Natural Expectations, Macroeconomic Dynamics, and Asset Pricing

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Abstract

How would an economy behave if (1) fundamentals are truly hump-shaped, exhibiting momentum in the short run and partial mean reversion in the long run and (2) agents do not know that fundamentals are hump-shaped and base their beliefs on parsimonious models that they fit to the data? A wide class of parsimonious models engender qualitatively similar biases and generate empirically observed patterns in asset prices and macroeconomic dynamics. First, parsimonious models will robustly pick up the short-term momentum in fundamentals but will generally fail to fully capture the long-run mean reversion. Beliefs will therefore be characterized by endogenous extrapolation bias and excess optimism will be pro-cyclical. Second, asset prices will be highly volatile and exhibit partial mean reversion—i.e., overreaction. Excess returns will be negatively predicted by lagged excess returns, P/E ratios, and consumption growth. Third, real economic activity will have amplified cycles. For example, consumption growth will be negatively auto-correlated in the medium run. Fourth, the equity premium will be large. Agents will perceive that equities are very risky when in fact long-run equity returns will covary only weakly with long-run consumption growth. If agents had rational expectations, the equity premium would be close to zero. Fifth, sophisticated agents—i.e., those who are assumed to know the true model—will hold far more equity than investors who use parsimonious models. Moreover, sophisticated agents will follow a countercyclical asset allocation policy. These predicted effects are qualitatively confirmed in U.S. data.

PRELIMINARY AND INCOMPLETE

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1 Introduction

Since the 1970's, most macroeconomic models have incorporated the assumption that people have rational expectations: i.e., people know the true model of the economy.

In the current paper, we follow a different tradition and assume that agents use simple prediction models, which are estimated using historical data. In other words, *agents adopt a parsimonious model that fits the available data*. In general, this parsimonious model will not nest the true model (though the true model may nest the parsimonious model). We call the resulting beliefs *natural expectations*. We assume that agents use simplified models because this is how, in practice, economists and non-economists – statisticians, professional forecasters, and firms – actually do build models.

People use simple models for a wide range of good reasons. Simple models are easier to understand, easier to explain, and easier to employ. Simplicity also reduces the risks of overfitting, which is the reasoning that underlies many formal model selection criteria. Whatever the mix of reasons – pragmatic, psychological/suboptimal, and statistical – economic agents usually *do* use simple models to understand economic dynamics. We show that a wide class of parsimonious models engender qualitatively similar biases and generate empirically observed patterns in asset prices and macroeconomic dynamics.

To illustrate this claim, we study an economy in which fundamentals are hump-shaped, exhibiting short-run momentum and long-run partial mean reversion. Hump-shaped dynamics are controversial in the sense that economists continue to debate whether such cyclical dynamics are present in aggregate fluctuations. This debate is consistent with our claims, since we only want to argue that hump-shaped dynamics are plausible. In fact, hump-shaped dynamics match the point estimates from ARIMA models of various economic time series[1], though standard errors are large enough that the data do not rule out dynamics that are far more persistent.[2]

[1]Fuster, Laibson and Mendel (2010) provide some empirical evidence for hump-shapes in different economic time series. That paper also presents a simplified version of the model in this paper.

[2]There is considerable debate about the cyclicality of economic activity. See Campbell and Mankiw

We will ask, "How would an economy behave if (1) fundamentals are truly hump-shaped, and (2) agents adopt a parsimonious model that fits the available data?"[3] We embed these two assumptions—hump-shaped fundamentals and natural expectations—in a consumption/asset-pricing model. We use a habit model to generate slow adjustment in consumption; however, as we combine the habit with CARA preferences (Alessie and Lusardi 1997), these habits do not produce counter-cyclical variation in risk premia.[4]

The following five sets of results emerge from our analysis. Some of these results are comparative: how does equilibrium behavior in an economy with natural expectations compare to equilibrium behavior that would have arisen if agents knew the true model—i.e., if agents had rational expectations?

First, simple models robustly pick up the short-term momentum in fundamentals but often fail to capture the full extent of long-run mean reversion. Consequently, under natural expectations beliefs will often be characterized by endogenous extrapolation bias in levels: forecasts about fundamentals will be too persistent since simple models tend to miss some of the long-run mean reversion. This implies that beliefs will be too optimistic in good times and too pessimistic in bad times relative to the rational expectations benchmark.

Second, under natural expectations asset prices will be highly volatile (LeRoy and Porter 1981, Shiller 1981) and exhibit partial mean reversion—i.e., overreaction. Excess returns will be negatively predicted by lagged excess returns (Fama and French 1988a, Poterba and Summers 1988), price/earnings ratios (Campbell and Shiller 1988, 2005), and consumption growth. Excess returns will be positively predicted by lagged 'cay', a measure of transitory deviations of consumption from wealth (Lettau and Ludvigson 2001).[5]

Third, real economic activity will have amplified cycles. For example, consumption

(1987), Cochrane (1988), Morley, Nelson, and Zivot (2003) and Perron and Wada (2009) for a range of opinions.

[3]To keep the analysis in our paper maximally tractable, we abstract away from learning and give agents a fixed simple model that is estimated from data available in 2011. Adding learning would complicate the analysis, but not change the qualitative results.

[4]In contrast, Campbell and Cochrane (1999) use a habit model that generates countercyclical risk premia, thereby explaining numerous asset pricing regularities.

[5]When 'cay' is low, wealth is transitorily high. In our economy, this predicts low future excess returns.

growth will be positively auto-correlated in the short run and *negatively* auto-correlated in the medium run. Consumption growth will be negatively predicted by lagged excess returns and P/E ratios.

Fourth, the equity premium will be large. Agents will perceive that equities are very risky when in fact long-run equity returns will covary only weakly with long-run consumption growth. The covariance of consumption growth and asset returns will be close to zero over short-run horizons (because of slow adjustment in consumption), it will be higher over medium-run horizons (as consumption catches up with asset prices), and it will fall again over long-run horizons (as asset prices and consumption both mean revert). If agents had rational expectations, the equity premium in our economy would be close to zero.

Fifth, sophisticated agents—i.e., those who are assumed to know the true model—will hold far more equity than investors with natural expectations. Moreover, sophisticated agents will be "value" investors, following a countercyclical investment policy.

These five sets of predicted effects are qualitatively confirmed in U.S. data. An economy in which agents estimate simple models – e.g., an AR(10) in earnings growth, instead of an AR(40) – generates simulated behavior that quantitatively matches the point estimates observed in U.S. data. However, the moments that we study have large standard errors because of the limited span of available data. It is therefore not possible to reject classical models in which excess returns are unpredictable and consumption is a random walk.

The body of the paper is divided into six sections; appendices are used for derivations. Section 2 discusses the econometric and psychological motivations for natural expectations, as well as the related literature. Section 3 solves and calibrates a consumption-based asset pricing model. Section 4 reports model simulations and compares these simulations to the empirical evidence from U.S. We focus on eight moments that summarize the key properties of the model. We show that a parsimonious version of the model matches these moments. Section 5 discusses the behavior of sophisticated agents. Section 6 concludes and identifies directions for future work.

2 The Appeal of Simple Models

The premise of our approach to understanding macroeconomic and financial dynamics is that economic agents tend to make forecasts based on statistical or mental models that are reasonable given the data available to them, but "too simple" to fully capture the long-term dynamics of many economic time series.

In this section, we motivate our assumptions both on statistical and psychological grounds, though we believe that the psychological motivations are more important.[6] We will also discuss how simple models lead agents to overestimate the persistence of shocks when the true process is hump-shaped, which will be observationally similar to agents extrapolating recent trends too far into the future. Finally, we summarize evidence from different settings that are related to our approach.

2.1 Statistical Perspective

Choosing the right model to forecast an economic time series is by no means a trivial task, and there is no single generally accepted way of doing so. When choosing how many parameters to include, a modeler faces a trade-off between improving the fit of the model in-sample and the risk of overfitting the available data, which may result in poor out-of-sample forecasts. A number of formal statistical criteria have been proposed to formalize the trade-off between fit and parsimony. The best-known and most popular ones are the Akaike Information Criterion (AIC) and the Schwarz or Bayesian Information Criterion (BIC).[7] These criteria are both asymptotically optimal, but in different ways. If the set of candidate models is not presumed to contain the true model (for instance because the true model is of infinite dimension), the AIC is *efficient* in that it will select the candidate model with minimum mean squared error distribution with probability 1 as the sample size grows to infinity. If

[6] Brav and Heaton (2002) emphasize that when explaining "financial anomalies," behavioral theories and rational theories with structural uncertainty are often very similar mathematically and also in terms of predictions. We remain agnostic as to whether the reliance on models that fail to capture long-term dynamics is "behavioral" or "rational" in our setting, and focus on the implications.

[7] McQuarrie and Tsai (1998) provide an overview of these and other selection criteria.

instead the true model is among the set of candidate models, the BIC will select it with probability 1 asymptotically (the BIC is *consistent*), while the AIC will tend to result in an overparametrized model (Hannan, 1980).

When the likelihood function is Gaussian, the two criteria can be written as follows:

$$\text{AIC} = \ln(\hat{\sigma}^2) + \frac{2k}{T}$$
$$\text{BIC} = \ln(\hat{\sigma}^2) + \frac{\ln(T) \cdot k}{T}$$

where $\hat{\sigma}^2$ is the estimated error variance, k the number of parameters (including the constant), and T the number of observations. One is supposed to pick the model with the smallest value of the preferred criterion. Both criteria trade off fit and parsimony: as k increases, $\hat{\sigma}^2$ decreases, but the second ("penalty") term increases. Generally, the BIC imposes a larger penalty for increasing the number of parameters, and thus will tend to select models with fewer parameters than the AIC. A relatively recent literature based on extensive simulation studies has argued that a version of the AIC corrected for small sample sizes, the AICc, tends to perform well (in various senses) and, relative to the AIC, reduces the likelihood of overfitting.[8]

It is not clear which criterion should be preferred. If one believes that the true model is among the candidate models, and if $T \to \infty$, there seems to be a clear case for the BIC. Yet, in practice, these conditions are rarely met, and it appears that which criterion is preferred seems to be to some extent a matter of taste.[9] While strictly speaking, each criteria picks one model, a reasonable pragmatic strategy would be to choose a model that is close to the best model according to different criteria, or perhaps to make predictions based on averaging

[8]The AICc can be written as $\ln(\hat{\sigma}^2) + \frac{T+k-1}{T-k-1}$.

[9]McQuarrie and Tsai (1998) indicate that "AIC is probably the most commonly used model selection criterion for time series data" (p. 2). On the other hand, Neath and Cavanaugh (1997) note that BIC "is often preferred over AIC by practitioners who find appeal in either its Bayesian justification or its tendency to choose more parsimonious models than AIC" (p. 559) For an interesting discussion on this topic from an online forum for "statisticians, data analysts, data miners and data visualization experts," see http://stats.stackexchange.com/questions/577/is-there-any-reason-to-prefer-the-aic-or-bic-over-the-other.

the predictions of different models.

For the purpose of our work, what matters is whether a modeler who is presented with a time series of length equal to the typical macroeconomic time series (e.g., 250 quarters) and who relies on (one of) these information criteria will generally pick a model that correctly captures the properties of the data-generating process. In particular, we are interested in time series that feature hump-shaped dynamics, in the sense that they are characterized by momentum (positive autocorrelation in growth rates) in the short run but (partially) revert back to the mean in the long run. To our knowledge, this is not a question that has been formally analyzed in the existing literature, so we now present some suggestive evidence from Monte Carlo simulations to shed light on this question.

