Econometrica Supplementary Material

SUPPLEMENT TO "A PARSIMONIOUS MACROECONOMIC MODEL FOR ASSET PRICING": TECHNICAL APPENDIX AND EXTENSIONS

(*Econometrica*, Vol. 77, No. 6, November, 2009, 1711–1750)

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This appendix has four parts. Part A presents the details of the computational algorithm and discusses issues about the accuracy of the solution method. Part B describes the discretization procedure for the AR(1) process used for the technology shocks in the model and discusses its accuracy. Part C presents the details of two experiments discussed in the text: (i) the effect of different stock market participation rates on the asset pricing results and (ii) generating heterogeneity in the EIS endogenously through benchmark consumption levels. Finally, Part D presents additional statistics from different versions of the model that are omitted from the main text to save space.

KEYWORDS: Equity premium puzzle, limited stock market participation, elasticity of intertemporal substitution, wealth inequality, Epstein–Zin preferences.

A. COMPUTATIONAL ALGORITHM

THIS APPENDIX DESCRIBES the numerical methods used to solve the limited participation model described in Section 3 of Guvenen (2009). Some of the material here has been summarized in that section. Here, I provide a more detailed description, which repeats some of the discussion for completeness.

In addition to the typical difficulties associated with solving incomplete markets asset pricing models (such as Krusell and Smith (1997) and Storesletten, Telmer, and Yaron (2007)), the present model is further complicated by three factors: (i) the existence of adjustment costs, (ii) Epstein–Zin preferences, and (iii) leverage. With adjustment costs, the firm's problem is dynamic, and the return on equity cannot be computed simply as the marginal return on capital from a Cobb–Douglas production function. With Epstein–Zin preferences (especially for the stockholders) the Intertemporal Marginal Rate of Substitution of stockholders—which is also the discount factor in the firm's dynamic problem—is potentially quite nonlinear, making deviations from the true solution (i.e., due to poor initial guess or aggressive updating) less forgiving. Finally, with leverage, the bond pricing function also enters the firm's objective, creating further feedback between the two pricing functions (in addition to those from market clearing). For an accurate solution, which is necessary for reliable asset pricing results, I use an algorithm that values precision over speed. I first describe the algorithm for solving the CONS model. Dealing with endogenous labor supply is straightforward conceptually but time-consuming in practice, because it not only adds one more choice variable to individuals' problems (which can be solved from the static first order condition), but it also introduces one more equilibrium function that needs to be updated until convergence.

Solving the CONS model amounts to finding the following functions which are part of the recursive equilibrium.

 DOI: 10.3982/ECTA6658

(i) Value functions $(V^i(\omega; \boldsymbol{Y}))$ and decision rules $c^i(\omega; \boldsymbol{Y})$, $b^{i\prime}(\omega; \boldsymbol{Y})$ for each agent $i = h, n$ and $s'(\omega; \boldsymbol{Y})$.

(ii) Optimal investment rule for the firm, $I(\boldsymbol{Y})$.

(iii) The equilibrium stock and bond pricing functions, $P^s(\boldsymbol{Y})$ and $P^f(\boldsymbol{Y})$.

(iv) The equilibrium laws of motion $\Gamma_K(\boldsymbol{Y})$ and $\Gamma_B(\boldsymbol{Y})$ for the wealth distribution.

Before describing the algorithm, two points need to be discussed. First, the investment decision of the firm is dynamic and is obtained as the solution to equations (1) and (2) in the text. Although this dynamic program has a single (dynamic) choice variable and is conceptually straightforward to solve, there are some practical issues that complicate the solution. First, with Epstein–Zin preferences, future dividends, D_{t+1}, in the firm's objective are discounted by

$$\frac{\Lambda_{t+1}}{\Lambda_t} = \beta^{(1-\alpha)/(1-\rho)} \left(\frac{c_{t+1}}{c_t}\right)^{-\rho} \left[\frac{\dfrac{V_{t+1}}{c_t}}{\left[\left(\dfrac{V_t}{c_t}\right)^{1-\rho} - (1-\beta)\right]^{1/(1-\rho)}}\right]^{\rho-\alpha},$$

which depends on the consumption decision rule, value function, and future values of individual and aggregate state variables.[1] The problem is that even if the initial guesses for these different functions are modestly different from the actual solutions, the values of state variables in the distant future—obtained by iterating on these initial guesses—may be quite far off their true values, which then distorts the objective function by changing the weights assigned to the dividend stream in different states. This problem becomes worse when β is close to 1 (as is here, $\beta = 0.9966$) so that future dividends have a greater impact on the objective function. This requires starting with a good initial guess—which is the challenge—and updating equilibrium functions very gradually.

