

NBER WORKING PAPER SERIES

OPTION PRICES IN A MODEL WITH STOCHASTIC DISASTER RISK

Sang Byung Seo
Jessica A. Wachter

Working Paper 19611
<http://www.nber.org/papers/w19611>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2013

We thank Hui Chen, Domenico Cuoco, Mikhail Chernov, Xavier Gabaix, Ivan Shaliastovich, Viktor Todorov and seminar participants at the 2013 NBER Summer Institute, Carnegie Mellon University, Cornell University and the Wharton school for helpful comments. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2013 by Sang Byung Seo and Jessica A. Wachter. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

Option Prices in a Model with Stochastic Disaster Risk
Sang Byung Seo and Jessica A. Wachter
NBER Working Paper No. 19611
November 2013, Revised January 2015
JEL No. G12,G13

ABSTRACT

Recent work suggests that the consumption disaster-based explanation of the equity premium is inconsistent with the average implied volatilities from option data. We resolve this inconsistency in a model with stochastic disaster risk (SDR). The SDR model explains average implied volatilities, even when calibrated to consumption and aggregate market data alone. We extend the benchmark SDR model to one that allows for variation in the risk of disaster at different time scales. This extension can match both the time series of implied volatilities, as well as the average implied volatility curve.

Sang Byung Seo
Finance Department, The Wharton School
3620 Locust Walk
Philadelphia, PA 19104
sangseo@wharton.upenn.edu

Jessica A. Wachter
Department of Finance
2300 SH-DH
The Wharton School
University of Pennsylvania
3620 Locust Walk
Philadelphia, PA 19104
and NBER
jwachter@wharton.upenn.edu

1 Introduction

Century-long evidence indicates that the equity premium, namely the, expected return from holding equities over short-term debt, is economically significant. Ever since Mehra and Prescott (1985) noted the puzzling size of this premium relative to what a standard model would predict, the source of this premium has been a subject of debate. One place to look for such a source is in options data. By holding equity and a put option, an investor can, at least in theory, eliminate the downside risk in equities. For this reason, it is appealing to explain both options data and standard equity returns together with a single model.

Such an approach is arguably of particular importance for a class of macro-finance models that explain the equity premium through the mechanism of consumption disasters (e.g. Rietz (1988), Barro (2006) and Weitzman (2007)). In these models, consumption growth rates and thus equity returns are subject to shocks that are rare and large. Options (assuming away, for the moment, the potentially important question of counterparty risk), offer a way to insure against the risk of these events. Thus it is of interest to know whether these models have the potential to explain option prices as well as equity prices.

Thus, option prices convey information about the price investors require to insure against losses, and therefore indirectly about the source of the equity premium. Indeed, prior literature uses option prices to infer information about the premium attached to crash risk (e.g. Pan (2002)); recent work connects this risk to the equity premium as a whole (Bollerslev and Todorov (2011) and Santa-Clara and Yan (2010)). Despite the clear parallel to the literature on consumption disasters and the equity premium, the literatures have advanced separately. The macro-finance literature takes as its source not options data, but rather international data on large consumption declines (see Barro and Ursúa (2008)). There is also a difference in terminology (which reflects a difference in the philosophy). In the options literature, the focus is on sudden negative changes in prices, called crashes; connections to

economic fundamentals are not modeled. In the macro-finance literature, the focus is on disasters as reflected in economic fundamentals like consumption or GDP, rather than the behavior of stock prices. However, in both literatures, risk premia are specifically attributed to events whose size and probability of occurrence renders a normal distribution essentially impossible.

Motivated by the parallels between these very different literatures, Backus, Chernov, and Martin (2011) study option prices in a consumption disaster model similar to that of Rietz (1988) and Barro (2006). They find, strikingly, that options prices implied by the consumption disaster model are far from their data counterparts. In particular, the implied volatilities resulting from a calibration to macroeconomic consumption data are lower than in the data, and are far more downward sloping as a function of the strike price. Thus options data appear to be inconsistent with consumption disasters as an explanation of the equity premium puzzle.

Like Barro (2006) and Rietz (1988), Backus, Chernov, and Martin (2011) assume that the probability of a disaster occurring is constant. Such a model can explain the equity premium, but cannot account for other features of equity markets, such as the volatility. Recent rare events models therefore introduce dynamics that can account for equity volatility (Gabaix (2012), Gourio (2012), Wachter (2013)). We derive option prices in a model based on that of Wachter (2013), and in a significant generalization of this model that allows for variation in the risk of disaster at different time scales. We show that allowing for a stochastic probability of disaster has dramatic effects on implied volatilities. Namely, rather than being much lower than in the data, the implied volatilities are at about the same level. The slope of the implied volatility curve, rather than being far too great, also matches that of the data. We then apply the model to understanding other features of option prices in the data, such as time-variation in the level and slope of the implied volatility curve. We show that the model

can account for these features of the data as well. In other words, a model calibrated to international consumption data on disasters can explain option prices after all.

We use the fact that our model generalizes the previous literature to better understand the difference in results. Because of time-variation in the disaster probability, the model endogenously produces the stock price changes that occur during normal times and that are reflected in option prices. These changes are absent in iid rare event models, because, during normal times, the volatility of stock returns is equal to the (low) volatility of dividend growth. Moreover, by assuming recursive utility, the model implies a premium for assets that covary negatively with volatility. This makes implied volatilities higher than what they would be otherwise.

Our findings relate to those of Gabaix (2012), who also reports average implied volatilities in a model with rare events.¹ Our model is conceptually different in that we assume recursive utility and time-variation in the probability of a disaster. Gabaix assumes a linearity-generating process (Gabaix (2008)) with a power utility investor. In his calibration, the sensitivity of dividends to changes in consumption is varying; however, the probability of a disaster is not. There are several important implications of our choice of approach. First, the tractability of our framework implies that we can use the same model for pricing options as we do for equities. Moreover, our model nests the simpler one with constant risk of disaster, allowing us to uncover the reason for the large difference in option prices between the models. We also show that the assumption of recursive utility is important for the accounting for the average implied volatility curve. Finally, we go beyond the average implied volatility curve for 3-month options, considering the time series in the level and slope of the implied volatility curve across different maturities. These considerations lead us naturally to a two-factor model for the disaster probability.

¹Recent work by Nowotny (2011) reports average implied volatilities as well. Nowotny focuses on the implications of self-exciting processes for equity markets rather than on option prices.

Other recent work explores implications for option pricing in dynamic endowment economies. Benzoni, Collin-Dufresne, and Goldstein (2011) derive options prices in a Bansal and Yaron (2004) economy with jumps to the mean and volatility of dividends and consumption. The jump probability can take on two states which are not observable to the agent. Their focus is on the learning dynamics of the states, and the change in option prices before and after the 1987 crash, rather than on matching the shape of the implied volatility curve. Du (2011) examines options prices in a model with external habit formation preferences as in Campbell and Cochrane (1999) in which the endowment is subject to rare disasters that occur with a constant probability. His results illustrate the difficulty of matching implied volatilities assuming either only external habit formation, or a constant probability of a disaster. Also related is the work of Drechsler and Yaron (2011), who focus on the volatility premium and its predictive properties. Our paper differs from these in that we succeed in fitting both the time series and cross-section of implied volatilities, as well as reconciling the macro-finance evidence on rare disasters with option prices.

A related strand of research on endowment economies focuses on uncertainty aversion or exogenous changes in confidence. Drechsler (2012) builds on the work of Bansal and Yaron (2004), but incorporates dynamic uncertainty aversion. He argues that uncertainty aversion is important for matching implied volatilities. Shaliastovich (2009) shows that jumps in confidence can explain option prices when investors are biased toward recency. These papers build on earlier work by Bates (2008) and Liu, Pan, and Wang (2005), who conclude that it is necessary to introduce a separate aversion to crashes to simultaneously account for data on options and on equities. Buraschi and Jiltsov (2006) explain the pattern in implied volatilities using heterogeneous beliefs. Unlike these papers, we assume a rational expectations investor with standard (recursive) preferences. The ability of the model to explain implied volatilities arises from time-variation in the probability of a disaster rather than a premium associated

with uncertainty.

Finally, a growing line of work focuses on the links between macroeconomic events, index option prices, and risk premia. Brunnermeier, Nagel, and Pedersen (2008) links option prices to the risk of currency crashes, Kelly, Lustig, and Van Nieuwerburgh (2012) use options to infer a premium for too-big-to-fail financial institutions, Gao and Song (2013) price crash risk in the cross-section using options, and Kelly, Pastor, and Veronesi (2014) demonstrate a link between options and political risk. The focus of these papers is empirical. Our model provides a model that can help in interpreting these results.

The remainder of this paper is organized as follows. Section 2 discusses a single-factor model for stochastic disaster risk (SDR). This model turns out to be sufficient to explain why stochastic disaster risk can explain the level and slope of implied volatilities, as explained in Section 3, which also compares the implications of the single-factor SDR model to the implications of a constant disaster risk (CDR) model. As we explain in Section 4, however, the single-factor model cannot explain many interesting features of options data. In this section, we explore a multi-factor extension, which we fit to the data in Section 5. We show that the multi-factor model can explain the time-series variation in the implied volatility slope. Section 6 concludes.

2 Option prices in a single-factor stochastic disaster risk model

2.1 Assumptions

In this section we describe a model with stochastic disaster risk (SDR). We assume an endowment economy with complete markets and an infinitely-lived representative agent.

Aggregate consumption (the endowment) solves the following stochastic differential equation

$$dC_t = \mu C_{t-} dt + \sigma C_{t-} dB_t + (e^{Z_t} - 1)C_{t-} dN_t, \quad (1)$$

where B_t is a standard Brownian motion and N_t is a Poisson process with time-varying intensity λ_t . This intensity follows the process

$$d\lambda_t = \kappa(\bar{\lambda} - \lambda_t) dt + \sigma_\lambda \sqrt{\lambda_t} dB_{\lambda,t}, \quad (2)$$

where $B_{\lambda,t}$ is also a standard Brownian motion, and B_t , $B_{\lambda,t}$ and N_t are assumed to be independent. For the range of parameter values we consider, λ_t is small and can therefore be interpreted to be (approximately) the probability of a jump. We thus will use the terminology probability and intensity interchangeably, while keeping in mind that the relation is an approximate one.

The size of a jump, provided that a jump occurs, is determined by Z_t . We assume Z_t is a random variable whose time-invariant distribution ν is independent of N_t , B_t and $B_{\lambda,t}$. We will use the notation E_ν to denote expectations of functions of Z_t taken with respect to the ν -distribution. The t subscript on Z_t will be omitted when not essential for clarity.

We will assume a recursive generalization of power utility that allows for preferences over the timing of the resolution of uncertainty. Our formulation comes from Duffie and Epstein (1992), and we consider a special case in which the parameter that is often interpreted as the elasticity of intertemporal substitution (EIS) is equal to 1. That is, we define continuation utility V_t for the representative agent using the following recursion:

$$V_t = E_t \int_t^\infty f(C_s, V_s) ds, \quad (3)$$

where

$$f(C, V) = \beta(1 - \gamma)V \left(\log C - \frac{1}{1 - \gamma} \log((1 - \gamma)V) \right). \quad (4)$$

The parameter β is the rate of time preference. We follow common practice in interpreting γ as relative risk aversion. This utility function is equivalent to the continuous-time limit (and the limit as the EIS approaches one) of the utility function defined by Epstein and Zin (1989) and Weil (1990).

2.2 Solving for asset prices

We will solve for asset prices using the state-price density, π_t .² Duffie and Skiadas (1994) characterize the state-price density as

$$\pi_t = \exp \left\{ \int_0^t \frac{\partial}{\partial V} f(C_s, V_s) ds \right\} \frac{\partial}{\partial C} f(C_t, V_t). \quad (5)$$

There is an equilibrium relation between utility V_t , consumption C_t and the disaster probability λ_t . Namely,

$$V_t = \frac{C_t^{1-\gamma}}{1-\gamma} e^{a+b\lambda_t},$$

where a and b are constants given by

$$a = \frac{1-\gamma}{\beta} \left(\mu - \frac{1}{2} \gamma \sigma^2 \right) + b \frac{\kappa \bar{\lambda}}{\beta} \quad (6)$$

$$b = \frac{\kappa + \beta}{\sigma_\lambda^2} - \sqrt{\left(\frac{\kappa + \beta}{\sigma_\lambda^2} \right)^2 - 2 \frac{E_\nu [e^{(1-\gamma)Z} - 1]}{\sigma_\lambda^2}}. \quad (7)$$

It follows that

$$\pi_t = \exp \left(\eta t - \beta b \int_0^t \lambda_s ds \right) \beta C_t^{-\gamma} e^{a+b\lambda_t}, \quad (8)$$

where $\eta = -\beta(a + 1)$. Details are provided in Appendix B.1.

²Other work on solving for equilibria in continuous-time models with recursive utility includes Benzoni, Collin-Dufresne, and Goldstein (2011), Eraker and Shaliastovich (2008), Fisher and Gilles (1999) and Schroder and Skiadas (1999).

Following Backus, Chernov, and Martin (2011), we assume a simple relation between dividends and consumption: $D_t = C_t^\phi$, for leverage parameter ϕ .³ Let $F(D_t, \lambda_t)$ be the value of the aggregate market (it will be apparent in what follows that F is a function of D_t and λ_t). It follows from no-arbitrage that

$$F(D_t, \lambda_t) = E_t \left[\int_t^\infty \frac{\pi_s}{\pi_t} D_s ds \right].$$

The stock price can be written explicitly as

$$F(D_t, \lambda_t) = D_t G(\lambda_t), \tag{9}$$

where the price-dividend ratio G is given by

$$G(\lambda_t) = \int_0^\infty \exp \{a_\phi(\tau) + b_\phi(\tau)\lambda_t\}$$

for functions $a_\phi(\tau)$ and $b_\phi(\tau)$ given by:

$$\begin{aligned} a_\phi(\tau) &= \left(\mu_D - \mu - \beta + \gamma\sigma^2(1 - \phi) - \frac{\kappa\bar{\lambda}}{\sigma_\lambda^2}(\zeta_\phi + b\sigma_\lambda^2 - \kappa) \right) \tau \\ &\quad - \frac{2\kappa\bar{\lambda}}{\sigma_\lambda^2} \log \left(\frac{(\zeta_\phi + b\sigma_\lambda^2 - \kappa)(e^{-\zeta_\phi\tau} - 1) + 2\zeta_\phi}{2\zeta_\phi} \right) \\ b_\phi(\tau) &= \frac{2E_\nu [e^{(1-\gamma)Z} - e^{(\phi-\gamma)Z}] (1 - e^{-\zeta_\phi\tau})}{(\zeta_\phi + b\sigma_\lambda^2 - \kappa)(1 - e^{-\zeta_\phi\tau}) - 2\zeta_\phi}, \end{aligned}$$

where

$$\zeta_\phi = \sqrt{(b\sigma_\lambda^2 - \kappa)^2 + 2E_\nu [e^{(1-\gamma)Z} - e^{(\phi-\gamma)Z}] \sigma_\lambda^2}$$

(see Wachter (2013)). We will often use the abbreviation $F_t = F(D_t, \lambda_t)$ to denote the value of the stock market index at time t .

³This implies that dividends respond more than consumption to disasters, an assumption that is plausible given the U.S. data (Longstaff and Piazzesi (2004)).

2.3 Solving for implied volatilities

Let $P(F_t, \lambda_t, \tau; K)$ denote the time- t price of a European put option on the stock market index with strike price K and expiration $t + \tau$. For simplicity, we will abbreviate the formula for the price of the dividend claim as $F_t = F(D_t, \lambda_t)$. Because the payoff on this option at expiration is $(K - F_{t+\tau})^+$, it follows from the absence of arbitrage that

$$P(F_t, \lambda_t, T - t; K) = E_t \left[\frac{\pi_T}{\pi_t} (K - F_T)^+ \right].$$

Let $K^n = K/F_t$, the normalized strike price (or “moneyness”), and define

$$P^n(\lambda_t, T - t; K^n) = E_t \left[\frac{\pi_T}{\pi_t} \left(K^n - \frac{F_T}{F_t} \right)^+ \right]. \quad (10)$$

We will establish below that P^n is indeed a function of λ_t , time to expiration and moneyness alone. Clearly $P_t^n = P_t/F_t$. Because our ultimate interest is in implied volatilities, and because, in the formula of Black and Scholes (1973), normalized option prices are functions of the normalized strike price (and the volatility, interest rate and time to maturity), it suffices to calculate P_t^n .⁴

⁴Given stock price F , strike price K , time to maturity $T - t$, interest rate r , and dividend yield y , the Black-Scholes put price is defined as

$$\text{BSP}(F, K, T - t, r, y, \sigma) = e^{-r(T-t)} KN(-d_2) - e^{-y(T-t)} FN(-d_1)$$

where

$$d_1 = \frac{\log(F/K) + (r - y + \sigma^2/2)(T - t)}{\sigma\sqrt{T - t}} \quad \text{and} \quad d_2 = d_1 - \sigma\sqrt{T - t}$$

Given the put prices calculated from the transform analysis, inversion of this Black-Scholes formula gives us implied volatilities. Specifically, the implied volatility $\sigma_t^{\text{imp}} = \sigma^{\text{imp}}(\lambda_t, T - t; K^n)$ solves

$$P_t^n(\lambda_t, T - t; K^n) = \text{BSP} \left(1, K^n, T - t, r_t^b, 1/G(\lambda_t), \sigma_t^{\text{imp}} \right)$$

where r_t^b is the model’s analogue of the Treasury Bill rate, which allows for a probability of a default in case of a disaster (see Barro (2006); as in that paper we assume a default rate of 0.4).

Returning to the formula for P_t^n , we note that, from (9), it follows that

$$\frac{F_T}{F_t} = \frac{D_T G(\lambda_T)}{D_t G(\lambda_t)}. \quad (11)$$

Moreover, it follows from (8) that

$$\frac{\pi_T}{\pi_t} = \left(\frac{C_T}{C_t}\right)^{-\gamma} \exp \left\{ \int_t^T (\eta - \beta b \lambda_s) ds + b(\lambda_T - \lambda_t) \right\}. \quad (12)$$

At time t , λ_t is sufficient to determine the distributions of consumption and dividend growth between t and T , as well as the distribution of λ_s for $s = t, \dots, T$. It follows that normalized put prices (and therefore implied volatilities) are a function of λ_t , the time to expiration, and moneyness.

