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

Jantje Sönksen* and Joachim Grammig†‡

October 4, 2017

Abstract

Econometric analyses of the rare disaster hypothesis are scarce, and the assumption that disasters shrink to one-period events is under suspicion of being the driving force of support for this hypothesis in extant calibrations. This study proposes a novel empirical strategy to estimate and test an asset pricing model that accounts for multi-period disasters, partial government defaults, and recursive investor preferences. The estimates of the coefficient of relative risk aversion, rate of time preference and intertemporal elasticity of substitution are economically reasonable, rather precise, and robust with respect to alternative model specifications. Moreover, the model-implied equity premium, mean T-bill return, and market Sharpe ratio are plausible and consistent with the empirical data. The empirical results affirm that the rare disaster hypothesis helps restore the nexus between the real economy and financial markets that is implied by the consumption-based asset pricing paradigm. We stress the importance of disentangling risk and intertemporal substitution preferences when allowing for multi-period disasters.

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

JEL: G12, C58

*University of Tübingen, School of Business and Economics, Mohlstrasse 36, D-72074 Tübingen. jantje.soenksen@uni-tuebingen.de.
†University of Tübingen, School of Business and Economics, and Centre for Financial Research (CFR), Cologne. joachim.grammig@uni-tuebingen.de.
‡Prior versions of this paper were presented at the 23rd Annual Meeting of the German Finance Association, the 2017 Vienna-Copenhagen Conference on Financial Econometrics, the 27th Annual Congress of the European Economic Association and the 10th Annual SoFiE Conference, and the 16th CFR Colloquium on Financial Markets. We thank participants at these sessions for helpful comments and encouragement, in particular Vikas Agarwal, Martijn Boons, Mathijs Cosemans, Ralf Elsas, Campbell Harvey, Christoph Meinerding, Julien Penasse, Stefan Rünzi, Christian Schlag, Bernd Schwaab, Kevin Sheppard, George Tauchen, Erik Theissen, and Julian Thimme.
1 Introduction

According to the rare disaster hypothesis (RDH; Rietz (1988)), the extraordinary mean excess returns of U.S. equity portfolios observed during the postwar period resulted because investors ex ante demanded compensation for possibly disastrous but very unlikely risks that they never actually suffered from ex post. The Cold War imposed an ever-present threat of nuclear disaster for several decades, so a sample selection effect appears plausible. The positive path that per capita consumption followed after World War II could not have been taken as given by an investor in 1945. In turn, the RDH can help explain the equity premium puzzle and poor empirical performance of Hansen and Singleton’s (1982) canonical consumption-based asset pricing model (C-CAPM) and its recent variants. The appeal of the RDH is its straightforwardness, but its weakness is that the hypothesis is difficult to refute using data that do not contain disastrous consumption contractions, such as those from U.S. postwar samples. Several studies use calibrations to illustrate that accounting for disaster risk can reconcile high equity premia with plausible investor preferences. However, econometric studies that test the RDH with empirical data are scarce.

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

The empirical analysis shows that the estimates of the investor preference parameters – relative risk aversion (RRA), the intertemporal elasticity of substitution (IES), and the subjective discount factor – fall within a range that is economically meaningful, and they feature narrow bootstrap confidence bounds. Specifically, the estimates of the subjective discount factor are smaller than but close to unity, as would be expected of an investor with a reasonable positive rate of time preference. The RRA coefficient estimates range between 1.5 and 1.7; generally, RRA values <10 describe a reasonably risk averse investor (e.g., Mehra and Prescott (1985), Rietz (1988), Bansal and Yaron (2004)). Cochrane (2005) caps the interval of sensible relative risk aversion more strictly at 5, in line with results reported by Meyer and Meyer (2005).

For the present study, the 95% confidence interval for the RRA estimate also lies within this strict plausibility range. In addition, the IES estimates are (significantly) greater than unity and of a magnitude that is frequently assumed for calibrations. Moreover, the estimated RRA coefficient is (significantly) greater than the reciprocal of the IES estimate, which provides evidence that investors prefer early resolution of uncertainty. Several studies emphasize that an IES greater than 1, combined with a preference for early resolution of uncertainty, is necessary to obtain meaningful asset pricing implications from a C-CAPM (e.g., Bansal and Yaron (2004), Barro (2009), Nakamura et al. (2013)).

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

The growing RDH literature, to which this paper contributes, has benefited greatly from Barro’s (2006, 2009) work, which largely revived interest in the RDH.¹ For example, Wachter (2013) modifies Barro’s (2006) model with recursive preferences and adds time-varying disaster probabilities to show that the RDH qualifies as a possible solution to the volatility puzzle. Barro and Ursúa (2008) assemble annual consumption and GDP data to study the size and frequency of disasters. 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 first-step estimation strategy used herein builds on that idea.

With an alternative approach, Backus et al. (2011) obtain the distribution of disastrous contractions from equity index options, and Gabaix (2012) proposes a model with changing disaster severity to solve ten puzzles in finance. Gourio (2012) considers time-varying disaster risk in a business cycle model; Martin (2013) shows that changes in the calibration of the disaster probability and average contraction size have substantial effects on the equity premium. By exposing corporate debt to time-varying tail risks, Gourio (2013) is able to replicate important features of credit spreads. Nakamura et al. (2013) also consider a multi-period disaster process using

¹ A nice survey of RDH literature is provided by Tsai and Wachter (2015).
Bayesian analysis. Assuming recursive preferences, they show that, when calibrated with plausible time preference and IES, the equity premium can be explained with a plausible RRA. The frequentist approach adopted for the present study complements and extends their Bayesian analysis.

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

Grammig and Sönksen (2016) also propose a simulated method of moments estimation strategy for a disaster-including power utility C-CAPM, but as in Barro (2006), disasters are assumed to shrink to one-period contractions. This assumption seemingly could be the driving force behind the success of the RDH, as argued by Julliard and Ghosh (2012) and reflected in Constantinides’ (2008) comment on Barro and Ursúa (2008). When they allow for multi-period disasters and model investor preferences by a power utility function, Julliard and Gosh 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 seem to attenuate the appeal of the RDH.

