Empirical Asset Pricing with Multi-Period Disasters and Partial Government Defaults

Jantje Sönksen *

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Abstract

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Key words: empirical asset pricing, rare disaster hypothesis, multi-period disasters, recursive preferences, partial government defaults, equity premium, simulation-based estimation

JEL: G12, C58

*Jantje Sönksen: University of Tübingen, School of Business and Economics, Mohlstrasse 36, D-72074 Tübingen, Germany. jantje.soenksen@uni-tuebingen.de. I thank Ralf Elsas, Christoph Meinerding, Stefan Rünzi, Christian Schlag, Erik Theissen and Julian Thimme for contributing several good suggestions.

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1 Introduction

According to the rare disaster hypothesis (RDH) by Rietz (1988), the extraordinary mean excess returns of U.S. equity portfolios observed during the postwar period resulted because investors ex ante demanded a compensation for possibly disastrous but very unlikely risks that they ex post did not suffer from. Given the Cold War with its ever-present thread of a nuclear resolution that overshadowed several decades, this idea of a sample selection effect appears plausible. The path that per capita consumption followed since WWII could not be taken for granted from the perspective of an investor in 1945. The RDH thereby offers an explanation for the equity premium puzzle and the poor empirical performance of Hansen and Singleton's (1982) canonical consumption-based asset pricing model (C-CAPM) and its recent variants. The appeal of the RDH is its straightforwardness, its weakness is that the hypothesis is difficult to refute using data that – like U.S. postwar samples – do not contain disastrous consumption contractions. Several studies use calibrations to illustrate that accounting for disaster risk can reconcile high equity premia with plausible investor preferences. However, econometric studies that test the RDH on empirical data are scarce.

With this study, I propose a novel empirical strategy to resolve the inherent sample selection problem and to estimate and test an asset pricing model with recursive investor preferences that accounts for the possibility of rare and severe consumption contractions and partial government defaults. The moment restrictions implied by such a disaster-including C-CAPM are used for a simulation-based estimation of its structural parameters. By allowing for multi-period disasters, which are modeled as a marked point process (MPP), I take into account the caveat that the success of the RDH may crucially hinge on the assumption that a consumption disaster must unfold within a single period. The econometric analysis is conducted in two consecutive steps, the first step relies on maximum likelihood to estimate the MPP parameters using cross-country consumption data, the second step consists of a simulation-based estimation of the investor preference parameters based on U.S. macro and financial data. A bootstrap procedure is used to gauge the estimation precision. To the best of my knowledge, this is the first study that estimates and tests a C-CAPM that accounts for the possibility of multi-period disasters and partial government defaults.

The empirical analysis shows that the estimates of the investor preference parameters – relative risk aversion (RRA), the intertemporal elasticity of substitution (IES), and the subjective discount factor – are in a range that is considered economically meaningful, and feature narrow bootstrap confidence bounds. Specifically, the estimates of the subjective discount factor are smaller than but close to unity, as would be expected of an investor with a reasonable positive rate of time preference. The RRA coefficient estimates range between 1.5 and 1.7. It is generally acknowledged that an RRA <10 describes a reasonably risk averse investor (see, e.g. Mehra and Prescott (1985), Rietz (1988), and Bansal and Yaron (2004)). Cochrane (2005) caps the interval of sensible relative risk aversion more strictly at 5, which is in line with the results reported by Meyer and Meyer (2005). In the present study, the 95% confidence interval for the RRA estimate also lies within this strict plausibility range.

The IES estimates are (significantly) greater than unity and of a magnitude that is frequently assumed for calibrations. Moreover, the estimated RRA coefficient is (significantly) greater than the reciprocal of the IES estimate, which provides evidence that investors have a preference for early resolution of uncertainty. Several studies emphasize that an IES>1, combined with a preference for early resolution of uncertainty is necessary to obtain meaningful asset pricing implications of a C-CAPM (see e.g. Barro (2009), Bansal and Yaron (2004), Nakamura et al. (2013)).

And accordingly, the model-implied key financial indicators – mean market return, T-bill return, equity premium, and market Sharpe ratio – are indeed of a meaningful magnitude and consistent with the empirically observed counterparts. These findings are robust with respect to alternative model specifications (e.g. first-step model, disaster definition, and data simulation procedures). Compared to other prominent attempts to vindicate the C-CAPM paradigm, these results are encouraging. Empirical asset pricing studies often find implausible and/or imprecise parameter estimates that entail doubtful asset pricing implications, calling into question the explanatory power of the C-CAPM paradigm. The present results indicate that accounting for rare disasters in a consumption-based asset pricing framework indeed helps to restore the nexus between financial markets and the real economy.

The growing RDH literature, to which this paper contributes, has benefited greatly from Barro's (2006; 2009) seminal work that revived the interest in the RDH.[1] Wachter (2013) modifies Barro's (2006) model with recursive preferences and adds time-varying disaster probabilities to show that the RDH qualifies as a possible solution to the volatility puzzle. Barro and Ursúa (2008) assemble annual consumption and GDP data to study the size and frequency of disasters. These data are used by Barro and Jin (2011) who fit power law densities to the empirical distribution of macroeconomic disasters. The first-step estimation strategy in the present paper builds on that idea.

Alternatively, Backus et al. (2011) obtain the distribution of disastrous contractions from equity index options, and Gabaix (2012) proposes a model with changing disaster severity and challenges ten puzzles in finance. Gourio (2012) considers time-varying disaster risk in a business cycle model and Martin (2013) shows that changes in the calibration of the disaster probability and average contraction size

[1] A lucid survey of the RDH literature is provided by Tsai and Wachter (2015).

have large effects on the equity premium. Exposing corporate debt to time-varying tail risks, Gourio (2013) is able to replicate important features of credit spreads. Nakamura et al. (2013) consider a multi-period disaster process using Bayesian analysis. Assuming recursive preferences, they show that – when calibrated with plausible time preference and IES – the equity premium can be explained with a plausible RRA. The frequentist approach of the present paper complements and extends their Bayesian analysis.

The RDH continues to spur current academic research. Bai et al. (2015) find that rare disasters can explain the value premium puzzle and Seo and Wachter (2015) show that stochastic disaster probabilities help to reconcile the volatility skew and the equity premium. In the model of Gillman et al. (2015), disasters affect the growth persistence of consumption and dividends, thereby matching a variety of pricing phenomena in the equity and bond market. Farhi and Gabaix (2016) describe how a model that uses a time-varying probability of world disasters can shed light on various exchange rate puzzles. With a model that includes rare booms and disasters, Tsai and Wachter (2016) provide an explanation for the empirical finding that growth stocks have lower returns than value stocks and are simultaneously riskier. Barro and Jin (2016) extend the model by Nakamura et al. (2013) by combining rare disasters with long-run risks and find that the rare disaster component accounts for the largest part of the equity premium.

Grammig and Sönksen (2016) also propose a simulated method of moments estimation strategy for a disaster-including power utility C-CAPM, but as in Barro (2006), disasters are assumed to shrink to one-period contractions, an assumption that is under suspicion of being the driving force behind the success of the RDH, as argued by Julliard and Ghosh (2012) and reflected in Constantinides' (2008) comment on Barro and Ursúa (2008). When allowing for multi-period disasters and modeling investor preferences by a power utility function, Julliard and Gosh conclude that in order to rationalize the equity premium puzzle with the help of the RDH, the puzzle itself must be a rare event. Their results thus seem to attenuate the appeal of the RDH. The present study re-emphasizes the explanatory power of the RDH in that it shows that the equity premium can be explained with plausible preference parameters and assumptions regarding the disaster process. However, it is important to assume Epstein-Zin preferences instead of a additive power utility. Similar to what has been pointed out in related literature, it is crucial to allow for a preference for early resolution of uncertainty, and that IES and RRA are both greater than unity. Accounting for the possibility of multi-period disasters and partial government default in an empirical C-CAPM yields conforming RRA and IES estimates and, consequently, meaningful asset pricing implications.

The remainder of the paper is structured as follows: Section 2 motivates a multi-period disaster-including C-CAPM with recursive preferences and derives moment restrictions that provide the basis for the simulated method of moments-type estimation strategy. It also introduces the marked point process to explain the size and the duration of and between disaster events. Section 3 presents the macroeconomic and financial data used in this study. Section 4 describes the two-step estimation strategy. Sections 5 discusses the estimation results and conducts robustness tests. Section 6 concludes.

2 Multi-period disasters in a C-CAPM

2.1 Asset pricing implications and moment restrictions

To formulate an empirically estimable asset pricing model that accounts for the possibility of multi-period disasters, I follow Barro (2006) and assume that consumption growth evolves as

$$\frac{C_{t+1}}{C_t} = e^{u_{t+1}} e^{v_{t+1}}, \tag{2.1}$$

where $u_{t+1} \sim (\tilde{\mu}, \sigma^2)$, $v_{t+1} = \ln(1 - b_{t+1}) d_{t+1}$, and $e^{u_{t+1}}$ describes consumption growth in non-disastrous times. The term $\ln(1 - b_{t+1})$ comes into force only if the respective period is affected by a disaster, that is, if the binary disaster indicator d_{t+1} equals 1. In this case, the non-disastrous consumption growth component shrinks by the contraction factor b_{t+1}. Time is discrete and the observation frequency is fixed (e.g. quarterly). In Barro's (2006) one-period disaster model, $b_{t+1} \in [q, 1]$, where q denotes the disaster threshold that differentiates between regular bad times and disasters.

The definition of the contraction factor b_{t+1} must be adapted when accounting for multi-period disasters. Here, a disaster is defined as succession of contractions that starts in period s_1 and lasts until period s_2 with $s_1 \leq t + 1 \leq s_2$, such that:

$$1 - \prod_{j=s_1}^{s_2} (1 - b_j) \geq q. \tag{2.2}$$

In words, I refer to a *disaster event* as a severe decline in consumption at least of size q. The decline may accrue over multiple *disaster periods* or it may come in the form of one sharp contraction. Disaster periods are indicated by $d_t = 1$ and are associated with a contraction factor $b_t \in (0, 1]$. If $d_t = 1$, asset returns will also contract. Adopting Barro's (2006) specification for the returns on treasury bills, I assume, analogous to Equation 2.1, for a gross return of an asset, R_i:

$$R_{i,t+1} = (1 - \tilde{b}_{i,t+1})^{d_{t+1}} R_{i,nd,t+1}, \tag{2.3}$$

where $R_{i,nd}$ denotes the asset's gross return in non-disastrous periods. $\tilde{b}_i$ is the return equivalent of the consumption contraction factor b.

A representative investor, who faces these consumption risks, has recursive preferences according to Epstein and Zin (1989). They show that the basic asset pricing equations for a gross return R_i and an excess return $R_i^e = R_i - R_j$, respectively, are then given by:

$$\mathbb{E}_t \left[m_{t+1}(\beta, \gamma, \psi) R_{i,t+1} \right] = 1 \qquad \text{and} \qquad \mathbb{E}_t \left[m_{t+1}(\beta, \gamma, \psi) R_{i,t+1}^e \right] = 0, \tag{2.4}$$

where the stochastic discount factor (SDF) reads:

$$m_{t+1}(\beta, \gamma, \psi) = \beta^\theta \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{\theta}{\psi}} R_{a,t+1}^{\theta-1} \qquad \text{with} \qquad \theta = \frac{1-\gamma}{1-\frac{1}{\psi}}. \tag{2.5}$$

In Equation (2.5), β denotes the subjective discount factor, ψ is the IES, and γ represents the coefficient of relative risk aversion; R_a is the return on aggregate wealth.