Appendix B.5 describes the calculation of (10). We first approximate the price-dividend ratio $G(\lambda_t)$ by a log-linear function of λ_t . As the Appendix describes, this approximation is highly accurate. We can then apply the transform analysis of Duffie, Pan, and Singleton (2000) to calculate put prices.

The implied volatility curve in the data represents an average of implied volatilities at different points in time. We follow the same procedure in the model, calculating an unconditional average implied volatility curve. To do so, we first solve for the implied volatility as a function of λ_t . We numerically integrate this function over the stationary distribution of λ_t . This stationary distribution is Gamma with shape parameter $2\kappa\bar{\lambda}/\sigma_\lambda^2$ and scale parameter $\sigma_\lambda^2/(2\kappa)$ (Cox, Ingersoll, and Ross (1985)).

2.4 The constant disaster risk model

Taking limits in the above model as σ_λ approaches zero implies a model with a constant probability of disaster (Appendix B.2 shows that this limit is indeed well-defined and is what would be computed if one were to solve the constant disaster risk model from first principles). We use this model to evaluate the role that stochastic disaster risk plays in the

model's ability to match the implied volatility data. We refer to this model in what follows as the CDR (constant disaster risk) model, to distinguish it from the more general SDR model.

The CDR model is particularly useful in reconciling our results with those of Backus, Chernov, and Martin (2011). Backus et al. solve a model with a constant probability of a jump in consumption, calibrated in a manner similar to Barro (2006). They call this the consumption-based model, to distinguish it from the reduced-form options-based model which is calibrated to fit options data. While Backus et al. assume power utility, their model can be rewritten as one with recursive utility with an EIS of one. The reason is that the endowment process is iid. In this special case, the EIS and the discount rate are not separately identified. Specifically, a power utility model has an identical stochastic discount factor, and therefore identical asset prices to a recursive utility model with arbitrary EIS as long as one can adjust the discount rate (Appendix B.3).⁵

⁵Backus et al. define option payoffs not in terms of the price, but in terms of the total return. In principal one could correct for this; however the correction requires a well-defined price-dividend ratio. For their parameters, and a riskfree rate of 2%, the price-dividend ratio is not well-defined (the value of the infinitely-lived dividend-claim does not converge). One can assess the difference between options on returns and the usual option definition with higher levels of the riskfree rate, which does lead to well-defined prices. It is small for ATM and OTM options which are the focus of our (and their) study. In what follows, for consistency with their study, we use their definition and pricing method when reporting results for the benchmark CDR calibration.

3 Average implied volatilities in the model and in the data

In this section we compare implied volatilities in the two versions of the model we have discussed with implied volatilities in the data. For now, we focus on three-month options.

Table 1 shows the parameter values for the SDR and the benchmark CDR model. The parameters in the SDR model are identical to those of Wachter (2013), and thus do not make use of options data. The parameters for the benchmark CDR model are as in the consumption-based model of Backus, Chernov, and Martin (2011). That is, we consider a calibration that is isomorphic to that of Backus, Chernov, and Martin (2011) in which the EIS is equal to 1. Assuming a riskfree rate of 2% (as in Backus et al.), we calculate a discount rate of 0.0189 . We could also use the same parameters as in the SDR model except with $\sigma_\lambda = 0$; the results are very similar.

The two calibrations differ in their relative risk aversion, in the volatility of normal-times consumption growth, in leverage, in the probability of a disaster, and of course in whether the probability is time-varying. The net effect of some of these differences turns out to be less important than what one may think: for example, higher risk aversion and lower disaster probability roughly offset each other. We explore the implications of leverage and volatility in what follows.

The two models also assume different disaster distributions. For the SDR model, the disaster distribution is multinomial, and taken from Barro and Ursúa (2008) based on actual consumption declines. The benchmark CDR model assumes that consumption declines are log-normal. For comparison, we plot the smoothed density for the SDR model along with the density of the consumption-based model in Figure 1. Compared with the lognormal model, the SDR model has more mass over small declines in the 10–20% region, and more mass over

large declines in the 50-70% region.⁶

Figure 2 shows the resulting implied volatilities as a function of moneyness, as well as implied volatilities in the data. Confirming previous results, we find that the CDR model leads to implied volatilities that are dramatically different from those in the data. First, the implied volatilities are too low, even though the model was calibrated to match the volatility of equity returns. Second, they exhibit a strong downward slope as a function of the strike price. While there is a downward slope in the data, it is not nearly as large. As a result, implied volatilities for at-the-money (ATM) options in the CDR model are less than 10%, far below the option-based implied volatilities, which are over 20%.

In contrast, the SDR model can explain both ATM and OTM (out-of-the-money) implied volatilities. For OTM options (with moneyness equal to 0.94), the SDR model gives an implied volatility of 23%, close to the data value of 24%. There is a downward slope, just as in the data, but it is much smaller than that of the CDR model. ATM options have implied volatilities of about 21% in both the model and the data. There are a number of differences between this model and the CDR model. We now discuss which of these differences is primarily responsible for the change in implied volatilities.

⁶One concern is the sensitivity of our results to behavior in the tails of the distribution. By assuming a multinomial distribution, we essentially assume that this distribution is bounded, which is probably not realistic. However, it makes very little difference if we consider a unbounded distribution that matches the observations in the data. Barro and Jin (2011) suggest this can be done with a power law distribution with tail parameter of about 6.5. We have tried this version of the model and the results are virtually indistinguishable. The reason is that, even though low realizations are possible in theory, their probability is so small as to not affect the model's results.

3.1 The role of leverage

In their discussion, Backus, Chernov, and Martin (2011) emphasize the role of very bad consumption realizations as a reason for the poor performance of the disaster model. Therefore, this seems like an appropriate place to start. The disaster distribution in the SDR benchmark actually implies a slightly higher probability of extreme events than the benchmark CDR model (Figure 1). However, the benchmark CDR model has much higher leverage: the leverage parameter is 5.1 for the CDR calibration versus 2.6 for the SDR calibration. Leverage does not affect consumption but it affects dividends, and therefore stock and option prices. A higher leverage parameter implies that dividends will fall further in the event of a consumption disaster. It is reasonable, therefore, to attribute the difference in the implied volatilities to the difference in the leverage parameter.

Figure 3 tests this directly by showing option prices in the CDR model for leverage of 5.1 and for leverage of 2.6 (denoted “lower leverage”) in the figure. Surprisingly, the slope for the calibration with leverage of 2.6 is slightly higher than the slope for leverage of 5.1. Lowering leverage results in a downward shift in the level of the implied volatility curve, not the slope. Thus the difference in leverage cannot be the explanation for why the slope in our model is lower than the slope for CDR.

Why does the change in leverage result in a shift in the level of the curve? It turns out that in the CDR model, changing normal-times volatility has a large effect. Leverage affects both the disaster distribution and normal-times volatility. Lowering leverage has a large effect on normal-times volatility and thus at-the-money options. This is why the level of the curve is lower, and the slope is slightly steeper.⁷

⁷Yan (2011) shows analytically that, as the time to expiration approaches zero, the implied volatility is equal to the normal-times volatility in the stock price, while the slope is inversely related to the normal-times volatility of the stock price.

3.2 The role of normal shocks

To further consider the role of normal-times volatility, we explore the impact of changing the consumption volatility parameter σ . In the benchmark CDR comparison, consumption volatility is equal to the value of consumption volatility over the 1889–2009 sample, namely 3.5%. Most of this volatility is accounted for by the disaster distribution, because, while the disasters are rare, they are severe. Therefore normal-times volatility is 1%, lower than the U.S. consumption volatility over the post-war period. The SDR model is calibrated differently; following Barro (2006), the disaster distribution is determined based on international macroeconomic data, and the normal-times distribution is set to match postwar volatility in developed countries. The resulting normal-times volatility is 2%. To evaluate the effect of this difference, we solve for implied volatilities in the CDR model with leverage of 5.1 and normal-times volatility of 2%. In Figure 3, the result is shown in the line denoted “higher normal-times volatility.”

As Figure 3 shows, increasing the normal-times volatility of consumption growth in the CDR model has a noticeable effect on implied volatilities: The implied volatility curve is higher and flatter. The change in the level reflects the greater overall volatility. The change in the slope reflects the greater probability of small, negative outcomes. However, the effect, while substantial, is not nearly large enough to explain the full difference. The level of the “higher normal-times volatility” smile is still too low and the slope is too high compared with the data.⁸

While raising the volatility of consumption makes the CDR model look somewhat more like the SDR model (though it does not account for the full difference), it is not the case

⁸Note further that leverage of 5.1, combined with a normal-times consumption volatility of 2% means that normal-times dividend volatility of dividends is 10.2%. However, annual volatility in postwar data is only 6.5%.

that lowering the volatility of consumption makes the SDR model more like the CDR model. Namely, reducing σ to 1% (which would imply a normal-times consumption volatility that is lower than in the post-war data) has almost no effect on the implied volatility curve of the SDR model. There are two reasons why this parameter affects implied volatilities differently in the two cases. First, the leverage parameter is much lower in the SDR model than the CDR model. Second, volatility in the SDR model comes from time-variation in discount rates (driven by λ_t) as well as in payouts ($\phi\sigma$). The first of these terms is much larger than the second.⁹

3.3 The price of volatility risk

One obvious difference between the CDR model and the SDR model is that the SDR model is dynamic. Because of recursive utility, this affects risk premia on options and therefore option prices and implied volatilities. As shown in Section 2.2, the state price density depends on the probability of disaster. Thus risk premia depend on covariances with this probability: assets that increase in price when the probability rises will be a hedge. Options are such an asset. Indeed, an increase in the probability of a rare disaster raises option prices, while at the same time increasing marginal utility.

To directly assess the magnitude of this effect, we solve for option prices using the same process for the stock price and the dividend yield, but with a pricing kernel adjusted to set the above effect equal to zero. Risk premia in the model arise from covariances with the pricing kernel. We replace the pricing kernel in (8) with one in which $b = 0$.¹⁰ Because b

⁹To be precise, total return volatility in the SDR model equals the square root of the variance due to λ_t , plus the variance in dividends. Dividend variance is small, and it is added to something much larger to determine total variance. Thus the effect of dividend volatility on return volatility is very small, and changes in dividend volatility also have relatively little effect.

¹⁰Note that a and η also depend on b : these expressions are also changed in the experiment. While it may

determines the risk premium due to covariance with λ_t , setting $b = 0$ will shut off this effect. Figure 4 shows, setting $b = 0$ noticeably reduces the level of implied volatilities, though the difference between the $b = 0$ model and the SDR is small compared to the difference between the CDR and the SDR model.

It is worth emphasizing that the assumption of $b = 0$ does not imply an iid model. This model still assumes that stock prices are driven by stochastic disaster risk; otherwise the volatility of stock returns would be equal to that of dividends.

3.4 The distribution of consumption growth implied by options

Our results show that a model with stochastic disaster risk can fit implied volatilities, thereby addressing one issue raised by Backus, Chernov, and Martin (2011). Backus et al. raise a second issue: assuming power utility and iid consumption growth, they back out a distribution for the left tail of consumption growth from option prices (we will call this the “option-implied consumption distribution”).¹¹ Based on this distribution, they conclude that the probabilities of negative jumps to consumption are much larger, and the magnitudes much smaller, than implied by the international macroeconomic data used by Barro (2006) and Barro and Ursúa (2008).

The resolution of this second issue is clearly related to the first. For if a model (like the one we describe) can explain average implied volatilities while assuming a disaster distribution

 first appear that b should also affect the riskfree rate, this does not occur in the model with EIS= 1. The riskfree rate satisfies a simple expression

$$r_t = \beta + \mu - \gamma\sigma^2 + \lambda_t E_\nu [e^{-\gamma Z} (e^Z - 1)].$$

¹¹A methodological problem with this analysis is that it assumes that options are on returns rather than on prices. See footnote 5.

from macroeconomic data, then it follows that this macroeconomic disaster distribution is one possible consumption distribution that is consistent with the implied volatility curve. Namely, the inconsistency between the extreme consumption events in the macroeconomic data and option prices is resolved by relaxing the iid assumption.

Of course, this reasoning does not imply that the stochastic disaster model is any better than the iid model with the option-implied consumption distribution. This distribution is, after all, consistent with option prices, the equity premium, and the mean and volatility of consumption growth observed in the U.S. in the 1889-2009 period (provided a coefficient of relative risk aversion equal to 8.7). However, it turns out that this consumption distribution can be ruled out based on other data: because it assumes that negative consumption jumps are relatively frequent (as they must be to explain the equity premium), some would have occurred in the 60-year postwar period in the U.S. The unconditional volatility of consumption growth in the U.S. during this period was less than 2%. Under the option-implied consumption growth distribution, there is less than a 1 in one million chance of observing a 60-year period with volatility this low.¹²

3.5 Summary

A consequence of stochastic disaster risk is high stock market volatility, not just during occurrences of disasters, but during normal periods as well. This is reflected in the level and shallowness of the volatility smile: while the existence of disasters leads to an upward slope for out-of-the money put options, high normal-period volatility implies that the level is high for put options that are in the money or only slightly out of the money. The same

¹²There are multiple additional objections to an iid model for returns. Another that arises in the context of options and rare disaster is that of Neuberger (2012), who shows that an iid model is unlikely based on the lack of decay in return skewness as the measurement horizon grows. We discuss this result further in Section 5.4.

mechanism, and indeed the same parameters that allow the model to match the level of realized stock returns enable the model to match implied volatilities.

Previous work suggests that allowing for stochastic volatility (and time-varying moments more generally) does not appear to affect the shape of the implied volatility curve.¹³ How is it, then, that this paper comes to such a different conclusion? The reason may arise from the fact that the previous literature mainly focused on reduced-form models, in which the jump dynamics and volatility of stock returns are freely chosen. However, in an equilibrium model like the present one, stock market volatility arises endogenously from the interplay between consumption and dividend dynamics and agents' preferences. While it is possible to match the unconditional volatility of stock returns and consumption in an iid model, this can only be done (given the observed data) by having all of the volatility occur during disasters. In such a model it is not possible to generate sufficient stock market volatility in normal times to match either implied or realized volatilities. While in the reduced-form literature, the difference between iid and dynamic models principally affects the conditional second moments, in the equilibrium literature, the difference affects the level of volatility itself.

¹³Backus, Chernov, and Martin (2011) write: "The question is whether the kinds of time dependence we see in asset prices are quantitatively important in assessing the role of extreme events. It is hard to make a definitive statement without knowing the precise form of time dependence, but there is good reason to think its impact could be small. The leading example in this context is stochastic volatility, a central feature of the option-pricing model estimated by Broadie et al. (2007). However, average implied volatility smiles from this model are very close to those from an iid model in which the variance is set equal to its mean. Furthermore, stochastic volatility has little impact on the probabilities of tail events, which is our interest here."

4 Option prices in a multi-factor stochastic disaster risk model

4.1 Why multiple factors?

The previous sections show how introducing time variation into conditional moments can substantially alter the implications of rare disasters for implied volatilities. The model presented there was parsimonious, with a single state variable following a square root process.

Closer examination of our results suggests an aspect of options data that may be difficult to fit to this model. Figure 5 shows implied volatilities for λ_t equal to the median and for the 1st and 99th percentile value for put options with moneyness as low as 0.85.¹⁴ Implied volatilities increase almost in parallel as λ_t increases. That is, ATM options are affected by an increase in the rare disaster probability almost as much as out-of-the-money options. The model therefore implies that there should be little variation in the slope of the implied volatility curve.

Figure 6 shows the historical time series of implied volatilities computed on one month ATM and OTM options with moneyness of 0.85. Panel C shows the difference in the implied probabilities, a measure of the slope of the implied volatility curve. Defined in this way, the average slope is 12%, with a volatility of 2%. Moreover, the slope can rise as high as 18% and fall as low as 6%. While the SDR model can explain the average slope, it seems unlikely that it would be able to account for the time-variation in the slope, at least under the current

¹⁴The figure also shows 99th and 1st percentile implied volatilities in the data at each moneyness level. While the 99th percentile values are high in the model, they are similarly high in the data; thus the single-factor model can accurately account for the range in implied volatilities. Because this graph is constructed looking at implied volatilities for each moneyness level, it does not answer the important question of whether the model can explain time-variation in the slope.

calibration. Moreover, comparing Panel C with Panels A and B of Figure 6 indicates that the slope varies independently of the level of implied volatilities. Thus it is unlikely that any model with a single state variable could account for these data.

The mechanism in the SDR model that causes time-variation in rare disaster probabilities is identical to the mechanism that leads to volatility in normal times. Namely, when λ_t is high, rare disasters are more likely *and* returns are more volatile. In order to account for the data, a model must somehow decouple the volatility of stock returns from the probability of rare events. This is challenging, because volatility endogenously depends on the probability of rare events. Indeed, the main motivation for assuming time-variation in the probability of rare events is to generate volatility in stock returns that seems otherwise puzzling. Developing such a model is our goal in this section of the paper.

