 | INTRODUCTION

Climate change is one of the big challenges of our time and noteworthy efforts are expanded on trying to understand how climate change can be addressed (Intergovernmental Panel on Climate Change, 2018). Nurturing a realistic perception of the severe and harmful consequences of climate change in individuals and populations (i.e., climate change risk perception) seems to play an important role in these efforts. This is because climate change risk perception has been found to motivate individuals to address climate change through individual action and support of meaningful policy initiatives (Bradley et al., 2020; Hornsey et al., 2016). It is not surprising then that researchers study the factors that shape individuals' climate change risk perception (CCRP) to gain a better understanding of how and why people differ in their risk perceptions and of how policymakers can cultivate a realistic CCRP in individuals (e.g., Fleming et al., 2021; Thaker et al., 2020; Visschers, 2018). Biospheric values (BV) seem to be one promising predictor of CCRP. High BV individuals consistently displayed stronger CCRP in extant studies compared to low BV individuals (Siegrist & Árvai, 2020; van der Linden, 2017). Even though promising, CCRP research has only recently started to explore the effects of BV, however (van der Linden, 2017). Accordingly, our understanding of the BV–CCRP relationship is in its early stages and more research is necessary. For example, it is not clear to what extent this relationship between BV and CCRP is shaped by the cultural or economic context that individuals are embedded in.

While the need for a better understanding of national differences in climate change risk perception and risk perception in general has been recognized and more such research is encouraged (Siegrist & Árvai, 2020; Van Boven et al., 2018), not much cross-national research on the antecedents of CCRP is available (see Arıkan & Günay, 2021; Duijndam & van Beukering, 2021; Echavarren et al., 2019; Lee et al., 2015; McCright et al., 2016; Poortinga et al., 2019; Shi et al., 2016 for exceptions). In particular, I am not aware of any research that studied between-country variation in the BV–CCRP relationship and how it can be explained.

The present research seeks to address this gap in the literature. In particular, I theoretically predict that the BV–CCRP relationship is stronger in individualistic leaning compared to collectivistic leaning nations and in wealthier compared to less wealthy nations. These predictions were tested in three different multinational datasets using different operationalizations of BV and CCRP. In doing so, the present research adds to our understanding of how BV shape individuals' CCRP in different societal contexts. The findings also provide insights for public policymakers who wish to use value-based interventions to increase awareness of climate change related risks in populations.

1.1 | Biospheric value orientation as predictor of climate change risk perception

Extant research has identified a number of determinants of CCRP. Among others, CCRP seems to depend on sociocultural influences on the individual level. Individual human values are among the most promising of these sociocultural predictors of CCRP (Siegrist & Árvai, 2020; van der Linden, 2017).

According to the theory of human values (Schwartz, 1992), values are defined as "trans-situational goals, varying in importance, that serve as guiding principles in the life of a person" (Schwartz et al., 2012, p. 664). One value orientation that is particularly important in the environmental domain is BV. BV reflect the extent to which an individual holds the general trans-situational goal of protecting the natural environment. Individuals high in biospheric values will be concerned about the well-being of the natural environment even if they will not have any direct benefits from protecting it (Steg & de Groot, 2012).

Human values influence how individuals evaluate experiences and information (Schwartz, 2012) and form the basis for beliefs (de Groot et al., 2013; Stern & Dietz, 1994; Stern et al., 1999). Climate change is directly related to high BV individuals' goals (i.e., environment conservation) because of its adverse effects on the natural environmental (Bellard et al., 2012; Weiskopf et al., 2020). Because of this, high BV individuals may perceive climate change as more threatening compared to individuals who do not hold strong BV. Low BV individuals, in contrast, might not perceive climate change as relevant, or indeed threatening, since environmental conservation is by definition not an important goal to that group of individuals (Bouman, Verschoor, et al., 2020).

Extant literature supports the notion that stronger BV are related to greater CCRP. A meta-analysis (Hornsey et al., 2016) and a literature review (van der Linden, 2017) suggest that BV is an important predictor of climate change related risk perception across studies. Evidence for the BV–CCRP relationship were found in different countries as well. For example, high BV individuals in a study in the United Kingdom perceived greater risk stemming from climate change compared to their low BV counterparts (van der Linden, 2015). Similarly, individual's environmental value orientation was associated with increased CCRP in individuals in a study in India (Thaker et al., 2020).

Importantly, the strength of this effect may vary between countries. Shi and colleagues (2016) studied the BV–CCRP relationship in six different countries. In their study, an increase of one point on their BV measure was associated with a 0.28-point increase on their CCRP measure (i.e., rated on a 6-point Likert scale) in their Swiss sample, while it was associated with a 0.56-point increase among their UK participants. The other countries were in between these two extremes in terms of the strength of the BV–CCRP relationship. However, to the best of my knowledge, no research has tested potential explanations for such differences.

1.2 | Differences between collectivistic and individualistic societies

Recent research suggest that the cultural context influences to which extent individuals rely on their individual value orientations when making judgments and decisions (Albarracin & Shavitt, 2018). Individualism on the society level is defined as the extent to which individuals understand themselves as independent beings or as part of social groups (Hofstede, 2011, Hofstede, Hofstede, & Minkov, 2010). There is a greater emphasis on "the individual" in individualistic leaning societies, while collectivistic leaning societies emphasize "the group" more strongly (Albarracin & Shavitt, 2018). Because of these differences in mindsets, it has been proposed that individuals in individualistic societies use information on who they are, their own thoughts and feelings, to inform their actions, opinions, and judgments to a greater extent than their counterparts in collectivistic societies. Individuals in collectivistic societies, on the other hand, rely more strongly on social information, such as their perception of what others belief or the behavior of others, to guide their own actions and judgments (Eom et al., 2016; Markus, 2016; Zou et al., 2009).

This theory has been tested in several recent environmental studies. For example, Chan (2019) studied the relationship between value orientations and different pro-environmental behaviors. He found that self-transcendent and biospheric value orientations were more predictive of individuals' pro-environmental intentions in individualistic leaning societies than in collectivistic leaning societies. Other authors replicated these findings in different behavioral contexts and in different country samples (Eom et al., 2016; Martin, 2021; Tam & Chan, 2017).

