Empirical Asset Pricing with Multi-Period Disasters
A Simulation-Based Approach

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Abstract

We propose a simulation-based strategy to estimate and test an asset pricing model that accounts for rare but severe consumption contractions that can extend over multiple periods. Our approach expands the scope of prevalent calibration studies and tackles the inherent sample selection problem faced when empirically assessing the effect of rare disaster risk on asset prices. The application of this new methodology using a combination of U.S. and cross-country panel data yields estimates of the investor preference parameters that are plausible, reasonably precise, and robust with respect to alternative model specifications. The market equity premium and Sharpe ratio implied by these parameter estimates are consistent with empirical data, and the timing premium computed as proposed by Epstein et al. (2014) has an economically meaningful magnitude. These results suggest that the rare disaster hypothesis can help restore the nexus between the real economy and financial markets when allowing for multi-period disasters.

Key words: empirical asset pricing, multi-period disasters, simulation-based estimation, equity premium puzzle

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1 Introduction

According to Rietz's (1988) rare disaster hypothesis (hereafter RDH), the extraordinary equity premia of U.S. portfolios during the postwar period resulted because investors ex ante demanded compensation for possibly disastrous but unlikely risks that they never suffered from. In turn, the RDH holds the promise to resolve the equity premium puzzle and the poor empirical performance of Hansen and Singleton's (1982) canonical consumption-based asset pricing model (C-CAPM). The weakness of the rare disaster explanation is that it is difficult to assess statistically using data that contain only very few or no disastrous consumption contractions. Most studies mitigate the sample selection problem by resorting to calibration methods. Yet, there is a paucity of econometric analyses that test the RDH, and those that exist question its explanatory power when disastrous consumption contractions can build up over multiple time periods.

We contribute to this discussion by proposing a novel methodology that aims to resolve the inherent sample selection problem that hampers the empirical assessment of the RDH. As suggested by Blanchard (2008), we cast off the straightjacket of a fully parametrized structural model and instead identify the parameters of interest through moment conditions implied by the basic asset pricing equation of a disaster-including C-CAPM. By allowing for multi-period disaster events, which are conceived of as a marked point process (MPP), we take account of the caveat that the success of the RDH may hinge on the assumption that consumption disasters unfold within a single period.

The empirical challenges demand a non-standard methodological solution. Inspired by ideas put forth by Dridi et al. (2007), our simulation-based approach combines advantages of econometric analysis – the appraisal of loss functions and conditions for validity – with calibration practices, like the use of different data sources for estimation of different parts of a model. The econometric analysis consists of two consecutive steps: using maximum likelihood to estimate the parameters of the MPP based on historical cross-country consumption data, and then a simulation-based estimation of the investor preference parameters using U.S.

macroeconomic and financial data. Heaton's (1995) simulated method of moments (SMM) approach can be seen as an early progenitor of our estimation strategy. We establish conditions for consistency of the estimates of the parameters of interest and employ a bootstrap simulation to assess the estimation precision. As recommended by Dridi et al. (2007), the empirical assessment focuses on the plausibility of the estimates of the parameters of interest (subjective discount factor, relative risk aversion, intertemporal substitution elasticity), and the risk and timing premia implied by the parameter estimates, as well as gauging whether the estimated model is able to account for salient financial economic facts.

We find that the estimates of the investor preference parameters are economically plausible, with meaningfully narrow confidence intervals. Specifically, the estimates of the subjective discount factor are smaller than but close to unity, as would be expected of an investor with a positive rate of time preference. Depending on the chosen test assets, the relative risk aversion (RRA) coefficient estimates range between 1.5 and 1.7; generally, values between 0 and 10 describe reasonable risk preferences. Cochrane (2005) caps the upper bound at RRA=5, in line with experimental evidence reported by Meyer and Meyer (2005). For the present study, the 95% confidence bounds for the RRA estimate also lie within that narrower range of plausibility. The RRA point estimate is strikingly close to the implied RRA estimate that one obtains when conceiving the Fama-French three-factor model as an instance of an intertemporal CAPM (cf. Grammig and Jank, 2016). The estimate of the intertemporal elasticity of substitution (IES) is significantly greater than unity, and of a magnitude that is frequently chosen for calibrations. Moreover, the difference of the estimated RRA coefficient and reciprocal of the IES estimate is significantly greater than 0, which implies a preference for early resolution of uncertainty. Several studies emphasize that an IES > 1 is necessary to obtain meaningful asset pricing implications (cf. Bansal and Yaron, 2004 and Epstein et al., 2014), but, as documented by Havránek (2015), IES estimates are notoriously smaller than unity.

Consequently, the estimates-implied key financial indicators – mean T-Bill return, market equity premium and Sharpe ratio – exhibit meaningful magnitudes that are consistent with the empirically observed counterparts. Moreover, the timing premium, measured as proposed by Epstein et al. (2014), and computed using the parameter estimates, is economically meaningful. This is a noteworthy result, because most estimated/calibrated C-CAPMs imply a timing premium that is far too high to be considered economically plausible. These conclusions are invariant to alternative model specifications (like disaster definition and simulation procedure). Empirical C-CAPM studies often find implausible and/or imprecise parameter estimates that entail doubtful asset pricing implications. The results presented herein suggest instead that accounting for rare disasters within a consumption-based asset pricing framework can help restore the nexus between financial markets and the real economy also when allowing for multi-period disasters and when relying on econometric analysis instead of calibration practices.