Second, unlike in models without adjustment costs (such as Krusell and Smith (1997)), here the return on capital is not equal to the marginal product of capital and depends on the stock price in the next period as well. Thus, one must solve jointly for $P^f(\boldsymbol{Y})$ and $P^s(\boldsymbol{Y})$. It turns out to be simpler (and more stable) to obtain the stock price using the present value condition of the firm rather than searching jointly for the market clearing stock and bond prices. The details of the algorithm are as follows:

Step 0—Initialization:

(a) First choose a grid for the state space. I use 25 points[2] each for ω^h and ω^n; 5 and 20 points in K and B directions, respectively (using 60—10 and

[1]Notice that when $\alpha = \rho$, this IMRS reduces to the standard one under expected utility: $\beta(C^h_{t+1}/C^h_t)^{-\alpha}$.

[2]Notice that I am using very few points in the ω direction. This is because the Epstein–Zin formulation of the utility function yields a linear value function in ω when markets are complete.

30 points in each of these directions, respectively—had no noticeable impact); and a 15-state Markov approximation to Z. In the rest, let i and j index grid points and iteration number, respectively. All the steps below are performed for each point in the state space, $\boldsymbol{Y}$, and off-grid values are obtained by cubic spline interpolation.

(b) As explained above, the initial choices for the laws of motion and pricing functions are critical because they affect future values of state variables (for a given fixed state today) and thus the objective function of the firm. Initial guesses for $\Gamma_K^0(\boldsymbol{Y})$, $\Gamma_B^0(\boldsymbol{Y})$, $P^{B,0}(\boldsymbol{Y})$, and $c^{h,0}(\omega; \boldsymbol{Y})$ are obtained by solving a simpler model where adjustment costs and leverage are eliminated and $\alpha = \rho$. This model is much simpler to solve, and the solution algorithm is described in an earlier paper (Guvenen (2006)) and is therefore omitted here. To obtain $P^{s,0}(\boldsymbol{Y})$ I proceed as follows:

(i) First, solve the firm's investment problem using the initial guesses above to construct the discount factor and future values of aggregate state variables. Note, however, that stockholders' wealth, $\varpi^{h\prime} = ((P^{s\prime} + D') - B')/\mu$, needed to construct the discount factor, itself depends on $(P^s + D)$, which I do not have yet. Thus, I replace it with $(1 + R(K, Z))K$, where R is simply the marginal return on capital using the Cobb–Douglas production function. The two values become closer as adjustment costs are relaxed.

(ii) Using $I^0(\boldsymbol{Y})$, obtain $D^0(\boldsymbol{Y})$ using the definition of dividends. Define and initialize the auxiliary variable $\overline{P}^0(K, B, Z) = K$, where the superscript indexes the iteration number in the miniloop below (indexed by m). Now iterate on the mapping until $m = 50$,

$$\text{(S1)} \qquad \overline{P}^{m+1}(\boldsymbol{Y}) = E\left[\beta \frac{\Lambda(\boldsymbol{Y}')}{\Lambda(\boldsymbol{Y})}(D^0(\boldsymbol{Y}') + \overline{P}^m(\boldsymbol{Y}'))|\boldsymbol{Y}\right],$$

and set $P^{s,0}(\boldsymbol{Y}) = \overline{P}^{50}(\boldsymbol{Y})$.

Taking the initial conditions above and setting $j = 1$, start the iteration:

Step 1—Solve Each Agent's Dynamic Problem: This is a standard dynamic programming problem, so I omit a detailed description. Having said that, I should also note that this problem has one distinguishing feature: Epstein–Zin preferences. This feature actually makes the solution faster than with CRRA preferences. To see why, note that with CRRA utility and complete markets,[3] the value function has the same isoelastic form—and the same curvature—as the period utility function (cf. Samuelson (1969)). Consequently, when risk aversion is high the value function inherits the same high curvature, which then necessitates a large number of grid points in the financial

In this framework, markets are incomplete but deviations from linearity are not substantial except all lower wealth levels, so a small number of points together with a spline interpolation provides an accurate approximation.

