Supplement to "Relative Risk Aversion: A Meta-Analysis"*

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December 17, 2024

Abstract

This supplement includes additional summary statistics, results, and discussion of estimation methods and heterogeneity.

Keywords: Euler equation, risk aversion, Epstein-Zin preferences, meta-analysis, publication bias, Bayesian model averaging

JEL Codes: C83, D81, D90

1 Estimation of Relative Risk Aversion and Additional Summary Statistics

As we have noted, there are several ways how to estimate relative risk aversion, and a useful overview is available in Zhang *et al.* (2014). Potential frameworks include human subject experiments and surveys, labor-supply behavior, deductible choices in insurance contracts, auction behavior, option prices, and contestant behavior on game shows. In this paper we focus on the consumption Euler equation, which constitutes by far the most common framework used in the fields of economics and finance.

Underlying the framework is the concept of expected utility (even though, in order to separate risk aversion from intertemporal substitution, the exact form of recursive preferences used

*The main body of the paper with data and code is available at `meta-analysis.cz/risk`. Corresponding author: Zuzana Irsova, `zuzana.irsova@ies-prague.org`.

in most studies in our sample generally does not imply expected utility). The expected utility hypothesis assumes that agents in the economy are risk-averse, meaning that their preferences are concave and exhibit a diminishing marginal return utility. Hence, the degree of risk aversion is related to the curvature of the utility function. Given a form of utility function $u(c)$ where c denotes consumption, the coefficient of relative risk aversion (RRA) is defined as

$$RRA = -\frac{u''(c)}{u'(c)}c. \tag{B1}$$

The degree of relative risk aversion can be increasing, decreasing, or constant. In economics and finance, the largest strand of the literature employs preferences with constant relative risk aversion (CRRA), i.e., isoelastic utility (power utility function), to study agents' behavior within the economy. Measuring the structural parameters associated with household preferences, such as the coefficient of relative risk aversion and the elasticity of intertemporal substitution (EIS), is important since they affect decisions on savings/investing and, consequently, asset prices in the economy. For instance, the degree of risk aversion plays a crucial role in the capital asset pricing model (CAPM) or consumption capital asset pricing model (CCAPM) since it heavily affects the investor's consumption and wealth portfolio, which ultimately alter asset prices.

Within the expected theory framework, a standard isoelastic utility function does not disentangle the attitude towards risk from intertemporal substitution as they are reciprocals of each other. The nonseparability of RRA and EIS ranks among the main critiques of the standard power utility function. The property means that when one of the parameters is large, the other has to be low, which is not necessarily realistic and consistent with empirical findings and commons sense. Hence, other forms of nonexpected utility must be considered to measure the degree of relative risk aversion isolated from the EIS. The most common solutions are recursive preferences of the type developed by Epstein & Zin (1989, 1991) and Weil (1989) (EZW hereinafter). This form of preferences constitutes a generalization of the standard power utility function in which the parameters governing EIS and RRA are separated. The separability of attitudes toward risk and intertemporal substitution makes the EZW recursive utility a suitable choice to estimate the degree of relative risk aversion. The EZW recursive utility function is a constant elasticity of substitution (CES) aggregator over the current and discounted future utility of consumption, taking the following form:

$$U_t = \left[(1-\beta)c_t^{1-\frac{1}{\psi}} + \beta\mu_t\left(U_{t+1}\right)^{1-\frac{1}{\psi}}\right]^{\frac{\psi}{\psi-1}}, \tag{B2}$$

where $0 < \beta < 1$ is the discount factor and $\psi \geq 0$ is the EIS. Households' private consumption in period t is denoted by c_t and the risk-adjusted expectation operator is given by

$$\mu_t\left(U_{t+1}\right) = \left(\mathbb{E}_t U_{t+1}^{1-\gamma}\right)^{\frac{1}{1-\gamma}}. \tag{B3}$$

Employing (B1) with some modifications, it is straightforward to show that $\gamma \geq 0$ is the coefficient of relative risk aversion for EZW preferences. The recursive utility preferences collapse to the familiar standard CRRA utility function if $\gamma = \frac{1}{\psi}$. Additionally, when $\gamma > \frac{1}{\psi}$, the EZW preferences imply that the household prefers an early resolution of uncertainty, and a late resolution of uncertainty if $\gamma < \frac{1}{\psi}$. Assuming a representative agent model with one type of consumption goods, maximizing the intertemporal utility of the household in (B2) subject to an intertemporal budget constraint results in two types of Euler equations:

$$\mathbb{E}_t\left[\left(\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\psi}}\right)^{\eta}(R_{t+1}^M)^{\eta-1}R_{t+1}^i\right] = 1, \tag{B4}$$

and

$$\mathbb{E}_t\left[\left(\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\psi}}\right)^{\eta}(R_{t+1}^M)^{\eta}\right] = 1, \tag{B5}$$

where $\eta = \frac{1-\gamma}{1-\frac{1}{\psi}}$, R_{t+1}^M is the gross return on the optimal portfolio, and R_{t+1}^i is the gross return on asset i between t and $t+1$. To test the separability hypothesis, it is necessary to include the following equation

$$E_t\left[\frac{\left(\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\psi}}R_{t+1}^M\right)^{\eta} - 1}{\eta}\right] = 0. \tag{B6}$$

Moreover, assuming that consumption growth and asset returns are jointly log-normally distributed, (B5) takes the form of an equivalent log-linearized version. In the log-linearized version of the equation, the riskiness of an asset depends on the conditional variance of the

