

HETEROGENEOUS BELIEFS AND TESTS OF PRESENT VALUE MODELS

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ABSTRACT. This paper develops a dynamic asset pricing model with persistent heterogeneous beliefs. The model features competitive traders who receive idiosyncratic signals about an underlying fundamentals process. We adapt Futia's (1981) frequency domain methods to derive conditions on the fundamentals that guarantee noninvertibility of the mapping between observed market data and the underlying shocks to agents' information sets. When these conditions are satisfied, agents must 'forecast the forecasts of others'. The paper provides an explicit analytical characterization of the resulting higher-order belief dynamics. These additional dynamics can account for observed violations of variance bounds, predictability of excess returns, and rejections of cross-equation restrictions.

JEL Classification Numbers: G12, D82

1. INTRODUCTION

The standard present value model has a difficult time explaining several features of observed asset prices. From the perspective of this model, prices seem to be excessively volatile. Excess returns seem to be predictable. The model's cross-equation restrictions are typically rejected as well. As a result, linear present value models have all but disappeared from serious academic research on asset pricing.¹ Instead, attention has shifted to models with time-varying risk premia. Unfortunately, these models offer little improvement empirically, although Constantinides and Duffie (1996) achieve some success by introducing heterogeneity, in the form of nondiversifiable labor income risk.

Date: January, 2010.

We would like to thank Tim Cogley, Martin Evans, Ron Michener, Bart Taub, Pierre-Olivier Weill and seminar participants at NYU, the Federal Reserve Board, UC Berkeley, UC Davis, UC Santa Cruz, Indiana University, VPI, UNC, and the Atlanta Fed for helpful discussions. Support from the National Science Foundation under grant SES85-10505 is gratefully acknowledged. This paper subsumes and extends Walker and Whiteman's *Equilibrium Volatility and Heterogeneity in a Simple Asset Pricing Model* and Kasa's *Asset Pricing with Heterogeneous Beliefs: A Frequency Domain Approach*.

¹Cochrane (2001) discusses the empirical failings of constant discount rate models. He argues that many of these apparently distinct anomalies are manifestations of the same underlying problem; namely, misspecification of the discount rate. He also points out that the same problems show up in all asset markets, e.g., stocks, bonds, foreign exchange, real estate, etc.

Our paper returns to the linear constant discount rate setting, and argues that *informational* heterogeneity can account for many of the model's apparent empirical shortcomings. In particular, we make two simple changes to the standard present value model: (1) We assume some fundamentals are unobserved by *all* speculative traders. Although the variance of these unobserved fundamentals can be arbitrarily small, some noise is needed to avoid the no trade theorems of Milgrom and Stokey (1982) and Tirole (1982). (2) More importantly, we assume speculative traders are heterogeneously informed about the observable fundamentals. Specifically, we assume observed fundamentals consist of a sum of orthogonal components, and that in addition to observing the sum, each trader observes realizations of one of the underlying components. We think this as a natural information structure. For example, all traders no doubt observe current earnings or dividends, but at the same time they are likely to have heterogeneous information about their underlying determinants.

We show that under certain conditions traders are unable to infer the realizations of the other components of fundamentals. Instead, they are only able to infer a weighted average of them. These weighted averages encode each trader's forecast of other traders' forecasts (Townsend (1983)). Our paper provides an explicit analytical characterization of the resulting higher-order belief dynamics. We show these additional dynamics play a crucial role in observed asset prices.

Of course, this is not the first paper to study asymmetric information in asset markets, nor is it the first to study higher-order beliefs.² However, our paper *is* the first to combine several key ingredients. First, our model is *dynamic*. It features *persistent* heterogeneous beliefs, and a *stationary* equilibrium. Following Grossman and Stiglitz (1980), most work on asset pricing with asymmetric information is confined to static, or nonstationary finite-horizon models. Although this is a useful abstraction for some theoretical questions, it is obviously problematic for empirical applications. Although there has been some work devoted to dynamic extensions of the Grossman-Stiglitz framework (see, e.g., Wang (1993)), this literature postulates hierarchical information structures, with 'informed' and 'uninformed' traders. Again, this assumption has its uses, but from our perspective it 'throws the baby out with the bath water', since it eliminates the forecasting the forecasts of others problem (Townsend (1983)). Our model postulates a more natural symmetric information structure.

Second, our approach features *signal extraction from endogenous prices*. This distinguishes our work from most work on global games and imperfect common knowledge (Morris and Shin (1998, 2003)). Although this literature has made important contributions to our understanding of higher-order beliefs, it is not directly applicable to asset pricing, since it abstracts from asset markets. As Atkeson (2000) notes,

²See Brunnermeier (2001) for an overview of the existing literature.

prices play an important role in aggregating information, and it remains to be seen how robust the work on global games is to the inclusion of asset markets.³

Third, our approach delivers an *analytical solution*, with explicit closed-form expressions for the model's higher-order belief dynamics. Although this may seem like a minor contribution given the power of computation these days, it turns out that analytical solutions are extremely useful in models featuring an infinite regress of higher-order beliefs. Numerical methods in this setting are fraught with dangers. In particular, they require prior knowledge of the relevant state. As first noted by Townsend (1983), it is not at all clear what the state is when agents forecast the forecasts of others. Townsend argued that the logic of infinite regress produces an infinite-dimensional state. He short-circuited the infinite regress and obtained a tractable numerical solution by assuming that information becomes common knowledge after a (small) number of periods. This truncation strategy has been refined by a number of subsequent researchers (see, e.g., Singleton (1987), Bacchetta and van Wincoop (2006, 2008), and Nimark (2007)). However, recent work by Pearlman and Sargent (2005) and Walker (2007) demonstrates that numerical approaches can be misleading. Pearlman and Sargent, employing a clever 'guess and verify' strategy based on the incorporation of lagged forecast errors in the state, show that one of Townsend's models in fact produces an equilibrium that is fully revealing, and that its higher-order belief dynamics are a numerical artifact. Walker (2007) does the same thing for Singleton's asset pricing version of Townsend's model. Using the same approach as this paper, he obtains an analytical solution *without* truncation, and shows that the equilibrium is in fact fully revealing.

Our approach adapts and extends the frequency domain methods of Futia (1981). These methods exploit the power of the Riesz-Fischer Theorem. This theorem allows us to transform a difficult time-domain/sequence-space signal extraction problem into a much easier function space problem. Rather than guess a state vector and then solve a Kalman filter's Riccati equation, a frequency domain approach leads to the construction of so-called Blaschke factors. Finding these Blaschke factors is the key to solving an agent's signal extraction problem.⁴ In general, finding Blaschke factors is no easier than solving Riccati equations. However, a key innovation in our approach is to work *backwards* from postulated Blaschke factors to the supporting set of fundamentals. This reverse engineering strategy allows us to isolate necessary conditions for the existence of a heterogeneous beliefs equilibrium. The advantages gained from knowing these conditions cannot be overestimated. For example, recent work by Makarov and Rytchkov (2008) also applies frequency domain methods to a

³Recent work by Angeletos and Werning (2006) incorporates signal extraction from prices into the Morris-Shin framework. However, their model is essentially static. Moreover, their informational assumptions preclude even the possibility that prices could be fully revealing. In contrast, our work focuses on the conditions required for a non-revealing equilibrium.

⁴Kasa (2000) uses frequency domain methods to solve Townsend's model. He comes to the same conclusion as Pearlman and Sargent (2005).

linear present value asset pricing model. In contrast to our approach, they begin by postulating a time series process for fundamentals, and then search for an equilibrium price process. Interestingly, they argue that a finite-state equilibrium does not exist. However, their fundamentals specification does not satisfy our existence condition, which perhaps explains why they are unable to find a finite-state equilibrium.

Besides Makarov and Rytchkov (2008), the only other papers we are aware of that apply frequency domain methods to asset pricing are Bernhardt, Seiler, and Taub (2009) and Rondina and Walker (2009). Bernhardt et. al. (2009) also study a dynamic infinite-horizon model with symmetric, heterogeneously informed traders. However, their work differs from ours in two important respects. First, following Kyle (1985), they focus on the strategic use of information when individual traders influence asset prices, which are set in a competitive dealership market. In contrast, our model is Walrasian. Second, the added complexity of their model requires numerical methods. This gives rise to the above noted difficulties associated with guessing correct functional forms and appropriate state vectors. It also makes it difficult to distinguish higher-order belief dynamics from the strategic use of private information. In terms of methodology, the recent work of Rondina and Walker (2009) is perhaps closest to our paper. Building on the results of our paper, they relate higher-order belief dynamics to the Hansen-Sargent prediction formula, and show explicitly how these dynamics represent deviations from the law of iterated expectations. However, they confine their attention to a one-shock, stochastically singular model, with no commonly observed fundamentals. Hence, their results cannot be taken to the data in any meaningful way.

Our model's solution takes the form of a nonfundamental (i.e., noninvertible) moving-average representation, mapping the underlying shocks to agents' information sets to observed prices and fundamentals. Blaschke factors convert this to a Wold representation. The (statistical) innovations of the Wold representation turn out to be complicated moving averages of the entire histories of the underlying (economic) shocks. These moving averages encode the model's higher-order belief dynamics. An important contribution of our approach is that this equilibrium representation can be taken to the data in a direct, *quantitative* way. In contrast, existing work on higher-order beliefs is purely qualitative. This allows us to revisit past empirical failures of linear present value asset pricing models. We ask the following question - Suppose asset markets feature heterogeneous beliefs, but an econometrician mistakenly assumes agents have homogeneous beliefs. What will he conclude? One might think, based on the conditioning down arguments of Hansen and Sargent (1991a) and Campbell and Shiller (1987), that this would not create any problems. Interestingly, this is not the case. Conditioning down does not work here. The arguments of Hansen-Sargent and Campbell-Shiller apply to settings where agents and *econometricians* have different information sets. They do *not* apply in general to settings where there is informational heterogeneity among the agents themselves. This is because

the law of iterated expectations does not apply to the average beliefs operator (Allen, Morris, and Shin (2006), Morris and Shin (2003)). We show that present value models with heterogeneous beliefs generate predictable excess returns, produce violations of variance bound inequalities, and rejections of cross-equation restrictions. Hence, our paper sounds a note of caution when interpreting previous rejections of present value models. Perhaps it is not the constant discount rate that is the problem, but rather the (usually implicit) assumption of homogeneous beliefs, or equivalently, a fully revealing equilibrium.