The present study re-emphasizes the explanatory power of the RDH by showing that the equity premium can be explained with plausible preference parameters and
assumptions regarding the disaster process. However, it is important to assume Epstein-Zin preferences instead of an additive power utility. As some related literature implies, it is crucial to allow for a preference for early resolution of uncertainty, and the IES and RRA both must be greater than unity. Accounting for the possibility of multi-period disasters and partial government default in an empirical C-CAPM yields conforming RRA and IES estimates and thus meaningful asset pricing implications.

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, I follow Barro (2006) and assume that consumption growth evolves as

\[
\frac{C_{t+1}}{C_t} = e^{u_{t+1}} e^{v_{t+1}},
\]

where \( u_{t+1} \sim (\bar{\mu}, \sigma^2) \), \( v_{t+1} = \ln(1 - b_{t+1}) d_{t+1} \), 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

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

In words, I refer to a disaster event as a severe decline in consumption at least of size $q$. The decline may accrue over multiple disaster periods or 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, I assume, analogous to Equation 2.1, that for a gross return of an asset $R_i$:

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

where $R_{i,nd}$ denotes the asset’s gross return in non-disastrous periods, and $\tilde{b}_{t}$ 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:

$$\mathbb{E}_t [m_{t+1}(\beta, \gamma, \psi) R_{i,t+1}] = 1 \quad \text{and} \quad \mathbb{E}_t [m_{t+1}(\beta, \gamma, \psi) R_{i,t+1}^e] = 0, \quad (2.4)$$
where the stochastic discount factor (SDF) reads:

\[ m_{t+1}(\beta, \gamma, \psi) = \beta^\theta \left( \frac{C_{t+1}}{C_t} \right)^{\frac{\theta}{\psi}} R_{a,t+1}^{\theta-1}, \quad \text{with} \quad \theta = \frac{1 - \gamma}{1 - \frac{1}{\psi}}. \]  

(2.5)

In Equation (2.5), \( \beta \) denotes the subjective discount factor, \( \psi \) is the IES, and \( \gamma \) 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:

\[
\mathbb{E} \left[ \beta^\theta (e^{u_t} e^{u_t})^{\frac{\theta}{\psi}} R_{a,t}^{\theta-1} R_{i,t} \right] = p \mathbb{E} \left[ \beta^\theta ((1 - b_t)e^{u_t})^{\frac{\theta}{\psi}} R_{a,t}^{\theta-1} R_{i,t} \mid d_t = 1 \right] \\
+ (1 - p) \mathbb{E} \left[ \beta^\theta (e^{u_t})^{\frac{\theta}{\psi}} R_{a,nd,t}^{\theta-1} R_{i,nd,t} \mid d_t = 0 \right] \\
= 1,
\]

\[ \text{(2.6)} \]

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:

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

\[ \text{(2.7)} \]

The corresponding moment restriction for an excess return \( R_{i}^e \) reads:

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

\[ \text{(2.8)} \]

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:

\[ \mathbb{E}\left[ \beta^\theta (e^{u_t})^{- \frac{\theta}{\psi}} R_{a,nd,t} R_{i,nd,t} \mid d_t = 0 \right] \approx \frac{1}{T} \sum_{t=1}^{T} \beta^\theta c_{g_{nd,t}} R_{a,nd,t} R_{i,nd,t}, \]  

(2.9)

where \( c_{g_{nd,t}} \) denotes observable, non-disastrous consumption growth. Similarly,

\[ \mathbb{E}\left[ \beta^\theta (e^{u_t})^{- \frac{\theta}{\psi}} R_{a,nd,t}^{\theta-1} R_{i,nd,t} \mid d_t = 0 \right] \approx \frac{1}{T} \sum_{t=1}^{T} \beta^\theta c_{g_{nd,t}}^{- \frac{\theta}{\psi}} R_{a,nd,t}^{\theta-1} R_{i,nd,t}. \]  

(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:

\[ \frac{1 - p}{1 - p} \mathbb{E}\left[ \beta^\theta ((1 - b_t) e^{u_t})^{- \frac{\theta}{\psi}} R_{a,d,t}^{\theta-1} R_{i,d,t} \mid d_t = 1 \right] \approx \frac{1 - \frac{1}{T} \sum_{s=1}^{T} \beta^\theta c_{g_s}^{- \frac{\theta}{\psi}} R_{a,s}^{\theta-1} R_{s} d_s}{1 - D_T}, \]  

(2.11)

and

\[ \frac{1 - p}{1 - p} \mathbb{E}\left[ \beta^\theta ((1 - b_t) e^{u_t})^{- \frac{\theta}{\psi}} R_{a,d,t}^{\theta-1} R_{i,d,t}^{e} \mid d_t = 1 \right] \approx \frac{- \frac{1}{T} \sum_{s=1}^{T} \beta^\theta c_{g_s}^{- \frac{\theta}{\psi}} R_{a,s}^{\theta-1} R_{s}^{e} d_s}{1 - D_T}, \]  

(2.12)

where \( c_{g_s}, R_{a,s}, R_{s}, \) and \( R_{s}^{e} \) denote simulated (disaster-including) consumption growth and (excess) returns, and \( D_T = \sum_{s=1}^{T} d_s \). A large \( T \) 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 $\beta$, $\gamma$, and $\psi$. 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

I 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.

I 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,

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

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, \( \mu \) and \( \tilde{\mu} \):

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

where \( d_t^* \) is a binary indicator, such that

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

where \( 1[\cdot] \) 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, I 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:

\[
h_t = \left[ \left( \mu (1 - d_{t-1}) + \alpha \tau_{M(t-1)} + \delta b_{M(t-1)}^* \right) (1 - d_{t-1}) 
+ (\tilde{\mu} + \tilde{\alpha} \tilde{\tau}_{M(t-1)} + \tilde{\delta} b_{N(t-1)}^*) d_{t-1} \right) (1 - d_{t-1}^* + d_{t-1}^*) \right]^{-1}, \tag{2.16}
\]