Table B1: Studies included in the meta-analysis

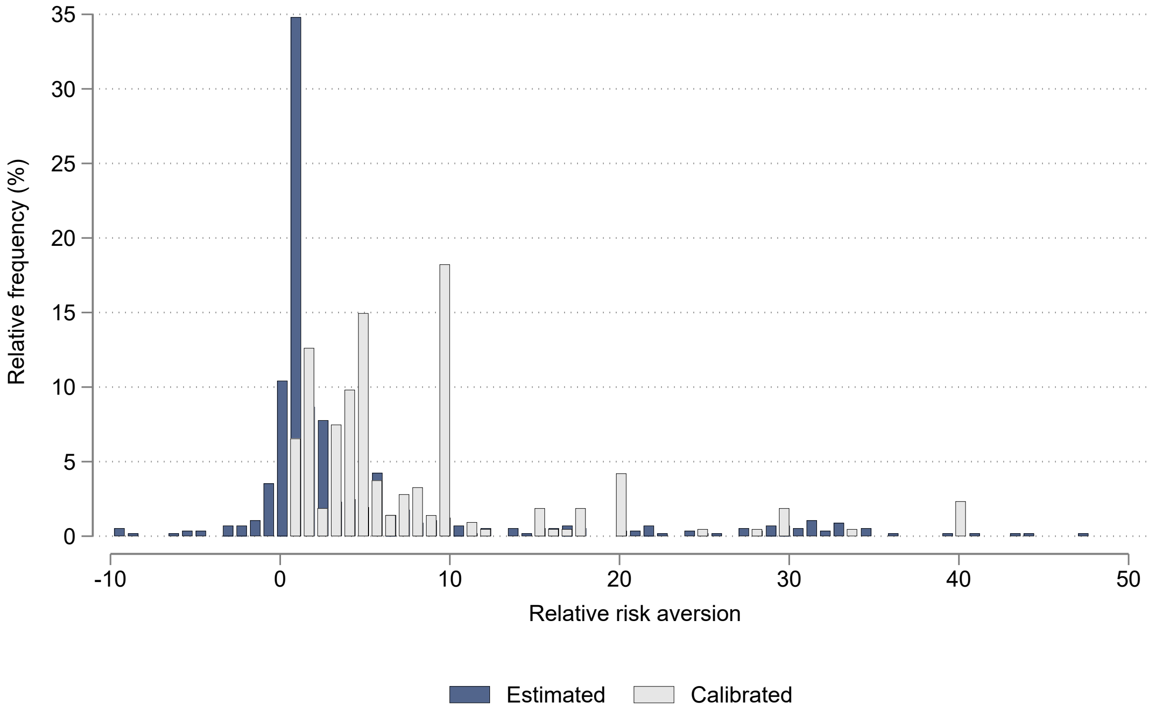
Albuquerque *et al.* (2016)	Dave & Tsang (2014)	Inkmann *et al.* (2011)
Ampudia *et al.* (2018)	Delikouras (2017)	Issler & Piqueira (2000)
Andersen *et al.* (2018)	Delikouras & Korniotis (2021)	Jeong *et al.* (2015)
Andreasen (2012)	Doh (2013)	Jorion & Giovannini (1993)
Andreasen *et al.* (2018)	Pommeret & Epaulard (2001)	Kim & Ryou (2012)
Attanasio & Weber (1989)	Epstein & Zin (1991)	Kim *et al.* (2010)
Augustin & Tédongap (2016)	Epstein & Zin (2001)	Kogan *et al.* (2020)
Bakshi & Naka (1997)	Eraker *et al.* (2016)	Koskievic (1999)
Bansal & Shaliastovich (2013)	Faria *et al.* (2016)	Kuwahara & Ohkusa (1996)
Bansal *et al.* (2008)	Fulop *et al.* (2022)	Kwan *et al.* (2015)
Bansal *et al.* (2007a)	Fulop *et al.* (2021)	Lee (1997)
Bansal *et al.* (2007b)	Garcia & Luger (2012)	Lence (2000)
Bansal *et al.* (2016)	Garcia *et al.* (2003)	Lybbert & McPeak (2012)
Bednarek & Patel (2015)	Garcia *et al.* (2015)	Maio (2018)
Biswas & Mandal (2016)	Ghosh & Roussellet (2020)	Malloy *et al.* (2009)
Bretscher *et al.* (2020)	Gomes & Ribeiro (2015)	Meissner & Pfeiffer (2022)
Briggs *et al.* (2021)	Gomes *et al.* (2009)	Normandin & St-Amour (1998)
Brown & Kim (2014)	Goswami & Tan (2012)	Ruge-Murcia (2017)
Bufman & Leiderman (1990)	Goswami *et al.* (2014)	Samson & Armstrong (2007)
Campbell (1996)	Grammig & Küchlin (2018)	Schwartz & Torous (1999)
Carmichael & Samson (1993)	Grammig & Schrimpf (2009)	Semenov (2003)
Chen *et al.* (2013)	Gu & Huang (2013)	Smith (1999)
Cho & Dokko (1993)	Guo (2006)	Sönksen & Grammig (2021)
Choi *et al.* (2017)	Hamori (1995)	Stock & Wright (2000)
Christensen (2017)	Hardouvelis *et al.* (1996)	Thimme & Völkert (2015)
Coble & Lusk (2010)	Hasseltoft (2012)	Van Binsbergen *et al.* (2012)
Colacito & Croce (2011)	Horvath *et al.* (2021)	Vissing-Jørgensen & Attanasio (2003)
Colacito *et al.* (2018)	Huang *et al.* (2014)	Weber (2000)
Constantinides (2021)	Hugonnier *et al.* (2013)	Xu-Song *et al.* (2006)
Constantinides & Ghosh (2011)	Hyde & Sherif (2005a)	Yogo (2006)
Cooper & Zhu (2016)	Hyde & Sherif (2005b)	