The RDH literature, to which this paper contributes and draws inspiration from, and that has been triggered by Barro's (2006) seminal work, is lucidly surveyed by Tsai and Wachter (2015). Amongst the studies that link the RDH to various aspects of finance,[1] there are some that relate closely to the present study. Barro and Ursúa (2008) collect annual consumption and GDP data to study the size and frequency of disasters. As used by Barro and Jin (2011), these data also enable the authors to fit power law densities to the empirical distribution of macroeconomic disasters. The estimation strategy proposed herein extends their ideas. Nakamura et al. (2013) consider a multi-period disaster process within a Bayesian framework. They show that, when calibrated with a reasonable rate of time preference and IES, the equity premium can be explained with a plausible RRA coefficient. The frequentist approach pursued in the present study complements and extends their Bayesian analysis.

In Barro (2006) and many of the papers surveyed by Tsai and Wachter (2015), disas-

[1] These include the volatility puzzle (Wachter, 2013), the business cycle (Gourio, 2012), credit spreads (Gourio, 2013), index options (Backus et al., 2011), the value premium (Bai et al., 2015 and Tsai and Wachter, 2016), exchange rate puzzles (Farhi and Gabaix, 2016), the volatility skew (Seo and Wachter, 2015, and the persistence of dividend and consumption growth (Gillman et al., 2015 and Barro and Jin, 2016).

ters occur as one-period events. This assumption seemingly could be the driving force behind the success of the RDH, as argued by Julliard and Ghosh (2012) and suggested by Constantinides's (2008) comment on Barro and Ursúa's (2008) work. Julliard and Ghosh's (2012) is one of the few studies that performs a comprehensive econometric analysis to empirically assess the RDH. When allowing for multi-period disasters and modeling investor preferences by time-additive power utility, they conclude that to rationalize the equity premium puzzle with the help of the RDH, the puzzle itself must be a rare event. Their results thus attenuate the appeal of the rare disaster explanation. The present study re-emphasizes, based on econometric analysis, the explanatory power of the RDH even when multi-period disasters are allowed for. However, to reach this conclusion, one must abandon time-additive power utility. It is necessary to allow for both IES and RRA to be greater than unity by adopting a recursive utility specification.

The remainder of this paper is structured as follows: Section 2 details the motivation for 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 a marked point process to explain the size and duration of and between disaster events. Section 3 contains the macroeconomic and financial data used in this study, and Section 4 describes the two-step estimation strategy. After a discussion of the estimation results and robustness tests in Section 5, 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, we 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 regular bad times from 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 a succession of contractions that starts in period s_1 and lasts until period s_2, where $s_1 \leq t + 1 \leq s_2$, such that

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

In words, we 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 come in the form of one sharp contraction. Disaster periods are indicated by $d_t = 1$ and 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 returns on treasury bills, we assume, analogous to Equation 2.1, that 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, and $\tilde{b}_i$ is the return equivalent of the consumption contraction factor b.

A representative investor, who faces these consumption risks, has recursive preferences; as Epstein and Zin (1989) show, 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.

By 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 consumption growth and return data that do not include disasters, we can approximate the left-hand side of Equation (2.7) as follows:

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

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

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

Because U.S. postwar data do not incorporate any disasters, attempting to approximate the right-hand side moments in Equations (2.7) and (2.8) using 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, such as:

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

and

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

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 same spirit by which 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 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 specify the stochastic process that generates the disastrous consumption contractions.

2.2 Multi-period disasters as a marked point process

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

We draw on Hamilton and Jorda's (2002) autoregressive conditional hazard (ACH) framework to model the duration between disaster periods. Initially, this approach would set a threshold q to define a disaster event and thereby establish the respective disaster periods and their contraction sizes. Suppose that the sequence of consumption disaster events thus defined is observable at a quarterly frequency. Let $M(t)$ denote the number of disasters that 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 also 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 a 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. That is, $d_t^+ = 1$ 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 be a disaster period too, 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 is possible too. For example, we could 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:

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

where τ_m denotes the 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. Furthermore, 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, we 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 disaster size, we adopt an idea from Barro and Jin (2011) and employ a power law distribution (PL) to describe the transformed contraction size $z_c = \frac{1}{1-b}$.[2] We 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 those 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,

[2] Specifically, Barro and Jin (2011), who implicitly assume single-period disasters, use a double power law distribution that 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.

which we refer to as an ACH-PL model, can be written as:

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

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 the contractions that contribute to reaching the disaster threshold and the size of contractions to 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 we use in two consecutive estimation steps. The estimation of the ACH-PL parameters relies on annual cross-country panel data about consumption that Barro and Ursúa (2008) assembled for 42 countries and that feature prominently in prior rare disaster literature.[3] From these data, we select the same 35 countries that Barro (2006) considered. Table 1 lists the countries and the years for which consumption data are available.

[insert Table 1 here]

To detect disaster events in these data, we rely on Barro's (2006) identification scheme, which implies that any sequence of downturns in consumption growth greater than or equal to $q = 0.145$ qualifies as a disaster. The same disaster threshold is used by Barro (2009) and Barro and Jin (2011). A disaster may pan out over multiple periods or occur as one sharp

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

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, we detect 89 disaster events. Figure 1 depicts their size and the periods over which they accrue.

[insert Figure 1 here]

As previously mentioned, we assume that the ACH-PL process is observable at a quarterly frequency. However, Barro and Ursúa's (2008) data only permit the computation of annual contractions. We therefore generate quarterly observations by randomly distributing the annual contraction. Appendix A.1 contains the details of this procedure.

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

[4] For services, see http://research.stlouisfed.org/fred2/series/A797RX0Q048SBEA. For nondurable goods, see 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.

