

Exploring Recursive Utility*

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1 Introduction

We use an approximation method to explore implications of the recursive utility preference specification of Kreps and Porteus (1978) and Epstein and Zin (1989) and counterparts to these preferences that capture concerns about model misspecification. We present formulas for (nonstandard) first and second-order approximations to dynamic, stochastic equilibria for models in which economic agents have such recursive preferences. The approximations build formulations from Schmitt-Grohé and Uribe (2004) and Lombardo and Uhlig (2018), we extend them in a that features the uncertainty contributions more prominently. By design, the implied approximations of stochastic discount factors used to represent market or shadow values reside within the exponential linear quadratic class. This class is known to give tractable formulas for asset valuation over alternative investment horizons. See, for instance, Ang and Piazzesi (2003) and Borovička and Hansen (2014). Moreover, they are applicable to production-based macro-finance models with investment opportunities in alternative forms of capital.

We use the approximations to provide further understanding of the preferences and their implications for asset pricing. This opens the door as well to other connections in the macroeconomics-finance literature in which productive, investment and capital accumulation are central model ingredients. As a central part of our analysis, we capture the important uncertainty preference contribution as a change in the probability distribution of the underlying economic dynamics. We link this change of measure to the robust preferences specifications of

*The approximations and computations described in these notes are supported by a jupyter notebook entitled ‘uncertainexpansion.jpynb’ in a repository <https://github.com/lphansen/RiskUncertaintyValue>. This repository also contains a complementary jupyter notebook entitled ‘shockelasticity.jpynb’ that computes impulse responses and shock elasticities for models represented by their second-order approximations.

Hansen and Sargent (2001) and Anderson et al. (2003). The robust preferences formulations build on a robust control literature initiated by Jacobson (1973) and Whittle (1981).

2 Small noise expansion of the state dynamics

We follow Lombardo and Uhlig (2018) by considering the following class of stochastic processes indexed by a scalar perturbation parameter \mathbf{q} :¹

$$X_{t+1}(\mathbf{q}) = \psi[X_t(\mathbf{q}), \mathbf{q}W_{t+1}, \mathbf{q}]. \quad (1)$$

Here X is an n -dimensional stochastic process and $\{W_{t+1}\}$ is an i.i.d. normally distributed random vector with conditional mean vector 0 and conditional covariance matrix I . We parameterize this family so that $\mathbf{q} = 1$ gives the model of interest.

We denote a zero-order expansion $\mathbf{q} = 0$ limit as:

$$X_{t+1}^0 = \psi(X_t^0, 0, 0), \quad (2)$$

and assume that there exists a second-order expansion of X_t around $\mathbf{q} = 0$:

$$X_t \approx X_t^0 + \mathbf{q}X_t^1 + \frac{\mathbf{q}^2}{2}X_t^2 \quad (3)$$

where X_t^1 is a first-order contribution and X_t^2 is a second-order contribution.

In the remainder of this chapter we shall construct instances of the second-order expansion (3) in which the generic random variable X_t is replaced, for example, by the logarithm of consumption, a value function, and so on. In approximation (3), the stochastic processes X^j , $j = 0, 1, 2$ are appropriate derivatives of X with respect to the perturbation parameter \mathbf{q} .

Processes $X_t^j, j = 0, 1, 2$ have a recursive structure: the stochastic process X_t^0 can be computed first, then the process X_t^1 next (it depends on X_t^0), and then the process X_t^2 (it depends on both X_t^0 and X_t^1).

We use a prime ($'$) to denote a transpose of a matrix or vector. When we include x' in a partial derivative of a scalar function it means that the partial derivative is a row vector. Consistent with this convention, let $\psi_{x'}^i$, the i^{th} entry of $\psi_{x'}$, denote the row vector of first derivatives with respect to the vector x , and similarly for $\psi_{w'}^i$. Since \mathbf{q} is scalar, $\psi_{\mathbf{q}}^i$ is the

¹Lombardo and Uhlig (2018) provide a discussion of how their approach builds on more general perturbation methods as discussed by Holmes (2012) and Judd (1998).

scalar derivative with respect to \mathbf{q} . Derivatives are evaluated at X_t^0 , which in many examples is invariant over time, unless otherwise stated. This invariance follows when we impose a steady state on the deterministic system.

The first-derivative process obeys a recursion

$$X_{t+1}^1 = \begin{bmatrix} \psi_{x'}^1 \\ \psi_{x'}^2 \\ \vdots \\ \psi_{x'}^n \end{bmatrix} X_t^1 + \begin{bmatrix} \psi_{w'}^1 \\ \psi_{w'}^2 \\ \vdots \\ \psi_{w'}^n \end{bmatrix} W_{t+1} + \begin{bmatrix} \psi_{\mathbf{q}}^1 \\ \psi_{\mathbf{q}}^2 \\ \vdots \\ \psi_{\mathbf{q}}^n \end{bmatrix} \quad (4)$$

that we can write compactly as the following *first-order vector autoregression*:

$$X_{t+1}^1 = \psi_{x'} X_t^1 + \psi_{w'} W_{t+1} + \psi_{\mathbf{q}}$$

We assume that the matrix ψ'_{xx} is stable in the sense that all of its eigenvalues are strictly less than one in modulus.

It is natural for us to denote second derivative processes with double subscripts. For instance, for the double script used in conjunction with the second derivative matrix of ψ^i , the first subscript without a prime (') reports the row location; second subscript with a prime (') reports the column location. Differentiating recursion (4) gives:

$$\begin{aligned} X_{t+1}^2 = & \psi_{x'} X_t^2 + \begin{bmatrix} X_t^{1'} \psi_{xx'}^1 X_t^1 \\ X_t^{1'} \psi_{xx'}^2 X_t^1 \\ \vdots \\ X_t^{1'} \psi_{xx'}^n X_t^1 \end{bmatrix} + 2 \begin{bmatrix} X_t^{1'} \psi_{xw'}^1 W_{t+1} \\ X_t^{1'} \psi_{xw'}^2 W_{t+1} \\ \vdots \\ X_t^{1'} \psi_{xw'}^n W_{t+1} \end{bmatrix} + \begin{bmatrix} W_{t+1}' \psi_{ww'}^1 W_{t+1} \\ W_{t+1}' \psi_{ww'}^2 W_{t+1} \\ \vdots \\ W_{t+1}' \psi_{ww'}^n W_{t+1} \end{bmatrix} \\ & + 2 \begin{bmatrix} \psi_{\mathbf{q}x'}^1 X_t^1 \\ \psi_{\mathbf{q}x'}^2 X_t^1 \\ \vdots \\ \psi_{\mathbf{q}x'}^n X_t^1 \end{bmatrix} + 2 \begin{bmatrix} \psi_{\mathbf{q}w'}^1 W_{t+1} \\ \psi_{\mathbf{q}w'}^2 W_{t+1} \\ \vdots \\ \psi_{\mathbf{q}w'}^n W_{t+1} \end{bmatrix} + \begin{bmatrix} \psi_{\mathbf{q}\mathbf{q}}^1 \\ \psi_{\mathbf{q}\mathbf{q}}^2 \\ \vdots \\ \psi_{\mathbf{q}\mathbf{q}}^n \end{bmatrix} \end{aligned} \quad (5)$$

Recursions (4) and (5) have a linear structure with some notable properties. The law of motion for X^0 is deterministic and is time invariant if (1) comes from a stationary $\{X_t\}$ process. The dynamics for X^2 are nonlinear only in X^1 and W_{t+1} . Thus, the stable dynamics for X^1 that prevail when ψ_x is a stable matrix imply stable dynamics for X^2 .

Let C denote consumption and \hat{C} the logarithm of consumption. Suppose that the loga-

rithm of consumption evolves as:

$$\widehat{C}_{t+1} - \widehat{C}_t = \kappa(X_t, \mathbf{q}W_{t+1}, \mathbf{q}).$$

Approximate this process by:

$$\widehat{C}_{t+1} - \widehat{C}_t \approx \widehat{C}_{t+1}^0 - \widehat{C}_t^0 + \mathbf{q} \left(\widehat{C}_{t+1}^1 - \widehat{C}_t^1 \right) + \frac{\mathbf{q}^2}{2} \left(\widehat{C}_{t+1}^2 - \widehat{C}_t^2 \right) \quad (6)$$

where

$$\begin{aligned} \widehat{C}_{t+1}^0 - \widehat{C}_t^0 &= \kappa(X_t^0, 0, 0) \stackrel{\text{def}}{=} \eta_0^c \\ \widehat{C}_{t+1}^1 - \widehat{C}_t^1 &= \kappa_{x'} X_t^1 + \kappa_{w'} W_{t+1} + \kappa_q \\ \widehat{C}_{t+1}^2 - \widehat{C}_t^2 &= \kappa_{x'} X_t^2 + X_t^{1'} \kappa_{x,x'} X_t^1 + 2X_t^{1'} \kappa_{xw'} W_{t+1} + W_{t+1}' \kappa_{ww'} W_{t+1} \\ &\quad + 2\kappa_{q,x'} X_t^1 + 2\kappa_{qw'} W_{t+1} + \kappa_{qq}. \end{aligned}$$

In models with endogenous investment and savings, the consumption dynamics and some of the state dynamics will emerge as the solution to a dynamic stochastic equilibrium model. We use the approximating processes (3) and (6) as inputs into the construction of an approximating continuation value process and its risk-adjusted counterpart for recursive utility preferences.

3 Approximating a recursive utility value function

In this section, we construct second-order expansions for components of a continuation value process. This process along with its associated stochastic discount factor process are important constituents of models.

The homogeneous of degree one representation of recursive utility is

$$V_t = \left[(1 - \beta) (C_t)^{1-\rho} + \beta (R_t)^{1-\rho} \right]^{\frac{1}{1-\rho}} \quad (7)$$

where

$$R_t = \left(\mathbb{E} \left[(V_{t+1})^{1-\gamma} \mid \mathfrak{A}_t \right] \right)^{\frac{1}{1-\gamma}}. \quad (8)$$

Notice that in equation (7), V_t is a homogeneous of degree one function of C_t and R_t . In equation (8), R_t is a homogeneous of degree one function of another function, namely, V_{t+1} as it varies over date $t+1$ information. In equation (7), $0 < \beta < 1$ is a subjective discount factor

and ρ describes attitudes toward intertemporal substitution. Formally, $\frac{1}{\rho}$ is the elasticity of intertemporal substitution. In equation (8), γ describes attitudes towards risk.