Table B2: Summary statistics of benchmark calibrations

	Observations	Mean	Median	Standard deviation
All studies	200	13.13	5.93	28.62
Economics	115	16.58	5.20	36.61
Finance	85	8.47	6.00	9.14

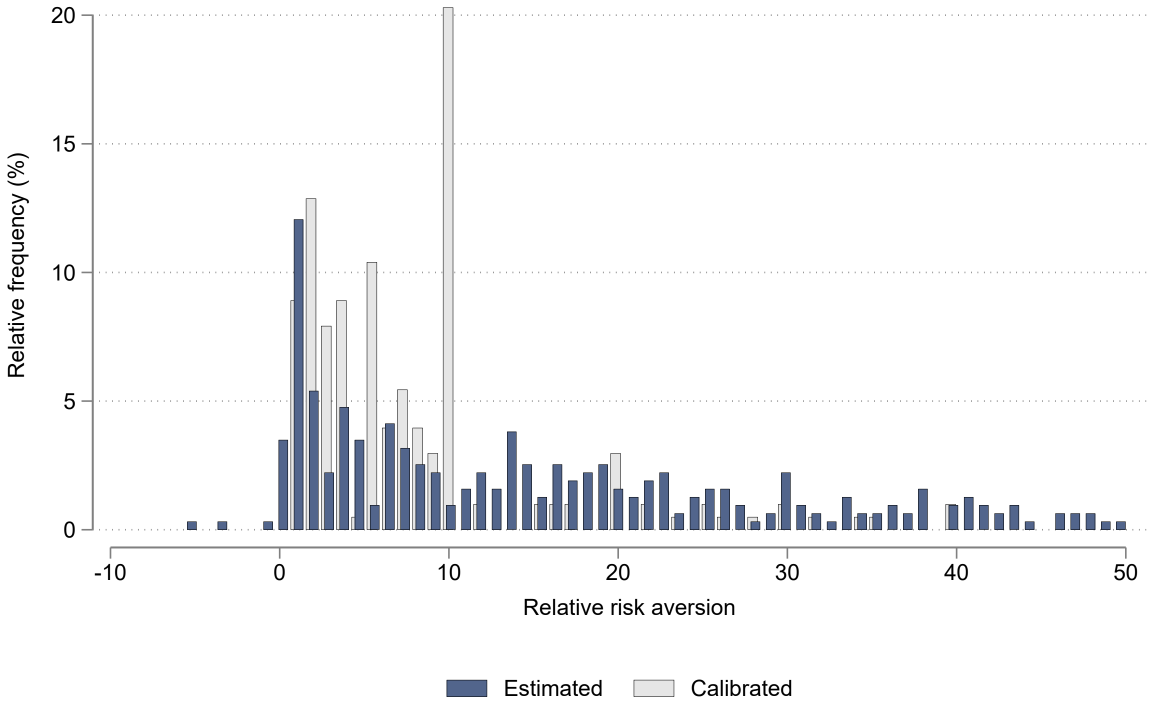
Notes: The table only considers one benchmark calibration per study (the calibration most stressed by the authors) and only includes published studies that separate risk aversion from intertemporal substitution. Studies are classified into economics and finance categories based on the journals they were published in and using the journal classification of the Web of Science. If in the Web of Science the journal is included in both categories, we follow the classification of the "most similar" journal according to the Scientific Journal Ranking.

Figure B1: Estimated and calibrated relative risk aversion in economics



Notes: The figure shows histograms of i) 590 estimates or relative risk aversion collected from 58 economics studies and ii) 237 calibrations of relative risk aversion collected from 115 economics studies. In both cases we only consider studies that separate risk aversion from intertemporal substitution. Studies are classified into economics and finance categories based on the journals they were published in and using the journal classification of the Web of Science. If in the Web of Science the journal is included in both categories, we follow the classification of the "most similar" journal according to the Scientific Journal Ranking. For ease of exposition, values below -10 and above 50 are excluded from the figure but included in all statistical tests.

Figure B2: Estimated and calibrated relative risk aversion in finance



Notes: The figure shows histograms of i) 431 estimates or relative risk aversion collected from 34 finance studies and ii) 209 calibrations of relative risk aversion collected from 85 finance studies. In both cases we only consider studies that separate risk aversion from intertemporal substitution. Studies are classified into economics and finance categories based on the journals they were published in and using the journal classification of the Web of Science. If in the Web of Science the journal is included in both categories, we follow the classification of the "most similar" journal according to the Scientific Journal Ranking. For ease of exposition, values below -10 and above 50 are excluded from the figure but included in all statistical tests.

asset's real return, the conditional covariance of the asset's real return with both consumption growth and the portfolio's real return. If the preferences reduce to the standard power utility function, i.e., $\eta = 1$, covariance risk becomes irrelevant, while in the case of EZW preferences, both covariance risk and consumption risk effectively explain assets' riskiness. Regarding the theoretical and empirical implications, Epstein & Zin (1991), Campbell (1996), and Vissing-Jørgensen & Attanasio (2003) provide more details on the log-linearized Euler equation.

The most frequently employed econometric approach to estimate the structural parameters of (B4) and (B6) or the log-linearized versions of the equations is the generalized method of moments (GMM) proposed by Hansen (1982) and Hansen & Singleton (1982). Unlike other methods in the literature, the assumptions regarding the absence of heteroskedasticity and autocorrelation of residuals do not need to hold. Moreover, the GMM estimates are consistent and asymptotically efficient, unlike ordinary least squares (OLS). To implement the technique, it is necessary to identify a set of instruments that are correlated with the included endogenous variables. Market returns, stock returns, disposable income, human capital, consumption growth, and their lagged values (one-period or more) are some of the most common instruments used in the literature (see e.g., Chen *et al.*, 2013; Faria *et al.*, 2016; Jeong *et al.*, 2015; Yogo, 2006).