Conditioning down the basic asset pricing equation for a gross return, applying the law of total expectations, and using the consumption growth and return specifications from Equations (2.1) and (2.3), we can write:

$$\begin{aligned} \mathbb{E}\left[\beta^\theta \left(e^{u_t} e^{v_t} \right)^{-\frac{\theta}{\psi}} R_{a,t}^{\theta-1} R_{i,t} \right] &= p \mathbb{E}\left[\beta^\theta \left((1-b_t) e^{u_t} \right)^{-\frac{\theta}{\psi}} R_{a,d,t}^{\theta-1} R_{i,d,t} \middle| d_t = 1 \right] \\ &\quad + (1-p) \mathbb{E}\left[\beta^\theta \left(e^{u_t} \right)^{-\frac{\theta}{\psi}} R_{a,nd,t}^{\theta-1} R_{i,nd,t} \middle| d_t = 0 \right] \\ &= 1, \end{aligned} \tag{2.6}$$

where $p = \mathbb{P}(d_t = 1)$ is the unconditional disaster probability, and $R_{i,d,t} = R_{i,nd,t}(1-\tilde{b}_{i,t})$. Rearranging terms in Equation (2.6) yields the following moment restriction:

$$\mathbb{E}\left[\beta^\theta \left(e^{u_t} \right)^{-\frac{\theta}{\psi}} R_{a,nd,t}^{\theta-1} R_{i,nd,t} \middle| d_t = 0 \right] = \frac{1 - p\mathbb{E}\left[\beta^\theta \left((1-b_t) e^{u_t} \right)^{-\frac{\theta}{\psi}} R_{a,d,t}^{\theta-1} R_{i,d,t} \middle| d_t = 1 \right]}{1-p}. \tag{2.7}$$

The corresponding moment restriction for an excess return R_i^e reads:

$$\mathbb{E}\left[\beta^{\theta}\left(e^{u_t}\right)^{-\frac{\theta}{\psi}}R_{a,nd,t}^{\theta-1}R_{i,nd,t}^{e}\middle|\,d_t=0\right]=\frac{-p\mathbb{E}\left[\beta^{\theta}\left((1-b_t)e^{u_t}\right)^{-\frac{\theta}{\psi}}R_{a,d,t}^{\theta-1}R_{i,d,t}^{e}\middle|\,d_t=1\right]}{1-p},\tag{2.8}$$

where $R_{i,d}^e=R_{i,d}-R_{j,d}$ and $R_{i,nd}^e=R_{i,nd}-R_{j,nd}$.

Equations (2.7) and (2.8) are of particular interest, because they suggest how theoretical moments that can be approximated using the available non-disastrous data (left-hand sides) can be disentangled from expressions that rely on information about disasters (right-hand sides). In particular, using non-disaster-including consumption growth and return data, one can use for the left hand side of Equation (2.7):

$$\mathbb{E}\left[\beta^{\theta}\left(e^{u_t}\right)^{-\frac{\theta}{\psi}}R_{a,nd,t}^{\theta-1}R_{i,nd,t}\middle|\,d_t=0\right]\approx\frac{1}{T}\sum_{t=1}^{T}\beta^{\theta}cg_{nd,t}^{-\frac{\theta}{\psi}}R_{a,nd,t}^{\theta-1}R_{i,nd,t},\tag{2.9}$$

where $cg_{nd,t}$ denotes observable non-disastrous consumption growth. Similarly,

$$\mathbb{E}\left[\beta^{\theta}\left(e^{u_t}\right)^{-\frac{\theta}{\psi}}R_{a,nd,t}^{\theta-1}R_{i,nd,t}^{e}\middle|\,d_t=0\right]\approx\frac{1}{T}\sum_{t=1}^{T}\beta^{\theta}cg_{nd,t}^{-\frac{\theta}{\psi}}R_{a,nd,t}^{\theta-1}R_{i,nd,t}^{e}.\tag{2.10}$$

The U.S. postwar data do not incorporate any disasters, so attempting to approximate the right-hand side moments in Equations (2.7) and (2.8) by sample means of the available data would be futile. However, if it were possible to simulate consumption and return processes that account for the possibility of rare disasters, we could consider an approximation by simulated moments, viz:

$$\frac{1-p\mathbb{E}\left[\beta^{\theta}\left((1-b_t)e^{u_t}\right)^{-\frac{\theta}{\psi}}R_{a,d,t}^{\theta-1}R_{i,d,t}\middle|\,d_t=1\right]}{1-p}\approx\frac{1-\frac{1}{\mathcal{T}}\sum_{s=1}^{\mathcal{T}}\beta^{\theta}cg_s^{-\frac{\theta}{\psi}}R_{a,s}^{\theta-1}R_sd_s}{1-\frac{D_{\mathcal{T}}}{\mathcal{T}}},\tag{2.11}$$

and

$$\frac{-p\mathbb{E}\left[\beta^{\theta}\left((1-b_t)e^{u_t}\right)^{-\frac{\theta}{\psi}}R_{a,d,t}^{\theta-1}R_{i,d,t}^{e}\middle| d_t=1\right]}{1-p}\approx\frac{-\frac{1}{\mathcal{T}}\sum\limits_{s=1}^{\mathcal{T}}\beta^{\theta}cg_s^{-\frac{\theta}{\psi}}R_{a,s}^{\theta-1}R_s^{e}d_s}{1-\frac{D_{\mathcal{T}}}{\mathcal{T}}},\tag{2.12}$$

where cg_s, $R_{a,s}$, R_s and R_s^e denote simulated (disaster-including) consumption growth and (excess) returns, and $D_{\mathcal{T}}=\sum_{s=1}^{\mathcal{T}}d_s$. A large $\mathcal{T}$ ensures a good approximation of population moments by sample means, provided that a uniform law of large numbers holds. In the spirit of a quote with which K. Singleton motivates the simulated method of moments (SMM), *more fully specified models allow experimentation with alternative formulations of economies and, perhaps, analysis of processes that are more representative of history for which data are not readily available* (Singleton, 2006, p. 254), the simulation should produce consumption and return data that are representative of history assuming that the RDH is true.

Equations (2.11) and (2.12) provide the basis for the SMM-type estimation of the preference parameters β, γ, and ψ. Before explaining the details of the estimation strategy, it is necessary to be more specific about the stochastic process that generates the disastrous consumption contractions.

2.2 Multiperiod disasters as a marked point process

In the following, I introduce a marked point process (MPP) to model the time duration between disastrous consumption contractions and their size and also, because I want to account for multi-period disasters, the duration of a disaster. In the present application, the disaster periods are the points of the MPP; the contraction sizes are the marks.

I draw on Hamilton and Jorda's (2002) autoregressive conditional hazard (ACH) framework to model the time duration between disaster periods. The initial choice for this approach is to set the threshold q that defines a disaster event and thereby the respective disaster periods and their contraction sizes. Suppose that the sequence of consumption disaster events thus defined is observable at the quarterly frequency. Let $M(t)$ denote the number of disasters that have occurred as of quarter t and let $N(t)$ refer to the respective number of disaster periods. The probability of quarter t being a disaster period, conditional on the information available in $t-1$, is the discrete-time hazard rate,

$$h_t = \mathbb{P}(N(t) \neq N(t-1)|\mathcal{F}_{t-1}). \tag{2.13}$$

Hamilton and Jorda's (2002) ACH framework allows for flexible parametrization of the hazard rate in Equation (2.13). In a parsimonious specification, the hazard rate depends on just two parameters, μ and $\tilde{\mu}$:

$$h_t = \left[(\mu(1-d_{t-1}) + \tilde{\mu}d_{t-1})(1-d^+_{t-1}) + d^+_{t-1}\right]^{-1}, \tag{2.14}$$

where d^+_t is binary indicator such that:

$$d^+_t = \mathbb{1}(d_t = 1) \cdot \mathbb{1}\left[[1 - \prod_{j=s_1}^{t-1}(1-b_j)] < q\right], \tag{2.15}$$

where $\mathbb{1}(\cdot)$ is the indicator function. In words, $d^+_t = 1$ if quarter t belongs to a disaster that commenced in period $s_1 \leq t$ and the accrued contractions up to t do not yet qualify as a disaster. In this case, quarter $t+1$ must also be a disaster period, such that $h_{t+1} = 1$. If $d^+_t = 0$ and $d_t = 1$ then $h_{t+1} = 1/\tilde{\mu}$. If $d_t = 0$ then $h_{t+1} = 1/\mu$.

More extensive parametrization of the hazard rate are possible, too. For example, one can include the time durations of and between previous disaster events, the aggregate size of the previous disaster, and the size of the contraction of the last disaster period to explain the hazard rate:

$$h_t = \Big[\big[(\mu + \alpha\tau_{M(t-1)-1} + \delta b^+_{M(t-1)})(1 - d_{t-1}) \\ +(\tilde{\mu} + \tilde{\alpha}\tilde{\tau}_{M(t-1)-1} + \tilde{\delta} b_{N(t-1)})d_{t-1}\big](1 - d^+_{t-1}) + d^+_{t-1}\Big]^{-1}, \tag{2.16}$$

where τ_m denotes the time duration, measured in quarters, between the mth and $(m+1)$th disaster, and $\tilde{\tau}_m$ denotes the number of quarters that the mth disaster lasted. b_n is the contraction size of the nth disaster period and b^+_m is the aggregate size of the mth disaster. For the empirical analysis, I consider several special cases of Equation (2.16). For example, the hazard rate specification in Equation (2.14) emerges when $\alpha = \delta = \tilde{\alpha} = \tilde{\delta} = 0$.

To model the disaster size, I adopt an idea of Barro and Jin (2011) and employ a power law distribution (PL) to describe the transformed contraction size $z_c = \frac{1}{1-b}$.[2] I assume that contractions that contribute to reaching the disaster threshold q (when $d_t = 1$ and $d^+_t = 1$) follow a different PL distribution than contractions that add to a disaster after q was reached (when $d_t = 1$, but $d^+_t = 0$).

The joint conditional probability density function of the resulting marked point process, which I refer to as an ACH-PL model, can then be written as:

$$\begin{aligned} f(d_t, d^+_t, z_{c,t}|\mathcal{F}_{t-1}; \boldsymbol{\theta}_{ACH}, \theta^+_{PL}, \theta_{PL}) &= f(d_t, d^+_t|\mathcal{F}_{t-1}) \times f(z_{c,t}|d_t, d^+_t, \mathcal{F}_{t-1}) \\ &= [h_t(\boldsymbol{\theta}_{ACH})]^{d_t} \times [1 - h_t(\boldsymbol{\theta}_{ACH})]^{1-d_t} \\ &\times \left(f_{PL}(z_{c,t}; \theta^+_{PL})^{d^+_t} \times f_{PL}(z_{c,t}; \theta_{PL})^{1-d^+_t}\right)^{d_t}, \end{aligned} \tag{2.17}$$

where $\boldsymbol{\theta}_{ACH}$ contains the ACH parameters. f_{PL} denotes the power law density and θ^+_{PL} and θ_{PL} are the power law tail coefficients that describe the size of contractions

[2] More precisely, Barro and Jin (2011), who implicitly assume single-period disasters, use a double power law distribution which consists of two power law distributions that morph into each other at a certain threshold value. It turns out that the flexibility of the double power law distribution is not required when modeling multi-period disasters.

that contribute to reaching the disaster threshold and the size of contractions that add on top of q, respectively. The probability density function in Equation (2.17) is an essential ingredient for the estimation strategy, which entails drawing from that distribution to simulate disaster-including consumption data.

3 Data

The empirical analysis of the disaster-including C-CAPM relies on two data sources, which are used in two consecutive estimation steps. The estimation of the ACH-PL parameters is based on annual cross-country panel data on consumption that Barro and Ursúa (2008) have assembled for 42 countries, and which feature prominently in the rare disaster literature.[3] From these data, I select the same 35 countries as Barro (2006). Table 1 lists the countries and the years for which consumption data are available.

[insert Table 1 here]

For the detection of disaster events in these data, I rely on Barro's (2006) identification scheme, which implies that any sequence of downturns in consumption growth greater or equal to $q = 0.145$ qualifies as a disaster. The same disaster threshold is used by Barro (2006), Barro (2009), and Barro and Jin (2011). A disaster may pan out over multiple periods or occur as one sharp contraction. Positive intermezzos of consumption growth within a disaster are allowed if (1) this positive growth is smaller in absolute value than the negative growth in the following year and (2) the size of the disaster does not decrease by including the intermezzo. Using this disaster identification scheme, I detect 89 disaster events. Figure 1 shows their size and the period over which they accrue.

[3] The data are available at http://scholar.harvard.edu/barro/publications/barro-ursua-macroeconomic-data, accessed 04/24/2015.

[insert Figure 1 here]

As previously mentioned, I assume the ACH-PL process is observable at the quarterly frequency. However, the Barro and Ursúa (2008) data only permit the computation of annual contractions. I therefore generate quarterly observations by randomly distributing the annual contraction. Appendix A.1 explains the details.

The estimation of the preference parameters is based on quarterly U.S. real personal consumption expenditures per capita on services and nondurable goods in chained 2009 U.S. dollars, as provided by the Federal Reserve Bank of Saint Louis.[4] These data span the period 1947:Q2–2014:Q4. Financial data at a monthly frequency come from CRSP and Kenneth French's data library.[5] The data used for the empirical analysis are (1) the CRSP market portfolio, comprised of NYSE, AMEX, and NASDAQ traded stocks (*mkt*), (2) ten size-sorted portfolios (*size dec*), and (3) ten industry portfolios (*industry*). All portfolios are value-weighted. The gross return of the CRSP market portfolio serves as the proxy for R_a.[6] Nominal monthly returns are converted to real returns at a quarterly frequency, using the growth of the consumer price index of all urban consumers.[7] In line with Beeler and Campbell (2012), I approximate the ex-ante non-disastrous T-bill return $R_{b,nd}$ (the "risk-free rate" proxy) by forecasting the ex-post $R_{b,nd}$ based on the quarterly T-bill yield and the average of quarterly log inflation across the past year. The three-month nominal

[4] For services: http://research.stlouisfed.org/fred2/series/A797RX0Q048SBEA. For nondurable goods: http://research.stlouisfed.org/fred2/series/A796RX0Q048SBEA. Both accessed 03/09/2016.