Assume that the true data generating process is an ARIMA(0,1,16), and for simplicity assume that the modeler considers univariate models of the ARIMA$(p, 1, 0)$ and ARIMA$(0, 1, q)$ classes. The process we are interested in has a hump-shaped impulse response function with a long-term persistence of 0.5.[10] We draw 100 samples of length 255 (which is the number of observations we will use in the estimation of the aggregate earnings process) and estimate AR$(p, 1, 0)$ models for $p = 1, ..., 25$ and MA$(0, 1, q)$ models for $q = 4, 8, 12, 16, 20, 24$.[11]

In our 100 simulations, the AICc selects an AR(1), AR(2), or AR(3) in 60 cases; the BIC does so in all cases. The average estimated long-term persistence of a shock implied by the AICc-selected model equals 1.02, and is below 0.8 only in 25% of cases. For the BIC-selected model, it is never below 1. Thus, in the vast majority of cases, a modeler who considers

[10]The MA coefficients are: +0.15, +0.1, -0.02, -0.05, -0.05, -0.05, -0.05, -0.05, -0.06, -0.06, -0.06, -0.06, -0.06, -0.06, -0.06, -0.06. The long-term persistence of an ARIMA$(p, 1, q)$ process is given by (1+sum of MA coefficients)/(1-sum of AR coefficients).

[11]Estimating MA models with a large number of terms is computationally demanding, which is why we only estimate a subset of the possible models one might consider. In our simulations the maximum likelihood estimation of MA models sometimes failed to converge, or the maximum likelihood estimator of the root (i.e., the negative of the sum of the lagged MA coefficients) tended to "pile up" at a value of 1, which means that the predicted long-term persistence of a shock equaled 0. This pileup occurs because the sample likelihood function is locally flat at an MA root of 1, so that it is a local maximum of the likelihood function and may be the global maximum in finite samples, even if the true MA root is less than unity (see Campbell and Mankiw 1987 or Stock 1994 for discussions). It seems likely that a modeler would be highly skeptical of such a result. Also, our modeler does not consider ARIMA$(p, 1, q)$ models with both p and $q > 0$. While such models are often estimated in practice, based on our results, it seems very unlikely that estimating more models would change our qualitative conclusions.

this set of candidate models and selects based on AICc or BIC would grossly overestimate the persistence of shocks to the process. Note that while it appears difficult to capture the mean-reversion in a sample of this length, it is not impossible: for instance, the implied persistence from an estimated MA(16) (the correct model) averages 0.56 and is below 0.8 in 88% of cases.[12] Yet the improvement that the MA(16) brings in terms of fit relative to an AR(2), say, is only rarely worth its increased complexity here (an MA(q) with $q \geq 16$ is selected nine times by the AICc).

In large part, the difficulty that these models have in detecting mean reversion seems due to the relatively short sample length. If we repeat the same exercise but with 1255 observations instead of 255 (the equivalent of an additional 250 years of data, if this series were quarterly), the AICc selects the MA(16) in 75% of cases, and the mean long-term persistence of a shock estimated by the preferred model decreases to 0.53, i.e. very close to the actual persistence of the process.

We have conducted similar simulations with other data generating processes. While with somewhat less complicated hump-shape patterns, the AICc often does well in terms of selecting a model that gets the long-term persistence approximately right, the BIC with its greater emphasis on parsimony tends to select low-order models (with 5 coefficients or less) in the vast majority of cases. Thus, overall our simulations suggest that even a sophisticated modeler who goes through the trouble of estimating and comparing a wide selection of candidate models may well end up with a model that vastly overestimates the long-term persistence of shocks. To be clear, we are not claiming that it is ever impossible to find a model that gets the long-term dynamics right, in particular if one uses more sophisticated methods than ARIMAs (e.g., multivariate models) or adds more ex-ante imposed structure to the model—we are saying that it is not straightforward.

So far, we have discussed the model selection problem under the assumption that the stochastic process of interest is stable over time and that economic agents should normatively

[12]For these calculations, we drop simulations in which the sum of MA coefficients equalled exactly -1 (cf. previous footnote).

use all the historical data that is available to them in estimating a model, and weigh all observations equally. However, it is possible that the properties of the data generating process change over time, and so it may well be optimal for an agent to downweight or discard old data.[13] While we will not attempt a normative analysis of optimal model selection under the possibility that parameters of the data generating process (such as the mean growth rate of earnings) change over time, it seems intuitive that in such a world, agents would tend to use shorter effective samples to estimate their models, and this would increase the likelihood of picking a low-order model.[14]

2.2 Psychological Perspective

Psychological factors also lead agents to adopt simple models. In fact, we believe that psychological considerations are far more important in driving preferences for simplicity than the statistical considerations reviewed above. Even *if* non-parsimonious, complicated models were statistically optimal, real people would probably not adopt such models.

Constraints on memory and cognition make it difficult for agents to work with complicated models, leading decision-makers to adopt simplifications and heuristics (e.g., Tversky and Kahneman 1973, 1974; Gigerenzer and Goldstein 1996; Gabaix, Laibson, Moloche and Weinberg 2006; Gabaix 2011). Simple models are relatively easy to comprehend, use, revise, and explain. Complicated "black-box" models are viewed with a degree of suspicion; programmers themselves are boundedly rational so high-dimensional computational models often have subtle programming errors and other unintended or poorly understood features that make them unreliable. Even when people do use complicated computational models, the conclusions are rarely taken at face value and usually tempered with "common sense" about how the world works.

The 'psychological' motives for simplicity can also be interpreted through a rational lens.

[13] A large literature in statistics and economics studies methods to detect regime switching or structural breaks.

[14] Model selection criteria like the AIC, AICc, and BIC all *increase* the penalty for model complexity as the sample size falls.

If complicated models tend to induce confusion or mistakes, then simple models may be the lesser of two evils. Complicated models also engender high costs for agents with costly cognition[15], providing another rational explanation for complexity avoidance.

There are also some specific psychological biases that reinforce our approach. The heuristic of representativeness (Kahneman and Tversky 1973; Tverksy and Kahneman 1974) leads people to believe that small samples are representative of the world at large. Representativeness has two implications for our analysis.

First, the last few quarters of data may be viewed as representative of the future. Thus representativeness bias leads agents to underappreciate the degree of mean reversion (Kahneman and Tversky 1973).

Second, the representativeness heuristic leads one to mistakenly conclude that the properties of a time series can be inferred by studying only a short sub-sample. This willingness to draw strong conclusions from short sub-samples was arguably instrumental in driving the mis-judgments of the rating agencies on the likely performance of structured finance products during the run-up in housing prices from 2000 to 2006. More generally, a willingness to rely on short sub-samples will reinforce the tendency to rely on parsimonious models (without long lag effects).

The availability heuristic (Tversky and Kahneman 1973) also reinforces our modeling approach. Availability leads people to overweight information that is easily accessible and salient. Hence, availability bias also implies that people will overweight recent data and underweight data from the distant past.

Some observors have argued that these biases play an important role in driving aggregate dynamics. For instance, Reinhart and Rogoff (2009) document how investors time and time again fall prey to the belief that "this time is different" and that this causes recurrent financial crises. Relatedly, Shiller (2005) points out the lure of "new era" stories and how they are associated with episodes of bubbles in asset markets. Barberis (2010) notes that

[15]For example, see Sims (1998, 2003), Woodford (2009), Gabaix, Laibson, Moloche and Weinberg (2006).

over-extrapolation of past prices changes may have been an important psychological driving force during the run-up to the Great Recession. We now turn to a large body of related economic research.

2.3 Additional Related Literature

Evidence from a variety of settings is consistent with people using simple (mental) models which lead them to extrapolate recent trends. For instance, lab experiments in which subjects are asked to forecast financial or other time series find that extrapolative expectations or "trend following" provide a good description of observed beliefs (DeBondt 1993; Hey 1994) and may be a key driving force behind the well-documented bubbles that are observed in asset-market experiments (Haruvy, Lahav, and Noussair 2007; Hommes et al. 2008).[16]

In field data, a number of papers have documented that individuals' asset allocation is affected by the extrapolation of recent growth rates of prices or portfolio values, even though these growth rates have little subsequent persistence (Chevalier and Ellison 1997; Sirri and Tufano 1998; Benartzi 2001; Choi et al 2004, 2009; Benartzi and Thaler, 2007; Chalmers and Reuter, 2009; Previtero 2010; Malmendier and Nagel 2011). One could argue that biases in expectations do not matter for aggregate asset pricing, because investors with extrapolative beliefs hold relatively little wealth. However, Vissing-Jorgensen (2003) documents, based on survey data, that at the peak of the market in 2000-01, even wealthy investors expected stock returns to remain high. Bacchetta, Mertens, and van Wincoop (2009) conduct a similar exercise and find that, in several asset markets, investors' expectational errors about future returns are predicted by the same variables that predict excess returns.[17]

One might alternatively think that the expectations held (and made public) by financial

[16]Dwyer et al. (1993) find that subjects' forecasts of a random walk series (in which growth has no persistence) do not deviate systematically from the rational expectations forecast. This is consistent with our model, where extrapolation is not "baked in" but depends on the particular time series at hand.

[17]For instance, a high dividend/price ratio is a significant predictor of subsequent equity returns being higher than expected by investors. Similarly, when 'cay' is high, excess returns tend to be higher than anticipated (as the surveyed investors tend to expect low excess returns when 'cay' is high). Both these observations are difficult to reconcile with rational asset pricing theories.

analysts are less biased. However, various studies have put this into question. For instance, De Bondt and Thaler (1990) argue that security analysts overreact and make earnings-per-share forecasts that are too extreme.[18] Most of the studies in this literature look at relatively short-run forecasts, while our model mostly has implications for long-run forecasts. Bulkley and Harris (1997) study five-years earnings forecasts for about 500 U.S. companies and report results which are very much consistent with our model: i) analysts appear to extrapolate past growth in earnings when forecasting future growth, even though there is pronounced negative serial correlation in earnings growth over five-year periods, and ii) analysts' forecasts and excess returns over the subsequent five years are significantly negatively correlated.[19] Chan, Karceski, and Lakonishok (2003) provide further evidence that there is little predictability of long-term earnings growth rates, but that investors and analysts behave as if recent growth rates were positive predictors of future growth.

A significant literature in behavioral finance has accumulated evidence on cross-sectional stock return patterns that are consistent with such biases in expectations having strong effects on prices: DeBondt and Thaler (1985, 1989) and Lakonishok, Shleifer, and Vishny (1994) are among the best-known examples of such work.[20] Apart from stock markets, other asset markets may also be influenced by biased beliefs. For instance, Greenwood and Hanson (2010) document patterns in bond risk premia that can be explained by investors extrapolating recent returns or default rates. Periods of high returns on corporate bonds are followed by a decline in issuer quality and low or negative excess returns on corporate debt in a highly predictable manner. Also, biased (extrapolative) beliefs have been advanced

[18]Other studies instead find that analysts underreact. Easterwood and Nutt (1999) argue that analysts overreact to positive information but underreact to negative information. Lim (2001) argues that considering analysts' objective function can "rationalize" their biases.

[19]La Porta (1996) finds a negative relation between analysts' long-term growth estimates and future one-year risk-adjusted returns. Bergman and Roychowdhury (2008) document a positive relation between the consumer confidence index (a proxy for market sentiment) and the error in long-horizon earnings estimates of financial analysts, consistent with the idea that when times are good, market participants may insufficiently adjust for subsequent mean reversion.

[20]More recently, Chen, Moise and Zhao (2009) argue that myopic extrapolation can also explain momentum, if investors completely miss the hump-shaped dynamics of firm-specific earnings shocks and simply treat current earnings shocks as permanent. They point out that apart from cognitive biases, the practice to price securities using earnings multiples can also contribute to this phenomenon.

as a key explanation behind the recent housing bubble as well as earlier boom-bust cycles (Abraham and Hendershott 1996, Muellbauer and Murphy 1997, Case and Shiller 2003, Gerardi et al. 2008, Goetzman, Peng and Yen 2009, Piazzesi and Schneider 2009, Glaeser, Gottlieb and Gyourko, 2010).