Besides OLS and GMM methods, maximum likelihood estimation (MLE) is another econometric technique used to estimate the relative risk aversion parameter (e.g., Hugonnier *et al.*, 2013; Normandin & St-Amour, 1998). Conditional on distributional assumptions, this method can provide estimates with higher statistical power than those of GMM. In the case of equilibrium models, such as dynamic stochastic general equilibrium (DSGE) models, MLE-based estimations are widely used. For instance, using an MLE procedure, Van Binsbergen *et al.* (2012) estimate RRA in a DSGE model with recursive preferences. The Bayesian method of estimation is another approach widely used in the literature and, in particular, DSGE models. Among others, Bretscher *et al.* (2020) follow a Bayesian approach to estimate the relative risk aversion parameter of EZW preferences in a New-Keynesian DSGE model. The economics literature often relies on the latter two methods to deal with investors' behavior and asset returns along with the equilibrium of the whole economy at the aggregate level. On the other hand, finance literature mainly focuses on a narrower part of the economy, i.e., the behavior of investors within the asset markets, and uses extensive data on stock market returns. Hence, the finance literature mainly employs CAPM or CCAPM models (or their extensions and alternatives) that traditionally require GMM or OLS techniques to estimate the coefficient of RRA.

Additionally, one strand of literature uses simulation-based methods to estimate the degree of risk aversion along with other structural parameters. For example, the simulated method of moments that can be considered a particular case of GMM is a widely used simulation-based technique to estimate the coefficient of relative risk aversion in the Euler equation derived from recursive preferences as it tackles the problem of aggregating consumption over time (see e.g., Albuquerque *et al.*, 2016). Moerover, the presence of internal habit formation in households' preferences can lead to a wedge between the RRA and the EIS as they are not the inverse of each other. Similar to models with recursive preferences, habit formation models employ estimation techniques such as GMM and OLS to estimate the coefficient of risk aversion. In this regard, Korniotis (2010) provides a detailed discussion on the estimation procedure regarding risk aversion in internal and external habit formation models. Other alternative models include expected utility with a reference level of consumption (Garcia *et al.*, 2006), multiple-priors recursive utility with ambiguity aversion (Jeong *et al.*, 2015), recursive preferences with smooth ambiguity aversion (Thimme & Völkert, 2015), and recursive preferences with disappointment aversion (Delikouras, 2017). Finally, a relatively limited literature estimates the RRA by combining the nonexpected utility model and (quasi) experimental methods. See Brown & Kim (2014) and Briggs *et al.* (2021) for a detailed procedure of quasi-experimental estimation of relative risk aversion in the presence of recursive preferences.

2 Extensions and Tests of Publication Bias Models

Table C1: Tests of p-hacking due to Elliott *et al.* (2022)

	All studies	Economics	Finance
Test for non-increasingness	0.004	0.104	1.000
Test for monotonicity and bounds	0.001	0.142	0.577
Observations ($p <= 0.15$)	755	409	346
Total observations	1,021	590	431

Notes: The table shows p-values for each test; the null hypothesis is no p-hacking. The techniques rely on the conditional chi-squared test of Cox & Shi (2023). The first technique is a histogram-based test for non-increasingness of the p-curve, the second technique is a histogram-based test for 2-monotonicity and bounds on the p-curve and the first two derivatives.

Table C2: Specification test for the Andrews & Kasy (2019) model

	All studies	Economics	Finance
Correlation	0.606	0.517	0.530
	[0.552, 0.656]	[0.434, 0.593]	[0.413, 0.643]

Notes: Following Kranz & Putz (2022), the table shows the correlation coefficient between the logarithm of the absolute value of the estimated inverse elasticity and the logarithm of the corresponding standard error, weighted by the inverse publication probability estimated by the Andrews & Kasy (2019) model. If the assumptions of the model hold, the correlation is zero. Bootstrapped 95% confidence interval in parentheses.