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

To model disaster size, I adopt an idea from Barro and Jin (2011) and employ a
power law distribution (PL) to describe the transformed contraction size $z_c = \frac{1}{1-b}$. I assume that contractions that contribute to reaching the disaster threshold $q$ (when $d_t = 1$ and $d_{t+} = 1$) follow a different PL distribution than 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, which I refer to as an ACH-PL model, can be written as:

$$f(d_t, d_{t+}, z_{c,t} | \mathcal{F}_{t-1}; \theta_{ACH}, \theta_{PL}^+, \theta_{PL}^-) = f(d_t, d_{t+} | \mathcal{F}_{t-1}) \times f(z_{c,t} | d_t, d_{t+}, \mathcal{F}_{t-1})$$

$$= [h_t(\theta_{ACH})]^{d_t} \times [1 - h_t(\theta_{ACH})]^{1-d_t} \times \left(f_{PL}(z_{c,t}; \theta_{PL}^+) \times f_{PL}(z_{c,t}; \theta_{PL}^-) \right)^{d_{t+}}$$

(2.17)

where $\theta_{ACH}$ contains the ACH parameters, $f_{PL}$ denotes the power law density, and $\theta_{PL}^+$ and $\theta_{PL}^-$ 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 I 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. From these data, I select the same 35 countries

---

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.

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, I 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 contraction. Positive intermezzos of consumption growth within a disaster are allowed if (1) this positive growth is smaller in absolute value than the negative growth in the following year and (2) the size of the disaster does not decrease by including the intermezzo. Using this disaster identification scheme, I detect 89 disaster events. Figure 1 depicts their size and the periods over which they accrue.

[insert Figure 1 here]

As previously mentioned, I 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. I 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

---

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.
frequency, come from CRSP and Kenneth French’s data library. 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 \(R_a\). Nominal monthly returns are converted to real returns at a quarterly frequency, using the growth of the consumer price index of all urban consumers. In line with Beeler and Campbell (2012), I 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. I first compute maximum likelihood estimates of the ACH-PL parameters \(\theta_{ACH}\), \(\theta_{PL}^*\), and \(\theta_{PL}\). Using these estimates, it is possible to simulate disaster-including data,
which are required for the simulation-based estimation of the preference parameters \( \beta, \gamma, \) and \( \psi \) in the second stage. Consider the maximum likelihood estimation step. Equation (2.17) implies the following conditional ACH-PL log likelihood function:

\[
L(\theta_{ACH}, \theta_{PL}^+; \theta_{PL}) = \sum_{t=1}^{T} \left( d_t \ln h_t(\theta_{ACH}) + (1 - d_t) \ln [1 - h_t(\theta_{ACH})] \right) \\
+ \sum_{t=1}^{T} d_t^+ \ln f_{PL}(z_{c,t}; \theta_{PL}^*) + (1 - d_t^+) \ln f_{PL}(z_{c,t}; \theta_{PL}).
\]  

Equation (4.1)

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

\[
L(\theta_{ACH}) = \sum_{t=1}^{T} \left( d_t \ln h_t(\theta_{ACH}) + (1 - d_t) \ln [1 - h_t(\theta_{ACH})] \right)
\]  

yields \( \hat{\theta}_{ACH} \), whereas estimates of \( \hat{\theta}_{PL}^+ \) and \( \hat{\theta}_{PL} \) can be obtained by maximizing

\[
L(\theta_{PL}) = \sum_{t=1}^{T} d_t^+ \ln f_{PL}(z_{c,t}; \theta_{PL}^*) + (1 - d_t^+) \ln f_{PL}(z_{c,t}; \theta_{PL}).
\]  

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 \( \tau_m \), which equals the time duration between the \( m \)th and \( (m + 1) \)th disaster. Moreover, \( \hat{\tau}_m \) 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 \( \theta_{ACH} \) 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, \( \tau_0 \) 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, I 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 \( R_b \)

\[
g^r(\vartheta) = \left[ \frac{1}{T} \sum_{t=1}^{T} \beta^\vartheta c g_{nd,t} R^{\vartheta-1}_{a,nd,t} R_{b,nd,t} - \frac{1 - \beta^\vartheta c g_{nd,t} R^{\vartheta-1}_{a,nd,t} R_{b,nd,t}}{1 - \beta^\vartheta c g_{nd,t} R^{\vartheta-1}_{a,nd,t} R_{b,nd,t}} \right], \quad (4.4)
\]

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

\[
g^e(\vartheta) = \left[ \frac{1}{T} \sum_{t=1}^{T} \beta^\vartheta c g_{nd,t} R^{\vartheta-1}_{a,nd,t} R^e_{i,nd,t} - \frac{1 - \beta^\vartheta c g_{nd,t} R^{\vartheta-1}_{a,nd,t} R^e_{i,nd,t}}{1 - \beta^\vartheta c g_{nd,t} R^{\vartheta-1}_{a,nd,t} R^e_{i,nd,t}} \right]. \quad (4.5)
\]

---

\(^8\) 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.
Combining Equation (4.4) with Equation (4.5), and applied to the excess returns of \( N \) test assets, I obtain:

\[
G(\vartheta) = \begin{bmatrix}
\frac{1}{T} \sum_{t=1}^{T} \beta^\vartheta c g_{nd,t} R_{a,nd,t} - R_{b,nd,t} \\
\frac{1}{T} \sum_{t=1}^{T} \beta^\vartheta c g_{nd,t} R_{a,nd,t} - R_{b,nd,t}
\end{bmatrix}
\]

\[
\frac{1}{T} \sum_{t=1}^{T} \beta^\vartheta c g_{nd,t} R_{a,nd,t} - R_{b,nd,t} - \frac{1 - \frac{1}{T} \sum_{s=1}^{T} \beta^\vartheta c g_{s} R_{a,s} - R_{b,s}}{1 - \frac{1}{T} \sum_{s=1}^{T} \beta^\vartheta c g_{s} R_{a,s} - R_{b,s}}
\]

\[
, \quad (4.6)
\]

where \( R^c = [R^c_1, \ldots, R^c_N]' \). Choosing \( N \geq 2 \), SMM-type estimation of the preference parameters can then be attempted by:

\[
\hat{\vartheta} = \arg \min_{\vartheta \in \Theta} G(\vartheta)'W G(\vartheta), \quad (4.7)
\]

where \( \Theta \) denotes the admissible parameter space and \( W \) is a symmetric and positive semi-definite weighting matrix.