A variety of "behavioral" models have been proposed to explain stock return patterns, with DeLong et al. (1990), Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999) as the best-known examples.[21] Closely related are models in which investors continuously update their belief about future dividend growth or other parameters. This learning, which can be interpreted as behavioral or fully rational (similar to our model), generates predictability in returns as well as excess volatiliy. Among the best known papers in this literature are Barsky and DeLong (1993) and Timmermann (1993). While our approach is obviously closely related to these earlier papers, most previous authors consider simpler setups (often partial equiliibrium valuation models without consumption) to illustrate the consequences of biased beliefs or learning, and do not study the interrelation between asset prices and other macroeconomic variables. An exception to this, and closely related to our exercise, is for instance a paper by Cecchetti, Lam, and Mark (2000). They show that beliefs about the growth rate of aggregate endowment that are distorted in a particular way can generate high, volatile, and predictable excess returns on equity, as in the data.[22] Similarly, Lansing (2006), Choi (2006) and Adam and Marcet (2010) study economies where (all or a subset of) investors hold extrapolative beliefs, or learn about dividend growth, in otherwise standard Lucas tree economies with CRRA utility, and show that this can generate realistic asset pricing dynamics.

More generally, a large literature in macroeconomics and finance, surveyed in Evans and Honkapohja (2001, 2009) and Pastor and Veronesi (2009) assumes that agents are rational

[21] Rabin and Vayanos (2010) present a model based on the gambler's fallacy that can generate similar effects.

[22] The type of distortion that Cecchetti et al. focus on has agents *underestimate* the persistence of good and bad shocks to endowment growth (see Gourinchas and Tornell 2004 for a related model in an international finance context), while our "natural expectations" agents will *overestimate* the persistence of shocks to earnings growth.

(in the sense that they think like highly sophisticated statisticians) but have to learn the relevant parameters of the reduced form equations governing the economy over time. While the early papers in this literature mostly focused on whether expectations would ultimately converge to the rational expectations equilibrium, more recent work has considered what happens if agents have misspecified models and/or downweight older data, and finds that this can generate additional volatility and persistence of shocks in asset prices and/or the economy (e.g. Branch and Evans 2007, 2010; Hong, Stein, and Yu 2007; Huang, Liu and Zha 2009; Eusepi and Preston forthcoming). In these models, "misspecification" means that agents omit a relevant variable from their forecasting equation, while in our model, it means that they may not include enough lags of the variable they are trying to forecast.[23]

An alternative modeling approach, exemplified by the agent-based literature, assumes that agents (probabilistically) select among different forecasting models based on past performance of the models (for example, LeBaron et al. 1999; Tesfatsion and Judd 2006; De Grauwe 2010; LeBaron 2010). An advantage of such models, which are usually analyzed computationally, is that they generate heterogeneity in beliefs, which our model omits. Such heterogeneity allows for instance the study of wealth dynamics and trading volume.[24]

Finally, there is of course a very large literature that studies asset pricing and macroeconomic dynamics under the assumption of perfect rationality and knowledge of the economy's structure.[25] While basic rational models are rather unsuccessful in generating realistic asset pricing patterns, more elaborate versions can generate a high equity premium, volatile asset prices, and excess return predictability. Perhaps the most successful and influential consumption-based models over the past 15 years are a) Campbell and Cochrane's (1999) habit model, which matches many of the main observed empirical asset pricing phenomena through countercyclical and (on average) high effective risk aversion, and b) the "long-run

[23]The downweighting of old data is often captured by assuming "constant gain" rather than "decreasing gain" (least squares) learning. Some papers, such as Marcet and Nicolini (2003), endogenize agents' choice between constant and decreasing gain based on recent prediction errors.

[24]See Hong and Stein (2007) for a discussion of models of disagreement in a finance context.

[25]See Campbell (2003) and Cochrane (2007) for surveys of the rational asset pricing literature.

risks" model by Bansal and Yaron (2004), who engage in an exercise somewhat similar to ours: they assume that the world is characterized by a statistical process for which evidence is statistically rather weak (namely, a consumption growth process with a small predictable component as well as time-varying volatility) and study the implications for asset pricing (in their case, using Epstein-Zin-Weil preferences with an elasticity of intertemporal substitution above 1). We will discuss some differences between these models and our approach in the next two sections.

3 Consumption Model with Asset Pricing

We now illustrate our approach by characterizing general equilibrium in an economy in which agents hold natural expectations.

We study an open endowment economy with two assets. The first asset is foreign debt, b_t, which is borrowed at a fixed international (gross) interest rate R. We introduce foreign debt since we do not want a mechanistic linkage between production and consumption. The second asset is a domestic equity tree, which generates a dividend, d_t, that is stationary in first differences. In other words, Δd_t is an AR(n),

$$\Delta d_t = \rho_1 \Delta d_{t-1} + ... + \rho_n \Delta d_{t-n} + \sigma \varepsilon_t$$

where ε_t is an iid Gaussian shock with unit variance.[26] We assume that the equity tree must be held by domestic agents.[27] We will distinguish between the "true" data generating process for dividends, and the perceived data generating process for dividends. When the true data generating process matches the perceived data generating process, agents hold rational expectations. Our focus, however, is on cases in which the perceived data generating process

[26] Without loss of generality, we assume that the process has no deterministic drift. Adding deterministic would not change any of our results on comovement.

[27] If the equity tree were held by foreign investors, this would drastically dilute the associated risk. Domestic ownership can be motivated by home bias.

has fewer lags than the true data generating processes. As discussed in Section 2, this can occur for various reasons, and we will refer to this as "natural expectations."

Our timing conventions and wealth definitions follow. Period t is divided into the following sequential subperiods. We describe the model using a "quarterly" frequency – since this is the calibration that we will use – but the model can be calibrated for any period of observation.

1. On the first day of the quarter – "January 1" – households start with debt,

$$b_t = w_{t-1} - c_{t-1} - \theta_{t-1} p_{t-1},$$

   and θ_{t-1} units of claims to the risky asset.

2. Time passes and production occurs from January 1 to March 31. Households make no additional choices until the end of the quarter: March 31.

3. At the end of the quarter – March 31 – the dividend of the equity tree is realized and paid to households: d_t per unit of claim. So households receive $\theta_{t-1} d_t$ units of output.

4. The tree is priced (ex-dividend): p_t per unit of claim (where output units are the numeraire). So households can sell the tree for $\theta_{t-1} p_t$ units of output.

5. Wealth is measured at the end of the quarter,

$$\begin{aligned} w_t &= -R b_t + \theta_{t-1} d_t + \theta_{t-1} p_t \\ &= \left(w_{t-1} - c_{t-1} - \theta_{t-1} p_{t-1}\right) R + \theta_{t-1} \left(d_t + p_t\right). \end{aligned}$$

   So wealth, w_t, is measured after production has occured in the period but **before** consumption is chosen.

6. Consumption is chosen: c_t.

7. Asset allocation takes place: agent buys θ_t units of equity at price p_t.

8. End-of-quarter debt – after these transactions – is

$$b_{t+1} = w_t - c_t - \theta_t p_t.$$

9. Households start the next quarter (beginning on April 1, which is period $t+1$), with this level of debt.

Period $t+1$ continues and the cycle of subperiods restarts.

3.1 Preferences and the Bellman Equation

We have two desiderata for preferences. We want preferences that generate a closed form solution. We also want preferences – or technology – that will generate slow aggregate adjustment in consumption[28] *without* assuming procyclical risk tolerance.[29]

Motivated by these goals, we adopt exponential preferences (e.g., Caballero 1990) with habits, as studied by Alessie and Lusardi (1997):

$$u(c_t, c_{t-1}) = -\frac{1}{\alpha} \exp\left(-\alpha \left[c_t - \gamma c_{t-1}\right]\right)$$

The parameter $\gamma \in [0,1]$, reflects the strength of the habit. As we show below, in this formulation habits only serve to slow down consumption adjustments. Our habits are not operating as in Campbell and Cochrane (1999), where the habit is constructed in a way that generates counter-cyclical relative risk aversion.

Utility flows are weighted with discount factor δ, so that lifetime utility is given by

$$\sum_{s=0}^{\infty} \delta^s u(c_{t+s}, c_{t+s-1}).$$

[28] See e.g. Dynan and Maki (2001), Gabaix and Laibson (2001), Parker (2001), or Carroll, Sommer and Slacalek (forthcoming) for evidence on slowly adjusting consumption.

[29] We wish to avoid countercyclical risk aversion to draw a clear distinction between our approach and the habit model advanced by Campbell and Cochrane (1999).

Lifetime utility is maximized with respect to the dynamic budgets constraints summarized above. Here is the decentralized Bellman Equation.

$$V\left(c_{t-1}, w_t, p_t, \overrightarrow{d}_t\right) = \sup_{\theta_t, c_t} u(c_t, c_{t-1}) + E_t \delta V\left(c_t, \left(w_t - c_t - \theta_t p_t\right) R + \theta_t \left(d_{t+1} + p_{t+1}\right), p_{t+1}, \overrightarrow{d}_{t+1}\right)$$

since

$$w_{t+1} = \left(w_t - c_t - \theta_t p_t\right) R + \theta_t \left(d_{t+1} + p_{t+1}\right).$$

For now, we will not pin down the conditional expectation operator, E_t. It depends only on the perceived data generating process for dividends. We will study the predictions of the model under rational expectations and a large set of specifications for natural expectations.

The planner's Bellman Equation (which eliminates the asset allocation issue and eliminates price-based wealth measurement) is the following:

$$V\left(c_{t-1}, b_t, \overrightarrow{d}_t\right) = \sup_{c_t} u(c_t, c_{t-1}) + E_t \delta V\left(c_t, \left(c_t + Rb_t - d_t\right), \overrightarrow{d}_{t+1}\right).$$

since

$$b_{t+1} = c_t + Rb_t - d_t.$$

3.2 Value functions, policy functions, and asset pricing

We first study the planner's problem, since we begin by assuming that the economy is populated by homogeneous households – i.e., a representative agent. For the planner's problem, we can ignore the asset allocation decision as well as asset pricing. For the planner's problem, Appendix A shows that

$$c_t = \frac{\gamma}{R} c_{t-1} + \left(1 - \frac{\gamma}{R}\right) x_t - \psi. \tag{1}$$

This implies that consumption is a weighted average of lagged consumption and the (risk-neutral) annuity value of future dividends, x_t, down-shifted by an additive constant ψ.

$$x_t = \frac{R-1}{R}\left[-Rb_t + \sum_{s=0}^{\infty} \frac{E_t d_{t+s}}{R^s}\right] \tag{2}$$

$$\psi = \frac{1}{R-1}\left[\frac{1}{\alpha}\ln(R\delta) + \frac{\alpha}{2} Var_t(\Delta c_{t+1})\right]. \tag{3}$$

For the planner, the value function takes a simple form:

$$V\left(c_{t-1}, b_t, \overrightarrow{d}_t\right) = \frac{-1}{\alpha(1-\delta)} \exp\left(-\alpha\left[c_t - \gamma c_{t-1}\right]\right) \tag{4}$$

where c_t is given by equation (1).

