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The Dynamics of Crises and the Equity Premium

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Abstract

It is a major challenge for asset pricing models to generate a high equity premium and a low risk-free rate while imposing realistic consumption dynamics. To address this issue, our paper proposes a novel pricing channel: We allow for consumption drops that can spark an economic crisis. This new feature generates a large equity premium even if possible consumption drops are of moderate size. In turn, our model also matches the consumption data of 42 countries along several dimensions. In particular, our approach generates a realistic number of crises that have realistic durations and involve clustering of moderate consumption drops.

Keywords: General Equilibrium, Asset Pricing, Recursive Preferences, Long-Run Risk, Disaster Models

JEL: G01, G12

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1 Introduction

A major challenge for modern asset pricing models is to explain the empirically high equity premium and low risk-free rate (equity and risk-free rate puzzle) by relying on realistic dynamics of aggregate consumption. Disaster models such as Rietz (1988) and Barro (2006) typically assume that consumption drops in a crisis happen all at once. This approach is able to address the equity premium and risk-free rate puzzle, but misses out on capturing realistic features of consumption: Empirically, crises last for several years in which moderate consumption drops cluster. As emphasized by Constantinides (2008), integrating this feature into the above disaster models, i.e. replacing one large shock by a series of smaller shocks, reduces the equity premium significantly. Therefore, our paper entertains a novel, but parsimonious approach to model aggregate consumption. We allow for a new type of negative events that combine a cash-flow shock and a regime shift to a bad state of the economy. Since in this bad state subsequent shocks are supposed to be more likely, our approach generates a sizeable equity premium. Still the size of an individual cash-flow shock can be moderate and the same across all states without compromising the equity premium. In our benchmark case, the net size is less than 2% (after taking the expected consumption growth into account), which is significantly smaller than in typical disaster models (see, e.g., Barro (2006) and Wachter (2013)). Besides targeting the high equity premium, this feature of our model allows us to generate a realistic amount of crises that have realistic durations and involve clustering of moderate consumption drops. To demonstrate this fact, we simulate our model and verify that it can match an extensive consumption data set involving 42 countries along several dimensions.

Our approach can thus address the Constantinides (2008) critique on disaster models, which has been mentioned above. He challenges the suggestion by Rietz (1988) and Barro (2006, 2009) that the possibility of very large, but rare consumption shocks gives rise to a reasonable risk premium on US equity. Assuming a small unconditional jump probability of 1.7%, but an extreme average jump size of -36% leads to an equity premium of 5.4 percentage points with a risk aversion parameter of 4 in their model. Barro (2006) shows that such disasters can be found in consumption time series of many countries, while the US have been lucky to not experience such an event since World War II. Constantinides (2008) argues that the peak-to-trough method of Barro and Rietz does not match the consumption data. Disasters like World War II do not lead to a single shock of about -40%, but unfold in a series of moderate shocks that add up to an overall drop of -40%. Replacing one large shock by a series of smaller shocks in a model with CRRA preferences reduces the equity premium significantly. By contrast, our model can still generate a sizeable equity premium even if each individual consumption shock is of moderate size.

To describe our model in more detail, notice that it involves three types of risk channels: short-run risk, long-run risk, and a combination of both. The short-run risk channel is modeled via consumption drops that can happen with a certain probability. This channel affects the level, but not the growth rate of consumption. Its impact is instantaneous. The probability of a consumption drop is assumed to depend on the state of the economy (good, bad) modeled by a two-state Markov chain. It is larger in the bad state. This constitutes the long-run risk channel that affects the growth rate, but not the level of consumption. Its effect is long-lasting. As a third and novel channel, we introduce jump-induced regime switches that combine a consumption drop with a transition from the good into the bad state. In other words, there are certain consumption drops in the good state that spark an economic crisis (bad state). It turns out that this new channel gives rise to a significant extra risk premium as compared to a model without this channel, but the same local distribution of cash flow growth. Equally important, the new channel helps in matching international consumption data along several dimensions.

Following Duffie and Epstein (1992a), Bansal and Yaron (2004) and Wachter (2013), among others, we study an economy that is populated by a representative investor with recursive utility. His risk aversion and intertemporal elasticity of substitution are both larger than one. This implies that the investor has a preference for early resolution of uncertainty and demands a risk premium for both short-run and long-run risk. We solve for the equilibrium quantities in closed form, in particular for the equity risk premium. This allows us to decompose the equity risk premium into its three components (short run, long run, combined). To document that our new channel is of first-order importance for the sizes of the equity risk premium and risk-free rate, we compare our model with *jump-induced regime switches* to the following well-established alternatives: First, we consider a model with *separated regime switches* where short-run risk is decoupled from long-run risk in the sense that transitions to the bad state and consumption drops happen separately. Second, we study a *peak-to-trough* model that involves only short-run risk. Here the whole dynamics of an economic crisis are condensed to one consumption drop which is assumed to happen at a single point in time.[1]

[1] Notice that all three models are silent on the economic reasons for crises. In this sense, they are reduced-form approaches. For clarity, we also abstract from further risk factors like a stochastic drift or stochastic volatility, which would distract from our new channel and obscure our main point.

We calibrate our model to consumption growth rates of 42 different countries.[2] Our focus is on matching both the unconditional distribution of annual consumption declines and the clustering of downward jumps in bad times. This gives rise to a moderate jump size of -5% and an unconditional jump intensity of 0.28. Our model explains the left tail of the unconditional distribution of annual consumption growth rates almost perfectly. It also reproduces the distributions of the lengths and sizes of crises in the data. The hypothesis that the annual consumption data has been generated by our model cannot be rejected. The equity risk premium in the good state is 6.94 percentage points. The premium for jump-induced regime switches from the good to the bad state is 4.95 percentage points, which comprises a premium of 0.28 percentage points for short-run jump risk, 2.22 percentage points for long-run state variable risk, and 2.45 percentage points for the combination of both. This last term is solely present in our model. In the model with separated regime switches, the equity risk premium in the good state is only 4.99 percentage points. In the peak-to-trough model with the same local consumption distribution, the premium is 2.9 percentage points. Notice that one can boost the values of the equity premium in the model with separate regime switches and the peak-to-trough model. By allowing for extreme consumption drops (peak-to-trough calibration), one can reach a higher equity premium. But then the Constantinides (2008) critique applies and the calibration of the consumption data is off. To summarize, only our model is able to achieve a realistic fit of the consumption data and at the same time generate a realistic equity premium.

Finally, several robustness checks document that our results are not driven by one particular calibration of the model. The consumption data can be matched using different jump sizes between -3% and -7%. We also study whether our model can generate a long phase of "low volatility" such as in the US over the last 50 years. All calibrations lead to a sizeable risk premium for our new channel combining long-run and short-run risk. Regarding the preference parameters, we show that the elasticity of intertemporal substitution (EIS) plays a key role in our model. For low levels of the EIS where the investor no longer has a pronounced preference for early resolution of uncertainty, the extra risk premium for jump-induced regime switches shrinks dramatically and can even become negative. In particular, in the special case of constant relative risk aversion (CRRA), the total risk premium is higher in a model with separated regime switches than in a model with jump-induced regime switches. These findings are in line with the long-run-risk literature (see, e.g., Bansal and Yaron (2004)).

[2]We thank Robert Barro for providing this dataset on his webpage.

Our paper is related to the literature on asset pricing with rare disasters. Rietz (1988) and Barro (2006, 2009) entertain the disaster risk explanation to rationalize a high equity risk premium. Extensions of the basic model have been studied by Chen, Joslin, and Tran (2012) and Julliard and Ghosh (2012), among others. Gabaix (2012) analyzes a model with time-varying jump intensities. As a response to the critique by Constantinides (2008), Barro, Nakamura, Steinsson, and Ursua (2013) propose and estimate a complex macroeconomic model with recursive preferences where disasters unfold over several years including a recovery period afterwards. Their paper is similar in spirit to ours, but the mechanics of our model are simpler. Among other things, this simplicity allows us to disentangle the implications of short-run and long-run risk in closed form and to explicitly assess the impact of our combined channel of long-run and short-run risk. Similar to the critique of Constantinides (2008), the assumption of extreme jumps is also questioned by Backus, Chernov, and Martin (2011). They use index options to estimate the implied distribution of consumption jumps and document that option prices imply more frequent but less extreme outcomes than needed in disaster risk explanations of the equity premium. Finally, several papers study the implications of jump risk and/or regime switching processes in long-run risk models. Kandel and Stambaugh (1991) and Hung (1994) study models with Epstein-Zin utility in which market fundamentals follow a bivariate Markov switching process. Both settings are similar to the model with separated regime switches that we consider as one possible benchmark. These authors calibrate to purely U.S. data and in contrast to our paper thus make different assumptions about how extreme the regimes can be. The risk aversions needed to explain the equity premium are (much) higher than in our paper. Benzoni, Collin-Dufresne, and Goldstein (2011) analyze a model with jumps in the expected growth rate and volatility and show that this model provides an equilibrium foundation of the volatility smile. Drechsler and Yaron (2011) analyze the variance risk premium in a long-run risk model with time-varying jump risk. Wachter (2013) proposes a time-varying probability of rare disasters which can explain the high stock market volatility. Tsai and Wachter (2014) apply this model to growth and value stocks.

The remainder of the paper is organized as follows. Section 2 describes the different model setups used in this paper. Section 3 solves these models. Section 4 provides details on the calibration and a comparison with the stylized facts about consumption drops. Section 5 studies the equity risk premium and its components in regime switching as well as disaster models. Section 6 performs robustness checks. Section 7 concludes. All proofs are in the Appendix.

2 Consumption Dynamics

2.1 Model with Jump-induced Regime Switches

We consider a continuous-time Lucas tree economy with an infinite horizon. There is one tree generating a perishable consumption good which serves as numeraire. The economy can be in either of two states which we denote by g and b (for 'good' and 'bad'). The states are formally captured by a Markov chain Z. Conditional on the state of the economy $Z_t \in \{g, b\}$, the outcome of the tree follows a jump-diffusion process. If the economy is in the good state, then

$$\frac{dC_t}{C_{t-}} = \mu dt + \sigma dW_t + LdN_t^{g,g} + LdN_t^{g,b}. \tag{1}$$

In the bad state, the dynamics are

$$\frac{dC_t}{C_{t-}} = \mu dt + \sigma dW_t + LdN_t^{b,b}, \tag{2}$$

where W is a Wiener process. For simplicity, the drift μ, volatility σ and jump size $L < 0$ are constant and state-independent.[3] The probability for a downward jump in consumption however depends on the state Z of the economy. In line with the interpretation of the states as 'good' and 'bad', we assume that these consumption shocks are more frequent in the bad state than in the good state. This is achieved as follows: In the good state downward consumption jumps can be triggered by the jump processes $N^{g,g}$ and $N^{g,b}$ with intensities $\lambda^{g,g}$ and $\lambda^{g,b}$. In the bad state jumps are triggered by $N^{b,b}$ with intensity $\lambda^{b,b}$. Consequently, we assume that the sum of the jump intensities in the good state is smaller than in the bad state, i.e. $\lambda^{g,g} + \lambda^{g,b} < \lambda^{b,b}$.

Our model allows for two types of downward consumption jumps: First, *pure consumption jumps* are modeled via the jump processes $N^{g,g}$ and $N^{b,b}$ that count downward consumption jumps in the good and the bad state which do not have an effect on the regime. Second, in the good state we allow for consumption jumps that happen jointly with a transition from the good to the bad state. These *jump-induced regime switches* are captured by the jump process $N^{g,b}$. In the following, they are going to play a decisive role. This is because jump-induced regime switches combine negative consumption realizations ('cash flow shocks') with changes in the distribution of future consumption growth ('regime shifts').

[3] These assumptions can be relaxed, but this would not add additional insights concerning our main focus.

To close the model, there are also transitions from the bad to the good state which are triggered by a fourth counting process $N^{b,g}$. These jumps only change the state, but do not directly affect the level of consumption. For ease of exposition, we do not include jump-induced regime switches from the bad to the good state. We also do not allow for changes from the good to the bad state which are not linked to consumption jumps.

2.2 Model with Separated Regime Switches

To tease out the effect of jump-induced regime switches, we also consider a model with regime switches that do not induce immediate negative consumption realizations. We refer to these regime changes as 'separated regime switches'. The corresponding consumption dynamics become

$$\frac{dC_t}{C_{t-}} = \mu dt + \sigma dW_t + L\, dN_t^{g,g} \tag{3}$$

in the good state and

$$\frac{dC_t}{C_{t-}} = \mu dt + \sigma dW_t + L\, dN_t^{b,b}, \tag{4}$$

in the bad state, respectively. The counting process $N^{g,b}$ still triggers a regime change from the good to the bad state, but does not lead to an immediate consumption shock. When we compare jump-induced and separated regime switches, we assume that the local distribution of consumption and the transition probabilities of the Markov chain are the same in both models. The jump intensities for the regime switches $N^{g,b}$ and $N^{b,g}$ are thus identical, while the intensity of $N^{g,g}$ is larger with separated regimes than with jump-induced regimes.