Continuation values are determined only up to an increasing transformation. For computational and conceptual reasons, we find it advantageous to work with the logarithm $\widehat{V}_t = \log V_t$. The corresponding recursions for \widehat{V}_t expressed in terms of the logarithm of consumption \widehat{C}_t are

$$\widehat{V}_t = \frac{1}{1-\rho} \log \left[(1-\beta) \exp \left[(1-\rho) \widehat{C}_t \right] + \beta \exp \left[(1-\rho) \widehat{R}_t \right] \right] \quad (9)$$

where

$$\widehat{R}_t = \frac{1}{1-\gamma} \log \mathbb{E} \left(\exp \left[(1-\gamma) \widehat{V}_{t+1} \right] \mid \mathfrak{A}_t \right). \quad (10)$$

The right side of recursion (9) is the logarithm of a constant elasticity of substitution (CES) function of $\exp(\widehat{C}_t)$ and $\exp(\widehat{R}_t)$.

Remark 3.1 *The limit of \widehat{R}_t as γ approaches 1 is ordinary expected logarithmic utility:*

$$\lim_{\gamma \downarrow 1} \widehat{R}_t = \lim_{\gamma \downarrow 1} \frac{\log E \left(\exp \left[(1-\gamma) \widehat{V}_{t+1} \right] \mid \mathfrak{A}_t \right)}{1-\gamma} = \mathbb{E} \left(\widehat{V}_{t+1} \mid \mathfrak{A}_t \right).$$

Our approach will be to construct small noise expansions for both \widehat{V}_t and \widehat{R}_t and then to assemble them appropriately. Before doing so, we consider a reinterpretation of (10).

3.1 Robustness to Model Misspecification

A reinterpretation of the utility recursion and the small-noise expansion approach that we'll deploy comes from recognizing that when $\gamma > 1$, (10) emerges from an instance robust control theory in which $\frac{1}{\gamma-1}$ is a penalty parameter on entropy relative to alternatives that constrains the alternative probability models that a decision maker considers when evaluating consumption processes. This interpretation originated in work by Jacobson (1973) and Whittle (1981) that was extended and reformulated recursively by Hansen and Sargent (1995).

Let the random variable $N_{t+1} \geq 0$ satisfy $\mathbb{E}(N_{t+1} \mid \mathfrak{A}_t) = 1$ so that it is a likelihood ratio. Think of replacing the expected continuation value $\mathbb{E}(\widehat{V}_{t+1} \mid \mathfrak{A}_t)$ by the minimized value of the following problem:

$$\min_{N_{t+1} \geq 0, \mathbb{E}(N_{t+1} \mid \mathfrak{A}_t) = 1} \mathbb{E} \left(N_{t+1} \widehat{V}_{t+1} \mid \mathfrak{A}_t \right) + \xi \mathbb{E} (N_{t+1} \log N_{t+1} \mid \mathfrak{A}_t) \quad (11)$$

where ξ is a parameter that penalizes departures of N_{t+1} from unity as measured by relative entropy. Conditional relative entropy for an altered conditional probability induced by applying change of measure N_{t+1} is

$$\mathbb{E}(N_{t+1} \log N_{t+1} \mid \mathfrak{A}_t) \geq 0$$

where, because the function $y \log y$ is convex, the inequality follows from Jensen's inequality. Relative entropy is zero when $N_{t+1} = 1$.

Remark 3.2 *To solve minimization problem 11, introduce a Lagrange multiplier, ℓ , on the conditional expectation constraint. The Lagrangian problem separates across states, leading to the unconstrained problem:*

$$\min_n nv + \xi n \log n + \ell(n - 1)$$

where n is a potential realization of N_{t+1} and v is a realization of V_{t+1} . The first-order conditions are:

$$v + \xi + \xi \log n + \ell = 0.$$

The solution is

$$n^* = \exp \left[-\frac{1}{\xi} (v + \ell + \xi) \right],$$

and the minimizing objective

$$-\xi \exp \left[-\frac{1}{\xi} (v + \ell + \xi) \right] - \ell.$$

To complete the solution, we solve for ℓ ,

$$\max_{\ell} -\xi \mathbb{E} \left(\exp \left[-\frac{1}{\xi} (V_{t+1} + \ell + \xi) \right] \mid \mathfrak{A}_t \right) - \ell$$

The first-order conditions are:

$$\mathbb{E} \left(\exp \left[-\left(\frac{1}{\xi} \right) V_{t+1} \right] \mid \mathfrak{A}_t \right) \exp \left[-\left(\frac{\ell + \xi}{\xi} \right) \right] - 1 = 0.$$

Thus the solution for ℓ is

$$\ell^* = \xi \log \mathbb{E} \left(\exp \left[-\left(\frac{1}{\xi} \right) V_{t+1} \right] \mid \mathfrak{A}_t \right) - 1$$

with a minimized objective given by

$$-\xi \log \mathbb{E} \left(\exp \left[- \left(\frac{1}{\xi} \right) V_{t+1} \right] \mid \mathfrak{A}_t \right).$$

The implied minimizer for N_{t+1} is

$$N_{t+1}^* = \frac{\exp \left(-\frac{1}{\xi} \widehat{V}_{t+1} \right)}{\mathbb{E} \left[\exp \left(-\frac{1}{\xi} \widehat{V}_{t+1} \right) \mid \mathfrak{A}_t \right]}. \quad (12)$$

The minimizer of problem (11) given by (12) “tilts” probabilities towards low continuation values, a version of what Bucklew (2004) calls a stochastic version of Murphy’s law. Notice that the minimized objective satisfies

$$-\xi \log \mathbb{E} \left[\exp \left(-\frac{1}{\xi} \widehat{V}_{t+1} \right) \mid \mathfrak{A}_t \right] = \widehat{R}_t$$

where \widehat{R}_t was given previously by equation (10) if we set $\xi = \frac{1}{\gamma-1}$. The random variable N_{t+1}^* will play a central role in the discussion that follows.

3.2 Our expansion protocol

To approximate the recursive utility process, we deviate from common practice in macroeconomics by letting the risk aversion or robust parameter in preferences depend on \mathbf{q} :

$$\xi = \mathbf{q} \xi_o \quad \gamma - 1 = \frac{\gamma_o - 1}{\mathbf{q}}$$

The aversion to model misspecification or the aversion to risk moves inversely with the parameter \mathbf{q} when we embed the model of interest within a parameterized family of models. In effect, the variable \mathbf{q} is doing double duty. Reducing $\mathbf{q} > 0$ limits the overall exposure of the economy to the underlying shocks. This is offset by letting the preferences include a greater aversion to uncertainty. This choice of any expansion protocol has significant and enlightening consequences for continuation value processes and for the minimizing N process used to alter expectations. It has antecedents in the control theory literature, and it has the virtue that implied uncertainty adjustments occur more prominently at lower-order terms in the approximation.

3.2.1 Order-zero

Write the order-zero expansion of (9) as

$$\begin{aligned}\widehat{V}_t^0 &= \frac{1}{1-\rho} \log \left[(1-\beta) \exp \left[(1-\rho) \widehat{C}_t^0 \right] + \beta \exp \left[(1-\rho) \widehat{R}_t^0 \right] \right] \\ \widehat{R}_t^0 &= \widehat{V}_{t+1}^0,\end{aligned}$$

where the second equation follows from noting that randomness vanishes in the limit as \mathbf{q} approaches 0.

For order zero, write the consumption growth-rate process as

$$\widehat{C}_{t+1}^0 - \widehat{C}_t^0 = \eta_c^0.$$

The order-zero approximation of (9) is:

$$\widehat{V}_t^0 - \widehat{C}_t^0 = \frac{1}{1-\rho} \log \left[(1-\beta) + \beta \exp \left[(1-\rho) \left(\widehat{V}_{t+1}^0 - \widehat{C}_{t+1}^0 + \eta_c^0 \right) \right] \right]$$

We guess that $\widehat{V}_t^0 - \widehat{C}_t^0 = \eta_{v-c}^0$ and will have verified the guess if the following equation is satisfied

$$\exp \left[(1-\rho) (\eta_{v-c}^0) \right] = (1-\beta) + \beta \exp \left[(1-\rho) (\eta_{v-c}^0) \right] \exp \left[(1-\rho) \eta_c^0 \right],$$

which implies

$$\exp \left[(1-\rho) (\eta_{v-c}^0) \right] = \frac{1-\beta}{1-\beta \exp \left[(1-\rho) \eta_c^0 \right]}. \quad (13)$$

Equation (13) determines η_{v-c}^0 as a function of η_c^0 and the preference parameters ρ, β , but not the risk aversion parameter γ . Specifically,

$$\eta_{v-c}^0 = \frac{\log(1-\beta) - \log(1-\beta \exp[(1-\rho)\eta_c^0])}{1-\rho} \quad (14)$$

3.2.2 Order-one

We temporarily take $\widehat{R}_t^1 - \widehat{C}_t^1$ as given (we'll compute it in section (3.2.3)). We construct a recursion by taking a first-order approximation to the nonlinear utility recursion (9)

$$\widehat{V}_t^1 - \widehat{C}_t^1 = \lambda \left(\widehat{R}_t^1 - \widehat{C}_t^1 \right) \quad (15)$$

where

$$\begin{aligned}
\lambda &= \left[\frac{\beta \exp [(1-\rho)(\eta_{v-c}^0 + \eta_c^0)]}{(1-\beta) + \beta \exp [(1-\rho)(\eta_{v-c}^0 + \eta_c^0)]} \right] \\
&= \left[\frac{\beta \exp [(1-\rho)\eta_c^0]}{(1-\beta) \exp [-(1-\rho)\eta_{v-c}^0] + \beta \exp [(1-\rho)\eta_c^0]} \right] \\
&= \left[\frac{\beta \exp [(1-\rho)\eta_c^0]}{1 - \beta \exp [(1-\rho)\eta_c^0] + \beta \exp [(1-\rho)\eta_c^0]} \right] \\
&= \beta \exp [(1-\rho)\eta_c^0]
\end{aligned} \tag{16}$$

Notice how parameter ρ influences the weight λ when $\eta_c \neq 0$, in which case the log consumption process displays growth or decay. When $0 < \rho < 1$, the condition $\lambda < 1$ restricts the parameter ρ relative to the consumption growth rate η_c since

$$(1-\rho)\eta_c < -\log \beta$$

To facilitate computing some useful limits we construct:

$$\begin{aligned}
\tilde{V}_t &= \frac{\hat{V}_t - \hat{V}_t^0}{\mathbf{q}} \\
\tilde{R}_t &= \frac{\hat{R}_t - \hat{V}_{t+1}^0}{\mathbf{q}}
\end{aligned} \tag{17}$$

which we assume remain well defined as \mathbf{q} declines to zero, with limits denoted by $\tilde{V}_t^0, \tilde{R}_t^0$. Importantly,

$$\tilde{R}_t = \left(\frac{1}{1-\gamma_o} \right) \log \mathbb{E} \left(\exp \left[(1-\gamma_o) \tilde{V}_{t+1} \right] \mid \mathfrak{A}_t \right), \tag{18}$$