The remainder of the paper is organized as follows. The next section outlines the model. Section 3 shows how to construct a nonrevealing equilibrium, and uses it to derive the model's higher-order belief dynamics. Section 4 adopts the perspective of an outside econometrician, and addresses the model's empirical implications. Using updated data from Shiller (1989) on the U.S. stock market, we show that many of the empirical shortcomings documented by Shiller can be accounted for by higher-order belief dynamics, as opposed to fads or 'market psychology'. In fact, we argue that *rational* higher-order belief dynamics could well be mistaken for fads or irrational expectations. Finally, Section 5 concludes by discussing some extensions and applications.

2. THE MODEL

Consider the following linear present value model

$$p_t = \beta \int_0^1 E_t^i p_{t+1} di + f_t + u_t \quad (2.1)$$

where p_t represents the price of an asset (e.g., an equity price or an exchange rate), f_t represents a (commonly) observed fundamental (e.g., dividends or the money supply), and u_t represents the influence of unobserved fundamentals (e.g., noise or liquidity traders). The parameter, $\beta < 1$, represents a constant discount factor. The model in (2.1) is entirely standard, with two key exceptions. The first is the presence of the noise term, u_t . Since ultimately we are going to focus on nonrevealing, heterogeneous beliefs equilibria, it is important that some noise be present to sustain trade. (Milgrom and Stokey (1982), Tirole (1982))⁵. The second key difference is that expectations in (2.1) are indexed by traders, to acknowledge the possibility that beliefs may differ in equilibrium.

What gives rise to these heterogeneous beliefs? One possibility is heterogeneous priors (Harrison and Kreps (1978)). Besides posing awkward questions about the

⁵Although noisy rational expectations models have a long history in finance and macroeconomics, prior applications assume *homogeneous* beliefs. Whiteman (1983) uses frequency domain methods to characterize the solutions of equation (2.1) in the case of homogeneous expectations. He refers to models of the form (2.1) as 'perturbed equations'. Hansen and Sargent (1991a) refer to them as 'inexact' rational expectations models.

source of this heterogeneity, another problem with this approach is that it generates nonstationary equilibria, in which belief heterogeneity dissipates over time (Morris (1996)). In response, we instead suppose that belief heterogeneity arises from, and is sustained by, an exogenous ongoing process of heterogeneous information. The idea is that each period, as part of their normal routine, investors acquire information about some aspect of an asset's underlying observed fundamentals. To make the analysis as simple as possible, we suppose there are just two types of traders, Type 1 and Type 2, and that observed fundamentals are driven by the exogenous process:

$$f_t = a_1(L)\varepsilon_{1t} + a_2(L)\varepsilon_{2t} \quad (2.2)$$

where $a_1(L)$ and $a_2(L)$ are square-summable polynomials in the lag operator L . The innovations, ε_{1t} and ε_{2t} , are zero mean Gaussian random variables, and are assumed to be uncorrelated. Each period both traders observe p_t and f_t . However, in addition, Type 1 traders observe realizations of ε_{1t} , while Type 2 traders observe realizations of ε_{2t} . Both the model and the information structure are common knowledge. Besides (2.2), specification of the information structure also requires assumptions about the noise process, u_t . Although neither trader observes u_t , both its existence and its law of motion are common knowledge.⁶ Again to keep things simple, we suppose u_t is i.i.d., and is driven by:

$$u_t = b_1\varepsilon_{1t} + b_2\varepsilon_{2t} + v_t \quad (2.3)$$

where v_t is a zero mean, i.i.d. Gaussian random variable that is uncorrelated with both ε_{1t} and ε_{2t} . Notice that in general the noise process, u_t , can be correlated with the observable component of fundamentals, f_t .

It is important to keep in mind that both traders behave in a competitive, price-taking manner. By assumption, their only task each period is to forecast next period's price. We assume they do this in a statistically optimal way, given their information. In contrast to the global games literature, there is no *explicit* effort here to infer other agents' forecasts. In a Walrasian environment like this, there is no need to, since nothing you do can influence the expectations of others. However, and this is the crucial point, since traders use the current *endogenously* determined price as a basis for their own individual forecasts, and this price depends on other agents' forecasts, there is a sense in which each trader's optimal forecast does embody a forecast of other traders' forecasts, but these forecasts are simply a by-product of each agent's own atomistic efforts to forecast prices.

⁶Engel and West (2005) argue that noise, or unobserved fundamentals, appear to be necessary to reconcile present value models with observed exchange rates. Hamilton and Whiteman (1985) argue that the mere possibility of unobserved fundamentals vitiates standard bubbles tests. Our results suggest that it is the *interaction* between unobserved fundamentals and heterogeneous information about observed fundamentals that is critical to the success of present value models.

A key aspect of the environment here is that it is both stationary and linear. As a result, we can employ the tools of Wiener-Kolmogorov prediction theory to solve each trader's forecasting problem. The first step in doing this is to derive the mapping between what he observes and the underlying shocks driving the system. The symmetry between the agents, along with the orthogonality between ε_{1t} and ε_{2t} , implies that we can focus on the problem of a single trader, say Type 1. Given the solution to Type 1's problem, we can infer the solution to Type 2's via symmetry. For Type 1 traders, the mapping between observables and the underlying shocks takes the following form,

$$\begin{bmatrix} \varepsilon_{1t} \\ f_t \\ p_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ a_1(L) & a_2(L) & 0 \\ \pi_1(L) & \pi_2(L) & \pi_3(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ v_t \end{bmatrix} \quad (2.4)$$

where the $\pi_i(L)$ polynomials are equilibrium pricing functions. Each trader knows these functions when forecasting next period's price. Of course, these pricing functions depend on the forecasts via the equilibrium condition (2.1), so we have a fixed point problem. Traditionally, this fixed point problem is resolved in one of two ways. First, one may pursue a 'guess and verify' strategy. That is, posit functional forms for the $\pi_i(L)$ functions, use them to solve the agents' prediction problems, plug the predictions into the equilibrium condition, and then match coefficients. This approach works well when the relevant state is clear (and low dimensional). Unfortunately, in dynamic settings with potentially heterogeneous beliefs, it is not at all clear what the state is, or equivalently, what forms the $\pi_i(L)$ functions should take. What we are really searching for is an unknown *function* which, absent prior information, lies in an infinite dimensional space. Kasa (2000) shows that this infinite dimensional fixed point problem can be solved using frequency domain methods, and that will be the approach we pursue here.

Before doing that, however, it might be worth considering the second strategy that is commonly employed when solving this kind of fixed point problem. Rather than guessing an unknown pricing function, and using it to forecast next period's price, an alternative strategy is to iterate equation (2.1) forward. With homogeneous beliefs, this strategy is quite powerful as it produces an expression for the current price as a single conditional expectation of the discounted sum of future fundamentals, which can then be solved, for example, using the Hansen-Sargent prediction formula. No guessing and verifying is required. What makes this work is the law of iterated expectations. Unfortunately, as noted earlier, the law of iterated expectations does not apply when there are heterogeneous expectations. Still, one could in principle

approach the problem via iteration.⁷ To do this, define

$$\bar{\mathbb{E}}_t^0 f_{t+1} = \int_0^1 E[f_{t+1} | \Omega_t^i] di$$

where Ω_t^i denotes agent- i 's information set, and then analogously define

$$\bar{\mathbb{E}}_t^k f_{t+k+1} = \bar{\mathbb{E}}_t \bar{\mathbb{E}}_{t+1} \cdots \bar{\mathbb{E}}_{t+k} f_{t+k+1}$$

as the k -fold iteration of these averaged expectations. Using this notation we can then write the equilibrium condition in (2.1) as

$$p_t = f_t + u_t + \beta \sum_{k=0}^{\infty} \beta^k \bar{\mathbb{E}}_t^k (f_{t+k+1} + u_{t+k+1}) \quad (2.5)$$

The problem here is that $\bar{\mathbb{E}}_t^k$ depends on the information conveyed by p_t , but p_t in turn depends on the entire infinite sequence of $\bar{\mathbb{E}}_t^k$. Hence, we are back to an infinite dimensional fixed point problem. Existing approaches either approximate the solution of this infinite dimensional problem (e.g., Nimark (2007), Bernhardt, Seiler, and Taub (2009)) or effectively truncate it by supposing that all relevant information becomes common knowledge after a certain lag (e.g., Townsend (1983), Singleton (1987), Bacchetta and van Wincoop (2006, 2008)). In the next section we show how to tackle this problem head on by using frequency domain methods.

3. CONSTRUCTING A NONREVEALING EQUILIBRIUM

A frequency domain approach is useful here for two reasons. First, as noted above, we have to solve an infinite dimensional fixed point problem. Without prior knowledge of the functional forms of the equilibrium prices, we must be prepared to match an infinite number of unknown coefficients. By transforming the problem to the frequency domain we can convert this to the problem of finding a single analytic *function*, which via the Riesz-Fischer Theorem, is equivalent to the unknown coefficient sequence.⁸ Second, and related to this, the underlying source of our infinite dimensional fixed point problem is that we are attempting to calculate an *informational* fixed point. In particular, we must somehow guarantee that traders are unable to infer the private information of other traders via the *infinite history* of observed market data. This is a difficult problem to even formulate in the time domain. In contrast, handling this problem in the frequency domain is straightforward, as the information revealing properties of analytic functions are completely characterized by the locations of their zeros. Zeros inside the unit circle correspond to noninvertible moving average representations and unobservable shocks.⁹

⁷Bacchetta and van Wincoop (2008) adopt this approach.