4.2 Model assumptions

In this section, we introduce a mechanism that decouples the volatility of stock returns from the probability of rare events. We assume the same stochastic process for consumption (1) and for dividends. We now assume, however, that the probability of a rare event follows the process

$$d\lambda_t = \kappa_\lambda(\xi_t - \lambda_t)dt + \sigma_\lambda\sqrt{\lambda_t}dB_{\lambda,t}, \quad (13)$$

where ξ_t solves the following stochastic differential equation

$$d\xi_t = \kappa_\xi(\bar{\xi} - \xi_t)dt + \sigma_\xi\sqrt{\xi_t}dB_{\xi,t}. \quad (14)$$

We continue to assume that all Brownian motions are mutually independent. The process for λ_t takes the same form as before, but instead of reverting to a constant value $\bar{\lambda}$, λ_t reverts to a value that is itself stochastic. We will assume that this value, ξ_t itself follows a square root process. Though the relative values of κ_λ and κ_ξ do not matter for the form of the solution,

to enable an easier interpretation of these state variables, we will choose parameters so that shocks to ξ_t die out more slowly than direct shocks to λ_t . Duffie, Pan, and Singleton (2000) use the process in (13) and (14) to model return volatility. This model is also related to multi-factor return volatility processes proposed by Bates (2000), Gallant, Hsu, and Tauchen (1999), and Andersen, Fusari, and Todorov (2013).¹⁵ In our study, the process is for jump intensity rather than volatility; however, volatility, which arises endogenously, will inherit the two-factor structure. While we implement a model with two-factors in this paper, our solution method is general enough to encompass an arbitrary number of factors with linear dependencies through the drift term, as in the literature on the term structure of interest rates (Dai and Singleton (2002)).¹⁶

Like the one-factor SDR model, our two-factor extension is highly tractable. In Appendix C.1, we show that utility is given by

$$V_t = \frac{C_t^{1-\gamma}}{1-\gamma} e^{a+b_\lambda \lambda_t + b_\xi \xi_t} \quad (15)$$

¹⁵The purpose of this model is not to provide a better fit than existing multi-factor reduced form models; all else equal it will be easier for a reduced-form model which has fewer restrictions to fit the data than an equilibrium model.

¹⁶Equilibrium models that highlight the importance of variation across different time scales include Calvet and Fisher (2007) and Zhou and Zhu (2014). These papers do not discuss the fit to implied volatilities. Rather than rare disasters, these papers induce fluctuations in asset prices based on time-varying first and second moments of consumption growth; evidence from consumption growth itself suggests that this variation is insufficient to produce the observed volatility in stock prices (Beeler and Campbell (2012)). These papers require simultaneously high risk aversion and a high elasticity of intertemporal substitution; this model requires neither.

where

$$a = \frac{1-\gamma}{\beta} \left(\mu - \frac{1}{2}\gamma\sigma^2 \right) + \frac{b_\xi \kappa_\xi \bar{\xi}}{\beta} \quad (16)$$

$$b_\lambda = \frac{\kappa_\lambda + \beta}{\sigma_\lambda^2} - \sqrt{\left(\frac{\kappa_\lambda + \beta}{\sigma_\lambda^2} \right)^2 - 2 \frac{E_\nu [e^{(1-\gamma)Z_t} - 1]}{\sigma_\lambda^2}} \quad (17)$$

$$b_\xi = \frac{\kappa_\xi + \beta}{\sigma_\xi^2} - \sqrt{\left(\frac{\kappa_\xi + \beta}{\sigma_\xi^2} \right)^2 - 2 \frac{b_\lambda \kappa_\lambda}{\sigma_\xi^2}} \quad (18)$$

Equation 5 still holds for the state-price density, though the process V_t will differ. The riskfree rate and government bill rate are the same functions of λ_t as in the one-factor model. In Appendix C.3, we show that the price-dividend ratio is given by

$$G(\lambda_t, \xi_t) = \exp(a_\phi(\tau) + b_{\phi\lambda}(\tau)\lambda_t + b_{\phi\xi}(\tau)\xi_t), \quad (19)$$

where a_ϕ , $b_{\phi\lambda}$ and $b_{\phi\xi}$ solve the differential equations

$$\begin{aligned} a'_\phi(\tau) &= -\beta - \mu - \gamma(\phi - 1)\sigma^2 + \mu_D + b_{\phi\xi}(\tau)\kappa_\xi \bar{\xi} \\ b'_{\phi\lambda}(\tau) &= -b_{\phi\lambda}(\tau)\kappa_\lambda + \frac{1}{2}b_{\phi\lambda}(\tau)^2\sigma_\lambda^2 + b_\lambda b_{\phi\lambda}(\tau)\sigma_\lambda^2 + E_\nu [e^{(\phi-\gamma)Z_t} - e^{(1-\gamma)Z_t}] \\ b'_{\phi\xi}(\tau) &= -b_{\phi\lambda}(\tau)\kappa_\lambda - b_{\phi\xi}(\tau)\kappa_\xi + \frac{1}{2}b_{\phi\xi}(\tau)^2\sigma_\xi^2 + b_\xi b_{\phi\xi}(\tau)\sigma_\xi^2, \end{aligned}$$

with boundary condition

$$a_\phi(0) = b_{\phi\lambda}(0) = b_{\phi\xi}(0) = 0.$$

Similar reasoning to that of Section 2.3 shows that for a given moneyness and time to expiration, normalized option prices and implied volatilities are a function of λ_t and ξ_t alone. To solve for option prices, we approximate $G(\lambda_t, \xi_t)$ by a log-linear function of λ_t and ξ_t , as shown in Appendix C.3.

5 Fitting the multifactor model to the data

5.1 Parameter choices

For simplicity, we keep risk aversion γ , the discount rate β and the leverage parameter ϕ the same as in the one-factor model. We also keep the distribution of consumption in the event of a disaster the same. Note that κ_λ and σ_λ will not have the same interpretation in the two-factor model as κ and σ_λ do in the one-factor model.

Our first goal in calibrating this new model is to generate reasonable predictions for the aggregate market and for the consumption distribution. That is, we do not want to allow the probability of a disaster to become too high. One challenge in calibrating representative agent models is to match the high volatility of the price-dividend ratio. In the two-factor model, as in the one-factor model, there is an upper limit to the amount of volatility that can be assumed in the state variable before a solution for utility fails to exist. The more persistent the processes, namely the lower the values of κ_λ and κ_ξ , the lower the respective volatilities must be so as to ensure that the discriminants in (17) and (18) stay nonnegative. We choose parameters so that the discriminant is equal to zero; thus there is only one more free parameter relative to the one-factor model.

The resulting parameter choices are shown in Table 2. The mean reversion parameter κ_λ and volatility parameter σ_λ are relatively high, indicating a fast-moving component to the λ_t process, while the mean reversion parameter κ_ξ and σ_ξ are relatively low, indicating a slower-moving component. The parameter $\bar{\xi}$ (which represents both the average value of ξ_t and the average value of λ_t) is 2% per annum. This is lower than $\bar{\lambda}$ in our calibration of the one-factor model. In this sense, the two-factor calibration is more conservative. However, the extra persistence created by the ξ_t process implies that λ_t could deviate from its average for long periods of time. To clarify the implications of these parameter choices, we report

population statistics on λ_t in Panel C of Table 2. The median disaster probability is only 0.37%, indicating a highly skewed distribution. The standard deviation is 3.9% and the monthly first-order autocorrelation is 0.9858.

Implications for the riskfree rate and the market are shown in Table 3. We simulate 100,000 samples of length 60 years to capture features of the small-sample distribution. We also simulate a long sample of 600,000 years to capture the population distribution. Statistics are reported for the full set of 100,000 samples, and the subset for which there are no disasters (38% of the sample paths). The table reveals a good fit to the equity premium and to return volatility. The average Treasury Bill rate is slightly too high, though this could be lowered by lowering β or by lowering the probability of government default.¹⁷ The model successfully captures the low volatility of the riskfree rate in the postwar period. The median value of the price-dividend ratio volatility is lower than in the data (0.27 versus 0.43), but the data value is still lower than the 95th percentile in the simulated sample.¹⁸ For the market moments, only the very high AR(1) coefficient in postwar data falls outside the 90% confidence bounds: it is 0.92 (annual), while in the data, the median is 0.79 and the 95th percentile value is 0.91. As we will show below, there is a tension between matching the autocorrelation in the price-dividend ratio and in option prices. Moreover, so that utility converges, there is a tradeoff between persistence and volatility. One view is that the autocorrelation of the price-dividend ratio observed in the postwar period may in fact have been very exceptional and perhaps is not a moment that should be targeted too stringently.

¹⁷As in the one-factor model, we assume a 40% probability of government default.

¹⁸The one-factor model, which was calibrated to match the population persistence of the price-dividend ratio, has a median price-dividend ratio volatility of 0.21 for sample paths without disasters and a population price-dividend ratio volatility of 0.38.

5.2 Simulation results for the two-factor model

We first examine the fit of the model to the mean of implied volatilities in the data. We ask more of the two-factor model than its one-factor counterpart. Rather than looking only at 3-month options across a narrow moneyness range, we extend the range to options of moneyness of 0.85. We also look at 1- and 6-month options, and at moments of implied volatilities beyond the means. Moreover, rather than looking only at the population average, we consider the range of values we would see in repeated samples that resemble the data, namely, samples of length 17 years with no disaster. This is a similar exercise to what was performed in Table 3, though calculating option prices is technically more difficult than calculating equity prices.¹⁹

Figure 7 shows means and volatilities of implied volatilities for the three option maturities. We report the averages across each sample path, as well as 90% confidence intervals from the simulation. We see that this new model is successful at matching the average level of the implied volatility curve for all three maturities, even with this extended moneyness range, and even though we are looking at sample paths in which the disaster probability will be lower than average. In fact the slope in the model is slightly below that in the data. Similarly, the model's predictions for volatility of volatility are well within the standard error bars for all moneyness levels and for all three option maturities.

One issue that arises in fitting both options and equities with a single model is the very different levels of persistence in the option and equity markets. This tension is apparent in our simulated data as well. As Table 3 reports, the annual AR(1) coefficient for the price-

¹⁹Because of the extra persistence in this multifrequency model, it is important to accurately capture the dynamics when λ_t is near zero. We therefore simulate the model at a daily interval for 17 years. This simulation is repeated 1000 times for the options calculation, and more for the (easier) equity calculations. Along each simulation path, we pick monthly observations of the state variables and calculate option prices for these monthly observations.

dividend ratio in the data is extremely high: 0.92; just outside of our 10% confidence intervals. The median value from the simulations is still a very high 0.79; in monthly simulations, this value is 0.98. Implied volatilities in simulated data have much lower autocorrelations. Median autocorrelations are roughly the same across moneyness levels, and are in the 0.92 to 0.94 range; substantially below the level for the price-dividend ratio. The AR(1) coefficients in the data are lower still, though generally within the 10% confidence intervals.²⁰ While the same two factors drive equity and option prices, they do so to different extents. The model endogenously captures the greater persistence in equity prices, which represent value in the longer run than do option prices.

5.3 Implications for the time series

We now return to the question of whether the two-factor model can explain time-variation in the slope and the level of option prices. Before embarking on this exercise we note that matching the time series is not usually a target for general equilibrium models because these models operate under tight constraints. We expect that there will be some aspects of the time series that our model will not be able to match.

We consider the time series of one-month ATM and OTM implied volatilities (Figure 6). For each of these data points, we compute the implied value of λ_t and ξ_t . Note that this exercise would not be possible if the model were not capable of simultaneously matching the level and slope of the implied volatility curve for one-month options. We show the resulting values in Figure 8. For most of the sample period, the disaster probability λ_t varies between 0 and 6%, with spikes corresponding to the Asian financial crisis in the late 1990s and the large market declines in the early 2000s. However, the sample is clearly dominated by the

²⁰It is well known that the implied volatility series exhibits long-memory-like properties. Thus the first-order autocorrelation of volatility may understate the true persistence of the data.

events of 2008-2009, in which the disaster probability rises to about 20%.²¹ While we choose the state variables to match the behavior of one-month options exactly, Figure 9 shows that the model also delivers a good fit to the time series of implied volatilities from three-month and six-month options.

The exercise above raises the question of whether the time series of λ_t and ξ_t are reasonable given our assumptions on the processes for these variables. Table 4 calculates the distribution of moments for λ_t and ξ_t . With the exception of the first-order autoregressive coefficients, the data fall well within the 90% confidence intervals. That is, the average values of the state variables and their volatilities could easily have been observed in 17-year samples with no disasters. The persistence in the data is somewhat lower than the persistence implied by the model. This illustrates the same tension between matching the time series of option prices and the time series of the price-dividend ratio discussed in the previous section.

As discussed in Section 4.1, it is not clear why adding a second state variable would allow the model to capture the time series variation in both the level and the slope, since both of these observables would be endogenously determined by both state variables. To better understand the mechanisms that allow the model to match these data, we consider the relative contributions of two state variables to the implied volatility curve in Figure 10. Panel A of Figure 10 fixes ξ_t at its median value and shows implied volatilities for λ_t at its 80th percentile value, at its median, and at its 20th percentile value. Panel B of Figure 10 performs the analogous exercise, this time fixing λ_t but varying ξ_t . In contrast to its behavior in the one-factor model, increasing λ_t both increases implied volatilities and increases the slope. The state variable ξ_t has a smaller effect on the level of implied volatilities, but a

²¹While this model can formally capture the financial crisis, there is a tension in that the large spike in λ_t would be an extremely unlikely event in a model in which state variables are driven by Brownian shocks. Our methods can easily accommodate Poisson jumps in λ_t itself, or a third transitory factor that would drive λ_t .

greater effect on the slope. Moreover, an increase in ξ_t lowers the slope rather than raising it. To summarize, increases in λ_t raise both the level and the slope of the implied volatility curve. Increases in ξ_t slightly raise the level and decrease the slope.

Why does ξ_t affect the slope of the implied volatility curve? The reason is that ξ_t has a relatively small effect on the probability of disasters at the time horizon important for option pricing, but a large effect on the volatility of stock prices (because of the square root term on its own volatility). Thus increases in ξ_t flatten the slope of the implied volatility curve because they raise the implied volatility for ATM options much more than for OTM options. The process for λ_t , on the other hand, has a large effect on OTM implied volatilities because it directly controls the probability of a disaster. It has a smaller effect on ATM implied volatilities than in the one-factor model because of its lower persistence.

Finally, we ask what these implied volatilities say about equity valuations. Given the option-implied values of ξ and λ , we can impute a price-dividend ratio using (19). This price-dividend ratio uses no data on equities, only data on options and the model. Figure 12 shows the results, along with the price-dividend ratio from data available from Robert Shiller's webpage. The model can match the sustained level of the price-dividend ratio, and, most importantly, the time series variation after 2004.²² Indeed, between 2004 and 2013, the correlation between the option-implied price-dividend ratio and the actual price-dividend ratio is 0.84, strongly suggesting these two markets share a common source of risk.

²²Not surprisingly, the disaster-risk model is not able to match the run-up in stock prices from the late 90s until around 2004. It may be that time-varying fears of a disaster will not be able to capture the extreme optimism that characterized that period.

5.4 The implied volatility surface

We now take a closer look at what the model says about the implied volatility surface, namely implied volatilities across moneyness and time to expiration. Figures 11 show the implied volatilities for one, three and six-month options as a function of moneyness. We show the average implied volatilities computed using the time series of λ_t and ξ_t , and compare these to the data. Given that we have chosen λ_t and ξ_t to match the time series of implied volatilities on 1-month options, it is not surprising that the model matches these data points exactly. More interestingly, the model is able to match the three-month and the six-month implied volatility curves almost exactly, even though it was not calibrated to these curves.

The downward slope in implied volatilities from options expiring in as long as six months indicates that the risk-neutral distribution of returns exhibits considerable skewness at long horizons. This is known as the skewness puzzle (Bates (2008)) because the law of large numbers would suggest convergence toward normality as the time to expiration increases. Recently, Neuberger (2012) makes use of options data to conclude that the skewness in the physical distribution of returns is also more pronounced than has been estimated previously. Neuberger emphasizes the observed negative correlation between stock prices and volatility (French, Schwert, and Stambaugh (1987)) as a reason why skewness in long-horizon returns does not decay as the law of large numbers in an iid model suggests that it would (see also Bates (2000)).

Figures 7 and 11 show that our model can capture the downward slope in 6-month implied volatilities as well as the slope for shorter-term options. Thus stock returns in the model exhibit skewness at both long and short-horizons. The short-horizon skewness arises from the existence of rare disasters. Long-horizon skewness, however, comes about endogenously because of the time-variation in the disaster probability. An increase in the rare disaster probability leads to lower stock prices, and, at the same time, higher volatilities, thereby

accounting for this co-movement in the data. As a result, returns maintain their skewness at long horizons, and the model can explain six-month as well as one-month implied volatility curves.

6 Conclusion

Since the early work of Rubinstein (1994), the implied volatility curve has constituted an important piece of evidence against the Black-Scholes Model, and a lens through which to view the success of a model in matching option prices.

The implied volatility curve, almost by definition, has been associated with excess kurtosis in stock prices. Separately, a literature has developed linking kurtosis in consumption (which would then be inherited by returns in equilibrium) with the equity premium. However, much of the work up to now, as exemplified by a recent paper by Backus, Chernov, and Martin (2011) suggests that, at least for standard preferences, the non-normalities required to match the equity premium are qualitatively different from those required to match implied volatility.

We have proposed an alternative and more general approach to modeling the risk of downward jumps that can reconcile the implied volatility curve and the equity premium. Rather than assuming that the probability of a large negative event is constant, we allow it to vary over time. The existence of very bad consumption events leads to both the downward slope in the implied volatility curve and the equity premium. Moreover, the time-variation in these events moderates the slope, raises the level and generates the excess volatility observed in stock prices. Thus the model can simultaneously match the equity premium, equity volatility, and implied volatilities on index options. Option prices, far from ruling out rare consumption disasters, provide additional information for the existence of what has been referred to as the “dark matter” of asset pricing (Campbell (2008), Chen, Dou, and Kogan (2013)).

The initial model that we develop in the paper is deliberately simple and parsimonious. However, there are some interesting features of option and stock prices that cannot be matched by a model with a single state variable; for example, the imperfect correlation between the slope and the level of the implied volatility curve. For this reason, we investigate a more general model that allows for variation in disaster risk to occur at multiple time scales. This modification naturally produces time-variation in the slope of implied volatilities because it introduces variation in stock price volatility that can be distinguished from the risk of rare disasters. Taken together, these results indicate that options data support the existence of rare disasters in beliefs about the equity premium. Moreover, options data can provide information about the disaster distribution beyond that offered by stock prices. In particular, data from options suggest that modeling time-variation in disaster risk occurring at multiple time scales may be a fruitful avenue for future work.