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html, accessed 03/09/2016. Due to the frequent changes in the underlying CRSP data, newer or older downloads may results in different series.

[6] The approximation of the return of the wealth portfolio by the return of the portfolio of financial assets is also employed by Weber (2000), Stock and Wright (2000), and Yogo (2006). Thimme and Völkert (2015) offer a critique of this approach, arguing that a large fraction of the wealth portfolio is comprised of non-financial wealth. They propose an alternative proxy based on Lettau and Ludvigson's (2001) *cay*-variable that accounts for the return on human capital.

[7] These data are provided by the Federal Reserve Bank of Saint Louis: http:// research.stlouisfed.org/fred2/series/CPIAUCSL, accessed 03/09/2016.

T-bill yield is obtained from the CRSP database. Table 2 contains the descriptive statistics for these data.

[insert Table 2 about here]

4 Estimation strategy

4.1 ACH-PL maximum likelihood estimation

The parameter estimation of the disaster-including C-CAPM is performed in two consecutive steps. I first compute maximum likelihood estimates of the ACH-PL parameters $\boldsymbol{\theta}_{ACH}$, θ^{+}_{PL}, and θ_{PL}. Using these estimates, it becomes possible to simulate disaster-including data, which are required for the simulation-based estimation of the preference parameters β, γ, and ψ in the second stage. Let us first consider the maximum likelihood estimation step. Equation (2.17) implies the following conditional ACH-PL log likelihood function:

$$\begin{aligned}\mathcal{L}(\boldsymbol{\theta}_{ACH}, \theta^{+}_{PL}, \theta_{PL}) = &\sum_{t=1}^{T} \left(d_t \ln h_t(\boldsymbol{\theta}_{ACH}) + (1-d_t)\ln[1-h_t(\boldsymbol{\theta}_{ACH})]\right) \\ &+ \sum_{t=1}^{T} d_t \left(d^{+}_t \ln f_{PL}(z_{c,t};\theta^{+}_{PL}) + (1-d^{+}_t)\ln f_{PL}(z_{c,t};\theta_{PL})\right).\end{aligned} \tag{4.1}$$

The parameters in Equation (4.1) are variation-free, so it is possible to perform the estimation of $\hat{\boldsymbol{\theta}}_{ACH}$ and θ^{+}_{PL} and θ_{PL} separately. In particular, the maximization of

$$\mathcal{L}(\boldsymbol{\theta}_{ACH}) = \sum_{t=1}^{T} \left(d_t \ln h_t(\boldsymbol{\theta}_{ACH}) + (1-d_t)\ln[1-h_t(\boldsymbol{\theta}_{ACH})]\right) \tag{4.2}$$

yields $\hat{\boldsymbol{\theta}}_{ACH}$, while estimates of θ^{+}_{PL}, θ_{PL} can be obtained by maximizing

$$\mathcal{L}(\boldsymbol{\theta}_{PL}) = \sum_{t=1}^{T} d_t \left(d^{+}_t \ln f_{PL}(z_{c,t};\theta^{+}_{PL}) + (1-d^{+}_t)\ln f_{PL}(z_{c,t};\theta_{PL})\right). \tag{4.3}$$

To perform the maximization of the log likelihood function in Equation (4.2), the cross-country panel data are represented as event time data. For that purpose, sequences of the disaster indicators d_t and d_t^+ are computed for every country. Counting the number of quarters between disaster events gives τ_m, the time duration between the mth and $(m+1)$th disaster. Moreover, $\tilde{\tau}_m$ is obtained by counting the number of quarters over which the respective disaster lasted. These data are needed to compute the hazard rate in Equation (2.16)

The maximum likelihood estimation of the ACH parameters $\boldsymbol{\theta}_{ACH}$ is then performed on the concatenated country-specific event time data series. During the maximization of the log likelihood function in Equation (4.2), the disaster event and period counters $M(t)$ and $N(t)$ are reset to zero whenever a country change occurs in the concatenated data. If the hazard rate specification in (2.16) is used, τ_0 is re-initialized to the average duration between disasters (179.7 quarters), $\tilde{\tau}_0$ is reset to equal the average disaster length (13.1 quarters), and b_0^+ is reset to equal the average contraction size (0.268). These values are also the initial values for maximum likelihood estimation. They correspond to $q = 0.145$; different disaster thresholds use different initial values. The re-initialization procedure is adopted from Engle and Russell (1998), who introduce a ACH-like dynamic duration model for the time interval between intraday trading events, in which they must account for overnight interruptions of the trading process.

4.2 Financial moment restrictions and data simulation

The SMM-type estimation of the preference parameters entails exploiting the moment restrictions in Equations (2.7) and (2.8). In particular, I rely on a matching of empirical and simulated moments that is implied by the moment restriction in Equation (2.7), and that uses the sample moments in Equations (2.9) and (2.11).

Applied to the T-bill return R_b, we have:

$$g^r(\boldsymbol{\vartheta}) = \left[\frac{1}{T}\sum_{t=1}^{T}\beta^{\theta} cg_{nd,t}^{-\frac{\theta}{\psi}} R_{a,nd,t}^{\theta-1} R_{b,nd,t} - \left[\frac{1-\frac{1}{\mathcal{T}}\sum\limits_{s=1}^{\mathcal{T}} \beta^{\theta} cg_s^{-\frac{\theta}{\psi}} R_{a,s}^{\theta-1} R_{b,s} d_s}{1-\frac{D_{\mathcal{T}}}{\mathcal{T}}} \right] \right], \tag{4.4}$$

where $\boldsymbol{\vartheta} = (\beta, \gamma, \psi)'$. Similarly, I exploit the moment restriction in Equation (2.8) applied to an excess return $R_i^e = R_i - R_b$, which suggests the following matching of empirical and simulated moments:

$$g^e(\boldsymbol{\vartheta}) = \left[\frac{1}{T}\sum_{t=1}^{T}\beta^{\theta} cg_{nd,t}^{-\frac{\theta}{\psi}} R_{a,nd,t}^{\theta-1} R_{i,nd,t}^{e} - \left[\frac{-\frac{1}{\mathcal{T}}\sum\limits_{s=1}^{\mathcal{T}} \beta^{\theta} cg_s^{-\frac{\theta}{\psi}} R_{a,s}^{\theta-1} R_{i,s}^{e} d_s}{1-\frac{D_{\mathcal{T}}}{\mathcal{T}}} \right] \right]. \tag{4.5}$$

Combining Equation (4.4) with Equation (4.5) applied to the excess returns of N test assets, I obtain:

$$\mathbb{G}(\boldsymbol{\vartheta}) = \begin{bmatrix} \frac{1}{T}\sum_{t=1}^{T}\beta^{\theta} cg_{nd,t}^{-\frac{\theta}{\psi}} R_{a,nd,t}^{\theta-1} R_{b,nd,t} - \left[\frac{1-\frac{1}{\mathcal{T}}\sum\limits_{s=1}^{\mathcal{T}} \beta^{\theta} cg_s^{-\frac{\theta}{\psi}} R_{a,s}^{\theta-1} R_{b,s} d_s}{1-\frac{D_{\mathcal{T}}}{\mathcal{T}}} \right] \\ \frac{1}{T}\sum_{t=1}^{T}\beta^{\theta} cg_{nd,t}^{-\frac{\theta}{\psi}} R_{a,nd,t}^{\theta-1} \mathbf{R}_{nd,t}^{e} - \left[\frac{-\frac{1}{\mathcal{T}}\sum\limits_{s=1}^{\mathcal{T}} \beta^{\theta} cg_s^{-\frac{\theta}{\psi}} R_{a,s}^{\theta-1} \mathbf{R}_{s}^{e} d_s}{1-\frac{D_{\mathcal{T}}}{\mathcal{T}}} \right] \end{bmatrix}, \tag{4.6}$$

where $\mathbf{R}^e = [R_1^e, \ldots, R_N^e]'$. Choosing $N \geq 2$, SMM-type estimation of the preference parameters can then be attempted by:

$$\hat{\boldsymbol{\vartheta}} = \underset{\boldsymbol{\vartheta}\in\boldsymbol{\Theta}}{\arg\min}\ \mathbb{G}^(\boldsymbol{\vartheta})'\mathbf{W}\mathbb{G}(\boldsymbol{\vartheta}), \tag{4.7}$$

where $\boldsymbol{\Theta}$ denotes the admissible parameter space and $\mathbf{W}$ is a symmetric and positive semi-definite weighting matrix.

To evaluate $\mathbb{G}(\boldsymbol{\vartheta})$ within such an optimization, it is necessary to compute the moments of simulated disaster-including data. For that purpose, I use the first-step ACH-PL estimates $\hat{\boldsymbol{\theta}}_{ACH}$, $\hat{\theta}_{PL}^{+}$, and $\hat{\theta}_{PL}$ and simulate a series of hazard rates

$\{h_s(\hat{\boldsymbol{\theta}}_{ACH}, \hat{\theta}^+_{PL}, \hat{\theta}_{PL})\}_{s=1}^{\mathcal{T}}$. The resulting conditional disaster probabilities are then used to generate a sequence of disaster indicators $\{d_s\}_{s=1}^{\mathcal{T}}$ and $\{d^+_s\}_{s=1}^{\mathcal{T}}$.

I obtain simulated series of non-disastrous consumption growth and returns, $\{cg_{nd,s}, R_{a,nd,s}, R_{b,nd,s}, R_{i,nd,s}\}_{s=1}^{\mathcal{T}}$ by block-bootstrapping from the non-disastrous U.S. postwar data. For that purpose, I rely on the automatic block-length selection procedure proposed by Politis and White (2004) and corrected by Politis et al. (2009) in combination with the stationary bootstrap of Politis and Romano (1994), in which the respective block-length is drawn from a Geometric distribution. The draws from the consumption and return data are performed simultaneously to retain the contemporaneous covariance structure.

Because the cross-country consumption panel data collected by Barro and Ursúa (2008) do not include information on asset prices, further assumptions are needed when simulating disaster returns. In particular, I assume that the transformed contractions $z_c = 1/(1-b)$ and $z_R = 1/(1-\tilde{b})$ have the same marginal distribution,[8]

$$f(z_c; \theta^+_{PL}, \theta_{PL}) = f(z_R; \theta^+_{PL}, \theta_{PL}), \tag{4.8}$$

where

$$f(z; \theta^+_{PL}, \theta_{PL}) = f_{PL}(z; \theta^+_{PL})^{d^+} \times f_{PL}(z; \theta_{PL})^{1-d^+}, \tag{4.9}$$

and write their joint cumulative distribution function (cdf) using a copula function that links the two marginal distributions:

$$F(z_c, z_R; \theta^+_{PL}, \theta_{PL}, \boldsymbol{\theta}_C) = C(F(z_c; \theta^+_{PL}, \theta_{PL}), F(z_R; \theta^+_{PL}, \theta_{PL}); \boldsymbol{\theta}_C), \tag{4.10}$$

where $F(z_C; \theta^+_{PL}, \theta_{PL})$ and $F(z_R; \theta^+_{PL}, \theta_{PL})$ denote the marginal cdfs. The vector $\boldsymbol{\theta}_C$ collects the coefficients that determine the dependence of z_c and z_R. Using the

[8] The asset index i is omitted for brevity of notation.

Gaussian copula C_G, these dependencies are measured by a single parameter, the copula correlation ρ. Equation (4.10) then becomes:

$$F(z_c, z_R; \theta^+_{PL}, \theta_{PL}, \rho) = C_G(u_c, u_R; \rho), \tag{4.11}$$

where $u_c = F(z_c; \theta^+_{PL}, \theta_{PL})$ and $u_R = F(z_R; \theta^+_{PL}, \theta_{PL})$.

I consider three choices for the copula correlation. In the first, ρ_i is estimated by the empirical correlation between non-disastrous consumption growth and gross return. Second, I consider the extreme case that $\rho = 0.99$, which is motivated by the finding that the correlations between financial returns increase in the tails of their joint distribution (see Longin and Solnik (2001)). Third, I consider $\rho = 0$, which implies drawing b_s and $\tilde{b}_s$ independently from the same distribution.

