Towards a Typology of Risk Preference: Four Risk Profiles Describe Two Thirds of Individuals in a Large Sample of the U.S. Population

Renato Frey
University of Basel & Princeton University

Shannon M. Duncan
Columbia University & University of Pennsylvania

Elke U. Weber
Princeton University

Abstract

A longstanding goal in the behavioral sciences has been to model people's risk preferences. Previous approaches tended to measure risk preference *either* as a general *or* domain-specific construct, and typically assumed that it is necessary to describe different individuals separately on (possibly) multiple dimensions of risk preference. Here, we pursue a different approach and ask: Do different types of individuals with similar configurations of general and domain-specific dimensions of risk preference exist, and thus, can a substantial proportion of people be described with a small set of basic risk profiles? To answer this question we modeled data of a large and diverse sample of the U.S. population (N = 3,123) in a comprehensive and novel way. Our contribution is twofold: first, using data of the Domain-Specific Risk-Taking Scale (DOSPERT) we establish a multidimensional trait space of risk preference including general *and* domain-specific components. Second, model-based cluster analyses in this space indicated that 66% of participants in our sample can be described with four basic risk profiles, which are systematically related to socio-demographic indicators. Our typological approach has implications for current theories of risk preference as well as potential policy implications.

Keywords: risk preference | psychometric modeling | DOSPERT | Bayesian latent profile analyses

Risk preference is a key construct in the behavioral sciences (Bernoulli, 1738; Kahneman & Tversky, 1979), and for both scientific and applied reasons there has been great interest in gauging interindividual differences therein (Appelt, Milch, Handgraaf, & Weber, 2011; Frey, Pedroni, Mata, Rieskamp, & Hertwig, 2017; Frey, Richter, Schupp, Hertwig,

& Mata, in press). Yet, despite decades of research on the psychometric structure of risk preference and its measurement, two fundamental theoretical issues remain largely unaddressed.

The first issue concerns the *psychometric structure* of risk preference, with an ongoing debate whether this construct should be modeled as a broad and unidimensional trait, potentially explaining variance in risk taking across diverse behaviors and situations of life (Weber, 1999; Zhang, Highhouse, & Nye, 2018), or rather as a multidimensional construct, implying that risk taking may vary substantially across different domains (e.g., finance, health; Blais & Weber, 2006; Weber, Blais, & Betz, 2002). Recent psychometric investigations have suggested that these two views may not be mutually exclusive: risk preference appears to be best modeled by simultaneously accounting for general *and* domain-specific dimensions (Frey et al., 2017; Highhouse, Nye, Zhang, & Rada, 2016)—much like the general factor of intelligence ("g") and its various *facets* (Deary, 2012). These divergent theoretical perspectives have only rarely been compared rigorously and using state-of-the-art data-analytic methods (e.g., cross-validation in separate hold-out samples). And yet, a solid understanding of the *trait space* of risk preference is naturally the prerequisite for the successful modeling of interindividual differences therein.

The second issue concerns the origin and conceptualization of interindividual differences *within* multi-dimensional trait spaces (e.g., Big-Five personality dimensions; different facets of intelligence; domain-specific risk preferences; Costa & MacCrae, 1992; Deary, 2012; Weber et al., 2002). Specifically, the view that diverse trait dimensions capture unique dispositions—that is, that they are orthogonal from each other—implies that different persons could have, in principle, highly unique configurations of such dimensions. According to this view, it is thus necessary to describe each person with an idiosyncratic profile. But do indeed all profiles emerge that are theoretically possible in a trait space? According to an alternative view, certain groups of people may share similar configurations of traits; such prototypical profiles could have evolved (phylogenetically) or may develop (ontogenetically) because groups of people were (and still are) exposed to shared environments—that is, adaption processes may give rise to regularities within *types of persons*. When not taking into account potential types, an interdependence of traits may be "hidden" at the population level, and traits will appear uncorrelated (cf. Simpson's paradox; Simpson, 1951).