Taking limits as \mathbf{q} declines to zero:

$$\hat{R}_t^1 = \left(\frac{1}{1-\gamma_o} \right) \log \mathbb{E} \left(\exp \left[(1-\gamma_o) \hat{V}_{t+1}^1 \right] \mid \mathfrak{A}_t \right)$$

Subtracting \hat{C}_t^1 from both sides gives:

$$\hat{R}_t^1 - \hat{C}_t^1 = \left(\frac{1}{1-\gamma_o} \right) \log \mathbb{E} \left(\exp \left[(1-\gamma_o) \left(\hat{V}_{t+1}^1 - \hat{C}_{t+1}^1 \right) + (1-\gamma_o) \left(\hat{C}_{t+1}^1 - \hat{C}_t^1 \right) \right] \mid \mathfrak{A}_t \right) \tag{19}$$

Substituting formula (19) into the right side of (15) gives the recursion for the first-order

continuation value:

$$\widehat{V}_t^1 - \widehat{C}_t^1 = \left(\frac{\lambda}{1 - \gamma_o} \right) \log \mathbb{E} \left(\exp \left[(1 - \gamma_o) \left(\widehat{V}_{t+1}^1 - \widehat{C}_{t+1}^1 \right) + (1 - \gamma_o) \left(\widehat{C}_{t+1}^1 - \widehat{C}_t^1 \right) \right] \mid \mathfrak{A}_t \right) \quad (20)$$

Remark 3.3 *We produce a solution by “guess and verify.” Suppose that*

$$\widehat{V}_t^1 - \widehat{C}_t^1 = v_1' X_t^1 + v_0 \quad (21)$$

It follows from (20) that

$$\begin{aligned} v_1' &= \lambda (v_1' \psi_{x'} + \kappa_{x'}) \\ v_0 &= \lambda \left(v_0 + v_1' \psi_q + \kappa_q + \frac{(1 - \gamma_o)}{2} |v_1' \psi_{w'} + \kappa_{w'}|^2 \right). \end{aligned} \quad (22)$$

Deduce the second equation by observing that $\exp \left[(1 - \gamma_o) \left(\widehat{V}_{t+1}^1 - \widehat{C}_{t+1}^1 \right) + (1 - \gamma_o) \left(\widehat{C}_{t+1}^1 - \widehat{C}_t^1 \right) \right]$ is distributed as a log normal. The solutions to equations (22) are:

$$\begin{aligned} v_1 &= \lambda (I - \lambda \psi_{x'})^{-1} \kappa_{x'} \\ v_0 &= \frac{\lambda}{(1 - \lambda)} (v_1' \psi_q + \kappa_q) + \frac{\lambda(1 - \gamma_o)}{2(1 - \lambda)} |v_1' \psi_{w'} + \kappa_{w'}|^2. \end{aligned}$$

The continuation value has two components. The first is:

$$v_1' X_t^1 + \frac{\lambda}{(1 - \lambda)} (v_1' \psi_q + \kappa_q) = \mathbb{E} \left[\sum_{j=1}^{\infty} \lambda^j \left(\widehat{C}_{t+j}^1 - \widehat{C}_{t+j-1}^1 \right) \mid \mathfrak{A}_t \right]$$

and the second is a constant long-run risk adjustment given by:

$$\frac{\lambda(1 - \gamma_o)}{2(1 - \lambda)} |v_1' \psi_{w'} + \kappa_{w'}|^2.$$

This second term is the the variance of

$$\mathbb{E} \left[\sum_{j=1}^{\infty} \lambda^j \left(\widehat{C}_{t+j}^1 - \widehat{C}_{t+j-1}^1 \right) \mid \mathfrak{A}_{t+1} \right] \quad (23)$$

conditioned on \mathfrak{A}_t scaled by $\frac{\lambda(1 - \gamma_o)}{2(1 - \lambda)}$.

Remark 3.4 *The formula for v_1 depends on the parameter ρ . Moreover, v_1 has a well defined limit as λ tends to unity as does the variance of (23). This limiting variance:*

$$\lim_{\lambda \rightarrow 1} |v_1' \psi_{w'} + \kappa_{w'}|^2.$$

converges to the variance of the martingale increment of \widehat{C}^1 .

Remark 3.5 *Consider the logarithm of the risk adjusted continuation value approximated to the first order. Note that from (21),*

$$\widehat{V}_{t+1}^1 - \widehat{C}_t^1 = v_1' X_{t+1}^1 + v_0 + \kappa_{x'} X_t^1 + \kappa_{w'} W_{t+1}.$$

Substitute this expression into formula (19) and use the formula for the mean of random variable distributed as a log normal to show that

$$\widehat{V}_{t+1}^1 - \widehat{R}_t^1 = (v_1' \psi_{w'} + \kappa_{w'}) W_{t+1} - \left(\frac{1 - \gamma_o}{2} \right) |v_1' \psi_{w'} + \kappa_{w'}|^2$$

Equation (19) is a standard risk-sensitive recursion applied to log-linear dynamics. For instance, see Tallarini (2000)'s paper on risk-sensitive business cycles and Hansen et al. (2008)'s paper on measurement and inference challenges created by the presence of long-term risk. Both of those papers assumed a logarithmic one-period utility function, so that for them $\rho = 1$.

Here we have instead obtained the recursion as a first-order approximation without necessarily assuming log utility. Allowing for ρ to be different than one shows up in both the order zero and order one approximations as reflected in (14) and (20), respectively. As reflected by formula (20), for the first-order approximation the parameter $\lambda = \beta$ when $\rho = 1$. But otherwise, it is different. Equation (19) also is very similar to a first-order approximation proposed in Restoy and Weil (2011). Like formula (19), Restoy and Weil allow for $\rho \neq 1$. In contrast, our equation has an explicit constant term coming from the risk/robustness adjustment, and we have explicit formula for λ that depends on preference parameters and the consumption growth rate.

3.2.3 Order two

Differentiating equation (9) a second time gives:

$$\widehat{V}_t^2 = (1 - \lambda) \widehat{C}_t^2 + \lambda \widehat{R}_t^2 + (1 - \rho)(1 - \lambda) \lambda \left(\widehat{R}_t^1 - \widehat{C}_t^1 \right)^2. \quad (24)$$

Equivalently,

$$\widehat{V}_t^2 - \widehat{C}_t^2 = \lambda \left(\widehat{R}_t^2 - \widehat{C}_t^2 \right) + (1 - \rho)(1 - \lambda) \lambda \left(\widehat{R}_t^1 - \widehat{C}_t^1 \right)^2.$$

Rewrite transformation (17) as

$$\begin{aligned} \mathbf{q} \widetilde{V}_t &= \widehat{V}_t - \widehat{V}_t^0 \\ \mathbf{q} \widetilde{R}_t &= \widehat{R}_t - \widehat{V}_{t+1}^0 \end{aligned}$$

Differentiating twice with respect to \mathbf{q} and evaluated at $\mathbf{q} = 0$

$$\begin{aligned} 2 \frac{d}{d\mathbf{q}} \widetilde{V}_t + \mathbf{q} \frac{d^2}{d\mathbf{q}^2} \widetilde{V}_t \Big|_{\mathbf{q}=0} &= 2\widetilde{V}_t^1 = \widehat{V}_t^2 \\ 2 \frac{d}{d\mathbf{q}} \widetilde{R}_t + \mathbf{q} \frac{d^2}{d\mathbf{q}^2} \widetilde{R}_t \Big|_{\mathbf{q}=0} &= 2\widetilde{R}_t^1 = \widehat{R}_t^2 \end{aligned}$$

Differentiating (18) with respect to \mathbf{q}

$$\frac{d\widetilde{R}_t}{d\mathbf{q}} = \frac{\mathbb{E} \left(\exp \left[(1 - \gamma_o) \widetilde{V}_{t+1} \right] \frac{d\widetilde{V}_{t+1}}{d\mathbf{q}} \mid \mathfrak{A}_t \right)}{\mathbb{E} \left(\exp \left[(1 - \gamma_o) \widetilde{V}_{t+1} \right] \mid \mathfrak{A}_t \right)},$$

and thus

$$\begin{aligned} \widehat{R}_t^2 &= 2\widetilde{R}_t^1 = 2E \left(N_{t+1}^0 \widetilde{V}_{t+1}^1 \mid \mathfrak{A}_t \right) \\ &= E \left(N_{t+1}^0 \widehat{V}_{t+1}^2 \mid \mathfrak{A}_t \right), \end{aligned} \tag{25}$$

where N_{t+1}^0

$$\begin{aligned} N_{t+1}^0 &\stackrel{\text{def}}{=} \frac{\exp \left[(1 - \gamma_o) \widetilde{V}_{t+1}^0 \right]}{\mathbb{E} \left(\exp \left[(1 - \gamma_o) \widetilde{V}_{t+1}^0 \right] \mid \mathfrak{A}_t \right)} \\ &= \frac{\exp \left[(1 - \gamma_o) \widehat{V}_{t+1}^1 \right]}{\mathbb{E} \left(\exp \left[(1 - \gamma_o) \widehat{V}_{t+1}^1 \right] \mid \mathfrak{A}_t \right)}. \end{aligned} \tag{26}$$

Subtracting \widehat{C}_t^2 from \widehat{R}_t^2 and substituting into (25) gives:

$$\widehat{V}_t^2 - \widehat{C}_t^2 = \lambda \mathbb{E} \left(N_{t+1}^0 \left[\left(\widehat{V}_{t+1}^2 - \widehat{C}_{t+1}^2 \right) + \left(\widehat{C}_{t+1}^2 - \widehat{C}_t^2 \right) \mid \mathfrak{A}_t \right] + (1-\rho)(1-\lambda)\lambda \left(\widehat{R}_t^1 - \widehat{C}_t^1 \right)^2 \right). \quad (27)$$

Even if the second-order contribution to the consumption process is zero, there will be non-trivial adjustment to the approximation of $\widehat{V} - \widehat{C}$ because $\left(\widehat{R}^1 - \widehat{C}^1 \right)^2$ is different from zero. This term vanishes when $\rho = 1$, and its sign will be different depending on whether ρ is bigger or smaller than one.

Remark 3.6 *The calculation reported in Remark 3.5 implies that*

$$\log N_{t+1}^0 = (1 - \gamma_o) \left(\widehat{V}_{t+1}^1 - \widehat{R}_t^1 \right) = (1 - \gamma_o) (v_1' \psi_{w'} + \kappa_{w'}) W_{t+1} - \frac{(1 - \gamma_o)^2}{2} |v_1' \psi_{w'} + \kappa_{w'}|^2$$

As a consequence, under the change in probability measure induced by N_{t+1}^0 , W_{t+1} has a mean given by

$$\mu^0 \stackrel{\text{def}}{=} (1 - \gamma_o) (v_1' \psi_{w'} + \kappa_{w'})'$$

and with the same covariance matrix given by the identity. This is an approximation to robustness adjustment expressed as an altered distribution of the underlying shocks. It depends on $\gamma_o - 1 = \frac{1}{\xi_o}$ as well as the state dynamics as reflected by v_1 and by the shock exposure vectors $\psi_{w'}$ and $\kappa_{w'}$.