To evaluate \( G(\vartheta) \) within such an optimization, it is necessary to compute the moments of simulated disaster-including data. For that purpose, I use the first-step ACH-PL estimates \( \hat{\vartheta}_{ACH}, \hat{\vartheta}_{PL}^+, \) and \( \hat{\vartheta}_{PL} \) and simulate a series of hazard rates \( \{h_s(\hat{\vartheta}_{ACH}, \hat{\vartheta}_{PL}^+, \hat{\vartheta}_{PL})\}_{s=1}^{T} \). The resulting conditional disaster probabilities then can generate a sequence of disaster indicators \( \{d_s\}_{s=1}^{T} \) and \( \{d_s^+\}_{s=1}^{T} \).

I obtain simulated series of non-disastrous consumption growth and returns, \( \{c_{nd,s}, R_{a,nd,s}, R_{b,nd,s}, R_{i,nd,s}\}_{s=1}^{T} \) by block-bootstrapping from the non-disastrous U.S. postwar data. For that purpose, I rely on the automatic block-length selection procedure proposed by Politis and White (2004) and corrected by Politis et al. (2009), in combination with the stationary bootstrap of Politis and Romano (1994), in which the respective block-length 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, I assume that the transformed contractions $z_c = 1/(1 - b)$ and $z_R = 1/(1 - \tilde{b})$ have the same marginal distribution,\(^9\)

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

where

$$f(z; \theta_{PL}^*, \theta_{PL}) = f_{PL}(z; \theta_{PL}^*)^{d^*} \times f_{PL}(z; \theta_{PL})^{1-d^*}, \quad (4.9)$$

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

$$F(z_c, z_R; \theta_{PL}^*, \theta_{PL}, \theta_C) = C(F(z_c; \theta_{PL}^*, \theta_{PL}), F(z_R; \theta_{PL}^*, \theta_{PL}; \theta_C), \quad (4.10)$$

where $F(z_C; \theta_{PL}^*, \theta_{PL})$ and $F(z_R; \theta_{PL}^*, \theta_{PL})$ denote the marginal cdfs. The vector $\theta_C$ 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 $\rho$. Equation (4.10) then becomes:

$$F(z_c, z_R; \theta_{PL}^*, \theta_{PL}, \rho) = C_G(u_c, u_R; \rho), \quad (4.11)$$

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

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

\(^9\) The asset index $i$ is omitted for brevity.
distribution (see Longin and Solnik (2001)). Third, I 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: I draw \( y_{c,s} \) and \( y_{R,s} \) from a bivariate standard normal distribution with correlation \( \rho \), then compute \( u_{c,s} = \Phi(y_{c,s}) \) and \( u_{R,s} = \Phi(y_{R,s}) \), where \( \Phi \) denotes the standard normal cdf. Consumption growth and return contraction factors then can be obtained by

\[
b_s = 1 - \frac{1}{F^{-1}(u_{c,s}; \hat{\theta}_PL, \hat{\theta}_{PL})} \quad \text{and} \quad \tilde{b}_s = 1 - \frac{1}{F^{-1}(u_{R,s}; \hat{\theta}_PL, \hat{\theta}_{PL})},
\]

where

\[
F^{-1}(u; \theta^+_PL, \theta_{PL}) = \left(F^{-1}_PL(u; \theta^+_PL)\right)^{d^s} \times \left(F^{-1}_PL(u; \theta_{PL})\right)^{1-d^s}.
\]

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 \( R_{b,s} \), I 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 \( d_{s-1} = 0 \)), I 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 \( R_{b,s} = (1 - \tilde{b}_{b,s})^{d_s} R_{b,nd,s} \). 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 \( G(\boldsymbol{\theta}) \) 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. I therefore find it useful to identify and estimate the IES separately from $\beta$ and $\gamma$, 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

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

(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, $\mu_i$ 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 $\Delta c_{t+1}$, such that a linear projection of $r_{i,t+1}$ on $\Delta c_{t+1}$ and a constant would not identify the IES. Instead, the IES is identified according to the orthogonality conditions,

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

(4.15)

where $z_t$ consists of variables known at $t$ (instrumental variables), which are correlated with $\Delta c_{t+1}$.\(^{10}\)

I 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,

---

\(^{10}\) 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).
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 estimate $\hat{\psi}$ must fulfill the first-order conditions:

$$
\begin{bmatrix}
-1 & -E_T(\Delta c_s) & -E_T(r_{b,s}) \\
\frac{E_T(\Delta c_s)}{\psi^2} & \frac{E_T(\Delta c_s r_{b,s-2})}{\psi^2} & \frac{E_T(r_{b,s})}{\psi^2}
\end{bmatrix}
\begin{bmatrix}
E_T(r_{b,s}) - \hat{\mu}_b - \frac{1}{\psi} E_T(\Delta c_s) \\
E_T(r_{b,s} \Delta c_{s-2}) - \hat{\mu}_b E_T(\Delta c_{s-2}) - \frac{1}{\psi} E_T(\Delta c_s \Delta c_{s-2}) \\
E_T(r_{b,s} r_{b,s-2}) - \hat{\mu}_b E_T(r_{b,s-2}) - \frac{1}{\psi} E_T(\Delta c_s r_{b,s-2})
\end{bmatrix}
= 0,
$$

(4.16)

which reflect Hansen’s (1982) notation $E_T(\cdot) = \frac{1}{T} \sum_{t=1}^{T} (\cdot)$. 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:

$$
G^+(\tilde{\vartheta}) =
\begin{bmatrix}
\frac{1}{T} \sum_{t=1}^{T} \beta^\vartheta c g_{a,nd,t} R_{a,nd,t}^\vartheta R_{b,nd,t} - \frac{1}{1 - \beta^\vartheta} \left[ 1 - E_T \left( \beta^\vartheta c g_{s} \frac{\vartheta}{\psi} R_{a,s}^{\vartheta-1} R_{b,s} \right) \right] \\
\frac{1}{T} \sum_{t=1}^{T} \beta^\vartheta c g_{a,nd,t} R_{a,nd,t}^\vartheta R_{b,nd,t} - \frac{1}{1 - \beta^\vartheta} \left[ -E_T \left( \beta^\vartheta c g_{s} \frac{\vartheta}{\psi} R_{a,s}^{\vartheta-1} R_{s} \right) \right]
\end{bmatrix}
\begin{bmatrix}
D_T(\Delta c_s) \\
D_T(\Delta c_s r_{b,s-2}) \\
E_T(r_{b,s}) - \hat{\mu}_b - \frac{1}{\psi} E_T(\Delta c_s)
\end{bmatrix},
$$