Accordingly, in personality research it has been questioned whether people are as "exquisitely different as to defy a useful categorization" (Block & Haan, 1971; Robins, John, Caspi, Moffitt, & Stouthamer-Loeber, 1996), challenging the predominant *variable-centered* approach (Costa & MacCrae, 1992; Goldberg, 1990). Recent empirical evidence using sophisticated modeling methods supports a *person-centered view*, suggesting the existence of a relatively small number of types of people who share similar configurations of personality traits (Asendorpf & van Aken, 1999; Gerlach, Farb, Revelle, & Amaral, 2018). To date, typological approaches to modeling individual differences in risk preference have not yet been considered. As such, it remains an open question whether a small set of prototypical

Renato Frey, Center for Cognitive and Decision Sciences, Department of Psychology, University of Basel.
Corresponding author: Renato Frey, Department of Psychology, University of Basel, Missionsstrasse 60-62, 4055 Basel, Switzerland. E-mail: renato.frey@unibas.ch

risk profiles may account well for a large portion of individuals in the population.

In this article, we address these two issues by modeling self-reported risk preferences of 3,123 adults sampled from the U.S. general population, who completed one of the most commonly implemented questionnaires of risk preference; the Domain-Specific Risk-Taking Scale (DOSPERT; Blais & Weber, 2006; Weber et al., 2002). As its name suggest, this questionnaire was developed to assess people's risk preferences in (five) specific domains of life, which does not preclude the possibility that it also captures a general dimension (Highhouse et al., 2016). To clarify the issue of how to best model risk preference, we thus revisit the psychometric structure as captured by the DOSPERT scale with the largest dataset that has been collected to date. Using separate exploratory and confirmatory subsamples (i.e., cross-validation), we address the first of the two reviewed issues and establish a robust trait space of risk preference. In this space, we then conduct latent profile analyses (Oberski, 2016) using model-based cluster algorithms (Gerlach et al., 2018; Pedregosa et al., 2011), to examine whether individual differences cover all niches of this multi-dimensional space of risk preference—or, alternatively, whether groups of people (i.e., types) with similar configurations of risk preference can be identified.

Methods

Participants and Procedure.

Three thousand and seven hundred participants aged 18 and over were recruited via Amazon's Mechanical Turk (mTurk). The inclusion criteria were as follows: at least 50 Human Intelligence Tasks (HITs) completed with a 95% approval rate, and location in the US. All participants completed a study presented with Qualtrics, starting with the most recent version of the DOSPERT scale (see SOM-R for a detailed description, including all items used; Blais & Weber, 2006), followed by one to four other brief questionnaires unrelated to risk preference and the present analyses, and finally, seven one-item questions asking for a self-assessment of general and domain-specific risk preference (for a subset of participants, see SOM-R; Dohmen et al., 2011; Falk, Becker, Dohmen, Huffman, & Sunde, 2016). The study ended with a battery of demographic questions. Overall, participants took approximately 15 minutes to complete the study and were paid USD 1.70 on average, with a range from USD 1.25 to USD 4. Only participants who completed all parts of the study were included in our analyses, making the total sample 3,123 individuals (50.2% female, mean age: 35.6 years, age range: 18—-77 years). Table S1 provides the full sample characteristics. The study was approved by the institutional review board of Columbia University.

Open Research Practices and Multi-Stage Analysis Plan.

We followed a pre-registered multi-stage analysis plan to reduce our degrees of freedom in the exploratory analyses and to thus increase the likelihood of obtaining robust results. At the onset of the project, we detailed the specification of the theoretical rationale and a conceptual analysis plan in a stage-I registration (available from https://osf.io/pjt57).