(2012), we approximate the ex ante non-disastrous T-bill return $R_{b,nd}$ (i.e., the "risk-free rate" proxy) by forecasting ex post $R_{b,nd}$ on the basis of the quarterly T-bill yield and the average of quarterly log inflation across the past year. The three-month nominal T-bill yield comes 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 involves two consecutive steps. We first compute maximum likelihood estimates of the ACH-PL parameters $\boldsymbol{\theta}_{ACH}$, θ_{PL}^{+}, and θ_{PL}. Using these estimates, it is 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. 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 $\hat{\boldsymbol{\theta}}_{ACH}$, 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 $\hat{\boldsymbol{\theta}}_{ACH}$, whereas estimates of θ_{PL}^{+} and 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, which equals 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 Equation (2.16) is used, τ_0 must be 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 the 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).[8]

4.2 Financial moment restrictions and data simulation

An SMM-type estimation of the preference parameters entails exploiting the moment restrictions in Equations (2.7) and (2.8). In particular, we rely on matching between empirical and simulated moments, as is implied by the moment restriction in Equation (2.7), that uses the sample moments in Equations (2.9) and (2.11). Applied to the T-bill return R_b

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

[8] They consider an ACH-like dynamic duration model for the time interval between intraday trading events. In this framework, the re-initialization accounts for overnight interruptions of the trading process.

where $\boldsymbol{\vartheta} = (\beta, \gamma, \psi)'$. Similarly, we 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:

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

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

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

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, we 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 then can generate a sequence of disaster indicators $\{d_s\}_{s=1}^{\mathcal{T}}$ and $\{d_s^+\}_{s=1}^{\mathcal{T}}$.

We 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, we 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 gets drawn from a geometric distribution. The draws from the consumption and return data are simultaneous, 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 to simulate disaster returns. In particular, we assume that the transformed contractions $z_c = 1/(1-b)$ and $z_R = 1/(1-\tilde{b})$ have the same marginal distribution,[9]

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

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 Gaussian copula C_G, these dependencies can be 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 $u_R = F(z_R;\theta_{PL}^{+},\theta_{PL})$.

We consider three choices for the copula correlation. First, ρ_i may be estimated by the empirical correlation between non-disastrous consumption growth and gross return. Second,

[9] The asset index i is omitted for brevity.

we consider the extreme case that $\rho = 0.99$, motivated by the finding that the correlations between financial returns increase in the tails of their joint distribution (see Longin and Solnik (2001)). Third, we address the case when $\rho = 0$, 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 proceeds as follows: We draw $y_{c,s}$ and $y_{R,s}$ from a bivariate standard normal distribution with correlation ρ, then 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 then can be 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

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

In this case, F^{-1}_{PL} denotes the quantile function of the PL distribution. The combination of the contraction factors with the bootstrapped non-disastrous series allows simulating 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 $R_{b,s}$, we draw on Barro (2006), who identifies partial government default in 42% of the disasters that he finds in the GDP series of 35 countries. Using this result, at the beginning of each disaster (that is, $d_s = 1$ but $d_{s-1} = 0$), we draw a government default indicator $d_{b,s}$ from a Bernoulli distribution with a 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 for the returns of the test assets, such that $R_{b,s} = (1 - \tilde{b}_{b,s})^{d_{b,s}} R_{b,nd,s}$. The simulated excess returns then can be 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 (2017) points out that a joint estimation of the investor preference parameters that relies exclusively on moment restrictions obtained from conditioning down 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. We therefore find it useful to identify and estimate the IES separately from β 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 Equation (2.5). Yogo (2004) shows that this procedure leads to the following 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 $\Delta c_{t+1} = \ln C_{t+1} - \ln C_t$. In addition, 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 according to 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}.[10]

We adopt the instrumental variables approach to estimate the IES and use the log T-bill return $r_{b,t+1} = \ln R_{b,t+1}$ in Equation (4.14), the twice-lagged log T-bill return, log consumption growth, and a constant as instruments. The estimation is performed on the simulated disaster-including data. Using a linear GMM with an identity weighting matrix, the IES

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

estimate $\hat{\psi}$ must fulfill the first-order conditions:

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

which reflect Hansen's (1982) notation $\mathbb{E}_{\mathcal{T}}(\cdot) = \frac{1}{\mathcal{T}}\sum_{s=1}^{\mathcal{T}}(\cdot)$. The estimation of the IES is appropriate when 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, but it also is possible to augment Equation (4.6) with the IES-identifying moment matches of Equation (4.16) to obtain:

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

where $\tilde{\boldsymbol{\vartheta}} = (\beta, \gamma, \psi, \mu_b)'$. The 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 Equation

(4.17) ensures that the IES will be identified by Equation (4.16). In particular, we 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, though we could rely on asymptotic maximum likelihood inference about the first-step ACH-PL estimates. Therefore, we combine a parametric and non-parametric bootstrap to obtain the standard errors and confidence intervals of the preference parameter estimates. The bootstrap procedure is detailed 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, the aggregate size of the previous disaster has an effect on the hazard rate, but the contraction of the previous disaster period does not (i.e., $\tilde{\delta} = \alpha = \tilde{\alpha} = 0$).

[insert Table 3 about here]

Table 3 shows that the AIC favors the ACH_4, but the SBC prefers the ACH_0, for which the baseline hazard parameter estimates $\hat{\mu}$ and $\hat{\hat{\mu}}$ 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, at the 1% significance level, are only rejected in the case of the AIC-preferred ACH_4. Therefore, the subsequent analysis is confined to ACH_0 and ACH_4.