(4.17)

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

$$
\hat{\vartheta} = \arg \min_{\tilde{\vartheta} \in \tilde{\Theta}} G^+(\tilde{\vartheta})' W G^+(\tilde{\vartheta}).
$$

(4.18)

Choosing $W$ 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, I use

\[
W = \begin{bmatrix}
I_{N+1} & 0 \\
0 & 10^6 \times I_2
\end{bmatrix}.
\]  

(4.19)

Because of the two-step approach, standard inference is not available for the second-step estimates, though I could rely on asymptotic maximum likelihood inference about the first-step ACH-PL estimates. Therefore, I 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 ACH₁, estimates all parameters in Equation (2.16). The most parsimonious parametrization, referred to as ACH₀, corresponds to the hazard rate in Equation (2.14), such that only the baseline hazard parameters \( \mu \) and \( \tilde{\mu} \) are estimated (while \( \delta = \tilde{\delta} = \alpha = \tilde{\alpha} = 0 \)). The ACH₂ 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 ACH₃ 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 ACH₄ 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., \( \delta = \alpha = \ddot{\alpha} = 0 \)).

[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 \( \hat{\mu} \) are highly significant. The estimates of \( \hat{\mu} \) and \( \delta \) in the ACH\(_4\) specification are significant at the 5% level, but the baseline hazard parameter \( \mu \) 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\(_4\).

I obtain maximum likelihood estimates of the ACH\(_0\) parameters equal to \( \hat{\mu} = 178.3 \) 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 I use these estimates as a foundation for the second estimation step, it is prudent to check their economic plausibility in advance. Accordingly, I 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 I count the number of replications for which no disastrous consumption contraction occurs. The ACH\(_0\) specification yields 21.9%, the ACH\(_4\) 14.1% disaster-free replications. The estimated disaster-including consumption process thus implies that 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 $\theta_{PL}$ and $\theta_{PL}^{+}$ 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 $T=10^7$. The table contains the point estimates of the preference parameters $\beta$, $\gamma$, and $\psi$ 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. Furthermore, the Table 4 shows the p-values of Hansen’s (1982) $J$-statistic,

$$J = \mathbb{G}(\hat{\theta})' \text{Avar}(\mathbb{G}[\hat{\theta}])^{+} \mathbb{G}(\hat{\theta}),$$

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

\footnote{More formally, for a parameter $\hat{\theta}$, the $\alpha$-quantile is computed as $\hat{\theta}^{-1}(\alpha)$, where $\hat{\theta}(\hat{\theta}) = \sum_{k=1}^{K} 1(\hat{\theta}(\hat{\theta}) < \alpha) / K$.}
squared errors (RMSEs; reported in Table 4) are computed as

\[ R = \sqrt{\frac{1}{N+1}G(\hat{\vartheta})'G(\hat{\vartheta}) \times 10^4}. \]  (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.\(^\text{12}\)

[insert Table 4 about here]

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).\(^\text{13}\)

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

---

\(^\text{12}\) In this case, the RMSE is 0, and \( R \) and the \( J \)-statistic are not reported.

\(^\text{13}\) It is worth noting that the estimation of \( \psi \) 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.
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 ACH₀-PL first-step estimates yields a slightly smaller RMSE than using the ACH₄-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 ˆβ, 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.

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 (ˆγ=9.1) but only moderate estimation precision (s.e.=17.2). By measuring consumption with waste, Savov (2011) obtains an RRA estimate of ˆγ=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 γ = 1/ψ). 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 ˆγ=174.5 (s.e.=23.3), and the IES estimates reach ˆψ=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 \( \theta = \frac{1 - \gamma}{1 + \psi} \), 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, \( \theta \) 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 (2004) assume \( \gamma=10 \) and \( \psi=1.5 \)), 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 \( \theta \). 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

\(^{14}\) An alternative interpretation of \( \theta \) is given by Hansen and Sargent (2010), where a \( \theta < 0 \) captures the agent’s aversion to model mis-specification.
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. I test whether the model-implied mean market portfolio and T-bill return, the equity premium, and the market Sharpe ratio are economically plausible. To estimate the model-implied mean T-bill return and mean market return, I approximate the population moments by averaging over the $T$ simulated observations, such that

$$
\hat{E}(R_b) = \frac{1 - \text{cov}_T(m(\hat{\beta}, \hat{\gamma}, \hat{\psi}), R_b)}{E_T(m(\hat{\beta}, \hat{\gamma}, \hat{\psi}))},
$$

and

$$
\hat{E}(R_a) = \frac{1 - \text{cov}_T(m(\hat{\beta}, \hat{\gamma}, \hat{\psi}), R_a)}{E_T(m(\hat{\beta}, \hat{\gamma}, \hat{\psi}))},
$$

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 $\text{cov}_T(x, y) = E_T(xy) - E_T(x)E_T(y)$. The model-implied equity premium can be estimated by $\hat{E}(R_a) - \hat{E}(R_b)$, and the model-implied Sharpe ratio by

$$
\frac{\hat{E}(R_a) - \hat{E}(R_b)}{\sigma_T(R_a - R_b)},
$$

where $\sigma_T = \sqrt{E_T(x^2) - E_T(x)^2}$. 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.
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 \( \hat{E}(R_b) \) and \( \hat{E}(R_a) \) 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, \( \hat{E}(R_a) \) 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 Robustness checks

As robustness check, I perform bias corrections on the parameter estimates and confidence bounds, and report the results in Table 6. Following Efron and Tibshirani (1986), I compute bias-corrected estimates of a parameter \( \vartheta \) 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 

\[
\vartheta_{BCl}(\alpha) = \hat{G}^{-1}[\Phi(z_{\alpha/2} + 2\Phi^{-1}[\hat{G}(\hat{\vartheta})])]
\]

and 

\[
\vartheta_{BCu}(\alpha) = \hat{G}^{-1}[\Phi(z_{1-\alpha/2} + 2\Phi^{-1}[\hat{G}(\hat{\vartheta})])],
\]

respectively, where \( \Phi \) denotes the cdf, \( \Phi^{-1} \) is the quantile function, and \( z_{\hat{\alpha}} \) is the \( \hat{\alpha} \)-quantile of the standard normal distribution.\(^{15}\) Comparing the results in Table 6 with those in Table 4, I find that in all instances, the corrections are rather benign. The similarity of the bias-corrected estimates and confidence intervals to the uncorrected counterparts offers a sign of robustness.