Similarly, a meta-analysis of the values—attitude relationship suggests that self-enhancement and self-transcendence values are more strongly related to relevant attitudes (e.g., attitudes toward fairness and pro-environmental attitudes) in individualistic compared to collectivistic societies (Boer & Fischer, 2013). Research in other domains is also broadly supportive of individualism effects. For example, self-perception appears to be little influenced by the judgments of others for individuals with an individualistic background. For individuals from collectivistic cultures, on the other hand, self-perception may incorporate the (anticipated) view of others to a greater extent (Kim et al., 2014). Similarly, individuals' risk perception may be shaped by the anticipated risk perception of others more strongly when individuals have a collectivistic mindset compared to when they have an individualistic mindset (Savani et al., 2015). This was shown in a set of studies where individuals were primed with an individualistic or collectivistic mindset before they were asked to evaluate the risk related to a new drug. If individuals in the collectivistic prime conditions were told that they needed to justify their evaluation to others, they adjusted their evaluation compared to a control group, while individuals in the individualistic prime condition did not (Torelli, 2006).

While the reviewed research provides important insights, there are no studies available that test directly whether values influence risk perceptions differently in different societal contexts. Prior research either focused on variation in values—behavior or values—attitude relationships or did not include values as predictors. Nonetheless, I predict that the same principle that explains between-country differences in the values—behavior and values—attitude relationships between societies will also apply to the values—risk perception relationship. That is, I anticipate that an individual's risk perception is more purely based on that individuals' own judgment, which in turn is rooted in that person's value orientation (see 1.1.) in individualistic leaning cultures. In collectivistic societies, values should be less relevant for determining an individuals' risk perception than in individualistic societies. More formally:

H1: BV will relate to CCRP more strongly in individualistic societies compared to collectivistic societies.

1.3 | Differences between wealthier and less wealthy societies

Research indicates that individuals who live in economically prosperous contexts are more independent in developing their own opinions and preferences, while the same is more difficult for their counterparts who live in poorer conditions. Individuals in wealthy economic conditions typically have the resources that allow them to be independent of others in their daily life (Kraus et al., 2012). They therefore can afford to form and voice their own opinions without the need to conform to and adopt the views of others (Stephens et al., 2007).

Individuals who live in more economically restrained environments, on the other hand, may depend on others to a larger extent to reach their goals. They may therefore be more motivated to avoid being rejected by others in their social environment compared to individuals in more affluent environments (Ogihara, 2018). Indeed, individuals have been found to place more importance on activities that benefit their community and other individuals around them in economically difficult compared to economically prosperous times (Park et al., 2014, 2017).

In addition, in less affluent conditions, individuals may try to avoid being rejected by others by adopting group norms and views, rather than risking standing out by forming their own opinions and following their own preferences (Chan, 2019; Stephens et al., 2007; Welzel & Inglehart, 2010). Baby name choices are one example for this mechanism. That is, parents seem to be more likely to select more common (vs. less common) names for their children in economically less prosperous times (Bianchi, 2016; Ogihara et al., 2015) and environments (Varnum & Kitayama, 2011).

Accordingly, individually held values and identities should be more relevant and therefore more predictive of views and perceptions in affluent (vs. less affluent) contexts. This indeed seems to be the case. For example, BV was found to be more predictive of pro-environmental (vs. pro-economic) preferences in more versus less developed countries (Milfont & Markowitz, 2016). Gender identity, which is supposedly related to individuals' value orientations (Brough et al., 2016), was a weaker predictor of environmental concern in less compared to more wealthy societies (Chan et al., 2019). Not all studies reported findings in support of the role of national wealth however (see e.g., Boer & Fischer, 2013 for an exception). Nonetheless, the available theorizing and accompanying empirical evidence indicates that the affluence of societies is a predictor of the strength of the effects of human values and identities on preferences and views.

Translating these insights to the BV–CCRP relationship, I predict that personally held BV will be important in forming CCRP as suggested in extant research (van der Linden, 2017). This relationship will be more pronounced in affluent societal contexts, however. Individuals in less wealthy contexts, on the other hand, will be less likely to form their risk perception based on internally held values (Kraus et al., 2012), such as their CCRP based on their BV.

H2: The BV–CCRP relationship will be stronger in wealthier societies compared to less wealthy societies.

2 | METHOD

2.1 | Dataset

The theoretical model was tested with data from Wave 5 (version v20180912) of the World Values Survey (WVS; Inglehart et al., 2018). The WVS is a multipurpose survey project that collected data for its 5th wave in 58 countries between 2005 and 2009. The WVS dataset was combined with information on country level characteristics. Country level data for 2005 (i.e., the year when individual level data collection started) were used for country level characteristics for which data on different years were available. Not all variables are available for all countries. Data on the dependent variable and biospheric values were collected in 48 countries (see Table 1). In 47 of these countries (i.e., except for Argentina), the complete set of individual level control variables was included in the questionnaire. Gross domestic product is available for 46 and society level individualism scores for 34 of the 48 relevant countries. The different variables are discussed in more detail in the following.

2.2 | Measures

2.2.1 | Climate change risk perception

Individuals' CCRP was assessed with one question. Participants were asked to rate as how serious they perceive "Global warming or the greenhouse effect" to be. Participants responded on a four-point Likert scale ranging from 1 = very serious to 4 = not serious at all. To facilitate interpretation, the item was reverse scored so that higher scores represent a more pronounced risk perception. For the robustness checks (see section 2.3.), the dependent variable was dichotomized. Answer categories "not very serious" and "not serious at all" were coded as 0 = "low risk perception" and categories "very serious" and "somewhat serious" as 1 = "high risk perception." Table 2 includes descriptive information on the CCRP measure.

2.2.2 | Biospheric and altruistic values

BV were measured using Schwartz and colleagues' portrait value questionnaire technique (Schwartz et al., 2001). That is, a short portrait of an individual was presented to participants (i.e., "Looking after the environment is important to this person; to care for nature"). Participants were then asked to rate the extent to which they felt that the portraited individual is similar to them. In the WVS, a six-point scale was used (1 = very much like me; 6 = not at all like me). Scores were recoded so that higher scores reflect stronger BV.