To calculate the equilibrium price of the Lucas tree, we consider the asset allocation problem (as opposed to the planner's problem). We then solve for the asset price that leads the representative agent to hold one unit of the equity tree. These calculations are provided in Appendix B, where we show that the equilibrium price of the Lucas tree is given by:

$$p_t = \sum_{s=1}^{\infty} \frac{E_t d_{t+s}}{R^s} - \frac{R\alpha \times Var_t(\Delta c_{t+1})}{\left(1-\frac{\gamma}{R}\right)(R-1)^2}.$$

Appendix B also provides a closed form expression as a function of $\overrightarrow{\Delta d}_t$. Note that this is not bounded below, since earnings are not bounded below in this arithmetic (exponential utility) model.

Using the asset pricing relationship it is possible to re-express the consumption function in terms of total wealth, $w_t = -Rb_t + d_t + p_t$. Here we will are studying a representative

agent economy so that $\theta_t = 1$ for all t.

$$\begin{aligned} c_t &= \frac{\gamma}{R} c_{t-1} + \left(1 - \frac{\gamma}{R}\right) x_t - \psi \\ &= \frac{\gamma}{R} c_{t-1} + \left(1 - \frac{\gamma}{R}\right) \left(\frac{R-1}{R} \left[-Rb_t + d_t + p_t + \frac{R\alpha \times Var_t(c_{t+1})}{\left(1 - \frac{\gamma}{R}\right)(R-1)^2} \right] \right) - \psi \\ &= \frac{\gamma}{R} c_{t-1} + \left(1 - \frac{\gamma}{R}\right) \left(\frac{R-1}{R} \right) w_t + \Lambda \end{aligned}$$

where

$$\Lambda = \frac{\alpha}{2} \frac{Var_t(c_{t+1})}{R-1} - \frac{1}{R-1} \frac{1}{\alpha} \ln(R\delta).$$

We can rewrite the value function in the following simplified form (redefining the earlier value function notation):

$$V(c_{t-1}, w_t) = \frac{-1}{\alpha(1-\delta)} \exp\left(-\alpha \left[c_t - \gamma c_{t-1}\right]\right)$$

Relative risk aversion is given by:

$$\begin{aligned} CRRA &= -\frac{w\, V_{ww}}{V_w} \\ &= w\, \alpha\, \frac{\partial c_t}{\partial w_t} \\ &= w\alpha \left(1 - \frac{\gamma}{R}\right) \left(\frac{R-1}{R}\right) \\ &\simeq c\alpha \left(1 - \frac{\gamma}{R}\right). \end{aligned}$$

3.3 Calibration

To match historical data, we assume that the quarterly risk free (world) interest rate is $R = 1.0025$, implying that the annualized (net) rate is 0.01. We set the product of the discount factor and the gross interest rate to unity: $\delta R = 1$. The (quarterly) habit parameter

is set to $\gamma = 0.9$, implying a half-life of adjustment of about 6 quarters.[30] Finally, we set the curvature of the utility function so that

$$\alpha = \frac{4}{d_0\left(1 - \frac{\gamma}{R}\right)}.$$

This implies that relative risk aversion (at initialization) is approximately four.[31]

The stochastic driving process is exogenous earnings, which are calibrated using real capital income from the NIPA accounts.[32] We use capital income from the NIPA accounts because it is seasonally adjusted (unlike corporate earnings) and is not artificially smoothed (like corporate dividends). Figure 1 plots the natural log of real capital income at a quarterly frequency from 1947:1 to 2010:3.

Using this data, Figure 2 plots the resulting impulse response functions using a range of ARIMA(p,1,0) models, with $p = 1, 10, 20, 30, 40$. We will henceforth refer to these as AR(p) models of the *differenced* data. Figure 2 reveals that the order of the model is critical in determining inferences about persistence. Low order models ($p = 1$ and 10) generate persistence estimates that are greater than or equal to 1. As the order of the model increases, estimated persistence falls dramatically. For an AR(40), estimated persistence after 40 quarters is about 1/3.

For AR(p) models with $p \leq 20$, there is a substantial gap between the persistence implied

[30] Recall that the consumption function is

$$c_t = \frac{\gamma}{R} c_{t-1} + \left(1 - \frac{\gamma}{R}\right)\left(\frac{R-1}{R}\right) w_t + \text{constant}$$

[31] At initialization, with $b_0 = 0$, relative risk aversion in our CARA economy is

$$\begin{aligned}\left(\frac{R-1}{R}\right) w\alpha\left(1 - \frac{\gamma}{R}\right) &\simeq c_0\alpha\left(1 - \frac{\gamma}{R}\right) \\ &\simeq d_0\alpha\left(1 - \frac{\gamma}{R}\right).\end{aligned}$$

[32] Specifically, we study the natural log of real net operating surplus of private enterprises as reported in the U.S. National Income and Product Accounts (Bureau of Economic Analysis, 1947:1 to 2010:3). The net operating surplus of private enterprises is reported in NIPA Table 1.10, line 12. This definition is net of capital depreciation. To adjust for inflation, we use the GDP deflator.

by the estimated model and the persistence implied by what we are assuming to be the true model: the AR(40). Hence, parsimonious AR(p) models yield a form of extrapolation bias in *levels* (not growth rates). In other words, "low" order AR(p) models imply that shocks are far more persistent than they are actually likely to be; low order models imply excess optimism in good times and excess pessimism in bad times.

The associated coefficient estimates from the five AR(p) models in Figure 2 are reported in Table 1. There are few significant coefficients after the 10th lag.[33]

We use AR(p) regressions to calibrate the model. We will always assume that the *true data generating process* is the AR(40) estimated in the final column of Table 1 and plotted as an impulse response function in Figure 2. We are not loyal to this particular specification. Instead it is merely a convenient way of capturing hump-shaped dynamics: short-run momentum and long-run partial mean reversion. We will assume that this is the true data generating process because this case is interesting, and *not* because we believe that there is overwhelming evidence for this specification. We only wish to argue that this hump-shaped process—the point estimate from the AR(40) case—is plausible.

The only remaining thing to specify is the beliefs of the agents in the economy. We don't have strong views about this either. We will therefore study the beliefs generated by every AR(p) model with $p = 1, 2, ..., 40$. In other words, we will assume that the true model is the AR(40) in the last column of Table 1, but that agents believe some AR(p) model which may not be the AR(40). We will study the properties of all of these belief assumptions: $p = 1, ..., 40$. When we assume $p = 40$, we are implicitly assuming that the agents know the true model (exactly); $p = 40$ is the rational expectations benchmark. When $p < 40$, we are assuming that agents use a simpler model than the true model.

[33]It is well-known that estimating AR coefficients is small samples yields biased coefficients (e.g., Shaman and Stine 1988). Monte Carlo simulations indicate that with our sample size, this does not significantly affect estimated persistence.

4 Simulation and Empirical Evaluation

To characterize the qualitative predictions of our model, we begin by reporting two impulse response functions—one for asset returns and one for consumption growth—that summarize the key mechanisms that are at work in the model. We then describe eight empirical moments that enable us to quantitatively evaluate the model's predictions. These empirical moments characterize the joint evolution of asset prices and consumption. The moments are chosen because they represent a test of the anomalous predictions that the model makes—e.g., cyclical fluctuations in asset returns and consumption growth. We find that these anomalous predictions match the actual empirical evidence well. Specifically, when agents hold beliefs generated by an AR(p) with $p \leq 20$, and unlike in the rational expectations benchmark, the model provides a good quantitative fit to the empirical moments.

4.1 Impulse Response Functions

We begin by reporting the impulse response function for cumulative excess returns. In our economy with exponential (CARA) utility, the excess return is more naturally expressed as an "excess gain," which is defined as

$$g_t = p_t + d_t - Rp_{t-1.} \tag{5}$$

Note that

$$\begin{aligned} \frac{g_t}{p_{t-1}} &= \frac{p_t + d_t - Rp_{t-1}}{p_{t-1}} \\ &= \frac{p_t + d_t}{p_{t-1}} - R. \end{aligned} \tag{6}$$

which is the standard definition of excess return, since R is the gross risk free rate. We study g_t, without dividing through by scaling factor p_{t-1} since prices can fall below zero in our CARA economy (assuming no free disposal of negative earnings), so the usual definition of

excess return (6) is not appropriate. Henceforth, we will refer to excess gains – equation (5) – when studying asset returns in our model, but the reader should intuitively think of excess gains as excess returns, since excess gains are an appropriately rescaled version of excess returns.

Figure 3 reports the impulse response function for the 'cumulative excess gain' following a positive (one-unit) shock to the earnings process at date zero. The cumulative excess gain is defined as,

$$\text{cumulative excess gain } t \text{ periods after the shock} = \sum_{s=0}^{t} g_t.$$

The cumulative excess gain is the CARA analog of the cumulative excess return from date 0 to date t. In a rational expectations model, an impulse at date 0 should not forecast additional excess returns in periods after date zero. In a rational expectations model, the cumulative excess gain jumps up at date zero and immediately plateaus.

In Figure 3, the impulse response function is reported for five simulated economies. In every case, the *true* process for earnings is the same – the AR(40) described in section 3.3. The economies differ only with respect to the *beliefs* that agents hold. Figure 3 analyzes economies in which agents generate forecasts using the following AR(p) models for earnings: $p = 1, 10, 20, 30, 40$.

Since the true data generating process is an AR(40), let's start with the case in which agents use the same model, an AR(40), to form beliefs. The impulse response function in this economy is the (flat) purple line in Figure 3. This is the rational expectations case.

When agents generate beliefs from an AR(p) model with $p < 40$, we are studying an economy with natural expectations. For example, when agents use an AR(1), they mistakenly infer that earnings impulses are highly persistent (cf. Figure 2). This belief in persistence causes the asset price to jump up more than it should at date zero. Thereafter, the asset price tends to decline (and this decline is not foreseen by the agents). This decline is easy

to see on the impulse response function, since there is only one impulse at date 0 and no impulse at any other point in time. In a full-blown simulation of the economy, the stream of negative excess gains would be largely masked by other contemporaneous shocks in the economy. Hence, the predictable negative excess gains would be very hard to infer.

As the estimated AR(p) rises from $p = 1$ to $p = 40$, the impulse response functions look more and more like the rational expectations impulse response function. As p rises, the initial jump in the asset price becomes smaller, since agents with high p models correctly anticipate more mean reversion in the true data generating process. As p rises, the magnitude of the negative excess returns gets smaller.

Hence, models with low levels of p are characterized by a high degree of overreaction. Models with p equal to or near 40 are characterized by little or no overreaction and little or no return predictability.

Figure 4 reports the impulse response function for consumption following a positive (one-unit) shock to the earnings process at date zero. In a rational expectations model, a shock at date 0 would forecast a slow rise in consumption because the agents in our setting have a preference for slow adjustment – a habit. On the other hand, if the habit parameter, γ, were zero, the consumption series would jump up at date zero and immediately plateau.

In Figure 4, the impulse response function is reported for five simulated economies. In every case, the true process for earnings is the same – the AR(40) described in section 3.3. The economies differ with respect to the beliefs that agents hold. Figure 4 analyzes economies in which agents generate forecasts using the following AR(p) models for earnings: $p = 1, 10, 20, 30, 40$. (This structure mirrors Figure 3.)

Let's again start with the case in which agents have AR(40) beliefs, which is the rational expectations case. As expected, consumption rises concavely and eventually asymptotes, reflecting smooth habit-based adjustment.

When agents generate beliefs from an AR(p) model with $p < 40$, we are studying an economy with natural expectations. For example, when agents use an AR(1), they mistakenly

infer that the earnings impulse is highly persistent leading them to overreact to the earnings impulse (despite their preference for slow adjustment). About ten quarters after the initial impulse, they realize that they have gone too far and begin to reduce consumption. Over the long run, consumption falls from its peak level as households realize that their wealth is not as great as they initially thought (mirroring the negative excess gains in Figure 3). Since the NPV of these consumption lines must be the same across the p values – a consequence of the budget constraint – the long-run consumption asymptotes are different, reflecting pay-back for the short-run over-consumption.