Appendix

A Data construction

Our sample consists of daily data on option prices, volume and open interest for European put options on the S&P 500 index from OptionMetrics. Data are from 1996 to 2012. Options expire on the Saturday that follows the third Friday of the month. We extract monthly observations using data from the Wednesday of every option expiration week. We apply standard filters to ensure that the contracts on which we base our analyses trade sufficiently often for prices to be meaningful. That is, we exclude observations with bid price smaller than $1/8$ and those with zero volume and open interest smaller than one hundred contracts (Shaliastovich (2009)).

OptionMetrics constructs implied volatilities using the formula of Black and Scholes (1973) (generalized for an underlying that pays dividends), with LIBOR as the short-term interest rate. The dividend-yield is extracted from the put-call parity relation. We wish to construct a data set of implied volatilities with maturities of 1, 3 and 6 months across a range of strike prices. Of course, there will not be liquid options with maturity precisely equal to, say, 3 months, at each date. For this reason, we use polynomial interpolation across strike prices and times to expiration.²³ Specifically, at each date in the sample, we regress implied volatilities on a polynomial in strike price K and maturity T :

$$\sigma(K, T) = \theta_0 + \theta_1 K + \theta_2 K^2 + \theta_3 T + \theta_4 T^2 + \theta_5 KT + \theta_6 KT^2 + \epsilon_{K,T}$$

We run this regression on options with maturities ranging from 30 to 247 days, and with moneyness below 1.1. The implied volatility surface is generated by the fitted values of this regression.

²³See Dumas, Fleming, and Whaley (1998), Christoffersen and Jacobs (2004) and Christoffersen, Heston, and Jacobs (2009).

B Details of calculations for the single-factor model

B.1 The state-price density

Duffie and Skiadas (1994) show that the state-price density π_t equals

$$\pi_t = \exp \left\{ \int_0^t \frac{\partial}{\partial V} f(C_s, V_s) ds \right\} \frac{\partial}{\partial C} f(C_t, V_t). \quad (\text{B.1})$$

Equation (B.1) shows the state-price density can be expressed in terms of a locally deterministic term and a term that is locally stochastic. To obtain (12), we require both to be expressed in terms of C_t and λ_t . We derive the expression for the stochastic term first.

It follows from (4) that

$$\frac{\partial}{\partial C} f(C_t, V_t) = \beta(1 - \gamma) \frac{V_t}{C_t}. \quad (\text{B.2})$$

Wachter (2013) shows that continuation utility V_t can be expressed in terms of C_t as follows:²⁴

$$V_t = J(C_t, \lambda_t), \quad (\text{B.3})$$

where

$$J(C_t, \lambda_t) = \frac{C_t^{1-\gamma}}{1-\gamma} e^{a+b\lambda_t}, \quad (\text{B.4})$$

and

$$a = \frac{1-\gamma}{\beta} \left(\mu - \frac{1}{2} \gamma \sigma^2 \right) + b \frac{\kappa \bar{\lambda}}{\beta} \quad (\text{B.5})$$

$$b = \frac{\kappa + \beta}{\sigma_\lambda^2} - \sqrt{\left(\frac{\kappa + \beta}{\sigma_\lambda^2} \right)^2 - 2 \frac{E_\nu [e^{(1-\gamma)Z} - 1]}{\sigma_\lambda^2}}. \quad (\text{B.6})$$

For future reference, we note that b is a solution to the quadratic equation

$$\frac{1}{2} \sigma_\lambda^2 b^2 - (\kappa + \beta) b + E_\nu [e^{(1-\gamma)Z} - 1] = 0. \quad (\text{B.7})$$

²⁴Wachter (2013) expresses the value function in terms of wealth rather than consumption. Because the ratio of wealth to consumption is β^{-1} , it is straightforward to go from one expression to the other. The difference between the expressions is found in the definition of a . In the earlier paper, this expression has an extra term given by $(1 - \gamma) \log \beta$.

Substituting (B.3) and (B.4) into (B.2) implies that

$$\frac{\partial}{\partial C} f(C_t, V_t) = \beta C_t^{-\gamma} e^{a+b\lambda_t}. \quad (\text{B.8})$$

It also follows from (4) that

$$\frac{\partial}{\partial V} f(C_t, V_t) = \beta(1-\gamma) \left(\log C_t - \frac{1}{1-\gamma} \log((1-\gamma)V_t) \right) + \beta.$$

Substituting in for V_t from (B.3) and (B.4) implies

$$\frac{\partial}{\partial V} f(C_t, V_t) = -\beta(a+b\lambda_t) - \beta. \quad (\text{B.9})$$

Finally, we collect constant terms:

$$\eta = -\beta a - \beta \quad (\text{B.10})$$

so that

$$\frac{\partial}{\partial V} f(C_t, V_t) = \eta - \beta b \lambda_t.$$

Therefore, from (B.1) it follows that the state-price density can be written as

$$\pi_t = \exp \left(\eta t - \beta b \int_0^t \lambda_s ds \right) \beta C_t^{-\gamma} e^{a+b\lambda_t}.$$

B.2 The iid limit

In this section we compute the limit of the state price density as σ_λ approaches zero. Note that b in equation (B.6) can be rewritten as

$$b = \frac{1}{\sigma_\lambda^2} \left(\kappa + \beta - \sqrt{(\kappa + \beta)^2 - 2E_\nu [e^{(1-\gamma)Z} - 1] \sigma_\lambda^2} \right).$$

L'Hopital's rule implies

$$\begin{aligned} \lim_{\sigma_\lambda \rightarrow 0} b &= \lim_{\sigma_\lambda \rightarrow 0} \frac{1}{2} \left((\kappa + \beta)^2 - 2E_\nu [e^{(1-\gamma)Z} - 1] \sigma_\lambda^2 \right)^{-\frac{1}{2}} 2E_\nu [e^{(1-\gamma)Z} - 1] \\ &= \frac{E_\nu [e^{(1-\gamma)Z} - 1]}{\kappa + \beta}. \end{aligned}$$

It follows from the equation for a , (B.5), that

$$\begin{aligned} \lim_{\sigma_\lambda \rightarrow 0} (a + b\lambda_t) &= \lim_{\sigma_\lambda \rightarrow 0} (a + b\bar{\lambda}) \\ &= \frac{1 - \gamma}{\beta} \left(\mu - \frac{1}{2} \gamma \sigma^2 \right) + (\kappa + \beta) \frac{\bar{\lambda}}{\beta} \lim_{\sigma_\lambda \rightarrow 0} b \\ &= \frac{1 - \gamma}{\beta} \left(\mu - \frac{1}{2} \gamma \sigma^2 \right) + \frac{E_\nu [e^{(1-\gamma)Z} - 1] \bar{\lambda}}{\beta}, \end{aligned}$$

where we assume that $\lambda_0 = \bar{\lambda}$ and therefore that $\lambda_t = \bar{\lambda}$ for all t .

We now apply these results to calculate the limit of π_t/π_0 . It follows from (B.1), (B.8) and (B.9) that

$$\begin{aligned} \lim_{\sigma_\lambda \rightarrow 0} \frac{\pi_t}{\pi_0} &= \exp \left\{ \left(-\beta - \beta \lim_{\sigma_\lambda \rightarrow 0} (a + b\bar{\lambda}) \right) t \right\} \left(\frac{C_t}{C_0} \right)^{-\gamma} \\ &= \exp \left\{ \left(-\beta - (1 - \gamma) \left(\mu - \frac{1}{2} \gamma \sigma^2 \right) - E_\nu [e^{(1-\gamma)Z} - 1] \bar{\lambda} \right) t \right\} \left(\frac{C_t}{C_0} \right)^{-\gamma}, \end{aligned}$$

which is equivalent to the result one obtains by calculating the state price density in the iid case. Note that this result is not automatic, but rather holds because we choose the lower of the two roots of (B.7).²⁵

B.3 An isomorphism with power preferences under the iid assumption

In this section we show that, in an iid model, ratios of the state price density at different times implied by power utility are the same as those implied by recursive utility assuming the discount rate is adjusted appropriately. Thus the power utility model and the recursive utility model are isomorphic when the endowment process is iid.

Let $\pi_{p,t}$ be the state price density assuming power utility with discount rate β_p and relative risk aversion γ . Then

$$\frac{\pi_{p,t}}{\pi_{p,0}} = e^{-\beta_p t} \left(\frac{C_t}{C_0} \right)^{-\gamma}.$$

²⁵This point is also made by Tauchen (2005) for a model with stochastic volatility.

For convenience, let π_t be the state price density for recursive utility (with EIS equal to one). As shown in Appendix B.2,

$$\frac{\pi_t}{\pi_0} = e^{((1-\gamma)(-\mu + \frac{1}{2}\gamma\sigma^2) - \bar{\lambda}E_\nu[e^{(1-\gamma)Z} - 1] - \beta)t} \left(\frac{C_t}{C_0}\right)^{-\gamma}.$$

It follows that, for β given by

$$\beta = \beta_p + (1 - \gamma) \left(-\mu + \frac{1}{2}\gamma\sigma^2\right) - \bar{\lambda}E_\nu [e^{(1-\gamma)Z} - 1],$$

ratios of the state price densities are the same.

B.4 Approximating the price-dividend ratio

The formula for the price-dividend ratio in the SDR model is derived by Wachter (2013) and is given by

$$G(\lambda_t) = \int_0^\infty \exp \{a_\phi(\tau) + b_\phi(\tau)\lambda_t\} d\tau,$$

where $a_\phi(\tau)$ and $b_\phi(\tau)$ have closed-form expressions given in that paper. The algorithm for computing option prices that we use requires that $\log G(\lambda)$ be linear in λ . Define $g(\lambda) = \log G(\lambda)$. For a given λ^* , note that for λ_t close to λ^* ,

$$g(\lambda) \simeq g(\lambda^*) + (\lambda - \lambda^*)g'(\lambda^*). \quad (\text{B.11})$$

Moreover,

$$\begin{aligned} g'(\lambda^*) &= \frac{G'(\lambda^*)}{G(\lambda^*)} \\ &= \frac{1}{G(\lambda^*)} \int_0^\infty b_\phi(\tau) \exp \{a_\phi(\tau) + b_\phi(\tau)\lambda^*\} d\tau. \end{aligned} \quad (\text{B.12})$$

The expression (B.12) has an interpretation: it is a weighted average of the coefficients $b_\phi(\tau)$, where the average is over τ , and the weights are proportional to $\exp \{a_\phi(\tau) + b_\phi(\tau)\lambda^*\}$. With this in mind, we define the notation

$$b_\phi^* = \frac{1}{G(\lambda^*)} \int_0^\infty b_\phi(\tau) \exp \{a_\phi(\tau) + b_\phi(\tau)\lambda^*\} d\tau \quad (\text{B.13})$$

and the log-linear function

$$\hat{G}(\lambda) = G(\lambda^*) \exp \{b_\phi^*(\lambda - \lambda^*)\}. \quad (\text{B.14})$$

It follows from exponentiating both sides of (B.11) that

$$G(\lambda) \simeq \hat{G}(\lambda).$$

When we apply this method in this paper, we choose λ^* equal to the long-run mean $\bar{\lambda}$.

This log-linearization method differs from the more widely-used method of Campbell (2003), applied in continuous time by Chacko and Viceira (2005). However, in this application it is more accurate over the relevant range. This is not surprising, since we are able to exploit the fact that the true solution for the price-dividend ratio is known. In dynamic models with the EIS not equal to one, the solution is typically unknown.

Figure A.1 shows implied volatilities from option prices computed using the loglinear approximation described above, and from option prices computed by solving the expectation in (10) directly, using by averaging over simulated sample paths. To keep the computation tractable, we assume a single jump size of -30%. The implied volatilities are extremely close in the two cases.

B.5 Transform analysis

The normalized put option price is given as

$$P^n(\lambda_t, T - t; K^n) = E_t \left[\frac{\pi_T}{\pi_t} \left(K^n - \frac{F_T}{F_t} \right)^+ \right]. \quad (\text{B.15})$$

It follows from (11), (12), and (B.14) that

$$\begin{aligned} \frac{\pi_T}{\pi_t} &= \exp \left\{ - \int_t^T (\beta b \lambda_s - \eta) ds - \gamma \log \left(\frac{C_T}{C_t} \right) + b(\lambda_T - \lambda_t) \right\} \\ \frac{F_T}{F_t} &= \exp \left\{ \phi \log \left(\frac{C_T}{C_t} \right) + b_\phi^*(\lambda_T - \lambda_t) \right\}, \end{aligned}$$

where η , b and b_ϕ^* are constants defined by (B.10), (7) and (B.13), respectively. Then (B.15) can be rewritten as

$$P^n(\lambda_t, T-t; K^n) = E_t \left[e^{-\int_t^T (\beta b \lambda_s - \eta) ds - \gamma(\log C_T - \log C_t) + b(\lambda_T - \lambda_t)} K^n \mathbf{1}_{\left\{\frac{F_T}{F_t} \leq K^n\right\}} \right] \\ - E_t \left[e^{-\int_t^T (\beta b \lambda_s - \eta) ds + (\phi - \gamma)(\log C_T - \log C_t) + (b + b_\phi^*)(\lambda_T - \lambda_t)} \mathbf{1}_{\left\{\frac{F_T}{F_t} \leq K^n\right\}} \right]. \quad (\text{B.16})$$

Note that

$$\mathbf{1}_{\left\{\frac{F_T}{F_t} \leq K^n\right\}} = \mathbf{1}_{\left\{b_\phi^*(\lambda_T - \lambda_t) + \phi(\log C_T - \log C_t) \leq \log K^n\right\}}.$$

Equation (B.16) characterizes the put option in terms of expectations that can be computed using the transform analysis of Duffie, Pan, and Singleton (2000). This analysis requires only the solution of a system of ordinary differential equations and a one-dimensional numerical integration. Below, we describe how we use their analysis.

To use the method of Duffie, Pan, and Singleton (2000), it is helpful to write down the following stochastic process, which, under our assumptions, is well-defined for a given λ_t .

$$X_\tau = \begin{bmatrix} \log C_{t+\tau} - \log C_t \\ \lambda_{t+\tau} \end{bmatrix}.$$

Note that the $\{X_\tau\}$ process is defined purely for mathematical convenience. Further define

$$R(X_\tau) = [0, \beta b] X_\tau - \eta = \beta b \lambda_{t+\tau} - \eta \\ d_1 = [-\gamma, b]^\top \\ d_2 = [\phi, b_\phi^*]^\top,$$

and let

$$\mathcal{G}_{p,q}(y; X_0, T-t) = E \left[e^{-\int_0^{T-t} R(X_\tau) d\tau} e^{p^\top X_{T-t}} \mathbf{1}_{\{q^\top X_{T-t} \leq y\}} \right]. \quad (\text{B.17})$$

Note that $\{X_\tau\}$ is an affine process in the sense defined by Duffie et al. It follows that

$$P^n(\lambda, T-t; K^n) = e^{-b\lambda} K^n E \left[e^{-\int_0^{T-t} R(X_\tau) d\tau + d_1^\top X_{T-t}} \mathbf{1}_{d_2^\top X_{T-t} \leq \log K^n + b_\phi^* \lambda} \right] \\ - e^{-(b+b_\phi^*)\lambda} E \left[e^{-\int_0^{T-t} R(X_\tau) d\tau + (d_1 + d_2)^\top X_{T-t}} \mathbf{1}_{d_2^\top X_{T-t} \leq \log K^n + b_\phi^* \lambda} \right],$$

and therefore

$$P^n(\lambda, T - t; K^n) = e^{-b\lambda} \left(K^n \mathcal{G}_{d_1, d_2} (\log K^n + b_\phi^* \lambda, X_0, T - t) \right. \\ \left. - e^{-b_\phi^* \lambda} \mathcal{G}_{d_1 + d_2, d_2} (\log K^n + b_\phi^* \lambda, X_0, T - t) \right),$$

where $X_0 = [0, \lambda]$. The terms written using the function \mathcal{G} can then be computed tractably using the transform analysis of Duffie et al.

C Solution to the multifactor model

C.1 Utility

We conjecture that the value function is given by

$$J(C, \lambda, \xi) = \frac{C^{1-\gamma}}{1-\gamma} e^{a+b_\lambda \lambda + b_\xi \xi}. \quad (\text{C.1})$$

It follows from the form of $f(C, V)$ that

$$\begin{aligned} f(C, V) &= \beta(1-\gamma)V \left(\log C - \frac{1}{1-\gamma} \log [(1-\gamma)V] \right) \\ &= \beta(1-\gamma)V \log C - \beta V \log [(1-\gamma)V] \\ &= \beta V \log \left(\frac{C^{1-\gamma}}{(1-\gamma)V} \right) \\ &= -\beta V (a + b_\lambda \lambda + b_\xi \xi), \end{aligned}$$

where the last equation follows from the equilibrium condition that the utility process is equal to the value function under the optimal policies: $V_t = J(C_t, \lambda_t, \xi_t)$.