This item is closely related to the original measure proposed by Steg, de Groot and colleagues (de Groot & Steg,

TABLE 1 Countries and country specific coefficients

Country	ISO	N[a]	BV - CCRP	
			Slope[b]	r[c]
Andorra	AND	988	0.04*	0.07
Argentina	ARG	933	0.05***	0.12
Australia	AUS	1385	0.11***	0.2
Brazil	BRA	1442	0.05*	0.07
Bulgaria	BGR	836	0.13***	0.23
Burkina Faso	BFA	1332	0.04***	0.1
Canada	CAN	2089	0.11***	0.19
Chile	CHL	928	0.04***	0.11
China	CHN	1215	0.11***	0.15
Cyprus	CYP	1044	0.07***	0.16
Egypt	EGY	2977	0.03***	0.06
Ethiopia	ETH	1445	-0.03	-0.05
Finland	FIN	1004	0.13***	0.19
Georgia	GEO	1347	0.07***	0.1
Germany	DEU	1972	0.09***	0.16
Ghana	GHA	1172	-0.02	-0.03
Hungary	HUN	984	0.16***	0.25
India	IND	1183	0.12***	0.19
Indonesia	IDN	1717	-0.11***	-0.12
Iran	IRN	2593	0.10***	0.17
Japan	JPN	1038	0.08***	0.19
Jordan	JOR	998	0.07*	0.08
Malaysia	MYS	1199	0.06***	0.1
Mali	MLI	1368	0.05**	0.08
Mexico	MEX	1455	0.07***	0.11
Moldova	MDA	993	0.11***	0.19
Morocco	MAR	744	0.21***	0.33
Norway	NOR	1013	0.12***	0.19
Peru	PER	1165	0.04*	0.07
Poland	POL	974	0.13***	0.2
Romania	ROU	1345	0.09***	0.13
Rwanda	RWA	1435	0.10***	0.15
Serbia	SRB	1102	0.10***	0.17
Slovenia	SVN	958	0.05*	0.07
South Africa	ZAF	2432	0.09***	0.13
South Korea	KOR	1200	0.04**	0.08
Spain	ESP	1149	0.16***	0.31
Sweden	SWE	988	0.08***	0.16
Switzerland	CHE	1230	0.15***	0.21
Taiwan	TWN	1198	0.06***	0.11
Thailand	THA	1525	0.02	0.02
Trinidad and Tobago	TTO	927	0.07***	0.13
Turkey	TUR	1244	0.05***	0.11

(Continues)

TABLE 1 (Continued)

Country	ISO	N[a]	BV - CCRP	
			Slope[b]	r[c]
Ukraine	UKR	934	0.08***	0.16
United States	USA	1206	0.20***	0.28
Uruguay	URY	977	0.02	0.04
Vietnam	VNM	1275	0.17***	0.26
Zambia	ZMB	1183	0.01	0.02

Abbreviations: BV = biospheric values; CCRP = climate change risk perception; ISO = Country code.
[a]Only participants for which data on biospheric values and climate change risk perception is available are included.
[b]BV–CCRP regression slopes (no control variables included).
[c]Pearson correlation between BV and CCRP.
*p < 0.05.
**p < 0.01.
***p < 0.001.

TABLE 2 Descriptive statistics

Variable	N	M or %	SD	Min. – Max. or categories
Individual level				
CCRP	61841	3.47	0.74	1–4
BV	61841	4.61	1.19	1–6
AV	61478	4.72	1.13	1–6
Age	61654	41	16	15–98 years
Female	61780	51 %		0 = male; 1 = female
Income	57588	4.74	2.24	1–10
Education	61485	5.35	2.46	1–9
Country level				
Individualism	34	42.9	23.2	14–91
GDP	46	15386	12922	652–47772
CRI	46	70.51	35.52	15–152.25
BV	48	4.59	0.34	3.82–5.24

Note: All statistics are based on untransformed variables; Only participants for which data on biospheric values and climate change risk perception is available are included. Abbreviations: AV = altruistic values; BV = biospheric values; CCRP = climate change risk perception; CRI = climate risk index.

2008; Steg et al., 2014) and a variant of this item has been included in the updated portrait value questionnaire version of their BV measure (Bouman et al., 2018). In that research, the item correlated highly with a multi-item BV measure (i.e., $r = 0.81$ and $r = 0.8$).

Even though the current research focuses on BV, altruistic values (i.e., "It is important to this person to help the people nearby; to care for their well-being.") were analyzed as a robustness check (see Section 3.3.). Altruistic values and BV both belong to the self-transcendence values and are therefore theoretically similar (Steg & de Groot, 2012). Altruistic values were measured on the same scale as BV and scores were again reverse scored. Descriptive information on both value measures can be found in Table 2.

2.2.3 | Individual level control variables

Age was measured in years. The age variable was divided by 100 before it was entered in the model. Participants' gender was captured with a dummy variable where 1 represents female and 0 male gender. Educational attainment was assessed using nine categories where a higher score indicates higher attainment (i.e., from 1 = no formal education to 9 = university degree). Household income was measured by asking participants to indicate which country-specific income decile they belonged to. Table 2 contains descriptive information on all control variables.

2.2.4 | Country level variables

Society level individualism/collectivism (IDV) scores were adopted from Geert Hofstede's website (Hofstede, 2015). In the adopted version of the IDV index, the scale ranges from 0 to 100. Scores above 50 mean that a country is individualistic leaning and countries that scores below 50 are said to be collectivistic leaning. The further the score from the midpoint (i.e., 50) the stronger the individualistic or collectivistic mindset of a society (Hofstede, 2011). The IDV variable was divided by 100 to facilitate the interpretation of the results.

GDP scores were downloaded from the World Bank database (The World Bank, 2018). I used GDP per capita at purchasing power parity (PPP) in international $ for 2005. GDP values were skewed (i.e., there were comparably many low GDP countries in the dataset; see Fig. A.1 in the Supporting Information). Because of this, log-transformed values of GDP were used. The log-transformed values were divided by 10 before they were entered in the models.