As in Figure 3, the dynamics in Figure 4 are easy to see since there is only one impulse at date 0 and no impulses at any other point in time. In a full-blown simulation of the economy, this predictability in consumption dynamics would be masked by other contemporaneous shocks in the economy.

As the estimated AR(p) rises from $p = 1$ to $p = 40$ in Figure 4, the impulse response functions look more and more like the rational expectations impulse response function. As p rises, the initial growth in consumption becomes smaller, since agents that use high-p models believe in more mean reversion in the earnings process and therefore don't believe that the impulse to earnings has made them much more wealthy. As p is increased, the magnitude of the predictable fall in consumption gets smaller.

In summary, models with low levels of p are characterized by a high degree of overreaction. Models with p equal to or near 40 are characterized by little or no overreaction and little or no eventual declines in consumption.

4.2 Empirical Moments for Model Evaluation

We use the following eight moments to evaluate the empirical performance of our model under different assumptions. All data is annual, and goes from 1929 to 2010 (we use annual data so we can go further back in time, as the quarterly series in NIPA only start in 1947). To distinguish this *annual* data from the *quarterly* observation frequency of the

model/calibration, we use the new time subscript τ.

1. The correlation between excess returns of equity over the risk-free rate in year τ and cumulative excess returns from year $\tau + 2$ to year $\tau + 5$. This equals -0.22.[34]

2. The correlation between the ratio of S&P price at the end of year τ and average earnings over years $\tau - 9$ to τ (the *P/E_{10} ratio*) and excess returns from year $\tau + 2$ to year $\tau + 5$. This equals -0.38.[35]

3. The correlation between the one-year change in log consumption (i.e., $ln(c_\tau) - ln(c_{\tau-1})$) and cumulative excess returns from year $\tau + 2$ to year $\tau + 5$. This equals -0.30.[36]

4. The correlation between the P/E_{10} ratio and the change in log consumption from year $\tau + 2$ to year $\tau + 6$ (i.e., $ln(c_{\tau+6}) - ln(c_{\tau+2})$). This equals -0.17.

5. The correlation between $ln(c_\tau) - ln(c_{\tau-1})$ and $ln(c_{\tau+6}) - ln(c_{\tau+2})$. This equals -0.25.

6. The mean annual excess return of equity over the risk-free rate (the "equity premium"). This equals 7.44%.

7. The standard deviation of annual excess return of equity over the risk-free rate. This equals 20.83%.

[34]Excess returns are defined as "the value-weight return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the one-month Treasury bill rate (from Ibbotson Associates)." (source: Ken French's online data library). Early evidence on long-term mean reversion in stock prices was presented in Fama and French (1988a) and Poterba and Summers (1988). The significance of this evidence was subsequently challenged on statistical grounds, e.g. by Richardson (1993). Cutler, Poterba and Summers (1991) look at a variety of stocks, bonds and foreign exchange markets and find a relatively slight negative autocorrelation in returns in many markets over a horizons of 3 to 5 years. Balvers, Wu and Gilliland (2000) consider a panel of 18 countries and document strong mean reversion in national equity indexes relative to the world index.

[35]Data on stock prices and earnings come from Robert Shiller's website. Earnings and dividend yields as predictors of future returns are studied e.g. by Campbell and Shiller (1988ab, 2005) and Fama and French (1988b).

[36]As our consumption measure, we use real per capita expenditures on non-durable consumption and services, from NIPA. The nominal data on expenditures are in NIPA table 2.3.5, while price indices are in table 2.3.4. The population data come from table 2.1 Consumption growth is a relatively little studied predictor for excess returns. However, in recent work, Moller (2008) and Moller and Rangvid (2011) show that high consumption growth between quarters 3 and 4 significantly predicts low excess returns over the following year.

8. The standard deviation of $ln(c_\tau) - ln(c_{\tau-1})$. This equals 0.022.

While the directions and magnitudes of the correlations reported under 1) to 5) are suggestive, one has to be careful with the interpretation: as investigated in the finance literature by Stambaugh (1999), Volkanov (2003) and others, predictive regressions in short samples and with overlapping data can yield biased coefficients, and standard statistical inference may not be valid.[37]

To get an idea of the statistical significance of our results as well as the magnitude of a potential bias, we conduct a series of bootstrap exercises (similar to e.g. Nelson and Kim 1993). For moment 1), we draw repeatedly (with replacement) from the observed realization of excess returns under the assumption that excess returns are not serially correlated, and construct the measure of subsequent cumulative excess returns that we use in the empirical data. We then calculate the correlation between the two series and repeat this 10,000 times for samples of length 75 (corresponding to our empirical sample size), so we can construct a confidence interval under the null of independent returns. For moment 5), we instead assume one-period log consumption growth follows an AR(1) process.[38] We estimate this process and then simulate time series of consumption (of length equal to our empirical sample) by repeatedly drawing from the residuals. From this series, we construct the change in log consumption between years $\tau + 2$ and $\tau + 6$, and correlate it with the one-period change in log consumption. Again, this is repeated 10,000 times, and we construct confidence intervals based on the obtained correlations.

For moments 2) to 4), we proceed in a similar manner: e.g. for 2), i) we assume and estimate an AR(1) process for P/E_{10} (accounting for the small-sample bias in the autoregression coefficient); ii) we assume that excess returns are independently distributed (the null); and iii) draw residual pairs under the null (with replacement), construct the predicted variable we use in the data (for a sample of equal length to our data), and estimate the

[37] See Lettau and Ludvigson (2010) for an overview of the issues as well as potential remedies.

[38] This is the approximate process that consumption growth should follow when a consumer has habit preferences; see e.g. Dynan (2000).

correlation between the two series. We again repeat this 10,000 times and construct 90 and 95% confidence intervals for the correlation coefficient.

The results in Table 2 show that the correlations 3) and 5) are outside of the 90% confidence interval constructed under the null, but not outside the 95% interval. The "long-horizon autocorrelation" of excess returns (1) as well as the correlation of P/E_{10} with subsequent excess returns (2) are not quite significant at 10%, while the correlation between P/E and subsequent consumption growth (4) is far from significant.[39]

These relatively "weak" results do not come as a surprise, as a large literature in finance has established that predictability patterns that had appeared highly significant in the early (1980s) literature are much less significant once statistical complications are accounted for. That said, our use of annual rather than quarterly data (as is more common in the literature) presumably weakens our statistical power. Furthermore, there exist more sophisticated ways of testing for predictability, and overall the finance literature seems to have concluded that "despite complexities with statistical inference in return predictability regressions, it is difficult to reconcile the historical behavior of the U.S. stock market without admitting some degree of predictability in excess returns" (Lettau and Ludvigson 2010, p. 620). Finally, even where we cannot reject the null hypothesis of no predictability, we certainly also cannot reject an alternative null with economically high predictability—the currently available data just do not allow us to know.

4.3 Asset Return Predictability

For the next eight exhibits, we will illustrate the implications of the model for the full range of natural expectations cases. Specifically, beliefs about earnings are generated for all AR(p) models, for $p = 1, ..., 40$. As usual, we always assume that the true model generating earnings is an AR(40). The rational expectations case therefore coincides with the case

[39]The wide confidence intervals for 2) and 4) may seem surprising; they are due to the high persistence of the P/E_{10} and the use of overlapping data for consumption growth and excess returns (cf. Boudoukh, Richardson, and Whitelaw, 2008).

$p = 40$; natural expectations correspond to the cases $1 \leq p < 40$. It turns out that when p is between 10 and 20 the natural expectations model does a very good job of matching the point estimates for the eight empirical moments.

In the exhibits that follow, we always study simulations with 328 periods of quarterly data, matching the duration of our available empirical data (annual U.S. data since 1929). We then calculate the eight moments on these 328 simulated periods. We repeat this exercise 200 times and average the eight moments over these 200 (independent) simulations. We match the sample duration of our empirical data and the sample duration of our simulated data to make finite sample biases – e.g., Hurwicz bias and related variants – comparable across the empirical and simulated moments.

Figure 5 studies the correlation between excess returns in year τ and cumulative excess returns from year $\tau + 2$ to $\tau + 5$. The empirical correlation is -0.22. For low values of p, the simulated moment is about -0.3, rising to about -0.2 as p rises to 20. For the rational expectations case, $p = 40$, the correlation is approximately[40] zero. The natural expectations model matches this moment, because good earnings news at date zero generates over-reaction in asset prices. Over the next five years, some of that initial return will be reversed as agents discover that the good earnings news was not as persistent as they had anticipated.

Figure 6 studies the correlation between the P/E_{10} ratio at year-end τ and cumulative excess returns from year $\tau + 2$ to $\tau + 5$. The empirical correlation is -0.38. For low values of p, the simulated moment is about -0.5, rising to about -0.35 as p rises to 20. For the rational expectations case, $p = 40$, the correlation is approximately zero. Good earnings news increases the P/E_{10} ratio, since the denominator is relatively unresponsive given that it is averaged over 40 quarters. Over the next five years, some of that initial return will be reversed as natural expectations agents discover that the earnings news was not as persistent as they had anticipated.

In our model, Lettau and Ludvigson's (2001) *cay* variable is positively correlated with

[40]The rational expectations benchmark is slightly below zero due to a variant of Hurwicz bias.

excess returns (for the same reason that P/E predicts future excess returns). The *cay* variable is constructed by identifying the co-integration residual between consumption and wealth.

$$cay_t = c_t - \Psi w_t.$$

In our model, a positive earnings shock raises asset values but does relatively little to consumption in the short-run (due to slow adjustment). Thus a positive earnings shock causes *cay* to fall. Over the next five years, asset returns will tend to be low, due to unanticipated mean reversion in earnings. Hence, our model provides an alternative explanation for the observed positive correlation between *cay* and future excess returns.

Figure 7 studies the correlation between consumption growth at year τ and equity returns from year $\tau+2$ to $\tau+5$. The empirical correlation is -0.30. For low values of p, the simulated moment is about -0.5, rising to about -0.35 as p rises to 20. For the rational expectations case, $p = 40$, the correlation is approximately zero.[41] A high level of lag consumption growth is a proxy for a positive earnings shock (at that date or some proceeding date). Over the next five years, agents discover that the earnings news was not as persistent as they had anticipated leading to below average excess gains/returns.

4.4 Consumption Growth Predictability

Figure 8 studies the correlation between the P/E_{10} ratio at year-end τ and consumption growth from year $\tau + 2$ to $\tau + 6$. The empirical correlation is -0.17. For low values of p, the simulated moment is about -0.35, rising to about -0.15 as p rises to 20. For the rational expectations case, $p = 40$, the simulated correlation is approximately $+0.25$; this large positive value in the rational expectations case is due to habit formation and slow adjustment in consumption. For the natural expectations agents, $p < 40$, the negative correlations arise because unanticipated mean reversion in earnings swamps the effects of

[41] Once again, Hurwicz bias lowers the rational expectations correlation below zero.

habit formation. Good earnings news increases the P/E ratio, since the denominator is relatively unresponsive given that it is averaged over 40 quarters. Over the next five years, some of that initial return will be reversed as natural expectations agents discover that the earnings news was not as persistent as they had anticipated. This causes consumption to decline from year $\tau + 2$ to $\tau + 6$ for the natural expectations agents. This decline is strong enough to overcome the positive correlation that would otherwise arise because of habit formation. The consumption impulse response function—Figure 4—illustrates the effects of the countervailing forces of unanticipated mean reversion and habit formation. For the natural expectations agents, unanticipated mean reversion offsets the pure effects of habit formation.