Table C3: Regressing estimates on standard errors when $p < 0.005$

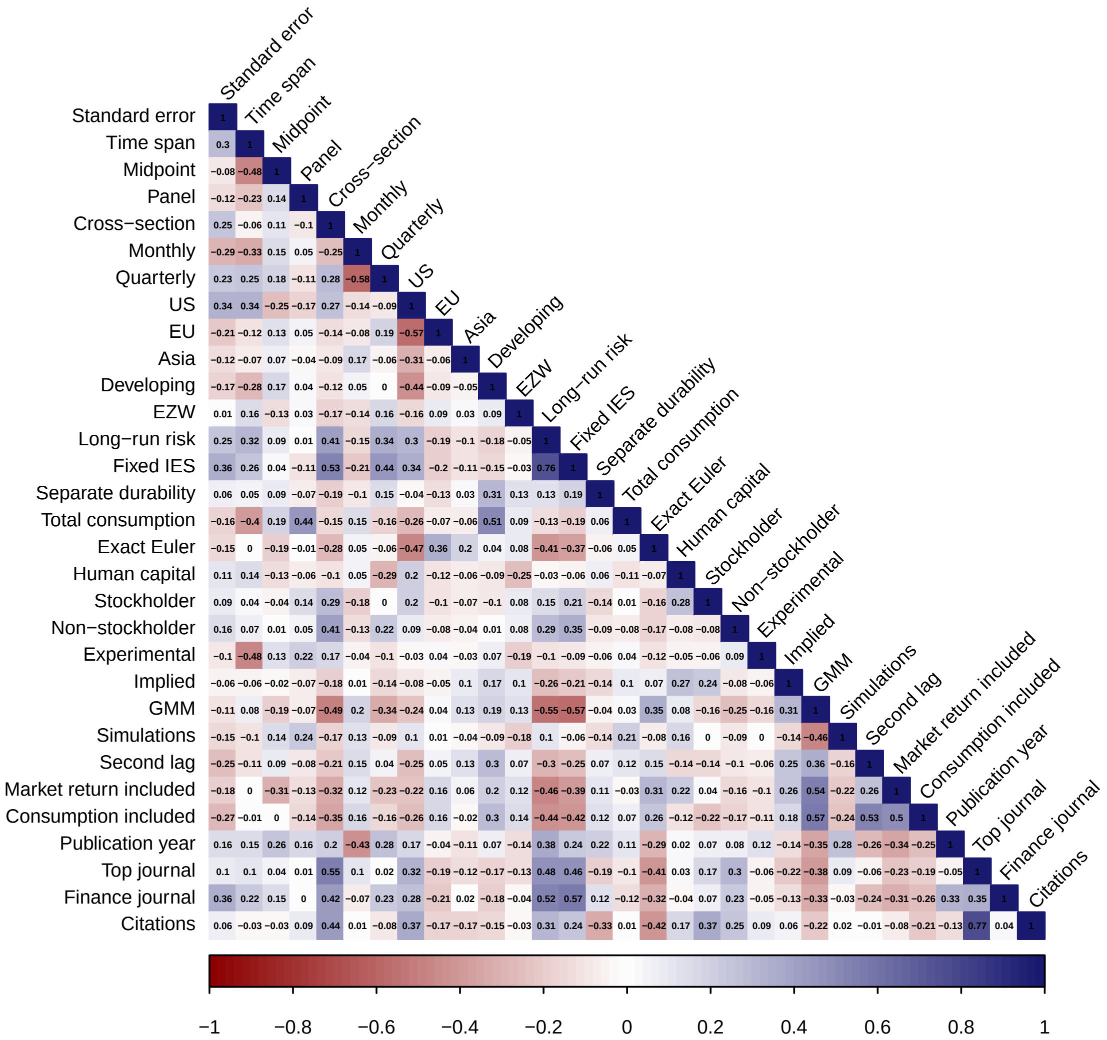
	All studies	Economics literature	Finance literature	Top journals	Implied estimate	Experimental study
Standard error	3.646^{***}	4.171^{***}	3.383^{***}	3.376^{***}	2.871^{***}	4.261^{***}
	(0.181)	(0.314)	(0.171)	(0.146)	(0.0134)	(0.136)
	[3.324, 4.131]	[3.016, 5.150]	[3.098, 3.866]	[2.094, 5.116]	[0.583, 4.067]	[-7.625, 16.230]
Observations	479	300	179	156	33	18
	United States	Developing country	OLS method	GMM method	Quarterly data	Annual data
Standard error	3.570^{***}	3.722^{***}	3.546^{***}	3.592^{***}	3.544^{***}	4.033^{***}
	(0.178)	(0.323)	(0.235)	(0.308)	(0.192)	(0.437)
	[3.259, 4.045]	[-8.862, 4.209]	[3.121, 4.325]	[2.974, 4.548]	[3.202, 4.046]	[2.848, 5.116]
Observations	327	39	155	232	247	82

Notes: The constant is included in the all regressions but not reported in the table. Standard errors, clustered at the study level, are shown in parentheses. 95% confidence intervals from the wild bootstrap are in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3 Summary Statistics, Extensions, and Additional Discussion of Heterogeneity Models

3.1 Variables

Figure D1: Correlation matrix of BMA variables



Notes: The figure shows Pearson correlation coefficients.

Data characteristics All the variables are defined and summarized in the main body of the paper. The first category that we consider is a set of variables concerning different characteristics of the samples used in the primary studies. We introduce eight dummy variables accounting for differences in the data. Two variables account for the difference in the data dimension: panel and cross-sectional data. Most of the reported estimates (about 76%) in primary studies are obtained using time series data, which we use as the reference category. Moreover, we codify two variables capturing data frequency. Datasets with monthly data or higher frequencies (i.e., weekly, daily) are used for 25% of the estimates, while 50% are obtained from more conventional datasets with quarterly data. Four other dummy variables denote the geographical coverage of the reported estimates. The largest group is based on the US data, accounting for 74% of estimates. The mean estimate from the US data is 31, which is substantially higher than the mean estimate of non-US data, which equals 3. This is consistent with the stream of the literature estimating higher relative risk aversion for American households compared to other countries (Gandelman & Hernández-Murillo, 2015).

On the other hand, the second largest group of estimates, using European data, exhibits the opposite pattern. The European sample, comprising around 11% of the collected estimates, yields a mean around 3, while the mean estimate of non-EU datasets is 26. Two other dummy variables denote Asian and developing countries consisting of 3% and 6% of the estimates, respectively. In addition to the dummy variables, we define two variables capturing the time properties of the datasets. The first variable, time span, captures the period of data (in terms of years) used to estimate risk aversion. To control for a potential time trend reflecting structural changes in preferences (Chiappori & Paiella, 2011; Schildberg-Hörisch, 2018), we include the midpoint of the data as an additional explanatory variable. The earliest median year of data is 1930 in Campbell (1996), which we subtract from other studies' median years to derive a relative midpoint for each study.