We then split the full sample into an exploratory subsample A (1,500 randomly selected participants) and a confirmatory subsample B (the remaining 1,623 participants). For the exploratory analyses informing the data-driven models 3, 5, and 6 (see Results

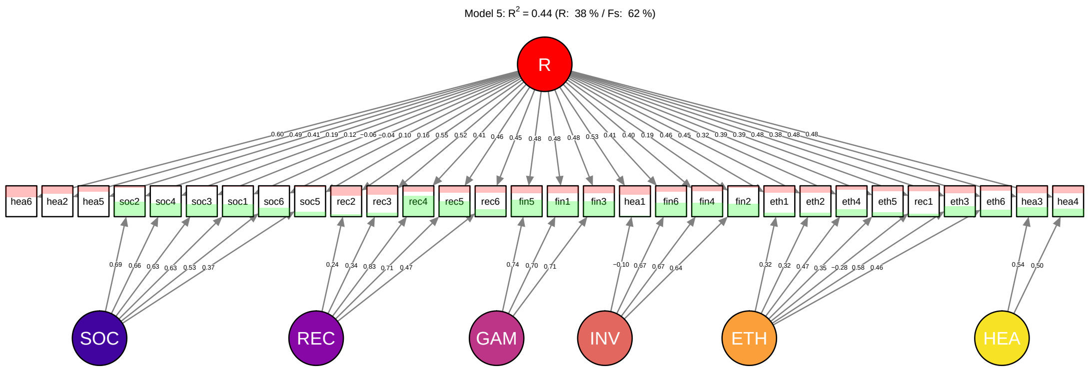


Fig. 1. Model 5 implementing a data-driven bifactor structure. All factors were implemented to be orthogonal. Loadings and factor intercorrelations were obtained from confirmatory factor analysis using the full sample. The red shaded areas depict the proportion of variance accounted for by the general factor, and the green shaded areas the proportion of variance accounted for by the domain-specific factors.

below), only the data of subsample A were made available to the main data analyst (R.F.). This exploratory dataset had blinded variable labels, with blinding conducted by S.M.D. The detailed procedure and intermediate results were reported in a stage-II registration (available from https://osf.io/pjt57).

The final analyses used the dataset with the unblinded variable labels. To assess whether any of the data-driven models overfitted the data, we compared the respective fits in the exploratory subsample A with those in the confirmatory subsample B. As Figure S1 shows, there was no indication of systematic declines in the model fits in subsample B, suggesting that the analyses were robust, due to the large exploratory sample. We therefore report the model fits across the full sample in Table S3 (see SOM-R for a discussion of the different fit criteria).

After having selected the best-performing model (see Results below) based on confirmatory factor analyses (CFA) across the full sample, we proceeded with the latent profile analyses (see SOM-R) to identify groups of people with similar profiles in the established multi-dimensional space of risk preference. We also repeated these analyses in the two subsamples to test the robustness of the identified clusters.

All details concerning the stage-I and stage-II registrations as well as the full dataset and the analyses scripts are available from https://osf.io/pjt57.

Results

Modeling the Psychometric Structure of Risk Preference.

To revisit the psychometric structure of risk preference and to establish a trait space thereof, we tested six models using CFA (for an overview, see Tab. S4). These models cover the full theoretical spectrum, at one extreme assuming risk preference to be a unitary trait (thus implying that a single factor will be sufficient to capture this construct), and at the other extreme assuming that risk preference is exclusively domain-specific (thus implying that multiple factors are required to capture this construct). To bridge the gap between these two extremes, we also implemented several different bifactor models (Frey et al., 2017; Highhouse et al., 2016; Holzinger & Swineford, 1937; Jennrich & Bentler, 2011). Bifactor models can account for general and domain-specific variance simultaneously and thus permit quantifying *to what extent* risk preference is general or specific. Moreover, as the general factor in a bifactor model accounts for the common variance across measures, it renders the specific factors more distinct. As such, bifactor models in principle promise to cover a wider range of the trait space of risk preference.

Model 1 (M1). The first model comprised only a general factor, implying that there exists no domain-specificity in risk preference (Fig. S2). This model accounted for 19% of the total variance and did not achieve a solid model fit according to all fit criteria (e.g., RMSEA = .12, CFI = .43; see Tab. S3).