2.3 Peak-to-Trough Model

The second model that we use for comparison abstracts from different states and assumes that consumption growth is i.i.d. The consumption dynamics are given by

$$\frac{dC_t}{C_{t-}} = \mu dt + \sigma dW_t + L dN_t, \tag{5}$$

where N is a Poisson process with intensity λ. This model represents a special case of the Barro (2006) model with constant jump size. It can explain the equity risk premium if jumps are disastrous but rare events. Barro (2006) calibrates the jump parameters to a panel of consumption data from different countries and argues that there is indeed evidence for disasters. An economic crisis is assumed to be a single (very) negative consumption realization. The size of this consumption shock is usually calibrated to the observed consumption drops from peak to trough. Crisis which may last over several years are thus mapped into a single event. The dynamics of crises are disregarded, which is criticized by Constantinides (2008).

We consider two calibrations of this model. In the first calibration ('local calibration'), we stick to the unconditional local distribution of consumption growth rates from the other two models. Consequently, we set the jump intensity λ equal to the unconditional average jump intensity and keep the jump size L fixed at the same value as in the other models. The second calibration ('disaster calibration') follows the idea of Rietz (1988) and Barro (2006) who model disasters as rare but extreme events. We set the jump size L equal to the average consumption drop during a crisis from peak to trough. The jump intensity in the disaster calibration is set equal to the probability of observing an extreme crisis in the model with jump-induced regime switches. We thus condense a crisis which usually stretches over several years to a single event. Consequently, under the disaster calibration, jumps are less frequent but more severe than under the local calibration.

3 Solution of the Model

3.1 Representative Investor

Our economy is populated by a representative investor with stochastic differential utility as introduced by Duffie and Epstein (1992b). His subjective time preference rate is β, his relative risk aversion is γ, and his elasticity of intertemporal substitution is ψ. The investor has an infinite planning horizon, and his indirect utility function is

$$J_t = \mathrm{E}_t \left[\int_t^{\infty} f(C_s, J_s) ds \right],$$

where the aggregator f is given by

$$f(C,J) = \frac{\beta C^{1-\frac{1}{\psi}}}{\left(1-\frac{1}{\psi}\right) \left[(1-\gamma)J\right]^{\frac{1}{\theta}-1}} - \beta\theta J$$

with $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$. Following Bansal and Yaron (2004), among others, we assume $\gamma > 1$ and $\psi > 1$. Therefore, the investor has a preference for early resolution of uncertainty. As a robustness check, we also study the CRRA case, $\psi = \frac{1}{\gamma}$, where the investor is indifferent towards the resolution of uncertainty.

3.2 Pricing Kernel

Following Duffie and Epstein (1992a,b) and Benzoni, Collin-Dufresne, and Goldstein (2011), we solve for the pricing kernel.[4] The agent's indirect utility J is

$$J_t = \frac{C_t^{1-\gamma}}{1-\gamma}\beta^\theta e^{\theta v^{Z_t}}.$$

The pricing kernel ξ is given by

$$\xi_t = \beta^\theta C_t^{-\gamma} e^{-\beta\theta t+(\theta-1)\left(\int_0^t e^{-v^{Z_u}}du+v^{Z_t}\right)}, \tag{6}$$

where v^{Z_t} is the logarithm of the wealth-consumption ratio.[5] It depends on the state of the economy Z and can thus take only two values, v^g and v^b, which solve the following system of equations:

$$\begin{aligned}
0 &= e^{-v^g} - \beta + \left(1-\frac{1}{\psi}\right)\mu - \frac{1}{2}\gamma\left(1-\frac{1}{\psi}\right)\sigma^2 \\
&\quad + \frac{1}{\theta}\lambda^{g,g}\left[(1+L)^{1-\gamma}-1\right] + \frac{1}{\theta}\lambda^{g,b}\left[(1+L)^{1-\gamma}e^{\theta(v^b-v^g)}-1\right] \\
0 &= e^{-v^b} - \beta + \left(1-\frac{1}{\psi}\right)\mu - \frac{1}{2}\gamma\left(1-\frac{1}{\psi}\right)\sigma^2 \\
&\quad + \frac{1}{\theta}\lambda^{b,b}\left[(1+L)^{1-\gamma}-1\right] + \frac{1}{\theta}\lambda^{b,g}\left[e^{\theta(v^g-v^b)}-1\right].
\end{aligned}$$

3.3 Price-Dividend Ratio

Given the pricing kernel (6), we can price all claims in the economy including the dividend claim. Following Bansal and Yaron (2004) and Wachter (2013), among others, dividends D_t are modeled as a levered claim to consumption with leverage parameter ϕ. The dividend dynamics are

$$\frac{dD_t}{D_{t-}} = \mu dt + \phi\sigma dW_t + \left[(1+L)^\phi - 1\right]dN_t^{g,g} + \left[(1+L)^\phi - 1\right]dN_t^{g,b}$$

in the good state and

$$\frac{dD_t}{D_{t-}} = \mu dt + \phi\sigma dW_t + \left[(1+L)^\phi - 1\right]dN_t^{b,b}$$

[4] Details of the derivation as well as the proofs of all following results can be found in Appendix A.

[5] See, e.g., Campbell, Chacko, Rodriguez, and Viceira (2004) and Benzoni, Collin-Dufresne, and Goldstein (2011).

in the bad state. Following Longstaff and Piazzesi (2004), we choose the same drift rate μ for consumption and dividends. The pricing equation for the dividend claim is

$$D_t e^{w_t} = \mathrm{E}_t \left[\int_t^\infty \frac{\xi_\tau}{\xi_t} D_\tau d\tau \right],$$

where w is the logarithm of the price-dividend ratio. Analogously to the log wealth-consumption ratio, the log price-dividend ratio w depends on the state of the economy. Its two possible values, w^g and w^b, satisfy a system of equations that is provided in Appendix A.

4 Consumption Data and Calibration

This section describes the data and explains how we calibrate the different models. First we calibrate our model with jump-induced regime switches so that it matches both the unconditional distribution of annual consumption growth rates and the durations of crises. Naturally, we focus on the left-hand side of the distribution which contains information about the nature of consumption crises. Then we turn to the model with separated regime switches. This model is identical to our model except that jump-induced regime switches are not possible. To tease out the effect of this channel, we take the calibration of the jump-induced regime switching model as given, switch off the jump-induced regime switches and then adjust the calibration such that the local distribution of consumption growth rates and the transition probabilities are the same as in the model with jump-induced regime switches.[6] Finally, we consider the peak-to-trough model and provide two calibrations. In the first one, we match the local distribution of consumption, whereas in the second one we apply the peak-to-trough approach by Barro (2006).

4.1 Consumption Data

The calibration is based on the consumption dataset that is available on Robert Barro's webpage. This dataset contains annual consumption growth rates of 42 different countries ranging (at most) from 1791 to 2009. Altogether, the dataset consists of 4,933 country-year consumption growth observations. The dataset also contains GDP growth rates for all the countries. Neither the parameters nor the numerical results will change significantly if we use GDP growth rates. Therefore, we do not report the corresponding results here.

[6] Alternative calibrations are discussed at the end of Section 4.3.

To mitigate potential Peso problems as discussed in Goetzmann and Jorion (1999), we use the full dataset rather than just US consumption data. For the same reason, we also do not exclude data points from the sample. We pool the consumption data from all countries into one single time series by adding country after country.[7] We exclusively use consumption data to calibrate the model and do not rely on asset price data in this section.

The row labeled 'Data' in Panel A of Table 1 reports the unconditional moments. The mean annual consumption growth rate is 0.02 and thus similar to the value observed for U.S. consumption data to which asset pricing models are usually calibrated. The standard deviation is 0.065 and significantly exceeds the value for U.S. data of around 0.02. The distribution is slightly right-skewed with a skewness of 0.37, and highly leptokurtic with a kurtosis of 10.04. Since the left tail of the growth rate distribution contains information about consumption crises, Panel B reports values of the empirical unconditional cumulative distribution function below zero. For instance, the probability that the annual consumption growth is below 0 (-10%) amounts to around 30% (3.3%).

Constantinides (2008) points out that understanding the part of the equity risk premium which can be attributed to potential consumption disasters requires a dynamic analysis. In particular, the duration of crises is of crucial importance, since annual consumption growth over the peak-to-trough period of a disaster is highly autocorrelated. Therefore, Table 2 provides some evidence on the durations of crises. We define the length of a crisis as the number of consecutive years where the consumption growth rates are below a given threshold. For a threshold of 0%, there are 1,492 observations with consumption growth rates below 0%. This gives rise to 906 crises periods of different lengths. Panel A of Table 2 reports the probabilities that a crisis in the sample has a length of one up to ten years. For instance, 61.6% of all crises in the data last only one year, 23% have a duration of two years and so on. Finally, there is exactly one crisis of 10 years in the dataset (India in the 1930s). Panels B and C report the corresponding probabilities for more pronounced annual consumption drops of at least -5% and -10%, respectively.

Notice that crises can last for several years even if consumption growth were i.i.d. Therefore, clustering per se should not be interpreted as evidence that observed crises are generated by a model with regimes. Appendix B reports results on whether consumption jumps are indeed more frequent than in models with i.i.d. consumption growth. We find

[7] In our calibrations, we make sure that we do not create 'artificial' crises across countries through this.

that compared to a model with i.i.d. consumption realizations, crises with a length of 3 years are 50% more likely in the data and crises with a length of 4 years are twice as likely. These results are in line with Constantinides (2008) and provide evidence that consumption drops cluster in reality.

4.2 Model with Jump-induced Regime Switches

We calibrate our model so that it matches both the unconditional distribution of annual consumption growth rates and the distribution of the durations of crises. The consumption dynamics in our model depend on seven parameters (μ, σ, L, and four intensities $\lambda^{j,k}$) whose values are reported in the first row of Table 3. We calibrate the model in several steps: First, we fix $\sigma = 0.04$. This choice makes sure that the probability for negative consumption growth rates is already of the right order without jumps. Additionally, jumps are essential to generate the right amount of severe negative outcomes. The jump parameters are however hard to estimate. We fix the loss size at $L = -0.05$ and choose the jump intensities $\lambda^{j,k}$ accordingly.[8] Finally, we fix the drift parameter $\mu = 0.033$ so that the corresponding calibration matches the unconditional expected consumption growth. This parameterization implies that after taking the expected consumption growth into account the net consumption loss in a given year is -1.7% if exactly one jump occurs.

The jump parameters are crucial to match the clustering of jumps and the durations of crises. The *unconditional* distribution of annual consumption growth rates can be fitted well by a small jump intensity $\lambda^{g,g} + \lambda^{g,b} = 0.1$ in the good state, a high jump intensity $\lambda^{b,b} = 1.9$ in the bad state, and unconditional probabilities of the good and the bad state of 90% and 10%, respectively. The empirical properties of crises then put restrictions on the relation between $\lambda^{b,b}$ and $\lambda^{b,g}$. Crises have to be sufficiently long to generate the right amount of autocorrelation in our model-generated data. We choose $\lambda^{b,g} = 0.72$ which implies an average duration of 1.39 years for the bad state. The unconditional probability of 10% for the bad state then implies $\lambda^{g,b} = 0.08$. Finally, we choose the intensity $\lambda^{g,g} = 0.02$ so that the sum $\lambda^{g,g} + \lambda^{g,b}$ is equal to 0.1 as explained above.

To document that our calibration can explain the consumption data, we focus on the above-mentioned dimensions of the data: the unconditional distribution of consumption growth rates and the dynamics of crises. We simulate 500,000 years of daily consumption realizations and aggregate the data to annual time series of consumption growth rates.

[8] Alternative loss sizes are studied in a robustness check in Section 6.2.

Table 1 reports the unconditional moments and tail probabilities of these simulated annual consumption growth rates. The unconditional annual mean consumption growth rate is 0.02, exactly as in the data. The unconditional annual standard deviation of consumption is 0.056. This is slightly below the value of 0.065 in the data. Furthermore, Panel B documents that the model fits the left tail almost perfectly.

To formally assess the fit of the simulated to the empirical data, we perform a Kolmogorov-Smirnov (KS) test. Since our focus is on the left tail of the distribution, we truncate the distribution at a level of 0% (and also −2% and −4% as a robustness check). The null hypothesis of the two-sample Kolmogorov-Smirnov test is that two data samples have been generated by the same (unconditional) distribution. In our data, the p-value from the KS test is always above 0.03 and exceeds 0.35 for a truncation level of −4%. Therefore, we cannot reject the null hypothesis at the 1% level that a model with jump-induced regime switches has generated the empirical consumption data.[9]

Our second objective is to match the dynamics of crises described by their lengths. Table 2 reports the distributions of the lengths of crises. Our model matches the data well in this dimension, too. Notice that for a threshold of −10% there are 132 crises only. All except of one have a duration of less than 4 years. The empirical probability of 0.008 that a crisis lasts for exactly 4 years is thus due to a single crisis (Netherlands 1940-1943).

To summarize, the left tail of the simulated consumption distribution is not statistically significantly different from the tail of the empirical distribution. Besides, the average durations of crises are similar to the durations in the empirical data. Notice that we focus on crises, i.e. on the left tail of the consumption distribution. By including features such as stochastic volatility, stochastic growth rates, or stochastic jump sizes, one could also try to fit the right tail of the distribution. This is beyond the scope of this paper.