Specification characteristics We codify nine dummy variables to capture different aspects of the specifications for estimating relative risk aversion. The first dummy variable denotes estimates based on the EZW recursive preferences, which are used for 90% of the estimates in our sample. The remaining 10% of the estimates are derived from other techniques that allow researchers to distinguish between risk aversion and intertemporal substitution: models with habits (Korniotis, 2010), expected utility with a reference level of consumption (Garcia *et al.*, 2006), multiple-priors recursive utility with ambiguity aversion (Jeong *et al.*, 2015), recursive preferences with smooth ambiguity aversion (Thimme & Völkert, 2015), and recursive preferences with disappointment aversion (Delikouras, 2017). Next, we define a dummy variable regarding the long-run risk (LLR) model proposed by Bansal & Yaron (2004). The LLR framework contains a representative agent consumer with recursive preferences allowing for distinguishing between the RRA and EIS. The framework's other main feature is the expected consumption growth containing a small but highly persistent long-run consumption risk.

Furthermore, the LLR framework also allows for a time-varying risk premium on assets and nonindependent and identically distributed consumption growth. Using the LLR model, Hansen *et al.* (2008) show that the long-run risk channel can explain several problematic stylized facts in asset markets. Almost one-third (32%) of the estimates in primary studies are obtained within the LLR framework. The next variable accounts for the case when the estimated coefficients of relative risk aversion are obtained when the elasticity of intertemporal substitution is fixed in the estimation process. Around 25% of coefficients in the sample are estimated in the presence of fixed EIS. Several studies document that the estimation of EIS within a model with recursive preferences is not only empirically tricky but also irrelevant to the estimated risk aversion (e.g., Constantinides & Ghosh, 2011; Malloy *et al.*, 2009). However, there is no consensus in the literature about the exact value of the EIS, as documented by Havranek (2015) and Havranek *et al.* (2015).

Around 13% of the estimates are obtained in a framework where the utility function allows for nonseparability between durables and nondurables. An extensive asset pricing literature estimates the risk aversion coefficient when only nondurable goods and services are considered for consumption. There are studies, however, documenting the importance of durable goods and two-good models in estimating risk aversion (e.g., Bednarek & Patel, 2015; Yang, 2011). Similarly, we codify a dummy variable corresponding to the use of total consumption. Furthermore, more than one-third of the reported coefficients of RRA in our sample are estimated using a nonlinear (exact) Euler equation. The log-linearization of the Euler equation requires parametric restrictions on the structural parameters and the consumption growth and asset return, resulting in different estimates from the nonlinear case. Hence, we consider the effect of linearization of the Euler equation on the estimated risk aversion by defining a dummy variable accounting for the reported estimates obtained from the exact Euler equation.

Additionally, we add a variable to control for the role of human capital in estimating the coefficient of relative risk aversion. Since the return on human capital is not observable, it is common to use returns on equity or labor income as a proxy in the literature (Campbell, 1996). Among others, Grammig & Schrimpf (2009) argue that asset pricing models augmented by human capital provide more reliable results. Slightly more than ten percent of the reported estimates are obtained using models that include human capital. Finally, two additional variables control for estimates computed exclusively for stockholders (or rich households) and nonstockholders (or poor households). Not surprisingly, stockholders often show lower risk aversion than nonstockholders. The mean estimate of the coefficient of relative risk aversion for stockholders is almost 10, while the mean estimate for nonstockholders is more than five times larger, equal to 53. Only 5% of the estimates correspond to non-stockholders and 12% for stockholders.

Estimation techniques The next category of variables considers various methods and approaches used to estimate RRA in the literature. The first dummy variable captures (quasi) experimental approaches. The variable indicates both laboratory experiments (e.g., Meissner & Pfeiffer, 2022) and quasi-experimental (e.g., Lybbert & McPeak, 2012) studies. The mean of such estimates is about 2, significantly lower than the mean estimate of non-experimental studies (24): though there are few (quasi) experimental studies that rely on the Euler equation. Next, we define a variable corresponding to the cases where the RRA is not directly estimated but implied by estimating other parameters in the model. The implied RRA might differ from the estimated coefficients in terms of magnitude and precision. The variable thus can be a source of heterogeneity among the estimates in the literature. The implied estimates form 12% of the sample.

Regarding the econometric approach, we define two variables capturing the techniques used in the literature. First, the GMM variable denotes the estimated coefficients obtained within the GMM framework, accounting for 59% of estimates reported in the primary studies. The second variable captures simulation-based estimates. The LLR models often employ simulation-based methods such as the simulated method of moments to estimate parameters (Hasseltoft, 2012). Almost 17% of estimates in our collected sample are simulation-based. We employ the OLS estimates as the baseline category. Estimates obtained by the generalized least squares (GLS) method are also included in the baseline category. The relevance and exogeneity of instruments are essential factors affecting the reliability of estimates. We thus introduce three dummy variables to control for the instruments used in the estimation procedure. The first variable captures estimates if the second or higher lags are included among instruments, accounting for almost 16% of estimates. We also control for the fact whether market returns are included among instruments by adding a dummy variable capturing 32% of the estimates in our sample. Finally, we include a similar dummy variable regarding the presence of consumption growth among instruments (35% of the estimates).

Publication characteristics The last group of variables reflects publication differences and measures of quality not captured by the previous variables. First, since more recent studies are more likely to provide newer methods and innovations regarding both theory and data, we control for the publication year of the estimate. Second, we categorize the estimates into economics literature and finance literature. To this end, we codify a dummy variable indicating estimates from the finance literature, which comprise 42% of the collected dataset. Studies are classified into economics and finance categories based on the journals they were published in and using the journal classification of the Web of Science. If in the Web of Science the journal is included in both categories, we follow the classification of the "most similar" journal according to the Scientific Journal Ranking. If a study is unpublished (15 studies in total), we classify it based on the prevailing publications of the corresponding author. The mean of finance estimates (45) is much higher than that of our reference category, economics literature (7.5). Finally, we control for publication in top-five economics or top-three finance journals. The estimates from top journals account for 30% of the estimates reported in the primary studies. We also consider the number of citations to be a proxy for the ex-post quality of a publication and introduce a variable reflecting the number of per-year citations of each study.