We 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%, and a probability of remaining in a disaster that is equal to 83%. Because we use these estimates as a foundation for the second estimation step, it is prudent to check their economic plausibility in advance. Accordingly, we use the ACH_0 and ACH_4 estimates to simulate disaster-including consumption time series with a number of observations that corresponds to the sample period, 1947:Q2-2014:Q4. The simulation is repeated 10k times, and we 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 U.S. postwar history represents a lucky but not unlikely path, and 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 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; Figure 2b uses $\hat{\theta}_{PL}$ and refers to 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 uses 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.[11] 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; 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.[12]

[insert Table 4 about here]

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

[12] In this case, the RMSE is 0, and R and the J-statistic are not reported.

Table 4 shows that all variants for estimating a disaster-including C-CAPM yield 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 has pointed out that the inequality $\gamma > 1/\psi$ is crucial for obtaining meaningful asset pricing implications (as detailed subsequently).[13]

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 ACH_4-PL are slightly bigger than those implied by 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 than the estimates 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 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 finding is not surprising. The p-values of the J-statistic indicate that the disaster-including C-CAPM cannot be rejected at conventional significance levels.

[13] It is worth noting that the estimation of ψ by reversing the regression in Equation (4.14) also yields an IES estimate greater than 1. As noted by Yogo (2004), such robustness cannot be expected when disaster-free data are used for IES estimation.

Compared with other prominent studies that assess empirical support for the C-CAPM paradigm, these results are certainly encouraging. Julliard and Parker (2005), for example, aggregate consumption over multiple periods and obtain an RRA estimate of plausible magnitude ($\hat{\gamma}$=9.1) but only moderate estimation precision (s.e.=17.2). By measuring consumption with waste, Savov (2011) obtains an 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, with an assumption of additive power utility (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 all play important roles. The relative size of the RRA coefficient and the IES 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 $\theta = 1$, the investor is indifferent to an early or late resolution of uncertainty, and the case of standard expected utility obtains. If $\gamma > \frac{1}{\psi}$, the agent has a preference for an early resolution of uncertainty, which is intuitively appealing, unless we were to resort to behavioral explanations (e.g. hope, 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 (e.g., Bansal and Yaron (2004); Huang and Shaliastovich (2015)). When risk aversion is greater than unity, θ should be negative.[14] Therefore, calibration studies tend to combine moderate risk aversion with an IES>1 to illustrate the explanatory power of the asset pricing model (e.g. Bansal and Yaron

[14] 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.

(2004) assume γ=10 and ψ=1.5), yet none of the previously cited empirical C-CAPM studies reports conforming RRA and IES estimates. Rather, the IES point estimate in most empirical studies is smaller than 1 (see the meta-analysis by Havránek (2015); survey by Thimme (2017)).

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 1. According to the previous reasoning, the empirical disaster-including C-CAPM thus should yield meaningful asset pricing implications. We 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, we approximate the population moments by averaging over the $\mathcal{T}$ simulated observations, such that

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

and

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

where $m(\hat{\beta}, \hat{\gamma}, \hat{\psi})$ is the Epstein-Zin SDF in Equation (2.5) evaluated according to 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 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 accounts 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; 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 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, because the model-implied indicators account for the possibility of consumption disasters that affect the simulated moments, whereas 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, which seemingly could drive the favorable results. However, exact identification does not imply that the empirical mean market return and mean T-bill return must 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. 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 their 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 rather are obtained from the application of an econometric estimation strategy. These results thus provide new empirical evidence that the rare disaster hypothesis offers a solution to the equity premium puzzle.

5.4 Implied timing premium

The aforementioned inequality $\gamma > \frac{1}{\psi}$ holds for the parameter selections in many calibration exercises of popular asset pricing models, such as Bansal and Yaron's (2004) long-run risk model or Barro's (2009) rare disaster model, which require $\psi > 1$ to ensure plausible model implications.[15] Using the calibrated parameters and the dynamics of the respective consumption process, Epstein et al. (2014) provide an empirical assessment of the fraction of lifetime consumption that investors would be willing to give up in order for all risk to be resolved in the next period.

[insert Table 6 about here]

Table 6 contains these timing premia (π^*) for varying asset pricing models and parameter specifications. In the example of Barro's (2009) single-period disaster model calibrated with $\gamma = 4$ and $\psi = 2$, investors would be willing to renounce 18% of their lifetime consumption to suspend uncertainty. For models that feature a higher persistence of the consumption process, the timing premia even increase (23% for Bansal and Yaron's (2004) long-run risk model and 42% for the persistent rare disaster model of Wachter (2013)). These premia are surprisingly high considering the fact that Epstein et al.'s (2014) study focuses on *consumption uncertainty*. When considering consumption uncertainty, as opposed to income uncertainty, there is no immediate planning advantage for the investor to be taken from knowing her future consumption in advance. Epstein et al. (2014) argue that the timing premium could be lowered to a plausible level by calibrating ψ close to the inverse of γ, which in turn would imply $\psi < 1$.

[15] E.g., $\psi < 1$ would result in a high level and volatility of the risk-free rate in Bansal and Yaron (2004) and imply a positive correlation between economic uncertainty and price-dividend ratios in Barro (2009).

We replicate Epstein et al.'s (2014) study using the multi-period disaster consumption process described previously and the preference parameter estimates presented in Table 4.[16] The resulting timing premium of 0.9% is obtained with both $\hat{\gamma}$ and $\hat{\psi}$ larger than but relatively close to unity, thereby reconciling plausible estimates of the preference parameters with a high model-implied equity premium (see Table 5) and a small timing premium. As a comparison, we reconsider Barro's (2009) single-period disaster model with our RRA coefficient and IES estimates, which reduce π^* from 18% to 1.9%. Thus, it is possible to unify γ and ψ both being larger than 1 with a small timing premium if the RRA coefficient is sufficiently small. This level of risk aversion, however, does not suffice to explain the size of the equity premium in Barro's (2009) calibrations.