⁸The Appendix provides a brief discussion of this theorem and its implications. See Whiteman (1983) for a more detailed discussion.

⁹This point has been emphasized in particular in the work of Bart Taub. See, e.g., Taub (1990).

3.1. The Signal Extraction Problem. In our model each trader observes a *vector* of new information each period, as summarized by (2.4), so noninvertibility relates to the zeros of the determinant of a matrix. In particular, write (2.4) as $\mathbf{x}_{1t} = \mathbf{M}_1(L)\boldsymbol{\varepsilon}_{1t}$. If $\det \mathbf{M}_1(L)$ has all its zeros outside the unit circle, then $\mathbf{M}_1(L)$ possesses a one-sided inverse in positive powers of L . In this case, the observed history of \mathbf{x}_t would reveal $\boldsymbol{\varepsilon}_{1t}$ to Type 1 traders, and therefore, they would be able to infer the private information of Type 2 traders, $\boldsymbol{\varepsilon}_{2t}$.

Letting $\mathbf{M}_1(z)$ denote the z -transform of $\mathbf{M}_1(L)$, one can readily verify from (2.4) that

$$\det \mathbf{M}_1(z) = a_2(z)\pi_3(z)$$

Analogously, one can easily verify that the observer system for Type 2 traders implies $\det \mathbf{M}_2(z) = a_1(z)\pi_3(z)$. Hence, a sufficient condition for neither trader to be able to infer the other trader's private information is if $\pi_3(z)$ turns out to have a zero inside the unit circle (while at the same time neither $a_i(z)$ possesses a corresponding pole). It turns out, however, to be more natural and convenient to suppose that noninvertibility stems from noninvertible roots in the $a_i(z)$ functions. At the same time, it proves to be convenient to suppose that these roots are identical, and that they are inherited by the equilibrium pricing functions. To summarize, we assume the following,

Assumption 3.1. *The analytic functions $a_1(z)$ and $a_2(z)$ have a single, identical root inside the unit circle. This common root is shared by the equilibrium pricing functions, $\pi_1(z)$ and $\pi_2(z)$. At the same time, the pricing component, $\pi_3(z)$, has no zeros inside the unit circle.*

These assumptions are more restrictive than necessary. Their main purpose is to simplify the mathematics. As long as $\det \mathbf{M}_1(L)$ and $\det \mathbf{M}_2(L)$ remain noninvertible, all the paper's substantive conclusions would survive.

Note that this assumption imposes restrictions on the *endogenous* functions $\pi_1(z)$ and $\pi_2(z)$. It is for this reason that we pursue a reverse engineering, or back-solving, strategy. Ensuring that Assumption 3.1 is satisfied imposes restrictions on the observed fundamentals, f_t . Constructing a nonrevealing equilibrium involves deriving these restrictions. Fortunately, as we shall see, these restrictions can be interpreted as merely imposing a scaling, or relative variance factor.

Assumption 3.1 allows us to easily derive the Wold representation of each trader's observer system. First write $a_i(z)$ and $\pi_i(z)$ as $(z - \lambda)\tilde{a}_i(z)$ and $(z - \lambda)\tilde{\pi}_i(z)$, where $\tilde{a}_i(z)$ and $\tilde{\pi}_i(z)$ are analytic functions with all roots outside the unit circle, and $|\lambda| < 1$ represents the common noninvertible root of the pricing and fundamentals processes. Applying the methods of Rozanov (1967) and Hansen and Sargent (1991b) then

delivers the following Wold representation for Type 1 traders

$$\begin{bmatrix} \varepsilon_{1t} \\ f_t \\ p_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ (L - \lambda)\tilde{a}_1(L) & (1 - \lambda L)\tilde{a}_2(L) & 0 \\ (L - \lambda)\tilde{\pi}_1(L) & (1 - \lambda L)\tilde{\pi}_2(L) & \pi_3(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \epsilon_{2t} \\ v_t \end{bmatrix} \quad (3.1)$$

where $\epsilon_{2t} = [(L - \lambda)/(1 - \lambda L)]\varepsilon_{2t}$. Write this system as $\mathbf{x}_{1t} = \mathbf{M}_1^*(L)\boldsymbol{\varepsilon}_{1t}^*$. Note that $\det \mathbf{M}_1^*(L) = (1 - \lambda L)\tilde{a}_2(L)\pi_3(L)$. Hence, we have effectively ‘flipped’ the root inside the unit circle, λ , to λ^{-1} , which is outside the unit circle. The key point here is that Type 1 traders are unable to use the observed history of \mathbf{x}_{1t} to infer realizations of Type 2 traders’ private information, ε_{2t} . The best they can do is estimate the moving average defined by ϵ_{2t} . The lag polynomial $(L - \lambda)/(1 - \lambda L)$, which relates ϵ_{2t} to ε_{2t} is an example of a ‘Blaschke factor’. It compactly summarizes Type 1’s best efforts to use Type 2’s information to forecast future prices and fundamentals. Although it may appear as if ϵ_{2t} is autocorrelated, one can easily show that it is in fact an i.i.d. innovation sequence.

Given (3.1), Type 1’s optimal forecast of $\mathbf{x}_{1,t+1}$ is a straightforward application of the Wiener-Kolmogorov prediction formula

$$\begin{aligned} E_t^1 \mathbf{x}_{1,t+1} &= \left[\frac{\mathbf{M}_1^*(L)}{L} \right]_+ \boldsymbol{\varepsilon}_{1t}^* \\ &= L^{-1} [\mathbf{M}_1^*(L) - \mathbf{M}_1(0)^*] \boldsymbol{\varepsilon}_{1t}^* \end{aligned} \quad (3.2)$$

A completely symmetrical expression characterizes Type 2’s forecast, with the crucial difference that the unobservable shock is now ε_{1t} . Using (3.2) and its Type 2 analog, yields the following expressions for the optimal price forecasts

$$E_t^1 p_{t+1} = L^{-1} \{ [(L - \lambda)\tilde{\pi}_1(L) + \lambda\tilde{\pi}_1(0)]\varepsilon_{1t} + [(1 - \lambda L)\tilde{\pi}_2(L) - \tilde{\pi}_2(0)]\epsilon_{2t} + [\pi_3(L) - \pi_3(0)]\varepsilon_{3t} \} \quad (3.3)$$

$$E_t^2 p_{t+1} = L^{-1} \{ [(1 - \lambda L)\tilde{\pi}_1(L) - \tilde{\pi}_1(0)]\epsilon_{1t} + [(L - \lambda)\tilde{\pi}_2(L) + \lambda\tilde{\pi}_2(0)]\varepsilon_{2t} + [\pi_3(L) - \pi_3(0)]\varepsilon_{3t} \} \quad (3.4)$$

As noted earlier, symmetry between the traders and the orthogonality between ε_{1t} and ε_{2t} allows us to focus on just one of the components. In what follows, let E_t^{i,ε_1} denote Type- i ’s projection onto the time- t history of ε_1 . If we further parameterize the unknown pricing functions as

$$\tilde{\pi}_i(L) = \rho_i + Lg_i(L) \quad (3.5)$$

we then have

$$E_t^{1,\varepsilon_1} p_{t+1} = [\rho_1 + (L - \lambda)g_1(L)]\varepsilon_{1t} \quad (3.6)$$

$$E_t^{2,\varepsilon_1} p_{t+1} = \left[\rho_1 + (L - \lambda)g_1(L) - \frac{\rho_1(1 - \lambda^2)}{1 - \lambda L} \right] \varepsilon_{1t} \quad (3.7)$$

where we have used Type 2’s Blaschke factor, $\epsilon_{1t} = [(L - \lambda)/(1 - \lambda L)]\varepsilon_{1t}$, to substitute out ϵ_{1t} in Type 2’s forecast function.

Equations (3.6) and (3.7) show explicitly how the forecasts of the two traders differ as a function of the entire history of past realizations of ε_{1t} . By combining these with the analogous expressions for the ε_{2t} projections, we obtain the following key result.

Proposition 3.2. *If ρ_1 and ρ_2 are negative, then traders respond more aggressively to realizations of other traders' (unobserved) signals.*

Proof. This can be seen by differencing (3.6) and (3.7),

$$E_t^1 p_{t+1} - E_t^2 p_{t+1} = \frac{1 - \lambda^2}{1 - \lambda L} (\rho_1 \varepsilon_{1t} - \rho_2 \varepsilon_{2t}). \quad (3.8)$$

□

At each point in time, forecasts of the two traders differ as a function of the infinite histories of their observed signals. If the equilibrium ρ_i parameters are negative, then the trader who has received higher signals (on average) will forecast *lower* prices. We shall see that ρ_i will be negative when the b_i coefficients in (2.3) are positive, i.e., when noise is positively correlated with observable fundamentals. The intuition here is simple - when noise and observable fundamentals affect prices in the same way, price increases due to noise, for example, are partly attributed to other traders having good news about observable fundamentals. Thus, traders 'overreact' to realizations of other traders' (unobserved) signals. In other words, since information about other traders' signals is only obtainable by observing prices and commonly observed fundamentals, Proposition 3.2 yields the well known result that agents overreact to public signals (Allen, Morris, and Shin (2006)). We shall see that this overreaction to public signals can generate apparent violations of variance bounds.

3.2. The Fixed Point Problem. From a technical standpoint, our paper makes two main contributions. The first is the use of Blaschke factors to solve the traders' otherwise difficult signal extraction problems, as summarized by equations (3.3) and (3.4) in the previous subsection. The second is to adopt a back-solving strategy to simplify the construction of a nonrevealing Rational Expectations equilibrium. It is to this task that we now turn.