Drawing b_s and $\tilde{b}_s$ in case of d_s=1 is then performed as follows. First, I draw $y_{c,s}$ and $y_{R,s}$ from a bivariate standard normal distribution with correlation ρ and compute $u_{c,s} = \Phi(y_{c,s})$ and $u_{R,s} = \Phi(y_{R,s})$, where Φ denotes the standard normal cdf. Consumption growth and return contraction factors are then obtained by

$$b_s = 1 - \frac{1}{F^{-1}(u_{c,s}; \hat{\theta}^+_{PL}, \hat{\theta}_{PL})} \qquad \text{and} \qquad \tilde{b}_s = 1 - \frac{1}{F^{-1}(u_{R,s}; \hat{\theta}^+_{PL}, \hat{\theta}_{PL})}, \tag{4.12}$$

where

$$F^{-1}(u; \theta^+_{PL}, \theta_{PL}) = \left(F^{-1}_{PL}(u; \theta^+_{PL})\right)^{d^+} \times \left(F^{-1}_{PL}(u; \theta_{PL})\right)^{1-d^+}. \tag{4.13}$$

F^{-1}_{PL} denotes the quantile function of the PL distribution. The contraction factors are then combined with the bootstrapped non-disastrous series to simulate disaster-including series for consumption growth, $cg_s = (1 - b_s)^{d_s} cg_{nd,s}$, test asset returns, $R_{i,s} = (1 - \tilde{b}_{i,s})^{d_s} R_{i,nd,s}$, $i = 1, \ldots, N$, and the return of the wealth portfolio proxy $R_{a,s} = (1 - \tilde{b}_{a,s})^{d_s} R_{a,nd,s}$.

For the simulation of the T-bill return $R_{b,s}$, I draw on Barro (2006) who finds that there was a partial government default for 42 percent of the disasters that he identifies in the GDP series of 35 countries. Using this result, I draw at the beginning of each disaster (that is, $d_s = 1$ but $d_{s-1} = 0$), a government default indicator $d_{b,s}$ from a Bernoulli distribution with success probability $\mathbb{P}(d_{b,s} = 1 | d_s = 1, d_{s-1} = 0) = 0.42$, which decides whether the T-bill return is affected by the disaster. If $d_{b,s} = 0$, the T-bill will not contract. If $d_{b,s} = 1$, a contraction factor $\tilde{b}_{b,s}$ is drawn in the same way as it is done for the returns of the test assets, such that $R_{b,s} = (1 - \tilde{b}_{b,s})^{d_{b,s}} R_{b,nd,s}$. Simulated excess returns are then computed as $R^e_{i,s} = R_{i,s} - R_{b,s}$, such that it becomes possible to evaluate $\mathbb{G}(\boldsymbol{\vartheta})$ in Equation (4.6).

4.3 Identifying the IES

Thimme (2015) points out that a joint estimation of the investor preference parameters that relies exclusively on moment restrictions obtained by conditioning down by the basic asset pricing equations in (2.4) yields rather imprecise estimates of the IES. Although the moment restrictions used in the present paper account for the possibility of disasters, they still conform to the basic asset pricing equation with an Epstein-Zin SDF, and the caveat applies. I therefore find it useful to identify and estimate the IES separately from δ and γ, and through moment restrictions that can be derived from a (second-order) log-linearization of the Euler Equation (2.4) with the SDF in (2.5). Yogo (2004) shows that this procedure leads to the regression equation

$$r_{i,t+1} = \mu_i + \frac{1}{\psi} \Delta c_{t+1} + \eta_{i,t+1}, \tag{4.14}$$

where $r_{i,t+1} = \ln R_{i,t+1}$ and $\Delta c_{t+1} = \ln C_{t+1} - \ln C_t$. μ_i is a constant and $\eta_{i,t+1}$ is a zero mean disturbance term. The derivation implies that $\eta_{i,t+1}$ is correlated with Δc_{t+1}, such that a linear projection of $r_{i,t+1}$ on Δc_{t+1} and a constant would not identify the

IES. Instead, the IES is identified via the orthogonality conditions,

$$\mathbb{E}\left((r_{i,t+1} - \mu_i - \frac{1}{\psi}\Delta c_{t+1})\mathbf{z}_t\right) = \mathbf{0}, \tag{4.15}$$

where $\mathbf{z}_t$ consists of variables known at t (instrumental variables), which are correlated with Δc_{t+1}.[9]

I adopt the instrumental variables approach towards estimating the IES and use the log T-bill return $r_{b,t+1} = \ln R_{b,t+1}$ in Equation (4.14), and the twice-lagged log T-bill return and log consumption growth as well as a constant as instruments. The estimation is performed on the simulated disaster-including data. Using linear GMM with an identity weighting matrix, the IES estimate $\hat{\psi}$ must then fulfill the first-order conditions:

$$\begin{bmatrix} -1 & -\mathbb{E}_{\mathcal{T}}(\Delta c_s) & -\mathbb{E}_{\mathcal{T}}(r_{b,s}) \\ \frac{\mathbb{E}_{\mathcal{T}}(\Delta c_s)}{\hat{\psi}^2} & \frac{\mathbb{E}_{\mathcal{T}}(\Delta c_s \Delta c_{s-2})}{\hat{\psi}^2} & \frac{\mathbb{E}_{\mathcal{T}}(\Delta c_s r_{b,s-2})}{\hat{\psi}^2} \end{bmatrix} \begin{bmatrix} \mathbb{E}_{\mathcal{T}}(r_{b,s}) - \hat{\mu}_b - \frac{1}{\hat{\psi}}\mathbb{E}_{\mathcal{T}}(\Delta c_s) \\ \mathbb{E}_{\mathcal{T}}(r_{b,s}\Delta c_{s-2}) - \hat{\mu}_b \mathbb{E}_{\mathcal{T}}(\Delta c_{s-2}) - \frac{1}{\hat{\psi}}\mathbb{E}_{\mathcal{T}}(\Delta c_s \Delta c_{s-2}) \\ \mathbb{E}_{\mathcal{T}}(r_{b,s} r_{b,s-2}) - \hat{\mu}_b \mathbb{E}_{\mathcal{T}}(r_{b,s-2}) - \frac{1}{\hat{\psi}}\mathbb{E}_{\mathcal{T}}(\Delta c_s r_{b,s-2}) \end{bmatrix} = \mathbf{0}, \tag{4.16}$$

where I use Hansen's (1982) notation $\mathbb{E}_{\mathcal{T}}(\cdot) = \frac{1}{\mathcal{T}}\sum_{s=1}^{\mathcal{T}}(\cdot)$.

While the estimation of the IES is effectively performed separately from that of the subjective discount factor and the RRA coefficient, which are estimated using Equation (4.7) with $\hat{\psi}$ held fixed, it is also possible to augment Equation (4.6) by

[9] Estimation of the IES by GMM or two-stage least squares based on Equation (4.14) (or its reciprocal) and the moment restrictions in (4.15) goes back to Hansen and Singleton (1983), is surveyed by Campbell (2003), and is critically discussed by Yogo (2004).

the IES-identifying moment matches of Equation (4.16) to obtain:

$$
\mathbb{G}^{+}(\tilde{\boldsymbol{\vartheta}}) = \begin{bmatrix}
\frac{1}{T}\sum_{t=1}^{T} \beta^{\theta} cg_{nd,t}^{-\frac{\theta}{\psi}} R_{a,nd,t}^{\theta-1} R_{b,nd,t} - \left[\frac{1-\mathbb{E}_{\mathcal{T}}\left(\beta^{\theta} cg_s^{-\frac{\theta}{\psi}} R_{a,s}^{\theta-1} R_{b,s} d_s\right)}{1-\frac{D_{\mathcal{T}}}{T}}\right] \\
\frac{1}{T}\sum_{t=1}^{T} \beta^{\theta} cg_{nd,t}^{-\frac{\theta}{\psi}} R_{a,nd,t}^{\theta-1} \mathbf{R}_{nd,t}^{e} - \left[\frac{-\mathbb{E}_{\mathcal{T}}\left(\beta^{\theta} cg_s^{-\frac{\theta}{\psi}} R_{a,s}^{\theta-1} \mathbf{R}_s^{e} d_s\right)}{1-\frac{D_{\mathcal{T}}}{T}}\right] \\
\begin{bmatrix} -1 & -\mathbb{E}_{\mathcal{T}}(\Delta c_s) & -\mathbb{E}_{\mathcal{T}}(r_{b,s}) \\ \frac{\mathbb{E}_{\mathcal{T}}(\Delta c_s)}{\psi^2} & \frac{\mathbb{E}_{\mathcal{T}}(\Delta c_s \Delta c_{s-2})}{\psi^2} & \frac{\mathbb{E}_{\mathcal{T}}(\Delta c_s r_{b,s-2})}{\psi^2} \end{bmatrix} \times \\
\begin{bmatrix} \mathbb{E}_{\mathcal{T}}(r_{b,s}) - \mu_b - \frac{1}{\psi}\mathbb{E}_{\mathcal{T}}(\Delta c_s) \\ \mathbb{E}_{\mathcal{T}}(r_{b,s}\Delta c_{s-2}) - \mu_b \mathbb{E}_{\mathcal{T}}(\Delta c_{s-2}) - \frac{1}{\psi}\mathbb{E}_{\mathcal{T}}(\Delta c_s \Delta c_{s-2}) \\ \mathbb{E}_{\mathcal{T}}(r_{b,s} r_{b,s-2}) - \mu_b \mathbb{E}_{\mathcal{T}}(r_{b,s-2}) - \frac{1}{\psi}\mathbb{E}_{\mathcal{T}}(\Delta c_s r_{b,s-2}) \end{bmatrix}
\end{bmatrix}. \tag{4.17}
$$

where $\tilde{\boldsymbol{\vartheta}} = (\beta, \gamma, \psi, \mu_b)'$. SMM-type estimates of the preference parameters are then obtained by:

$$
\hat{\tilde{\boldsymbol{\vartheta}}} = \underset{\tilde{\boldsymbol{\vartheta}} \in \tilde{\boldsymbol{\Theta}}}{\arg\min}\ \mathbb{G}^{+}(\tilde{\boldsymbol{\vartheta}})' \mathbf{W} \mathbb{G}^{+}(\tilde{\boldsymbol{\vartheta}}). \tag{4.18}
$$

Choosing $\mathbf{W}$ such that a large weight is placed on the last two moment matches in (4.17) ensures that the IES will be identified by Equation (4.16). In particular, I use

$$
\mathbf{W} = \begin{bmatrix} \mathbf{I}_{N+1} & 0 \\ 0 & 10^6 \times \mathbf{I}_2 \end{bmatrix}. \tag{4.19}
$$

Because of the two-step approach, standard inference is not available for the second-step estimates, although one can rely on asymptotic maximum likelihood inference about the first-step ACH-PL estimates. I therefore use a combination of a parametric and non-parametric bootstrap to obtain standard errors and confidence intervals of the preference parameter estimates. The bootstrap procedure is explained in Section A.2 of the Appendix.

5 Empirical results

5.1 First-step estimation results

Table 3 reports the maximum likelihood estimates of the ACH-PL parameters and the Akaike (AIC) and Schwarz-Bayes (SBC) information criteria for various ACH specifications that emerge as special cases of the hazard rate specification in Equation (2.16). The most comprehensive alternative, referred to as ACH_1, estimates all parameters in Equation (2.16). The most parsimonious parametrization, referred to as ACH_0, corresponds to the hazard rate in Equation (2.14), such that only the baseline hazard parameters μ and $\tilde{\mu}$ are estimated (while $\delta = \tilde{\delta} = \alpha = \tilde{\alpha} = 0$). The ACH_2 specification allows (only) for an effect of the durations between disasters and the disaster length on the hazard rate (while $\delta = \tilde{\delta} = 0$), and the ACH_3 allows (only) the magnitude of the previous disaster and the size of the contraction of the previous disaster period to affect the hazard rate (while $\alpha = \tilde{\ } alpha = 0$). In the ACH_4 specification, there is an effect of the aggregate size of the previous disaster on the hazard rate, but not the contraction of the previous disaster period (such that $\tilde{\delta} = \alpha = \tilde{\alpha} = 0$).

[insert Table 3 about here]

Table 3 shows that whilst the AIC favors the ACH_4, the SBC prefers the ACH_0, for which the baseline hazard parameter estimates $\hat{\mu}$ and $\hat{\tilde{\mu}}$ are highly significant. The estimates of $\tilde{\mu}$ and δ in the ACH_4 specification are significant at the 5% level, but the baseline hazard parameter μ is reduced in size and significance. Moreover, the likelihood-ratio statistics reported in Table 3 indicate that the constraints implied by the SBC-preferred ACH_0 are, at the one percent significance level, only rejected in case of the AIC-preferred ACH_4. For these reasons, the subsequent analysis is confined to ACH_0 and ACH_4.