3.2 Results

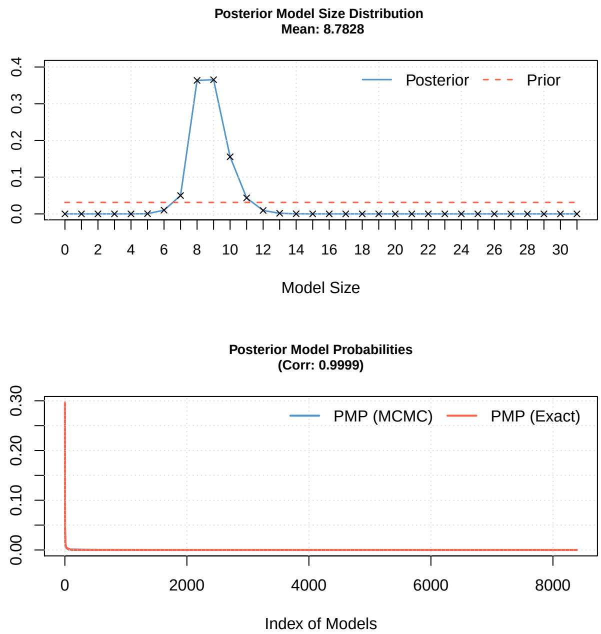
Figure 4 in the main body of the paper illustrates the results of Bayesian model averaging. The horizontal axis denotes the cumulative posterior model probabilities, and each column corresponds to one regression model. The explanatory variables are sorted by their posterior inclusion probabilities in descending order. The blue color (darker in grayscale) and red color (lighter in grayscale) denote the positive posterior mean and negative posterior mean, respectively. A blank cell means that the variable is not included in the model. The results indicate that there

Table D1: Summary of the benchmark BMA estimation

Mean no. regressors	*Draws*	*Burn-ins*	*Time*	*No. models visited*
8.794	$2 \cdot 10^6$	$1 \cdot 10^6$	2.654 mins	229,513
Modelspace	*Models visited*	*Topmodels*	*Corr PMP*	*No. Obs.*
$2.1 \cdot 10^9$	0.0011%	100	0.999	1,021
Model prior	*g-prior*	*Shrinkage-stats*		
Uniform/ 15.5	UIP	Av=0.999		

Notes: We account for collinearity among explanatory variables by employing the dilution prior suggested by George (2010); we also use the information prior recommended by Eicher *et al.* (2011). See Zeugner & Feldkircher (2015) for a detailed description of the priors.

Figure D2: Model size and convergence for the benchmark BMA model



Notes: The figure illustrates the posterior model size distribution and the posterior model probabilities of the BMA exercise reported in the main body of the paper.

Table D2: Results for alternative BMA priors

	BRIC g-prior			HQ g-prior		
Variable	Post. Mean	Post. SD	PIP	Post. Mean	Post. SD	PIP
Constant	-8.837	N.A.	1.000	-8.844	N.A.	1.000
Standard error	0.980	0.035	1.000	0.977	0.036	1.000
Data characteristics						
Time span	-0.044	0.225	0.052	-0.066	0.275	0.080
Midpoint	0.004	0.091	0.016	0.006	0.127	0.031
Panel	1.044	2.234	0.209	1.484	2.534	0.301
Cross-section	3.422	1.867	0.833	3.641	1.727	0.885
Monthly	-0.121	0.581	0.057	-0.200	0.724	0.099
Quarterly	4.467	0.959	0.994	4.378	0.981	0.993
US	6.068	1.007	1.000	6.108	1.052	1.000
EU	0.026	0.283	0.020	0.053	0.404	0.040
Asia	0.005	0.259	0.014	0.012	0.377	0.029
Developing	-0.055	0.495	0.025	-0.129	0.754	0.054
Specification characteristics						
Epstein-Zin	5.484	1.383	0.990	5.573	1.313	0.996
Long-run risk	0.005	0.139	0.015	0.006	0.198	0.031
Fixed EIS	0.025	0.290	0.020	0.038	0.350	0.037
Nonseparable durables	4.834	1.376	0.979	4.952	1.297	0.990
Total consumption	0.214	0.813	0.083	0.352	1.035	0.136
Exact Euler	0.068	0.360	0.049	0.142	0.518	0.096
Human capital	0.019	0.247	0.018	0.045	0.368	0.038
Stockholder	-5.767	1.350	0.995	-5.924	1.307	0.998
Nonstockholder	0.056	0.497	0.025	0.073	0.561	0.041
Estimation techniques						
Experimental	-0.071	0.640	0.025	-0.178	1.017	0.054
Implied	-0.001	0.162	0.016	0.002	0.218	0.028
GMM	-0.075	0.415	0.047	-0.093	0.461	0.066
Simulations	-0.007	0.249	0.019	-0.017	0.345	0.035
Second lag	-0.066	0.389	0.041	-0.107	0.488	0.070
Market return included	-0.119	0.492	0.072	-0.169	0.572	0.108
Consumption included	-0.199	0.633	0.110	-0.265	0.712	0.153
Publication characteristics						
Publication year	0.039	0.236	0.040	0.059	0.288	0.064
Top journal	0.001	0.151	0.016	0.001	0.217	0.033
Finance journal	6.358	0.949	1.000	6.251	0.938	1.000
Citations	-0.001	0.047	0.015	-0.002	0.068	0.031
Observations	1,021			1,021		
Studies	92			92		

Notes: The response variable is estimated relative risk aversion. SD = standard deviation, PIP = Posterior inclusion probability. The left-hand panel applies BMA based on the BRIC g-prior (the benchmark g-prior for parameters with the beta-binomial model prior). The right-hand panel reports the results of BMA based on HQ g-prior, which asymptotically mimics the Hannan-Quinn criterion. See Zeugner & Feldkircher (2015) for a detailed description of the priors.

are eight explanatory variables with the highest values of PIP that are likely systematically effective in explaining the size of the estimated coefficient of relative risk aversion reported in primary studies.