4 Stochastic discount factor process

A stochastic discount factor (SDF) process $S = \{S_t : t \geq 0\}$ tells how a consumer responds to small changes in uncertainty and thereby consequently how a consumer values risky payouts. SDF processes have a variety of uses. First, they provide shadow prices that tell how a consumer's uncertainty aversion shapes marginal valuations of risky assets. Second, they shape first-order conditions for optimally choosing financial and physical investments. Third, they underly tractable formulas for equilibrium asset prices. Fourth, they can help construct Pigouvian taxes for correcting adverse externalities under uncertainty. Fifth, they provide useful tools for assessing effects of small (local) changes in government policies.

To indicate how to deduce an SDF process, we begin by positing that the date zero value

of a risky date t consumption payout χ_t is

$$\pi_0^t(\chi_t) = E \left[\left(\frac{S_t}{S_0} \right) \chi_t \middle| \mathfrak{A}_0 \right]. \quad (28)$$

We compute the ratio $\frac{S_t}{S_0}$ that appears in formula (28) by evaluating the slope of an indifference curve that runs through both a baseline consumption process $\{C_t\}_{t=0}^\infty$ and a perturbed consumption process

$$(C_0 - P_0(\mathbf{q}), C_1, C_2, \dots, C_t + \mathbf{q}\chi_t, C_{t+1}, \dots).$$

We think of \mathbf{q} as parameterizing an indifference curve, so $P_0(\mathbf{q})$ expresses how much current period consumption must be reduced to keep a consumer on the same indifference curve after we replace C_t by $C_t + \mathbf{q}\chi_t$. We set $\pi_0^t(\chi_t)$ defined in equation (28) equal to the slope of that indifference curve:

$$\pi_0^t(\chi_t) = \frac{d}{d\mathbf{q}} P_0(\mathbf{q}) \Big|_{\mathbf{q}=0}.$$

The one-period increment in the stochastic discount factor process for recursive utility is:

$$\begin{aligned} \frac{S_{t+1}}{S_t} &= \beta \left(\frac{C_{t+1}}{C_t} \right)^{-\rho} \exp \left[(1 - \gamma) (\widehat{V}_{t+1} - \widehat{R}_t) \right] \exp \left[(\rho - 1) (\widehat{V}_{t+1} - \widehat{R}_t) \right] \\ &= \beta N_{t+1}^* \exp (\widehat{S}_{t+1} - \widehat{S}_t) \end{aligned} \quad (29)$$

where

$$\widehat{S}_{t+1} - \widehat{S}_t \stackrel{\text{def}}{=} \log \beta - \rho (\widehat{C}_{t+1} + \widehat{C}_t) + (\rho - 1) (\widehat{V}_{t+1} - \widehat{R}_t)$$

where N_{t+1}^* induces the change of probability measure that we described previously as the outcome of robustness problem. (See equation (12).) We will use this second formula in what follows.

Remark 4.1 *To verify formula (29), we compute a one-period intertemporal marginal rate of substitution. Given the valuation recursions (9) and (10), we construct two marginal utilities familiar from CES and exponential utility:*

$$\begin{aligned} mc &= (1 - \beta) (c)^{-\rho} \exp [(\rho - 1)\hat{v}] \\ m\hat{r} &= \beta \exp [(1 - \rho) (\hat{r} - \hat{v})] \end{aligned}$$

From the certainty equivalent formula, we construct the marginal utility of the next-period logarithm of the continuation value:

$$m\hat{v}^+ = \exp \left[(1 - \gamma) (\hat{v}^+ - \hat{r}) \right]$$

where the $+$ superscript is used to denote the next-period counterpart. In addition, the next-period marginal utility of consumption is

$$mc^+ = (1 - \beta) (c^+)^{-\rho} \exp \left[(\rho - 1) \hat{v}^+ \right]$$

Putting these four formulas together using the chain rule for differentiation gives a marginal rate of substitution:

$$\frac{(mr)(mv^+)(mc^+)}{mc} = \beta \left(\frac{c^+}{c} \right)^{-\rho} \exp \left[(1 - \gamma) (\hat{v}^+ - \hat{r}) \right] \exp \left[(\rho - 1) (\hat{v}^+ - \hat{r}) \right].$$

Now let $\hat{v}^+ = \hat{V}_{t+1}$, $c^+ = C_{t+1}$, $C_t = c$ and $\hat{r} = \hat{R}_t$ to obtain the formula for the one-period stochastic discount factor (29).

We approximate $\left[\hat{S}_{t+1} - \hat{S}_t \right]$ as

$$\hat{S}_{t+1} - \hat{S}_t \approx \left[\hat{S}_{t+1}^0 - \hat{S}_t^0 \right] + \left[\hat{S}_{t+1}^1 - \hat{S}_t^1 \right] + \frac{1}{2} \left[\hat{S}_{t+1}^2 - \hat{S}_t^2 \right]$$

where

$$\begin{aligned} \hat{S}_{t+1}^0 - \hat{S}_t^0 &\stackrel{\text{def}}{=} \log \beta - \rho \eta_c^0 \\ \hat{S}_{t+1}^1 - \hat{S}_t^1 &\stackrel{\text{def}}{=} -\hat{C}_{t+1}^1 + \hat{C}_t^1 + (\rho - 1) \left(\hat{V}_{t+1}^1 - \hat{C}_{t+1}^1 \right) - (\rho - 1) \left(\hat{R}_t^1 - \hat{C}_t^1 \right) \\ \hat{S}_{t+1}^2 - \hat{S}_t^2 &\stackrel{\text{def}}{=} -\hat{C}_{t+1}^2 + \hat{C}_t^2 + (\rho - 1) \left(\hat{V}_{t+1}^2 - \hat{C}_{t+1}^2 \right) - (\rho - 1) \left(\hat{R}_t^2 - \hat{C}_t^2 \right) \end{aligned}$$

We now consider three different approaches to approximating N_{t+1}^* .

4.1 Approach 1

Write

$$\begin{aligned} N_{t+1}^* &= \frac{\exp \left[(1 - \gamma_o) \tilde{V}_{t+1} \right]}{\mathbb{E} \left(\exp \left[(1 - \gamma_o) \tilde{V}_{t+1} \right] \mid \mathfrak{A}_t \right)} \\ &= \frac{\exp \left[(1 - \gamma_o) \tilde{V}_{t+1} \right]}{\exp \left[(1 - \gamma_o) \tilde{R}_t \right]} \end{aligned}$$

Form the “first-order” approximation:

$$\begin{aligned} \log N_{t+1}^* &\approx (1 - \gamma_o) \left[\left(\tilde{V}_{t+1}^0 - \tilde{R}_t^0 \right) + \mathfrak{q} \left(\tilde{V}_{t+1}^1 - \tilde{R}_t^1 \right) \right] \\ &= (1 - \gamma_o) \left[\left(\hat{V}_{t+1}^1 - \hat{R}_t^1 \right) + \frac{\mathfrak{q}}{2} \left(\hat{V}_{t+1}^2 - \hat{R}_t^2 \right) \right] \end{aligned} \quad (30)$$

This approach suggests using the following first-order approximation for the stochastic discount factor:

$$\begin{aligned} \log S_{t+1} - \log S_t &\approx (1 - \gamma_o) \left[\left(\hat{V}_{t+1}^1 - \hat{R}_t^1 \right) + \frac{1}{2} \left(\hat{V}_{t+1}^2 - \hat{R}_t^2 \right) \right] \\ &\quad + \left[\hat{S}_{t+1}^0 - \hat{S}_t^0 \right] + \left[\hat{S}_{t+1}^1 - \hat{S}_t^1 \right] \end{aligned}$$

While the implied N_{t+1}^* approximation is positive, it will not have conditional expectation equal to one. In contrast, the exponential of the first-order contribution $(1 - \gamma_o) \left(\hat{V}_{t+1}^1 - \hat{R}_t^1 \right)$ will have conditional expectation equal to one as we have noted previously.

4.2 Approach 2

If we were to use a second-order approximation of N_{t+1}^* , it would push us outside the class of exponentially quadratic stochastic discount factors. Instead we could combine a first-order approximation of $\log N_{t+1}^*$ with a second-order approximation of $\hat{S}_{t+1} - \hat{S}_t$:

$$\begin{aligned} \log S_{t+1} - \log S_t &\approx (1 - \gamma_o) \left[\left(\hat{V}_{t+1}^1 - \hat{R}_t^1 \right) + \frac{1}{2} \left(\hat{V}_{t+1}^2 - \hat{R}_t^2 \right) \right] \\ &\quad + \left(\hat{S}_{t+1}^0 - \hat{S}_t^0 \right) + \left(\hat{S}_{t+1}^1 - \hat{S}_t^1 \right) + \frac{1}{2} \left(\hat{S}_{t+1}^2 - \hat{S}_t^2 \right) \end{aligned}$$

which would preserve the quadratic approximation of $\log S_{t+1} - \log S_t$.

4.3 Approach 3

Next consider an alternative modification of Approach 1 whereby:

$$\begin{aligned} \log N_{t+1}^* &\approx \frac{\exp \left[(1 - \gamma_o) \left(\tilde{V}_{t+1}^0 + \tilde{V}_{t+1}^1 \right) \right]}{\mathbb{E} \left(\exp \left[(1 - \gamma_o) \left(\tilde{V}_{t+1}^0 + \tilde{V}_{t+1}^1 \right) \right] \mid \mathfrak{A}_t \right)} \\ &= \frac{\exp \left[(1 - \gamma_o) \left[\left(\hat{V}_{t+1}^1 - \hat{R}_t^1 \right) + \frac{1}{2} \left(\hat{V}_{t+1}^2 - \hat{R}_t^2 \right) \right] \right]}{\mathbb{E} \left(\exp \left[(1 - \gamma_o) \left[\left(\hat{V}_{t+1}^1 - \hat{R}_t^1 \right) + \frac{1}{2} \left(\hat{V}_{t+1}^2 - \hat{R}_t^2 \right) \right] \right] \mid \mathfrak{A}_t \right)}. \end{aligned}$$

is used in conjunction with

$$\left(\hat{S}_{t+1}^0 - \hat{S}_t^0 \right) + \left(\hat{S}_{t+1}^1 - \hat{S}_t^1 \right) + \frac{1}{2} \left(\hat{S}_{t+1}^2 - \hat{S}_t^2 \right).$$

By design, exponential counterpart of this approximation will have conditional expectation equal to one. With a little bit of algebraic manipulation, it may be shown that this approximation induces a distributional change for W_{t+1} with a conditional mean that is affine in X_{t+1} and an altered conditional variance that is constant over time.