5.5 Robustness checks

As robustness check, we perform bias corrections on the parameter estimates and confidence bounds, and report the results in Table 7. Following Efron and Tibshirani (1986), we 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 $\vartheta^u_{BC}(\alpha) = \hat{G}^{-1}[\Phi(z_{1-\alpha/2} + 2\Phi^{-1}[\hat{G}(\hat{\vartheta})])]$, respectively, where Φ denotes the cdf, Φ^{-1} is the quantile function, and $z_{\tilde{\alpha}}$ is the $\tilde{\alpha}$-quantile of the standard normal distribution.[17] Comparing the results in Table 7 with those in Table 4, we find that in all instances, the corrections are rather benign. The similarity of the the bias-corrected estimates and confidence intervals to the uncorrected counterparts offers a sign of robustness.

[insert Table 7 about here]

A second robustness check investigates the effect of varying the disaster threshold q. Panel A of Table 8 uses q=0.095, and Panel B reports the results for q=0.195. These

[16] We thank the authors for making their code available.

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

values are chosen in accordance with Barro and Jin (2011) and feature prominently in rare disaster literature. The results in Table 8 convey that the choice of q barely affects the parameter estimates; this finding may seem surprising at first, but it 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 $\theta^{+}_{PL}, \theta_{PL}$, obtained from quarterly (contraction) data that have been computed from annual (disaster) periods. Because θ^{+}_{PL} and θ_{PL} contain information about the distribution of quarterly contractions, they could vary strongly with q only if the distribution of the annual contraction sizes of disasters detected with a threshold of 0.095 were pronouncedly different from that of disasters that had been detected with q=0.195. This was not the case.

[insert Table 8 about here]

Therefore, 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 recommendation.

6 Conclusion

Empirical tests of Hansen and Singleton's (1982) canonical C-CAPM have been notoriously disappointing. Yet the model approach cannot be easily discarded, because it represents a rational link between the real economy and financial markets, such that 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); Yogo (2006); Savov (2011)). The main theoretical extensions of the canonical 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. too low model-implied equity premium, too high risk-free rate) has been mitigated at best.

Rietz (1988) has offered another explanation for the model's poor empirical performance: the rare disaster hypothesis, according to which the apparent failure of the C-CAPM is a consequence of the positive path that the U.S. economy took after World War II. However, this path may not be representative of 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 among multiple more unfavorable histories.

This study adopts Barro's (2006) specification of a disaster-including consumption process and derives moment restrictions that facilitate the estimation of a disaster-including C-CAPM by an SMM-type strategy. The approach presented herein takes into account three main drawbacks of previous studies that aim to test the rare disaster hypothesis empirically. First, we 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); Constantinides (2008)). Second, we use Epstein-Zin preferences instead of a power utility to acknowledge preferences for an early resolution of uncertainty. Third, we allow for the possibility of a partial government default. Accounting for these three issues is crucial for finding empirical support for the RDH.

For an SMM-type estimation, we 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, as well as the magnitude of contractions using a power law distribution. Parameter estimates of the MPP model are obtained through maximum likelihood, using chained country-panel data. Neither the choice of test assets nor the 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 95% confidence bounds) 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, in conjunction with an IES greater than unity, is an important condition for obtaining meaningful asset pricing implications. Computing the model-implied mean market return, T-bill rate, and market Sharpe ratio reveals that the disaster-including C-CAPM can explain these key financial indicators based on economically meaningful preference parameter estimates.

To the best of our knowledge, the present study is the first research to estimate all the preference parameters of a C-CAPM with Epstein-Zin preferences and multi-period disasters. It corroborates the notion that the rare disaster hypothesis can provide a 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, we 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. This procedure implies that the contraction in the first (last) quarter will be the largest (smallest), on average. To avoid such a seasonal pattern, we 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 of a disaster, or if the disaster consists of only one annual contraction, we determine the quarter when the contraction begins (ends) by a draw from a discrete uniform distribution, such that each quarter has a 1/4 probability of becoming the quarter when the disaster begins (ends). The annual contraction is then distributed across the disaster quarters in a way analogous to the method used 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 bootstraps. Using the first-step maximum likelihood estimates $\hat{\boldsymbol{\theta}}_{ACH}$, $\hat{\theta}_{PL}$, and $\hat{\theta}^{+}_{PL}$, we 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 $\{\hat{\boldsymbol{\theta}}^{(k)}_{ACH}, \hat{\theta}^{(k)}_{PL}, \hat{\theta}^{+(k)}_{PL}\}^{K}_{k=1}$. Because we 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 crucial input for inference about the second-step SMM estimates of the preference parameters.

For each of the K replications, we perform a block-bootstrap to obtain series of non-disastrous consumption growth $\{cg_{nd,l}^{(k)}\}_{l=1}^{T}$, market and T-bill returns $\{R_{nd,a,l}^{(k)}\}_{l=1}^{T}$, $\{R_{nd,b,l}^{(k)}\}_{l=1}^{T}$, and test asset returns $\{R_{nd,i,l}^{(k)}\}_{l=1}^{T}$. As described previously, we 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, we 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, we 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). Then the SMM-type estimation of the preference parameters β, γ, and ψ 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.

References

Backus, D., M. Chernov, and I. Martin (2011): "Disasters Implied by Equity Index Options," *Journal of Finance*, 66, 1969–2012.

Bai, H., K. Hou, H. Kung, and L. Zhang (2015): "The CAPM Strikes Back? An Investment Model with Disasters," Working Paper 21016, National Bureau of Economic Research.

Bansal, R., and A. Yaron (2004): "Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles," *Journal of Finance*, 59, 1481–1509.