By differentiating $J(C, \lambda, \xi)$, we obtain

$$\begin{aligned} \frac{\partial J}{\partial C} &= (1-\gamma) \frac{J}{C}, & \frac{\partial^2 J}{\partial C^2} &= -\gamma(1-\gamma) \frac{J}{C^2}, \\ \frac{\partial J}{\partial \lambda} &= b_\lambda J, & \frac{\partial^2 J}{\partial \lambda^2} &= b_\lambda^2 J, \\ \frac{\partial J}{\partial \xi} &= b_\xi J, & \frac{\partial^2 J}{\partial \xi^2} &= b_\xi^2 J. \end{aligned} \quad (\text{C.2})$$

Applying Ito's Lemma to $J(C, \lambda, \xi)$ with conjecture (C.1) and derivatives (C.2):

$$\begin{aligned} \frac{dV_t}{V_t^-} &= (1 - \gamma)(\mu dt + \sigma dB_t) - \frac{1}{2}\gamma(1 - \gamma)\sigma^2 dt \\ &\quad + b_\lambda \left(\kappa_\lambda(\xi_t - \lambda_t)dt + \sigma_\lambda \sqrt{\lambda_t} dB_{\lambda,t} \right) + \frac{1}{2}b_\lambda^2 \sigma_\lambda^2 \lambda_t dt \\ &\quad + b_\xi \left(\kappa_\xi(\bar{\xi} - \xi_t)dt + \sigma_\xi \sqrt{\xi_t} dB_{\xi,t} \right) + \frac{1}{2}b_\xi^2 \sigma_\xi^2 \xi_t dt + (e^{(1-\gamma)Z_t} - 1)dN_t. \end{aligned}$$

Under the optimal consumption path, it must be that

$$V_t + \int_0^t f(C_s, V_s) ds = E_t \left[\int_0^\infty f(C_s, V_s) ds \right] \quad (\text{C.3})$$

(see Duffie and Epstein (1992)). By the law of iterative expectations, the left-hand side of (C.3) is a martingale. Thus, the sum of the drift and the jump compensator of $(V_t + \int_0^t f(C_s, V_s) ds)$ equals zero. That is,

$$\begin{aligned} 0 &= (1 - \gamma)\mu - \frac{1}{2}\gamma(1 - \gamma)\sigma^2 + b_\lambda \kappa_\lambda(\xi_t - \lambda_t) + \frac{1}{2}b_\lambda^2 \sigma_\lambda^2 \lambda_t + b_\xi \kappa_\xi(\bar{\xi} - \xi_t) + \frac{1}{2}b_\xi^2 \sigma_\xi^2 \xi_t \\ &\quad + \lambda_t E_\nu [e^{(1-\gamma)Z_t} - 1] - \beta(a + b_\lambda \lambda_t + b_\xi \xi_t). \quad (\text{C.4}) \end{aligned}$$

By collecting terms in (C.4), we obtain

$$\begin{aligned} 0 &= \underbrace{\left[(1 - \gamma)\mu - \frac{1}{2}\gamma(1 - \gamma)\sigma^2 + b_\xi \kappa_\xi \bar{\xi} - \beta a \right]}_{=0} \\ &\quad + \lambda_t \underbrace{\left[-b_\lambda \kappa_\lambda + \frac{1}{2}b_\lambda^2 \sigma_\lambda^2 + E_\nu [e^{(1-\gamma)Z_t} - 1] - \beta b_\lambda \right]}_{=0} \\ &\quad + \xi_t \underbrace{\left[b_\lambda \kappa_\lambda - b_\xi \kappa_\xi + \frac{1}{2}b_\xi^2 \sigma_\xi^2 - \beta b_\xi \right]}_{=0}. \end{aligned}$$

Solving these equations gives us

$$\begin{aligned}
a &= \frac{1-\gamma}{\beta} \left(\mu - \frac{1}{2}\gamma\sigma^2 \right) + \frac{b_\xi \kappa_\xi \bar{\xi}}{\beta} \\
b_\lambda &= \frac{\kappa_\lambda + \beta}{\sigma_\lambda^2} - \sqrt{\left(\frac{\kappa_\lambda + \beta}{\sigma_\lambda^2} \right)^2 - 2 \frac{E_\nu [e^{(1-\gamma)Z_t} - 1]}{\sigma_\lambda^2}} \\
b_\xi &= \frac{\kappa_\xi + \beta}{\sigma_\xi^2} - \sqrt{\left(\frac{\kappa_\xi + \beta}{\sigma_\xi^2} \right)^2 - 2 \frac{b_\lambda \kappa_\lambda}{\sigma_\xi^2}},
\end{aligned}$$

where we have chosen the negative root based on the economic consideration that when there are no disasters, λ_t and ξ_t should not appear in the value function. Namely, for $Z_t = 0$, $b_\lambda = b_\xi = 0$. Lastly, note that these results verify the conjecture (C.1).

C.2 State-price density

Following the same steps for the SDR model, we can show that

$$\begin{aligned}
\frac{\partial}{\partial C} f(C_t, V_t) &= \beta C_t^{-\gamma} e^{a+b_\lambda \lambda_t + b_\xi \xi_t} \\
\frac{\partial}{\partial V} f(C_t, V_t) &= \eta - \beta b_\lambda \lambda_t - \beta b_\xi \xi_t.
\end{aligned}$$

Therefore, it follows that the state-price density can be written as

$$\pi_t = \exp \left(\eta t - \beta b_\lambda \int_0^t \lambda_s ds - \beta b_\xi \int_0^t \xi_s ds \right) \beta C_t^{-\gamma} e^{a+b_\lambda \lambda_t + b_\xi \xi_t}. \quad (\text{C.5})$$

By applying Ito's Lemma to (C.5), we derive the following stochastic differential equation:

$$\begin{aligned}
\frac{d\pi_t}{\pi_t} &= \{ -\beta - \mu + \gamma\sigma^2 - \lambda_t E_\nu [e^{(1-\gamma)Z_t} - 1] \} dt \\
&\quad - \gamma\sigma dB_t + b_\lambda \sigma_\lambda \sqrt{\lambda_t} dB_{\lambda,t} + b_\xi \sigma_\xi \sqrt{\xi_t} dB_{\xi,t} + (e^{-\gamma Z_t} - 1) dN_t.
\end{aligned}$$

In equilibrium, the sum of the drift and the jump compensator of the state-price density growth must equal the negative of the riskfree rate. The riskfree rate therefore equals

$$r_t = \beta + \mu - \gamma\sigma^2 + \lambda_t E_\nu [e^{(1-\gamma)Z_t} - e^{-\gamma Z_t}].$$

C.3 Dividend claim price

Let F_t denote the price of the dividend claim. The pricing relation implies

$$\begin{aligned} F_t &= E_t \left[\int_t^\infty \frac{\pi_s}{\pi_t} D_s ds \right] \\ &= \int_t^\infty E_t \left[\frac{\pi_s}{\pi_t} D_s \right] ds. \end{aligned}$$

Let $H(D_t, \lambda_t, \xi_t, s-t)$ denote the price of the asset that pays the aggregate dividend at time s , namely,

$$H(D_t, \lambda_t, \xi_t, s-t) = E_t \left[\frac{\pi_s}{\pi_t} D_s \right].$$

By the law of iterative expectations, it follows that $\pi_t H_t$ is a martingale:

$$\pi_t H(D_t, \lambda_t, \xi_t, s-t) = E_t[\pi_s D_s].$$

Conjecture that

$$H(D_t, \lambda_t, \xi_t, \tau) = D_t \exp(a_\phi(\tau) + b_{\phi\lambda}(\tau)\lambda_t + b_{\phi\xi}(\tau)\xi_t). \quad (\text{C.6})$$

Ito's Lemma implies

$$\begin{aligned} \frac{dH_t}{H_{t-}} &= \left\{ \mu_D + b_{\phi\lambda}(\tau)\kappa_\lambda(\xi_t - \lambda_t) + \frac{1}{2}b_{\phi\lambda}(\tau)^2\sigma_\lambda^2\lambda_t + b_{\phi\xi}(\tau)\kappa_\xi(\bar{\xi} - \xi_t) + \frac{1}{2}b_{\phi\xi}(\tau)^2\sigma_\xi^2\xi_t \right. \\ &\quad \left. - a'_\phi(\tau) - b'_{\phi\lambda}(\tau)\lambda_t - b'_{\phi\xi}(\tau)\xi_t \right\} dt \\ &\quad + \phi\sigma dB_t + b_{\phi\lambda}(\tau)\sigma_\lambda\sqrt{\lambda_t}dB_{\lambda,t} + b_{\phi\xi}(\tau)\sigma_\xi\sqrt{\xi_t}dB_{\xi,t} + (e^{\phi Z_t} - 1)dN_t. \end{aligned}$$

Combining the SDE for H_t with the one for π_t derived in the previous sections, we can derive the SDE for $\pi_t H_t$:

$$\begin{aligned}
\frac{d(\pi_t H_t)}{\pi_{t-} H_{t-}} = & \left\{ -\beta - \mu + \gamma\sigma^2 - \lambda_t E_\nu [e^{(1-\gamma)Z_t} - 1] \right. \\
& + \mu_D + b_{\phi\lambda}(\tau)\kappa_\lambda(\xi_t - \lambda_t) + \frac{1}{2}b_{\phi\lambda}(\tau)^2\sigma_\lambda^2\lambda_t \\
& + b_{\phi\xi}(\tau)\kappa_\xi(\bar{\xi} - \xi_t) + \frac{1}{2}b_{\phi\xi}(\tau)^2\sigma_\xi^2\xi_t \\
& - a'_\phi(\tau) - b'_{\phi\lambda}(\tau)\lambda_t - b'_{\phi\xi}(\tau)\xi_t \\
& \left. - \gamma\phi\sigma^2 + b_\lambda b_{\phi\lambda}(\tau)\sigma_\lambda^2\lambda_t + b_\xi b_{\phi\xi}(\tau)\sigma_\xi^2\xi_t \right\} dt \\
& + (\phi - \gamma)\sigma dB_t + (b_\lambda + b_{\phi\lambda}(\tau))\sigma_\lambda\sqrt{\lambda_t}dB_{\lambda,t} + (b_\xi + b_{\phi\xi}(\tau))\sigma_\xi\sqrt{\xi_t}dB_{\xi,t} \\
& + (e^{(\phi-\gamma)Z_t} - 1)dN_t.
\end{aligned}$$

Since $\pi_t H_t$ is a martingale, the sum of the drift and the jump compensator of $\pi_t H_t$ equals zero. Thus:

$$\begin{aligned}
0 = & -\beta - \mu + \gamma\sigma^2 - \lambda_t E_\nu [e^{(1-\gamma)Z_t} - 1] \\
& + \mu_D + b_{\phi\lambda}(\tau)\kappa_\lambda(\xi_t - \lambda_t) + \frac{1}{2}b_{\phi\lambda}(\tau)^2\sigma_\lambda^2\lambda_t \\
& + b_{\phi\xi}(\tau)\kappa_\xi(\bar{\xi} - \xi_t) + \frac{1}{2}b_{\phi\xi}(\tau)^2\sigma_\xi^2\xi_t \\
& - a'_\phi(\tau) - b'_{\phi\lambda}(\tau)\lambda_t - b'_{\phi\xi}(\tau)\xi_t \\
& - \gamma\phi\sigma^2 + b_\lambda b_{\phi\lambda}(\tau)\sigma_\lambda^2\lambda_t + b_\xi b_{\phi\xi}(\tau)\sigma_\xi^2\xi_t + \lambda_t E_\nu [e^{(\phi-\gamma)Z_t} - 1]. \quad (\text{C.7})
\end{aligned}$$

Collecting terms of (C.7) results in the following equation:

$$\begin{aligned}
0 = & \underbrace{[-\beta - \mu + \gamma\sigma^2 + \mu_D + b_{\phi\xi}(\tau)\kappa_\xi\bar{\xi} - \gamma\phi\sigma^2 - a'_\phi(\tau)]}_{=0} \\
& + \lambda_t \underbrace{\left[-b_{\phi\lambda}(\tau)\kappa_\lambda + \frac{1}{2}b_{\phi\lambda}(\tau)^2\sigma_\lambda^2 + b_\lambda b_{\phi\lambda}(\tau)\sigma_\lambda^2 + E_\nu [e^{(\phi-\gamma)Z_t} - e^{(1-\gamma)Z_t}] - b'_{\phi\lambda}(\tau) \right]}_{=0} \\
& + \xi_t \underbrace{\left[b_{\phi\lambda}(\tau)\kappa_\lambda - b_{\phi\xi}(\tau)\kappa_\xi + \frac{1}{2}b_{\phi\xi}(\tau)^2\sigma_\xi^2 + b_\xi b_{\phi\xi}(\tau)\sigma_\xi^2 - b'_{\phi\xi}(\tau) \right]}_{=0}.
\end{aligned}$$

It follows that

$$\begin{aligned}
a'_\phi(\tau) &= \mu_D - \mu - \beta + \gamma\sigma^2(1 - \phi) + \kappa_\xi\bar{\xi}b_{\phi\xi}(\tau) \\
b'_{\phi\lambda}(\tau) &= \frac{1}{2}\sigma_\lambda^2 b_{\phi\lambda}(\tau)^2 + (b_\lambda\sigma_\lambda^2 - \kappa_\lambda)b_{\phi\lambda}(\tau) + E_\nu [e^{(\phi-\gamma)Z_t} - e^{(1-\gamma)Z_t}] \\
b'_{\phi\xi}(\tau) &= \frac{1}{2}\sigma_\xi^2 b_{\phi\xi}(\tau)^2 + (b_\xi\sigma_\xi^2 - \kappa_\xi)b_{\phi\xi}(\tau) + \kappa_\lambda b_{\phi\lambda}(\tau).
\end{aligned} \tag{C.8}$$

This establishes that H satisfies the conjecture (C.6). We note that by no-arbitrage,

$$H(D_t, \lambda_t, \xi_t, 0) = D_t.$$

This condition provides the boundary conditions for the system of ODEs (C.8):

$$a_\phi(0) = b_{\phi\lambda}(0) = b_{\phi\xi}(0) = 0.$$

Recall that once we get $a_\phi(\tau)$, $b_{\phi\lambda}(\tau)$, and $b_{\phi\xi}(\tau)$,

$$\begin{aligned}
F_t &= \int_t^\infty E_t \left[\frac{\pi_s}{\pi_t} D_s \right] ds \\
&= \int_t^\infty H(D_t, \lambda_t, \xi_t, s - t) ds \\
&= D_t \int_t^\infty \exp(a_\phi(s - t) + b_{\phi\lambda}(s - t)\lambda_t + b_{\phi\xi}(s - t)\xi_t) ds \\
&= D_t \int_0^\infty \exp(a_\phi(\tau) + b_{\phi\lambda}(\tau)\lambda_t + b_{\phi\xi}(\tau)\xi_t) d\tau.
\end{aligned}$$

That is, the price-dividend ratio can be written as

$$G(\lambda_t, \xi_t) = \int_0^\infty \exp(a_\phi(\tau) + b_{\phi\lambda}(\tau)\lambda_t + b_{\phi\xi}(\tau)\xi_t) d\tau.$$

C.4 Approximating the price-dividend ratio

Let $g(\lambda, \xi) = \log G(\lambda, \xi)$. For given λ^* and ξ^* , the two-dimensional Taylor approximation implies

$$g(\lambda, \xi) \simeq g(\lambda^*, \xi^*) + \left. \frac{\partial g}{\partial \lambda} \right|_{\lambda^*, \xi^*} (\lambda - \lambda^*) + \left. \frac{\partial g}{\partial \xi} \right|_{\lambda^*, \xi^*} (\xi - \xi^*). \quad (\text{C.9})$$

We note that

$$\begin{aligned} \left. \frac{\partial g}{\partial \lambda} \right|_{\lambda^*, \xi^*} &= \frac{1}{G(\lambda^*, \xi^*)} \left. \frac{\partial G}{\partial \lambda} \right|_{\lambda^*, \xi^*} \\ &= \frac{1}{G(\lambda^*, \xi^*)} \int_0^\infty b_{\phi\lambda}(\tau) \exp(a_\phi(\tau) + b_{\phi\lambda}(\tau)\lambda^* + b_{\phi\xi}(\tau)\xi^*) d\tau. \end{aligned}$$

Similarly, we obtain

$$\begin{aligned} \left. \frac{\partial g}{\partial \xi} \right|_{\lambda^*, \xi^*} &= \frac{1}{G(\lambda^*, \xi^*)} \left. \frac{\partial G}{\partial \xi} \right|_{\lambda^*, \xi^*} \\ &= \frac{1}{G(\lambda^*, \xi^*)} \int_0^\infty b_{\phi\xi}(\tau) \exp(a_\phi(\tau) + b_{\phi\lambda}(\tau)\lambda^* + b_{\phi\xi}(\tau)\xi^*) d\tau. \end{aligned}$$

We define the notation

$$\begin{aligned} b_{\phi\lambda}^* &= \frac{1}{G(\lambda^*, \xi^*)} \int_0^\infty b_{\phi\lambda}(\tau) \exp(a_\phi(\tau) + b_{\phi\lambda}(\tau)\lambda^* + b_{\phi\xi}(\tau)\xi^*) d\tau \\ b_{\phi\xi}^* &= \frac{1}{G(\lambda^*, \xi^*)} \int_0^\infty b_{\phi\xi}(\tau) \exp(a_\phi(\tau) + b_{\phi\lambda}(\tau)\lambda^* + b_{\phi\xi}(\tau)\xi^*) d\tau, \end{aligned}$$

and the log-linear function

$$\hat{G}(\lambda, \xi) = G(\lambda^*, \xi^*) \exp \{ b_{\phi\lambda}^* (\lambda - \lambda^*) + b_{\phi\xi}^* (\xi - \xi^*) \}.$$

It follows from exponentiating both sides of (C.9) that

$$G(\lambda, \xi) \simeq \hat{G}(\lambda, \xi).$$

In our analysis, we pick λ^* and ξ^* as the stationary mean of λ_t and ξ_t , respectively.

References

- Andersen, Torben G., Nicola Fusari, and Viktor Todorov, 2013, The Risk Premia Embedded in Index Options, Working paper, Northwestern University.
- Backus, David, Mikhail Chernov, and Ian Martin, 2011, Disasters Implied by Equity Index Options, *The Journal of Finance* 66, 1969–2012.
- Bansal, Ravi, and Amir Yaron, 2004, Risks for the long-run: A potential resolution of asset pricing puzzles, *Journal of Finance* 59, 1481–1509.
- Barro, Robert J., 2006, Rare disasters and asset markets in the twentieth century, *Quarterly Journal of Economics* 121, 823–866.
- Barro, Robert J., and Tao Jin, 2011, On the size distribution of macroeconomic disasters, *Econometrica* 79, 1567–1589.
- Barro, Robert J., and José F. Ursúa, 2008, Macroeconomic crises since 1870, *Brookings Papers on Economic Activity* no. 1, 255–350.
- Bates, David S., 2000, Post-'87 crash fears in the S&P 500 futures option market, *Journal of Econometrics* 94, 181–238.
- Bates, David S., 2008, The market for crash risk, *Journal of Economic Dynamics and Control* 32, 2291–2321.
- Beeler, Jason, and John Y. Campbell, 2012, The long-run risks model and aggregate asset prices: An empirical assessment, *Critical Finance Review* 1, 141–182.
- Benzoni, Luca, Pierre Collin-Dufresne, and Robert S. Goldstein, 2011, Explaining asset pricing puzzles associated with the 1987 market crash, *Journal of Financial Economics* 101, 552 – 573.