Figure 9 studies the correlation between consumption growth at year τ and consumption growth from year $\tau + 2$ to $\tau + 6$. The empirical correlation is -0.25. For low values of p, the simulated moment is about -0.3, rising to about -0.2 as p rises to 20. For the rational expectations case, $p = 40$, the simulated correlation is approximately $+0.15$; once again, the positive correlation in the rational expectations case is due to habit formation. For the natural expectations agents, $p < 40$, the negative correlations arise because unanticipated mean reversion in earnings swamps the effects of habit formation. A high level of lag consumption growth is a proxy for a positive earnings shock (at that date or some proceeding date). Over the next five years, natural expectations agents discover that the initial positive earnings shock was not as persistent as they had anticipated leading to below average excess returns. This causes consumption to decline from year $\tau + 2$ to $\tau + 6$. This decline is strong enough to overcome the positive correlation that would otherwise arise because of habit-based slow adjustment.

The fact that consumption growth is only relatively weakly predicted by equity prices is a strength of our model. Beeler and Campbell (2009) point out that Bansal and Yaron's (2004) long-run risks model is problematic because it implies much more predictability of consumption growth from lagged price/dividend ratios than is present in the data, while at

the same time generating too little excess return predictability. Beeler and Campbell also note the empirical evidence for medium-run mean reversion in the level of consumption, while the long-run risks model implies that all autocorrelations of consumption growth should be positive.

4.5 The Equity Premium and Standard Deviations

In the natural expectations economy, agents perceive that equities are very risky. Agents believe that earnings innovations are highly persistent, so that equity returns are therefore highly volatile and anticipated to strongly covary with long-run consumption growth. This leads agents to require a high premium to hold equities when $p \leq 11$. When $p = 40$, which is the rational expectations case, the equity premium is only 1/10 of 1%. Figure 10 plots the (annual) equity premium for different values of p as well as the historical premium of 7.4%.

Finally, we are able to roughly match the equity premium without generating counterfactually high levels of asset return volatility – see Figure 11 – or consumption volatility – see Figure 12. No matter what the order of the forecasting model, the standard deviation of consumption volatility is less than the historical standard deviation of consumption volatility.

5 Agents with Rational Expectations

Starting with the natural expectations economy described above (with $p < 40$), we now add a vanishingly small measure of agents with rational expectations. These 'RE agents' know all of the coefficients in the true data generating process for dividends – the AR(40). This perfect knowledge is meant to proxy for the more plausible assumption that these new agents have a high degree of sophistication relative to the agents with natural expectations.

We solve for the behavior of the RE agents assuming that they have no effect on equilibrium prices. This *small mass* assumption is made for tractability and future work should

consider equilibria in which the rational agents are wealthy enough to influence equilibrium prices. The current analysis is indicative of the results that will apply in that more realistic case.

Appendix C derives the optimal policy function – both asset allocation and consumption – of the rational expectations agents. Later in this section, we present the optimal policy rules for the RE agent. Those policy rules take a large set of other objects as inputs. We now discuss and define those inputs before turning to the key theorem.

Let Φ be the vector of true autoregressive coefficients in the earnings process, which as always is an AR(40). Let $\hat{\Phi}$ be the vector of autoregressive coefficients in the earnings process as perceived by the NE agents. Let σ_ε be the true standard deviation of shock to dividend process. Let $\hat{\sigma}_c^2$ be the conditional variance of consumption changes as perceived by the NE agents. Let $e_{1,p} = [1\ 0\ 0\ ...\ 0]'$ be a standard basis vector of length p. Define the following variables:

$$\sigma_g = \frac{R}{R-1}\sigma_\varepsilon e_{1,p}' \left(I - \frac{1}{R}\hat{\Phi}\right)^{-1} e_{1,p}.$$

$$\mu = \frac{R\alpha}{(1-\frac{\gamma}{R})(R-1)}\hat{\sigma}_c^2.$$

$$M = \frac{R}{R-1}e_{1,p}' \left[\Phi - \hat{\Phi}\left(I - \frac{1}{R}\hat{\Phi}\right)^{-1}\left(I - \frac{1}{R}\Phi\right)\right].$$

$$B = \frac{1}{2R\left(1-\frac{\gamma}{R}\right)\alpha\sigma_g^2}\sum_{k=0}^{\infty} R^{-k}\hat{\Phi}'^k M' M \hat{\Phi}^k.$$

$$A' = \frac{2\mu}{R\sigma_g}\left(\frac{1}{2(1-\frac{\gamma}{R})\alpha\sigma_g}M + \sigma_e e_{1,p}' B\hat{\Phi}\right)\left(I - \frac{1}{R}\hat{\Phi}\right)^{-1}.$$

$$\lambda = (1-\frac{\gamma}{R})\sigma_e^2 e_{1,p}' B e_{1,p}$$

$$q = \frac{1+2\alpha\lambda}{2(R-1)(1-\frac{\gamma}{R})\alpha\sigma_g^2}\mu^2 - \frac{\mu\sigma_e}{\sigma_g(R-1)}A'e - \frac{1}{2\alpha(R-1)(1-\frac{\gamma}{R})}\ln(1+2\alpha\lambda).$$

We can now describe the policy function of RE agents.

Theorem 1 *For an agent with rational expectations, the optimal asset allocation, θ_t, is given*

by

$$\theta_t = \frac{R}{R-1}\frac{1}{\sigma_g}\left(\frac{\mu + M\Delta\vec{d}_t}{\left(1-\frac{\gamma}{R}\right)\alpha\sigma_g} + \frac{2\mu\sigma_e^2}{\sigma_g}e'_{1,p}Be_{1,p} - \sigma_e A'e - 2\sigma_e e'_{1,p}B\hat{\Phi}\Delta\vec{d}_t\right),$$

and the optimal consumption rule is given by:

$$c_t = \left(1-\frac{\gamma}{R}\right)\left(\frac{R-1}{R}w_t + A'\Delta\vec{d}_t + \Delta\vec{d}'_t B\Delta\vec{d}_t + q\right) + \frac{\gamma}{R}c_{t-1}.$$

The proof is provided in Appendix C. The consumption policy rule implies that consumption is still a weighted average of the annuity value of wealth and lag consumtion, with weights $\left(1-\frac{\gamma}{R}\right)$ and $\frac{\gamma}{R}$. There are two additional terms in the consumption policy, reflecting the impact of dividend shocks excluding their effect on wealth and prices. These terms represent the ability of the fully informed investor to predict future "returns" (gains), and adjust consumption accordingly. In our setting, where the rational agent knows about mean reversion that is not "priced in" to asset prices, and generally has positive equity holdings, the first order effect (A) is mostly negative—that is, the agent consumes more in response to a positive dividend shock, but less than their wealth gain would suggest. The second order effect (B) is mostly positive—the agent has some ability to predict future gains, and the benefits of this ability are larger when large shocks have occurred in the recent past.

The asset allocation result is harder to interpret than the consumption rule, other than that it is a linear function of the dividend history. However, we can write a simple lower bound on the average equity holding:

Corollary 2 *On average, rational agents will hold a quantity of equities greater than*

$$\overline{\theta}_{min} = \frac{\widehat{\sigma}_\varepsilon^2}{\sigma_\varepsilon^2}.$$

Note that $\frac{\widehat{\sigma}_\varepsilon^2}{\sigma_\varepsilon^2}$ is the ratio of variances of impulses to earnings. The numerator, $\widehat{\sigma}_\varepsilon^2$, is the variance perceived by the NE agents. The denominator, σ_ε^2, is the variance perceived by the RE agents. Since the NE agents estimate a simpler model than the (true) model used by

the RE agents, it follows that $\widehat{\sigma}_{\varepsilon}^2 > \sigma_{\varepsilon}^2$.

The average value of θ_t includes two terms related to the consumption policy matrices A and B. These terms reflect the contrarian nature of the consumption policy: because dividend shocks have a muted effect on consumption via A, and because shocks of any sort increase consumption via B, the Lucas tree is less risky for the rational investors than would otherwise be the case, and the equilibrium outcome is for them to hold even more equities. Because both of these terms have a positive impact on average equity holdings, discarding them and simplifying results in the lower bound described above.

We emphasize this lower bound because it reflects what a rational agent would do if they knew there was an equity premium, but were not able to time returns. In our framework, this would occur if $\hat{\sigma}_{\varepsilon} > \sigma_{\varepsilon}$ but $M = 0$.

In exhibit XXX (to be added), we report the average asset allocation, and this lower bound, over different model orders chosen by the intuitive forecasting agents. The extent to which intuitive agents choose low order models determines both the excessive variance they perceive, and the ability of rational agents to predict returns, and it is therefore unsurprising that the equity holdings for rational agents is essentially monotonically decreasing in the order of model chosen by the intuitive agents.

6 Conclusion

This paper examines an open endowment economy in which (1) fundamentals have hump-shaped dynamics (momentum in the short-run and partial mean reversion in the long-run), and (2) agents don't know these dynamics and generate beliefs by fitting parsimonious models. We show that these two assumptions have a large set of empirically valid implications: endogenous extrapolation bias; pro-cyclical excess optimism; over-reaction in asset pricing; mean reversion in returns; amplified dynamics in consumption; cyclical dynamics in consumption; a high equity premium; relatively highly levered equity exposure among

sophisticated investors; and counter-cyclical asset allocation among sophisticated investors.

We believe that our two assumptions also characterize other 'macro' markets. For example, the same approach could be used to study dynamics in housing prices, residential investment, non-residential investment, inventory accumulation, international capital flows, bond markets, or commodity prices.[42] Wherever our two assumptions apply, markets will be characterized by amplified cycles, overreaction, excess volatility, and asset returns that are negatively autocorrelated over the medium-run.

Finally, we wish to highlight a gap in our analysis. Our model is about belief formation, but all of our evidence about beliefs is indirect – for instance, consumption behavior and market prices. We believe that researchers should also measure beliefs directly. Some research on bubbles has moved in this direction (e.g., Vissing-Jorgenson 2003; Shiller 2005; Piazessi and Schneider 2009, 2011) and we hope that more will do so in the future.

[42]For some alternative approaches, see for example Lansing 2009, Hassan and Mertens 2010, Adam and Marcet 2010, LeBaron 2010, Burnside, Eichenbaum, and Rebelo 2011, and Piazzesi and Schneider 2011.