I also included two country level control variables in the analyses (i.e., climate risk index and country level BV)[1]. Climate risk index (CRI) scores were obtained from a report published by Germanwatch (Harmeling & Bals, 2007). Germanwatch created this index for each country based on different types of impact of weather-related events. Scores based on events from 1996 to 2005 were used to capture the extent to which a given country is exposed to climate related risk. Lower scores indicate greater risk. Details on how the CRI is calculated can be found in Harmeling and Bals' (2007) report. CRI scores were also divided by 100. Country level BV scores were calculated by averaging the BV scores of all participants in a given country. Information on the country level variables is included in Table 2. Table 3 shows the correlations between country level variables.

2.3 | Empirical strategy

I used multilevel models to test my theoretical predictions as they allow to model data where individuals i are nested in countries j (Aguinis et al., 2013). First, I tested the effect of

[1] I would like to thank an anonymous reviewer for this suggestion.

TABLE 3 Zero-order correlations among the country level variables

	1	2	3
1. IDV			
2. GDP (log)	0.61***		
3. CRI	0.06	−0.28	
4. BV	0.04	−0.15	0.21

Abbreviations: BV = biospheric values; CRI = climate risk index; IDV = Individualism.
*p < 0.05.
** p < 0.01
*** p < 0.001

BV on individuals' CCRP across all countries in the dataset using a fixed effects model:

$$\text{CCRP}_{ij} = \beta_0 + \beta_1 \left(\text{biospheric values}_{ij}\right) + \beta_{2-5} \left(\text{controls}_{ij}\right) + \alpha_j + e_{ij} \quad (1)$$

In Equation 1, β_0 is an intercept term, β_1 is the slope of biospheric values, $\beta_{2\text{-}5}$ are the slopes of control variables, e_{ij} is an error term, and α_j are country fixed effects. The country fixed effects were modeled using dummy variables. If regression slopes vary between countries as is predicted, normal standard errors will be anti-conservative (Bell et al., 2019; Heisig & Schaeffer, 2019). To remedy that, I used cluster robust standard errors (Cameron & Miller, 2015).

To study variation in the BV slopes between countries and to test the theoretical predictions regarding how this variation can be explained, I used the following multilevel model:

$$\text{Level 1}: \text{CCRP}_{ij} = \beta_{0j} + \beta_{1j}(\text{biospheric values}_{ij}) + \beta_{2j-5j}(\text{controls}_{ij}) + e_{ij} \quad (2)$$

$$\text{Level 2}: \widehat{\beta}_{1j} = \gamma_0 + \gamma_1(\text{country level predictor}_j) + u_j \quad (3)$$

In Equation 2, β_{0j} is the intercept term and β_{1j} the BV slope in country j. The association of GDP and cultural individualism with the size of the BV slopes β_{1j} is then modeled using Equation 3. In Equation 3, γ_1 represent the hypothesized effects of interest (see H1 and H2). The equation also includes an intercept γ_0 and a disturbance term u_j (Aguinis et al., 2013).

I estimated the equations using a two-step approach. First, I estimated the BV slopes for each country j individually (Equation 2). I then used the estimated slopes from Equation 2 as dependent variable in Equation 3 (Bates et al., 2014; Jusko & Shively, 2005). This approach is commonly used in the extant literature (see e.g., Chiarini et al., 2020; Martin, 2021; Quispe-Torreblanca et al., 2021). It has the advantage of being more robust as it makes less assumptions compared to an approach where Equations 2 and 3 are estimated simultaneously (Bates et al., 2014) and is suitable for datasets where the number of higher level units, in this case countries, is small (Bryan & Jenkins, 2016).

Equation 3 was estimated using robust regression with an MM-estimator (Maechler et al., 2021). Because heteroscedasticity may be a concern when estimates are used as dependent variables (Donald & Lang, 2007; Lewis & Linzer, 2005), I used robust standard errors. Other approaches, such as weighted least squares (WLS), feasible generalized least squares (FGLS), or ordinary least squares (OLS) with robust standard errors have been suggested (Lewis & Linzer, 2005). However, WLS and FGLS are not recommended for different reasons (Bryan & Jenkins, 2016; Lewis & Linzer, 2005). While OLS would have been viable, I used an MM-estimator rather than OLS. This is because one country in the dataset (i.e., Indonesia) is a potential outlier. The MM-estimator is similarly efficient to OLS when there are no outliers, and remains highly efficient and unbiased in the presence of outliers (Wilcox & Keselman, 2012). Using Equation 3, I estimated the effects of country level predictors individually (Aguinis et al., 2013; Becker et al., 2016) and two at a time. I did not model the effects of all predictors simultaneously in one model because the number of countries is too small for this to be meaningful.

3 | RESULTS

3.1 | Relationship between biospheric values and climate change risk perception

Fixed effects models (i.e., see Equation 1) indicate that stronger BV are associated with an elevated CCRP in the dataset (Model 1 in Table 4). The relationship remains similar in size when control variables were included in the model (Model 2 in Table 4). Regression slopes thereby varied from –0.114 in Indonesia to 0.207 in Morocco when they were estimated for each country without control variables (Equation 2 and Table 1). The slopes were statistically significant in 43 out of 48 countries. Since the size of regression slopes may be difficult to interpret, I replicated the analysis using correlation coefficients. Pearson correlation coefficients varied from –0.117 to 0.326 between countries with a median of 0.129. While there was a positive relationship between BV and CCRP in most countries, the strength of this relationship seems to vary between countries.