Model 2 (M2). M2 implemented the factor structure originally proposed for the DOSPERT scale, namely, five specific factors capturing ethical, financial, health/safety, social, and recreational risk-taking propensity (Fig. S3). Each factor was composed of six items, and the factors were permitted to be correlated with each other. M2 accounted for 38% of the total variance and approached but did not quite achieve a satisfactory model fit (e.g., RMSEA = .07, CFI = .80; see Tab. S3). The five factors were correlated relatively strongly with each other, with a mean factor-intercorrelation of .32 and a range from .01 to .69.

Model 3 (M3). M3 retained the assumption that risk preference is best modeled with a series of domain-specific factors, but the optimal number of factors and the factor structure was determined in a data-driven way (i.e., during the exploratory stage-II analyses using only subsample A). M3 had six factors, which were composed of between two and six items. We only included items that loaded at least .2 on any of the factors in the EFA, which resulted in retaining 26 of the 30 items. This model accounted for 41% of the total variance (i.e., slightly more than M2) and achieved a satisfactory fit (e.g., RMSEA = .05, CFI = .90; see Tab. S3). As in M2, the factors were correlated relatively strongly with each other, with a mean factor-intercorrelation of .34, and a range from .04 to .68.

Model 4 (M4). To test the extent to which the intercorrelations between the domain-specific factors (as observed in M2 and M3) can be modeled with a general factor (R) while simultaneously accounting for domain-specific variance, we next tested a bifactor model. Specifically, M4 had the same factor structure as originally proposed for the DOSPERT scale (i.e., the structure of M2) yet with an additional general factor modeling all items, and forcing all factors to be orthogonal (as is required in bifactor models; Fig. S5). M4 accounted for 43% of the total variance (i.e., again slightly more than the previous models) and approached a satisfactory fit (e.g., RMSEA = .06, CFI = .86; see Tab. S3). In M4, the general factor accounted for 35% of the explained variance whereas the five specific factors cumulatively accounted for the remaining 65% of the explained variance.

Model 5 (M5). We next implemented a model equivalent to M4, yet with a factor structure determined in a data-driven way (i.e., during the exploratory stage-II analyses using only subsample A). M5 had six specific factors (as for M3 described above) and one general factor (Fig. 1). M5 accounted for 44% of the total variance and achieved a satisfactory fit (e.g., RMSEA = .05, CFI = .89; see Tab. S3). In M5, the general factor accounted for 38% of the explained variance whereas the six specific factors cumulatively accounted for the remaining 62% of the explained variance.