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7 Appendix A: Matrix Representation of Consumption Model

7.1 Solving for CARA policy for ARIMA(p,1,0) case

$$\Delta d_t = \Phi(L)\Delta d_t + \sigma_e \epsilon_t$$

We can represent this system as a AR(1) system with evolution operator Φ:

$$\begin{bmatrix} \Delta d_t \\ \Delta d_{t-1} \\ ... \\ \Delta d_{t-p+1} \end{bmatrix} = \begin{bmatrix} \phi_1 & \phi_2 & ... & \phi_p \\ 1 & 0 & ... & 0 \\ 0 & 1 & ... & 0 \\ ... & & & \\ 0 & 0 & ... & 0 \end{bmatrix} \begin{bmatrix} \Delta d_{t-1} \\ \Delta d_{t-2} \\ ... \\ \Delta d_{t-p} \end{bmatrix} + \begin{bmatrix} \sigma_e \\ 0 \\ ... \\ 0 \end{bmatrix} \epsilon_t$$

There is also the foreign debt variable, b_t, which evolves as

$$b_{t+1} = c_t + Rb_t - d_t - y_t$$

Assume R and y_t are constant. Define the AR(1) representation state vector:

$$z_t = \begin{bmatrix} B_t \\ c_{t-1} \\ 1 \\ y_t \\ d_t \\ \Delta d_t \\ \Delta d_{t-1} \\ ... \\ \Delta d_{t-p+1} \end{bmatrix}$$

Use Alessie-Lusardi (1997) habits with CARA utility:

$$u(c_t, c_{t-1}) = -\frac{1}{\alpha}\exp(-\alpha(c_t - \gamma c_{t-1}))$$

Guess a linear policy function, $c_t = P' z_t$. Because the policy function is linear, we can define the AR1 evolution operator:

$$M = \bar{M} + NP' = \begin{bmatrix} R & 0 & 0 & -1 & -1 & \vec{0} \\ 0 & 0 & 0 & 0 & 0 & \vec{0}' \\ 0 & 0 & 1 & 0 & 0 & \vec{0}' \\ 0 & 0 & 0 & 1 & 0 & \vec{0}' \\ 0 & 0 & 0 & 0 & 1 & e'_{1,p}\Phi \\ \vec{0} & \vec{0} & \vec{0} & \vec{0} & \vec{0} & \Phi \end{bmatrix} + (e_{1,p+5} + e_{2,p+5})P'$$

Where $e_{i,n}$ is the $i'th$ basis vector of length n. This satisfies

$$z_t = Mz_{t-1} + C\epsilon_t$$

where C is a column vector that applies the random shock to Δd_t and is otherwise empty. An alternative evolution equation is

$$z_t = \bar{M}z_{t-1} + Nc_{t-1} + C\epsilon_t$$

We guess that the value function is of the form

$$V(z_t) = -\frac{\Psi}{\alpha}\exp(-\alpha(c_t - \gamma c_{t-1}))$$

Define $\hat{P} = P - \gamma e_{2,p+5}$, and plug into the Bellman:

$$-\frac{\Psi}{\alpha}e^{-\alpha\hat{P}'z_t} = -\frac{1}{\alpha}e^{-\alpha\hat{P}'z_t} + \delta E\left[-\frac{\Psi}{\alpha}e^{-\alpha\hat{P}'z_{t+1}}\right]$$

The expectation for $\hat{P}'z_{t+1}$ is $\hat{P}'Mz_t$, and the variance is $C'\hat{P}\hat{P}'C$. So the bellman simplifies to

$$-\frac{\Psi}{\alpha}e^{-\alpha\hat{P}'z_t} = -\frac{1}{\alpha}e^{-\alpha\hat{P}'z_t} + -\delta\frac{\Psi}{\alpha}e^{-\alpha(\hat{P}'Mz_t - \frac{\alpha}{2}C'\hat{P}\hat{P}'C)}$$

Right now, without worrying about optimality, i'd like to solve the bellman. Dividing through by common terms,

$$\Psi = 1 + \delta\Psi e^{-\alpha(\hat{P}'(M-I)z_t - \frac{\alpha}{2}C'\hat{P}\hat{P}'C)}$$

For this equation to be solved for all z_t, for some constant κ,

$$\hat{P}'(M-I)z_t = \kappa$$

Next, we need to derive an optimality condition for c_t. The first-order condition is that

$$\exp(-\alpha\hat{P}'z_t) + \delta E[\Psi\exp(-\alpha\hat{P}'z_{t+1})\hat{P}'N] = 0$$

Expanding the expectation, and noting that $\hat{P}'N$ is a scalar constant,

$$\exp(-\alpha\hat{P}'z_t) + \hat{P}'^{-\alpha(\hat{P}'Mz_t - \frac{\alpha}{2}C'\hat{P}\hat{P}'C)} = 0$$

Divding through,

$$0 = 1 + \hat{P}'^{-\alpha(\hat{P}'(M-I)z_t - \frac{\alpha}{2}C'\hat{P}\hat{P}'C)}$$

Again, note that if $\hat{P}(M-I)z_t = \kappa$ for all t, this equation can be satisfied for some constant Ψ. Combining the two equations, we can see that

$$0 = 1 + \hat{P}'N(\Psi - 1)$$

Solving,

$$\Psi = 1 - \frac{1}{\hat{P}'N}$$

At this point, we will try to guess P and show that our guess satisfies the equations above. For some constants K and Q,

$$P = \begin{bmatrix} -(R-1)(1-\frac{\gamma}{R}) \\ \frac{\gamma}{R} \\ Q \\ \frac{R-\gamma}{R} \\ \frac{R-\gamma}{R} \\ \left[Ke'_{1,p}(I - \frac{1}{R}\Phi)^{-1}\frac{1}{R}\Phi\right]' \end{bmatrix}$$

We can first solve for $\hat{P}'N$.

$$\hat{P}'N = (P - \gamma e_{2,p+5})N = -(R-1)(1-\frac{\gamma}{R}) + \frac{\gamma}{R} - \gamma = 1 - R$$

Therefore,

$$\Psi = 1 - \frac{1}{1-R} = \frac{R}{R-1}$$

Returning to the first order condition,

$$0 = 1 - R\delta e^{-\alpha(\hat{P}'(M-I)z_t - \frac{\alpha}{2}C'\hat{P}\hat{P}'C)}$$

Next, we need to confirm that $\hat{P}(M-I)z_t = \kappa$ for all t.

$$M - I = \bar{M} - I + NP' = \begin{bmatrix} R-1 & 0 & 0 & -1 & -1 & \vec{0} \\ 0 & 0 & 0 & 0 & 0 & \vec{0}' \\ 0 & 0 & 0 & 0 & 0 & \vec{0}' \\ 0 & 0 & 0 & 0 & 0 & \vec{0}' \\ 0 & 0 & 0 & 0 & 0 & e'_{1,p}\Phi \\ \vec{0} & \vec{0} & \vec{0} & \vec{0} & \vec{0} & \Phi - I \end{bmatrix} + NP'$$

$$NP' = \begin{bmatrix} -(R-1)(1-\frac{\gamma}{R}) & \frac{\gamma}{R} & Q & \frac{R-\gamma}{R} & \frac{R-\gamma}{R} & Ke'_{1,p}(I-\frac{1}{R}\Phi)^{-1}\frac{1}{R}\Phi \\ -(R-1)(1-\frac{\gamma}{R}) & \frac{\gamma}{R} & Q & \frac{R-\gamma}{R} & \frac{R-\gamma}{R} & Ke'_{1,p}(I-\frac{1}{R}\Phi)^{-1}\frac{1}{R}\Phi \\ 0 & 0 & 0 & 0 & 0 & \vec{0}' \\ 0 & 0 & 0 & 0 & 0 & \vec{0}' \\ 0 & 0 & 0 & 0 & 0 & \vec{0}' \\ \vec{0} & \vec{0} & \vec{0} & \vec{0} & \vec{0} & 0 \end{bmatrix}$$

$$M - I = \begin{bmatrix} (R-1)\frac{\gamma}{R} & \frac{\gamma}{R} & Q & \frac{-\gamma}{R} & \frac{-\gamma}{R} & Ke'_{1,p}(I - \frac{1}{R}\Phi)^{-1}\frac{1}{R}\Phi \\ -(R-1)(1-\frac{\gamma}{R}) & \frac{-R+\gamma}{R} & Q & \frac{R-\gamma}{R} & \frac{R-\gamma}{R} & Ke'_{1,p}(I - \frac{1}{R}\Phi)^{-1}\frac{1}{R}\Phi \\ 0 & 0 & 0 & 0 & 0 & \vec{0}' \\ 0 & 0 & 0 & 0 & 0 & \vec{0}' \\ 0 & 0 & 0 & 0 & 0 & e'_{1,p}\Phi \\ \vec{0} & \vec{0} & \vec{0} & \vec{0} & \vec{0} & \Phi - I \end{bmatrix}$$

$$\hat{P}'(M-I) = \begin{bmatrix} 0 \\ 0 \\ -Q(R-1) \\ 0 \\ 0 \\ -(R-1)Ke_{1,p}(I - \frac{1}{R}\Phi)^{-1}\frac{1}{R}\Phi + \frac{R-\gamma}{R}e_{1,p}\Phi + Ke_{1,p}(I - \frac{1}{R}\Phi)^{-1}\frac{1}{R}\Phi(\Phi - I) \end{bmatrix}$$

We need to solve for K so that the last element becomes zero. Simplifying,

$$0 = -RKe_{1,p}\left(I - \frac{1}{R}\Phi\right)^{-1}\frac{1}{R}\Phi + \frac{R-\gamma}{R}e_{1,p}\Phi + RKe_{1,p}\left(I - \frac{1}{R}\Phi\right)^{-1}\frac{1}{R}\Phi\frac{1}{R}\Phi$$

Noting that

$$(I - \frac{1}{R}\Phi)^{-1}\frac{1}{R}\Phi\frac{1}{R}\Phi = (I - \frac{1}{R}\Phi)^{-1}\frac{1}{R}\Phi - \frac{1}{R}\Phi$$

We can simplify to

$$0 = \frac{R-\gamma}{R}e_{1,p}\Phi - RKe_{1,p}\frac{1}{R}\Phi$$

Solving,

$$K = \frac{R-\gamma}{R} = \left(1 - \frac{\gamma}{R}\right)$$

For this value of K, and any value of Q, $\hat{P}(M-I)z_t = \kappa = -Q(R-1)$ for all t. To solve for Q, we can rewrite the FOC, replacing for our value of Ψ,

$$0 = 1 - \exp\left(-\alpha\left[\frac{-1}{\alpha}\ln(R\delta) - Q(R-1) - \frac{\alpha}{2}C'\hat{P}\hat{P}'C\right]\right)$$

$$\hat{P}'C = \sigma_e\left(1 - \frac{\gamma}{R}\right)e'_{1,p}\left(I - \frac{1}{R}\Phi\right)^{-1}e_{1,p} = \sigma_c$$

$$Q = \frac{1}{R-1}\left[-\frac{1}{\alpha}\ln(R\delta) - \frac{\alpha}{2}\sigma_c^2\right]$$

We have now fully solved for the linear policy function, and shown that it was optimal.

8 Appendix B: Asset pricing

Next, we derive a price for the dividend stream. Our timing convention is that the price at time t does not include the dividend at time t. To calculate the equilibrium price of the

Lucas tree, we consider the asset allocation problem (as opposed to the planner's problem). We then solve for the asset price that leads the representative agent to hold one unit of the equity tree.