The sense in which we are working backwards is that we *presume* the equilibrium pricing functions, $\pi_i(L)$, inherit a noninvertible root, λ , from the unobserved components of the fundamentals process, f_t . Clearly, this will not be the case for arbitrary specifications of f_t . Instead, specification of λ imposes a restriction on the fundamentals. In particular, we must make the following assumption

Assumption 3.3. *For any given value of $|\lambda| < 1$, the components of the observable fundamentals satisfy the restrictions*

$$\beta \tilde{a}_i(\beta) + b_i \frac{2 - \lambda\beta}{1 - \lambda\beta} = 0 \quad i = 1, 2$$

Although it won't be clear where this assumption comes from until we write down the fixed point problem, it should be clear at this point that Assumption 3.3 merely imposes a scaling, or relative variance, factor on the f_t process. For example, suppose the functions $\tilde{a}_i(L)$ are identical, and that $\tilde{a}_i(L) = \tilde{a}_i(0)/(1 - \gamma L)$, implying that f_t is ARMA(1,1). Then Assumption 3.3 requires the scaling factors, $\tilde{a}_i(0)$, be equal to $-b_i(1 - \gamma\beta)(2 - \lambda\beta)/[\beta(1 - \lambda\beta)]$.

From here on we can follow entirely standard procedures to compute a Rational Expectations equilibrium. Although we could solve the model for any (fixed) distribution of trader types, this added generality doesn't contribute any additional insights, so we adopt the natural assumption that there is an equal measure of each type, giving us the equilibrium condition

$$p_t = \beta \left[\frac{1}{2} E_t^1 p_{t+1} + \frac{1}{2} E_t^2 p_{t+1} \right] + f_t + u_t \quad (3.9)$$

Combining this with the solutions to the signal extraction problems in equations (3.3) and (3.4) produces the follow central result

Proposition 3.4. *Under Assumptions 3.1 and 3.3, for any $|\lambda| < 1$ there exists a heterogeneous beliefs Rational Expectations equilibrium for the model described by equations (3.9), (2.2) and (2.3). The z -transforms of the equilibrium pricing functions are given by:*

$$\pi_1(z) = (z - \lambda) \left\{ \tilde{a}_1(\beta) + b_1 \frac{\lambda}{1 - \lambda\beta} + \frac{z}{z - \beta} \left[\tilde{a}_1(z) - \tilde{a}_1(\beta) + b_1 \lambda \left(\frac{1}{1 - \lambda z} - \frac{1}{1 - \lambda\beta} \right) \right] \right\} \quad (3.10)$$

$$\pi_2(z) = (z - \lambda) \left\{ \tilde{a}_2(\beta) + b_2 \frac{\lambda}{1 - \lambda\beta} + \frac{z}{z - \beta} \left[\tilde{a}_2(z) - \tilde{a}_2(\beta) + b_2 \lambda \left(\frac{1}{1 - \lambda z} - \frac{1}{1 - \lambda\beta} \right) \right] \right\} \quad (3.11)$$

The proof is by construction. Notice that it is sufficient to verify the result for $\pi_1(z)$, due to symmetry. Substituting the conditional expectations (3.3) and (3.4) into the equilibrium condition (3.9), and using the notation in (3.5), gives

$$(L - \lambda)(\rho_1 + L g_1(L)) \varepsilon_{1t} = \beta \left[\rho_1 + (L - \lambda) g_1(L) - \frac{1}{2} \frac{\rho_1(1 - \lambda^2)}{1 - \lambda L} \right] \varepsilon_{1t} + (L - \lambda) \tilde{a}_1(L) \varepsilon_{1t} + b_1 \varepsilon_{1t}$$

The requirement that this hold for *all* realizations of ε_{1t} implies the z -transforms of the two sides must be identical as analytic functions inside the unit circle.¹⁰

$$(z - \lambda)(\rho_1 + z g_1(z)) = \beta \left[\rho_1 + (z - \lambda) g_1(z) - \frac{1}{2} \frac{\rho_1(1 - \lambda^2)}{1 - \lambda z} \right] + (z - \lambda) \tilde{a}_1(z) + b_1 \quad (3.12)$$

¹⁰The Appendix provides more detail concerning this solution method. See also Whiteman (1983).

Since $(\rho_1 + zg_1(z))$ is presumed analytic, the right-hand side of (3.12) must be zero when evaluated at $z = \lambda$. (This ‘removes’ the singularity at $z = \lambda$). Setting the right side to zero at $z = \lambda$ determines the unknown constant, $\rho_1 = -2b_1/\beta$. If we then substitute this back in, collect terms in $g_1(z)$, and divide by $z - \lambda$, we get

$$(z - \beta)g_1(z) = \tilde{a}_1(z) + \frac{2b_1}{\beta} + b_1 \frac{\frac{1-\lambda^2}{1-\lambda z} - 1}{z - \lambda} \quad (3.13)$$

Notice the right-hand side is analytic by construction. Since $g_1(z)$ is also assumed to be analytic, the right-hand side of (3.13) must be zero when evaluated at $z = \beta$. Evaluating the right-hand side at $z = \beta$ and setting it to zero yields the restriction

$$\beta \tilde{a}_1(\beta) + 2b_1 + \beta b_1 \frac{\frac{1-\lambda^2}{1-\lambda\beta} - 1}{\beta - \lambda} = 0 \quad (3.14)$$

which can be simplified to obtain the existence condition by Assumption 3.3. Finally, given $g_1(z)$ and ρ_1 , the expression for $\pi_1(z)$ given by (3.10) follows from plugging into $\pi_1(z) = (z - \lambda)(\rho_1 + zg_1(z))$.

Before turning to higher order beliefs, a few points are worth making about this result. First, notice that no mention of $\pi_3(z)$ is made in Proposition 3.4. Since v_t is known to be i.i.d., it’s clear that in equilibrium $\pi_3(z) = 1$. Second, the expressions in (3.10) and (3.11) are less formidable than they appear. They look complicated simply because they apply for *any* stationary specification of the observable fundamentals (subject to the constraints described in Assumptions 3.1 and 3.3). This kind of generality is a key virtue of a frequency domain approach. However, for simple specifications of the $\tilde{a}_i(z)$ functions, equations (3.10) and (3.11) produce simple expressions for equilibrium prices. For example, suppose both components are ARMA(1,1), with common AR coefficient γ and common MA root λ (i.e. $\tilde{a}_i(z) = \tilde{a}_i(0)/(1 - \gamma z)$). Substituting into (3.10) and (3.11), imposing the existence condition, and then simplifying, produces the following ARMA(2,2) process for prices¹¹

$$p_t = \left(\frac{L - \lambda}{\beta(1 - \lambda\beta)(1 - \gamma L)(1 - \lambda L)} \right) \left\{ \sum_{i=1,2} b_i [\beta(1 - \gamma L) - (2 - \lambda\beta)(1 - \lambda\beta)(1 - \lambda L)] \varepsilon_{it} \right\}$$

Third, note that no claim of uniqueness was made in Proposition 3.4. Uniqueness would require an additional ‘regularity’ condition on the traders’ Wold representations, which would impose analyticity conditions on the individual elements of $\mathbf{M}_i^*(z)$, in addition to conditions on the roots of the determinant. We’ve already imposed these conditions on the $\pi_i(z)$ functions, so if we impose them on the individual $a_i(z)$ functions we obtain uniqueness as well.¹²

¹¹Ignoring, for simplicity, the v_t term. One can readily verify that adding this term still produces an ARMA(2,2).

¹²See Whiteman (1983) for a discussion of the role of regularity in delivering unique solutions of multivariate Rational Expectations models.

3.3. Higher Order Beliefs. To interpret the heterogeneous beliefs equilibrium given by equations (3.10) and (3.11), it is useful to consider the benchmark case of homogeneous beliefs. Suppose each trader observes *both* ε_{1t} and ε_{2t} . In this case, we can solve for the equilibrium as usual by applying the Hansen-Sargent prediction formula. This yields,

$$\pi_i^s(z) = \frac{z(z - \lambda)\tilde{a}_i(z) - \beta(\beta - \lambda)\tilde{a}_i(\beta)}{z - \beta} + b_i \quad i = 1, 2 \quad (3.15)$$

where the superscript s in the $\pi_i^s(z)$ functions emphasizes the fact that they pertain to a *symmetric* information, homogeneous beliefs, equilibrium. Using these in (3.10) and (3.11) we obtain the following result

Proposition 3.5. *For any specification of observable fundamentals that satisfy Assumptions 3.1 and 3.3, the heterogeneous beliefs pricing functions can be decomposed as the following sum of the homogeneous beliefs pricing functions and an autoregressive component representing the model's higher order belief dynamics.*

$$\pi_i(z) = \pi_i^s(z) + \frac{b_i}{1 - \lambda\beta} \left(\frac{1 - \lambda^2}{1 - \lambda z} \right) \quad i = 1, 2 \quad (3.16)$$

where the $\pi_i^s(z)$ are given by (3.15).

This is the main result of the paper. The first term on the right-hand side of (3.16) shows how prices respond to commonly observed shocks to fundamentals. The second term then exhibits the additional dynamics induced when shocks to fundamentals are heterogeneously observed, and traders must ‘forecast the forecasts of others’. Thus, the second term captures in a clear and precise way the higher-order belief dynamics associated with a heterogeneous beliefs equilibrium.¹³ Remarkably, higher-order beliefs exhibit AR(1) dynamics, independently of any autoregressive components in the observed fundamentals. The persistence of higher order beliefs is solely determined by the (noninvertible) *moving average* components of fundamentals. Interestingly, Woodford (2003) obtains a qualitatively similar result in a quite different setup.

It is clear from (3.16) that higher-order beliefs can generate additional price volatility. One manifestation of this is the following,

Corollary 3.6. *If the b_i coefficients are positive, higher order beliefs amplify the initial response of asset prices to innovations in fundamentals.*

Proof. Evaluate (3.16) at $z = 0$. This yields

$$\pi_i(0) = \pi_i^s(0) + \frac{b_i(1 - \lambda^2)}{1 - \lambda\beta} > \pi_i^s(0)$$

□

¹³In principle, one could obtain this result in the time domain, by evaluating the cascade of conditional expectations in expression (2.5). Rondina and Walker (2009) do this for their one-shock example, and verify that it produces the same result.