Barro, R. J. (2006): "Rare Disasters and Asset Markets in the Twentieth Century," *Quarterly Journal of Economics*, 121, 823–866.

——— (2009): "Rare Disasters, Asset Prices, and Welfare Costs," *American Economic Review*, 99(1), 243–64.

Barro, R. J., and T. Jin (2011): "On the Size Distribution of Macroeconomic Disasters," *Econometrica*, 79, 1567–1589.

——— (2016): "Rare Events and Long-Run Risks," Working Paper 21871, National Bureau of Economic Research.

Barro, R. J., and J. F. Ursúa (2008): "Macroeconomic Crises since 1870," *Brookings Papers on Economic Activity*, 39(1), 255–335.

Beeler, J., and J. Y. Campbell (2012): "The Long-Run Risks Model and Aggregate Asset Prices: An Empirical Assessment," *Critical Finance Review*, 1(1), 141–182.

Blanchard, O. J. (2008): "Macroeconomic Crises since 1870. Comments and Discussion," *Brookings Papers on Economic Activity*, 2008, 336–340.

Campbell, J. Y. (2003): "Consumption-Based Asset Pricing," in *Handbook of the Economics of Finance*, ed. by G. Constantinides, M. Harris, and R. Stulz, chap. 10, pp. 804–887. Elsevier, Amsterdam.

Campbell, J. Y., and J. H. Cochrane (1999): "By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior," *Journal of Political Economy*, 104, 205–251.

Cochrane, J. H. (2005): *Asset Pricing*. Princeton University Press.

Constantinides, G. (2008): "Comment on: Macroeconomic Crises since 1870," *Brookings Papers on Economic Activity*, 39(1), 341–349.

Constantinides, G. M., and D. Duffie (1996): "Asset Pricing with Heterogeneous Consumers," *Journal of Political Economy*, 104, 219–240.

Dridi, R., A. Guay, and E. Renault (2007): "Indirect inference and calibration of dynamic stochastic general equilibrium models," *Journal of Econometrics*, 136(2), 397 – 430.

Efron, B., and R. J. Tibshirani (1986): "Bootstrap Methods for Standard Errors, Confidence Intervals, and Other Measures of Statistical Accuracy," *Statistical Science*, 1(1), 54–75.

Engle, R. F., and J. R. Russell (1998): "Autoregressive Conditional Duration: A New Model for Irregularly Spaced Transaction Data," *Econometrica*, 66(5), pp. 1127–1162.

Epstein, L. G., E. Farhi, and T. Strzalecki (2014): "How Much Would You Pay to Resolve Long-Run Risk?," *American Economic Review*, 104(9), 2680–97.

Epstein, L. G., and S. E. Zin (1989): "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework," *Econometrica*, 57:4, 937–969.

Farhi, E., and X. Gabaix (2016): "Rare Disasters and Exchange Rates," *Quarterly Journal of Economics*, 131(1), 1–52.

Gillman, M., M. Kejak, and M. Pakoš (2015): "Learning about Rare Disasters: Implications For Consumption and Asset Prices," *Review of Finance*, 19(3), 1053–1104.

Gourio, F. (2012): "Disaster Risk and Business Cycles," *American Economic Review*, 102, 2734–2766.

——— (2013): "Credit Risk and Disaster Risk," *American Economic Journal: Macroeconomics*, 5(3), 1–34.

Grammig, J., and S. Jank (2016): "Creative Destruction and Asset Prices," *Journal of Financial and Quantitative Analysis*, 51(6), 1739â1768.

Hamilton, J. D., and O. Jorda (2002): "A Model of the Federal Funds Rate Target," *Journal of Political Economy*, 110(5), 1135–1167.

Hansen, L., and T. Sargent (2010): "Fragile Beliefs and the Price of Model Uncertainty," *Quantitative Economics*, 1, 129–162.

Hansen, L. P. (1982): "Large Sample Properties of Generalized Method of Moments Estimators," *Econometrica*, 50, 1029–1054.

Hansen, L. P., and K. J. Singleton (1982): "Generalized Instrumental Variables Estimation of Nonlinear Rational Expectations Models," *Econometrica*, 50, 1269–1286.

——— (1983): "Stochastic Consumption, Risk Aversion, and the Temporal Behavior of Asset Returns," *Journal of Political Economy*, 91, 249–265.

Havránek, T. (2015): "Measuring Intertemporal Substitution: The Importance of Method Choices and Selective Reporting," *Journal of the European Economic Association*, 13(6), 1180–1204.

Heaton, J. (1995): "An Empirical Investigation of Asset Pricing with Temporally Dependent Preference Specifications," *Econometrica*, 63(3), 681–717.

Huang, D., and I. Shaliastovich (2015): "Risk Adjustment and the Temporal Resolution of Uncertainty," Working Paper Wharton University.

Julliard, C., and A. Ghosh (2012): "Can Rare Events Explain the Equity Premium Puzzle?," *Review of Financial Studies*, 25, 3037–3076.

Julliard, C., and J. A. Parker (2005): "Consumption Risk and the Cross-Section of Expected Returns," *Journal of Political Economy*, 113, 185–222.

Lettau, M., and S. Ludvigson (2001): "Resurrecting the (C)CAPM: A Cross-Sectional Test when Risk premia are Time-Varying," *Journal of Political Economy*, 109, 1238–1287.

Longin, F., and B. Solnik (2001): "Extreme Correlation of International Equity Markets," *Journal of Finance*, 56, 649–676.

Maio, P., and P. Santa-Clara (2012): "Multifactor Models and their Consistency with the ICAPM," *Journal of Financial Economics*, 106(3), 586–613.