I obtain maximum likelihood estimates of the ACH_0 parameters equal to $\hat{\hat{\mu}} = 178.3$ and $\hat{\mu} = 1.2$. These estimates imply a probability of entering a disaster from a non-disaster period of about 0.56 percent, and a probability of remaining in a disaster of 83 percent. Because I use these estimates as a foundation for the second estimation step, it is prudent to check their economic plausibility beforehand. For that purpose, I use the ACH_0 and ACH_4 estimates to simulate disaster-including consumption time series with number of observations corresponding to the sample period, 1947:Q2-2014:Q4. The simulation is repeated 10k times, and I count the number of replications for which no disastrous consumption contraction occurs. The ACH_0 specification yields 21.9%, the ACH_4 14.1% disaster-free replications. The estimated disaster-including consumption process thus implies that the U.S. postwar history represents a lucky, but not an unlikely path, and that the model-implied disaster probabilities are not implausibly large.

[insert Figure 2 about here]

Table 3 also shows that the estimates of the power law coefficients θ_{PL} and θ^{+}_{PL} are quite similar, so the distribution of contractions that occur before reaching the disaster threshold q is not very different from the distribution of contractions that occur after q is reached. The estimates $\hat{\theta}_{PL}$ and $\hat{\theta}^{+}_{PL}$ have encouragingly small standard errors. Figure 2 depicts the cdf of the power law distribution and the empirical cdf of quarterly contractions. Figure 2a uses the estimate $\hat{\theta}^{+}_{PL}$ and illustrates the fit for contractions that contribute to reaching the disaster threshold, whilst Figure 2b uses $\hat{\theta}_{PL}$ and refers to those contractions that add on top of the disaster threshold. In both cases, the fit is quite good.

5.2 Second-step estimation results

Table 4 reports the second-step estimation-results based on the SBC-preferred ACH_0-PL and the AIC-preferred ACH_4-PL first-step estimates. The estimation is performed using different sets of test assets and copula correlation coefficients. It is based on the moment matches in Equation (4.17), using the weighting matrix in Equation (4.19), and $\mathcal{T}$=10^7. The table contains the point estimates of the preference parameters β, γ, and ψ and their bootstrap standard errors as well as the associated 95% confidence bounds. These bounds are computed using the percentile method, meaning that they accord with the 0.025 and 0.975 quantiles of the respective bootstrap distribution.[10] Furthermore, the Table 4 shows the p-values of Hansen's (1982) J-statistic,

$$J = \mathbb{G}(\hat{\boldsymbol{\vartheta}})'\widehat{\text{Avar}}(\mathbb{G}[\hat{\boldsymbol{\vartheta}}])^{+}\mathbb{G}(\hat{\boldsymbol{\vartheta}}), \tag{5.1}$$

where $^+$ denotes the Moore-Penrose inverse, which is approximately $\chi^2(N+1)$ under the null-hypothesis that the financial moment restrictions are correct. The root mean squared errors (RMSEs) that are also reported in Table 4 are computed as

$$R = \sqrt{\frac{1}{N+1}\mathbb{G}(\hat{\boldsymbol{\vartheta}})'\mathbb{G}(\hat{\boldsymbol{\vartheta}})} \times 10^4. \tag{5.2}$$

When using only the market portfolio and the T-bill return as test assets, the number of moment restrictions is equal to the number of estimated parameters, so empirical and simulated moments are perfectly matched. In this case, the RMSE is zero, such that R and the J-statistic are not reported.

[insert Table 4 about here]

Table 4 shows that all variants to estimate a disaster-including C-CAPM yield

[10] More formally, for a parameter ϑ, the α-quantile is computed as $\hat{G}^{-1}(\alpha)$, where $\hat{G}(\hat{\vartheta}) = \frac{\sum_{k=1}^{K} 1(\hat{\vartheta}^{(k)}<\hat{\vartheta})}{K}$.

economically plausible estimates for the preference parameters. The subjective discount factor estimates are smaller but close to 1, as would be expected of an investor with a plausible positive rate of time preference. The estimates of the subjective discount factor range between 0.9915 and 0.9948. The RRA estimates are between 1.50 and 1.65, well within the plausibility interval mentioned by Cochrane (2005). The estimated IES is larger than 1, ranging between 1.50 and 1.68. The inverse of the estimated IES is always smaller than the RRA estimate, which indicates a preference for an early resolution of uncertainty. Previous literature pointed out that the inequality $\gamma < 1/\psi$ is crucial to obtain meaningful asset pricing implications (more below).[11]

The choice of the test assets, the copula correlation, and the first-step ACH-PL specification exert only minor effects on the size of the preference parameter estimates. The IES estimates based on the ACH_4-PL are slightly bigger than those implied by the ACH_0-PL. Using only the market portfolio and the T-bill return as test assets, the RRA coefficient and IES estimates tend to be a bit smaller compared to the estimation based on industry and size-sorted portfolios. Using the ACH_0-PL first-step estimates yields a slightly smaller RMSE than using the ACH_4-PL estimates.

In all instances, the estimation precision is more than satisfactory, as indicated by the small bootstrap standard errors and the narrow confidence bounds. It is noteworthy that the confidence bounds for the RRA estimates also fall within the stricter plausibility range, and that the lower bound of the 95% confidence interval for the IES is above unity, too. Regarding the subjective discount factor estimate $\hat{\beta}$, the upper confidence bound is sometimes larger than 1, but given that quarterly time preferences should to be very close to 1, this is not surprising. The p-values of

[11] It is worthwhile noting that the estimation of ψ by reversing the regression equation (4.14) also yields an IES estimate greater than one. As noted by Yogo (2004), such robustness cannot not to be expected when disaster-free data are used for IES estimation.

the J-statistic indicate that the disaster-including C-CAPM cannot be rejected at conventional significance levels.

Compared with other prominent studies that assess the empirical support for the C-CAPM paradigm, these results are certainly encouraging. Julliard and Parker (2005), for example, who aggregate consumption over multiple periods, obtain an RRA estimate of plausible magnitude ($\hat{\gamma}$=9.1) but estimation precision is moderate (s.e.=17.2). By measuring consumption with waste, Savov (2011) obtains a RRA estimate of $\hat{\gamma}$=17.0 with a rather large standard error (s.e.=9.0). In both studies, the subjective discount factor is calibrated and additive power utility is assumed (such that $\gamma = 1/\psi$). Yogo (2006) splits consumption into a durable and a non-durable component and assumes Epstein-Zin preferences, as in the present study. His smallest RRA estimate is $\hat{\gamma}$=174.5 (s.e.=23.3) and the IES estimates reach $\hat{\psi}$=0.024 (s.e.=0.009) at most.

5.3 Asset pricing implications

When assessing whether an empirical C-CAPM implies meaningful asset pricing implications, the magnitude and relative size of the subjective discount factor, relative risk aversion, and the IES play an important role. The relative size of the RRA coefficient and the IES that is reflected in the parameter $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$, which shows up in the Epstein-Zin SDF in Equation (2.5), is particularly important. If $\gamma = \frac{1}{\psi}$ then $\theta = 1$ and the investor is indifferent to an early or late resolution of uncertainty, and the case of standard expected utility obtains. If $\gamma > \frac{1}{\psi}$ then the agent has a preference for early resolution of uncertainty, which is intuitively appealing, unless one wants to resort to behavioral explanations (like hope or fear).

The C-CAPM literature, and in particular the branch concerned with long-run risk, argues that an IES greater than unity combined with a preference for early resolution of uncertainty are necessary to explain the key features of asset prices (see, e.g., Bansal and Yaron (2004) and Huang and Shaliastovich (2015)). With risk aversion greater than unity, this suggests that θ should be negative.[12] While in calibration studies, therefore, moderate risk aversion is combined with an IES>1 to illustrate the explanatory power of the asset pricing model (Bansal and Yaron (2004), for example, assume γ=10 and ψ=1.5), none of the previously mentioned empirical C-CAPM studies reports conforming RRA and IES estimates. In fact, the IES point estimate is in most empirical studies smaller than one (see the meta-analysis by Havránek (2015) and the survey by Thimme (2015)).

Table 5 reports the ACH$_0$-PL-based model-implied estimates of θ. We observe that for the alternative sets of test assets and choices of the copula-correlation, $\hat{\theta}$ is always negative. Moreover, the confidence bounds reveal that the hypothesis that $\theta > 0$ can be rejected at conventional significance levels, so there is empirical evidence for early resolution of uncertainty along with an IES greater than one. According to the previous reasoning, we should thus expect that the empirical disaster-including C-CAPM yields meaningful asset pricing implications. I therefore test whether the model-implied mean market portfolio and T-bill return, the equity premium, and the market Sharpe ratio are economically plausible. To estimate the model-implied mean T-bill return and mean market return, I approximate the population moments by averaging over the $\mathcal{T}$ simulated observations, such that:

$$\widehat{\mathbb{E}}(R_b) = \frac{1 - \mathrm{cov}_{\mathcal{T}}(m(\hat{\beta}, \hat{\gamma}, \hat{\psi}), R_b)}{\mathbb{E}_{\mathcal{T}}(m(\hat{\beta}, \hat{\gamma}, \hat{\psi}))}, \tag{5.3}$$

and

$$\widehat{\mathbb{E}}(R_a) = \frac{1 - \mathrm{cov}_{\mathcal{T}}(m(\hat{\beta}, \hat{\gamma}, \hat{\psi}), R_a)}{\mathbb{E}_{\mathcal{T}}(m(\hat{\beta}, \hat{\gamma}, \hat{\psi}))}, \tag{5.4}$$

[12] An alternative interpretation of θ is given by Hansen and Sargent (2010), where a $\theta < 0$ captures the agent's aversion to model mis-specification.

where $m(\hat{\beta}, \hat{\gamma}, \hat{\psi})$ is the Epstein-Zin SDF in Equation (2.5) evaluated at the parameter estimates presented in Table 4 and $\text{cov}_{\mathcal{T}}(x, y) = \mathbb{E}_{\mathcal{T}}(xy) - \mathbb{E}_{\mathcal{T}}(x)\mathbb{E}_{\mathcal{T}}(y)$. The model-implied equity premium can thus be estimated by $\widehat{\mathbb{E}}(R_a) - \widehat{\mathbb{E}}(R_b)$ and the model-implied Sharpe ratio by

$$\frac{\widehat{\mathbb{E}}(R_a) - \widehat{\mathbb{E}}(R_b)}{\sigma_{\mathcal{T}}(R_a - R_b)}, \tag{5.5}$$

where $\sigma_{\mathcal{T}} = \sqrt{\mathbb{E}_{\mathcal{T}}(x^2) - \mathbb{E}_{\mathcal{T}}(x)^2}$. Performing the computation for each of the bootstrap replications allows to account for parameter estimation uncertainty.

Table 5 contains the estimates of these model-implied financial indicators along with the 95% confidence interval bounds obtained by the percentile method. The panels break down the results by choice of the copula correlation parameter and each panel reports the estimates for the three sets of test assets. The column labeled *data* reports the values of the indicators in the sample period 1947:Q2-2014:Q4.

[insert Table 5 about here]

Table 5 shows that the magnitude of the model-implied equity premium, mean T-bill return and the market Sharpe ratio are perfectly plausible and comparable in to their sample equivalents. This finding is robust with respect to the choice of the copula correlation coefficient and the set of test assets. The model-implied $\hat{\mathbb{E}}(R_b)$ and $\hat{\mathbb{E}}(R_a)$ are somewhat smaller than the average T-bill return and the market return in the empirical data. This is due to the fact that the model-implied indicators account for the possibility of consumption disasters that affect the simulated moments, whilst the empirical data do not contain any disaster observation. However, the observed mean T-bill, mean market return and equity premium lie within the 95% confidence interval bounds, which account for the first- and second-step estimation error.

When using only the market portfolio and the T-bill as test assets, the model is exactly identified, so one may wonder whether this drives the favorable results.

However, exact identification does not imply that the empirical mean market return and mean T-bill return have to be matched by their model-implied counterparts. When using the *size dec* or *industry* portfolios, the market portfolio is not even among the set of test assets. Hence, these specifications serve as an out-of-sample plausibility test. In these instances, $\widehat{\mathbb{E}}(R_a)$ and the model-implied equity premium are still perfectly plausible and comparable to the empirical counterparts. In all instances, the confidence intervals overlap the empirically observed values.

The meaningful asset pricing implications of the estimated disaster-including C-CAPM show that the model can explain the considerable postwar equity premium and the relatively low T-bill return with plausible investor preferences. Unlike in previous studies of the rare disaster hypothesis, risk aversion, time preferences, and IES are not calibrated, i.e. conveniently chosen, but they are obtained from applying an econometric estimation strategy. These results thus provide new empirical evidence that the rare disaster hypothesis indeed offers a solution to the equity premium puzzle.