To understand better this choice of approximation, consider the family of random variables (indexed by \mathbf{q})

$$(1 - \gamma_o) \left(\tilde{V}_{t+1}^0 + \mathbf{q} \tilde{V}_{t+1}^1 \right) - \log \mathbb{E} \left(\exp \left[(1 - \gamma_o) \left(\tilde{V}_{t+1}^0 + \mathbf{q} \tilde{V}_{t+1}^1 \right) \right] \mid \mathfrak{A}_t \right). \quad (31)$$

The corresponding family of exponentials has conditional expectation one and the $\mathbf{q} = 1$ member is the proposed approximation for N_{t+1}^* . Differentiate the family with respect to \mathbf{q} :

$$\tilde{V}_{t+1}^1 - \frac{\mathbb{E} \left(\exp \left[(1 - \gamma_o) \tilde{V}_{t+1}^0 \right] \tilde{V}_{t+1}^1 \mid \mathfrak{A}_t \right)}{\mathbb{E} \left(\exp \left[(1 - \gamma_o) \tilde{V}_{t+1}^0 \right] \mid \mathfrak{A}_t \right)} = \tilde{V}_{t+1}^1 - \tilde{R}_t^1.$$

Thus this family of random variables has the same first-order approximation in \mathbf{q} as $\log N_{t+1}^*$ given in (30) and it remains within the linear-quadratic in logarithms formulation.

As a first-order change of probability measure, this approximation will induce state dependence in the conditional mean and will alter the covariance matrix of the shock vector. We

find this approach interesting because it links back directly to the outcome of the robustness formulation we described in Section 3.1. Moreover, the state dependence in the mean will induce a corresponding state dependence in the one-period uncertainty prices.

5 Long-run risk example

We consider a model with long-run risk components to consumption as suggested by Bansal and Yaron (2004). For the moment, we abstract from production; but as we will see later there is a production counterpart in consumption displays long-run risk. For now think simply specify a consumption process with a long-run risk component.

5.1 Approximation

By applying this approximation to the Bansal and Yaron (2004) model, we obtain the state dynamics:

$$\begin{aligned} X_{t+1}^0 &= \begin{bmatrix} 0 \\ 1 \end{bmatrix} \\ X_{t+1}^1 &= \begin{bmatrix} \theta_{11}^x & 0 \\ 0 & \theta_{22}^x \end{bmatrix} X_t^1 + \begin{bmatrix} \sigma_{11}^x & 0 & 0 \\ 0 & \sigma_{22}^x & 0 \end{bmatrix} W_{t+1} \\ X_{t+1}^2 &= \begin{bmatrix} \theta_{11}^x & 0 \\ 0 & \theta_{22}^x \end{bmatrix} X_t^2 + \begin{bmatrix} 2X_{2,t}^1 \sigma_{11}^x & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} W_{t+1}, \end{aligned}$$

where $0 < \theta_{11}^x < 1$ and $0 < \theta_{22}^x < 1$, and the consumption dynamics:

$$\begin{aligned} \widehat{C}_{t+1}^0 - \widehat{C}_t^0 &= \eta_c^0 \\ \widehat{C}_{t+1}^1 - \widehat{C}_t^1 &= \theta_1^c X_{1,t}^1 + \begin{bmatrix} 0 & 0 & \sigma_3^c \end{bmatrix} W_{t+1} \\ \widehat{C}_{t+1}^2 - \widehat{C}_t^2 &= \theta_1^c X_{1,t}^2 + \begin{bmatrix} 0 & 0 & 2X_{2,t}^1 \sigma_3^c \end{bmatrix} W_{t+1}. \end{aligned}$$

Thus we take consumption to evolve (approximately) as:

$$\begin{aligned} \widehat{C}_{t+1} - \widehat{C}_t &= \left(\widehat{C}_{t+1}^0 + \widehat{C}_{t+1}^1 + \frac{1}{2} \widehat{C}_{t+1}^2 \right) - \left(\widehat{C}_t^0 + \widehat{C}_t^1 + \frac{1}{2} \widehat{C}_t^2 \right) \\ &= \eta_c^0 + \theta_1^c \left(X_{1,t}^1 + \frac{1}{2} X_{1,t}^2 \right) + \begin{bmatrix} 0 & 0 & (1 + X_{2,t}^1) \sigma_3^c \end{bmatrix} W_{t+1}. \end{aligned}$$

The processes $\{X_{1,t}^1\}$ and $\{X_{1,t}^2\}$ contribute temporal dependence to the consumption growth dynamics. The process $\{X_{2,t}^1\}$ contributes stochastic volatility to the consumption dynamics while the stationary specification of the process $\{X_{2,t}^2\}$ is identically zero and can be ignored.

5.2 VAR approach

The Markov process governing the predictable component of macroeconomic growth is scalar in the Bansal and Yaron (2004) analysis. Motivated by empirical evidence, Hansen et al. (2008) study an extension of this model where X^1 is a vector autoregression. To relate to the VAR approach of Hansen et al., write the first-order approximation for the logarithm of consumption as:

$$\hat{C}_{t+1}^1 - \hat{C}_t = \eta_c^0 + \mathbb{D}X_t^1 + \mathbb{F}'W_{t+1}$$

where

$$\begin{aligned}\kappa_{x'} &= \mathbb{D} \\ \kappa_{w'} &= \mathbb{F}.\end{aligned}$$

Where the first-order process X^1 includes a predictable component of the macroeconomic growth-rate process and evolves as an autoregression:

$$X_{t+1}^1 = \mathbb{A}X_t^1 + \mathbb{B}W_{t+1},$$

where

$$\begin{aligned}\psi_{x'} &= \mathbb{A} \\ \kappa_{w'} &= \mathbb{B}.\end{aligned}$$

and \mathbb{A} is a stable matrix. Thus the first-order approximation to the Bansal and Yaron (2004) for the consumption dynamics is a special case of the formulation in Hansen et al. (2008).²

The row vector \mathbb{F} and matrix \mathbb{B} are configured so that the components of the shock vector, W_{t+1} , directly disturbs growth in the logarithm of consumption and its predictable (first-order)

²The Hansen et al. (2008) predictability evidence turned out to be “fragile” and was modified and updated in Hansen and Sargent (2021) Appendix B. This same appendix suggests a way to deduce a statistical approximation to the first order dynamics of Bansal and Yaron (2004) from a more general VAR representation of the consumption dynamics.

growth component X^1 . Notice, in particular that the conditional mean of $\widehat{C}_{t+j} - \widehat{C}_t$ is

$$j\eta_c^0 + \mathbb{D} \left(X_t + \mathbb{A}X_t + \dots + \mathbb{A}^{j-1} \right) X_t.$$

The corresponding multi-period forecast errors contribute to the variance of $\widehat{C}_{t+j} - \widehat{C}_t$ with a variance that increases with the horizon. When the process $\{\mathbb{D}X_t\}$ is highly persistent, there is said to be substantial “long-run risk” in consumption.

5.3 Approximating continuation values

Returning the original Bansal and Yaron (2004) specification, we consider the approximation of continuation values and the corresponding change in probabilities. The first-order continuation-value approximation is

$$\begin{aligned}\widehat{V}_t^1 - \widehat{C}_t^1 &= \left(\frac{\lambda}{1 - \lambda\theta_{11}^x} \right) \theta_1^c X_{1,t}^1 \\ \widehat{R}_t^1 - \widehat{C}_t^1 &= \left(\frac{1}{1 - \lambda\theta_{11}^x} \right) \theta_1^c X_{1,t}^1\end{aligned}$$

The implied change in probability measure is

$$N_{t+1}^0 = \exp \left(\mu^0 \cdot W_{t+1} - \frac{1}{2} |\mu^0|^2 \right)$$

where

$$\mu^0 = (1 - \gamma_o) \begin{bmatrix} \left(\frac{\lambda}{1 - \lambda\theta_{11}^x} \right) \theta_1^c \sigma_{11}^x \\ 0 \\ \sigma_3^c \end{bmatrix}$$

is the implied mean distortion. The negative of μ_0 gives the vector of one period shock exposure prices.

We use formula, (27), for the second-order adjustment. As a first step we compute

$$\mathbb{E} \left[N_{t+1}^0 \left(\widehat{C}_{t+1}^2 - \widehat{C}_t^2 \right) \mid \mathfrak{A}_t \right] = \theta_c X_{1,t}^2 + 2(\sigma_3)^2 X_{2,t}^1.$$

Thus we are lead to solve:

$$\widehat{V}_t^2 - \widehat{C}_t^2 = \lambda \mathbb{E} \left[N_{t+1}^1 \left(\widehat{V}_{t+1}^2 - \widehat{C}_{t+1}^2 \right) \mid \mathfrak{A}_t \right]$$

$$+ \theta_c X_{1,t}^2 + 2(\sigma_3)^2 X_{2,t}^1 + (1 - \rho)(1 - \lambda)\lambda \left[\left(\frac{1}{1 - \lambda\theta_{11}^x} \right) \theta_1^c X_{1,t}^1 \right]^2$$

forward using the change of probability measure under which the conditional expectation of W_{t+1} is equal to μ^0 .

5.4 Shock elasticities

We use the shock elasticities to explore pricing implications of this recursive utility specification. We conduct this exploration using the original parameter calibration in Bansal and Yaron (2004). These elasticities and their relation to impulse-response functions introduced first to macroeconomics by Frisch (1933) is described Borovička et al. (2014). In what follows, we use exponential/linear/quadratic implementation by Borovička and Hansen (2014) and by Borovička and Hansen (2016).

Figure 1 gives the shock exposure elasticities for consumption to each of the three shocks. This can be interpreted as nonlinear local impulse responses for consumption (in levels not logarithms). The elasticities for the growth rate shock and the stochastic volatility shock start small and increase over the time horizon as dictated by the persistence of the two exogenous state variable processes. The elasticities for the direct shock to consumption are flat over the horizon as to be expected since the shock directly impacts log consumption in a manner that is permanent. Notice that while elasticities for the volatility shock are different from zero, their contribution is much smaller than the other shocks.³ Nevertheless, for this Bansal and Yaron (2004) calibration of the long run risk model, stochastic volatility induces state dependence in the elasticities for growth rate and consumption shocks as reflected by quantiles given in the figures.

³It is notable that we are looking at levels and not logarithms of consumption. the local impulse response for the logarithms of consumption is in fact zero for the stochastic volatility shock.