[3]Complete markets are necessary to make human wealth tradeable.

wealth direction to obtain an accurate approximation during the value function iteration. In contrast, with the formulation of recursive preferences used in equation (S1), the value function becomes *linear* in financial wealth (cf. Epstein (1988)), which makes it extremely convenient to interpolate with far fewer grid points.[4] For example, using CRRA preferences with a risk aversion of 10, about 200 grid points were required for a sufficiently accurate approximation, whereas about 30 points were sufficient with the recursive preferences formulation.

Step 2—Update Equilibrium Functions:

(a) Solve the firm's investment problem as in (i) and (ii) in Step 0, using $c^{h,j}(\omega; \boldsymbol{Y})$ and $V^{h,j}(\omega; \boldsymbol{Y})$ obtained in Step 1 to construct the discount factor. Note also that $\varpi^{h\prime} = ((P^{s\prime} + D') - B')/\mu$.

(b) Obtain $D^j(\boldsymbol{Y})$ using $I^j(\boldsymbol{Y})$.

(c) Obtain $\Gamma_K^j(\boldsymbol{Y})$ using $I^j(\boldsymbol{Y})$: $K' = (1-\delta)K + \Phi(I^j/K)K$.

(d) Obtain $P^{s,j}(\boldsymbol{Y})$ using the updated consumption and dividend decision rules via the recursion (S1). Note that I set the initial condition $\overrightarrow{P}^0(\boldsymbol{Y}) = P^{s,j-1}(\boldsymbol{Y})$ in Step 0(b)(ii).

Step 3—Update the Bond Pricing Function: The method amounts to finding a bond price (at a given grid point $\boldsymbol{Y}_i$ in iteration j), which clears the bond market when both agents take $P^{f,j-1}(\boldsymbol{Y})$, and (the newly updated) $P^{s,j}(\boldsymbol{Y})$ to apply in all future periods (this approach follows Krusell and Smith (1997)).

Specifically, in iteration j, at each grid point for current state $\boldsymbol{Y}_i$, we want to find the new bond price $q^j(\boldsymbol{Y}_i)$ which clears the bond market today, when agents take $P^{f,j-1}(\boldsymbol{Y})$ to apply to all future dates. More specifically, first solve the following maximization problem for the stockholder and with $s' \equiv 0$ for the non-stockholder:

$$\max_{b',s'}\left((1-\beta)c^{1-\rho} + \beta\left(E[V(\omega'; \boldsymbol{Y}')^{1-\alpha}|\boldsymbol{Y}]\right)^{(1-\rho)/(1-\alpha)}\right)^{1/(1-\rho)}$$

s.t.

$$\begin{aligned}
&c + \widehat{q}b' + s' \le \omega + W(K, Z),\\
&\omega' = b' + s'(P^s(\boldsymbol{Y}') + D(\boldsymbol{Y}')),\\
&K' = \Gamma_K(\boldsymbol{Y}),\\
&B' = \Gamma_B(\boldsymbol{Y}),\\
&b' \ge \underline{B}.
\end{aligned}$$

[4]Of course, markets are incomplete in our environment, so the value function is not exactly linear. However, deviations from linearity are concentrated at the lower end of the wealth grid and, in any case, are far less severe than with CRRA utility, making recursive preferences still much more convenient to use.

Note that this is not a standard Bellman equation: agents treat the current period bond price as a parameter, $\widehat{q}$, but take future bond pricing function to be $P^{f,j-1}(\boldsymbol{Y})$. This problem will give rise to bond holding rules $\widetilde{b}^h(\omega; \boldsymbol{Y}, \widehat{q})$ and $\widetilde{b}^n(\omega; \boldsymbol{Y}, \widehat{q})$ as a function of the current bond price $\widehat{q}$. Then, at each grid point $\boldsymbol{Y}_i$, search over the bond price $\widehat{q}$ to find q_i^* such that the bond market clears:

$$|\mu\widetilde{b}^h(\omega; \boldsymbol{Y}, q_i^*) + (1-\mu)\widetilde{b}^n(\omega; \boldsymbol{Y}, q_i^*) - \chi\overline{K}/q_i^*| < 10^{-8}.$$

Then set $q^j(\boldsymbol{Y}_i) = q^*(\boldsymbol{Y}_i)$.