5.4 Robustness checks

As robustness check, I perform bias-corrections on the parameter estimates and confidence bounds, and report the results in Table 6. Following Efron and Tibshirani (1986), I compute bias-corrected estimates of a parameter ϑ as $\hat{\vartheta}_{BC} = 2\hat{\vartheta} - \frac{1}{K}\sum_{k=1}^{K}\hat{\vartheta}^{(k)}$. The lower and upper bounds of the bias-corrected $1-\alpha$ confidence interval are computed as $\vartheta^l_{BC}(\alpha) = \hat{G}^{-1}[\Phi(z_{\alpha/2} + 2\Phi^{-1}[\hat{G}(\hat{\vartheta})])]$ and $\vartheta^u_{BC}(\alpha) = \hat{G}^{-1}[\Phi(z_{1-\alpha/2} + 2\Phi^{-1}[\hat{G}(\hat{\vartheta})])]$, where Φ denotes the cdf, Φ^{-1} the quantile function, and $z_{\tilde{\alpha}}$ the $\tilde{\alpha}$-quantile of the standard normal distribution.[13] Comparing the results in Table 6 with those in Table 4, I find that in all instances the corrections are rather benign.

[13] According to this notation, the uncorrected confidence bounds reported in Table 4 are computed as $\vartheta^l(\alpha) = \hat{G}^{-1}[\Phi(z_{\alpha/2})]$ and $\vartheta^u(\alpha) = \hat{G}^{-1}[\Phi(z_{1-\alpha/2})]$.

That the bias-corrected estimates and confidence intervals are very similar to the uncorrected counterparts can be taken as a sign of robustness.

[insert Table 6 about here]

The second robustness check investigates the effect of varying the disaster threshold q. Panel A of Table 7 uses q=0.095 and Panel B reports results for q=0.195. These values are chosen in accordance with Barro and Jin (2011) and feature prominently in the rare disaster literature. The results contained in Table 7 convey that the choice of q barely affects the parameter estimates; a finding that may be surprising at first, but that is a consequence of the multi-period character of the disasters: The effects of different choices of q enter the data simulation procedure through the ACH-PL estimates $\hat{\boldsymbol{\theta}}_{ACH}$ and $\theta^{+}_{PL}, \theta_{PL}$ which are obtained from quarterly (contraction) data that are computed from annual (disaster) periods. As $\theta^{+}_{PL}, \theta_{PL}$ contain information on the distribution of quarterly contractions, they could only vary strongly with q if the distribution of annual contraction sizes of disasters that were detected with a threshold of 0.095 was pronouncedly different from the one of disasters that were detected with q=0.195, but this is not the case.

[insert Table 7 about here]

I conclude that the estimation results are robust with respect to alternative data simulation procedures, test assets, and disaster thresholds. The fact that they are also quite unbiased serves as a further plus.

6 Conclusion

Empirical tests of Hansen and Singleton's (1982) canonical C-CAPM have been notoriously disappointing. Yet, the model approach is not easily discarded because it represents the rational link between the real economy and financial markets, and consequently many attempts have been made to vindicate the C-CAPM paradigm. Within the canonical time-additive power-utility C-CAPM, scaled factors have been constructed to account for time-varying risk aversion (Lettau and Ludvigson (2001)) and alternative measures for the errors-in-variables-prone consumption data have been employed (e.g. Julliard and Parker (2005), Savov (2011), Yogo (2006)). The main theoretical extensions of the canoncial C-CAPM focus on investor heterogeneity (Constantinides and Duffie (1996)), habit formation (Campbell and Cochrane (1999)), and long-run-risks (Bansal and Yaron (2004)). Although these efforts can claim some empirical success, the problem of implausible and imprecise preference parameter estimates and problematic asset pricing implications of the estimated model (e.g. a too low model-implied equity premium and a too high risk-free rate) has been, at best, only mitigated.

Rietz (1988) offered another explanation for the model's poor empirical performance: the rare disaster hypothesis, according to which the apparent failure of the C-CAPM results as a consequence of the agreeable path that the U.S. economy took after WWII. Empirical tests of the explanations are, similarly to the RDH, hampered by the presence of unobservable model components, such that calibrations prevail. However, this path may not be representative for the potentially disastrous future consumption that investors in the 1950s to 1980s had in mind. In the middle of the Cold War, the benign U.S. consumption path was just one amongst more unfavorable histories.

This study adopts Barro's (2006) specification of a disaster-including consumption process and derives moment restrictions that allow to estimate a disaster-including C-CAPM by an SMM-type strategy. The approach presented in this paper takes into account three main drawbacks of previous studies that aim to test the rare disaster hypothesis empirically. First, I allow for multi-period disasters. It has been argued that the success of the rare disaster hypothesis in calibration studies relies on the assumption that the entire disastrous contraction occurs in one period (see Julliard and Ghosh (2012) and Constantinides' (2008) comment on Barro and Ursúa (2008)). Second, I use Epstein-Zin preferences instead of a power utility to allow for preferences for an early resolution of uncertainty. Third, I allow for the possibility of a partial government default. Accounting for these three issues is indeed crucial to back the rare disaster hypothesis empirically.

For SMM-type estimation, I simulate disaster-including consumption growth and return series by means of a discrete-time marked point process that models the time duration of and between disasters, and the magnitude of contractions using a power law distribution. Parameter estimates of the MPP model are obtained by maximum likelihood using chained country-panel data. Neither the choice of test assets or disaster thresholds change the results qualitatively: The magnitude of the estimated preference parameters is economically plausible, and the estimation precision is much higher than in previous C-CAPM studies. The subjective discount factor estimate is about 0.99 in all specifications; the RRA estimates (and the 95% confidence bounds, too) fall within a strict plausibility range, and the IES parameter estimates are significantly greater than unity. The relative magnitude of the estimated IES and RRA indicate a preference for early resolution of uncertainty, which is, in conjunction with an IES greater than unity, an important condition to obtain meaningful asset pricing implications. Computing model-implied mean market return, T-bill rate and market Sharpe ratio reveals that the disaster-including C-CAPM can indeed explain these key financial indicators based on economically meaningful preference parameter estimates.

To the best of my knowledge, the present study is the first that estimates all the preference parameters of a C-CAPM with Epstein-Zin preferences and multi-period disasters. It corroborates that the rare disaster hypothesis can serve as a possible solution to the equity premium puzzle even when disasters do not shrink to one-period events. The nexus between finance and the real economy postulated by the C-CAPM is, after all, empirically not refuted.

A Appendix

A.1 Transformation of annual into quarterly consumption contractions

The ACH-PL model assumes a quarterly observation frequency. To obtain four quarterly contractions from an annual observation, I draw from a standard uniform distribution and determine the fraction of the annual contraction that is assigned to the first quarter. How much of the remaining contraction is allocated to the second quarter is determined by another standard uniform draw. The contraction assigned to the third quarter is determined the same way. The last quarter takes what is left of the annual contraction. This procedure implies that the contraction in the first (last) quarter would be the largest (smallest) on average. To avoid such a seasonal pattern, I re-shuffle the four quarterly contractions randomly. This procedure applies to a year that is not the first or the last of a disaster. When dealing with the first (last) year within a disaster, or if the disaster consists of only one annual contraction, I determine the quarter when the contraction begins (ends) by a draw from a discrete uniform distribution, such that each quarter has probability 1/4 to become the quarter when the disaster begins (ends). The annual contraction is then distributed across the disaster quarters in an analogous way as for a "within" disaster year.

A.2 Bootstrap inference

Bootstrap inference for the second-step preference parameter estimates is based on a mix of parametric and non-parametric bootstrap. Using the first-step maximum likelihood estimates $\hat{\boldsymbol{\theta}}_{ACH}$, $\hat{\theta}_{PL}$, and $\hat{\theta}^{+}_{PL}$, I simulate a series of hazard rates, consumption contractions, and disaster indicators d_s and d^{+}_s as described in Section 4.2. The length of the simulated series is equal to the number of observations in the concatenated country data. Next, $\boldsymbol{\theta}_{ACH}$ and $\boldsymbol{\theta}_{PL}$ are re-estimated on the simulated series. These steps are repeated K times, and the estimates are collected in $\{\hat{\boldsymbol{\theta}}_{ACH}^{(k)}, \hat{\theta}_{PL}^{(k)}, \hat{\theta}_{PL}^{+(k)}\}_{k=1}^{K}$. Because I draw from the parametric ACH-PL distribution using the maximum likelihood estimates, this procedure can be characterized as a parametric bootstrap. It complements the asymptotic inference that is available for the first estimation step, but it is also the crucial input for the inference about the second-step SMM estimates of the preference parameters.

For each of the K replications, I then perform a block-bootstrap to obtain series of non-disastrous consumption growth $\{cg_{nd,l}^{(k)}\}_{l=1}^{T}$, market and T-bill returns $\{R_{nd,a,l}^{(k)}\}_{l=1}^{T}$, $\{R_{nd,b,l}^{(k)}\}_{l=1}^{T}$ as well as test asset returns $\{R_{nd,i,l}^{(k)}\}_{l=1}^{T}$. As described previously, I determine the mean of the geometric distribution, from which the block-lengths are drawn using Politis et al.'s (2009) automatic block-length selection algorithm. The length of the bootstrap data series (T) is the same as in the original financial and macro data. Draws from the series are exerted simultaneously to retain their contemporaneous dependence (see Maio and Santa-Clara (2012) for a similar approach).

To compute the simulated moments for each replication, I proceed as described in Section 4.2 and generate disaster-including data of length $\mathcal{T}$, $\{cg_s^{(k)}\}_{s=1}^{\mathcal{T}}$, $\{R_{i,s}^{(k)}\}_{s=1}^{\mathcal{T}}$, $\{R_{b,s}^{(k)}\}_{s=1}^{\mathcal{T}}$, and $\{R_{a,s}^{(k)}\}_{s=1}^{\mathcal{T}}$. For that purpose, I use the parametric bootstrap estimates $\hat{\boldsymbol{\theta}}_{ACH}^{(k)}$, $\hat{\theta}_{PL}^{(k)}$, and $\hat{\theta}_{PL}^{+(k)}$ obtained from the maximum likelihood estimation on the simulated data (instead of the original data). The block-bootstrap from non-disastrous data that is required to compute the simulated moments is performed on $\{cg_{nd,l}^{(k)}\}_{l=1}^{T}$, $\{R_{nd,a,l}^{(k)}\}_{l=1}^{T}$, $\{R_{nd,b,l}^{(k)}\}_{l=1}^{T}$, and $\{R_{nd,i,l}^{(k)}\}_{l=1}^{T}$ (instead of the original data). SMM-type estimation of the preference parameters β, γ, and ψ then proceeds as described in Section 2.1. Performing these steps for each of the K replications yields $\{\hat{\beta}^{(k)}, \hat{\gamma}^{(k)}, \hat{\psi}^{(k)}\}_{k=1}^{K}$, for which standard deviations and confidence intervals using the percentile method can be computed.

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Tables and Figures

Table 1: **Country panel data used for the first-step estimation**
This table lists the 35 countries and time periods with available data that provide the basis for the ACH-PL estimation. The second column reports the time periods for which consumption data assembled by Barro and Ursúa (2008) are available (beginning with 1800 onwards).

Country	Barro and Ursúa
Argentina	1875 – 2009
Australia	1901 – 2009
Austria	1913 – 1918, 1924 – 1944, 1947 – 2009
Belgium	1913 – 2009
Brazil	1901 – 2009
Canada	1871 – 2009
Chile	1900 – 2009
Colombia	1925 – 2009
Denmark	1844 – 2009
Finland	1860 – 2009
France	1824 – 2009
Germany	1851 – 2009
Greece	1938 – 2009
India	1919 – 2009
Indonesia	1960 – 2009
Italy	1861 – 2009
Japan	1874 – 2009
Malaysia	1900 – 1939, 1947 – 2009
Mexico	1900 – 2009
the Netherlands	1807 – 1809, 1814 – 2009
New Zealand	1878 – 2009
Norway	1830 – 2009
the Philippines	1946 – 2009
Peru	1896 – 2009
Portugal	1910 – 2009
South Korea	1911 – 2009
Spain	1850 – 2009
Sri Lanka	1960 – 2009
Sweden	1800 – 2009
Switzerland	1851 – 2009
Taiwan	1901 – 2009
UK	1830 – 2009
USA	1834 – 2009
Uruguay	1960 – 2009
Venezuela	1923 – 2009

Table 2: **Descriptive statistics: Consumption and test asset returns 1947:Q2–2014:Q4** This table contains the descriptive statistics of consumption growth and gross returns of the three sets of test assets. Panel A: CRSP value-weighted market portfolio R_a and T-bill return R_b (*mkt*), Panel B: ten size-sorted portfolios and R_b (*size dec*), and Panel C: ten industry portfolios and R_b (*industry*). The data range is 1947:Q2–2014:Q4. In Panel B, 1^{st}, 2^{nd}, and so on refer to the deciles of the the ten size-sorted portfolios. The ten industry portfolios in Panel C are: non-durables (*NoDur*: food, textiles, tobacco, apparel, leather, toys), durables (*Durbl*: cars, TVs, furniture, household appliances), manufacturing (*Manuf*: machinery, trucks, planes, chemicals, paper, office furniture), energy (*Engry*: oil, gas, coal extraction and products), business equipment (*HiTec*: computers, software, and electronic equipment), telecommunication (*Telcm*: telephone and television transmission), shops (*Shops* : wholesale, retail, laundries, and repair shops), health (*Hlth*: healthcare, medical equipment, and drugs), utilities (*Utils*), and others (*Other*: transportation, entertainment, finance, and hotels). The column labeled *ac* gives the first order autocorrelation, and *std* is the standard deviation.