4.3 Model with Separated Regime Switches

The model with separated regime switches (3) and (4) does not allow for jump-induced regime changes. We choose the parameters such that the local distribution of consumption growth rates and the transition probabilities are the same as in the model with jump-induced regime switches. The row labeled "Separated regime switches" of Table 3

[9] As a robustness check, we also performed KS tests at the country level, i.e. we compared the model-generated time series to each of the 42 country-specific time series of consumption growth rates in the dataset. For a truncation level of 0%, the p-values are above 0.01 for 37 countries and above 0.1 for 24 countries.

summarizes the resulting calibration. The parameters μ, σ and L remain unchanged. Also the probability of consumption jumps in the good state is the same as before. Therefore, the value of $\lambda^{g,g}$ is now equal to the sum of $\lambda^{g,g}$ and $\lambda^{g,b}$ in the model with jump-induced regime switches, i.e. we set $\lambda^{g,g} = 0.02 + 0.08 = 0.10$. The other jump intensities remain unchanged.

Crises periods no longer start with an initial drop in consumption, which implies that the total consumption loss over a crisis is smaller. This also materializes in the simulations. The probabilities for extreme crises are smaller, and the measured durations of crises are also smaller than before. In line with these findings, the KS test now rejects the hypothesis that the model with separated regime switches has generated the empirical consumption data.

Alternatively, we could also calibrate the model such that it fits the consumption data as close as possible. Results not reported here, show that one can find calibrations that the KS test cannot reject. These calibrations differ only slightly from the ones presented above. For instance, one would have to set the volatility parameter σ to 0.042 instead of 0.04 and increase the jump intensities by a small amount. However, such calibrations generate an equity premium that is still too low (about 4–5 percentage points). Only our model with jump-induced regime switches is able to achieve a realistic fit of the consumption data and at the same time generate a realistic equity premium.

4.4 Peak-to-Trough Model

For the peak-to-trough model (5), we consider two calibrations. In the first calibration (reported in the column labeled 'local calibration' of Table 3), we match the local distribution of consumption. The jump intensity λ is set to 0.28, which is the unconditional average jump intensity in the model with jump-induced regime switches. The jump size L and the volatility σ have the same values as in the previous models. Not surprisingly, Table 2 shows that the model fails to match the distribution of consumption growth rates over one year and over several years. In particular, the model fails to generate enough long-lasting crises of two or more consecutive years with consumption growth below -5% or -10%. Nevertheless, we include this model in our asset pricing analysis. This allows us to not only study the impact of jump-induced regime switches on asset prices, but also the effect of regime switches per se. The local calibration of the peak-to-trough model serves as one benchmark for this analysis.

The second calibration follows the peak-to-trough calibration approach of Barro (2006). We use the model with jump-induced regime switches and simulate 500,000 years of consumption realizations. We then extract all crises with one or several consecutive years of negative consumption growth. The peak-to-trough consumption loss is the total drop in consumption over these years. The number of crisis periods in our simulated samples is roughly 96,000. Figure 1 depicts the resulting histogram of peak-to-trough disaster sizes. We then extract all crises for which the peak-to-trough disaster size exceeds -15%, which is also the threshold used by Barro (2006). This leaves us with about $12,000$ disasters. For the peak-to-trough 'disaster calibration', we set the jump intensity λ equal to the number of disasters divided by 500,000 and the jump size equal to the average peak-to-trough consumption loss. The column 'disaster calibration' of Table 3 reports the exact parameter values.

The simulated time series generated from this disaster calibration are similar to the data-generating processes used by Barro (2006) except that we assume a constant jump size. It is not surprising that the disaster calibration of the peak-to-trough model is not able to match the stylized facts of the consumption data. For instance, the KS tests reject the peak-to-trough model. Similar as the model with separated regime switches, the peak-to-trough model cannot resolve the tradeoff between matching consumption data and generating a sizeable equity premium.

5 Asset Pricing Implications

We now turn to the asset-pricing implications of our model. As preference parameters we choose $\beta = 0.03$, $\psi = 2$, and $\gamma = 6$. Furthermore, we choose a leverage parameter of $\phi = 2$ for both diffusion risk and jump risk.[10] Section 6 analyzes alternative parametrizations.

5.1 Price-Dividend Ratio

In our model with jump-induced regime switches, the wealth-consumption ratio is $e^{v^g} = 32.65$ in the good state and $e^{v^b} = 30.25$ in the bad state. In line with intuition, the agent's total wealth is smaller in the bad state, i.e. $v^b < v^g$. Since dividends are a claim to levered

[10] In the literature, one can find different choices of the leverage parameter. Barro, Nakamura, Steinsson, and Ursua (2013) assume a rather low leverage of $\phi = 1.5$, whereas Bansal and Yaron (2004) set $\phi = 3$. In Section 6.3, we will study alternative parametrizations.

consumption, the price-dividend ratio is smaller than the wealth-consumption ratio. It is $e^{w^g} = 11.91$ in the good state and $e^{w^b} = 9.38$ in the bad state. Upon a jump from the good to the bad state, the price-dividend ratio thus drops by 21.16%.

In the model with separated regime switches, the price-dividend ratio is $e^{w^g} = 13.24$ and $e^{w^b} = 10.13$, and the drop in the price-dividend ratio is 23.49%. Compared to our model the higher price-dividend ratios reflect the lower overall risk in this economy. Regime switches from the good to the bad state are disentangled from consumption losses. Since the agent is less averse to two small downward jumps in prices than to one large jump, prices are higher. With less risk in the good state, the price difference between the two states has to be larger in the model with separated regime switches, too.

In the peak-to-trough model, the price-dividend ratio is constant. It is equal to 19.31 for the local calibration and 17.19 for the disaster calibration. There is no state-variable risk and so the price-dividend ratio is much larger than in each of the models with regimes. The price-dividend ratio is smaller for the disaster calibration than for the local calibration since potential consumption jumps are more severe in this case.

5.2 Equity Risk Premium

Table 4 reports the local equity risk premia resulting from the different approaches. In the model with jump-induced regime switches, the local equity risk premium is 0.0694 in the good state and 0.1956 in the bad state. Since the economy is in the good state 90% of the time, this yields an unconditional equity risk premium of 0.0820. The model with separated regime switches gives rise to an equity risk premium of 0.0499 in the good state and 0.2164 in the bad state, leading to an unconditional average of 0.0665. Finally, the peak-to-trough model implies an equity risk premium of 0.0290 for the local calibration and 0.0671 for the disaster calibration.

Since we can solve our model in closed form, we can explicitly decompose the equity risk premium into its components. This allows us to explicate the mechanism through which our model generates a large equity premium. The instantaneous asset return is defined by $dR = dP/P + D/P\,dt$. The expected excess return on the dividend claim can be decomposed into diffusion and jump risk premia:

$$\frac{\mathrm{E}_t[dR_t^i]}{dt} - r_f^i = \phi\sigma \cdot \gamma\sigma + \sum_{k=g,b} RP^{i,k},$$

where $i \in \{g, b\}$ denotes the state of the economy.

The first term is the diffusion risk premium. It depends on the exposure of the price to diffusive risk and on the market price of risk, which follows from the dynamics of the pricing kernel. As the diffusion parameters are the same across all specifications, the diffusion risk premium is equal to 0.0192 in all models.

The differences in the unconditional equity risk premia across models and parametrizations arise from the jump risk premia. Each jump risk factor gives rise to a jump risk premium, i.e. there is one jump risk premium in the peak-to-trough model and two jump risk premia in every state of the models with regimes. Table 4 reports the components of the conditional risk premia in all models. In the two models with regimes, the good state prevails 90% of the time, and so the unconditional risk premia mainly depend on the risk premia in the good state. Taking this into account our numerical results show that the premium for jump-induced regime switches is quantitatively the most important component of the unconditional risk premium. This holds true for our model, but also compared to the components of all other model specifications.

To explain this finding, we explicitly decompose the jump risk premia further into their constituents. In general, the risk premium for a jump risk factor N is

$$RP = -\lambda \, \mathrm{E}_\Delta \left[\left(e^{\Delta \ln P} - 1 \right) \left(e^{\Delta \ln \xi} - 1 \right) \right] .$$

It is equal to the jump intensity, multiplied by the negative of the covariance between the relative change in the price, $e^{\Delta \ln P} - 1$, and the relative change in the pricing kernel upon that jump, $e^{\Delta \ln \xi} - 1$. Here E_Δ denotes the expectation w.r.t. the joint distribution of $\Delta \ln P$ and $\Delta \ln \xi$. Since the jump sizes are deterministic in all models under consideration, the risk premium simplifies to

$$RP = -\lambda \left(e^{\Delta \ln P} - 1 \right) \left(e^{\Delta \ln \xi} - 1 \right) = -\lambda \, \zeta \, \eta$$

where we denote the change in the price by ζ and the change in the pricing kernel by η in the following.

The differences in the jump risk premia across models arise because a jump can have two distinct effects. First of all, a jump can impact the *level* of cash flows immediately. This is for instance true for all jumps in the peak-to-trough model. We refer to this form of risk as *short-run risk* or *consumption risk* in the following. The changes in the price and in the pricing kernel upon such an event depend on the size of the consumption jump:

$$\zeta = e^{\phi \Delta \ln C} - 1 = (1 + L)^{\phi} - 1 \qquad \eta = e^{-\gamma \Delta \ln C} - 1 = (1 + L)^{-\gamma} - 1.$$

Second, a jump can impact the state of the economy and thus change the *distribution* of future cash flow growth. We refer to this type of risk as *long-run risk* or *state-variable risk* in the following because it is similar in spirit to the risk factors which are analyzed by Bansal and Yaron (2004). In our paper, the regime mainly controls the intensity of pure consumption jumps, which is similar to the idea of Wachter (2013) who allows for a stochastic disaster intensity. The changes in the price and in the pricing kernel upon a switch from the good to the bad state depend on the reaction of the valuation ratios:

$$\zeta = e^{w^b - w^g} - 1 \qquad \eta = e^{-(1-\theta)(v^b - v^g)} - 1.$$

Long-run risk is priced if the investor is not indifferent towards the timing of the resolution of uncertainty ($\theta \neq 1$). If he has a preference for early resolution of uncertainty, he demands a positive premium for adverse changes of state variables.

The jump risk premia in all models under consideration can now be expressed as different combinations of these terms. In the peak-to-trough model, jumps involve only short-run risk. In the model with separated regime switches, there are jumps with long-run impact only (regime switches) and jumps with short-run impact only (pure consumption jumps). Our model with jump-induced regime switches entertains a third channel which couples long-run risk (stochastic jump intensities) and short-run consumption risk. As we document below, the extra risk premium arising from this new channel has about the same order of magnitude as the premium for pure long-run risk.

Table 5 reports the decompositions of the jump risk premia for all model specifications. The peak-to-trough model solely allows for pure consumption jumps, leading to one jump risk premium only. The local calibration of the peak-to-trough model results in the lowest overall equity risk premium. The value of 0.029 is significantly smaller than the typical values estimated from the data which are between 0.05 and 0.08 . The significant difference between the two calibrations can be attributed to the impact of jumps on the pricing kernel. The disaster calibration involves more severe, but less frequent jumps, i.e. it amplifies short-run consumption risk. The expected annual loss due to consumption jumps, $\lambda((1 + L)^{\phi} - 1)$, is even larger in the local calibration than in the disaster calibration (-0.0273 as compared to -0.0105). The response of the pricing kernel to a shock in the disaster calibration, however, is more than ten times higher than in the local calibration. The disproportionally higher response of the pricing kernel overcompensates the smaller average cash flow impact of jumps and leads to a larger equity risk premium. This finding mirrors the results of Barro (2006) and Rietz (1988) who propose disaster models to solve the equity premium puzzle. A risk-averse agent dislikes rare severe jumps more than frequent small jumps.

In the model with separated regime switches, there are two types of jump risk premia in each state: pure consumption jumps and jumps triggering separated regime switches. Pure consumption jumps, denoted by the superscripts 'g, g' and 'b, b', lead to an immediate drop in consumption and dividends, but have no effect on the regime. Consequently, the increase in the pricing kernel and the drop in the price only reflect short-run consumption risk and are the same in both states. The risk premia in the good and bad state only differ because of different jump intensities. By contrast, separated regime switches solely affect the economic regime, but have no immediate impact on consumption and dividends. The changes in the pricing kernel and in the price are thus driven by changes in the valuation ratios only. When the economy switches from the good to the bad state, the price drops. An agent with a preference for early resolution of uncertainty is averse to this switch so that the wealth-consumption ratio drops and the pricing kernel increases. This results in a positive risk premium for the regime switch of 0.0272. When the economy switches back from the bad to the good state, the price increases, while the pricing kernel drops. The resulting risk premium is positive again and amounts to 0.1304.