4. EMPIRICAL IMPLICATIONS

As noted in the Introduction, there are by now many papers that discuss theoretical aspects of higher order belief dynamics in asset pricing. However, ours is the first to embed these dynamics within a conventional, *econometric*, asset pricing model, which allows us to explore the *quantitative* significance of higher order beliefs in real world asset markets. Obviously, if conventional homogeneous beliefs versions of these models were successful, this would not be an interesting exercise. However, in light of the well documented failures of this model, it is of some interest to revisit these failures accounting for the possibility that higher order belief dynamics are present. Specifically, this section addresses the following question - Suppose the world is described by a heterogeneous expectations equilibrium, but an outside econometrician interprets the data as if it were generated from a homogeneous expectations equilibrium. What kind of inferential errors could result? We focus on three empirical results that have been common in the asset pricing literature: (1) violations of variance bounds, (2) predictability of excess returns, and (3) rejections of cross-equation restrictions.

Although it seems likely that heterogeneous expectations and higher order belief dynamics are present in *all* asset markets, we focus our attention on the U.S. stock market, since this has been the most widely studied case. Figure 1 displays annual data on real stock prices and dividends for the period 1871-2006, downloaded from Shiller's website.

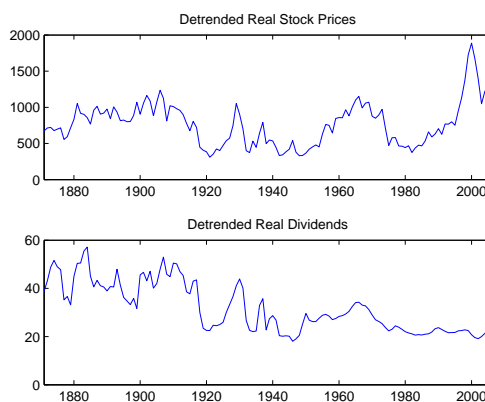


FIGURE 1. Data Plots

Following the original work of Shiller (1981), a common exponential trend was removed from both series. Of course, Shiller's work unleashed a deluge of responses, many of which pointed to biases in his methods. Removing a common deterministic trend is one of them. However, we are not going to be too concerned with this subsequent literature, for a couple of reasons. First, as documented in Shiller (1989), the

basic message from Shiller's original work survives these subsequent criticisms. Second, since the subsequent literature argued that Shiller's methods tended to produce false rejections, if we can explain his results with higher order beliefs, that strengthens our argument (albeit at the cost of producing inflated estimates of the magnitude of higher order beliefs).

4.1. Wold Representation. As noted above, in this section we are putting ourselves in the shoes of an outside econometrician. By 'outside' we mean the econometrician is not an active participant in the market. In particular, he does not observe any of the underlying shocks driving observable fundamentals. Instead, he just witnesses the realizations of prices and the fundamentals themselves. Using this information, he wants to see whether a linear present value model can explain the data he observes, under the *assumption* that market participants have homogeneous beliefs.

One mistake he doesn't make is to assume the data-generating process is linear. Thus, like any econometrician his starting point is to fit VARs, or perhaps VARMA, to the data. His mistake will arise when using and interpreting these VARs. Specifically, he will make two mistakes: (1) He will misinterpret the residuals as representing innovations to the information sets of *traders*, when in fact they are not, and (2) He will incorrectly apply the law of iterated expectations when constructing estimates of traders' multiperiod forecasts.

The first step in our analysis, therefore, is to derive the Wold representation that the econometrician will estimate. Estimates of this Wold representation are the best the econometrician can do, given his (false) model and his information. Note first that deriving the econometrician's Wold representation requires a spectral factorization, since there are three underlying shocks, yet the econometrician only observes the realization of two random processes. In general, this is a messy problem. However, we can greatly simplify it by making two assumptions: (1) the components of observable fundamentals are identical, i.e., $\tilde{a}_1(L) = \tilde{a}_2(L) = \tilde{a}(L)$, and (2) the correlation between the noise and observed fundamentals is identical for each of the two observable components, i.e., $b_1 = b_2$. Given these assumptions the econometrician's Wold representation becomes¹⁴

$$\begin{bmatrix} f_t \\ p_t \end{bmatrix} = \begin{bmatrix} (1 - \lambda L)\tilde{a}(L) & 0 \\ (1 - \lambda L)\tilde{\pi}(L) & 1 \end{bmatrix} \begin{bmatrix} \epsilon_t \\ v_t \end{bmatrix} \quad (4.1)$$

where

$$\epsilon_t = \left(\frac{L - \lambda}{1 - \lambda L} \right) (\varepsilon_{1t} + \varepsilon_{2t}) \quad (4.2)$$

It is natural to ask at this point what U.S. stock market data suggest about this Wold representation. Note that the crucial parameter, λ , can be inferred directly from the estimated MA root of dividends, which play the role of observed fundamentals, f_t , in this case. Table 1 displays estimates of univariate ARMA(1,1) models for stock

¹⁴See Hansen and Sargent (1991b) or Rozanov (1967) for details.

prices and dividends, which is what the model would predict if $\tilde{a}(L) = \tilde{a}(0)/(1 - \gamma L)$. (Higher order terms are insignificant).

TABLE 1
ARMA(1,1) ESTIMATES: ANNUAL DATA (1871-2006)

	AR(1)	MA(1)
d_t	.889 (.043)	-.197 (.092)
p_t	.865 (.050)	-.260 (.092)

Notes: (1) Estimates pertain to the model, $x_t = \frac{1-\lambda L}{1-\gamma L} \epsilon_t$
(2) Asymptotic standard errors are in parentheses.

These estimates suggest that $\lambda = -.20$ would be a reasonable value. One can see from our earlier example that the *estimated* price process is also predicted to be ARMA(1,1), although it is ARMA(2,2) when expressed in terms of the underlying shocks. However, its MA root will be a complicated function of λ and the other parameters, so it is easier to infer λ from dividends. The estimates in Table 1 also suggest that one cannot statistically reject the model's prediction that the the AR coefficients of prices and dividends are identical. Hence, in our subsequent simulations we will assume $\tilde{a}(L) = \tilde{a}(0)/(1 - \gamma L)$, and set $\lambda = -.20$ and $\gamma = .9$. The value of $\tilde{a}(0)$ will be set to satisfy the model's existence condition in Assumption 3.3, and will be a function of the free parameter, $b_1 (= b_2)$.

4.2. Variance Bounds. Corollary 3.6 suggests that higher-order belief dynamics might make asset prices appear to be 'too volatile' relative to their fundamentals. One of the main contributions of this paper is the ability to *quantify* the degree of excess volatility associated with higher-order belief dynamics. One way of doing this is to show that heterogeneous beliefs equilibria can violate standard variance bounds inequalities. Violations of these bounds are a robust empirical finding.

Variance bounds are based on the idea that observed asset prices should be less volatile than their perfect foresight counterparts (i.e., the subsequent realization of discounted future fundamentals). Since prices represent *expectations* of discounted future fundamentals, it makes sense that they should be smoother than the realizations of discounted future fundamentals. However, the logic behind this rests on two key assumptions. First, there are no missing fundamentals.¹⁵ Note, however, that the logic of variance bounds can still be applied when agents use *unobserved information* to forecast *observed fundamentals*.¹⁶ Since our model embodies unobserved fundamentals, in the form of forecasts of other agents' forecasts, we will not emphasize this distinction, although when reporting estimates of cross-equation restrictions,

¹⁵Hamilton and Whiteman (1985) emphasize this point.

¹⁶See, e.g., West (1988) and Campbell and Shiller (1987).

we report variance bounds that are robust to inside information. Second, and more importantly, the logic of variance bounds is premised on the assumption that forecast errors are orthogonal to forecasts. In models with heterogeneous beliefs, this simply isn't the case. Although each trader's own individual forecasts are of course orthogonal to his own information set, which includes prices, there is no guarantee that market-wide *average* forecast errors are also orthogonal to prices. It is this loss of orthogonality that is the ultimate source of our econometrician's biased inferences.¹⁷

To show that heterogeneous beliefs equilibria can violate variance bounds, it therefore suffices to show that the variance of observed prices can exceed the variance of perfect foresight prices. Rather than prove this in general, we simply provide an example based on an ARMA(1,1) specification for observed fundamentals. From Table 1, this specification appears consistent with observed dividend data. Of course, since our model contains noise, it would be a silly exercise to generate violations of variance bounds with an arbitrary noise process. To make the analysis interesting we shall first set $\sigma_v^2 = 0$ and then show that violations occur for arbitrarily small values of b_1 . This minimizes the role of noise in generating, by itself, violations of the variance bound. Instead, it will be the *interaction* between noise and dispersed information that generates violations of the bound. Since in practice variance bounds tests are based solely on observed price and dividend data, it is important that we derive our results using the econometrician's Wold representation, using the observable shocks, ϵ_t , in equation (4.2).

Proposition 4.1. *If fundamentals are ARMA(1,1) (ie., $a_i(L) = a_0(1-\lambda L)/(1-\gamma L)$), then asset prices violate the standard variance bound whenever γ is sufficiently close to β , λ is sufficiently close to one, and $\beta > 4/5$.*

The proof is algebraically messy, so it is relegated to the Appendix. Admittedly, this is a rather ugly result, but it's important nonetheless. Previous criticisms of Shiller's work were based on *statistical* problems. By way of contrast, this result is based on the *economic assumptions* that lie behind it, namely, the assumption that prices fully reveal private information, so that in equilibrium everyone makes the same forecasts. Without this assumption, the orthogonality that drives the result goes out the window.