Panel A: mkt

	mean	std	ac	correlations	
				$\frac{C_{t+1}}{C_t}$	R_b
market	1.0211	0.0816	0.084	0.175	0.026
R_b	1.0017	0.0045	0.857	0.204	
$\frac{C_{t+1}}{C_t}$	1.0048	0.0051	0.311		

Panel B: size dec

	mean	std	ac	correlations										
				$\frac{C_{t+1}}{C_t}$	R_b	10^{th}	9^{th}	8^{th}	7^{th}	6^{th}	5^{th}	4^{th}	3^{rd}	2^{nd}
1^{st}	1.0290	0.1251	0.061	0.178	-0.015	0.711	0.818	0.857	0.884	0.895	0.912	0.931	0.949	0.964
2^{nd}	1.0271	0.1177	-0.001	0.172	0.005	0.781	0.871	0.915	0.933	0.947	0.961	0.974	0.982	
3^{rd}	1.0287	0.1115	-0.024	0.165	-0.001	0.818	0.907	0.943	0.956	0.968	0.976	0.985		
4^{th}	1.0270	0.1072	-0.018	0.165	0.002	0.830	0.914	0.948	0.962	0.976	0.983			
5^{th}	1.0274	0.1036	0.013	0.167	0.019	0.855	0.936	0.967	0.972	0.982				
6^{th}	1.0262	0.0971	0.019	0.143	0.001	0.868	0.946	0.970	0.977					
7^{th}	1.0262	0.0964	0.042	0.157	0.009	0.892	0.965	0.982						
8^{th}	1.0249	0.0923	0.022	0.145	0.019	0.906	0.975							
9^{th}	1.0237	0.0841	0.068	0.148	0.021	0.935								
10^{th}	1.0198	0.0767	0.119	0.178	0.043									

Panel C: industry

	mean	std	ac	correlations										
				$\frac{C_{t+1}}{C_t}$	R_b	Other	Utils	Hlth	Shops	Telcm	HiTec	Engry	Manuf	Durbl
NoDur	1.0238	0.0811	0.047	0.090	0.105	0.838	0.674	0.800	0.871	0.656	0.642	0.445	0.829	0.685
Durbl	1.0236	0.1156	0.103	0.190	0.009	0.801	0.484	0.520	0.773	0.581	0.690	0.490	0.832	
Manuf	1.0229	0.0899	0.082	0.173	0.014	0.901	0.580	0.745	0.825	0.647	0.807	0.635		
Engry	1.0253	0.0888	0.041	0.163	-0.039	0.592	0.534	0.423	0.422	0.432	0.497			
HiTec	1.0258	0.1159	0.070	0.167	-0.000	0.758	0.470	0.663	0.733	0.659				
Telcm	1.0187	0.0805	0.148	0.099	0.104	0.695	0.627	0.568	0.668					
Shops	1.0238	0.0957	0.039	0.158	0.044	0.837	0.557	0.704						
Hlth	1.0271	0.0909	0.054	0.092	0.085	0.726	0.542							
Utils	1.0195	0.0711	0.080	0.069	0.071	0.655								
Other	1.0217	0.0982	0.078	0.159	0.034									

Table 3: **Estimation results for the ACH-PL model**
This table reports the ACH-PL maximum likelihood estimates. $\mathcal{L}$ is the log likelihood value at the maximum, and AIC = $2k - 2\ln(\mathcal{L})$ and SBC = $-2\ln\mathcal{L} + k\ln(T)$, where k is the number of ACH model parameters, denote the Akaike and Schwarz-Bayes information criteria. $\mathcal{LR}$ gives the p-values (in percent) of the likelihood ratio tests of the null hypothesis that the parameter restrictions implied by the ACH_0 specification are correct. The respective alternative is the ACH_1, the ACH_2, the ACH_3, or the ACH_4 model. The estimation results are based on the updated country panel data originally assembled by Barro and Ursúa (2008), using the concatenated event data representation described in Section 3 and $q = 0.145$. Asymptotic standard errors are reported in parentheses.

	θ^+_{PL}	θ_{PL}	μ	$\tilde{\mu}$	α	$\tilde{\alpha}$	δ	$\tilde{\delta}$	$\mathcal{L}$	AIC	SBC	$\mathcal{LR}$
ACH_0			178.3	1.201					-790.3	1584.7	**1600.1**	
			(18.8)	(0.023)								
ACH_4			64.9	1.201			441.1		-787.0	**1580.0**	1603.2	<1.0
			(49.3)	(0.023)			(211.5)					
ACH_3			64.9	1.214			441.1	-0.375	-786.8	1581.5	1612.5	2.9
			(49.3)	(0.032)			(211.5)	(0.537)				
ACH_2			198.7	1.221	-0.145	-0.002			-789.9	1587.7	1618.7	63.5
			(30.9)	(0.052)	(0.153)	(0.004)						
ACH_1			71.4	1.237	-0.030	-0.002	431.0	-0.399	-786.6	1585.3	1631.7	11.8
			(55.0)	(0.058)	(0.161)	(0.004)	(120.4)	(0.542)				
PL	37.255	35.687										
	(1.478)	(1.696)										

Table 4: **SMM estimates of the C-CAPM preference parameters**

This table reports the estimates of the subjective discount factor β, the coefficient of relative risk aversion γ, and the IES ψ using the moment matches in Equation (4.17), $\mathcal{T}$=10^7 and the weighting matrix in Equation (4.19). The second-step SMM-type estimates are based on the first-step ACH_4-PL and ACH_0-PL estimates, respectively, reported in Table 3. The numbers in parentheses are bootstrap standard errors. The numbers in brackets are the upper and lower bounds of the 95% confidence intervals computed as the α=0.025 and α=0.975 quantiles of the bootstrap distribution (percentile method). The table also reports the p-values (in percent) of Hansen's (1982) J-statistic (see Equation (5.1)) and root mean squared errors (R), computed according to Equation (5.2). Panels A-C break down the results by the copula correlation assumed in the data simulation procedure. Each panel reports the results by set of test assets, the excess returns of *mkt*, *size dec*, and *industry*, each augmented by the T-bill return.

	mkt			**size dec**					**industry**				
Panel A: ρ = Corr($cg_{nd,t}$, $R_{nd,t}$)													
	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	J	R	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	J	R
ACH_0	**0.9917** (0.0022)	**1.51** (0.30)	**1.50** (0.15)	**0.9939** (0.0047)	**1.60** (0.29)	**1.50** (0.15)	83.5	9	**0.9944** (0.0038)	**1.62** (0.32)	**1.50** (0.15)	11.7	39
	[0.9872 0.9957]	[1.10 2.29]	[1.31 1.88]	[0.9864 1.0052]	[1.24 2.34]	[1.29 1.88]			[0.9887 1.0032]	[1.20 2.44]	[1.29 1.88]		
ACH_4	**0.9920** (0.0023)	**1.54** (0.30)	**1.67** (0.15)	**0.9945** (0.0052)	**1.63** (0.29)	**1.65** (0.16)	68.7	11	**0.9947** (0.0071)	**1.64** (0.31)	**1.65** (0.16)	7.2	40
	[0.9872 0.9960]	[1.08 2.33]	[1.31 1.87]	[0.9862 1.0057]	[1.22 2.40]	[1.28 1.87]			[0.9891 1.0035]	[1.17 2.40]	[1.28 1.86]		
Panel B: ρ = 0.99													
	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	J	R	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	J	R
ACH_0	**0.9915** (0.0022)	**1.51** (0.30)	**1.51** (0.15)	**0.9938** (0.0047)	**1.61** (0.29)	**1.51** (0.15)	83.3	9	**0.9942** (0.0038)	**1.62** (0.32)	**1.51** (0.15)	11.9	39
	[0.9870 0.9957]	[1.09 2.26]	[1.31 1.88]	[0.9861 1.0051]	[1.24 2.34]	[1.29 1.87]			[0.9885 1.0031]	[1.20 2.43]	[1.29 1.87]		
ACH_4	**0.9917** (0.0023)	**1.54** (0.31)	**1.68** (0.15)	**0.9942** (0.0067)	**1.64** (0.29)	**1.67** (0.15)	68.2	11	**0.9944** (0.0053)	**1.65** (0.32)	**1.67** (0.16)	7.6	40
	[0.9869 0.9959]	[1.05 2.32]	[1.30 1.87]	[0.9864 1.0061]	[1.19 2.33]	[1.29 1.87]			[0.9883 1.0035]	[1.17 2.46]	[1.28 1.87]		
Panel C: ρ = 0													
	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	J	R	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	J	R
ACH_0	**0.9917** (0.0022)	**1.51** (0.30)	**1.50** (0.15)	**0.9939** (0.0047)	**1.60** (0.29)	**1.50** (0.15)	83.5	9	**0.9944** (0.0038)	**1.62** (0.32)	**1.50** (0.15)	11.7	39
	[0.9871 0.9959]	[1.10 2.28]	[1.31 1.88]	[0.9863 1.0052]	[1.24 2.34]	[1.29 1.88]			[0.9887 1.0032]	[1.20 2.44]	[1.29 1.88]		
ACH_4	**0.9920** (0.0024)	**1.54** (0.30)	**1.66** (0.15)	**0.9945** (0.0050)	**1.63** (0.28)	**1.64** (0.16)	68.7	11	**0.9948** (0.0069)	**1.64** (0.31)	**1.64** (0.15)	7.2	40
	[0.9872 0.9963]	[1.07 2.26]	[1.33 1.87]	[0.9863 1.0055]	[1.22 2.34]	[1.28 1.86]			[0.9889 1.0026]	[1.18 2.39]	[1.28 1.87]		

Table 5: **Model-implied key financial indicators**

The table presents estimates of the mean T-bill return, mean market return, equity premium and market Sharpe ratio implied by the disaster-including C-CAPM and computed according to Equations (5.3)-(5.5). The computation uses the SMM-type estimates of β, γ and ψ based on the ACH_0 first-step estimates (see Table 4). The numbers in brackets are the lower and upper bounds of the 95% confidence intervals computed using the percentile method. Panels A-C break down the results by the copula correlation coefficient used in the data simulation procedure, and each panel reports the results by set of test assets. The column labeled *data* reports the values of the indicators in the empirical data, 1947:Q2–2014:Q4.

		Panel A: ρ = Corr(cg_{nd}, R_{nd})		
	data	**mkt**	**size dec**	**industry**
$\hat{\theta} = (1-\hat{\gamma})/(1-\frac{1}{\hat{\psi}})$		-1.54	-1.81	-1.86
		[-3.55 -0.21]	[-3.77 -0.64]	[-4.07 -0.48]
mean T-bill return	*0.17*	0.10	0.12	0.14
(% per qtr)		[-0.13 0.29]	[-0.18 0.33]	[-0.17 0.36]
equity premium	*1.94*	1.85	2.06	2.11
(% per qtr)		[0.98 2.76]	[1.36 2.83]	[1.23 3.08]
mean market return	*2.11*	1.95	2.19	2.25
(% per qtr)		[1.13 2.80]	[1.51 2.89]	[1.38 3.09]
Sharpe ratio	*0.237*	0.226	0.252	0.257
(market)		[0.111 0.378]	[0.154 0.394]	[0.139 0.427]

	Panel B: $\rho = 0.99$		
	mkt	**size dec**	**industry**
$\hat{\theta} = (1-\hat{\gamma})/(1-\frac{1}{\hat{\psi}})$	-1.53	-1.80	-1.85
	[-3.51 -0.20]	[-3.75 -0.63]	[-4.05 -0.47]
mean T-bill return	0.10	0.13	0.14
(% per qtr)	[-0.12 0.29]	[-0.18 0.33]	[-0.16 0.36]
equity premium	1.85	2.06	2.11
(% per qtr)	[0.97 2.72]	[1.36 2.83]	[1.23 3.08]
mean market return	1.95	2.19	2.25
(% per qtr)	[1.13 2.78]	[1.50 2.89]	[1.38 3.09]
Sharpe ratio	0.226	0.252	0.257
(market)	[0.111 0.370]	[0.153 0.394]	[0.139 0.427]

	Panel C: $\rho = 0$		
	mkt	**size dec**	**industry**
$\hat{\theta} = (1-\hat{\gamma})/(1-\frac{1}{\hat{\psi}})$	-1.54	-1.80	-1.86
	[-3.50 -0.21]	[-3.76 -0.64]	[-4.07 -0.48]
mean T-bill return	0.10	0.13	0.14
(% per qtr)	[-0.12 0.29]	[-0.18 0.34]	[-0.16 0.36]
equity premium	1.84	2.05	2.09
(% per qtr)	[0.97 2.71]	[1.35 2.79]	[1.22 3.05]
mean market return	1.94	2.18	2.23
(% per qtr)	[1.12 2.76]	[1.50 2.87]	[1.37 3.07]
Sharpe ratio	0.225	0.251	0.256
(market)	[0.110 0.368]	[0.153 0.391]	[0.139 0.423]

Table 6: **Bias-corrected C-CAPM preference parameter estimates and confidence intervals**
This table presents bias-corrected estimates (bold) and 95% confidence bounds (in brackets) of the subjective discount factor β, the coefficient of relative risk aversion γ, and the IES ψ. The bias-correction of the point estimates and confidence bounds in Table 4 is performed according to Efron and Tibshirani (1986).