3.2 | Effects of country level predictors

Next, I tested whether variation in the relationship between BV and CCRP can be explained by a nation's wealth and/or the strength of societies' individualistic orientation. The setup of these models is described in Section 2.3. I estimated Equation 2 (i.e., country specific BV slopes models) with and without control variables. The results of the country level models of the BV slopes (i.e., Equation 3) are presented in Tables 5A–6B. In support for H1, BV–CCRP slopes appear to

TABLE 4 Fixed effects models of climate change risk perception

	Dependent variable:				
	CCRP		CCRP (binary)	CCRP	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Intercept	3.329***	3.148***	1.944***	3.468***	3.266***
	(0.042)	(0.048)	(0.164)	(0.034)	(0.052)
BV	0.075***	0.074***	0.179***		
	(0.008)	(0.009)	(0.031)		
AV				0.049***	0.047***
				(0.007)	(0.007)
Age		0.003	0.229		0.051
		(0.036)	(0.138)		(0.034)
Female		0.016	0.077		0.014
		(0.010)	(0.045)		(0.010)
Income		0.0002	0.011		−0.0003
		(0.004)	(0.018)		(0.004)
Education		0.027***	0.102***		0.029***
		(0.004)	(0.018)		(0.004)
Country FE	Yes	Yes	Yes	Yes	Yes
Model	linear	linear	logit	linear	linear
Observations	61,841	57,149	57,149	61,478	56,839
R^2	0.099	0.104		0.090	0.096
Log Likelihood			−17,380.460		

Note: Standard errors are clustered at the country level.
Abbreviations: AV = altruistic values BV = biospheric values; CCRP = climate change risk perception.
*p < 0.05.
**p < 0.01.
***p < 0.001.

TABLE 5A Models of the within country BV slopes (Linear 1st step without controls)

	Model 1	**Model 2**	**Model 3**	**Model 4**
Intercept	0.038*	−0.080	0.123***	0.087
	(0.016)	(0.075)	(0.016)	(0.094)
IDV	0.125***			
	(0.030)			
log GDP		0.175*		
		(0.078)		
CRI			−0.056**	
			(0.019)	
BV				−0.001
				(0.020)
Countries	34	46	46	48
R^2	0.328	0.126	0.149	0.0001

Abbreviations: BV = biospheric values (country level); CRI = climate risk index; IDV = Individualism.
*p < 0.05.
**p < 0.01.
***p < 0.001.

TABLE 5B Models of the within country BV slopes (Linear 1st step without controls)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.287*	0.056*	−0.024	−0.002	−0.121	0.023
	(0.131)	(0.023)	(0.086)	(0.090)	(0.124)	(0.100)
IDV	0.172***	0.126***	0.121***			
	(0.035)	(0.028)	(0.033)			
log GDP	−0.278[a]			0.125	0.178*	
	(0.139)			(0.085)	(0.077)	
CRI		−0.032		−0.043*		−0.061**
		(0.023)		(0.021)		(0.018)
BV			0.014		0.009	0.023
			(0.021)		(0.021)	(0.021)
Countries	33	33	34	45	46	46
R^2	0.388	0.366	0.330	0.196	0.128	0.165

Abbreviations: BV = biospheric values (country level); CRI = climate risk index; IDV = Individualism.
[a]p = .055
*p < 0.05.
**p < 0.01.
***p < 0.001.

TABLE 6A Models of the within country BV slopes (Linear 1st step with controls)

	Model 1	Model 2	Model 3	Model 4
Intercept	0.035*	−0.117	0.121***	0.108
	(0.016)	(0.072)	(0.018)	(0.094)
IDV	0.133***			
	(0.029)			
log GDP		0.214**		
		(0.075)		
CRI			−0.054**	
			(0.020)	
BV				−0.006
				(0.021)
Countries	33	45	45	47
R^2	0.344	0.173	0.124	0.001

Abbreviations: BV = biospheric values (country level); CRI = climate risk index; IDV = Individualism.
*p < 0.05.
**p < 0.01.
***p < 0.001.

be larger the more individualistic leaning countries are. This effect remained even when other variables were controlled for. Similarly, GDP explained between-country variation in the BV–CCRP slopes. Slopes were larger in wealthier countries. This effect again remained statistically significant when country level control variables were included with two exceptions. First, when individualism and GDP were included simultaneously, the GDP effect was no longer statistically significant. The same was true when climate change risk (CRI) was included as a control in the model without individual level controls (Model 4 in Table 5B). However, in the model with individual level controls, GDP remained a significant predictor even when CRI was controlled for (Model 4 in Table 6B). Overall, the results are in line with H2. The results of Models 1 and 2 in Table 5A are visualized in Figures 1 and 2.

CRI had a negative effect, indicating that BV–CCRP slopes are smaller in lower risk countries. This relationship was not always statistically significant when other predictors were included in the models (see Tables 5B and 6B). Country level BV was not statistically significantly related to the size of the BV–CCRP slopes in any of the models.

TABLE 6B Models of the within country BV slopes (Linear 1st step with controls)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.212	0.044	−0.010	−0.054	−0.157	0.041
	(0.162)	(0.025)	(0.079)	(0.087)	(0.127)	(0.100)
IDV	0.172***	0.135***	0.131***			
	(0.034)	(0.030)	(0.031)			
log GDP	−0.201			0.174*	0.217**	
	(0.171)			(0.081)	(0.076)	
CRI		−0.017		−0.036		−0.058**
		(0.022)		(0.023)		(0.020)
BV			0.010		0.008	0.018
			(0.019)		(0.020)	(0.022)
Countries	32	32	33	44	45	45
R^2	0.374	0.354	0.341	0.210	0.174	0.135

Abbreviations: BV = biospheric values (country level); CRI = climate risk index; IDV = Individualism.
*p < 0.05.
**p < 0.01.
***p < 0.001.