Of course, the real issue here is whether the bound is breached for plausible parameter values. Again, it's the ability to assess the *quantitative* significance of higher order beliefs that is the distinguishing feature of our analysis. Although it seems plausible that β is close to γ and that β exceeds $4/5$, Table 1 suggests that λ is actually negative, and rather small. Moreover, Shiller's work suggests that the bound is

¹⁷To see this, let $\bar{E}_t p_{t+1}$ denote the average forecast of next period's price (i.e., $\bar{E}_t p_{t+1} = \frac{1}{2} E_t^1 p_{t+1} + \frac{1}{2} E_t^2 p_{t+1}$). Thus, the market forecast error is $p_{t+1} - \bar{E}_t p_{t+1}$. Observe that $\text{cov}(p_t, p_{t+1} - \bar{E}_t p_{t+1}) = 0$ and $\text{cov}(p_t, p_{t+1} - E_t^2 p_{t+1}) = 0$ does *not* imply $\text{cov}(p_t, p_{t+1} - (\frac{1}{2} E_t^1 p_{t+1} + \frac{1}{2} E_t^2 p_{t+1})) = 0$.

violated by a significant margin, by a factor of 2-5 depending on statistical assumptions. However, since Proposition 4.1 is only a sufficient condition, not a necessary condition, the question remains whether the bound is violated for reasonable parameter values. For this we must resort to numerical simulations. Figure 2 reports plots of $\text{var}(p)/\text{var}(p^{pf})$ for alternative parameter values. Since the unobserved noise biases us toward rejection, we set the variance of v_t to zero in these calculations. Also, it is apparent that b_1 merely scales up both variances by the same amount, so for these plots the value of b_1 is irrelevant. We set it at $b_1 = 0.2$. Finally, given annual data, we set $\beta = .95$ since this is in the middle of the range used in previous empirical work.

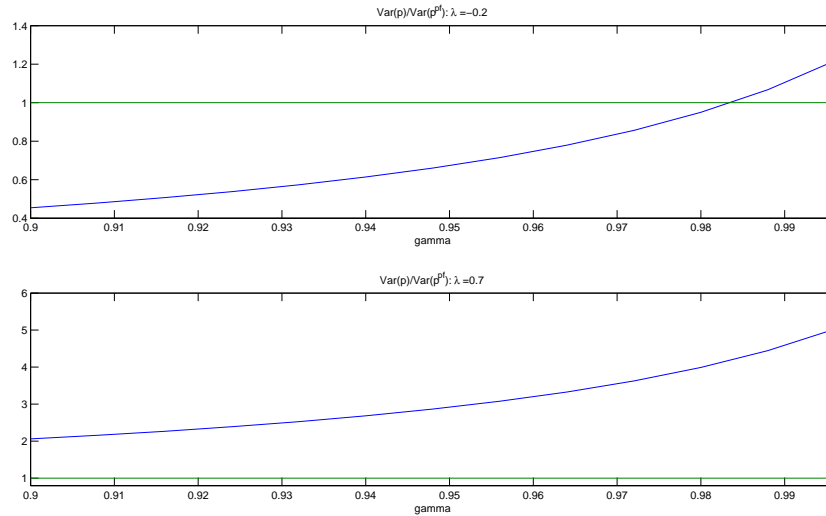


FIGURE 2. Shiller Bound

Figure 2 plots the variance ratio as a function of γ , for two different values of λ . The top panel displays the results when $\lambda = -0.20$, the value suggested by the univariate ARMA estimates for dividends. One can see that the bound is comfortably satisfied for values of γ close to the point estimates in Table 1. However, estimates of persistence are notoriously fragile, and are known to be biased downward in small samples. Hence, it is of some interest that the bound *is* violated for values of $\gamma > .98$, since these are not entirely implausible. Still, even when $\gamma = .995$ we can see that it is only exceeded by a margin of 20%, far below even the most conservative of Shiller's estimates.

In retrospect, it is not too surprising that small values of λ generate only a small amount of additional volatility. One can see why by inspecting the price function decomposition in Proposition 3.5. Notice that the *persistence* of higher order beliefs is dictated by λ . When λ is close to one, higher order beliefs will be very persistent. Conversely, when λ is close to zero, as in the top panel of Figure 2, higher order

beliefs just add a small amount high frequency noise to prices. In particular, since the variance of higher order beliefs is proportional to $(1 - \lambda^2)/(1 - \lambda\beta)^2$, one can see that it is an increasing function of λ for plausible values of λ and β .

This intuition is confirmed in the bottom panel of Figure 2, which displays the variance ratio when $\lambda = 0.7$. Now we see significant violations of the bound, of the same order of magnitude that Shiller found. For example, when $\gamma = .98$ the variance of observed prices is four times its hypothetical upper bound! Note this is not an artifact of biased statistical procedures, since we are comparing *population* moments. Although at first sight, $\lambda = .7$ is significantly different from the point estimate of $\lambda = -.2$, keep in mind that differences in moving average estimates can be difficult to spot with the naked eye. For example, even with $\lambda = .7$ the first-order autocorrelation of dividends is 0.745, which then damps out at the slow rate of .98. Although we can statistically reject this specification, it doesn't produce wildly implausible sample paths.

This point is reinforced in Figure 3, which compares the sample path of observed stock prices with their perfect foresight counterparts. The top panel updates Shiller's (1981) original plot. This graph, more than anything else, is what struck a chord

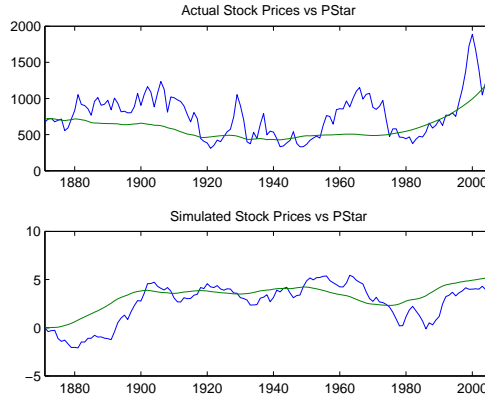


FIGURE 3. Stock Prices vs Present Value of Future Dividends

with the profession (and its potential to be misleading is what motivated subsequent critics). The only difference is that we've used the observed terminal price as the end-of-sample estimate of discounted future dividends, rather than Shiller's original strategy of using the sample average price. It is now well known that using average prices produces a bias toward rejection, whereas use of the terminal price is unbiased. (See, e.g., Mankiw, Romer, and Shapiro (1985)). The bottom panel of Figure 3 follows the same procedure using data generated by our nonrevealing Rational Expectations model. All the parameters are the same as before, except now we've gone back to the point estimate $\lambda = -.2$ and set $\gamma = .98$. Although it is perhaps not quite as striking

as in the data, the plot still gives the distinct impression that prices are too volatile relative to their fundamentals.

4.3. Return Predictability. Another widely documented failure of linear present value models is the ability to predict excess returns, which in the case of a constant discount rate, just means the ability to predict returns themselves. Initially, excess volatility and return predictability were presented as distinct puzzles. However, it is now well known that they are two sides of the same coin.¹⁸ In fact, a finding of excess volatility can be interpreted as long (i.e., infinite) horizon return predictability. Both puzzles are driven by the *apparent* violation of the model's implied orthogonality conditions. Still, it is useful to show how and why this occurs even in the case of one-period returns.

Of course, by construction the model's orthogonality condition in (2.1) is satisfied. The equilibrium pricing functions were computed by imposing this condition. However, this is not the condition our econometrician is testing. He is falsely assuming that everyone has the same expectation. Although *average* expectations of returns are indeed zero, our econometrician does not observe the underlying shocks that generate these expectations, so he cannot test this prediction of the model. Instead, he uses the the Wold representation in (4.3) to construct what he (falsely) believes is the 'market's' expectation of next period's price. The results are summarized as follows

Proposition 4.2. *Define the time- $t+1$ excess return as $R_{t+1} = \beta p_{t+1} + d_t - p_t$. Then the Wold representation in (4.3) generates the following projection of R_{t+1} onto the (econometrician's) time- t information set*

$$R_{t+1} = - \left(\frac{b_1 \lambda}{1 - \lambda \beta} \right) \left(\frac{\tilde{a}^{-1}(L)}{1 - \lambda L} \right) d_t$$

Again, the proof is by construction. When $\tilde{a}_1(L) - \tilde{a}_2(L) = \tilde{a}(L)$ and $b_1 = b_2$, we can write the equilibrium price as follows

$$p_t = (L - \lambda) \left[\frac{L\tilde{a} - \beta\tilde{a}(\beta)}{L - \beta} + \frac{b_1 \lambda}{1 - \lambda \beta} \frac{1}{1 - \lambda L} \right] (\varepsilon_{1t} + \varepsilon_{2t}) + b_3 v_t$$

Expressed in terms of the Wold representation we have

$$\begin{aligned} p_t &= (1 - \lambda L) \left[\frac{L\tilde{a}(L) - \beta\tilde{a}(\beta)}{L - \beta} \right] \epsilon_t + \frac{b_1 \lambda}{1 - \lambda \beta} \epsilon_t + b_3 v_t \\ &\equiv A(L) \epsilon_t + \frac{b_1 \lambda}{1 - \lambda \beta} \epsilon_t + b_3 v_t \end{aligned}$$

¹⁸Both Cochrane (2001) and Shiller (1989) emphasize this point.

where $\epsilon_t = [(L - \lambda)/(1 - \lambda L)](\varepsilon_{1t} + \varepsilon_{2t})$. Therefore,

$$\begin{aligned} \beta E_t p_{t+1} + d_t - p_t &= \{ \beta L^{-1}[A(L) - A(0)] + (1 - \lambda L)\tilde{a}(L) - [A(L) + b_1/(1 - \lambda\beta)] \} \epsilon_t - b_3 v_t \\ &= - \left(\frac{b_1 \lambda}{1 - \lambda\beta} \right) \epsilon_t - b_3 v_t \end{aligned}$$

Since $d_t = (1 - \lambda L)\tilde{a}(L)\epsilon_t$ and v_t is not in the econometrician's information set, the result is proved.