- Black, Fischer, and Myron Scholes, 1973, The Pricing of Options and Corporate Liabilities, *Journal of Political Economy* 81, 637–654.
- Bollerslev, Tim, and Viktor Todorov, 2011, Tails, Fears, and Risk Premia, *The Journal of Finance* 66, 2165–2211.
- Broadie, Mark, Mikhail Chernov, and Michael Johannes, 2007, Model specification and risk premia: Evidence from futures options, *Journal of Finance* 62, 1453–1490.
- Brunnermeier, Markus, Stefan Nagel, and Lasse H. Pedersen, 2008, Carry trades and currency crashes, *NBER Macroeconomics Annual* 23, 313–347.
- Buraschi, Andrea, and Alexei Jiltsov, 2006, Model Uncertainty and Option Markets with Heterogeneous Beliefs, *The Journal of Finance* 61, 2841–2897.
- Calvet, Laurent E., and Adlai J. Fisher, 2007, Multifrequency news and stock returns, *Journal of Financial Economics* 86, 178–212.
- Campbell, John Y., 2003, Consumption-based asset pricing, in G. Constantinides, M. Harris, and R. Stulz, eds.: *Handbook of the Economics of Finance, vol. 1b* (Elsevier Science, North-Holland).
- Campbell, John Y., 2008, Risk and return in stocks and bonds, Lecture 2, Princeton Lectures in Finance.
- Campbell, John Y., and John H. Cochrane, 1999, By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205–251.
- Chacko, George, and Luis Viceira, 2005, Dynamic consumption and portfolio choice with stochastic volatility in incomplete markets, *Review of Financial Studies* 18, 1369–1402.

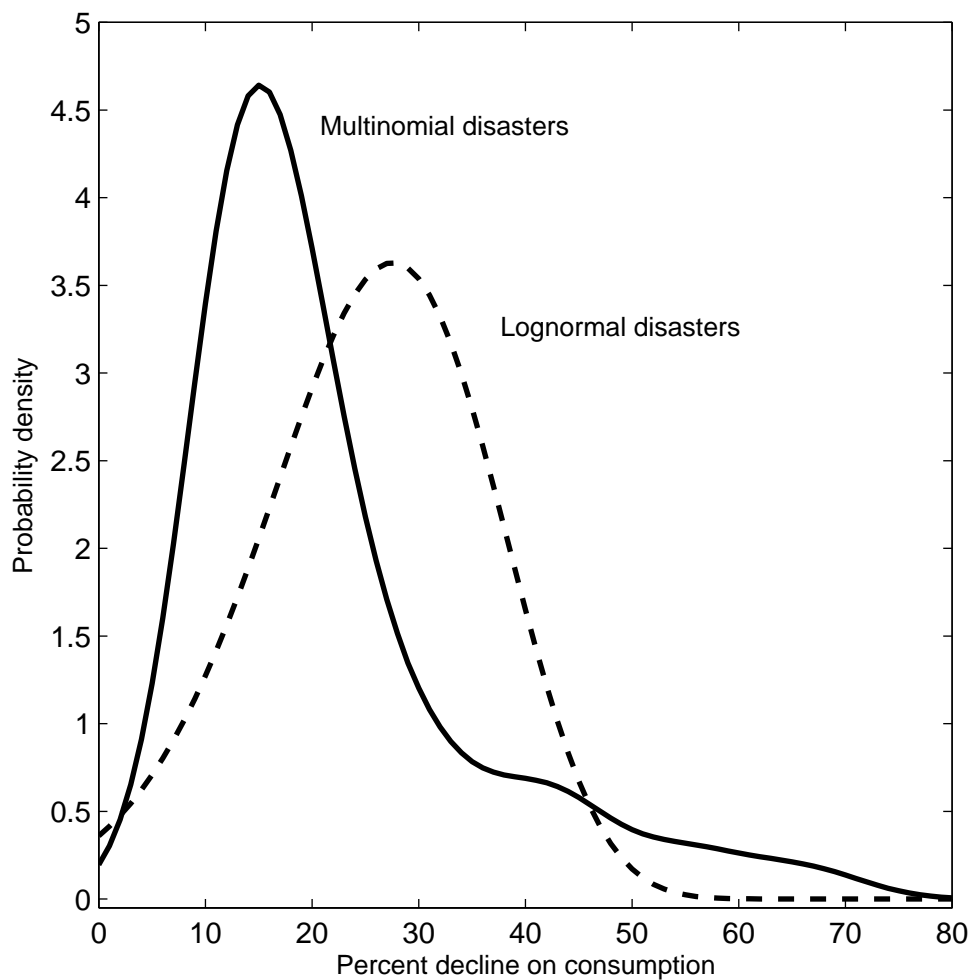
- Chen, Hui, Winston Wei Dou, and Leonid Kogan, 2013, Measuring the “Dark Matter” in Asset Pricing Models, Working paper, MIT.
- Christoffersen, Peter, Steven Heston, and Kris Jacobs, 2009, The Shape and Term Structure of the Index Option Smirk: Why Multifactor Stochastic Volatility Models Work So Well, *Management Science* 55, 1914–1932.
- Christoffersen, Peter, and Kris Jacobs, 2004, The importance of the loss function in option valuation, *Journal of Financial Economics* 72, 291–318.
- Cox, John C., Jonathan C. Ingersoll, and Stephen A. Ross, 1985, A theory of the term structure of interest rates, *Econometrica* 53, 385–408.
- Dai, Qiang, and Kenneth Singleton, 2002, Expectations puzzles, time-varying risk premia, and affine models of the term structure, *Journal of Financial Economics* 63, 415–442.
- Drechsler, Itamar, 2012, Uncertainty, Time-Varying Fear, and Asset Prices, forthcoming, *Journal of Finance*.
- Drechsler, Itamar, and Amir Yaron, 2011, What’s vol got to do with it, *Review of Financial Studies* 24, 1–45.
- Du, Du, 2011, General equilibrium pricing of options with habit formation and event risks, *Journal of Financial Economics* 99, 400–426.
- Duffie, Darrell, and Larry G Epstein, 1992, Asset pricing with stochastic differential utility, *Review of Financial Studies* 5, 411–436.
- Duffie, Darrell, Jun Pan, and Kenneth Singleton, 2000, Transform analysis and asset pricing for affine jump-diffusions, *Econometrica* 68, 1343–1376.

- Duffie, Darrell, and Costis Skiadas, 1994, Continuous-time asset pricing: A utility gradient approach, *Journal of Mathematical Economics* 23, 107–132.
- Dumas, Bernard, Jeff Fleming, and Robert E. Whaley, 1998, Implied Volatility Functions: Empirical Tests, *The Journal of Finance* 53, 2059–2106.
- Epstein, Larry, and Stan Zin, 1989, Substitution, risk aversion and the temporal behavior of consumption and asset returns: A theoretical framework, *Econometrica* 57, 937–969.
- Eraker, Bjorn, and Ivan Shaliastovich, 2008, An equilibrium guide to designing affine pricing models, *Mathematical Finance* 18, 519–543.
- Fisher, Mark, and Christian Gilles, 1999, Consumption and asset prices with homothetic recursive preferences, Working paper, 99-17 Federal Reserve Bank of Atlanta.
- French, Kenneth R., G. William Schwert, and Robert F. Stambaugh, 1987, Expected stock returns and volatility, *Journal of Financial Economics* 19, 3–29.
- Gabaix, Xavier, 2008, Linearity-generating processes: A modelling tool yielding closed forms for asset prices, Working paper, New York University.
- Gabaix, Xavier, 2012, An exactly solved framework for ten puzzles in macro-finance, *Quarterly Journal of Economics* 127, 645–700.
- Gallant, A. Ronald, Chien-Te Hsu, and George Tauchen, 1999, Using Daily Range Data to Calibrate Volatility Diffusions and Extract the Forward Integrated Variance, *Review of Economics and Statistics* 81, 617–631.
- Gao, George P., and Zhaogang Song, 2013, Rare disaster concerns everywhere, Working paper, Cornell University.

- Gourio, François, 2012, Disaster risk and business cycles, *American Economic Review* 102, 2734–2766.
- Kelly, Bryan T., Hanno N. Lustig, and Stijn Van Nieuwerburgh, 2012, Too-Systemic-To-Fail: What Option Markets Imply About Sector-Wide Government Guarantees, NBER Working Paper # 17149.
- Kelly, Bryan T., Lubos Pastor, and Pietro Veronesi, 2014, The Price of Political Uncertainty: Theory and Evidence from the Option Market, Working paper, University of Chicago.
- Liu, Jun, Jun Pan, and Tan Wang, 2005, An equilibrium model of rare-event premia and its implication for option smirks, *Review of Financial Studies* 18, 131–164.
- Longstaff, Francis A., and Monika Piazzesi, 2004, Corporate earnings and the equity premium, *Journal of Financial Economics* 74, 401–421.
- Mehra, Rajnish, and Edward Prescott, 1985, The equity premium puzzle, *Journal of Monetary Economics* 15, 145–161.
- Neuberger, Anthony, 2012, Realized Skewness, *Review of Financial Studies* 25, 3423–3455.
- Nowotny, Michael, 2011, Disaster begets crisis: The role of contagion in financial markets, Working paper, Boston University.
- Pan, Jun, 2002, The jump-risk premia implicit in options: evidence from an integrated time-series study, *Journal of Financial Economics* 63, 3–50.
- Rietz, Thomas A., 1988, The equity risk premium: A solution, *Journal of Monetary Economics* 22, 117–131.
- Rubinstein, Mark, 1994, Implied Binomial Trees, *The Journal of Finance* 49, 771–818.

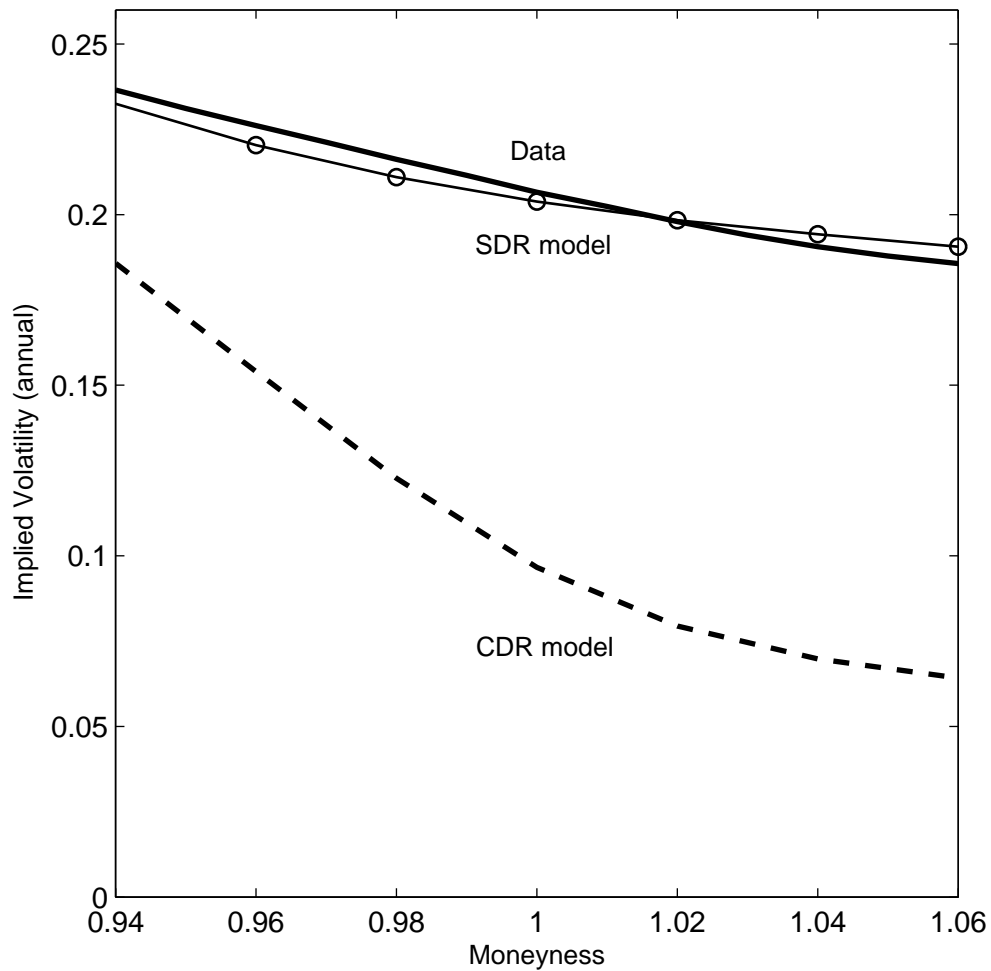
- Santa-Clara, Pedro, and Shu Yan, 2010, Crashes, Volatility, and the Equity Premium: Lessons from S&P 500 Options, *Review of Economics and Statistics* 92, 435–451.
- Schroder, Mark, and Costis Skiadas, 1999, Optimal consumption and portfolio selection with stochastic differential utility, *Journal of Economic Theory* 89, 68–126.
- Shaliastovich, Ivan, 2009, Learning, Confidence and Option Prices, working paper, University of Pennsylvania.
- Tauchen, George, 2005, Stochastic volatility in general equilibrium, Working paper, Duke University.
- Wachter, Jessica A., 2013, Can time-varying risk of rare disasters explain aggregate stock market volatility?, *The Journal of Finance* 68, 987–1035.
- Weil, Philippe, 1990, Nonexpected utility in macroeconomics, *Quarterly Journal of Economics* 105, 29–42.
- Weitzman, Martin L., 2007, Subjective expectations and asset-return puzzles, *American Economic Review* 97, 1102–1130.
- Yan, Shu, 2011, Jump risk, stock returns, and slope of implied volatility smile, *Journal of Financial Economics* 99, 216–233.
- Zhou, Guofu, and Yingzi Zhu, 2014, Macroeconomic Volatilities and Long-run Risks of Asset Prices, Working paper, Washington University and Tsinghua University.

Figure 1: Probability density functions for consumption declines



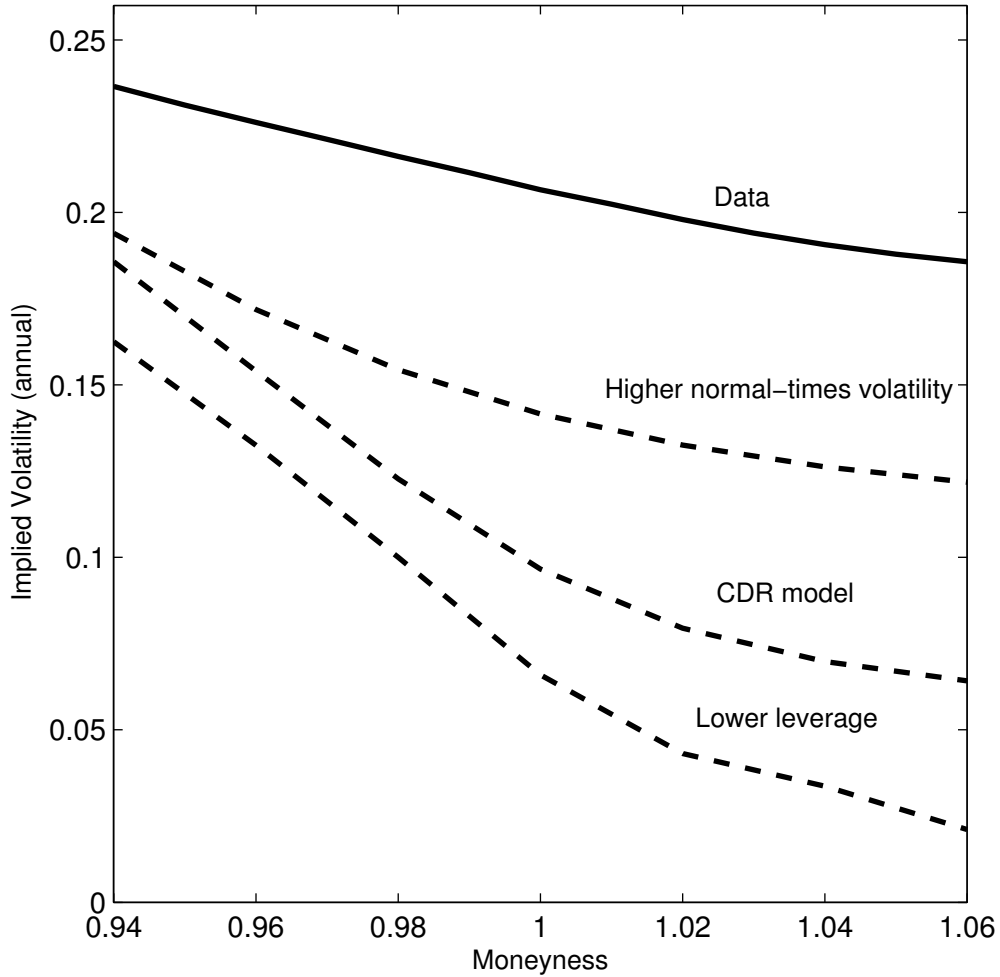
Notes: The probability density functions (pdfs) for consumption declines for log-normally distributed disasters and for the multinomial distribution assumed in the stochastic disaster risk (SDR) model. In the case of the SDR model, the pdf approximates the multinomial distribution from Barro and Ursúa (2008). The exact multinomial distribution is used to calculate the results in the paper. The pdfs are for the quantities $1 - e^Z$ in each model.