The model with jump-induced regime switches leads to the highest overall risk premium in the good state. The biggest share of this risk premium can be attributed to the premium for jump-induced regime switches. The increase in the pricing kernel upon a jump-induced regime switch reflects the downward jump both in consumption and in the wealth-consumption ratio:

$$\eta^{g,b} = \underbrace{(1+L)^{-\gamma}}_{\eta^{jump}+1}\underbrace{e^{-(1-\theta)(v^b-v^g)}}_{\eta^{RS}+1} - 1 = \eta^{jump} + \eta^{RS} + \eta^{jump}\eta^{RS} \tag{7}$$

Importantly, it is not just the sum of the increases resulting from the downward jump in consumption and the regime switch. Additionally, it involves an interaction term $\eta^{jump}\eta^{RS}$. Numerically, we get $\eta^{g,b} = 2.1449$, which can be decomposed into $\eta^{jump} = 0.3604$, $\eta^{RS} = 1.3118$, and $\eta^{jump}\eta^{RS} = 0.4727$. The size of the interaction term is significant. In particular, its contribution to the increase in the pricing kernel is larger than the contribution of consumption losses η^{jump}.[11]

To provide an intuition for the additional term in the pricing kernel, we can again draw an analogy to the peak-to-trough model of Barro (2006) and Rietz (1988). As seen above, the representative agent favors small jumps occurring with a large probability over one

[11] Note that, since the wealth-consumption ratios are in general different in the two models, η^{RS} is not the same as $\eta^{g,b}$ in the model with separated regime switches. The same applies to ζ^{RS} and $\zeta^{g,b}$ below.

large jump happening with a small probability (given that the average loss is the same in both cases). The change in the pricing kernel and equity premium is thus nonlinear in the severity of the disasters. By the same line of argument, the agent dislikes joint downward jumps in consumption and in the wealth-consumption ratio much more than separate ones.

Similarly, the change in the price upon a jump-induced regime switch also combines a short-run dividend component and a long-run price-dividend ratio component:

$$\zeta^{g,b} = \underbrace{(1+L)^{\phi}}_{\zeta^{\text{jump}}+1}\underbrace{e^{w^b-w^g}}_{\zeta^{RS}+1} - 1 = \zeta^{jump} + \zeta^{RS} + \zeta^{jump}\zeta^{RS}, \tag{8}$$

Numerically, we have $\zeta^{\text{jump}} = -0.0975$, $\zeta^{\text{RS}} = -0.2116$ and an interaction term of $\zeta^{jump}\zeta^{RS} = 0.0206$. Here the interaction term has a different sign than the other two terms. Having jump-induced regime switches instead of separated ones thus slightly reduces the overall impact of adverse jumps on the asset price.

Putting (7) and (8) together yields the risk premium for jump-induced regime switches:

$$-\lambda^{g,b}\zeta^{g,b}\eta^{g,b} = -\lambda^{g,b}\left(\zeta^{jump} + \zeta^{RS} + \zeta^{jump}\zeta^{RS}\right)\left(\eta^{jump} + \eta^{RS} + \eta^{jump}\eta^{RS}\right)$$

It is significantly bigger than the sum of the (hypothetical) single risk premia for consumption jumps and regime switches. Table 6 decomposes this risk premium into its components. The first part of the risk premium can be regarded as the compensation for (hypothetical) pure consumption jumps and (hypothetical) pure regime switches:

$$-\lambda^{g,b}\zeta^{jump}\eta^{jump} - \lambda^{g,b}\zeta^{RS}\eta^{RS} = 0.0028 + 0.0222.$$

These two terms are structurally equal to the risk premia in a model with separated regime switches.[12] They contribute 0.025 to the risk premium. In line with the long-run risk literature, the risk premium earned on state-variable risk is much larger than the premium on short-run consumption risk.

The second part consists of "cross risk premia":

$$-\lambda^{g,b}\zeta^{jump}\eta^{RS} - \lambda^{g,b}\zeta^{RS}\eta^{jump} = 0.0102 + 0.0061$$

Technically, these cross risk premia appear because the product of the sums $-\eta^{jump} - \eta^{RS}$ and $\zeta^{jump} + \zeta^{RS}$ is bigger than the sum of the products $-\zeta^{jump}\eta^{jump}$ and $-\zeta^{RS}\eta^{RS}$.

[12]Numerically, they are slightly different because η^{RS} and ζ^{RS} are not equal to their counterparts $\eta^{g,b}$ and $\zeta^{g,b}$ in the model with separated regime switches.

Economically, these two cross premia reflect the key mechanism of our model. Exactly at the time of a consumption jump, there is a regime switch which causes an additional upward shift η^{RS} in the pricing kernel. This gives rise to the additional risk premium $-\lambda^{g,b}\zeta^{jump}\eta^{RS}$. Analogously, at the time of a regime switch, a consumption jump occurs which triggers an additional upward shift η^{jump} in the pricing kernel. This gives rise to the risk premium $-\lambda^{g,b}\zeta^{RS}\eta^{jump}$. The premia for consumption jumps and regime switches are thus amplified by their joint occurrences. The two terms are unique to our model and add up to 0.0163, i.e. they are economically significant.

The third part of the risk premium involves additional interaction terms:

$$-\lambda^{g,b}\zeta^{jump}\zeta^{RS}(\eta^{jump}+\eta^{RS})-\lambda^{g,b}(\zeta^{jump}+\zeta^{RS})\eta^{jump}\eta^{RS}-\lambda^{g,b}\zeta^{jump}\zeta^{RS}\eta^{jump}\eta^{RS}$$

They add up to 0.0081. Here, the most important contribution comes from the additional interaction term $\eta^{jump}\eta^{RS}$ in the change of the pricing kernel. Once again, this term reflects that the agent dislikes the joint occurrence of consumption jumps and adverse regime switches more than the separate events.

Putting everything together, the overall premium for jump-induced regime switches is around 0.05. About half of this premium can be attributed to the joint occurrence of consumption jumps and regime switches. The unconditional equity risk premium is also the largest in the economy with jump-induced regime switches. It exceeds the unconditional equity risk premium in a model with separated regime switches by around 1.5 percentage points although the local distribution of future consumption is the same in both economies. The link between state-variable risk and short-run consumption risk adds a significant component to the risk premium. It has about the same order of magnitude as the premium for pure long-run jump intensity risk or pure short-run consumption risk.

5.3 Risk-free interest rate

Table 7 reports the risk-free rates in all economies. The unconditional risk-free rate in the model with jump-induced regime switches is 0.0155 and thus about 70 basis points lower than in the model with separated regime switches. In the peak-to-trough model, the numbers are 0.0284 (local calibration) and 0.0136 (disaster calibration). Similar to the analysis of the equity premium, the numbers show that our model with jump-induced regime switches can also resolve the tradeoff between matching consumption data and generating a low risk-free rate.

The risk-free rate follows from the (negative) expected growth rate of the pricing kernel. It equals

$$r_f^j = \beta + \frac{1}{\psi}\frac{\mathrm{E}_t\left[dC_t\right]}{C_t\ dt} - \pi^{\mathit{diff}} - \sum_{k=g,b} \pi^{j,k},$$

in state $j \in \{g, b\}$. The risk-free interest rate comprises the subjective time preference rate β, the expected growth rate of consumption scaled by the inverse of the EIS, and several precautionary savings terms for the different risk factors in our model:

$$\begin{aligned}\pi^{\mathit{diff}} &= \frac{1}{2}\gamma(1+\frac{1}{\psi})\sigma^2 \\ \pi^{j,k} &= \lambda^{j,k}\left[\eta^{j,k} + \frac{1}{\psi}L + \frac{1-\theta}{\theta}\left((1+L)^{1-\gamma}e^{\theta(v^k-v^j)} - 1\right)\right]\end{aligned}$$

for $(j, k) \in \{(g, g), (g, b), (b, b)\}$ and

$$\pi^{b,g} = \lambda^{b,g}\left[\eta^{b,g} + \frac{1-\theta}{\theta}\left(e^{\theta(v^g-v^b)} - 1\right)\right].$$

Table 7 also reports the decomposition of the risk-free rate into its components. The first three components (time preference rate, expected consumption growth, precautionary savings term for diffusive risk) are straightforward and identical across settings (except for the expected consumption growth in the disaster calibration).[13]

Since the good state prevails 90% of the time, differences in the unconditional risk-free rate are mainly driven by differences in the conditional risk-free rate in the good state. These differences arise from the precautionary savings terms for jump risk. In the economy with jump-induced regime switches, these terms reduce the risk-free rate by almost 1 percentage point as compared to the model with separated regime switches. The mechanism driving this finding is similar as for the equity premium. The precautionary savings term for a model with jump-induced regime switches is $\pi^{g,b} = 0.0140$ compared to $\pi^{g,b} = 0.0053$ for a model with separated regime switches.

[13] Notice that the expected consumption growth in the local calibration of the peak-to-trough model equals the unconditional expected consumption growth in the other two models. However, the expected consumption growth is slightly higher with the disaster calibration.

6 Robustness Checks

6.1 Elasticity of Intertemporal Substitution

The upper panel of Figure 2 depicts the local equity premium in the good state of the regime switching models and the unconditional local equity premium in the peak-to-trough specifications as functions of the elasticity of intertemporal substitution ψ. The other panels of Figure 2 depict the risk premium for regime switches from the good to the bad state, the pricing kernel response $\eta^{g,b}$ and the price response $\zeta^{g,b}$ in the two regime switching models. The independent variable EIS ranges from 0.02 to 2 so that the figures capture our baseline case ($\psi = 2$) as well as the special case with CRRA preferences ($\psi = 1/6$) which is indicated by the left dotted line. Table 8 reports the same equity premium decomposition as Table 4, but for the power utility case ($\psi = 1/6$).

Comparing Table 8 to Table 4 confirms that only the risk premium for (jump-induced or separated) regime switches depends on the EIS. All other risk factors in our model (diffusion and pure consumption jumps) are pure cash flow risk and do not affect the state variable. Therefore the exact degree of the agent's preference for early resolution of uncertainty (i.e. the tradeoff between γ and ψ) does not matter for these risk premia. Consequently, the risk premium in the peak-to-trough model does not depend on ψ.

As Figure 2 shows, the total risk premia in the regime switching models are nonmonotonic functions of ψ with minima around the CRRA case ($\psi = 1/6$). This nonmonotonicity derives from the premium for (jump-induced or separated) regime switches $-\lambda^{g,b}\eta^{g,b}\zeta^{g,b}$, which is depicted in the second panel. The lower graphs of Figure 2 depict $\eta^{g,b}$ and $\zeta^{g,b}$ as a function of the EIS. The nonmonotonic behavior of the risk premium comes from two ingredients: (i) the monotonicity of $\eta^{g,b}$ and $\zeta^{g,b}$ and (ii) their signs.

The change in the pricing kernel upon a regime switch, $\eta^{g,b}$, is monotonically increasing in ψ. Recall that we can decompose $\eta^{g,b}$ as follows

$$\eta^{g,b} = \underbrace{(1+L)^{-\gamma}}_{1+\eta^{\text{jump}}} \underbrace{e^{-(1-\theta)\left(v^b - v^g\right)}}_{1+\eta^{RS}} - 1.$$

As η^{jump} does not depend on ψ, the monotonic pattern comes from η^{RS}. For the log wealth-consumption ratios, it holds true that $v^b > v^g$ for $\psi < 1$ and $v^b < v^g$ for $\psi > 1$. In the latter case, the substitution effect dominates the income effect and the wealth-consumption ratio is higher in the good state. The term $-(1-\theta)$ is positive for $\psi \in (1/6, 1)$ and negative otherwise. Altogether, this results in a monotonically increasing η^{RS}. For $\psi = 1/6$, η^{RS}

is equal to zero, since the CRRA investor does not price state-variable risk. For $\psi > 1/6$, adverse changes in the state lead to a positive response of the pricing kernel, which increases in the preference for early resolution of uncertainty (and thus in ψ).

In the model with separated regime switches, $\eta^{g,b}$ is essentially equal to η^{RS} (except that the exact values for v^g and v^b are different). In the model with jump-induced regime switches, the pricing kernel response is amplified by the term involving η^{jump}. Therefore, $\eta^{g,b}$ is always larger than in the model with separated regime switches and has a null below $\psi = 1/\gamma$.

The impact of separated or jump-induced regime switches on the price, $\zeta^{g,b}$, is decreasing in ψ. The more the investor cares about the timing of the resolution of uncertainty, the larger is the price difference between the good and the bad state, and this price difference is reflected in $\zeta^{g,b}$. The price response is always lower with jump-induced regime switches than with separated regime switches. This is because of the additional cash flow shock to which the regime switch is coupled. Similar to the pricing kernel response, the price response switches sign and becomes positive if the EIS becomes sufficiently low for both model specifications. If the preference for early resolution of uncertainty is not very pronounced, a switch from the good to the bad regime increases all prices in the economy. For CRRA utility ($\psi = 1/6$), we thus find the usual counterintuitive result that the price-dividend ratio is higher in bad than in good states of the world. For recursive utility with $\psi > 1$, the direction of the relation reverses. Consequently, $\zeta^{g,b}$ has a null between $\psi = 1/6$ and $\psi = 1$.

The properties of $\eta^{g,b}$ and $\zeta^{g,b}$ explain the nonmonotonicity of the jump risk premium depicted in the second graph. For high values of the EIS, $\eta^{g,b}$ is positive and monotonically increasing, whereas $\zeta^{g,b}$ is negative and monotonically decreasing. Thus, the risk premium $-\lambda^{g,b}\eta^{g,b}\zeta^{g,b}$ is positive and monotonically increasing. For very low values of the EIS, $\eta^{g,b}$ is negative and monotonically increasing, whereas $\zeta^{g,b}$ is positive and monotonically decreasing, which results in a positive and monotonically decreasing risk premium. In between, the risk premium has a minimum for $\psi \approx 0.2$. For values of ψ around 1/6, the risk premium $-\lambda^{g,b}\eta^{g,b}\zeta^{g,b}$ becomes even negative, so that the total risk premium in the first graph is close to zero.