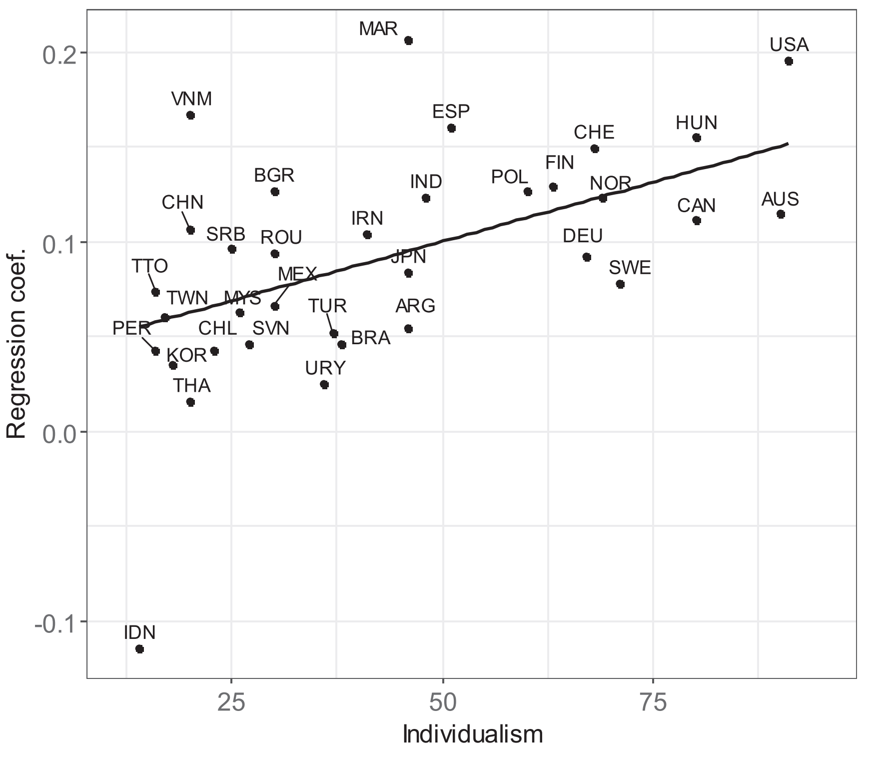

FIGURE 1 Association between individualism and biospheric values regression slopes.
Note: See Table 1 for country codes; line was estimated using robust regression (see Section 2.3.)

3.3 | Robustness checks and replication studies

I tested the robustness of the findings in several ways. First, I reran the models with a logit first step. The dependent variable used in this research is ordinal in nature. Some researchers argue that linear models are useful even if a dependent variable is not continuous and that linear models produce meaningful results that are equivalent to the results obtained from models that are designed to handle categorical variables (Angrist & Pischke, 2009). Indeed, multilevel studies which checked the robustness of their findings by comparing linear and multilevel logit or probit model results tend to find no practically relevant differences between the results based on both types of methods (e.g., Fairbrother et al., 2019; Umit et al., 2019). Nonetheless, some researchers have voiced concern over the usage of linear models with ordinal dependent variables (Liddell & Kruschke, 2018). To

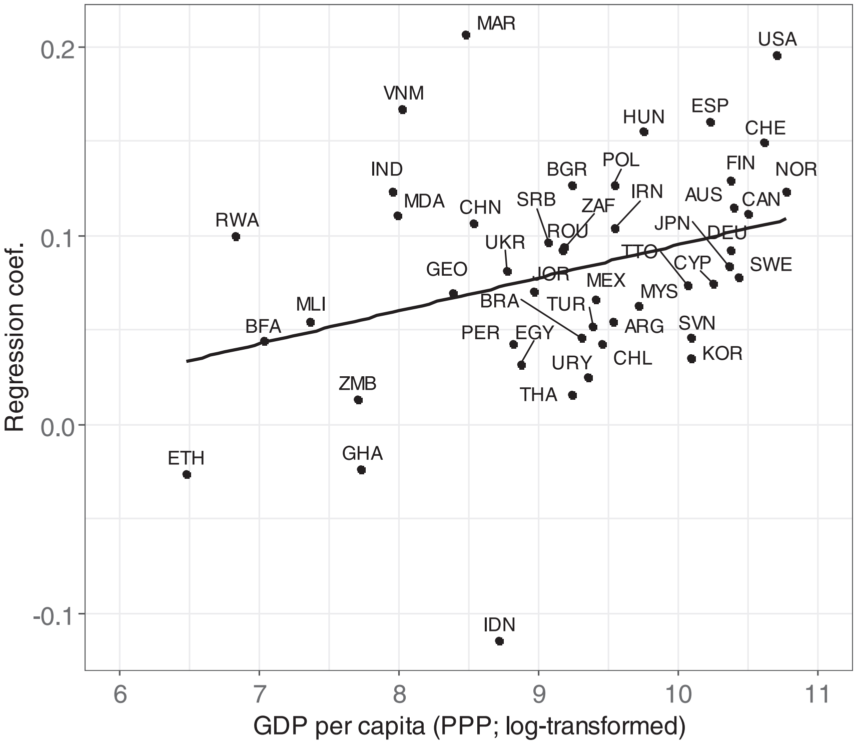

FIGURE 2 Association between GDP per capita (PPP, log-transformed) and biospheric values regression slopes.
Note: Line was estimated using robust regression (see Section 2.3.); Values on the *x*-axis correspond to the following GDP values: 7 = approx. 1,100; 8 = approx. 3,000; 9 = approx. 8,100; 10 = approx. 22,000; 11 = approx. 60,000; See Table 1 for country codes

address this concern, I dichotomized CCRP scores (see Section 2.2.1.) and estimated the country specific BV–CCRP slopes using logistic regression. Apart from the different coding of the dependent variable, the logit first step models were identical in their setup to the linear models that were used in the main analyses (i.e., Equation 2). The second step models (i.e., Equations 3) in the robustness checks were identical to the ones used in the previous analyses.

The results of these models are similar to the results from the linear first step models (see Tables A.Ia and A.Ib in the Supporting Information). That is, individualism and GDP had a positive relationship with the BV–CCRP slopes. In line with H1 and H2, this again indicates that slopes are larger in more individualistic and in wealthier countries. While there was a statistically significant effect of CRI in the main analyses, this effect was no longer statistically significant when a logit first step was used. Country level BV again was not a statistically significant predictor of the size of the BV–CCRP relationship.

Second, I used altruistic values (AV) as focal predictor of CCRP instead of biospheric values. This is to test whether my theoretical reasoning applies to other value orientations that might relate to CCRP in the same way as BV or whether it is limited to BV. The fixed effects models indicate that larger AV scores were associated with stronger CCRP. Compared to the BV–CCRP relationship, the AV–CCRP relationship appears to be somewhat weaker, however (see Table 4). Importantly, the pattern of variation in the AV–CCRP relationship was similar to the one in the BV–CCRP slopes. That is, the results suggest that AV–CCRP slopes are larger in more individualistic and in wealthier societies (see Tables A.IIa and A.IIb in the Supporting Information). These findings lend further support to H1 and H2. No consistently statistically significant relationships emerged for CRI and country level BV. The country level BV effect was statistically significant only in one of the models (i.e., when GDP was controlled for, see Model 5 in Table A.IIb).