Trying to simultaneously clear both markets and update the stock price as well in this step creates instability in the algorithm and often fails to converge. Instead, the iterative method described here (updating $P^{s,j}$ from (S1) and $P^{f,j}$ from market clearing) works quite well in practice. At the end, I will also verify that the stock market clears: $\mu s' = 1$.

Step 4—Obtain $\Gamma_B^j(\boldsymbol{Y})$: $B' = (1-\mu)b^n(\varpi^n, \boldsymbol{Y})$, where b^n is the non-stockholders' bond choice at the market clearing bond price in Step 3 (and not the one obtained in Step 1).

Step 5—Iterate on Steps 1–4 until convergence. I require maximum percentage deviation in consecutive updates to be less than 10^{-6} for P^f, 10^{-4} for P^s, and 10^{-5} for aggregate laws of motion and market clearing conditions. Tightening these convergence criteria did not have any noticeable effect on the results. (That is, the statistics of interest reported in the paper stabilize once these discrepancies are below the stated tolerances and further iteration on Steps 1–4 does not change these results.) Finally, I also check $\mu s' = 1$ even though this condition was not explicitly imposed in updating the stock price. It holds very precisely (deviation less than 10^{-5}) at the solution.

Another point that should be kept in mind is that the convergence of the algorithm also depends on the particular choice of parameters. As a rough guideline, parameter choices that imply higher curvature in various functions (e.g., higher adjustment costs (lower ξ), higher risk aversion of stockholders, lower EIS of non-stockholders, large amounts of leverage, etc.) make it harder for the algorithm to converge successfully. In such cases, it is useful to start from an easier case (say, a lower risk aversion) and use the solution to this problem as the initial guess for the subsequent case which gradually increases the risk aversion toward the ultimate parametrization of interest.

The results reported in the paper are obtained by compiling these codes using the Absoft V10.1 compiler for Mac OSX with relatively aggressive optimization (-m64 -O3 -speed_math=8, autoparallel). On a MacPro Workstation with 8-core 3.2 GHz Xeon processors, it takes about 9 hours 15 minutes for the CONS model and 13 hours and 35 minutes for the GHH model without leverage to converge to the bounds specified above. With leverage, the required times are about 55 hours for the CONS model and about 65 hours for the GHH model.

TABLE SI

AUTOCORRELATION STRUCTURE OF THE MARKOV CHAIN APPROXIMATION

	Autocorrelation at Lag				
	1	2	3	4	5
AR(1)	0.976	0.953	0.929	0.907	0.885
Markov approximation	0.974	0.951	0.926	0.902	0.878

B. DISCRETIZING THE AR(1) PROCESS FOR Z

The discretization method understates the true persistence of the AR(1) process. Therefore, to get a first order autocorrelation of 0.976 at monthly frequency, we first simulate an AR(1) process with $\rho = 0.984$ for 100,000 periods. By applying Tauchen's (1986) method as described by Aiyagari (1993) using 15-state points, we obtain the desired transition matrix. Table SI shows that the generated Markov process provides a fairly accurate approximation.

C. EXTENSIONS AND DISCUSSIONS

C.1. *Rising Participation in the Stock Market*

Given the various implications of limited participation for asset prices presented in the paper, a natural question to ask is, "What are the implications of the rising participation in the stock market observed since the 1990s?" A complete answer to this question would require solving for the transition path during this period, which will add substantially to the already high computational demands of the model. However, some insights can be gained by comparing outcomes across stationary equilibria with different participation rates, keeping in mind the well-known caveats associated with drawing inference from such a comparison for transitions.