Notice that the two curves in the first graph intersect around $\psi = 0.25$, i.e. for values below $\psi = 0.25$ the total risk premium is higher in a model with separated regime switches than with jump-induced regime switches. This is again in line with the well-known intuition from the long-run risk literature that both state-variable risk and recursive preferences are necessary to generate sizeable risk premia. On the other hand, the difference between the risk premia of both models is still sizeable for intermediate values of ψ between 0.5 and 1.5. Our findings are thus robust to variations of the EIS as long as the preference for early resolution of uncertainty stays reasonably pronounced.

To summarize, the risk premium for regime switches reaches a minimum around $\psi = 1/\gamma$ which is the CRRA case. This minimum is even negative. For other values of ψ, the risk premium can be significantly larger. This pattern is particularly pronounced in an economy with jump-induced regime switches.

6.2 Jump Sizes and Intensities

Our results so far are based on a loss size of $L = -0.05$. Now, we study the effects if this size is varied. As mentioned in Section 4.2, there are trade-offs between the jump size and the jump intensities. We therefore have to vary the jump intensities as well in order to still match the consumption data.[14]

Table 9 reports five different calibrations of the model with jump-induced regime switches. The jump size L increases (in absolute terms) from -0.03 to -0.07. The calibration with $L = -0.05$ is the baseline case that is discussed in Section 4. The jump intensity $\lambda^{g,g}$ is 0.02 in all specifications. To match the consumption data, the other intensities are decreased if L gets more extreme: $\lambda^{g,b}$ ranges from 0.12 to 0.04, $\lambda^{b,b}$ from 2.9 to 0.9, and $\lambda^{b,g}$ from 1.08 to 0.36. In all specifications, the values of $\lambda^{b,g}$ and $\lambda^{g,b}$ imply unconditional probabilities of the two states of 90% and 10%, respectively. Notice that the probability of entering a crisis becomes smaller if the loss size L is larger.[15]

Figure 3 depicts the unconditional local equity premium and the risk-free rate for these cases and for all models under consideration. The parameters for the other three specifications (separated regime switches and the two peak-to-trough cases) are obtained by performing exactly the same steps as in Section 4.

The figure shows that the equity premium remains high for all parametrizations of our

[14] A given *unconditional* distribution of annual consumption growth rates can be fitted either by a small value of L (e.g. -0.03) and a high value of the average jump probability, i.e. large values of $\lambda^{g,g} + \lambda^{g,b}$ and $\lambda^{b,b}$, or by a large value of L and a small average jump probability. As explained in Section 4.2, the empirical properties of crises then put restrictions on the relation between $\lambda^{b,b}$ and $\lambda^{b,g}$. Finally, for given values of $\lambda^{g,b}$ and L, we choose the intensity $\lambda^{g,g}$ so that the sum $\lambda^{g,g} + \lambda^{g,b}$ is in the right range.

[15] The alternative calibrations of our model match the consumption data similarly well as our benchmark parametrization discussed in Section 4.2. Detailed results are available upon request.

model. It is the highest for $L = -0.06$. Overall, we conclude that the size of the equity premium is robust to varying the jump size. In all cases, our additional channel of jump-induced regime switches increases the equity premium significantly. The additional premium is in all cases about the same order of magnitude as the premium for separated regime switches, which is a pure long-run risk premium as in Bansal and Yaron (2004). The lower figure shows the risk-free rate for all cases. The effect of our new channel on the risk-free rate is essentially a mirror image of the findings for the equity premium.

6.3 Leverage

Figure 4 depicts the unconditional local equity premium as a function of the leverage parameter ϕ ranging between 1 and 3. So far, we have assumed $\phi = 2$. For large values of ϕ, the two models with regimes generate higher premia than both parametrizations of the peak-to-trough model. One reason for this finding is that the jump size in all our models is constant. In the peak-to-trough model, this implies that there is only one jump risk factor with a constant jump size, i.e. no jump *size* risk. In the regime switching models, conditional on the state of the economy, there are always two jump risk factors which have different price impacts. Essentially, this is comparable to a situation with one jump risk factor where the jump size is drawn from a distribution with two possible outcomes. Stated differently, one can interpret the regime switching models, conditional on the economic state, as models with constant jump intensity, but jump *size* risk. The larger the leverage parameter, the larger is the average size and variance of price jumps. As compared to the peak-to-trough model, the risk premium in the regime switching models thus increases disproportionately as a function of the leverage parameter.

Finally, notice that the additional equity premium resulting form our jump-induced regime switch channel is robust to changes in the leverage parameter. This can be seen by comparing the red solid line and the blue dotted line. The difference shall be interpreted as this additional premium. Obviously, it is almost constant across leverage levels.

6.4 Volatility of Consumption Growth

In our calibration we have tried to match an extensive consumption data set involving 42 countries along several dimensions. This leads to the following tension: The empirical consumption volatility across all 42 countries is about 6.5%, whereas it is for instance around 2% for the US since 1960 if we consider 15 years moving averages. To fit the volatility of the full sample our calibration involves a diffusive volatility of 4%, which is twice as high as the US number for the last 50 years. Therefore, the question arises whether our model can generate such a streak of 50 “low volatility” observations with a reasonable probability or whether the US is a true outlier. It turns out that with a consumption volatility of 4% it is in fact very unlikely to observe such a phase of low volatility. This is similar to the findings in Julliard and Ghosh (2012). These authors show that the observation of the equity premium puzzle itself would be a rare event if the rare disaster model of Barro (2006) is used as a data-generating model.

We thus reduce the diffusive volatility to 3% and perform the following exercises: Given a choice of $\sigma = 0.03$ we determine the probabilities of seeing a realized volatility below 2.5% over a time span of 40, 50, or 60 years. Simulating our model and the model with separated regime switches leads to several interesting insights: (i) In our model all three probabilities are twice as high as in a model with separated regime switches. Therefore, our model can better explain long phases of low realized volatility.[16] (ii) The p-value[17] for seeing a realized volatility below 2.5% over 50 years is above 5% in our model, whereas it is below 5% for a model with separated regime switches. Consequently, in our model the US data is not necessarily an outlier (at the 5% level). For a time span of 60 years, the p-value in our model is above 1%, whereas it is below 1% in the model with separated regime switches. Therefore, in contrast to the model with separated regime switches, our model cannot be rejected at the 1% level.[18]

To make sure that lowering the volatility does not compromise the other criteria which we impose in our calibration, we check these criteria: First, we verify that the choice of $\sigma = 0.03$ still leads to a sizeable equity premium. As can be seen from Table 10, the equity premium in the good state is still about 0.06, which is 0.02 higher than in a model with separated regime switches. Second, we consider the left-tail of the consumption distribu-

[16] We thank an anonymous referee for making us aware of the fact that this might be an additional feature which distinguishes our model from a model with separated regime switches.

[17] These p-values are computed as follows: We simulate 500,000 years of daily consumption realizations and aggregate the data to annual time series of consumption growth rates. Then we determine the fraction π_{50} of 50-year episodes in the simulated data in which the realized volatility of consumption growth is at most 2.5%. Finally, we compute the probability of at least one success for a binomial distribution with 98 trials and a success probability of π_{50}. Notice that the Barro dataset contains 4,933 annual consumption growth rates, which gives rise to 98 episodes of 50 years. For the 60-year p-values, we repeat this procedure with a $B(82, \pi_{60})$ distribution, for the 40-year p-values, we use a $B(123, \pi_{40})$ distribution.

[18] For a time span of 40 years, the p-values are above 10% in both models, i.e. both models are likely to generate such a time span of low volatility.

tion of the full sample. The p-value of a KS test is larger than 2% for our model, whereas it is between 5% and 10% for the model with separated regime switches. For $\sigma = 0.03$ the latter model can thus slightly better explain the consumption distribution, but both models cannot be rejected at the 1% level. Finally, Table 11 reports the distributions of the disaster durations in both models. It can be seen that the numbers are still reasonably in line with the data, but the fit is not as good as in the benchmark calibration. Recall that the main focus of our paper is to address the Constantinides (2008) critique by matching an extensive international consumption data set along several dimensions. For this reason we have used a higher volatility in the main part of the paper.

7 Conclusion

This paper entertains a tractable way to model the joint occurrence of negative consumption realizations and changes in the distribution of future consumption growth. This new channel combines short-run and long-run risk. We calibrate our model to consumption data covering 42 countries and show that it matches the data well. Our model generates disasters that are realistic both from their total size, but also from their duration. In particular, it avoids the so-called peak-to-trough calibration where the total size of a disaster is realized at a single point in time. By contrast, our model produces sufficiently many long-lasting periods in which moderate negative consumption realizations cluster. Nevertheless, this approach leads to a sizeable equity premium. Therefore, our results address the critique by Constantinides (2008). We also find that a stylized model that disentangles long-run and short-run risk cannot simultaneously generate a realistic equity premium and match the dynamics of consumption if the risk aversion of the representative agent is in a reasonable range.

Since our novel channel leads to a tractable class of models and allows for closed-form solutions of the equity premium and the risk-free rate, it could potentially be embedded in other asset pricing models. This might help future research to match the equity premium and the risk-free rate even if the focus is not particularly on this research question. In other words, our findings support the argument that by incorporating a combination of long-run and short-run risk one can achieve a sizeable equity premium without making unrealistic assumptions about the dynamics of crises.

A Solving for the Equilibrium

A.1 Wealth-Consumption Ratio

Let $Z_t \in \{g, b\}$ denote the state of the economy at time t. Then the representative investor has two value functions, one for each state:

$$J_t^{Z_t} = \mathrm{E}_t\left[\int_t^\infty f\left(C_s, J_s^{Z_s}\right) ds\right].$$

For the sake of readability, we will, however, suppress the dependence of the value function, the pricing kernel, the aggregate consumption and other variables on the state $Z_t \in \{g, b\}$ in the following. As usual, the aggregator f is defined as

$$f(C, J) = \frac{\beta C^{1-\frac{1}{\psi}}}{\left(1 - \frac{1}{\psi}\right)\left[(1-\gamma)J\right]^{\frac{1}{\theta}-1}} - \beta\theta J.$$

β denotes the subjective time discount rate, ψ the elasticity of intertemporal substitution, and γ the relative risk aversion. We also define $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$. A Feynman-Kac-like computation then gives

$$0 = f\left(C_t, J_t\right) + \mathcal{D}J_t \tag{9}$$

i.e. one Bellman equation for each state.

The dynamics of consumption in the good state are

$$\frac{dC_t}{C_{t-}} = \mu dt + \sigma dW_t + L dN_t^{g,g} + L dN_t^{g,b}, \tag{10}$$

its dynamics in the bad state are

$$\frac{dC_t}{C_{t-}} = \mu dt + \sigma dW_t + L dN_t^{b,b}. \tag{11}$$

We apply the following conjecture for the functional form of the value function J:

$$J = \frac{C^{1-\gamma}}{1-\gamma}\beta^\theta e^{\theta v^Z} \tag{12}$$

where v^Z can take two values, one in each state. Campbell, Chacko, Rodriguez, and Viceira (2004) and Benzoni, Collin-Dufresne, and Goldstein (2011) show that, with this conjecture, v^Z is the log wealth-consumption ratio. Plugging the guess (12) for J into the aggregator function results in

$$f(C, J) = \theta J\left(e^{-v^Z} - \beta\right).$$

The infinitesimal generator $\mathcal{D}J$ follows via Itô's Lemma:

$$\begin{aligned}
\mathcal{D}J = {} & \left(1 - \frac{1}{\psi}\right)\theta J^g \mu - \frac{1}{2}\gamma\left(1 - \frac{1}{\psi}\right)\theta J^g \sigma^2 \\
& + \lambda^{g,g} J^g \left[(1+L)^{1-\gamma} e^{\theta v^g - \theta v^g} - 1\right] \\
& + \lambda^{g,b} J^g \left[(1+L)^{1-\gamma} e^{\theta v^b - \theta v^g} - 1\right]
\end{aligned}$$

in the good state and

$$\begin{aligned}
\mathcal{D}J &= \left(1-\frac{1}{\psi}\right)\theta J^b\mu - \frac{1}{2}\gamma\left(1-\frac{1}{\psi}\right)\theta J^b\sigma^2 \\
&\quad + \lambda^{b,b}J^b\left[(1+L)^{1-\gamma}e^{\theta v^b-\theta v^b}-1\right] \quad + \lambda^{b,g}J^b\left[e^{\theta v^g-\theta v^b}-1\right]
\end{aligned}$$

in the bad state. Plugging these expressions into (9), dividing by θJ^g and θJ^b respectively, and rearranging some terms gives the following two algebraic equations for the two unknowns v^g and v^b:

$$\begin{aligned}
0 &= e^{-v^g}-\beta+\left(1-\frac{1}{\psi}\right)\mu-\frac{1}{2}\gamma\left(1-\frac{1}{\psi}\right)\sigma^2 \\
&\quad +\frac{1}{\theta}\lambda^{g,g}\left[(1+L)^{1-\gamma}-1\right]+\frac{1}{\theta}\lambda^{g,b}\left[(1+L)^{1-\gamma}e^{\theta(v^b-v^g)}-1\right] \\
0 &= e^{-v^b}-\beta+\left(1-\frac{1}{\psi}\right)\mu-\frac{1}{2}\gamma\left(1-\frac{1}{\psi}\right)\sigma^2 \\
&\quad +\frac{1}{\theta}\lambda^{b,b}\left[(1+L)^{1-\gamma}-1\right]+\frac{1}{\theta}\lambda^{b,g}\left[e^{\theta(v^g-v^b)}-1\right].
\end{aligned}$$