Proposition 4.2 suggests that if we regress R_t onto lagged prices and dividends we should find statistically significant coefficients. (The result is stated in terms of lagged dividends, but it could just as easily have been stated in terms of lagged prices, given their equilibrium relationship). Table 3 contains a small set of results from these kinds of regressions, using Shiller's annual data. (Since in Shiller's data prices are sampled in January and dividends accrue throughout the year, I do not assume time- t dividends are in the time- t information set).

TABLE 2
RETURN PREDICTABILITY: ANNUAL DATA (1871-2006)

	R_{t-1}	R_{t-2}	P_{t-1}	P_{t-2}	D_{t-1}	D_{t-2}	\bar{R}^2	DW
$R_t =$.344 (.195)						.111	1.89
$R_t =$.398 (.166)	-.160 (.141)					.127	2.03
$R_t =$.019 (.051)				.000	1.35
$R_t =$.341 (.205)	-.342 (.227)			.099	1.87
$R_t =$					3.19 (1.29)		.034	1.38
$R_t =$					12.9 (4.58)	-10.2 (5.10)	.046	1.45

Notes: (1) $R_t \equiv P_t + D_t - P_{t-1}$.

(3) All regressions include a constant.

(2) Heteroskedasticity-robust standard errors in parentheses.

The results here are quite consistent with previous results. There is some modest evidence in favor of predictability, but it is not overwhelming. There are of course a plethora of statistical pitfalls associated with these regressions, but again, our results suggest that even if one had access to the *population* second moments, we should still observe predictability. Finding that returns are predictable is not a puzzle if investors have heterogeneous expectations of returns.

4.4. Cross-Equation Restrictions. The Rational Expectations revolution ushered in many methodological changes. One of the most important concerned the way econometricians identify their models. Instead of producing zero restrictions, the Rational Expectations Hypothesis imposes cross-equation restrictions. Specifically, parameters describing the laws of motion of exogenous forcing processes enter the laws of motion of endogenous decision processes. In fact, in a oft-repeated phrase, Sargent dubbed these restrictions the ‘hallmark of Rational Expectations’. Hansen and Sargent (1991b) and Campbell and Shiller (1987) proposed useful procedures for testing these restrictions. When these tests are applied to present value asset pricing models, they are almost without exception rejected, and in a resounding way. There have been many responses to these rejections. Some interpret them as evidence in favor of stochastic discount factors. Others interpret them as evidence against the Rational Expectations Hypothesis. We offer a different response. We show that rejections of cross-equation restrictions may simply reflect an informational misspecification, one that presumes a revealing equilibrium and homogeneous beliefs when in fact markets are characterized by heterogeneous beliefs.

For reference purposes we repeat the Wold Representation given by equation (4.3)

$$\begin{bmatrix} f_t \\ p_t \end{bmatrix} = \begin{bmatrix} (1 - \lambda L)\tilde{a}(L) & 0 \\ K(\tilde{a}(L)) & 1 \end{bmatrix} \begin{bmatrix} \epsilon_t \\ v_t \end{bmatrix} \quad (4.3)$$

where we now write the pricing function $(1 - \lambda L)\tilde{\pi}(L)$ as $K(\tilde{a}(L))$ to emphasize the fact that it is the output of a linear operator, $K(\cdot)$, defined by equations (3.10) and (3.11). By inspection, we can immediately see one problem. Given the underlying noise, v_t , the model is ‘inexact’. Hence, if the econometrician falsely neglects the potential existence of unobserved noise he will incorrectly make one of two predictions: (1) either prices are an exact function of fundamentals, or (2) prices Granger cause fundamentals. Neither is true in this case. However, we are not going to focus on this issue, simply because by now it is well understood (see, e.g., Engel and West (2005)), and more importantly, it has nothing to do *per se* with higher order beliefs.

A more subtle error arises from the fact that the heterogeneous beliefs pricing operator actually consists of the sum of *two* linear operators, $K = K^s + K^h$, where K^s denotes the conventional symmetric information operator, given by the Hansen-Sargent formula, and K^h denotes the higher order beliefs operator defined in Proposition 3.5. This gives rise to the following result,

Proposition 4.3. *Standard cross-equation restriction tests, which falsely presume a common information set, can produce spurious rejections.*

Proof. When there are heterogeneous beliefs, $\pi_i(L) = K(a_i(L))$, where $K = K^s + K^h$. Cross-equation restriction tests based on the false assumption of homogeneous beliefs amount to dropping the K^h component of the pricing operator. This can produce strong rejections when $K^h(a_i(L))$ is ‘big’ (in the operator sense). \square

Again, the real issue here is the quantitative significance of this result. Although one could perhaps investigate this analytically, it is simpler to just perform a simulation. Table 3 contains two sets of results.

TABLE 3
CROSS-EQUATION RESTRICTIONS: ANNUAL DATA (1871-2006)

<u>Data</u>	D_{t-1}	P_{t-1}	\bar{R}^2	DW	$\chi^2(2)$	$\text{var}(P)/\text{var}(\hat{P})$	$\text{corr}(P, \hat{P})$
$D_t =$.912 (.036)	.001 (.001)	.842	1.72	11.8	19.5	.53
$P_t =$	-1.28 (1.16)	.927 (.040)	.814	1.72			
<u>Simulation</u>							
$D_t =$.951 (.042)	.002 (.002)	.955	1.63	91.4	1.71	.91
$P_t =$	14.5 (1.84)	.126 (.097)	.761	1.97			

Notes: (1) $\chi^2(2)$ is the Wald statistic for the cross-equation restrictions $(0, 1)[I - \beta\psi] = (1, 0)\beta\psi$, where ψ is the VAR(1) coefficient matrix.

(2) $\hat{P} \equiv$ Expected present discounted value of dividends with $\beta = .95$.

(3) Asymptotic standard errors in parentheses.

The top panel replicates the VAR testing strategy of Campbell and Shiller (1987) using updated data from Shiller's website.¹⁹ Given the annual frequency, a VAR(1) appears adequate. The final three columns report the outcomes of various tests and diagnostics. The $\chi^2(2)$ column reports the Wald statistic for the model's two cross-equation restrictions. As many others have found, these restrictions are strongly rejected. The $\text{var}(P)/\text{var}(\hat{P})$ column reports the ratio between the variance of observed prices and the variance of predicted prices, using the VAR to construct the present discounted value of future dividends. Under the null, this ratio should be one. The point estimate suggests even a stronger rejection than the earlier variance bound results, which is somewhat surprising in light of the fact that this estimate is robust to presence of inside information, which would tend to make observed prices more volatile than expected. The final column reports the sample correlation coefficient between actual and predicted prices. As Campbell and Shiller (1987) emphasized, even though the model is strongly rejected statistically, it does have some ability to track observed prices.

The bottom panel reports the results from following the exact same procedures using data generated by the model, with the parameter values $\lambda = -.20$ and $\gamma =$

¹⁹In contrast to Campbell and Shiller (1987), we do not assume unit roots and cointegration. To maintain consistency with our previous results we use detrended data.

.98. Interestingly, applying the Campbell-Shiller method would lead us to reject the model, although the variance bound rejection is less spectacular. The strange looking coefficient estimates in the price equation arise from the near ‘exactness’ of the model. With lagged dividends included, prices *should* have little additional explanatory power for future prices. As in the data, the model’s predicted price tracks the actual price quite well. This can be seen in Figure 4, which plots actual versus predicted prices for both observed data and model-generated data.

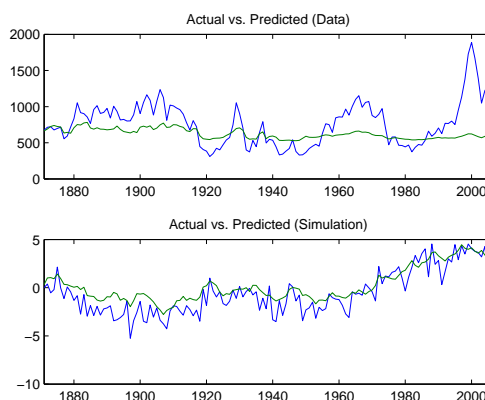


FIGURE 4. Actual vs. Predicted Stock Prices

As the above statistics indicate, predicted prices do track actual prices much closer in the simulation. Still, there is some tendency for prices to be more volatile than their ‘fundamentals’. It is noteworthy that we reject the model despite using procedures that are robust to the possibility that agents have more information than the econometrician. This kind of asymmetric information is not the issue here. Rather it is the presence of asymmetric information among the agents themselves that is the source of the problem. When the agents themselves have asymmetric information, prices are determined by *average* expectations, and these averaged expectations do not adhere to the law of iterated expectations. Unfortunately, the clever VAR procedures of Hansen and Sargent (1991a) and Campbell and Shiller (1987) rely heavily on the law of iterated expectations.

5. CONCLUSION

For more than thirty years now, economists have been rejecting linear present value asset pricing models. These rejections have been interpreted as evidence in favor of time-varying risk premia. Unfortunately, linking risk premia to observable data has been quite challenging. Promising approaches for meeting the challenge involve introducing incomplete markets and agent heterogeneity into models.

This paper has suggested that a different sort of heterogeneity, an *informational heterogeneity*, offers an equally promising route toward reconciling asset prices with observed fundamentals. Unfortunately, heterogeneous information does not automatically translate into heterogeneous beliefs, and it is only the latter that generates the ‘excess volatility’ that is so commonly seen in the data. The hard work in the analysis, therefore, is deriving the conditions that prevent market data from fully revealing the private information of agents in dynamic settings. We have argued that frequency-domain methods possess distinct advantages over time-domain methods in this regard. The key to keeping information from leaking out through observed asset prices is to ensure that the mappings between the two are ‘noninvertible’. These noninvertibility conditions are easy to derive and manipulate in the frequency domain.