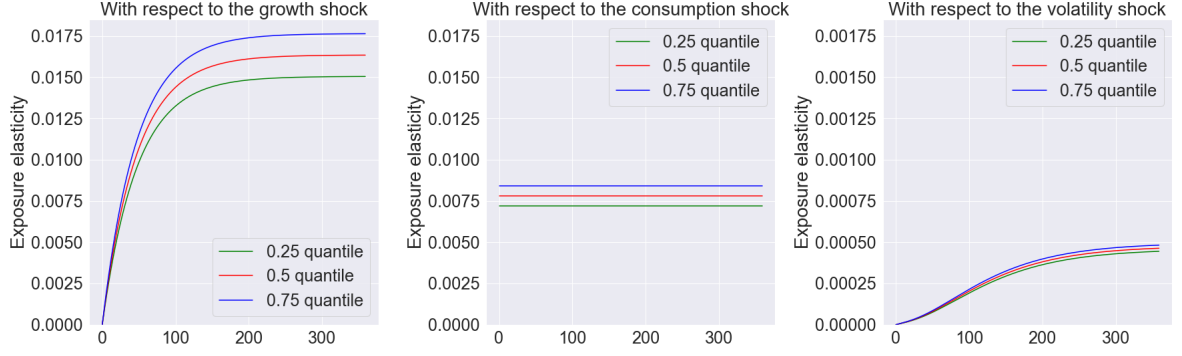


Figure 1: Exposure elasticities for three shocks. The time scale is in months.

Figure 2 gives the corresponding shock price elasticities for $\rho = 2/3$ and $\gamma = 10$. The recursive utility preferences are forward looking as reflected by the continuation-value contribution to the one-period increment to the stochastic discount factor process as given in (29). This forward-looking contribution is reflected in shock price elasticities that are now flat for both the growth rate shock and the shock to stochastic volatility. The magnitudes are substantially higher for the shock-price elasticities. While the relative magnitudes are very different, the shock price elasticities are much smaller than the other elasticities.⁴

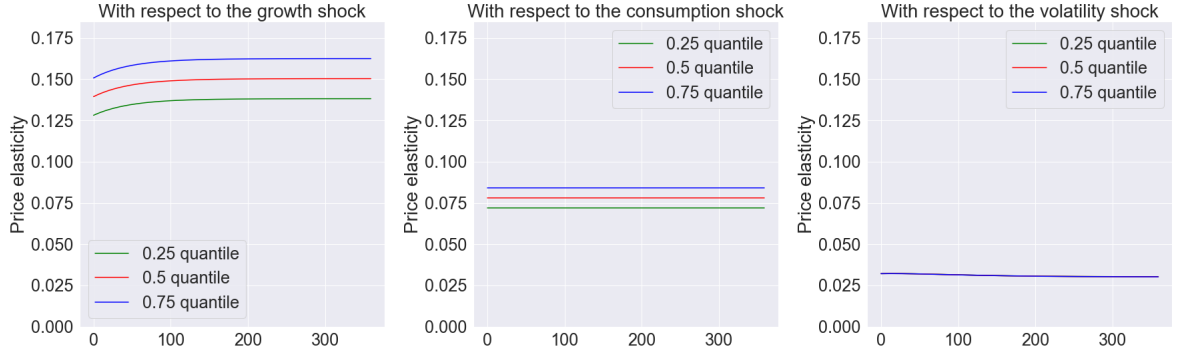


Figure 2: Price elasticities for three shocks. $\rho = 2/3, \gamma = 10, \beta = .998$. The time scale is in months.

Figures 3 and 4 provide the analogous plots for $\rho = 1, 1.5$. The shock price elasticities are very similar given these modes increases in ρ . It is evidently the risk aversion parameter

⁴We normalized the stochastic volatility shock σ_x^2 to be negative implying that a positive shock reduces the stochastic volatility state variable. Under this normalization, the shock price elasticities are positive.

$\gamma = 10$ that is important for determining the magnitude of these elasticities. Figure 5 sets $\rho = \gamma = 10$ which corresponds to preferences that are time separable. The forward-looking component to the stochastic discount factor is shut down as is evident from formula (29). Now the shock price elasticities and shock exposure elasticities show a very similar trajectory except that the shock price elasticities are about ten times larger. The stochastic volatility shock price is increased by about seventy-five times. Notice that for longer horizons the $\gamma = \rho = 10$ preference model has prices that are very similar in magnitude to the recursive preference models with more modest specifications of ρ .

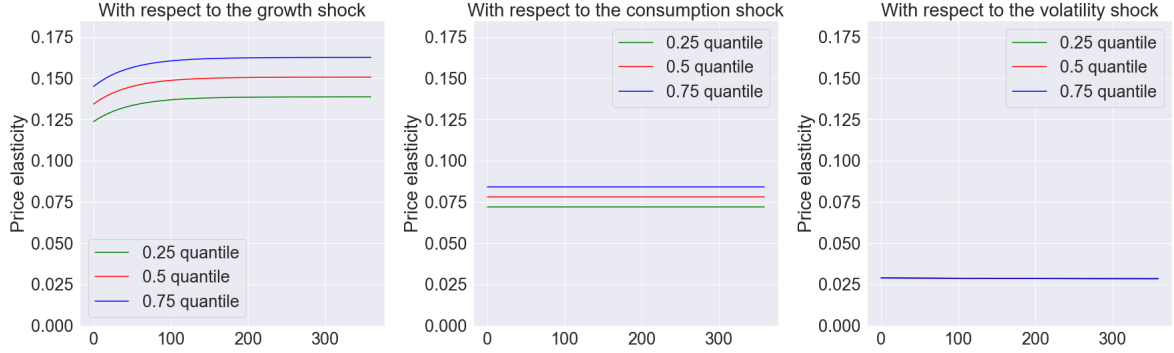


Figure 3: Price elasticities for three shocks. $\rho = 1, \gamma = 10, \beta = .998$. The time scale is in months.

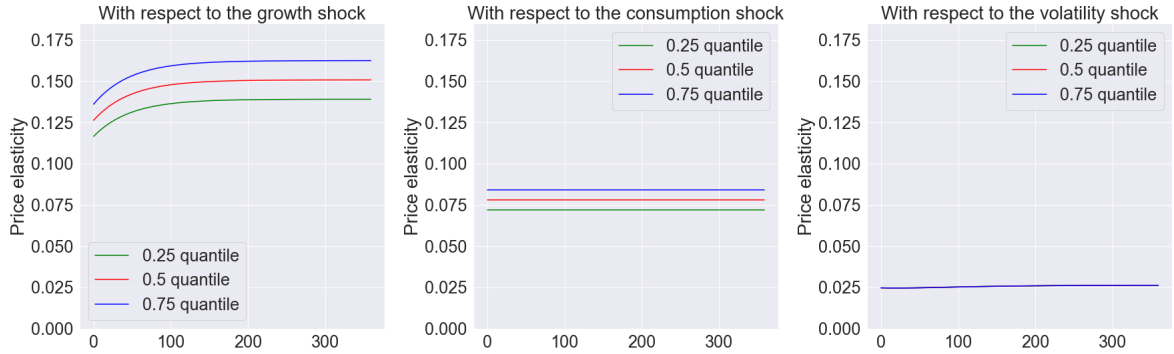


Figure 4: Price elasticities for three shocks. $\rho = 3/2, \gamma = 10, \beta = .998$. The time scale is in months.

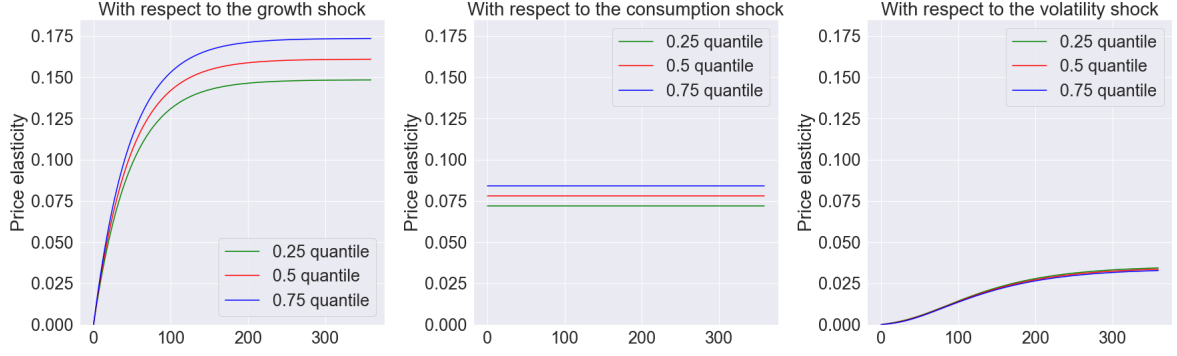


Figure 5: Price elasticities for three shocks. $\rho = 10, \gamma = 10, \beta = .998$. The time scale is in months.

6 Solving models

The Bansal and Yaron (2004) example along with many others building connections between the macro economy and asset value take aggregate consumption as pre-specified. As we open the door to a richer collection of macroeconomic models, it becomes important to entertain more endogeneity, including investment and other variables familiar to macroeconomics. In this section, we briefly describe one way to extend the approach that builds directly on previous second-order approaches of Kim et al. (2008), Schmitt-Grohé and Uribe (2004), and Lombardo and Uhlig (2018). While such methods should not be viewed as being generically applicable to nonlinear stochastic equilibrium models, we find them useful pedagogically and often as at least initial steps to understanding models that are arguably “smooth.” See Pohl et al. (2018) for a careful study of nonlinearity in asset pricing models with recursive utility.⁵

We implement these methods for second-order approximation using the following steps.

- i) Solve for $\mathbf{q} = 0$ deterministic model.
- ii) Take as given a $\mu^0, \Upsilon_0^2, \Upsilon_1^2$ used in

$$\begin{aligned}\hat{V}_{t+1}^1 - \hat{R}_t^1 &= \frac{1}{1 - \gamma_o} \left[\mu^0 \cdot (W_{t+1} - \mu^0) + \frac{1}{2} \mu^0 \cdot \mu^0 \right] \\ \hat{V}_{t+1}^2 - \hat{R}_t^2 &= \frac{1}{2} (W_{t+1} - \mu^0)' \Upsilon_2^2 (W_{t+1} - \mu^0) - \frac{1}{2} \text{tr}(\Upsilon_2^2)\end{aligned}$$

⁵Pohl et al. provide examples of when log-linear or local methods of computation fail to provide good approximations.

$$+ (W_{t+1} - \mu^0)' (\Upsilon_1^2 X_t^1 + \Upsilon_0^2), \quad (32)$$

- iii) Compute the first-order expansion solve the resulting equations following the previous literature . When constructing these equations, use expectations computed using the probabilities induced by N_{t+1}^0 . Under the change in probability W_{t+1} is normally distributed with μ^0 , where μ^0 is given in step ii). Make an additional recursive utility adjustment to the equations that also depends on μ^0 . It comes from a first-order approximation for $(\rho - 1) (\widehat{V}_{t+1} - \widehat{R}_t)$ as a plug in for the construction of the logarithm of the stochastic discount factor.
- iv) Compute the second-order expansion and solve the resulting equations following the previous literature. Again use the expectations induced by N_{t+1}^0 . In addition, make another recursive utility adjustment expressed in terms of $\mu^0, \Upsilon_0^2, \Upsilon_1^2$ taking the inputs from ii. This comes from It comes from a second-order approximation for $(\rho - 1) (\widehat{V}_{t+1} - \widehat{R}_t)$ needed for the logarithm of the stochastic discount factor.
- v) Form new values for $\mu^0, \Upsilon_0^2, \Upsilon_1^2$ used in representations (32) and return to ii). Repeat until convergence.