A.2 Pricing Kernel

As Duffie and Epstein (1992a) and Benzoni, Collin-Dufresne, and Goldstein (2011) show, the pricing kernel is given by

$$\xi_t=\beta^\theta C_t^{-\gamma}e^{-\beta\theta t+(\theta-1)\left(\int_0^t e^{-v_u^{Z_u}}du+v_t^{Z_t}\right)}. \tag{13}$$

The dynamics of the pricing kernel can be computed via Itô's Lemma. The partial derivatives of ξ with respect to C and v follow from (13). The dynamics of C are given in (10) and (11). The dynamics of the pricing kernel are

$$\begin{aligned}
\frac{d\xi_t}{\xi_{t-}} &= \left[-\beta\theta+(\theta-1)e^{-v^g}\right]dt-\gamma\mu dt+\frac{1}{2}\gamma(1+\gamma)\sigma^2dt \\
&\quad -\eta^{\mathit{diff},g}dW_t+dN_t^{g,g}\eta^{g,g}+dN_t^{g,b}\eta^{g,b}
\end{aligned}$$

in the good state and

$$\begin{aligned}
\frac{d\xi_t}{\xi_{t-}} &= \left[-\beta\theta+(\theta-1)e^{-v^b}\right]dt-\gamma\mu dt+\frac{1}{2}\gamma(1+\gamma)\sigma^2dt \\
&\quad -\eta^{\mathit{diff},b}dW_t+dN_t^{b,b}\eta^{b,b}+dN_t^{b,g}\eta^{b,g}
\end{aligned}$$

in the bad state. For later use, we abbreviate the drift of the pricing kernel by

$$\mu_\xi^Z = -\beta\theta+(\theta-1)e^{-v^Z}-\gamma\mu+\frac{1}{2}\gamma(1+\gamma)\sigma^2.$$

The market price of diffusion risk is $\eta^{\mathit{diff},Z}=\gamma\sigma$. The changes of the pricing kernel upon a jump/regime switch are:

$$\begin{aligned}
\eta^{g,g} &= (1+L)^{-\gamma}-1 \\
\eta^{g,b} &= (1+L)^{-\gamma}e^{(\theta-1)\left(v^b-v^g\right)}-1 \\
\eta^{b,b} &= (1+L)^{-\gamma}-1 \\
\eta^{b,g} &= e^{(\theta-1)\left(v^g-v^b\right)}-1.
\end{aligned}$$

The risk-free rate is equal to the negative expected growth rate of the pricing kernel ξ_t:

$$\begin{aligned}
r_f^g &= \beta + \frac{1}{\psi}\left(\mu + L\lambda^{g,g} + L\lambda^{g,b}\right) - \frac{1}{2}\gamma(1+\frac{1}{\psi})\sigma^2 \\
&\quad -\lambda^{g,g}\left[\eta^{g,g} + \frac{1}{\psi}L + \frac{1-\theta}{\theta}\left((1+L)^{1-\gamma}-1\right)\right] \\
&\quad -\lambda^{g,b}\left[\eta^{g,b} + \frac{1}{\psi}L + \frac{1-\theta}{\theta}\left((1+L)^{1-\gamma}e^{\theta(v^b-v^g)}-1\right)\right] \\
r_f^b &= \beta + \frac{1}{\psi}\left(\mu + L\lambda^{b,b}\right) - \frac{1}{2}\gamma(1+\frac{1}{\psi})\sigma^2 \\
&\quad -\lambda^{b,b}\left[\eta^{b,b} + \frac{1}{\psi}L + \frac{1-\theta}{\theta}\left((1+L)^{1-\gamma}-1\right)\right] \\
&\quad -\lambda^{b,g}\left[\eta^{b,g} + \frac{1-\theta}{\theta}\left(e^{\theta(v^g-v^b)}-1\right)\right].
\end{aligned}$$

A.3 Pricing the Dividend Claim

For the price-dividend ratio of the claim to dividends, we apply the Feynman-Kac formula. Let w denote the log price-dividend ratio. Defining $g(\xi, D, w) = \xi D e^w$ results in

$$g(\xi_t, D_t, w_t) = \xi_t D_t e^{w_t} = \mathrm{E}_t\left[\int_t^\infty \xi_\tau D_\tau d\tau\right] = \mathrm{E}_t\left[\int_t^\infty \frac{g(\xi_\tau, D_\tau, w_\tau)}{e^{w_\tau}} d\tau\right].$$

The Feynman-Kac formula yields

$$\mathcal{D}g(\xi, D, w) + \frac{g(\xi, D, w)}{e^w} = 0 \qquad \Longleftrightarrow \qquad \frac{\mathcal{D}g(\xi, D, w)}{g(\xi, D, w)} + e^{-w} = 0. \tag{14}$$

The dividend dynamics in our model are

$$\frac{dD_t}{D_{t-}} = \mu dt + \phi\sigma dW_t + \left[(1+L)^\phi - 1\right] dN_t^{g,g} + \left[(1+L)^\phi - 1\right] dN_t^{g,b}$$

in the good state and

$$\frac{dD_t}{D_{t-}} = \mu dt + \phi\sigma dW_t + \left[(1+L)^\phi - 1\right] dN_t^{b,b}$$

in the bad state. Itô's Lemma gives

$$\frac{\mathcal{D}g}{g} = \mu_\xi + \mu_D + \mu_w + \frac{1}{2}\frac{d\langle w^c\rangle}{dt} + \frac{d\langle \xi^c, D^c\rangle}{\xi D dt} + \frac{d\langle w^c, D^c\rangle}{D dt} + \frac{d\langle w^c, \xi^c\rangle}{\xi dt} + \text{ Jump Terms.}$$

The log price-dividend ratio w can take the two values w^g and w^b only, i.e. μ_w is 0. From (14), we get the following two algebraic equations:

$$\begin{aligned} 0 &= e^{-w^g} + \mu_\xi^g + \mu - \eta^{diff,g}\phi\sigma \\ &\quad +\lambda^{g,g}\left[(1+\eta^{g,g})(1+L)^{\phi} - 1\right] \\ &\quad +\lambda^{g,b}\left[(1+\eta^{g,b})(1+L)^{\phi}e^{w^b-w^g} - 1\right] \\ 0 &= e^{-w^b} + \mu_\xi^b + \mu - \eta^{diff,b}\phi\sigma \\ &\quad +\lambda^{b,b}\left[(1+\eta^{b,b})(1+L)^{\phi} - 1\right] \\ &\quad +\lambda^{b,g}\left[(1+\eta^{b,g})e^{w^g-w^b} - 1\right]. \end{aligned}$$

A.4 Equity Risk Premium

Conditional on the state, the dynamics of the asset price $P = e^w D$ follow via Itô's Lemma. In the good state, we have

$$\begin{aligned} \frac{dP_t}{P_{t-}} &= \mu dt + \phi\sigma dW_t + \left[(1+L)^{\phi} - 1\right] dN_t^{g,g} \\ &\quad + \left[(1+L)^{\phi}e^{w^b-w^g} - 1\right] dN_t^{g,b}. \end{aligned}$$

In the bad state, the dynamics are

$$\begin{aligned} \frac{dP_t}{P_{t-}} &= \mu dt + \phi\sigma dW_t + \left[(1+L)^{\phi} - 1\right] dN_t^{b,b} \\ &\quad + \left[e^{w^g-w^b} - 1\right] dN_t^{b,g}. \end{aligned}$$

We abbreviate the sensitivities of the asset price to the different risk factors as

$$\begin{aligned} \zeta^{diff} &= \phi\sigma \\ \zeta^{g,g} &= (1+L)^{\phi} - 1 \\ \zeta^{g,b} &= (1+L)^{\phi}e^{w^b-w^g} - 1 \\ \zeta^{b,b} &= (1+L)^{\phi} - 1 \\ \zeta^{b,g} &= e^{w^g-w^b} - 1. \end{aligned}$$

The expected excess return on the dividend claim, i.e. the equity risk premium, follows from these price sensitivities and the responses of the pricing kernel to the respective risk factors. In the good state, it is equal to

$$\begin{aligned} \gamma\phi\sigma^2 &- \lambda^{g,g}\left[(1+L)^{\phi} - 1\right]\left[(1+L)^{-\gamma} - 1\right] \\ &- \lambda^{g,b}\left[(1+L)^{\phi}e^{w^b-w^g} - 1\right]\left[(1+L)^{-\gamma}\,e^{(\theta-1)\left(v^b-v^g\right)} - 1\right]. \end{aligned}$$

The equity risk premium in the bad state is

$$\begin{aligned} \gamma\phi\sigma^2 &- \lambda^{b,b}\left[(1+L)^{\phi} - 1\right]\left[(1+L)^{-\gamma} - 1\right] \\ &- \lambda^{b,g}\left[e^{w^g-w^b} - 1\right]\left[e^{(\theta-1)\left(v^g-v^b\right)} - 1\right]. \end{aligned}$$

B Some Numerical Results on Crises Durations

To study whether consumption jumps are indeed more frequent than in models with i.i.d. consumption growth, we calculate various conditional probabilities that bad years follow an initial bad year. We then check wether these conditional probabilities are larger than the corresponding unconditional probabilities. We formalize this idea by studying sequences of Bernoulli trials. The year-t outcome X_t is 0 if "consumption growth is above the threshold" and 1 if "consumption growth is below the threshold". We consider thresholds of 0%, −5%, or −10%, respectively. The numbers in Table 2 are the probabilities for a certain duration of a crisis given that year t has been the beginning of the crisis. For a threshold of 0%, the first four conditional probabilities are given by (see first line in Panel A of Table 2):

$$
\begin{aligned}
\text{Prob}(X_{t+1}=0|X_t=1,X_{t-1}=0) &= 0.616 \\
\text{Prob}(X_{t+2}=0,X_{t+1}=1|X_t=1,X_{t-1}=0) &= 0.230 \\
\text{Prob}(X_{t+3}=0,X_{t+2}=1,X_{t+1}=1|X_t=1,X_{t-1}=0) &= 0.092 \\
\text{Prob}(X_{t+4}=0,X_{t+3}=1,X_{t+2}=1,X_{t+1}=1|X_t=1,X_{t-1}=0) &= 0.038.
\end{aligned}
\tag{15}
$$

For a threshold of 0%, the empirical unconditional probability of being in a crisis is $\text{Prob}(X_t=1)=0.302$. Therefore, if the data were generated by a sequence of *independent identical* Bernoulli trials[19], then the probabilities (15) could be calculated in the following way:

$$
\begin{aligned}
\text{Prob}(X_t=0) &= 0.698 \\
\text{Prob}(X_t=0)\text{Prob}(X_t=1) &= 0.698\cdot 0.302 = 0.211 \\
\text{Prob}(X_t=0)\text{Prob}(X_t=1)^2 &= 0.698\cdot 0.302^2 = 0.064 \\
\text{Prob}(X_t=0)\text{Prob}(X_t=1)^3 &= 0.698\cdot 0.302^3 = 0.019
\end{aligned}
$$

i.e. only the unconditional probabilities of (not) being in a crisis would matter.

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[19]Notice that this implies $\text{Prob}(X_{t+k}=n)=\text{Prob}(X_t=n)$ for all $k=1,2,\ldots$ and $n\in\{0,1\}$.

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Panel A: Mean and standard deviation of consumption growth rates

	annual mean	annual std	5-year mean	5-year std	10-year mean	10-year std
Data	0.020	0.065	0.103	0.182	0.221	0.280
Jump-induced regime switches	0.020	0.056	0.082	0.132	0.197	0.228
Separated regime switches	0.020	0.054	0.081	0.124	0.193	0.212
Peak-to-trough model: local calibration	0.019	0.049	0.079	0.104	0.185	0.172
Peak-to-trough model: disaster calibration	0.027	0.057	0.114	0.124	0.275	0.214

Panel B: Tail probabilities

	Percentage of country-year observations below ...							
	0	−0.02	−0.04	−0.05	−0.06	−0.08	−0.10	−0.15
Data	0.302	0.181	0.109	0.083	0.066	0.044	0.033	0.015
Jump-induced regime switches	0.306	0.190	0.117	0.093	0.075	0.051	0.035	0.013
Separated regime switches	0.315	0.194	0.115	0.089	0.069	0.043	0.028	0.009
Peak-to-trough model: local calibration	0.336	0.206	0.114	0.082	0.057	0.026	0.011	0.001
Peak-to-trough model: disaster calibration	0.230	0.117	0.057	0.042	0.033	0.026	0.024	0.023

Table 1: Unconditional distribution of annual consumption growth rates

The table reports moments and tail probabilities of the unconditional distribution of annual consumption growth rates as discussed in Section 4. The rows labeled ‘Data’ are based on the Barro dataset. The other rows are derived from Monte Carlo simulations over 500,000 years. The parameters for the model simulations are reported in Table 3.