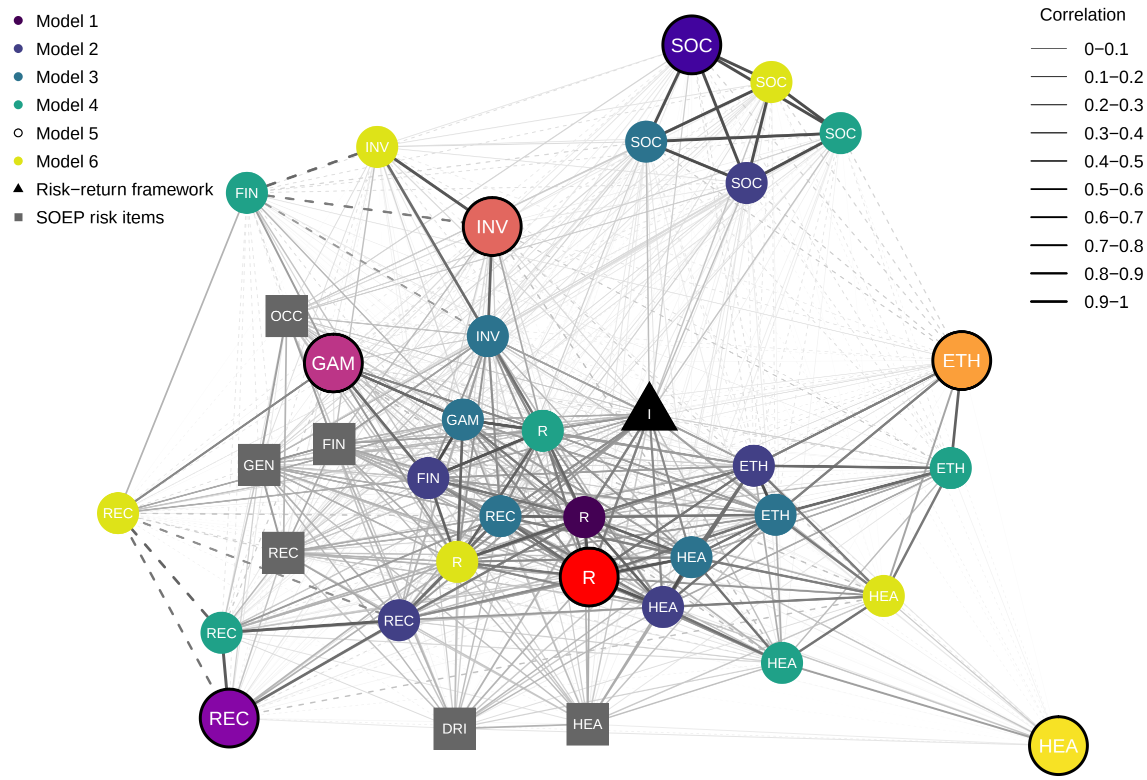


Fig. 2. Network plot of the correlations between all general and domain-specific factors of all models, including the intercepts from the risk–return framework (see SOM-R), and the general and domain-specific risk items of the socio-economic panel (SOEP; see SOM-R). The factors of the selected model (M5) are highlighted with black circles. ETH = ethical, FIN = financial, HEA = health, SOC = social, REC = recreational, GEN = general, OCC = occupational, DRI = driving. I = intercept of the risk–return framework.

Model 6 (M6). Finally, we also implemented a reduced bifactor model (Fig. S6) because the preceding EFAs indicated that a model with only four specific factors (instead of six, as in M5 described above) may account for about the same amount of variance. In the confirmatory analyses using the full sample, M6 accounted for 41% of the total variance and achieved an approximately satisfactory fit (e.g., RMSEA = .06, CFI = .87; see Tab. S3). The general factor accounted for 41% of the explained variance whereas the four specific factors cumulatively accounted for the remaining 59% of the explained variance.

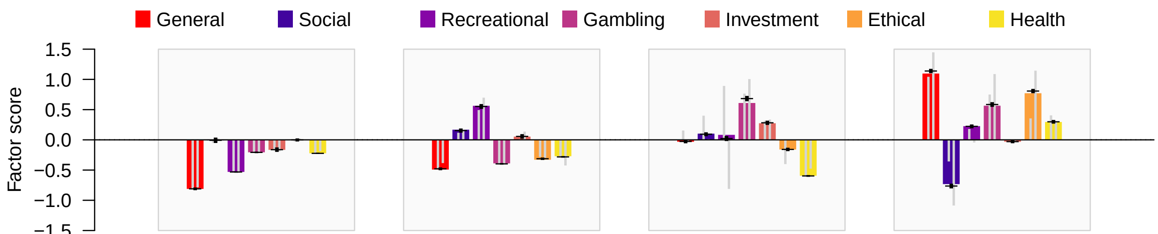
Model comparison and selection. To gauge how strongly the six different models captured the same or similar constructs, we computed and compared the correlations between all domain-specific and general latent variables (i.e., factors) from all models. This combined trait space is displayed in Figure 2. The center of this network plot shows a convergence of several factors, the general factor of M1 as well as the three general factors of the bifactor models (M4, M5, and M6). Moreover, several of the supposedly domain-specific factors clustered close to the center of this "positive manifold", such as the factors ETH and HEA of M2, or ETH, HEA, and REC of M3. However, there were also clearly domain-specific clusters, such as the SOC factors of all models (except for M1, which did not implement any domain-specific factors). As a general pattern, the domain-specific factors of the bifactor models (M4, M5, and M6) tended to be the most dispersed across the entire network, reflecting the fact that they are specified to be orthogonal from each other as well as from the general factors.