Table 5 in the main body of the paper presents the corresponding numerical results. The left panel presents BMA results for each explanatory variable by reporting posterior mean, posterior inclusion probability, and posterior standard deviation. Apart from the intercept, there are three *decisive* (according to the Raftery *et al.*, 1997, classification) variables with PIP equal to 1 (standard error, US data, and finance journal). Four other variables have PIPs between 0.95 and 0.99 (quarterly data, stockholder, EZW preferences, and separate durability). We label these coefficients as variables with a *strong* impact. Finally, one *substantial* explanatory variable has a PIP between 0.75 and 0.95 (cross-sectional data). Additionally, Table 5 reports the results of the frequentist check (OLS) in the right-hand panel, including the explanatory variables with PIP larger than 0.5. The results reported in both panels are consistent since the estimated coefficients exhibit similar signs and magnitude. However, two variables estimated by OLS are marginally statistically insignificant.

Data characteristics Our findings indicate the importance of three decisive variables among data characteristics affecting the size of the estimates. First, studies based on US data tend to report higher estimates than those of other countries. The empirical literature shows contradicting results regarding cross-country heterogeneity in risk aversion. Our BMA results are consistent with the stream of the literature indicating a higher risk aversion for the United States. Gandelman & Hernández-Murillo (2015) show that the United States has a relatively high degree of risk aversion among developed countries. On the other hand, a fraction of studies find the share of American households holding risky assets is higher than their counterparts in other countries, and this implies a lower degree of risk aversion in the United States (Bekhtiar *et al.* 2020).

Second, our results suggest that estimates based on cross-sectional data tend to be typically larger than the estimates obtained from time series or longitudinal data. This result is consistent with the strand of the literature concerning the cross-section of stock returns that requires a higher degree of risk aversion to reconcile aggregate consumption and market returns (see e.g., Grammig & Schrimpf, 2009; Malloy *et al.*, 2009). Significant cross-sectional variations in excess returns conflate the relationship of assets and consumption risk, which results in larger estimates of structural parameters such as the coefficient of RRA. Third, BMA results indicate that studies employing quarterly data tend to report larger estimates of relative risk aversion. On the other hand, the variable denoting frequencies higher than quarterly data, i.e., monthly frequency data, is not an insignificant explanatory variable in all BMA settings. In addition, our results suggest that the other data characteristics are not systematically correlated with the magnitude of the coefficient of relative risk aversion.

Specification characteristics Our results suggest that differences in assumed preferences may have a systematic effect on the size of the estimate. Studies that employ Epstein-Zin-Weil preferences report a higher degree of risk aversion on average than those with other types of preferences, e.g., internal habit formation model. Furthermore, we find that allowing for nonseparability of durables in the utility function is associated positively with larger reported estimates. A linear combination of the discounted future nondurable and durable consumption growth determines these models' expected asset log returns. For instance, Yogo (2006) and Bednarek & Patel (2015) show that durable consumption growth plays a significant role in the pricing of stock returns, and a higher share of durable consumption in the total expenditure will result in larger estimates of relative risk aversion. Similarly, Yang (2011) finds that since both equity premium and the stock return volatility change linearly with the share of durable goods, an increase in the risk aversion coefficient can explain the increase in the premium due to the presence of durable goods in the model.

In addition, we find that stockholders are systematically less risk-averse compared to the general population. This finding aligns with the economic theory intuition that participating in stock markets indicates a lower risk aversion, while non-stockholders show a higher level of risk aversion that prevents them from holding risky assets. There is an extensive literature documenting results similar to our BMA results. Using the 17 years of data from PSID, Mankiw & Zeldes (1991) document that the implied coefficient of relative risk aversion based on stockholder consumption is one-third of those of all families in the US. Similarly, using the EZW preferences, Malloy *et al.* (2009) find that the risk aversion coefficient is, in general, lower for the stockholders and decreases with the level of wealth of stockholders. Their structural estimates for the stockholders and the wealthiest third of stockholders are 15 and 10, respectively. We do not find evidence that the estimates obtained within the LLR model or a nonlinear Euler equation are systematically different from the rest of the estimates. Similarly, BMA results do not show that a fixed EIS and total consumption or human capital in the estimated model systematically affect the size of reported estimates.

Estimation techniques All variables related to the estimation approaches are negatively associated with the magnitude of reported estimates. However, the posterior mean for most of them is barely different from zero. More importantly, BMA results show that none of them is systematically important in determining the size of the coefficient of relative risk aversion. Among the variables in this category, only the variable reflecting instrumented consumption growth exhibits a PIP larger than 0.10, while the rest have PIPs between 0.01 and 0.07. These results remain the same also when we employ alternative BMA priors (Table D2).

Publication characteristics Regarding the variables controlling for the quality of publications, we do not find evidence that publication year, publication in a top-five and top-three journal, or the number of citations are systematically effective in explaining the size of the reported estimates. In contrast, we confirm our previous observation that the finance literature tends to report higher estimates of RRA compared to the economics literature. BMA results indicate that finance estimates are larger than those reported in the economics literature by 6.4 on average. One explanation might be the impact of the influential studies in the finance literature. There are high-quality publications widely cited within the finance literature reporting huge estimates (e.g., Yogo, 2006; Malloy *et al.*, 2009). Such studies become benchmark studies that other researchers follow, resulting in larger estimates of the coefficient of RRA in the field.

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