Lastly, I conceptually replicated the findings in two additional datasets using different operationalizations of the individual level variables (Crandall & Sherman, 2016), see Sections B and C in the online supplemental materials for more details. The first replication study used the International Social Survey Project—Environmental III dataset (ISSP Research Group, 2019). The results of that study again suggest that BV – CCRP slopes are steeper in more individualistic and in wealthier countries (see Tables B.Va and B.Vb in the the Supporting Information). This lends further support to H1 and H2. As in the other robustness checks, CRI again did not have a statistically significant relationship with the size of the BV–CCRP slopes. Contrary to the previous analyses, country level BV was positively related to the size of the BV–CCRP slopes. That is, slopes were larger in societies that scored higher on BV on average.

The second replication study used the Eurobarometer 92.4 dataset (European Commission, Brussels, 2020). The results are summarized in Tables C.Va and C.Vb in the online supplemental materials. This second replication study again suggests that there is an effect of GDP in line with H2. Surprisingly, no statistically significant effect of individualism was found. The findings from this study do therefore not support H1. There again were no statistically significant effects of the country level control variables, with one exception. The CRI effect was marginally statistically significant when GDP was controlled for (Model 4 in Table C.Vb).

Taken together, the robustness checks indicate that the effects of GDP and individualism are stable across different statistical methods and different operationalizations of the focal constructs and replicate in different datasets. The only exception was the effect of individualism which failed to replicate in one dataset but was supported in two others.

4 | DISCUSSION

Taken together, the multilevel model results suggest that BV are related to individuals' CCRP in the analyzed multinational datasets. The stronger individuals' BV the greater their CCRP. These findings are in line with prior research on the effects of BV on CCRP (e.g., Hornsey et al., 2016; Siegrist & Árvai, 2020; van der Linden, 2017).

Importantly, however, there seems to be variation in the strength of the BV–CCRP association between societies. There even were a few countries in the datasets where no statistically significant relationship between both constructs was found. While this variation between countries may be in part due to chance, the results suggest that there is systematic variation in the size of the BV–CCRP slopes as well. The BV–CCRP relationship was stronger in wealthier and more individualistic societies compared to less wealthy or more collectivistic societies. These findings were robust to methodological choices (i.e., linear or logit models). The results replicated in different datasets which included different sets of countries and which operationalized the focal constructs in slightly different ways. The findings even replicated for altruistic values, which is a value orientation similar to yet theoretically distinct from BV (Steg & de Groot, 2012). This indicates that the developed theory of how the societal context may influence the extent to which values relate to CCRP is not limited to BV but applies to at least one other value orientation (i.e., altruistic values).

There was one country (i.e., Indonesia in the WVS data) where the BV–CCRP relationship was statistically significant and negative. Since this was the only instance of such an effect in all three studied datasets, the most likely explanation for this negative slope is that it emerged due to chance.

Surprisingly, while there was a statistically significant relationship between society level individualism and the size of the BV–CCRP slopes in the WVS and ISSP data, the individualism effect was not statistically significant in the Eurobarometer data. There are different possible explanations for this. First, the absence of an individualism effect in the Eurobarometer data might simply have been due to chance. When a given relationship is tested for statistical significance multiple times in multiple datasets, it is possible that some of the tests do not reject the null hypothesis of no effect, even if the focal relationship exists in reality (Stock & Watson, 2006). Another possible explanation is related to differences in the countries that were included in each dataset. It may be that European countries (i.e., the countries in the Eurobarometer dataset) might be culturally too similar for individualism effects to be relevant at least in the context of the BV–CCRP relationship. Overall, given the WVS and ISSP results, there seems to be an effect of individualism on the strength of the BV–CCRP relationship in culturally diverse sets of countries. The findings of all three datasets combined indicate, however, that the relevance of this effect may depend on the degree to which societies are culturally different from each other.

The society level individualism and GDP effects do not always reach statistical significance when both variables were included in the same model, even when they were statistically significant predictors when tested individually. This is likely because, as is well-established in the literature (Hofstede, 2011), both variables correlate highly and the number of countries in the dataset is somewhat small (e.g., individualism scores and GDP are available for only 33 countries in the WVS dataset). Because of this, it may not be possible to reliably distinguish effects of both variables statistically (see e.g., Tam & Chan, 2018 for a similar argument). Consistent with such an explanation, there is no stable pattern of which predictor was statistically significant when both predictors were tested in the same model. For example, in Model 1 in Table 6B, GDP is no longer statistically significant when individualism was also included. However, in Model 1 in Table A.IIb in the Supporting Information none of the two variables was statistically significant, while in Model 1 in Table B.Vb both variables remained statistically significant when both effects were tested in the same model.

Lastly, effects of country level control variables (i.e., CRI and society level BV) were sometimes statistically significant as well. However, these effects did not replicate consistently and need to be interpreted with caution. A potential explanation for these inconsistent effects may be that effects were statistically significant by chance on a few occasions (Stock & Watson, 2006). In line with this explanation, even when a CRI effect was found in a dataset (e.g., in the WVS data), it did not consistently replicate in the same dataset. A possible explanation for why there was a statistically significant society level BV effect in the ISSP dataset but not in the other datasets may be related to the question wording. BV was measured in absolute terms (i.e., how important environmental protection is) in the WVS and Eurobarometer datasets. In the ISSP dataset, it was measured in relative terms (i.e., are there more important things in life than environmental protection?). It could be that even high BV individuals may focus their attention on issues other than climate change risk if other issues are prominent in the public discourse. This may affect the strength of the BV–CCRP relationship in a society. Only the BV measure in the ISSP captured this (i.e., how important BV is compared to other issues in society). Importantly, however, the individualism and GDP effects appear to be stable across these differences in the measurement of BV and even when society level BV effects were statistically significant.

4.1 | Theoretical contribution

The present research adds to our understanding of the BV–CCRP relationship by studying between-country variation in its strength. In particular, the results suggest that theorizing on self-expression (Eom et al., 2016; Tam & Chan, 2017) and socioeconomic constraints (Chan, 2019; Chan et al., 2019) can be applied to value-based processes related to individuals' CCRP. In doing so, it sheds light on how individual level and contextual factors interact in forming individuals' CCRP. So far, it was not clear whether BV relate to CCRP systematically differently in different countries and no research was available that investigated how these differences can be explained.