Figure 2: Average implied volatilities in the SDR and CDR models



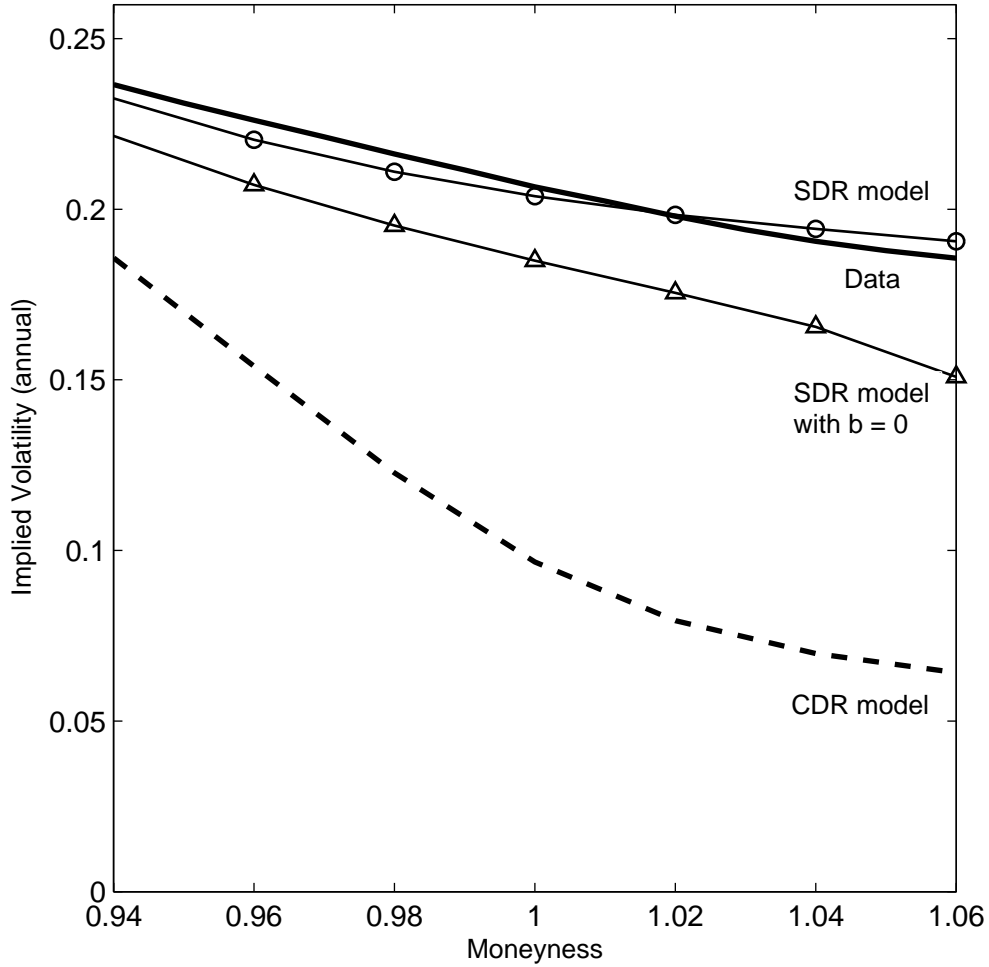
Notes: Average implied volatilities for 3-month options as a function of moneyness for the stochastic disaster risk (SDR) model, for the constant disaster risk (CDR) model (under the benchmark calibration given in Table 1) and in the data. Average implied volatilities are shown as functions of moneyness, defined as the exercise price divided by the asset price.

Figure 3: Comparative statics for the CDR model



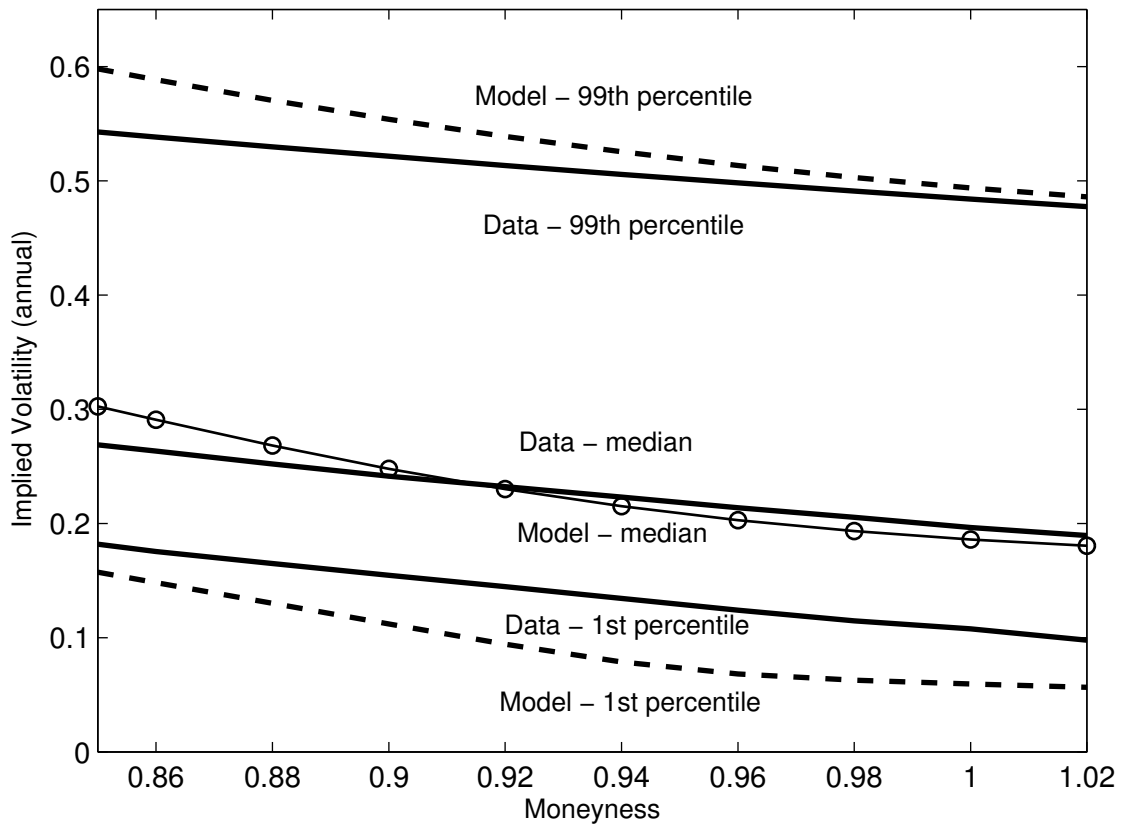
Notes: Implied volatilities for 3-month options as a function of moneyness in the data and for three parameterization of the CDR model. The line labeled “CDR” shows the benchmark calibration. The line labeled “higher normal-times volatility” raises the volatility of consumption shocks that are not associated with disasters from 1% to 2% per annum but keeps all other parameters, including the consumption disaster distribution, the same. The line labeled “lower leverage” lowers the term multiplying dividends from 5.1 to 2.6, while keeping all other parameters the same.

Figure 4: Evaluating the role of recursive utility



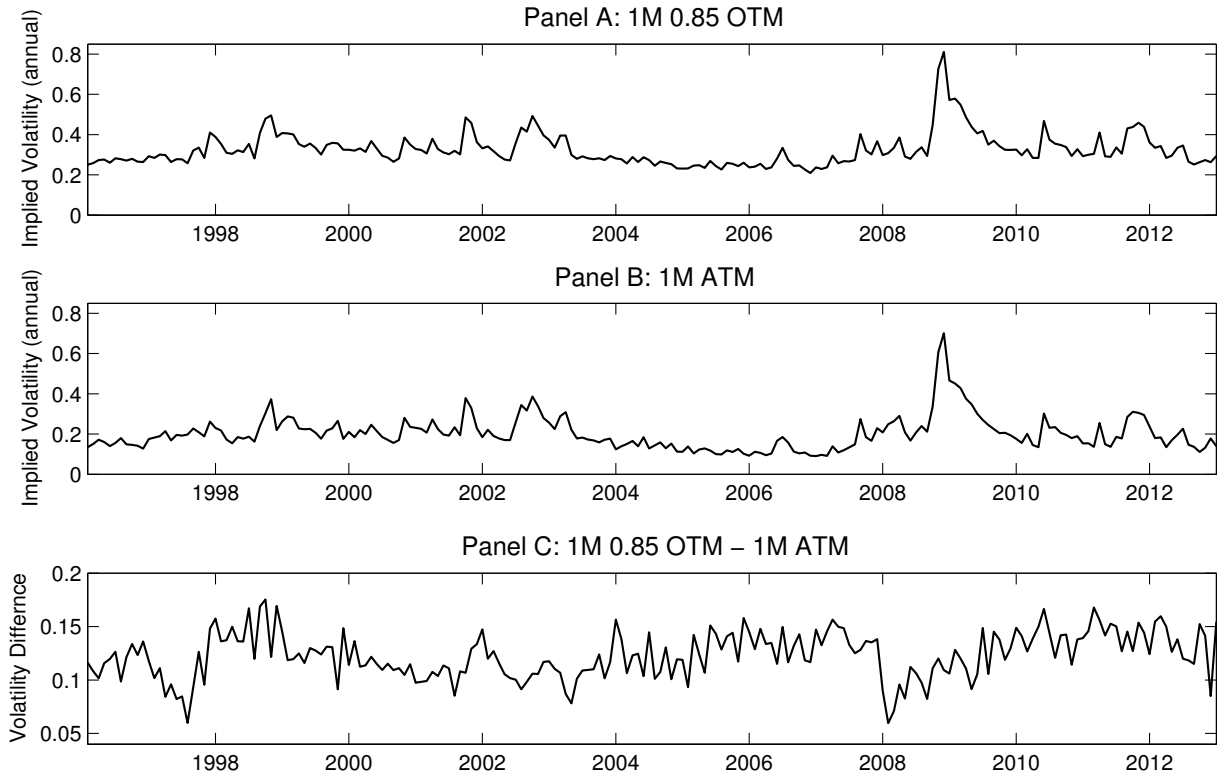
Notes: Implied volatilities for 3-month options as a function of moneyness in the data, in the CDR model (calibrated as in Table 1) and in the SDR model. Also shown are implied volatilities in the SDR model computed under the assumption that the premium associated with time-variation in the disaster probability is equal to zero (SDR model with $b = 0$). Note both the benchmark and the $b = 0$ version of the SDR model are dynamic models with stochastic moments. The CDR model is iid.

Figure 5: Implied volatilities for given values of the disaster probability



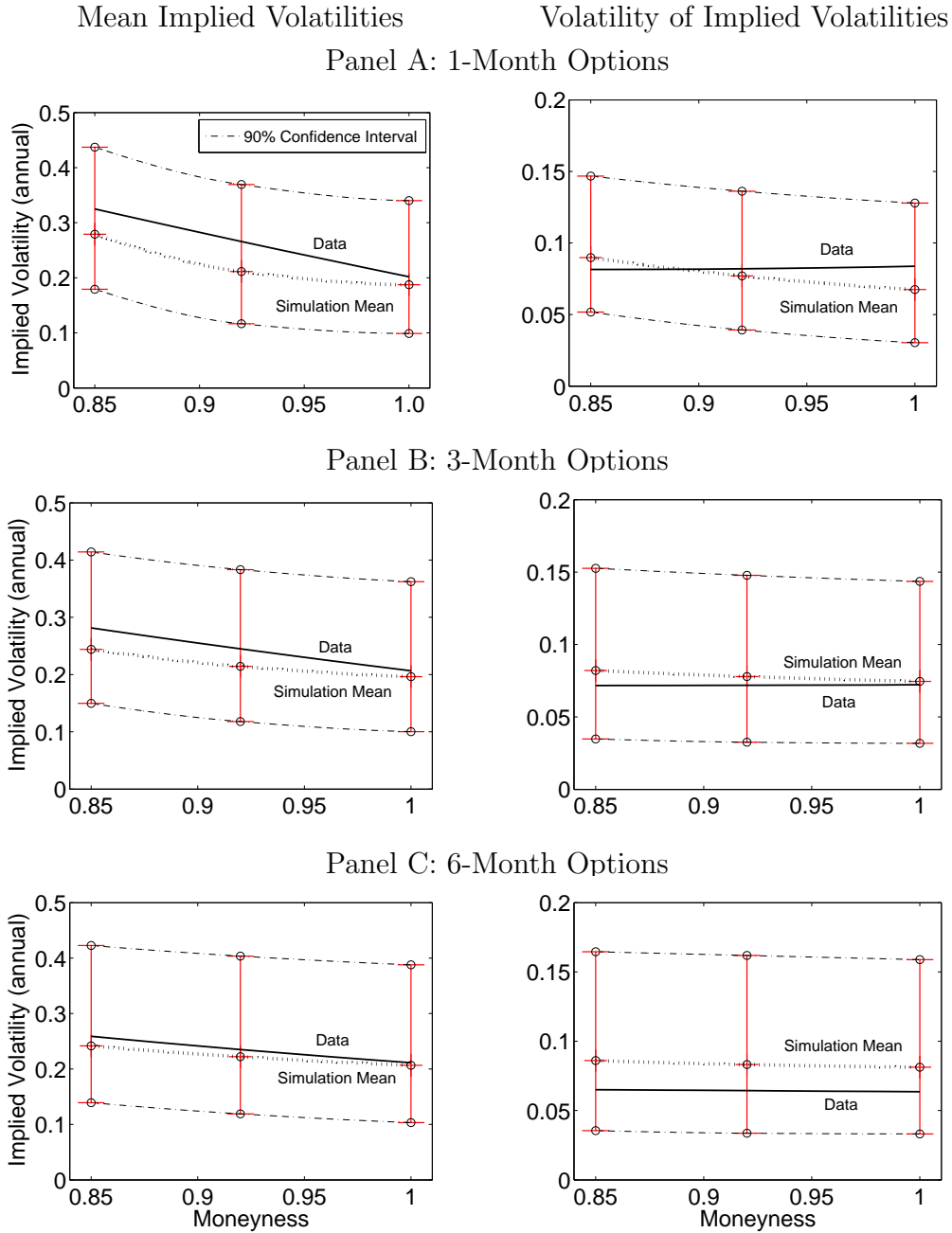
Notes: Implied volatilities on 3-month options as a function of moneyness for various percentile values of the probability of a disaster in the single-factor SDR model. Also shown are average implied volatilities in the data, and, for each moneyness value, 99th and 1st percentile implied volatilities in the data.

Figure 6: 1-month implied volatility time series



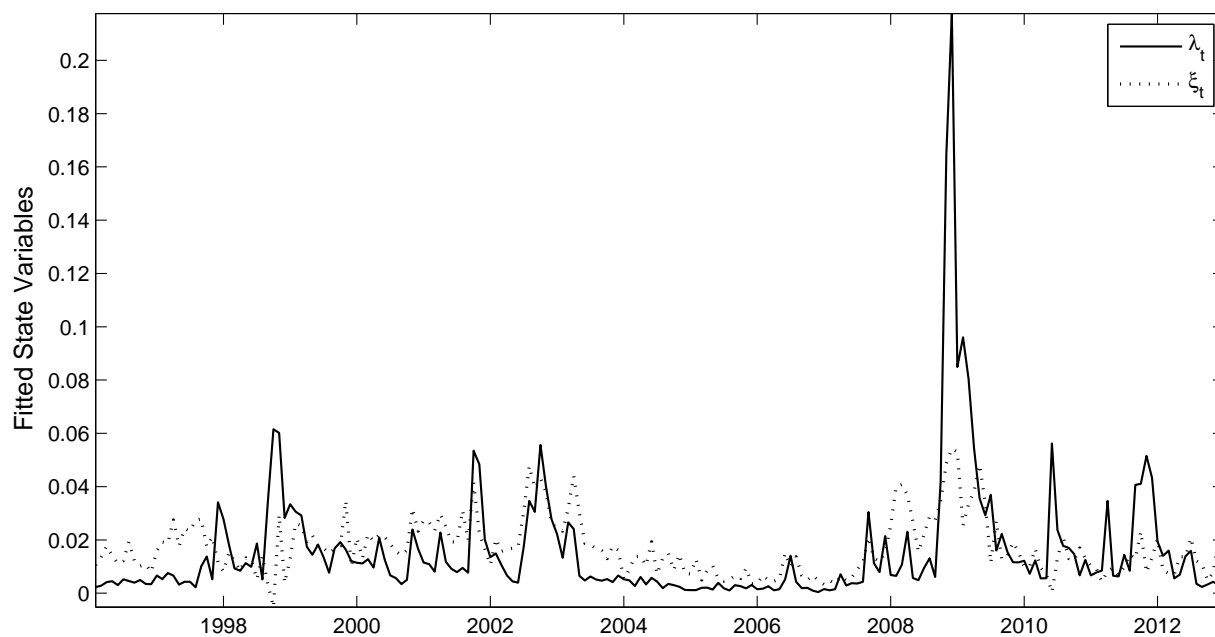
Notes: Monthly time series of implied volatilities on 1-month options in the data and of the difference in implied volatilities. Implied volatilities are calculated for at-the-money (ATM) options and out-of-the-money (OTM) options with moneyness equal to 0.85.