Meyer, D. J., and J. Meyer (2005): "Relative Risk Aversion: What Do We Know?," *The Journal of Risk and Uncertainty*, 31(3), 243–262.

Nakamura, E., J. Steinsson, R. Barro, and J. F. Ursúa (2013): "Crises and Recoveries in an Empirical Model of Consumption Disasters," *American Economic Journal: Macroeconomics*, 5(3), 35–74.

Politis, D. N., and J. P. Romano (1994): "The Stationary Bootstrap," *Journal of the American Statistical Association*, 89(428), 1303–1313.

Politis, D. N., and H. White (2004): "Automatic Block-Length Selection for the Dependent Bootstrap," *Econometric Reviews*, 23(1), 53–70.

Politis, D. N., H. White, and A. J. Patton (2009): "Correction: Automatic Block-Length Selection for the Dependent Bootstrap," *Econometric Reviews*, 28(4), 372–375.

Rietz, T. A. (1988): "The Equity Risk Premium - A Solution," *Journal of Monetary Economics*, 22, 117–131.

Savov, A. (2011): "Asset Pricing with Garbage," *Journal of Finance*, 66, 177–201.

Seo, S. B., and J. A. Wachter (2015): "Option Prices in a Model with Stochastic Disaster Risk," Working Paper 19611, National Bureau of Economic Research.

Singleton, K. J. (2006): *Empirical Dynamic Asset Pricing*. Princeton University Press.

Stock, J., and J. Wright (2000): "GMM with Weak Identification," *Econometrica*, 68, 1055–1096.

Thimme, J. (2017): "Intertemporal Substitution of Consumption: A Literature Review," *Journal of Economic Surveys*, 31(1), 226–257.

Thimme, J., and C. Völkert (2015): "Ambiguity in the Cross-Section of Expected Returns: An Empirical Assessment," *Journal of Business and Economic Statistics*, 33, 418–429.

Tsai, J., and J. A. Wachter (2015): "Disaster Risk and Its Implications for Asset Pricing," *Annual Review of Financial Economics*, 7, 219–252.

——— (2016): "Rare Booms and Disasters in a Multisector Endowment Economy," *Review of Financial Studies*, 29(5), 1113–1169.

Wachter, J. A. (2013): "Can Time-Varying Risk of Rare Disasters Explain Aggregate Stock Market Volatility?," *Journal of Finance*, 68, 987–1035.

Weber, C. (2000): ""Rule-of-Thumb" Consumption, Intertemporal Substitution, and Risk Aversion," *Journal of Business and Economic Statistics*, 18, 497–502.

Yogo, M. (2004): "Estimating the Elasticity of Intertemporal Substitution When Instruments are Weak," *Review of Economics and Statistics*, 86, 797–810.

——— (2006): "A Consumption-Based Explanation of Expected Stock Returns," *Journal of Finance*, 61, 539–580.

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*); 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. Here, $\mathcal{L}$ is the log-likelihood value at the maximum; 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, respectively. Furthermore, $\mathcal{LR}$ 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, 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 the set of test assets, namely, the excess returns of *mkt*, *size dec*, and *industry*, each augmented by the T-bill return.

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

	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** (0.0022)	**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: $\rho = 0.99$

	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	**0.9915** (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: $\rho = 0$

	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** (0.0022)	**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 the set of test assets. The column labeled *data* reports the values of the indicators in the empirical data, 1947:Q2–2014:Q4.

		Panel A: $\rho = \text{Corr}(\text{cg}_{\text{nd}}, \text{R}_{\text{nd}})$		
	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: Timing premia

The table contains the timing premia (π^*) that are simulated for a variety of popular asset pricing models. Columns 2-5 list the preference parameters used for the simulations. For Wachter (2013), Barro (2009), and Bansal and Yaron (2004), these parameter values are used in their calibration exercises. The specification labeled Barro II uses Barro's (2009) single-period disaster consumption process in combination with the RRA and IES parameters obtained from our estimation approach. The premia reported for Wachter (2013) and Bansal and Yaron (2004) are taken from Epstein et al. (2014). We obtain premia for the remaining model specifications from Epstein et al.'s (2014) programs when basing the simulation on 100,000 consumption growth series of length 200 (for Barro (2009), Barro II, and the i.i.d. process) or 1000 (for this study), respectively.

	γ	ψ	β	$\pi^*(\%)$
This study	1.51	1.50	0.992	0.9
Wachter (2013)	3.00	1.00	0.988	42
Barro (2009)	4.00	2.00	0.951	18
Barro II	1.51	1.50	0.951	1.9
Bansal and Yaron (2004)	7.50	1.50	0.998	23
i.i.d.	1.51	1.50	0.951	0.2

Table 7: 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 follows the method proposed by Efron and Tibshirani (1986).

Panel A: ρ = 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: ρ = 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: ρ = 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 8: 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: $q = 0.095/\rho = \mathrm{Corr}(\mathrm{cg}_{\mathrm{nd}}, \mathrm{R}_{\mathrm{nd}})$

	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: $q = 0.195/\rho = \mathrm{Corr}(\mathrm{cg}_{\mathrm{nd}}, \mathrm{R}_{\mathrm{nd}})$

	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. 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.