We proceeded with selecting a model for the further analyses, striving for a balance between reasonable fit criteria and conceptual interpretability of the model. We dismissed M1 given its bad fit and low proportion of explained variance. That is, we could clearly reject the assumption that risk preference is uni-dimensional. For the remaining five models, the differences in model fit and proportion of explained variance were smaller (Tab. S3 and Fig. S1). Specifically, among the two models *without* a general factor (i.e., M2 and M3) there existed small differences in terms of model fit and proportion of explained variance, yet the resulting factor structures were very similar. That is, in the data-driven M3 the factor structure originally proposed for the DOSPERT scale was recovered almost perfectly, with only two differences: First, the factor capturing financial risk-taking propensity was split into a "gambling" (GAM) and an "investment" (INV) factor—an observation that has already been made previously (Weber et al., 2002). Second, four of the six items supposedly capturing recreational risk-taking propensity were removed in M3, as they did not load with at least .2 on any of the factors in the EFA. In sum, M3 included fewer items, which potentially improved some of the fit indices, but overall there were only minor differences in terms of factor structure.

Among the three models *with* a general factor, the differences in model fit were also relatively small. However, a comparison of M4 (Fig. S5) and M5 (Fig. 1) indicated that the general factor in the latter was broader, that is, capturing variance across more measures. Moreover, the fit indices and the proportion of explained variance slightly favored M5. Conversely, the reduced bifactor model with fewer items (as implemented in M6) achieved a similar fit as compared to M5, but explained slightly less variance. Finally, a direct comparison between M5 and M2—both including all 30 DOSPERT items and thus being nested models—favored the bifactor model M5 in terms of most fit indices (e.g., smaller BIC and AIC), and also from a conceptual perspective. Due to their orthogonality, the specific factors in M5 may be cleaner indicators of people's domain-specific risk preferences and thus easier to interpret, as opposed to the factors of M2 that were correlated relatively strongly with each other (see Fig. S7 for a direct comparison of all within- and across-model correlations of these factors). The distributions of the seven factor scores extracted from the selected model (M5) are depicted in Figure S8.

Do Types of People With Distinct Risk Profiles Exist?

Using the multi-dimensional space of risk preference established above, we next examined whether a finite number of different types of people with similar configurations of risk preference exist, and whether such potential types are systematically associated with specific socio-demographic variables. To this end we conducted a latent profile analysis based on the continuous factor scores extracted from M5 (i.e., the bifactor model specifying a slightly revised factor structure for the DOSPERT scale plus one general factor). The implementation of this analysis was done with a Gaussian-mixture model and Bayesian estimation methods, using the *mixture* package from the Python-library *scikit-learn* (Pedregosa



	Profile I (C1)	Profile II (C3)	Profile III (C5)	Profile IV (C2)
N	654	550	459	405
Female	71%	59%	40%	26%
Mean Age	39.1y	36.1y	34.4y	30.3y
Age (SD)	1	0.84*	0.77*	0.41*
Gender (male)	1	1.51*	3.1*	5.87*
With partner	1	1.15	1.14	1.12
Children	1	0.96	0.87*	1.03
Education	1	1.02	1.06	1.13
Income	1	0.99	1.08*	1.01
Democrat	1	0.83	0.97	1.08
Republican	1	0.67*	0.8	1.54*

Fig. 3. The four identified risk profiles, ordered according to their cumulative degree of risk preference from left to right. Colored bars represent the mean factor score at the cluster centers, and the black indicators the empirical means of factor scores of all participants assigned to the respective clusters (including two standard errors of the mean as error bars). Gray bars depict the cluster centers as extracted independently and separately for the two subsamples. The lower panel depicts the odds-ratios for various predictors, indicating the relative probability of being assigned to a specific profile over being assigned to the reference profile I (i.e., with N=654 the largest cluster). The coefficients depict the change of a one-unit increase in the predictor variable (e.g., one standard deviation of age) or the change from the reference level to the effect level in the case of categorical variables (e.g., from "independent" to either "democrat" or "republication"). Significant odds-ratios are marked with an asterisk.

et al., 2011).