The effects sizes found in different countries further illustrate the contribution of this research to our understanding of the BV–CCRP relationship. That is, the median correlations in two of the three datasets (i.e., $r = 0.129$ in the WVS and 0.162 in the ISSP) were close to what extant research would define as small effect sizes (Hornsey et al., 2016). One might therefore conclude that BV is only a weak predictor of CCRP. This conclusion may be too simplistic however. The present research suggests that there is systematic variation in effect sizes. Accordingly, in some societies (e.g., in wealthier and more individualistic leaning countries), BV may be an important predictor of CCRP that deserves attention, while in other countries, BV effects on CCRP may be less relevant.

Lastly, research suggests that CCRP has been increasing over time (Ballew et al., 2019; Duijndam & van Beukering, 2021). One implication of this may be that results based on older datasets, such as the WVS data, could overestimate the BV effect and/or variation in this effect between countries. It is possible that predominantly high BV individuals experienced higher levels of CCRP in the past. In the present day, on the other hand, broader groups of individuals may perceive a high risk posed by climate change, not just high BV individuals. The presented results do not support such a conclusion, however. The median BV–CCRP correlation was somewhat larger in more recent datasets (i.e., $r = 0.129$, 0.162, and 0.426 in the WVS, ISSP, and Eurobarometer datasets respectively). Even though the datasets are not directly comparable because they sampled different countries and used slightly different measures of the focal constructs, this may still indicate that BV remain a relevant predictor of CCRP. Moreover, the fact that GDP predicted the size of BV–CCRP slopes in all three datasets indicates that the nature of the between-country variation in the effect sizes is comparable in older and more recent datasets. This suggests that BV–CCRP related findings based on older datasets are still informative in the present day and that future efforts to gain a better understanding of the BV–CCRP relationship seem important and justified.

4.2 | Implications for public policy

In addition to the theoretical implications, the presented findings have implications for public policymakers as well. It has been argued in the extant literature that increasing the public's awareness of climate change related consequences and the risk they pose may be instrumental for tackling the climate crisis (Fleming et al., 2021; Visschers, 2018). In line with previous research (van der Linden, 2017), the present research suggests that an individual's BV predict how they will perceive climate change related risk. A tempting conclusion for public policymakers may therefore be to use value congruent appeals to increase sensitivity to climate change related risks (Bouman & Steg, 2022; Thaker et al., 2020). The presented findings suggest that this may not be equally promising in all countries. Rather, such strategies may be more effective in wealthier nations or nations characterized by a stronger individualism orientation, where the BV–CCRP relationship tends to be stronger. In less wealthy countries or countries with a stronger collectivistic orientation, BV congruent appeals may be less effective as far as influencing CCRP is concerned. In the latter type of countries, policymakers may have more success focusing on other strategies instead. For example, it has been suggested that social norms may be more important than individual value orientations in collectivistic leaning societies or in contexts where economic resources are scarce (Chan, 2019; Eom et al., 2018; Eom et al., 2016). Similarly, measures that target the perception of how others feel about environmental issues (Bouman, Steg et al., 2020; Chiu et al., 2010) may be more effective in less wealthy or collectivistic leaning societies. Unfortunately, it was not possible to test these propositions directly with the available data. Future research could compare different BV congruent strategies with interventions that target perceived social norms or perceived environmental concern of ingroups. Such research would shed light on which strategies are most effective at influencing individuals' perception of climate change risk in different societies.

4.3 | Limitations

The current research adds to our understanding of CCRP. In particular, it generated novel insights into how BV relate to individuals' CCRP across different countries. However, the typical limitations of multinational comparative research apply to this research as well (e.g., Chan et al., 2019; Fairbrother et al., 2019; Martin, 2021). First, the research is limited by the cross-sectional nature of its data. It is not possible to test whether BV actually cause CCRP. Since value orientations are stable over time (Schwartz, 2012), it may be difficult to investigate causality with experimental methods. Future research could, however, use longitudinal designs to study causality in the BV–CCRP relationship.

Second, the focal constructs in this research (i.e., BV and CCRP) were measured using single-item scales. While some researchers are concerned about the use of single-item measures (e.g., Diamantopoulos et al., 2012), extant research suggests that single-item measures perform well when one wishes to measure concrete constructs (Bergkvist, 2015; Bergkvist & Rossiter, 2007). Accordingly, single-item measures have been used successfully for a wide range of psychological constructs in cross-country research (e.g., Gebauer et al., 2017). In my view, BV and CCRP are concrete constructs that can be captured well with single-item measures as defined by Bergkvist (2015). CCRP is centered around a single concept (i.e., risk attached to climate change) with a simple and clear evaluation (i.e., how severe). In line with this reasoning, single items were used to measure CCRP in extant literature (e.g., Arıkan & Günay, 2021). However, future research could replicate the presented findings using multi-item scales to empirically rule out any potential concerns related to the use of single-item measures.

Lastly, it is not clear whether participants in all countries have interpreted the questions in the same way (Davidov et al., 2014). Unfortunately, it is not possible to empirically test whether this was the case with the available data. Extant research suggests, however, that individuals tend to interpret measures of environmental constructs similarly across different countries (e.g., Marquart-Pyatt et al., 2019; Mayerl, 2017). This suggests that self-reported measures of environmental constructs can be used in international comparative research.

4.4 | Conclusions

This research studies how BV relate to individuals' CCRP. It adds to our understanding of how this relationship manifests itself in different countries and how differences between countries can be explained. In this way, the findings help to build a more nuanced theory of how CCRPs are formed. The presented results also have implications for policymakers and NGOs who wish to increase individuals' engagement with climate change and its consequences in different populations. However, I belief that much more is to be learned about the BV–CCRP relationship and about how CCRP are formed in general. A better understanding of this is needed urgently to help us motivate individuals around the world to join the fight against the climate crisis. Accordingly, more research into how CCRP are formed is encouraged.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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