See Appendix A for more details and substantive elaboration.

This first algorithm includes the use of first and second-order approximation of N_{t+1}^* . While the second-order approximation of N_{t+1}^* has conditional expectation one, it is not restricted to be positive. A second algorithm enforces positivity on the implied approximation of N_{t+1}^* .

- i) Solve for $\mathbf{q} = 0$ deterministic model.
- ii) Take as given an an exponential linear-quadratic approximation \widetilde{N}_{t+1} for N_{t+1}^* , along with $\mu^0, \Upsilon_0^2, \Upsilon_1^2, \Upsilon_2^2$ used in formulas (32).
- iii) Compute the first-order expansion solve the resulting equations following the previous literature. When constructing these equations, use expectations computed using the probabilities induced by N_{t+1}^a . In addition, make an additional recursive utility adjustment to the equations that comes from a first-order approximation for $(\rho - 1) (\widehat{V}_{t+1} - \widehat{R}_t)$ as a plug in for the construction of the logarithm of the stochastic discount factor. Use the first-order adjustment from step ii.

- iv) Compute the second-order expansion and solve the resulting equations following the previous literature. Again use the expectations induced by \tilde{N}_{t+1} . In addition, make another recursive utility adjustment expressed in terms of $\mu^0, \Upsilon_0^2, \Upsilon_1^2$ taking the inputs from ii. This comes from a second-order approximation for $(\rho - 1) \left(\hat{V}_{t+1} - \hat{R}_t \right)$ needed for the construction of the logarithm of the stochastic discount factor.
- v) Form new values for $\mu^0, \Upsilon_0^2, \Upsilon_1^2, \Upsilon_2^2$ used in representations (32), construct

$$\tilde{N}_{t+1} = \frac{\exp \left[(1 - \gamma_o) \left[\hat{V}_{t+1}^1 - \hat{R}_t^1 + \frac{1}{2} \left(\hat{V}_{t+1}^2 - \hat{R}_t^2 \right) \right] \right]}{\mathbb{E} \left(\exp \left[(1 - \gamma_o) \left[\hat{V}_{t+1}^1 - \hat{R}_t^1 + \frac{1}{2} \left(\hat{V}_{t+1}^2 - \hat{R}_t^2 \right) \right] \right] \mid \mathfrak{A}_t \right)},$$

and return to ii). Repeat until convergence.

- vi) Compute

$$N_{t+1} = \frac{\exp \left[(1 - \gamma_o) \left[\hat{V}_{t+1}^1 - \hat{R}_t^1 + \frac{1}{2} \left(\hat{V}_{t+1}^2 - \hat{R}_t^2 \right) \right] \right]}{\mathbb{E} \left(\exp \left[(1 - \gamma_o) \left[\hat{V}_{t+1}^1 - \hat{R}_t^1 + \frac{1}{2} \left(\hat{V}_{t+1}^2 - \hat{R}_t^2 \right) \right] \right] \mid \mathfrak{A}_t \right)},$$

and set $N_{t+1}^a = N_{t+1}$.

A Approximating solutions

For the purposes of this appendix, write:

$$\frac{S_{t+1}}{S_t} = N_{t+1}^* Q_{t+1} \beta \exp[-\rho (\log C_{t+1} - \log C_t)]$$

where

$$\begin{aligned} N_{t+1}^* &= \exp \left[(1 - \gamma_o) (\tilde{V}_{t+1} - \tilde{R}_t) \right] \\ Q_{t+1}^* &= \exp \left[(\rho - 1) (\hat{V}_{t+1} - \hat{R}_t) \right] \end{aligned}$$

are terms that are contributed by recursive utility.

A.1 N_{t+1}^* derivatives

$$\begin{aligned} N_{t+1}^0 &\stackrel{\text{def}}{=} \exp \left[(1 - \gamma_o) (\tilde{V}_{t+1}^0 - \tilde{R}_t^0) \right] = \exp \left[(1 - \gamma_o) (\hat{V}_{t+1}^1 - \hat{R}_t^1) \right] \\ N_{t+1}^1 &\stackrel{\text{def}}{=} \frac{d}{d\mathbf{q}} \exp \left[(1 - \gamma_o) (\tilde{V}_{t+1} - \tilde{R}_t) \right] \Big|_{\mathbf{q}=0} \\ &= (1 - \gamma_o) N_{t+1}^0 (\tilde{V}_{t+1}^1 - \tilde{R}_t^1) = \left(\frac{1 - \gamma_o}{2} \right) N_{t+1}^0 (\hat{V}_{t+1}^2 - \hat{R}_t^2). \end{aligned}$$

It may be directly verified that N_{t+1}^1 has conditional expectation equal to zero.

A.2 Q_{t+1}^* derivatives

$$\begin{aligned} Q_{t+1}^0 &\stackrel{\text{def}}{=} \exp \left[(\rho - 1) (\hat{V}_{t+1}^0 - \hat{R}_t^0) \right] = 1 \\ Q_{t+1}^1 &\stackrel{\text{def}}{=} \frac{d}{d\mathbf{q}} \exp \left[(\rho - 1) (\hat{V}_{t+1} - \hat{R}_t) \right] \Big|_{\mathbf{q}=0} = (\rho - 1) (\hat{V}_{t+1}^1 - \hat{R}_t^1) \\ Q_{t+1}^2 &\stackrel{\text{def}}{=} \frac{d^2}{d\mathbf{q}^2} \exp \left[(\rho - 1) (\hat{V}_{t+1} - \hat{R}_t) \right] \Big|_{\mathbf{q}=0} = (\rho - 1)^2 (\hat{V}_{t+1}^1 - \hat{R}_t^1)^2 + (\rho - 1) (\hat{V}_{t+1}^2 - \hat{R}_t^2) \end{aligned}$$

Express

$$\hat{V}_{t+1}^1 - \hat{R}_t^1 = \frac{1}{1 - \gamma_o} \left[\mu^0 \cdot (W_{t+1} - \mu^0) + \frac{1}{2} \mu^0 \cdot \mu^0 \right]$$

$$\begin{aligned}\widehat{V}_{t+1}^2 - \widehat{R}_t^2 &= \frac{1}{2} (W_{t+1} - \mu^0)' \Upsilon_2^2 (W_{t+1} - \mu^0) - \frac{1}{2} \text{tr} (\Upsilon_2^2) \\ &\quad + (W_{t+1} - \mu^0)' (\Upsilon_1^2 X_t^1 + \Upsilon_0^2),\end{aligned}\tag{33}$$

Recall from (25) that $\widehat{V}_{t+1}^2 - \widehat{R}_t^2$ has mean zero under the probability distribution induced by N_{t+1}^0 , which is consistent with its representation in (33).

B Approximating expectation equations

Consider the equation:

$$\mathbb{E} (N_{t+1} Q_{t+1} H_{t+1} \mid \mathfrak{A}_t) + L_t = 0.$$

where $\beta \exp[-\rho(\log C_{t+1} - \log C_t)]$ is absorbed into the construction of H_{t+1} . This is the subsystem of the equations not including the state evolution equations.

B.1 Order zero

The order zero approximation of the product: $N_{t+1} Q_{t+1} H_{t+1} + L_t$ is:

$$N_{t+1}^0 H_{t+1}^0 + L_t^0 = 0$$

where we have substituted $Q_{t+1}^0 = 1$. Thus the order zero approximate equation is:

$$\mathbb{E} [N_{t+1}^0 (H_{t+1}^0 + L_{t+1}^0) \mid \mathfrak{A}_t] = H_{t+1}^0 + L_t^0 = 0$$

since N_{t+1}^0 has conditional expectation equal to one. We add to this subsystem the $\mathbf{q} = 0$ state dynamic equation inclusive of jump variables, and we compute a stable steady state solution.

B.2 Order one

The order one approximation of the product: $N_{t+1} Q_{t+1} H_{t+1} + L_t$ is:

$$N_{t+1}^1 H_{t+1}^0 + N_{t+1}^0 Q_{t+1}^1 H_{t+1}^0 + N_{t+1}^0 H_{t+1}^1 + L_t^1$$

where we have substituted $Q_{t+1}^0 = 1$. Thus the order one approximate equation is:

$$\begin{aligned} & \mathbb{E} (N_{t+1}^1 H_{t+1}^0 + N_{t+1}^0 H_{t+1}^1 \mid \mathfrak{A}_t) + \mathbb{E} (N_{t+1}^0 Q_{t+1}^1 H_{t+1}^0 \mid \mathfrak{A}_t) + L_t^1 \\ &= \mathbb{E} [N_{t+1}^0 (H_{t+1}^1 + Q_{t+1}^1 H_{t+1}^0) \mid \mathfrak{A}_t] + L_t^1 \\ &= 0 \end{aligned}$$

where we used the implication that $H_{t+1}^0 + L_{t+1}^0 = 0$. The contribution:

$$\mathbb{E} (N_{t+1}^0 H_{t+1}^1 \mid \mathfrak{A}_t) + L_t^1$$

is of the form used for the first-order approximation without the recursive utility modification, except that the expectation is evaluated under the probability measure implied by N_{t+1}^0 . The recursive utility adjustment has us include the additional term:

$$\mathbb{E} (N_{t+1}^0 Q_{t+1}^1 H_{t+1}^0 \mid \mathfrak{A}_t) = \frac{(\rho - 1)}{2(1 - \gamma_o)} |\mu^o|^2 H_{t+1}^0 \stackrel{\text{def}}{=} \overline{H}^1$$

which is constant over time. Thus we write the first-order subsystem of equations as:

$$\mathbb{E} (N_{t+1}^0 H_{t+1}^1 \mid \mathfrak{A}_t) + L_t^1 + \overline{H}^1 = 0.$$

We add to this the first-order approximation of the state dynamics inclusive of jump variables and evaluate expectations under the N_{t+1}^0 change of probability measure. Thus the one-period conditional expectation of W_{t+1} is μ^0 .