Panel A: $\rho = \mathbf{Corr}(\mathbf{cg_{nd}}, \mathbf{R_{nd}})$									
	mkt			**size dec**			**industry**		
	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$
ACH_0	**0.9918**	**1.44**	**1.40**	**0.9938**	**1.50**	**1.40**	**0.9942**	**1.52**	**1.40**
	[0.9877 0.9963]	[1.01 2.11]	[1.13 1.69]	[0.9871 1.0068]	[1.19 2.18]	[1.08 1.72]	[0.9893 1.0043]	[1.12 2.26]	[1.08 1.72]
ACH_4	**0.9924**	**1.49**	**1.73**	**0.9947**	**1.59**	**1.70**	**0.9948**	**1.61**	**1.69**
	[0.9881 0.9972]	[1.05 2.29]	[1.41 1.93]	[0.9871 1.0088]	[1.21 2.34]	[1.36 1.93]	[0.9894 1.0050]	[1.16 2.38]	[1.33 1.91]
Panel B: $\rho = 0.99$									
	mkt			**size dec**			**industry**		
	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$
ACH_0	**0.9916**	**1.46**	**1.41**	**0.9937**	**1.51**	**1.42**	**0.9940**	**1.53**	**1.42**
	[0.9875 0.9961]	[1.03 2.13]	[1.14 1.70]	[0.9869 1.0068]	[1.19 2.19]	[1.09 1.72]	[0.9891 1.0043]	[1.12 2.27]	[1.09 1.72]
ACH_4	**0.9918**	**1.50**	**1.75**	**0.9940**	**1.59**	**1.74**	**0.9944**	**1.60**	**1.74**
	[0.9873 0.9963]	[1.06 2.33]	[1.44 1.93]	[0.9876 1.0090]	[1.17 2.28]	[1.41 1.95]	[0.9887 1.0050]	[1.16 2.44]	[1.42 1.94]
Panel C: $\rho = 0$									
	mkt			**size dec**			**industry**		
	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$
ACH_0	**0.9918**	**1.45**	**1.39**	**0.9938**	**1.50**	**1.40**	**0.9942**	**1.51**	**1.40**
	[0.9877 0.9965]	[1.00 2.12]	[1.13 1.68]	[0.9871 1.0068]	[1.19 2.18]	[1.08 1.71]	[0.9894 1.0045]	[1.12 2.26]	[1.08 1.71]
ACH_4	**0.9923**	**1.50**	**1.73**	**0.9949**	**1.57**	**1.69**	**0.9950**	**1.59**	**1.69**
	[0.9878 0.9968]	[1.07 2.25]	[1.39 1.92]	[0.9877 1.0104]	[1.17 2.27]	[1.35 1.90]	[0.9896 1.0041]	[1.16 2.36]	[1.38 1.93]

Table 7: **C-CAPM preference parameters with varying disaster thresholds**

This table presents the SMM-type estimates of the preference parameters β, γ, and ψ using $\rho = 0.99$. Panel A relies on $q = 0.095$ and Panel B contains results for $q = 0.195$. Other estimation settings and the reported statistics correspond to Table 4.

Panel A: $q = 0.095/\rho = \mathrm{Corr}(\mathrm{cg_{nd}}, \mathrm{R_{nd}})$

	mkt			**size dec**					**industry**				
	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	J	R	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	J	R
ACH_0	**0.9918** (0.0047)	**1.49** (0.29)	**1.48** (0.14)	**0.9938** (0.0050)	**1.56** (0.26)	**1.49** (0.14)	78.9	10	**0.9942** (0.0090)	**1.57** (0.32)	**1.49** (0.14)	11.5	39
	[0.9878 0.9960]	[1.03 2.15]	[1.33 1.86]	[0.9864 1.0050]	[1.24 2.24]	[1.34 1.87]			[0.9891 1.0047]	[1.14 2.41]	[1.34 1.87]		
ACH_4	**0.9919** (0.0023)	**1.51** (0.30)	**1.58** (0.14)	**0.9941** (0.0051)	**1.56** (0.29)	**1.58** (0.14)	67.0	11	**0.9942** (0.0089)	**1.57** (0.32)	**1.58** (0.14)	8.9	39
	[0.9874 0.9962]	[1.07 2.23]	[1.34 1.87]	[0.9868 1.0053]	[1.22 2.33]	[1.31 1.86]			[0.9893 1.0037]	[1.14 2.39]	[1.31 1.86]		

Panel B: $q = 0.195/\rho = \mathrm{Corr}(\mathrm{cg_{nd}}, \mathrm{R_{nd}})$

	mkt			**size dec**					**industry**				
	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	J	R	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\psi}$	J	R
ACH_0	**0.9917** (0.0023)	**1.51** (0.30)	**1.49** (0.16)	**0.9938** (0.0044)	**1.58** (0.27)	**1.47** (0.16)	84.9	9	**0.9943** (0.0034)	**1.60** (0.31)	**1.47** (0.16)	13.1	39
	[0.9869 0.9958]	[1.08 2.25]	[1.26 1.86]	[0.9863 1.0044]	[1.24 2.28]	[1.27 1.86]			[0.9893 1.0021]	[1.21 2.34]	[1.27 1.86]		
ACH_4	**0.9917** (0.0023)	**1.57** (0.30)	**1.63** (0.17)	**0.9940** (0.0061)	**1.66** (0.36)	**1.63** (0.19)	80.2	9	**0.9943** (0.0087)	**1.68** (0.48)	**1.63** (0.20)	11.4	39
	[0.9869 0.9959]	[1.08 2.22]	[1.26 1.89]	[0.9862 1.0063]	[1.15 2.32]	[1.19 1.88]			[0.9886 1.0040]	[1.08 2.44]	[1.17 1.88]		

Figure 1: **Consumption disasters**

This figure depicts the 89 consumption disasters identified from Barro and Ursúa's (2008) country panel data (updated). The sampling period is 1800–2009. The disaster threshold q=0.145 in both cases. Black lines denote European countries, red lines South American countries and Mexico, golden lines Western offshores (Australia, Canada, New Zealand, and U.S.A.), and blue lines represent Asian countries. The dotted horizontal line depicts the average contraction size.

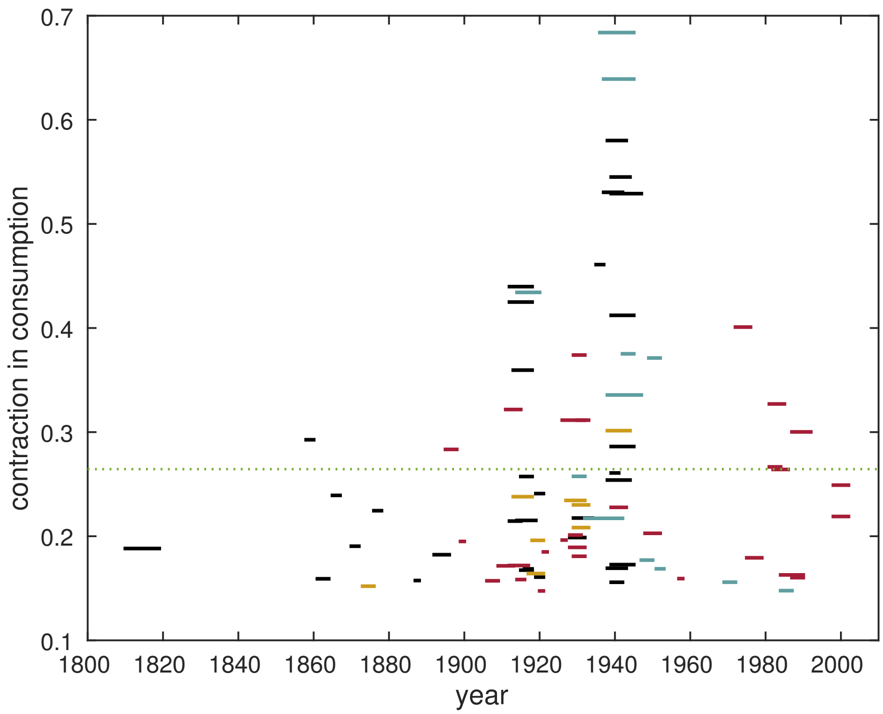
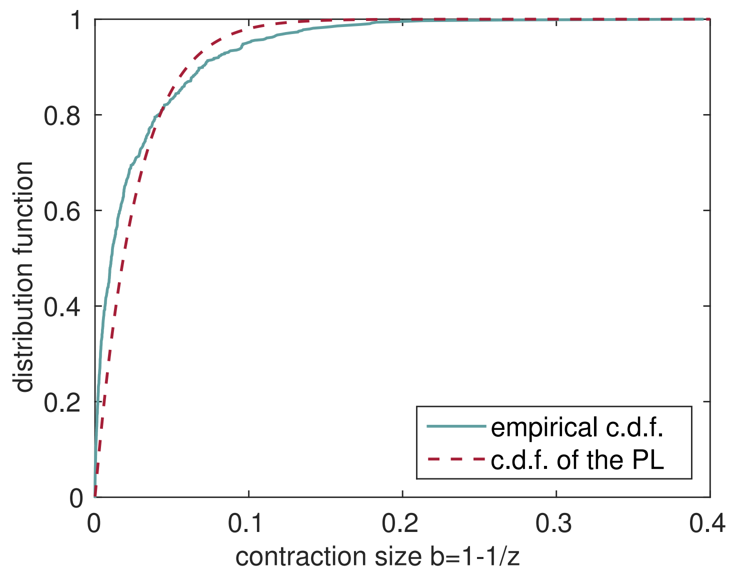
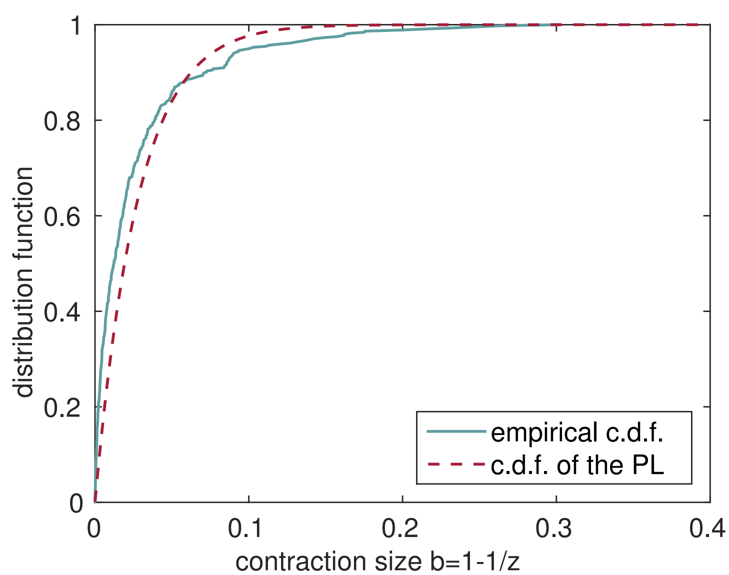


Figure 2: **Fitted Power Law vs. empirical cdf**
This figure illustrates the empirical cdfs (solid lines) and the fitted cdf (dotted lines) of the contractions identified in Barro and Ursúa's (2008) data using a disaster threshold of q=0.145. Panel (a) captures the distribution of contractions that occur at the beginning of a disaster and contribute to reaching the disaster threshold. Panel (b) refers to contractions that add on top of the disaster threshold. The fitted cdfs use the PL parameter estimates from Table 3.



(a) cdf fit for contractions that contribute to reaching q



(b) cdf fit for contractions that add on top of q