Panel A: Threshold 0%

	1 year	2 years	3 years	4 years	5 years	6 years	7 years	8 years	9 years	10 years
Data	0.6160	0.2300	0.0920	0.0380	0.0140	0.0080	0	0.0020	0	0.0010
Jump-induced regime switches	0.6559	0.2074	0.0778	0.0325	0.0156	0.0060	0.0028	0.0014	0.0004	0.0002
Separated regime switches	0.6631	0.2096	0.0756	0.0307	0.0120	0.0052	0.0024	0.0010	0.0003	0.0002
Peak-to-trough model: local calibration	0.6634	0.2219	0.0771	0.0252	0.0085	0.0025	0.0008	0.0004	0.0002	0
Peak-to-trough model: disaster calibration	0.7709	0.1758	0.0414	0.0090	0.0022	0.0005	0	0	0	0

Panel B: Threshold −5%

	1 year	2 years	3 years	4 years	5 years	6 years	7 years	8 years	9 years	10 years
Data	0.7990	0.1520	0.0340	0.0120	0	0.0030	0	0	0	0
Jump-induced regime switches	0.7579	0.1726	0.0499	0.0139	0.0043	0.0011	0.0002	0.0001	0	0
Separated regime switches	0.8060	0.1440	0.0364	0.0100	0.0024	0.0009	0.0003	0	0	0
Peak-to-trough model: local calibration	0.9174	0.0749	0.0061	0.0006	0	0	0	0	0	0
Peak-to-trough model: disaster calibration	0.9567	0.0421	0.0012	0	0	0	0	0	0	0

Panel C: Threshold −10%

	1 year	2 years	3 years	4 years	5 years	6 years	7 years	8 years	9 years	10 years
Data	0.8260	0.1290	0.0380	0.0080	0	0	0	0	0	0
Jump-induced regime switches	0.8482	0.1293	0.0188	0.0031	0.0005	0.0001	0	0	0	0
Separated regime switches	0.8603	0.1202	0.0167	0.0024	0.0003	0	0	0	0	0
Peak-to-trough model: local calibration	0.9887	0.0111	0.0002	0	0	0	0	0	0	0
Peak-to-trough model: disaster calibration	0.9753	0.0241	0.0006	0	0	0	0	0	0	0

Table 2: Distributions of the lengths of crisis periods

The table reports the distributions of the lengths of crisis periods as discussed in Section 4. The length of a crisis is defined as the number of consecutive years where the consumption growth rates are below a threshold (0% for Panel A, −5% for Panel B, −10% for Panel C). The table reports the probabilities that a crisis in the sample has a length of one up to ten years. The rows labeled 'Data' are based on the Barro dataset. The other rows are derived from Monte Carlo simulations over 500,000 years. The parameters for the simulations are reported in Table 3.

	μ	σ	L	$\lambda^{g,g}$	$\lambda^{g,b}$	$\lambda^{b,b}$	$\lambda^{b,g}$	$\lambda^{uncond.}$
Jump-induced regime switches	0.033	0.04	-0.05	0.02	0.08	1.9	0.72	*0.28*
Separated regime switches	0.033	0.04	-0.05	0.1	0.08	1.9	0.72	*0.28*
Peak-to-trough model: local calibr.	0.033	0.04	-0.05	—	—	—	—	0.28
Peak-to-trough model: disaster calibr.	0.033	0.04	-0.249	—	—	—	—	0.024

Table 3: Parameters of the consumption processes

The table reports the parameters of the consumption processes resulting from the calibration in Section 4. All parameters are annualized. The value for λ^{uncond} in the models with regimes is derived from the other parameters.

	Diffusion risk	Pure cons. jumps	Jump-induced regime switches	Separated regime switches	**Total premium**
Model with jump-induced regime switches					
Good state	0.0192	0.0007	**0.0495**	—	0.0694
Bad state	0.0192	0.0668	—	0.1096	0.1956
Unconditional					0.0820
Model with separated regime switches					
Good state	0.0192	0.0035	—	0.0272	0.0499
Bad state	0.0192	0.0668	—	0.1304	0.2164
Unconditional					0.0665
Peak-to-trough model					
Local calibration	0.0192	0.0098	—	—	0.0290
Disaster calibration	0.0192	0.0479	—	—	0.0671

Table 4: Decomposition of the local equity risk premium

The table reports the local equity risk premium in the different economies as discussed in Section 5.2 as well as a decomposition into its various components. The jump risk premia in the second, third and fourth column are further decomposed in Table 5. The premium for jump-induced regime switches in the first row is also decomposed in Table 6. All results have been generated with the parameters reported in Table 3.

Model with jump-induced regime switches							
$\lambda^{g,g}$	0.02	$\lambda^{g,b}$	0.08	$\lambda^{b,b}$	1.9	$\lambda^{b,g}$	0.72
$\eta^{g,g}$	0.3604	$\eta^{g,b}$	2.1449	$\eta^{b,b}$	0.3604	$\eta^{b,g}$	-0.5682
$\zeta^{g,g}$	-0.0975	$\zeta^{g,b}$	-0.288	$\zeta^{b,b}$	-0.0975	$\zeta^{b,g}$	0.268
$RP^{g,g}$	0.0007	$RP^{g,b}$	0.0495	$RP^{b,b}$	0.0668	$RP^{b,g}$	0.1096
Model with separated regime switches							
$\lambda^{g,g}$	0.10	$\lambda^{g,b}$	0.08	$\lambda^{b,b}$	1.9	$\lambda^{b,g}$	0.72
$\eta^{g,g}$	0.3604	$\eta^{g,b}$	1.4494	$\eta^{b,b}$	0.3604	$\eta^{b,g}$	-0.5917
$\zeta^{g,g}$	-0.0975	$\zeta^{g,b}$	-0.2349	$\zeta^{b,b}$	-0.0975	$\zeta^{b,g}$	0.3070
$RP^{g,g}$	0.0035	$RP^{g,b}$	0.0272	$RP^{b,b}$	0.0668	$RP^{b,g}$	0.1304
Peak-to-trough model							
local		λ	0.28	disaster		λ	0.024
calibration		η	0.3604	calibration		η	4.5739
		ζ	-0.0975			ζ	-0.4360
		RP	0.0098			RP	0.0479

Table 5: Decomposition of the jump risk premia

The table decomposes all jump risk premia from Table 4 into jump intensities λ, pricing kernel responses η and price responses ζ. All results have been generated with the parameters reported in Table 3.

Premium for pure consumption jumps	$-\lambda^{g,b}\eta^{jump}\zeta^{jump}$	0.0028
Premium for pure regime switches	$-\lambda^{g,b}\eta^{RS}\zeta^{RS}$	0.0222
Cross risk premia	$-\lambda^{g,b}\eta^{RS}\zeta^{jump}$	0.0102
	$-\lambda^{g,b}\eta^{jump}\zeta^{RS}$	0.0061
Super-additivity terms	$-\lambda^{g,b}(\eta^{jump}+\eta^{RS})\zeta^{jump}\zeta^{RS}$	-0.0028
	$-\lambda^{g,b}\eta^{jump}\eta^{RS}(\zeta^{jump}+\zeta^{RS})$	0.0117
	$-\lambda^{g,b}\eta^{jump}\eta^{RS}\zeta^{jump}\zeta^{RS}$	-0.0008
Total	$-\lambda^{g,b}\eta^{g,b}\zeta^{g,b}$	**0.0495**

Table 6: Decomposition of the risk premium for jump-induced regime switches

The table decomposes the risk premium for jump-induced regime switches given in the first row of Table 4 into its components as discussed in Section 5.2. All results have been generated with the parameters reported in Table 3.

	β	$\frac{1}{\psi}\frac{\mathrm{E}_t[dC_t]}{C_t\ dt}$	Precautionary savings terms: Diffusion risk	Pure cons. jumps	Jump-ind. RS	Separated RS	**Total risk-free rate**
Model with jump-induced regime switches							
Good state	0.03	0.0140	-0.0072	-0.0003	-0.0140	—	0.0226
Bad state	0.03	-0.310	-0.0072	-0.0262	—	-0.0137	-0.0481
Unconditional							0.0155
Model with separated regime switches							
Good state	0.03	0.0140	-0.0072	-0.0014	—	-0.0053	0.0302
Bad state	0.03	-0.0310	-0.0072	-0.0262	—	-0.0152	-0.0496
Unconditional							0.0222
Peak-to-trough model							
Local calibration	0.03	0.0095	-0.0072	-0.0039	—	—	0.0284
Disaster calibration	0.03	0.0135	-0.0072	-0.0227	—	—	0.0136

Table 7: Decomposition of the local risk-free rate

The table reports the local risk-free rate in the different economies as discussed in Section 5.3 as well as a decomposition into its various components. All results have been generated with the parameters reported in Table 3.

	Diffusion risk	Pure cons. jumps	Jump-induced regime switches	Separated regime switches	**Total premium**
Model with jump-induced regime switches					
Good state	0.0192	0.0007	-0.0160	—	0.0039
Bad state	0.0192	0.0668	—	0	0.0860
Unconditional					0.0121
Model with separated regime switches					
Good state	0.0192	0.0035	—	0	0.0227
Bad state	0.0192	0.0668	—	0	0.0860
Unconditional					0.0290
Peak-to-trough model					
Local calibration	0.0192	0.0098	—	—	0.0290
Disaster calibration	0.0192	0.0479	—	—	0.0671

Table 8: Decomposition of the local equity premium (CRRA utility)

The table reports the local equity premium in the different economies as discussed in Section 6.1 as well as a decomposition into its various components. All results have been generated with the parameters reported in Table 3, but with an EIS of $\psi = 1/\gamma = 1/6$.

Case	μ	σ	L	$\lambda^{g,g}$	$\lambda^{g,b}$	$\lambda^{b,b}$	$\lambda^{b,g}$	$\lambda^{uncond.}$
$L = -0.03$	0.032	0.04	-0.03	0.02	0.12	2.9	1.08	*0.416*
$L = -0.04$	0.033	0.04	-0.04	0.02	0.10	2.4	0.90	*0.348*
$L = -0.05$	0.033	0.04	-0.05	0.02	0.08	1.9	0.72	*0.280*
$L = -0.06$	0.032	0.04	-0.06	0.02	0.06	1.4	0.54	*0.212*
$L = -0.07$	0.030	0.04	-0.07	0.02	0.04	0.9	0.36	*0.144*

Table 9: Parameters of the consumption processes for different jump sizes

The table reports the parameters of the consumption processes in the model with jump-induced regime switches as discussed Section 6.2. All parameters are annualized. The value for λ^{uncond} in the models with regimes is derived from the other parameters.

	Diffusion risk	Pure cons. jumps	Jump-induced regime switches	Separated regime switches	**Total premium**
Model with jump-induced regime switches					
Good state	0.0108	0.0007	**0.0498**	—	0.0613
Bad state	0.0108	0.0668	—	0.1108	0.1883
Unconditional					0.0740
Model with separated regime switches					
Good state	0.0108	0.0035	—	0.0275	0.0418
Bad state	0.0108	0.0668	—	0.1319	0.2095
Unconditional					0.0586
Peak-to-trough model					
Local calibration	0.0108	0.0098	—	—	0.0206
Disaster calibration	0.0108	0.0479	—	—	0.0587

Table 10: Decomposition of the local equity risk premium for $\sigma = 0.03$

The table reports the local equity risk premium in the different economies as discussed in Section 6.4 as well as a decomposition into its various components. All results have been generated with the parameters reported in Table 3, but with $\sigma = 0.03$.

Panel A: Threshold 0%

	1 year	2 years	3 years	4 years	5 years	6 years	7 years	8 years	9 years	10 years
Data	0.6160	0.2300	0.0920	0.0380	0.0140	0.0080	0	0.0020	0	0.0010
Jump-induced regime switches	0.6776	0.1932	0.0732	0.0314	0.0137	0.0063	0.0028	0.0011	0.0005	0.0002
Separated regime switches	0.6959	0.1919	0.0673	0.0259	0.0112	0.0044	0.0020	0.0009	0.0004	0.0002

Panel B: Threshold -5%

	1 year	2 years	3 years	4 years	5 years	6 years	7 years	8 years	9 years	10 years
Data	0.7990	0.1520	0.0340	0.0120	0	0.0030	0	0	0	0
Jump-induced regime switches	0.7266	0.1948	0.0563	0.0162	0.0042	0.0014	0.0004	0.0002	0	0
Separated regime switches	0.7818	0.1579	0.0448	0.0111	0.0034	0.0007	0.0001	0.0001	0	0

Panel C: Threshold -10%

	1 year	2 years	3 years	4 years	5 years	6 years	7 years	8 years	9 years	10 years
Data	0.8260	0.1290	0.0380	0.0080	0	0	0	0	0	0
Jump-induced regime switches	0.8525	0.1253	0.0190	0.0028	0.0004	0.0001	0	0	0	0
Separated regime switches	0.8641	0.1253	0.0190	0.0028	0.0004	0.0001	0	0	0	0

Table 11: Distributions of the lengths of crisis periods for $\sigma = 0.03$

The table reports the distributions of the lengths of crisis periods, similar to Table 2. All results have been generated with the parameters reported in Table 3, but with $\sigma = 0.03$, and are discussed in Section 6.4. The rows labeled 'Data' are based on the Barro dataset. The other rows are derived from Monte Carlo simulations over 500,000 years.