A second robustness check investigates the effect of varying the disaster threshold \( q \). Panel A of Table 7 uses \( q=0.095 \), and Panel B reports the results for \( q=0.195 \). These values are chosen in accordance with Barro and Jin (2011) and feature prominently in rare disaster literature. The results in Table 7 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 \( \hat{\theta}_{ACH} \) and \( \theta_{PL}^{r}, \theta_{PL} \), obtained from quarterly (contraction) data that have been computed from annual (disaster) periods. Because \( \theta_{PL}^{r} \) and \( \theta_{PL} \) contain information about the

\(^{15}\) According to this notation, the uncorrected confidence bounds in Table 4 are computed as 

\[
\vartheta_l(\alpha) = \hat{G}^{-1}[\Phi(z_{\alpha/2})] \text{ and } \vartheta_u(\alpha) = \hat{G}^{-1}[\Phi(z_{1-\alpha/2})].
\]
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 7 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 no-
toriously 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 con-
structed 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 heterogene-
ity (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, I allow for multi-period disasters. It has been argued that the success of the rare disaster hypothesis in calibration studies relies on the assumption that the entire disastrous contraction occurs in one period (see Julliard and Ghosh (2012); Constantinides (2008)). Second, I use Epstein-Zin preferences instead of a power utility to acknowledge preferences for an early resolution of uncertainty. Third, I 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, I simulate disaster-including consumption growth and return series by means of a discrete-time marked point process that models the time duration of and between disasters, 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 my 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, I draw from a standard uniform distribution and determine the fraction of the annual contraction that is assigned to the first quarter. How much of the remaining contraction is allocated to the second quarter is determined by another standard uniform draw. The contraction assigned to the third quarter is determined the same way. The last quarter takes what is left. This procedure implies that the contraction in the first (last) quarter will be the largest (smallest), on average. To avoid such a seasonal pattern, I re-shuffle the four quarterly contractions randomly. This procedure applies to a year that is not the first or the last of a disaster. When dealing with the first (last) year of a disaster, or if the disaster consists of only one annual contraction, I determine the quarter when the contraction begins (ends) by a draw from a discrete uniform distribution, such that each quarter has 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 $\hat{\theta}_{ACH}$, $\hat{\theta}_{PL}$, and $\hat{\theta}^{+}_{PL}$, I simulate a series of hazard rates, consumption contractions, and disaster indicators $d_s$ and $d_s^{+}$ as described in Section 4.2. The length of the simulated series is equal to the number of observations in the concatenated
country data. Next, $\theta_{ACH}$ and $\theta_{PL}$ are re-estimated on the simulated series. These steps are repeated $K$ times, and the estimates are collected in $\{\hat{\theta}^{(k)}_{ACH}, \hat{\theta}^{(k)}_{PL}, \hat{\theta}^{+(k)}_{PL}\}_{k=1}^K$.

Because I draw from the parametric ACH-PL distribution using the maximum likelihood estimates, this procedure can be characterized as a parametric bootstrap. It complements the asymptotic inference that is available for the first estimation step, but it is also crucial input for inference about the second-step SMM estimates of the preference parameters.

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

To compute the simulated moments for each replication, I proceed as described in Section 4.2 and generate disaster-including data of length $T$, $\{cg^{(k)}_s\}_{s=1}^T$, $\{R^{(k)}_{i,s}\}_{s=1}^T$, $\{R^{(k)}_{b,s}\}_{s=1}^T$, and $\{R^{(k)}_{a,s}\}_{s=1}^T$. For that purpose, I use the parametric bootstrap estimates $\hat{\theta}^{(k)}_{ACH}$, $\hat{\theta}^{(k)}_{PL}$, and $\hat{\theta}^{+(k)}_{PL}$ 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 $\{cg^{(k)}_{nd,l}\}_{l=1}^T$, $\{R^{(k)}_{nd,a,l}\}_{l=1}^T$, $\{R^{(k)}_{nd,b,l}\}_{l=1}^T$, and $\{R^{(k)}_{nd,i,l}\}_{l=1}^T$ (instead of the original data). Then the SMM-type estimation of the preference parameters $\beta$, $\gamma$, and $\psi$ 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


LETTAU, M., and S. LUDVIGSON (2001): “Resurrecting the (C)CAPM: A Cross-


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).