I solve the GHH model with μ set equal to 30%, corresponding to the high-participation economy.[5] In this case, the equity premium is lower—3.8% compared to 4.2% before—since aggregate risk is now shared among a larger group of households. It is also less volatile, which mitigates the fall in the Sharpe ratio: 0.22 versus 0.24 before. It is important to note that the 3.8% figure is the ex ante equity premium, that is, what investors expect to receive looking forward. Therefore, this lower ex ante premium in the new steady state

[5]Although the fraction of households who own any positive amount of equity has been around 50% in the United States since 2000, many of the new participants hold very small amounts of equity. The 30% figure is chosen to roughly correspond to the set of households who own 99% of all equity outstanding (including indirect holdings through defined contribution plans; see, for example, Poterba (2000)).

does not necessarily imply that the *realized* premium during the transition is low. To the contrary, because equity becomes a less risky asset with higher participation, its price rises (27.8 compared to 24.7 in the first steady state), which is likely to generate a higher realized equity premium along the transition due to capital gains. This would be consistent with the experience of the U.S. economy after the 1990s (with a booming stock market and high realized premium).[6] However, these results should be viewed as suggestive about the potential impact of rising participation on asset prices, because it is not clear how long such a transition would take given that the new participants are entering the stock market with a substantially lower wealth level than existing stockholders.

C.2. *Endogenizing the Heterogeneity in the EIS*

In the paper, heterogeneity in the EIS is assumed as an exogenously given characteristic of stockholders and non-stockholders. Here, I show how this heterogeneity can be generated endogenously. To this end, assume that both agents have identical expected utility functions that feature "benchmark consumption levels": $u^i = (c^i - a\overline{C})^{1-\rho}/(1-\rho)$, where $\overline{C}$ is the aggregate consumption in a given period, which is taken to be exogenous by individuals. Because these preferences are nonhomothetic, the EIS of an individual endogenously rises with his consumption and, therefore, with his wealth level. But note that wealth inequality in this framework is mainly due to limited participation and is quite robust to changes in the curvature of the utility of both agents (see Guvenen (2006) for a detailed analysis of this point). Therefore, with these new preferences, stockholders continue to be much wealthier and, consequently, to consume more than non-stockholders, endogenously generating the same kind of heterogeneity in the EIS assumed exogenously in the main framework above.

I solve the model with these preferences, and set $\rho = 3$ and $a = 0.6$. When aggregate consumption is normalized to 1, the per capita consumption in this model is 1.55 for stockholders and 0.89 for non-stockholders, which generates $\text{eis}^h \approx \rho c^h/(c^h - a\overline{C}) = 0.21$ and $\text{eis}^n \approx 0.11$ (and stockholders are much wealthier than non-stockholders—holding 91% of aggregate wealth in the economy—as conjectured above). We set the stockholders' EIS to a lower value than in the baseline calibration so as not to generate a risk aversion that is too low: with this utility function, it is approximately equal to $1/\text{eis}^h \approx 4.77$. The resulting equity premium is 5.1% and the Sharpe ratio is 0.23. The volatility of the interest rate is 7.1%. One notable difference from before is seen in the dynamics of asset prices where the countercyclicality of the Sharpe ratio and equity premium become stronger (correlation with output is −0.82 and

[6]In addition, $E(R^f) = 1.65\%$, $\sigma(R^f) = 6.41\%$, $\sigma(\log(P^s/D)) = 23.5\%$, and $\sigma(\Delta \log(D)) = 13.1\%$.

TABLE SII

COUNTERPART OF FIGURE 2: CYCLICAL BEHAVIOR OF CONDITIONAL MOMENTS OF EQUITY PREMIUM

	Cross-Correlation With Output		
Case:	$E_t(R^s_{t+1} - R^f_t)$	$\sigma_t(R^s_{t+1} - R^f_t)$	$\frac{E_t(R^s_{t+1} - R^f_t)}{\sigma_t(R^s_{t+1} - R^f_t)}$
1	−0.36	−0.20	−0.32
2	−0.62	−0.51	−0.55
3	−0.21	−0.26	−0.19
4	−0.51	−0.58	−0.40
5	−0.47	−0.52	−0.36
6	−0.82	−0.40	−0.91

−0.90, respectively), which is due to the fact that now the risk aversion of both agents changes over the business cycle in a countercyclical fashion.[7]

D. TABLES FOR THE EXTENSIONS DISCUSSED IN THE MAIN TEXT

Tables SIII–SV report the full set of statistics regarding asset price dynamics and business cycle behavior for six different parametrizations introduced as extensions in the main text. Each of the cases referred to in the tables is explained below. The paper contains more detailed descriptions of the calibration for each of these cases. The main text reports the results on asset price dynamics for the GHH model. The counterparts for the CONS and CD models are reported as Cases 1 and 2.