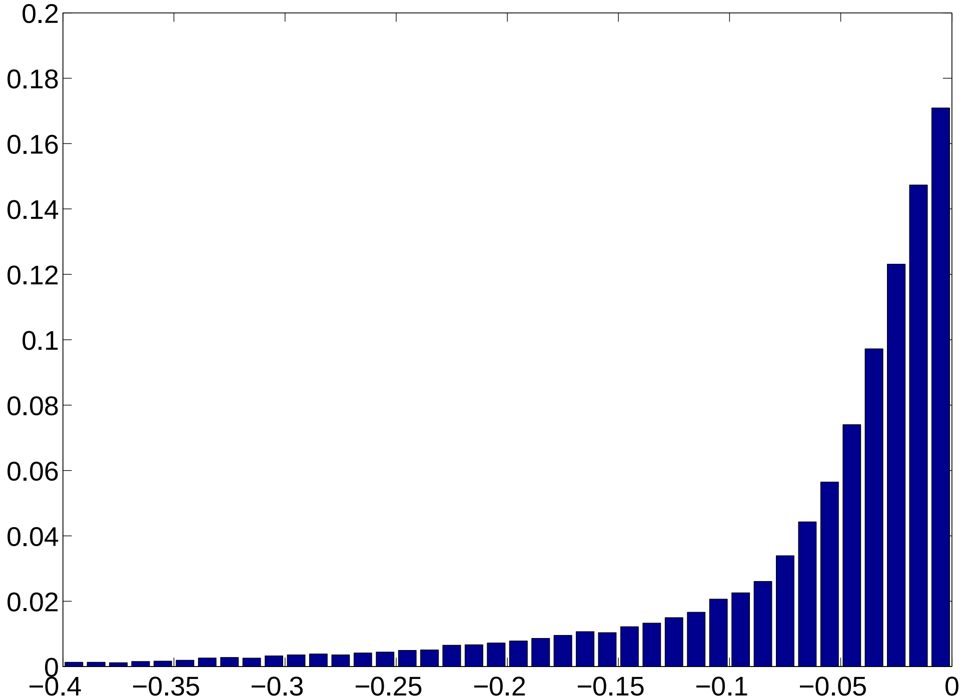

Figure 1: Histogram of peak-to-trough disaster sizes

The figure depicts the histogram of disaster sizes in our simulated data, measured by the peak-to-trough method. We simulate 500,000 years of consumption data using the model with jump-induced regime switches. Next, we isolate all consumption-growth observations below 0%. Finally, if there are several consecutive observations below 0%, we compute the total drop in consumption over all these years and call this the peak-to-trough disaster size. The figure plots the histogram of these peak-to-trough disaster sizes.

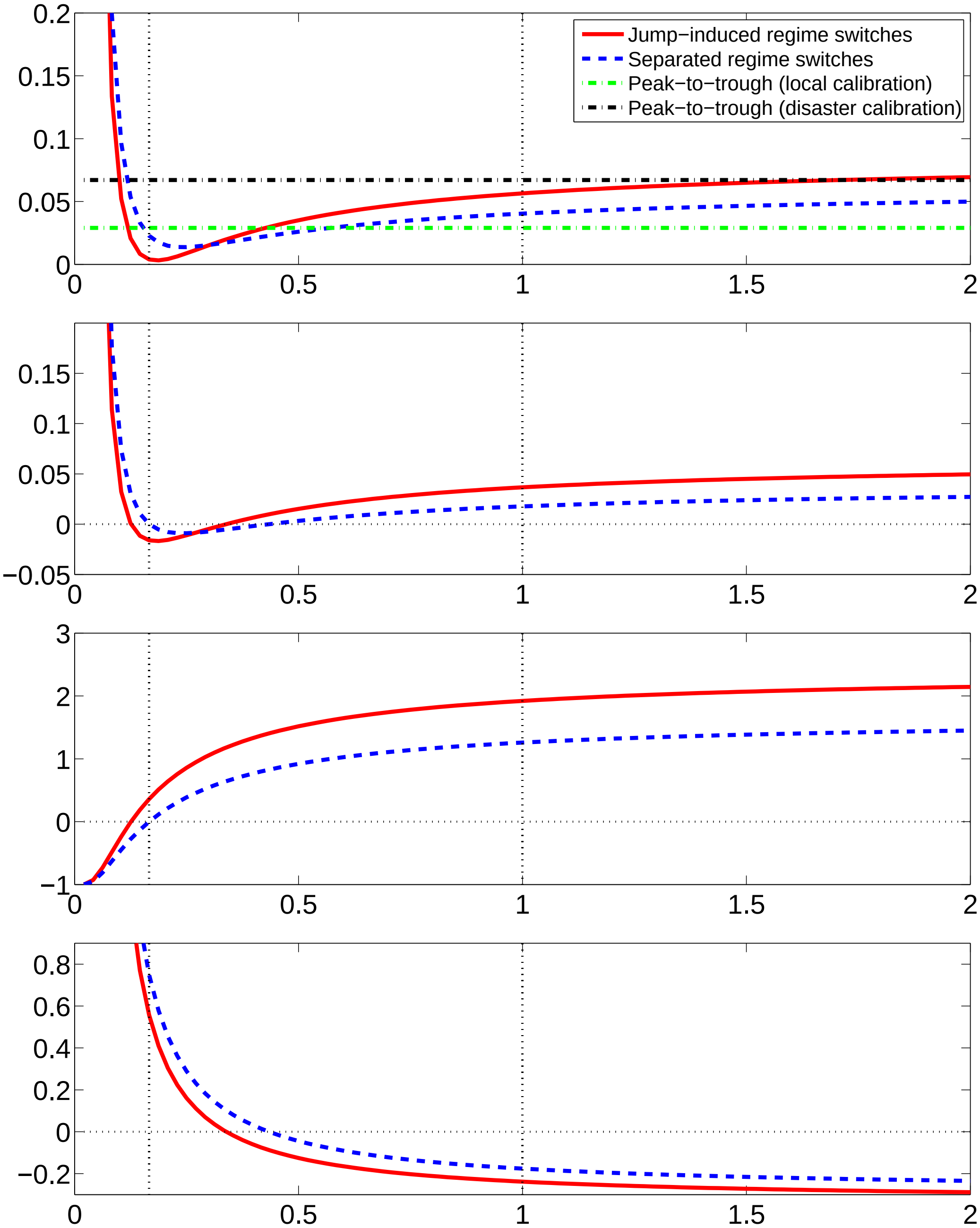

Figure 2: Robustness check: elasticity of intertemporal substitution

The figure depicts the local equity premium in the good state (first picture), the risk premium for jump-induced and separated regime switches from the good to the bad state (second picture), the pricing kernel response $\eta^{g,b}$ (third picture) and the price response $\zeta^{g,b}$ (fourth picture) as a function of ψ. The lines represent the model with jump-induced regime switches (red solid line), separated regime switches (blue dashed line) and the peak-to-trough model with local calibration (green dash-dotted line) and disaster calibration (black dash-dotted line). The vertical dotted lines mark $\psi = 1/\gamma = 1/6$ and $\psi = 1$. All results have been generated with the parameters from Table 3. All numbers are annualized.

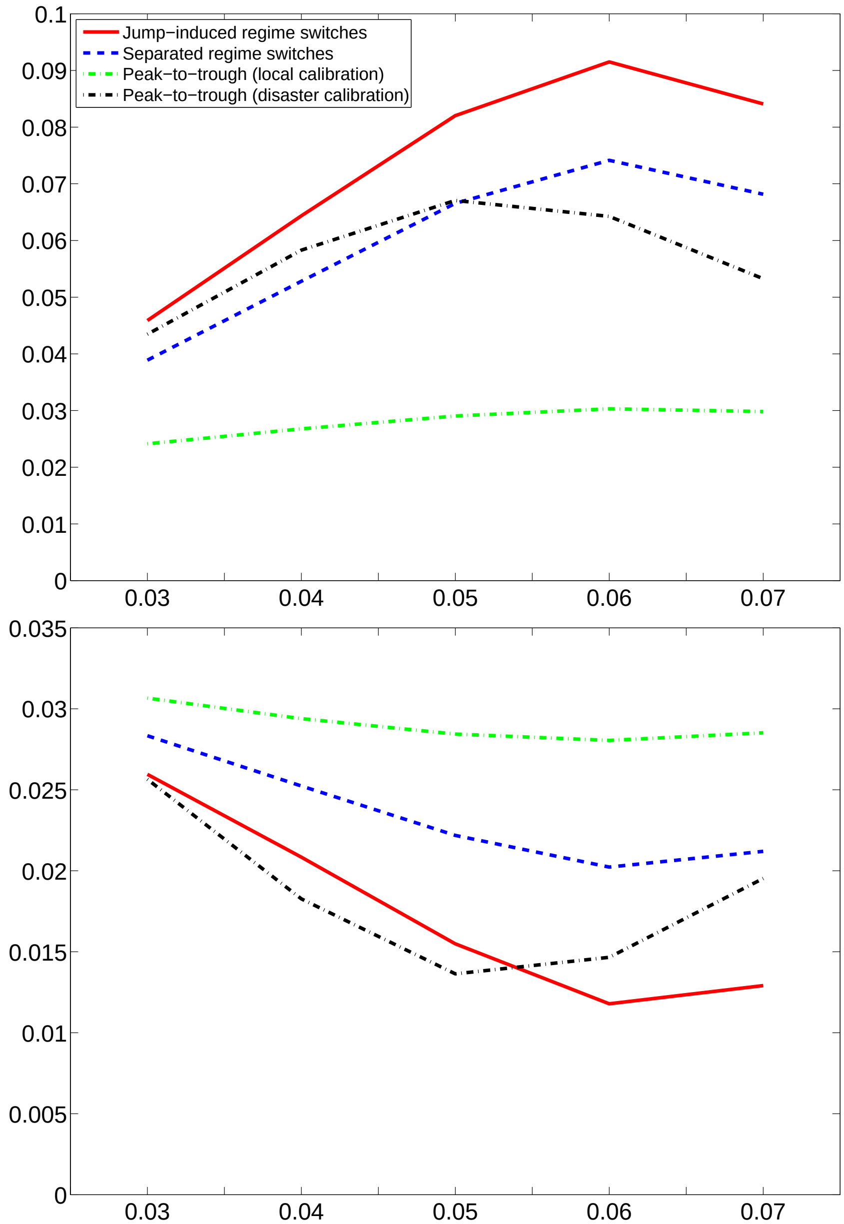

Figure 3: Unconditional local equity premium and risk-free rate for different jump sizes

The figure depicts the unconditional local equity premium (upper picture) and the unconditional local risk-free rate (lower picture) as a function of the jump size $-L$. The lines represent the model with jump-induced regime switches (red solid line), separated regime switches (blue dashed line) and the peak-to-trough model with local calibration (green dash-dotted line) and disaster calibration (black dash-dotted line). Note that, for each value of L, the jump intensities are adjusted such that the consumption data is matched as close as possible. The resulting calibrations are reported in Table 9. All numbers are annualized.

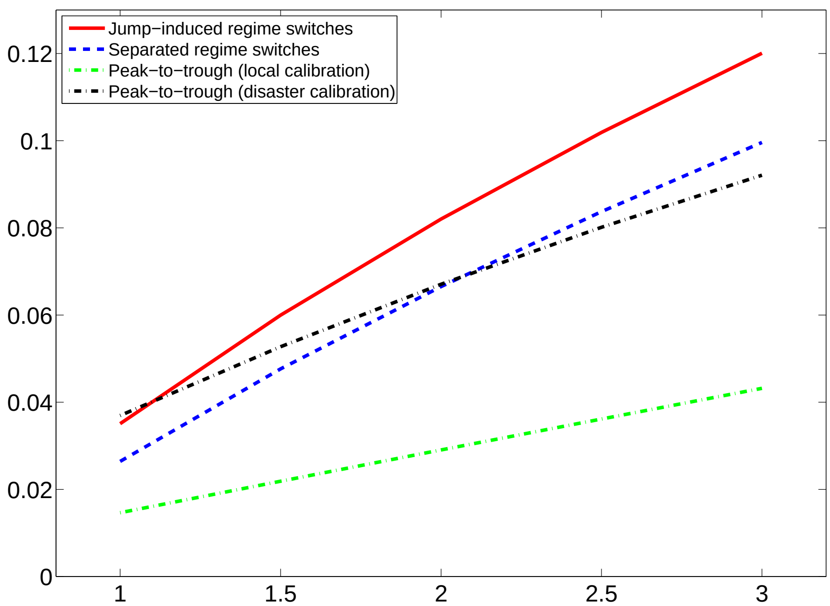

Figure 4: Unconditional local equity premium as a function of the leverage parameter

The figure depicts the unconditional local equity premium as a function of ϕ . The lines represent the model with jump-induced regime switches (red solid line), separated regime switches (blue dashed line) and the peak-to-trough model with local calibration (green dash-dotted line) and disaster calibration (black dash-dotted line). All results have been generated with the parameters from Table 3. All numbers are annualized.

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