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

<table>
<thead>
<tr>
<th>Panel A: mkt</th>
<th>( \frac{C_{t+1}}{C_t} )</th>
<th>( R_b )</th>
<th>mean</th>
<th>std</th>
<th>ac</th>
<th>correlations</th>
</tr>
</thead>
<tbody>
<tr>
<td>market</td>
<td>1.0211</td>
<td>0.0816</td>
<td>0.084</td>
<td>0.175</td>
<td>0.026</td>
<td></td>
</tr>
<tr>
<td>( R_b )</td>
<td>1.0017</td>
<td>0.0045</td>
<td>0.857</td>
<td>0.204</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \frac{C_{t+1}}{C_t} )</td>
<td>1.0048</td>
<td>0.0051</td>
<td>0.311</td>
<td>0.175</td>
<td>0.026</td>
<td></td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Panel C: industry</th>
<th>( \frac{C_{t+1}}{C_t} )</th>
<th>( R_b )</th>
<th>NoDur</th>
<th>Durbl</th>
<th>Manuf</th>
<th>Engry</th>
<th>HiTec</th>
<th>Telcm</th>
<th>Shops</th>
<th>Hlth</th>
<th>Utils</th>
<th>Other</th>
<th>correlations</th>
</tr>
</thead>
<tbody>
<tr>
<td>NoDur</td>
<td>1.0238</td>
<td>0.0811</td>
<td>0.047</td>
<td>0.090</td>
<td>0.105</td>
<td>0.838</td>
<td>0.674</td>
<td>0.800</td>
<td>0.871</td>
<td>0.656</td>
<td>0.642</td>
<td>0.445</td>
<td>0.829 0.685</td>
</tr>
<tr>
<td>Durbl</td>
<td>1.0236</td>
<td>0.1156</td>
<td>0.103</td>
<td>0.190</td>
<td>0.009</td>
<td>0.801</td>
<td>0.484</td>
<td>0.520</td>
<td>0.773</td>
<td>0.581</td>
<td>0.690</td>
<td>0.490</td>
<td>0.832</td>
</tr>
<tr>
<td>Manuf</td>
<td>1.0229</td>
<td>0.0899</td>
<td>0.082</td>
<td>0.173</td>
<td>0.014</td>
<td>0.901</td>
<td>0.580</td>
<td>0.745</td>
<td>0.825</td>
<td>0.647</td>
<td>0.807</td>
<td>0.635</td>
<td></td>
</tr>
<tr>
<td>Engry</td>
<td>1.0253</td>
<td>0.0888</td>
<td>0.041</td>
<td>0.163</td>
<td>-0.039</td>
<td>0.592</td>
<td>0.534</td>
<td>0.423</td>
<td>0.422</td>
<td>0.432</td>
<td>0.497</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HiTec</td>
<td>1.0258</td>
<td>0.1159</td>
<td>0.070</td>
<td>0.167</td>
<td>-0.000</td>
<td>0.758</td>
<td>0.470</td>
<td>0.663</td>
<td>0.733</td>
<td>0.659</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Telcm</td>
<td>1.0187</td>
<td>0.0805</td>
<td>0.148</td>
<td>0.099</td>
<td>0.104</td>
<td>0.695</td>
<td>0.627</td>
<td>0.568</td>
<td>0.668</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shops</td>
<td>1.0238</td>
<td>0.0957</td>
<td>0.039</td>
<td>0.158</td>
<td>0.044</td>
<td>0.837</td>
<td>0.557</td>
<td>0.557</td>
<td>0.704</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hlth</td>
<td>1.0271</td>
<td>0.0909</td>
<td>0.054</td>
<td>0.092</td>
<td>0.085</td>
<td>0.726</td>
<td>0.542</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Utils</td>
<td>1.0195</td>
<td>0.0711</td>
<td>0.080</td>
<td>0.069</td>
<td>0.071</td>
<td>0.655</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>1.0217</td>
<td>0.0982</td>
<td>0.078</td>
<td>0.159</td>
<td>0.034</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
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; $\text{AIC} = 2k - 2\ln(\mathcal{L})$ and $\text{SBC} = -2\ln\mathcal{L} + k\ln(T)$, where $k$ is the number of ACH model parameters, denote the Akaike and Schwarz-Bayes information criteria, respectively. Furthermore, $\mathcal{L}R$ 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.

<table>
<thead>
<tr>
<th></th>
<th>$\theta^*_PL$</th>
<th>$\theta_{PL}$</th>
<th>$\mu$</th>
<th>$\tilde{\mu}$</th>
<th>$\alpha$</th>
<th>$\tilde{\alpha}$</th>
<th>$\delta$</th>
<th>$\tilde{\delta}$</th>
<th>$\mathcal{L}$</th>
<th>AIC</th>
<th>SBC</th>
<th>$\mathcal{L}R$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACH$_0$</td>
<td>178.3</td>
<td>1.201</td>
<td>-790.3</td>
<td>1584.7</td>
<td>1600.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACH$_1$</td>
<td>64.9</td>
<td>1.201</td>
<td>441.1</td>
<td>-787.0</td>
<td>1580.0</td>
<td>1603.2</td>
<td>&lt;1.0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACH$_2$</td>
<td>64.9</td>
<td>1.214</td>
<td>441.1</td>
<td>-0.375</td>
<td>786.8</td>
<td>1581.5</td>
<td>1612.5</td>
<td>2.9</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACH$_3$</td>
<td>198.7</td>
<td>1.221</td>
<td>-0.145</td>
<td>-0.002</td>
<td>789.9</td>
<td>1587.7</td>
<td>1618.7</td>
<td>63.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACH$_4$</td>
<td>71.4</td>
<td>1.237</td>
<td>-0.030</td>
<td>-0.002</td>
<td>431.0</td>
<td>-0.399</td>
<td>786.6</td>
<td>1585.3</td>
<td>1631.7</td>
<td>11.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PL</td>
<td>37.255</td>
<td>35.687</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.478)</td>
<td>(1.696)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 4: SMM estimates of the C-CAPM preference parameters
This table reports the estimates of the subjective discount factor $\beta$, the coefficient of relative risk aversion $\gamma$, and the IES $\psi$ using the moment matches in Equation (4.17), $T=10^4$, and the weighting matrix in Equation (4.19). The second-step SMM-type estimates are based on the first-step ACH$_1$-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 $\alpha=0.025$ and $\alpha=0.975$ 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.

<table>
<thead>
<tr>
<th>Panel A: $\rho = \text{Corr}(c_{n,i,t}, R_{n,i,t})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
</tr>
<tr>
<td>mkt</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: $\rho = 0.99$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
</tr>
<tr>
<td>mkt</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: $\rho = 0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
</tr>
<tr>
<td>mkt</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>
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 $\beta$, $\gamma$, and $\psi$ 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.