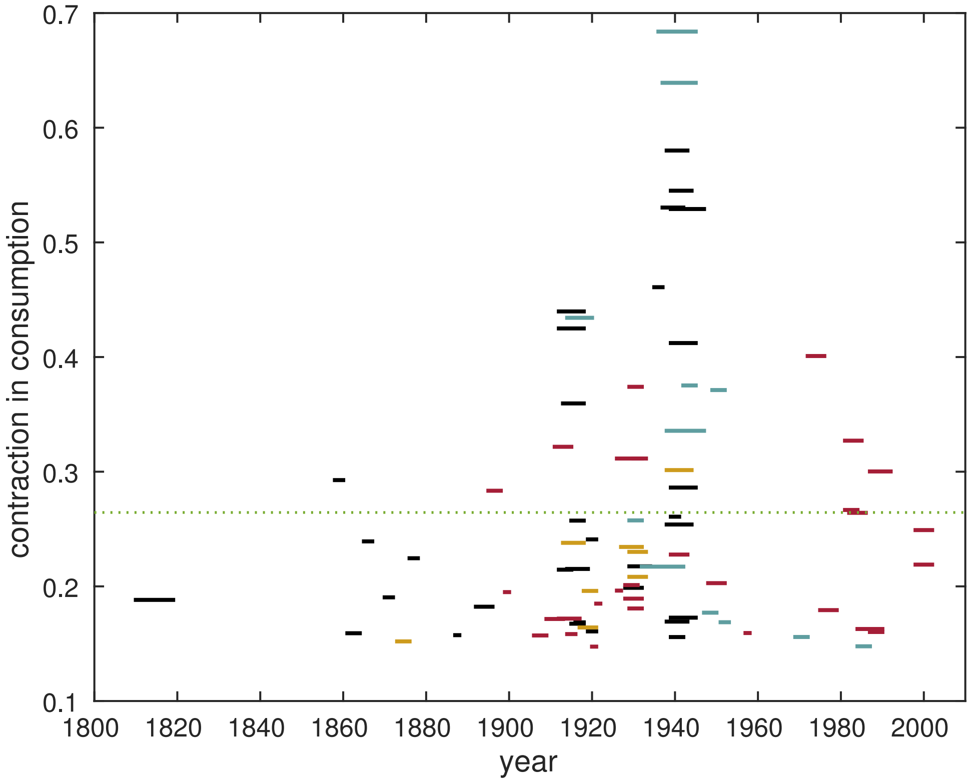
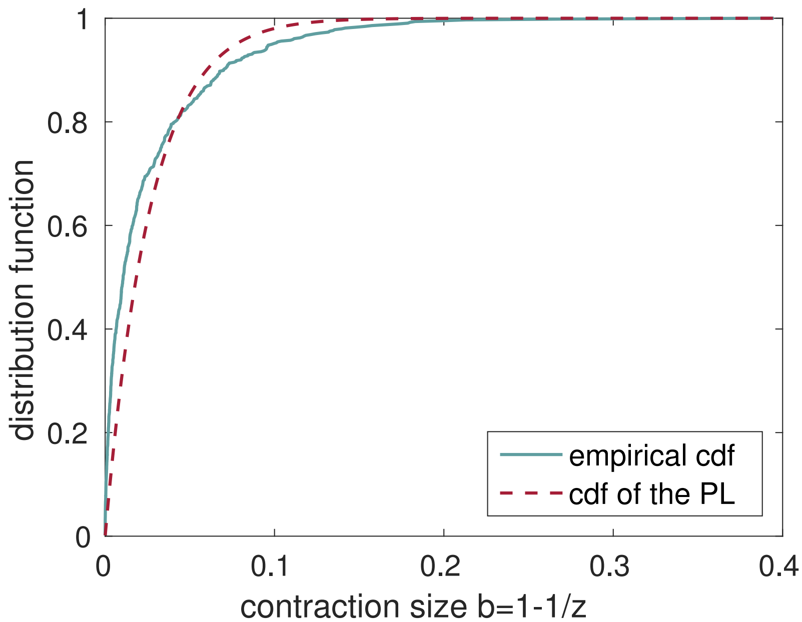
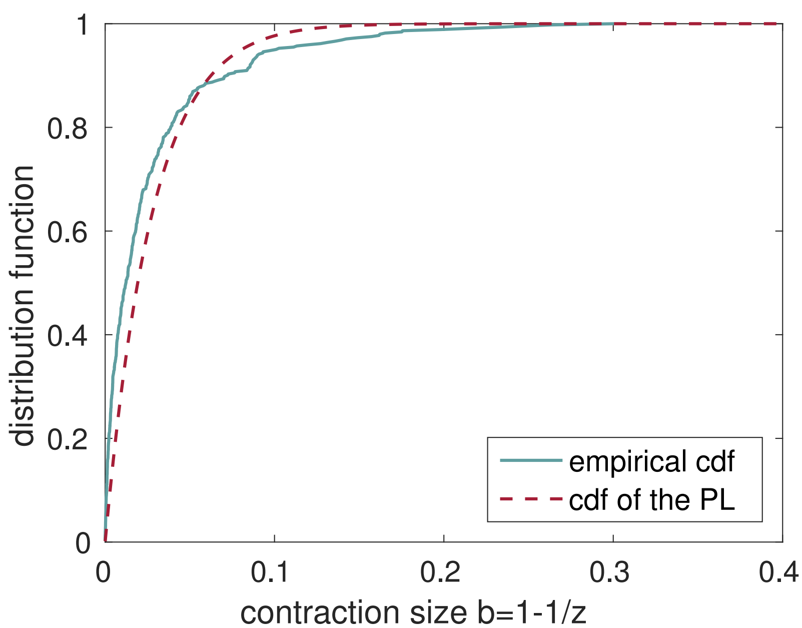


Figure 2: Fitted power law vs. empirical cdf
This figure illustrates the empirical cdfs (solid lines) and the fitted cdf (dotted lines) of the contractions identified in Barro and Ursúa's (2008) data using a disaster threshold of q=0.145. Panel (a) captures the distribution of contractions that occur 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