B.3 Order two

The order two approximation of the product: $N_{t+1} Q_{t+1} H_{t+1} + N_{t+1} L_{t+1}$ is:

$$\begin{aligned} & N_{t+1}^0 H_{t+1}^2 + N_{t+1}^2 H_{t+1}^0 + 2N_{t+1}^1 H_{t+1}^1 + L_t^2 \\ & + 2N_{t+1}^1 Q_{t+1}^1 H_{t+1}^0 + 2N_{t+1}^0 Q_{t+1}^1 H_{t+1}^1 + N_{t+1}^0 Q_{t+1}^2 H_{t+1}^0 \end{aligned}$$

The term $N_{t+1}^2 H_{t+1}^0$ is zero and the term

$$\mathbb{E} (N_{t+1}^0 H_{t+1}^2 \mid \mathfrak{A}_t) + L_t^2$$

coincides with the contribution for the second-order approximation abstracting from recursive utility but evaluated under the change of measure induced by N_{t+1}^0 . Express H_{t+1}^1 as

$$H_{t+1}^1 = \Theta_0^1 + \Theta_1^1 X_t^1 + \Theta_2^1 (W_{t+1} - \mu^0). \quad (34)$$

We now consider the additional terms

$$\begin{aligned} 2\mathbb{E} (N_{t+1}^1 H_{t+1}^1 \mid \mathfrak{A}_t) &= (1 - \gamma_o) \mathbb{E} \left[N_{t+1}^0 \left(\widehat{V}_{t+1}^2 - \widehat{R}_t^2 \right) H_{t+1}^1 \mid \mathfrak{A}_t \right], \\ &= (1 - \gamma_o) \Theta_2^1 (\Upsilon_1^2 X_t^1 + \Upsilon_0^2) \\ 2\mathbb{E} (N_{t+1}^1 Q_{t+1}^1 H_{t+1}^0 \mid \mathfrak{A}_t) &= (\rho - 1)(1 - \gamma_o) \mathbb{E} \left[N_{t+1}^0 \left(\widehat{V}_{t+1}^2 - \widehat{R}_t^2 \right) \left(\widehat{V}_{t+1}^1 - \widehat{R}_t^1 \right) \mid \mathfrak{A}_t \right] H_{t+1}^0 \\ &= (\rho - 1) \mu^o \cdot (\Upsilon_1^2 X_t^1 + \Upsilon_0^2) H_{t+1}^0 \\ 2\mathbb{E} (N_{t+1}^0 Q_{t+1}^1 H_{t+1}^1 \mid \mathfrak{A}_t) &= 2(\rho - 1) \mathbb{E} \left[N_{t+1}^0 \left(\widehat{V}_{t+1}^1 - \widehat{R}_t^1 \right) [\Theta_0^1 + \Theta_1^1 X_t^1 + \Theta_2^1 (W_{t+1} - \mu^0)] \mid \mathfrak{A}_t \right] \\ &= 2 \frac{(\rho - 1)}{(1 - \gamma_o)} \left[\Theta_2^1 \mu^0 + \frac{1}{2} \mu^0 \cdot \mu^0 (\Theta_0^1 + \Theta_1^1 X_t^1) \right] \\ \mathbb{E} (N_{t+1}^0 Q_{t+1}^2 H_{t+1}^0 \mid \mathfrak{A}_t) &= (\rho - 1)^2 \mathbb{E} \left[N_{t+1}^0 \left(\widehat{V}_{t+1}^1 - \widehat{R}_t^1 \right)^2 \mid \mathfrak{A}_t \right] H_{t+1}^0 \\ &= \left(\frac{1 - \rho}{1 - \gamma_o} \right)^2 \left(|\mu^0|^2 + \frac{1}{4} |\mu^0|^4 \right) H_{t+1}^0 \end{aligned} \quad (35)$$

Denote the sum of the four terms in (35) as \overline{H}_t^2 . This random variable will be affine in X_t^1 , with a dynamic evolution determined by solving the first-order approximation. Thus we write the subsystem of equations to be solved as:

$$\mathbb{E} (N_{t+1}^0 H_{t+1}^2 \mid \mathfrak{A}_t) + L_t^2 + \overline{H}_t^2 = 0.$$

We add to this second-order subsystem, the second-order approximation of the state dynamics inclusive of the of jump variables. We substitute in the solution for the first-order approximation for the jump variables into both the first and second-order approximate state dynamics. In solving the second-order jump variable adjustment we use expectations induced by N_{t+1}^0 zero throughout under which W_{t+1} is conditionally normally distributed with mean μ^0 and

covariance I .

C Steps for implementation

We implement these methods for second-order approximation using the following steps.

- i) Solve H_{t+1}^0 and L_{t+1}^0 for order zero state and jump variables. The outcome will be state invariant.
- ii) Take as given a $\mu^0, \Upsilon_0^2, \Upsilon_1^2$ used in representations (33).
- iii) Compute the first-order contribution to approximation by following the previous literature with expectations computed using the probabilities induced by N_{t+}^0 , which imply that W_{t+1} has mean μ^0 . Express the solution as in (34).
- iv) Compute the second-order contribution to the approximation by following the previous literature, again with the expectations induced by N_{t+1}^0 .
- v) Form new values for $\mu^0, \Upsilon_0^2, \Upsilon_1^2$ used in representations (33) and return to ii). Repeat until convergence.

D Second approach

For this solution, we iterate over N_{t+1}^* approximation. Call the approximation \tilde{N}_{t+1} with an induced distribution for W_{t+1} that is normal with conditional mean $\tilde{\mu}_t$ and covariance matrix $\tilde{\Sigma}$. This distribution is used in both the first-order and second-order contributions to the approximation. The conditional mean for $\tilde{\mu}_t$ is affine in X_t^1 . The following delineates the changes that need to be made.

D.1 First-order adjustment

Compute:

$$\begin{aligned} \mathbb{E} \left(\tilde{N}_{t+1} Q_{t+1}^1 H_{t+1}^0 \mid \mathfrak{A}_t \right) &= (\rho - 1) \mathbb{E} \left[\tilde{N}_{t+1} \left(\hat{V}_{t+1}^1 - \hat{R}_t^1 \right) \mid \mathfrak{A}_t \right] H_{t+1}^0 \\ &= \left(\frac{\rho - 1}{1 - \gamma_o} \right) \left[\mu^0 \cdot (\tilde{\mu}_t - \mu^0) + \frac{1}{2} \mu^0 \cdot \mu^0 \right] H_{t+1}^0 \\ &\stackrel{\text{def}}{=} \tilde{H}_t^1. \end{aligned}$$

Then the equation to be solved is:

$$\mathbb{E} \left(\tilde{N}_{t+1} H_{t+1}^1 \mid \mathfrak{A}_t \right) + L_t^1 + \tilde{H}_t^1 = 0.$$

D.2 Second-order adjustment

$$\begin{aligned} 2\mathbb{E} \left(\tilde{N}_{t+1} Q_{t+1}^1 H_{t+1}^1 \mid \mathfrak{A}_t \right) &= 2(\rho - 1) \mathbb{E} \left[\tilde{N}_{t+1} \left(\hat{V}_{t+1}^1 - \hat{R}_t^1 \right) \left[\Theta_0^1 + \Theta_1^1 X_t^1 + \Theta_2^1 (W_{t+1} - \mu^0) \right] \mid \mathfrak{A}_t \right] \\ &= 2 \frac{(\rho - 1)}{(1 - \gamma_o)} \Theta_2^1 \tilde{\Sigma} \mu^0 \\ &\quad + 2 \frac{(\rho - 1)}{(1 - \gamma_o)} \left[\mu^0 \cdot (\tilde{\mu}_t - \mu^0) + \frac{1}{2} \mu^0 \cdot \mu^0 \right] \left[\Theta_0^1 + \Theta_1^1 X_t^1 + \Theta_2^1 (\tilde{\mu}_t - \mu^0) \right] \end{aligned}$$

$$\begin{aligned} \mathbb{E} \left(\tilde{N}_{t+1} Q_{t+1}^2 H_{t+1}^0 \mid \mathfrak{A}_t \right) &= (\rho - 1)^2 \mathbb{E} \left[\tilde{N}_{t+1} \left(\hat{V}_{t+1}^1 - \hat{R}_t^1 \right)^2 \mid \mathfrak{A}_t \right] H_{t+1}^0 \\ &\quad + (\rho - 1) \mathbb{E} \left[\tilde{N}_{t+1} \left(\hat{V}_{t+1}^2 - \hat{R}_t^2 \right) \mid \mathfrak{A}_t \right] H_{t+1}^0 \\ &= \left(\frac{1 - \rho}{1 - \gamma_o} \right)^2 \left[\mu^{0'} \tilde{\Sigma} \mu^0 + \left(\mu^0 \cdot \tilde{\mu}_t - \frac{1}{2} |\mu^0|^2 \right)^2 \right] H_{t+1}^0 \\ &\quad + \frac{(\rho - 1)}{2} \left[\text{tr} \left(\Upsilon_2^2 \tilde{\Sigma} - \Upsilon_2^2 \right) + (\tilde{\mu}_t - \mu^0)' \Upsilon_2^2 (\tilde{\mu}_t - \mu^0) \right] H_{t+1}^0 \\ &\quad + (\rho - 1) (\tilde{\mu}_t - \mu^0)' (\Upsilon_1^2 X_t^1 + \Upsilon_0^2) H_{t+1}^0 \end{aligned} \tag{36}$$

Denote the sum of the two terms in (36) as \tilde{H}_t^2 . Then the equation to be solved is

$$\mathbb{E} \left(\tilde{N}_{t+1} H_{t+1}^2 \mid \mathfrak{A}_t \right) + L_t^2 + \tilde{H}_t^2 = 0.$$

D.3 Updated recursive utility adjustments

Form new values for $\mu^0, \Upsilon_0^2, \Upsilon_1^2, \Upsilon_2^2$ used in representations (33). Compute a new version of

$$\tilde{N}_{t+1} = \frac{\exp \left[(1 - \gamma_o) \left[\hat{V}_{t+1}^1 - \hat{R}_t^1 + \frac{1}{2} \left(\hat{V}_{t+1}^2 - \hat{R}_t^2 \right) \right] \right]}{\mathbb{E} \left(\exp \left[(1 - \gamma_o) \left[\hat{V}_{t+1}^1 - \hat{R}_t^1 + \frac{1}{2} \left(\hat{V}_{t+1}^2 - \hat{R}_t^2 \right) \right] \right] \mid \mathfrak{A}_t \right)},$$

and deduce the implied $\tilde{\mu}_t$ and $\tilde{\Sigma}$. The conditional mean $\tilde{\mu}_t$ satisfies:

$$\tilde{\Sigma}^{-1}\tilde{\mu}_t = \mu^0 + \frac{(1 - \gamma_o)}{2} (\Upsilon_0^2 + \Upsilon_1^2 X_t^1 - \Upsilon_2^2 \mu^0)$$

where the formula for $\tilde{\Sigma}$ is

$$\tilde{\Sigma} = \left[\mathbb{I} - \frac{(1 - \gamma_o)}{2} \Upsilon_2^2 \right]^{-1}.$$

With these adjustments, we iterate to convergence.

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