CASE 1: Baseline CONS model (referenced in text footnote 14).

CASE 2: Baseline CD model (referenced in text footnote 14).

CASE 3: CONS model with tight borrowing constraints (referenced in text footnote 6; no leverage; both agents' borrowing limit is set to 1 month's labor income).

CASE 4: CONS model with high risk aversion for non-stockholders ($\text{RRA}^h = 12$; Table II, fifth column; referenced in text footnote 12).

CASE 5: GHH model with high participation rate: $\mu = 0.30$ (Section C.1 above).

CASE 6: Endogenous heterogeneity in the EIS (introduced in text footnote 7 and Section C.2 above).

[7]Other statistics are $E(R^f) = 1.45\%$, $E(\log(P^s/D)) = 26.8$, $\sigma(\log(P^s/D)) = 24.8$, and $\sigma(\log(P^s/D)) = 27.5$. The results on asset price dynamics for the parametrizations in this section are reported in Section D below.

TABLE SIII

COUNTERPART OF TABLE IV: AUTOCORRELATION STRUCTURE OF KEY FINANCIAL VARIABLES

	Lag (Years)				
	1	2	3	5	7
	Autocorrelation				
$r^s - r^f$					
Case 1	−0.02	−0.01	−0.01	−0.02	−0.02
Case 2	−0.02	−0.01	−0.01	−0.02	−0.02
Case 3	−0.02	−0.00	−0.01	−0.01	−0.02
Case 4	−0.03	−0.03	−0.02	−0.02	−0.01
Case 5	−0.02	−0.00	−0.01	−0.01	−0.02
Case 6	−0.03	−0.03	−0.02	−0.02	−0.01
$\sum_{i=1}^{j} \rho[(r^s - r^f)_t, (r^s - r^f)_{t-i}]$					
Case 1	−0.02	−0.03	−0.04	−0.07	−0.10
Case 2	−0.02	−0.03	−0.04	−0.07	−0.09
Case 3	−0.02	−0.02	−0.03	−0.05	−0.08
Case 4	−0.03	−0.06	−0.08	−0.12	−0.14
Case 5	−0.02	−0.02	−0.03	−0.05	−0.08
Case 6	−0.03	−0.06	−0.08	−0.14	−0.17

TABLE SIV

COUNTERPART OF TABLE V: LONG-HORIZON REGRESSIONS ON PRICE–DIVIDEND RATIO

	R^2 Values					
Horizon (k) Case:	1	2	3	4	5	6
	A. Stock Returns					
1	0.13	0.09	0.10	0.09	0.10	0.07
3	0.23	0.22	0.18	0.21	0.22	0.18
5	0.31	0.26	0.25	0.28	0.30	0.23
7	0.35	0.32	0.30	0.34	0.35	0.27
	B. Excess Returns					
1	0.03	0.01	0.03	0.02	0.03	0.01
3	0.06	0.04	0.05	0.06	0.06	0.05
5	0.10	0.08	0.09	0.10	0.11	0.08
7	0.12	0.11	0.10	0.12	0.13	0.11

TABLE SV

COUNTERPART OF TABLE VII: BUSINESS CYCLE STATISTICS

	Case					
	1	2[a]	3	4	5	6
			Volatilities			
$\sigma(Y)$	1.92	1.97	1.94	1.94	1.93	1.90
$\sigma(C)/\sigma(Y)$	0.80	0.92	0.89	0.79	0.82	0.78
$\sigma(I)/\sigma(Y)$	1.96	1.38	1.55	1.98	1.65	1.98
$\sigma(L)/\sigma(Y)$	0.0	0.07	0.0	0.0	0.48	0.0
			Cross-Correlation With Output			
$\rho(Y, C)$	0.99	0.99	0.99	0.99	0.99	0.98
$\rho(Y, I)$	0.99	0.99	0.99	0.99	0.95	0.99
$\rho(Y, L)$	0.0	0.96	0.0	0.0	0.99	0.0

[a] The business cycle statistics for Case 2 have already been reported in the paper (Table VII, third column) and are simply repeated here for completeness. The model statistics are computed after simulated data have been aggregated to quarterly frequency, logged, and then HP filtered.

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Manuscript received August, 2006; final revision received August, 2009.