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

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

<table>
<thead>
<tr>
<th>Panel C: $\rho = 0$</th>
<th>mkt</th>
<th>size dec</th>
<th>industry</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{\theta} = (1 - \hat{\gamma}) / (1 - \frac{1}{\hat{\psi}})$</td>
<td>-1.54</td>
<td>-1.80</td>
<td>-1.86</td>
</tr>
<tr>
<td></td>
<td>[-3.50, -0.21]</td>
<td>[-3.76, -0.64]</td>
<td>[-4.07, -0.48]</td>
</tr>
<tr>
<td>mean T-bill return (%) per qtr</td>
<td>0.10</td>
<td>0.13</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>[-0.12, 0.29]</td>
<td>[-0.18, 0.34]</td>
<td>[-0.16, 0.36]</td>
</tr>
<tr>
<td>equity premium (%) per qtr</td>
<td>1.84</td>
<td>2.05</td>
<td>2.09</td>
</tr>
<tr>
<td></td>
<td>[0.97, 2.71]</td>
<td>[1.35, 2.79]</td>
<td>[1.22, 3.05]</td>
</tr>
<tr>
<td>mean market return (%) per qtr</td>
<td>1.94</td>
<td>2.18</td>
<td>2.23</td>
</tr>
<tr>
<td></td>
<td>[1.12, 2.76]</td>
<td>[1.50, 2.87]</td>
<td>[1.37, 3.07]</td>
</tr>
<tr>
<td>Sharpe ratio (market)</td>
<td>0.225</td>
<td>0.251</td>
<td>0.256</td>
</tr>
<tr>
<td></td>
<td>[0.110, 0.368]</td>
<td>[0.153, 0.391]</td>
<td>[0.139, 0.423]</td>
</tr>
</tbody>
</table>
Table 6: Bias-corrected C-CAPM preference parameter estimates and confidence intervals
This table presents bias-corrected estimates (bold) and 95% confidence bounds (in brackets) of the subjective discount factor $\beta$, the coefficient of relative risk aversion $\gamma$, and the IES $\psi$. The bias correction of the point estimates and confidence bounds in Table 4 follows the method proposed by Efron and Tibshirani (1986).

<table>
<thead>
<tr>
<th></th>
<th>Panel A: $\rho = \text{Corr}(c_{\text{ind}}, R_{\text{nd}})$</th>
<th>Panel B: $\rho = 0.99$</th>
<th>Panel C: $\rho = 0$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mkt</td>
<td>size dec</td>
<td>industry</td>
</tr>
<tr>
<td>mkt</td>
<td>$\hat{\beta}$</td>
<td>$\hat{\gamma}$</td>
<td>$\hat{\psi}$</td>
</tr>
<tr>
<td>ACH_0</td>
<td>0.9918</td>
<td>1.44</td>
<td>1.40</td>
</tr>
<tr>
<td></td>
<td>[0.9877 0.9963]</td>
<td>[1.01 2.11]</td>
<td>[1.13 1.69]</td>
</tr>
<tr>
<td>ACH_4</td>
<td>0.9924</td>
<td>1.49</td>
<td>1.73</td>
</tr>
<tr>
<td></td>
<td>[0.9881 0.9972]</td>
<td>[1.05 2.29]</td>
<td>[1.41 1.93]</td>
</tr>
<tr>
<td>mkt</td>
<td>$\hat{\beta}$</td>
<td>$\hat{\gamma}$</td>
<td>$\hat{\psi}$</td>
</tr>
<tr>
<td>ACH_0</td>
<td>0.9916</td>
<td>1.46</td>
<td>1.41</td>
</tr>
<tr>
<td></td>
<td>[0.9875 0.9961]</td>
<td>[1.03 2.13]</td>
<td>[1.14 1.70]</td>
</tr>
<tr>
<td>ACH_4</td>
<td>0.9918</td>
<td>1.50</td>
<td>1.75</td>
</tr>
<tr>
<td></td>
<td>[0.9873 0.9963]</td>
<td>[1.06 2.33]</td>
<td>[1.44 1.93]</td>
</tr>
<tr>
<td>mkt</td>
<td>$\hat{\beta}$</td>
<td>$\hat{\gamma}$</td>
<td>$\hat{\psi}$</td>
</tr>
<tr>
<td>ACH_0</td>
<td>0.9918</td>
<td>1.45</td>
<td>1.39</td>
</tr>
<tr>
<td></td>
<td>[0.9877 0.9965]</td>
<td>[1.00 2.12]</td>
<td>[1.13 1.68]</td>
</tr>
<tr>
<td>ACH_4</td>
<td>0.9923</td>
<td>1.50</td>
<td>1.73</td>
</tr>
<tr>
<td></td>
<td>[0.9878 0.9968]</td>
<td>[1.07 2.25]</td>
<td>[1.39 1.92]</td>
</tr>
</tbody>
</table>
Table 7: C-CAPM preference parameters with varying disaster thresholds
This table presents the SMM-type estimates of the preference parameters $\beta$, $\gamma$, and $\psi$ 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.

<table>
<thead>
<tr>
<th></th>
<th>mkt</th>
<th>size dec</th>
<th>industry</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta$</td>
<td>$\gamma$</td>
<td>$\psi$</td>
</tr>
<tr>
<td>Panel A: $q = 0.095/\rho = \text{Corr}(c_{\text{nd}}, R_{\text{nd}})$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACH$_0$</td>
<td>0.9918 (0.0047)</td>
<td>1.49 (0.29)</td>
<td>1.48 (0.14)</td>
</tr>
<tr>
<td></td>
<td>[0.9878 0.9960]</td>
<td>[1.03 2.15]</td>
<td>[1.33 1.86]</td>
</tr>
<tr>
<td>ACH$_4$</td>
<td>0.9919 (0.0023)</td>
<td>1.51 (0.30)</td>
<td>1.58 (0.14)</td>
</tr>
<tr>
<td></td>
<td>[0.9874 0.9962]</td>
<td>[1.07 2.23]</td>
<td>[1.34 1.87]</td>
</tr>
<tr>
<td>Panel B: $q = 0.195/\rho = \text{Corr}(c_{\text{nd}}, R_{\text{nd}})$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACH$_0$</td>
<td>0.9917 (0.0023)</td>
<td>1.51 (0.30)</td>
<td>1.49 (0.16)</td>
</tr>
<tr>
<td></td>
<td>[0.9869 0.9958]</td>
<td>[1.08 2.25]</td>
<td>[1.26 1.86]</td>
</tr>
<tr>
<td>ACH$_4$</td>
<td>0.9917 (0.0023)</td>
<td>1.57 (0.30)</td>
<td>1.63 (0.17)</td>
</tr>
<tr>
<td></td>
<td>[0.9869 0.9959]</td>
<td>[1.08 2.22]</td>
<td>[1.26 1.89]</td>
</tr>
</tbody>
</table>
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 $q$