We first screened solutions ranging from one to ten clusters, and a comparison of the resulting BICs indicated that the solution with seven clusters achieved the best fit (Fig. S9). We next subjected these seven clusters to an enrichment analysis using a permutation test, in which we repeatedly shuffled bootstrapped datasets to estimate the density under the null-model (i.e., implementing the assumption that there exist no clusters in the data; see Fig. S10). Only four of the seven clusters turned out to be robust. 66% of participants were best described by one of these four clusters, and these participants were classified to one of these four clusters with very high probabilities (i.e., on average with p = .98, .93, 87, and .92 for the four clusters, respectively). Conversely, the average probability that these participants were assigned to *any* of the other clusters was only .06 (see Fig. S11), implying a very clear overall cluster solution.

Figure 3 depicts the risk profiles (i.e., profiles I–IV) of the four identified clusters. Specifically, the upper panel shows the factor scores (for each dimension extracted from M5) at the centers of the four clusters (as well as the mean empirical factor scores of all participants assigned to the clusters, including two standard errors of the mean as error bars; depicted in black). Profile I represents the largest cluster (containing 21% of our sample), whose members can be described as the "cautious"—that is, people who are relatively more risk-averse in all domains except the social and ethical domains (where their risk preference is at average level). Profile II (18% of our sample) represents people who are relatively more risk-averse in general, but more risk-seeking in the recreational domain (i.e., "recreational adventurers"). Profile III (15% of our sample) represents "financial gamblers", who are relatively more risk-seeking regarding financial investments and gambling, but more risk-averse regarding health, and about average otherwise. Finally, profile IV (13% of our sample) represents the "daredevils", who are more risk-seeking than average in most domains, except for investment where their risk preference is at an average level, and in the social domain, where they are relatively more risk-averse. Extracting the clusters separately using the two subsamples A and begin resulted in highly similar profiles (depicted as gray bars), further corroborating the robustness of this analysis.

A multinomial log-linear model provided evidence that several socio-demographic variables were systematically associated with these four risk profiles (see lower panel of Fig. 3; values represent odds-ratios relative to the reference profile I). For example, an increase of one standard deviation in age was associated with monotonically decreasing odds-ratios of .84, .77, and .41 of being assigned to the profiles II, III, or IV, relative to profile I. In other words, older people are about half as likely to belong to the "daredevil" type than to the "cautious" type. Gender was also systematically associated with particular profiles: for instance, men were 5.87 times more likely to be "daredevils" than "cautious". Finally, people with higher income were relatively more likely to be "financial gamblers", whereas people with (more) children were relatively less likely in this group.

Discussion

This article makes two key contributions with direct implications for current theories of risk preference and the assessment of people's risk preferences in scientific and applied settings. First, in line with recent research (Frey et al., 2017; Highhouse et al., 2016) our results decisively suggest that risk preference comprises both a general as well as multiple domain-specific dimensions. The existence of a general component has always been theoretically attractive and practically desirable, as both researchers and the general public have strong intuitions about being able to evaluate different individuals on their general level of risk-aversion or risk-seeking (Weber & Milliman, 1997). Second, we identified four types of persons with similar configurations of risk preference. Specifically, four basic risk profiles accounted for two thirds of the participants in our large and diverse sample of the U.S. population. A typological approach to measuring risk preference may thus be promising in future applications—for instance, the possibility of targeting specific types (e.g., based on sociodemographic proxy variables) may constitute a promising alternative for addressing large-scale problems at the population level, where targeting individuals is rarely feasible. Moreover, the newly provided evidence for a typology of risk preference may inform future work on the origins and the development of traits, suggesting that certain traits may evolve or develop according to systematic patterns in subgroups of the population.

Risk Preference: General, Domain-Specific, or Both?