Our results demonstrate how informational heterogeneity can in principle explain well-known empirical anomalies, such as excess volatility, excess return predictability, and rejections of cross-equation restrictions. Ever since Townsend (1983) and Singleton (1987), (or in fact, ever since Keynes!) economists have suspected that higher-order beliefs could be responsible for the apparent excess volatility in financial markets. Our results at last confirm these suspicions. Although we believe we have made substantial progress, there are still many avenues open for future research. Two seem particularly important. First, like the recent work Engel, Mark, and West (2007), our paper offers some hope for linear present value models. Unlike their work, however, which is largely based on statistical and calibration issues, our paper points to a more radical reorientation of VAR methodology. In particular, it would be useful to develop and implement empirical procedures that are robust to higher order beliefs, and perhaps even develop test statistics that could reliably detect their presence. Second, the entire analysis here rests heavily on linearity. However, most macroeconomic models feature nonlinearities of one form or another. It is not at all clear whether standard linearization methods are applicable in models featuring higher-order beliefs. Resolving this issue will also be important for future applications.

APPENDIX A. FREQUENCY DOMAIN TECHNIQUES

This appendix offers a brief introduction to the frequency domain techniques used to solve the model. In lieu of matching an infinite sequence of unknown coefficients, we employ the following theorem and solve for a fixed point in a function space.

Theorem (Riesz-Fischer): *Let $\{c_n\}$ be a square summable sequence of complex numbers (i.e., $\sum_{n=-\infty}^{\infty} |c_n|^2 < \infty$). Then there exists a complex-valued function, $g(\omega)$, defined for $\omega \in [-\pi, \pi]$, such that*

$$g(\omega) = \sum_{j=-\infty}^{\infty} c_j e^{-i\omega j} \quad (\text{A.1})$$

where convergence is in the mean-square sense

$$\lim_{n \rightarrow \infty} \int_{-\pi}^{\pi} \left| \sum_{j=-n}^n c_j e^{-i\omega j} - g(\omega) \right|^2 d\omega = 0$$

and $g(\omega)$ is square (Lebesgue) integrable

$$\int_{-\pi}^{\pi} |g(\omega)|^2 d\omega < \infty$$

Conversely, given a square integrable $g(\omega)$ there exists a square summable sequence such that

$$c_k = \frac{1}{2\pi} \int_{-\pi}^{\pi} g(\omega) e^{i\omega k} d\omega \quad (\text{A.2})$$

The Fourier transform pair in (A.1) and (A.2) defines an isometric isomorphism (i.e., a one-to-one onto transformation that preserves distance and linear structure) between the space of square summable sequences, $\ell^2(-\infty, \infty)$, and the space of square integrable functions, $L^2[-\pi, \pi]$. The sequence space, ℓ^2 , is referred to as the ‘time domain’ and the function space, L^2 , is referred to as the ‘frequency domain’. The equivalence between these two spaces allows us to work in whichever is most convenient. A basic premise of this paper is that in models featuring heterogeneous beliefs, the frequency domain is analytically more convenient.

In the context of linear prediction and signal extraction, it is useful to work with a version of Riesz-Fischer theorem that is generalized in one sense and specialized in another. In particular, it is possible to show, via Poisson’s integral formula, that the statement of the theorem applies not only to functions defined on an interval (the boundary of the unit circle), but to analytic functions defined within the entire unit circle of the complex plane. However, when extending the theorem in this way we exclude functions with Fourier coefficients that are nonzero for negative k . That is, we limit ourselves to functions where $c_{-k} = 0$ in equations (A.1) and (A.2). This turns out to be useful, since it is precisely these functions that represent the ‘past’ in

the time domain. A space of analytic functions in the unit disk defined in this way is called a Hardy space, with an inner product defined by the contour integral,

$$(g_1, g_2) = \frac{1}{2\pi i} \oint g_1(z) \overline{g_2(z)} \frac{dz}{z}.$$

Rather than postulate a functional form and match coefficients, we solve for a single analytic function which represents, in the sense of the Riesz-Fischer theorem, this unknown pricing function. The approach is still ‘guess and verify’, but it takes place in a function space, and it works because the Riesz-Fischer theorem tells us that two stochastic processes are ‘equal’ (in the sense of mean-squared convergence) if and only if their z -transforms are identical as analytic functions inside the (open) unit disk. The real advantage of this approach stems from the ease with which it handles noninvertibility (i.e., nonrevealing information) issues. Invertibility hinges on the absence of zeros inside the unit circle of the z -transform of the observed market data. By characterizing these zeros, we characterize the information revealing properties of the equilibrium.

APPENDIX B. PROOF OF PROPOSITION 4.1

The proof is by brute force computation. Let p_t^{pf} denote the perfect foresight price. It is given by

$$p_t^{pf} = \sum_{j=0}^{\infty} \beta^j f_{t+j} = \frac{La_0(1-\lambda L)}{(L-\beta)(1-\gamma L)} \epsilon_t$$

Using the residue calculus, we have

$$\begin{aligned} \text{var}(p^{pf}) &= \frac{a_0^2}{2\pi i} \oint \frac{(1-\lambda z)(1-\lambda z^{-1})}{(1-\gamma z)(1-\beta z^{-1})(1-\gamma z^{-1})(1-\beta z)} \frac{dz}{z} \\ &= \frac{a_0^2}{(1-\gamma\beta)(\beta-\gamma)} \left[\frac{(1-\lambda\beta)(\beta-\lambda)}{1-\beta^2} - \frac{(1-\lambda\gamma)(\gamma-\lambda)}{1-\gamma^2} \right] \end{aligned}$$

Next, using the equilibrium pricing function, we know that observed prices have the following ARMA(1,1) representation

$$p_t = \left[\frac{a_0(1-\lambda\beta) + b_1\lambda(1-\gamma\beta)}{(1-\gamma\beta)(1-\lambda\beta)} \right] \left(\frac{1-\psi L}{1-\gamma L} \right)$$

where

$$\psi = \frac{a_0\lambda(1-\lambda\beta) - b_1\lambda\gamma(1-\gamma\beta)}{a_0(1-\lambda\beta) + b_1\lambda(1-\gamma\beta)}$$

Again applying the residue calculus we obtain,

$$\text{var}(p) = \left[\frac{a_0(1-\lambda\beta) + b_1\lambda(1-\gamma\beta)}{(1-\gamma\beta)(1-\lambda\beta)} \right]^2 \left(\frac{1+\psi^2-2\psi\gamma}{1-\gamma^2} \right)$$

Therefore,

$$\text{var}(p) - \text{var}(p^{pf}) = \left[\frac{a_0(1 - \lambda\beta) + b_1\lambda(1 - \gamma\beta)}{(1 - \gamma\beta)(1 - \lambda\beta)} \right]^2 \left(\frac{1 + \psi^2 - 2\psi\gamma}{1 - \gamma^2} \right) + \left(\frac{a_0^2}{(1 - \gamma\beta)(\beta - \gamma)} \right) \left[\frac{(1 - \lambda\gamma)(\gamma - \lambda)}{1 - \gamma^2} - \frac{(1 - \lambda\beta)(\beta - \lambda)}{1 - \beta^2} \right] \quad (\text{B.1})$$

The existence condition implies $a_0 = -b_1(1 - \gamma\beta)(2 - \lambda\beta)/[\beta(1 - \lambda\beta)]$. Using this to eliminate a_0 gives

$$\text{var}(p) - \text{var}(p^{pf}) = \frac{b_1^2}{\beta^2(1 - \gamma^2)} \left[4(1 + \psi^2 - 2\psi\gamma) + \left(\frac{1 - \gamma\beta}{1 - \beta^2} \right) \left(\frac{2 - \lambda\beta}{1 - \lambda\beta} \right)^2 [2\lambda(\beta + \gamma) - (1 + \lambda^2)(1 + \beta\gamma)] \right] \quad (\text{B.2})$$

Using the existence condition to eliminate a_0 from the above expression for ψ gives

$$\psi = \frac{\lambda}{2} \left(1 + \frac{1 + \gamma\beta}{1 - \lambda\beta} \right)$$

Substituting this into (B.2) gives $\text{var}(p) - \text{var}(p^{pf}) =$

$$\frac{(b_1/\beta(1 - \lambda\beta))^2}{(1 - \gamma^2)(1 - \beta^2)} \left\{ 4(1 - \beta^2) \left[(1 - \lambda\beta)^2 + \frac{\lambda^2}{4} (2 - \beta(\lambda - \gamma))^2 - \lambda\gamma(1 - \lambda\beta)(2 - \beta(\lambda - \gamma)) \right] + (1 - \gamma\beta)(2 - \lambda\beta)^2 [2\lambda(\beta + \gamma) - (1 + \lambda^2)(1 + \beta\gamma)] \right\}$$

Setting, $\gamma = \beta$ and ignoring the coefficient in front, since it is unambiguously positive, we see that when γ is sufficiently close to β a sufficient condition for $\text{var}(p) > \text{var}(p^{pf})$ is:

$$4 \left[(1 - \lambda\beta)^2 + \frac{\lambda^2}{4} (2 - \beta(\lambda - \beta))^2 - \lambda\beta(1 - \lambda\beta)(2 - \beta(\lambda - \beta)) \right] + (2 - \lambda\beta)^2 [4\lambda\beta - (1 + \lambda^2)(1 + \beta^2)] > 0$$

This can be simplified to the condition,

$$(1 - \lambda\beta)^2 + (2 - \lambda\beta)^2 \left[\lambda\beta - \frac{1}{4}(1 + \beta^2 + \lambda^2\beta^2) \right] + \lambda\beta(2 - \lambda\beta) \left[\frac{1}{2}\lambda\beta - (1 - \lambda\beta) \right] + \lambda\beta^3 \left(\frac{5}{4}\lambda\beta - 1 \right) > 0$$

One can now readily verify that if $\beta > 4/5$ the final three terms are positive when λ is sufficiently close to one.

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