Figure 7: Mean and volatility of implied volatilities in simulated data



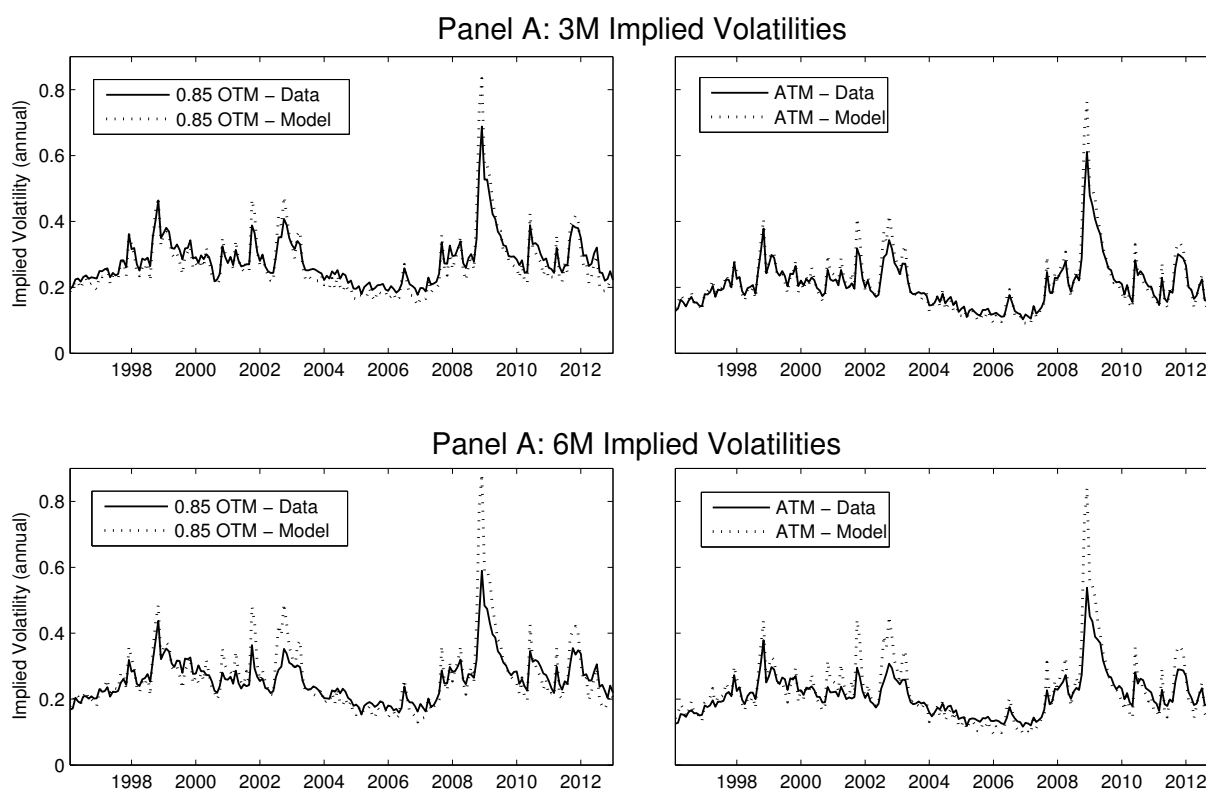
Notes: We simulate 1000 samples of length 17 years from the two-factor model. For each sample path, we compute the mean and volatility of implied volatilities at three different moneyness levels and for three maturities. The dotted line shows the means of these statistics across sample paths, while the dashed-dotted lines show 95th and 5th percentiles. The solid line shows the data.

Figure 8: Fitted values of state variables



Notes: Fitted state variables in the two-factor SDR model. State variables are fitted to the time series of 1-month implied volatilities of ATM options and OTM options with moneyness equal to 0.85. The variable λ_t represents the (annual) probability of disaster. λ_t reverts to a time-varying value ξ_t .

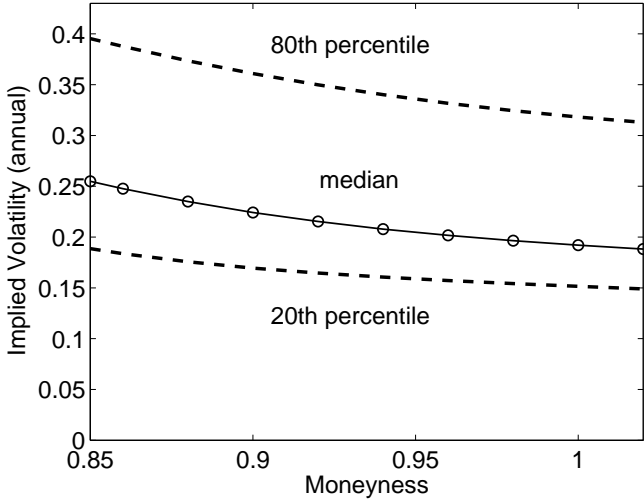
Figure 9: 3- and 6-month implied volatility time series



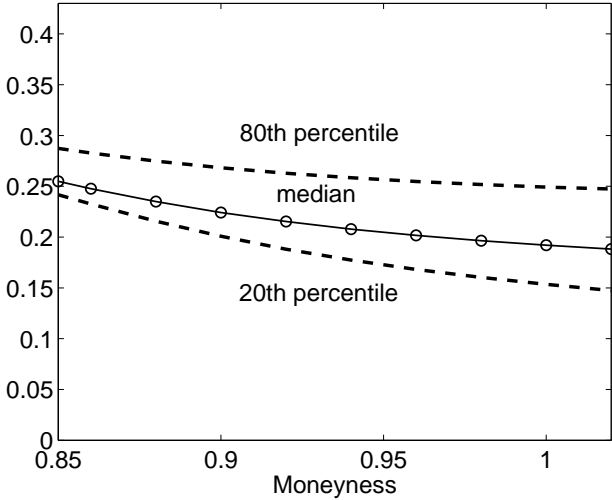
Notes: Monthly time series of implied volatilities on 3- and 6-month options in the data and in the two-factor SDR model. Implied volatilities are calculated for ATM options and OTM options with moneyness equal to 0.85. In the model, we compute option prices using state variables fit to the time series of 1-month ATM and OTM options with moneyness of 0.85.

Figure 10: Implied volatilities as functions of the state in the two-factor SDR model

Panel A: Varying λ_t

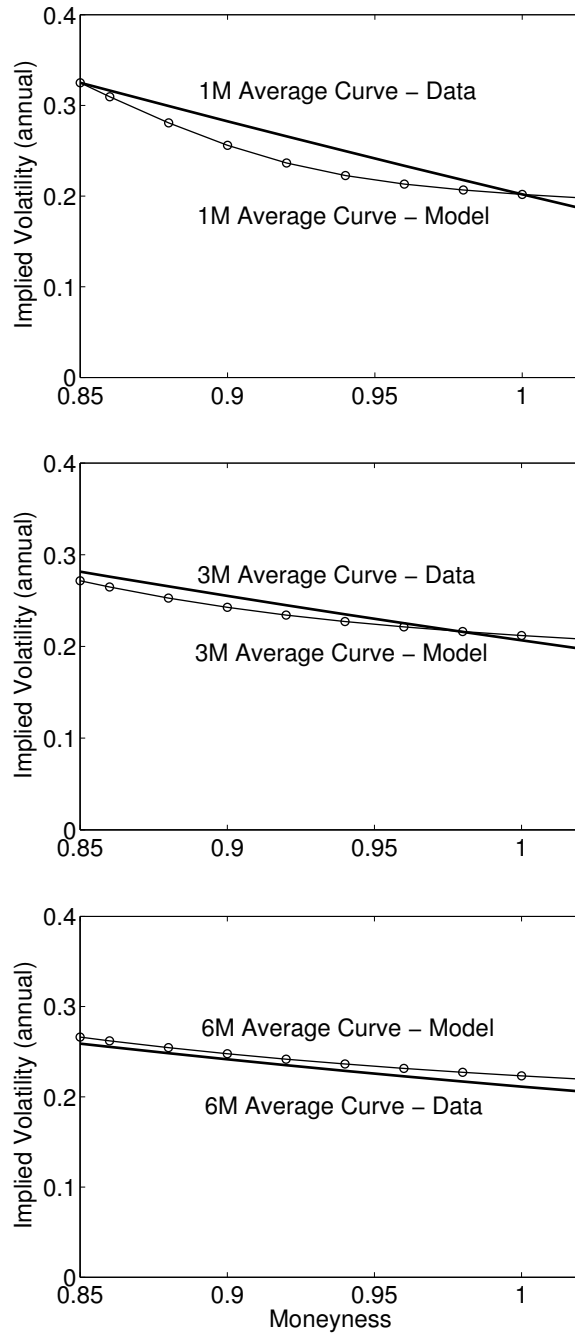


Panel B: Varying ξ_t



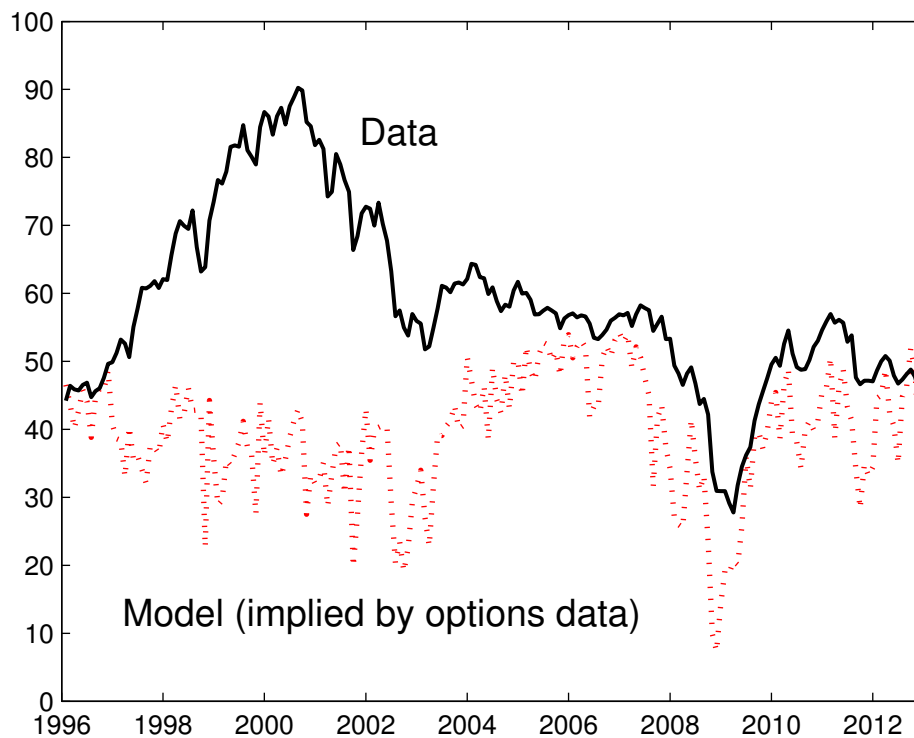
Notes: Implied volatilities on 3-month options as functions of moneyness. The figures show the effects of varying the state variables λ_t (the disaster probability) and ξ_t (the value to which λ_t reverts). Panel A sets ξ_t equal to its median value and varies λ_t , while Panel B sets λ_t equal to its median value and varies ξ_t .

Figure 11: Average implied volatilities from the time series of state variables



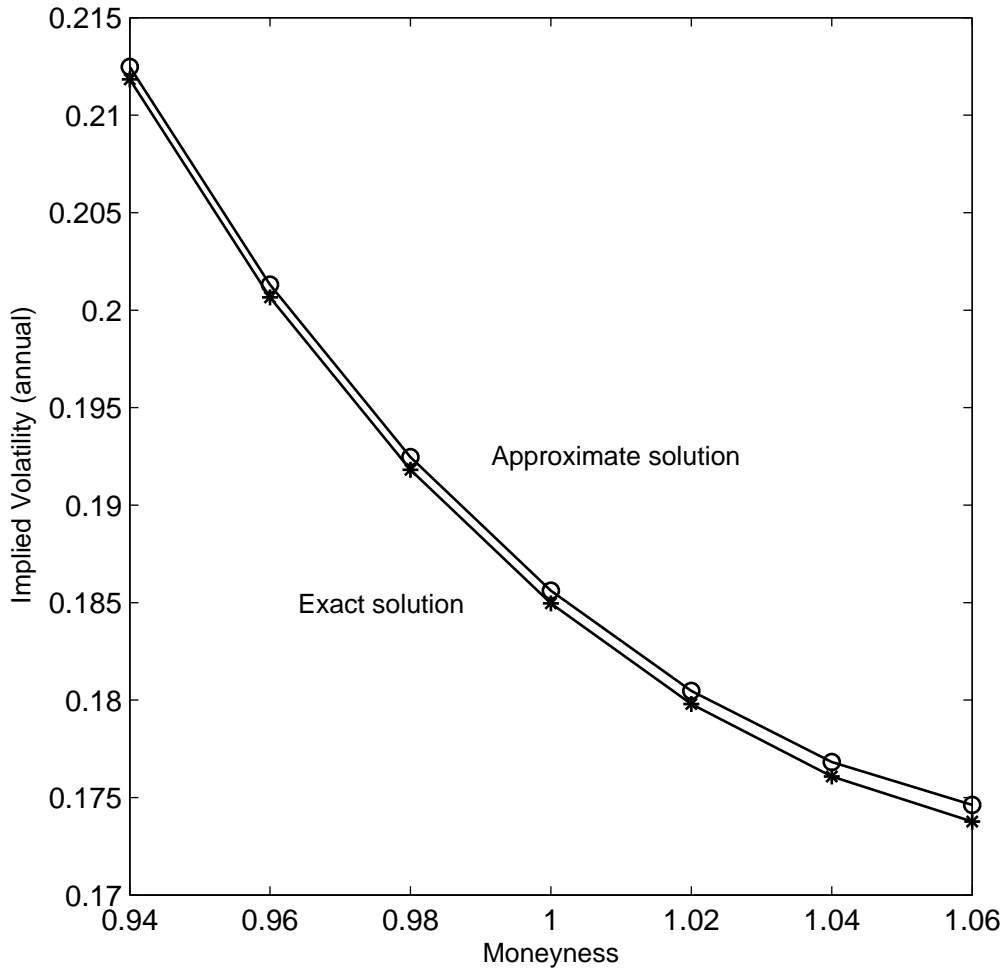
Average implied volatilities on put options in the data and in the two-factor SDR model. In the model, we compute option prices using state variables fit to the time series of 1-month ATM and OTM options with moneyness of 0.85. We compute an implied volatility for each option price and then take the average.

Figure 12: The price-dividend ratio in the data and in the model



Notes: The solid line shows the time series of the price-dividend ratio on the data. The red line shows the price-dividend ratio implied by the model for state prices chosen to fit the one-month ATM and OTM (0.85 moneyness) put options.

Figure A.1: Exact versus approximate solution



Notes: This figure shows implied volatilities when option prices are computed exactly (line with stars) versus when they are computed using an approximation (line with circles) in the SDR model. Implied volatilities assume that the disaster probability is fixed at its mean and that, in the event of disaster, consumption falls by a fixed amount, namely 30%.

Table 1: Parameter values

	SDR	CDR
Relative risk aversion γ	3.0	5.19
EIS ψ	1	1
Rate of time preference β	0.0120	0.0189
Average growth in consumption (normal times) μ	0.0252	0.0231
Volatility of consumption growth (normal times) σ	0.020	0.010
Leverage ϕ	2.6	5.1429
Average probability of a rare disaster $\bar{\lambda}$	0.0355	0.010
Mean reversion κ	0.080	NA
Volatility parameter σ_λ	0.067	0

Notes: Parameters for stochastic disaster risk (SDR) model and for the benchmark constant disaster risk (CDR) model, in annual terms.

Table 2: Parameter values for the two-factor SDR model

Panel A: λ process	
Mean reversion κ_λ	0.2
Volatility parameter σ_λ	0.1576
Panel B: ξ process	
Mean $\bar{\xi}$	0.02
Mean reversion κ_ξ	0.1
Volatility parameter σ_ξ	0.0606
Panel C: Population statistics of λ	
Median	0.0037
Standard deviation	0.0386
AR(1) coefficient	0.9858

Notes: Parameter values for the two-factor SDR model. The processes are as follows:

$$d\lambda_t = \kappa_\lambda(\xi_t - \lambda_t)dt + \sigma_\lambda\sqrt{\lambda_t}dB_{\lambda,t}$$

$$d\xi_t = \kappa_\xi(\bar{\xi} - \xi_t)dt + \sigma_\xi\sqrt{\xi_t}dB_{\xi,t}.$$

Parameter values are expressed in annual terms. Panel C shows population statistics for the disaster probability λ_t calculated by simulation at a monthly frequency (so that the AR(1) coefficient should be interpreted in monthly terms).

Table 3: Moments for the government bill rate and the market return for the two-factor SDR model

	Data	No-Disaster Simulations			All Simulations			Population
		0.05	0.50	0.95	0.05	0.50	0.95	
$E[R^b]$	1.25	1.68	2.96	3.46	-0.47	2.41	3.37	2.02
$\sigma(R^b)$	2.75	0.34	1.07	2.71	0.48	2.06	7.14	3.69
$E[R^m - R^b]$	7.25	5.40	8.01	12.36	5.30	8.49	14.25	9.00
$\sigma(R^m)$	17.8	13.24	19.26	27.91	14.59	22.59	34.38	24.13
Sharpe Ratio	0.41	0.32	0.42	0.55	0.26	0.39	0.53	0.37
$\exp(E[p - d])$	32.5	28.96	40.63	48.88	22.93	36.95	47.41	35.36
$\sigma(p - d)$	0.43	0.15	0.27	0.47	0.17	0.33	0.59	0.43
$AR1(p - d)$	0.92	0.59	0.79	0.91	0.62	0.82	0.92	0.90

Notes: Data moments are calculated using annual data from 1947 to 2010. Population moments are calculated from simulating data from the two-factor stochastic disaster risk (SDR) model at a monthly frequency for 600,000 years and then aggregating monthly growth rates to an annual frequency. We also simulate 100,000 60-year samples and report the 5th, 50th and 95th percentile for each statistic, both from the full set of simulations and for the subset of samples for which no disasters occur. R^b denotes the government bill return, R^m denotes the return on the aggregate market and $p - d$ denotes the log price-dividend ratio.

Table 4: Moments of state variables in the two-factor SDR model

	No-Disaster Simulations				All Simulations		
	Data	0.05	0.50	0.95	0.05	0.50	0.95
$E[\lambda]$	1.57	0.11	0.83	4.64	0.13	1.17	7.54
$\sigma(\lambda)$	2.37	0.22	1.18	4.37	0.26	1.53	5.92
$AR1(\lambda)$	0.74	0.76	0.93	0.98	0.78	0.94	0.98
$E[\xi]$	1.70	0.43	1.42	4.29	0.46	1.58	4.95
$\sigma(\xi)$	1.06	0.32	0.83	2.02	0.34	0.90	2.22
$AR1(\xi)$	0.70	0.90	0.96	0.98	0.91	0.96	0.98

Notes: Data moments of state variables are calculated using state variables extracted from monthly data on option prices from 1996 to 2012. The parameter λ_t is the probability of a disaster. The probability of a disaster reverts to the state variable ξ_t . Means and standard deviations are in percentage terms. We simulate 100,000 17-year samples at a monthly frequency and report the 5th, 50th and 95th percentile for each statistic, both from the full set of simulations and for the subset of samples for which no disasters occur.