In the past, the view of preferences as stable and enduring (Stigler & Becker, 1977) has implied that people's appetite for risk may originate from a general and uni-dimensional trait. Conversely, from research assuming that preferences are largely "constructed" (Lichtenstein & Slovic, 2006) it followed that people's risk preferences may vary substantially across different domains of life (e.g., health, finance, etc.), because people perceive consistently different risks and benefits therein (Weber & Milliman, 1997). Instruments such as the DOSPERT scale (Weber et al., 2002), or a brief battery of questions capturing domain-specific risk preferences (Falk et al., 2016), have repeatedly provided evidence in this regard. Yet, when controlling for such differences in perceived risks and benefits that may emerge across various life domains, people's "perceived risk-attitudes" also reflected a relatively general dimension of risk preference (Weber & Milliman, 1997).

More recently, psychometric modeling analyses implementing bifactor models (Frey et al., 2017; Highhouse et al., 2016) have provided evidence that risk preference comprises general *and* domain-specific dimensions—an observation that has also been made for other major psychological constructs (e.g., intelligence; Deary, 2012). Our observations are in line with these results, and thus challenge theories of risk preference that do not predict any domain-specific variation (e.g., traditional economic theories of risk preference); clearly, future measurement efforts will profit from modeling both general and specific components of people's risk preferences. As our analyses have illustrated, a simple bifactor model succeeds in doing so, rendering time-consuming and effortful assessments of people's risk perceptions and expected benefits obsolete (as was necessary to employ a risk–return framework to extract people's general "perceived risk-attitudes"; Weber & Milliman, 1997).

Towards a Typology of Risk Preference.

Our latent profile analyses resonate with recent efforts in personality research, which has started to examine the possibility that different individuals may not be as unique as previously thought, in the sense that personality characteristics potentially do not vary from person to person in an entirely unpredictable way. Rather, in line with many lay persons' intuitions, there appears to be a small set of distinct personality types (Asendorpf & van Aken, 1999; Gerlach et al., 2018; Robins et al., 1996).

These approaches have originally used relatively simplistic methods (Asendorpf & van Aken, 1999; Robins et al., 1996) but meanwhile shifted to more sophisticated machine-learning algorithms (Gerlach et al., 2018). Following the latter approach, our analyses yielded similar conclusions for the construct of risk preference: specifically, our model-based cluster analyses suggest that 66% of the participants in our sample could be classified confidently to one of four basic risk profiles (i.e., the "cautious", the "recreational adventurers", the "financial gamblers", and the "daredevils"). These profiles were systematically associated with socio-demographic indicators, such as a person's age or gender.

With no doubt, these profiles and their predictive value for particular economic or social behaviors remain to be further validated in future research. Moreover, as in all instances of unsupervised learning (i.e., when no absolute criterion for a "correct" classification is available), there are certain degrees of freedom. Yet, in our approach we have implemented a robust model-based approach and conducted extensive simulation analyses, in order to identify potential spurious clusters (cf. Gerlach et al., 2018). We are thus confident that the four identified risk profiles are meaningful, in particular given their high "face validity", that is, their clear associations with relevant socio-demographic indicators, and the high probabilities by which classified participants were assigned to one of the profiles, but not to the others (Fig. S11). In sum, these findings constitute an important first step in substantiating our novel theoretical contribution.

Conclusions.

This article suggests a novel typological approach to modeling individual differences in risk preference. To this end we established a trait space of risk preference comprising general and domain-specific dimensions. Although a minority of people appears to have highly idiosyncratic configurations of risk preferences, two thirds of participants could be well described by one of four identified risk profiles. These findings have important implications for current theories of risk preference, and challenge theories that assume that risk preference is either a general *or* domain-specific construct, as well as theories assuming that most people have highly idiosyncratic configurations of risk preferences.

Future measurement approaches may profit from assessing general *and* domain-specific dimensions of risk preference. Moreover, in scientific and applied settings where detailed assessments of people's multi-dimensional risk preferences are not feasible, predicting participants' risk profiles based on socio-demographic indicators may turn out to be a promising alternative.

Author contributions.

R.F. and E.U.W. conceptualized the research. S.M.D. collected and blinded the dataset. R.F. conducted the formal analyses and wrote the paper. E.U.W. and S.M.D. provided critical revisions.

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