Return to the asset allocation problem:

$$V\left(c_{t-1}, w_t, p_t, \overrightarrow{d}_t\right) = \sup_{\theta_t, c_t} u(c_t, c_{t-1}) + E_t \delta V\left(c_t,\, \left(w_t - c_t - \theta_t p_t\right) R + \theta_t \left(d_{t+1} + p_{t+1}\right),\, \overrightarrow{d}_{t+1}\right)$$

since

$$w_{t+1} = \left(w_t - c_t - \theta_t p_t\right) R + \theta_t \left(d_{t+1} + p_{t+1}\right)$$

We can rewrite this as

$$V\left(c_{t-1}, x_t, p_t, \overrightarrow{d}_t\right) = \frac{-1}{\alpha(1-\delta)} \exp\left(-\alpha\left[c_t - \gamma c_{t-1}\right]\right)$$

where

$$c_t = \frac{\gamma}{R} c_{t-1} + \left(1 - \frac{\gamma}{R}\right) x_t - \psi. \tag{7}$$

Consumption is a weighted average of lagged consumption and the (risk-neutral) annuity value of future dividends, x_t, shifted down by an additive constant ψ. Let's write x_t so that we allow the agent to buy more or less of the risky tree. Buying more means raise θ above unity.

$$x_t = \frac{R-1}{R}\left[-Rb_t - (\theta - 1)\, p_t + d_t + \theta \sum_{s=1}^{\infty} \frac{E_t d_{t+s}}{R^s}\right] \tag{8}$$

$$\psi = \frac{1}{R-1}\left[\frac{1}{\alpha}\ln(R\delta) + \frac{\alpha}{2} Var_t(c_{t+1})\right]. \tag{9}$$

In equilibrium, $\theta = 1$. In other words, supply equals demand. The associated first order condition is:

$$\frac{dV}{d\theta} = 0 \text{ at } \theta = 1.$$

We can expand this derivative.

$$\frac{dV}{d\theta} = \frac{\partial V}{\partial c_t}\left[\frac{\partial c_t}{\partial x_t}\frac{\partial x_t}{\partial \theta} + \frac{\partial c_t}{\partial \psi}\frac{\partial \psi}{\partial \theta}\right] = 0$$

which implies that the asset price, p_t, is chosen such that

$$\frac{\partial c_t}{\partial x_t}\frac{\partial x_t}{\partial \theta} + \frac{\partial c_t}{\partial \psi}\frac{\partial \psi}{\partial \theta} = 0 \text{ at } \theta = 1 \tag{10}$$

Let's evaluate each of these partial derivatives in turn:

$$\begin{aligned}
\frac{\partial c_t}{\partial x_t} &= \left(1-\frac{\gamma}{R}\right) \\
\frac{\partial x_t}{\partial \theta} &= \frac{R-1}{R}\left[-p_t+\sum_{s=1}^{\infty}\frac{E_t d_{t+s}}{R^s}\right] \\
\frac{\partial c_t}{\partial \psi} &= -1 \\
\frac{\partial \psi}{\partial \theta_t} &= \frac{1}{R-1}\frac{\alpha}{2}\frac{\partial Var_t(c_{t+1})}{\partial \theta} \\
&= \frac{1}{R-1}\frac{\alpha}{2}2\theta Var_t(c_{t+1})
\end{aligned}$$

Now we are ready to use our equilibrium condition: equation **??**.

$$\begin{aligned}
\frac{\partial c_t}{\partial x}\frac{\partial x}{\partial \theta} &= -\frac{\partial c_t}{\partial \psi}\frac{\partial \psi}{\partial \theta} \quad \text{(evaluated at } \theta=1\text{)} \\
\left(1-\frac{\gamma}{R}\right)\frac{R-1}{R}\left[-p_t+\sum_{s=1}^{\infty}\frac{E_t d_{t+s}}{R^s}\right] &= \frac{1}{R-1}\frac{\alpha}{2}2Var_t(c_{t+1})
\end{aligned}$$

Rearranging we have

$$\begin{aligned}
-p_t+\sum_{s=1}^{\infty}\frac{E_t d_{t+s}}{R^s} &= \frac{R\alpha \times Var_t(c_{t+1})}{\left(1-\frac{\gamma}{R}\right)(R-1)^2} \\
p_t &= \sum_{s=1}^{\infty}\frac{E_t d_{t+s}}{R^s}-\frac{R\alpha \times Var_t(c_{t+1})}{\left(1-\frac{\gamma}{R}\right)(R-1)^2}
\end{aligned}$$

We can also express the expectation of the discounted stream of dividends using our earlier matrix notation, implying that

$$p_t = \frac{1}{R-1}d_t+\frac{R}{R-1}e'_{1,p}\left(I-\frac{1}{R}\Phi\right)^{-1}\frac{1}{R}\Phi\Delta\vec{d}_t-\frac{R\alpha}{(1-\frac{\gamma}{R})(R-1)^2}\sigma_c^2$$

8.1 Equity premium

Assume that $d_t = d$ and $\Delta\vec{d}_t = 0$, so that mistakes don't matter (and note that our theory also has a prediction about the high frequency relationship between $\Delta\vec{d}_t$ and the equity premium). The average quarterly return is $\frac{d}{p_t}$ where

$$p_t = \frac{d}{R-1}-\frac{R\alpha}{(1-\frac{\gamma}{R})(R-1)^2}\sigma_c^2.$$

Hence,

$$\frac{d}{p} = \frac{d}{\frac{d}{R-1} - \frac{R\alpha}{\left(1-\frac{\gamma}{R}\right)(R-1)^2}\sigma_c^2}$$

Therefore the annualized equity premium when dividends have a flat history (i.e., $\Delta\vec{d}_t = 0$) is given by

$$4 \times \left[\frac{d}{\frac{d}{R-1} - \frac{R\alpha}{\left(1-\frac{\gamma}{R}\right)(R-1)^2}\sigma_c^2} - (R-1) \right]$$

9 Appendix C: Rational Expectations Investors in the Consumption Model

9.1 Excess Gains in Natural Expectations

We start with the definition of the price in the natural expectations framework:

$$p_t = \frac{1}{R-1}d_t + \frac{R}{R-1}e'_{1,p}\left(I - \frac{1}{R}\Phi\right)^{-1}\frac{1}{R}\Phi\Delta\vec{d}_t - \frac{R\alpha}{(1-\frac{\gamma}{R})(R-1)^2}\sigma_c^2$$

We would like to understand the gains process, defined as

$$g_{t+1} = p_{t+1} + d_{t+1} - Rp_t$$

We replace the Φ matrix and σ_c with their 'hat' equivalents, to denote misspecification. Expanding the definitions of p_t and p_{t+1}, we find that

$$\begin{aligned} g_{t+1} = {} & d_{t+1} + \frac{1}{R-1}(d_{t+1} - Rd_t) + \\ & \frac{R}{R-1}e'_{1,p}\left(I - \frac{1}{R}\hat{\Phi}\right)^{-1}\frac{1}{R}\hat{\Phi}\left(\Delta\vec{d}_{t+1} - R\Delta\vec{d}_t\right) + \frac{R\alpha}{(1-\frac{\gamma}{R})(R-1)}\hat{\sigma}_c^2 \end{aligned}$$

Define

$$\mu = \frac{R\alpha}{(1-\frac{\gamma}{R})(R-1)}\hat{\sigma}_c^2$$

Using the definition of the AR process driving d_t, we can rewrite this as

$$\begin{aligned} g_{t+1} = {} & \frac{R}{R-1}e'_{1,p}\left(\Phi\Delta\vec{d}_t + \sigma_e\epsilon_{t+1}e_{1,p}\right) + \\ & \frac{R}{R-1}e'_{1,p}\left(I - \frac{1}{R}\hat{\Phi}\right)^{-1}\hat{\Phi}\left(\frac{1}{R}\Phi\Delta\vec{d}_t - \Delta\vec{d}_t + \frac{1}{R}\sigma_e\epsilon_{t+1}e_{1,p}\right) + \mu \end{aligned}$$

Regrouping terms,

$$g_{t+1} = \frac{R}{R-1}e'_{1,p}\left(\Phi - \hat{\Phi}\left(I - \frac{1}{R}\hat{\Phi}\right)^{-1}\left(I - \frac{1}{R}\Phi\right)\right)\Delta\vec{d_t} + \frac{R}{R-1}\sigma_e e'_{1,p}\left(I - \frac{1}{R}\hat{\Phi}\right)^{-1}e_{1,p}\epsilon_{t+1} + \mu$$

We can define the vector M and constant σ_g so that the equation above is

$$g_{t+1} = M\Delta\vec{d_t} + \sigma_g\epsilon_{t+1} + \mu$$

9.2 Budget Constraint

Let w_t be the agent's wealth in period t before consumption is chosen. Assume the agent can hold either risk-free assets with return R, or a risky asset. There are no shorting/leverage constraints. The agent's budget constraint is

$$\begin{aligned} w_{t+1} &= (w_t - c_t - \theta_t p_t)R + \theta_t(d_{t+1} + p_{t+1}) \\ &= (w_t - c_t)R + \theta_t g_{t+1} \end{aligned}$$

where the choice variables c_t and θ_t are the consumption and dollar amount in the risky asset. We can rewrite the budget constraint in terms of the evolution of g_t,

$$w_{t+1} = R(w_t - c_t) + \theta_t M\Delta\vec{d_t} + \theta_t\sigma_g\epsilon_{t+1} + \theta_t\mu.$$

9.3 Utility and Value Functions

The agent has flow utility of the form

$$u(c_t, c_{t-1}) = -\frac{1}{\alpha}e^{-\alpha(c_t - \gamma c_{t-1})}$$

It is convenient to define

$$\hat{c}_t = c_t - \gamma c_{t-1}$$

The state is captured entirely by w_t, c_{t-1}, and $\Delta\vec{d_t}$. The Bellman is

$$V(w_t, c_{t-1}, \Delta\vec{d_t}) = \max_{\hat{c}_t, \theta_t} u(\hat{c}_t) + \delta E[V(w_{t+1}, \hat{c}_t + \gamma c_{t-1}, \Delta\vec{d}_{t+1})]$$

The first order conditions are

$$u'(\hat{c}_t) = \delta E\left[R\frac{\partial V_{t+1}}{\partial w_{t+1}} - \frac{\partial V_{t+1}}{\partial c_t}\right] \tag{11}$$

and

$$\delta E\left[\frac{\partial V_{t+1}}{\partial w_{t+1}}\left(M\Delta\vec{d_t} + \mu + \sigma_g\epsilon_{t+1}\right)\right] = 0 \tag{12}$$

The envelope condition for w_t is

$$\frac{\partial V_t}{\partial w_t} = \delta E_t \left[\frac{\partial V_{t+1}}{\partial w_{t+1}} R \right] \tag{13}$$

From the inter-temporal budget constraint (see 20)

$$\frac{\partial V_t}{\partial c_{t-1}} = \frac{-\gamma}{1 - \frac{\gamma}{R}} \frac{\partial V_t}{\partial w_t} \tag{14}$$

We use this to derive the Euler equations, which will be verified after deriving a solution.

Rewriting (11), and then using (13),

$$\begin{aligned} u'(\hat{c}_t) &= \delta E \left[R \frac{\partial V_{t+1}}{\partial w_{t+1}} + \frac{\gamma}{1 - \frac{\gamma}{R}} \frac{\partial V_{t+1}}{\partial w_{t+1}} \right] \\ \left(1 - \frac{\gamma}{R}\right) u'(\hat{c}_t) &= \delta E \left[R \frac{\partial V_{t+1}}{\partial w_{t+1}} \right] = \frac{\partial V_t}{\partial w_t} \end{aligned}$$

Advancing time by one unit, and taking expectations,

$$\left(1 - \frac{\gamma}{R}\right) E\left[u'(\hat{c}_{t+1})\right] = E\left[\frac{\partial V_{t+1}}{\partial w_{t+1}}\right]$$

The consumption Euler equation, assuming $\delta R = 1$, is therefore

$$u'(\hat{c}_t) = E\left[u'(\hat{c}_{t+1})\right]$$

The asset Euler equation is

$$0 = E\left[\left(1 - \frac{\gamma}{R}\right) u'(\hat{c}_{t+1}) \left(M \Delta \vec{d}_t + \mu + \sigma_g \epsilon_{t+1}\right)\right] \tag{15}$$

9.4 Guess and check

We guess that

$$\hat{c}_t = D c_{t-1} + \left(1 - \frac{\gamma}{R}\right) \left(\frac{R-1}{R} w_t + A' \Delta \vec{d}_t + \Delta \vec{d}_t' B \Delta \vec{d}_t + q \right)$$

where A is a vector and B is a matrix. From this guess, we can see that

$$\hat{c}_{t+1} = D c_t + \left(1 - \frac{\gamma}{R}\right) \left(\frac{R-1}{R} w_{t+1} + A' \Delta \vec{d}_{t+1} + \Delta \vec{d}_{t+1}' B \Delta \vec{d}_{t+1} + q \right)$$

Expanding the budget and evolution of $\Delta\vec{d_t}$,

$$\begin{array}{l}\hat{c}_{t+1} = Dc_t + \\ \left(1-\frac{\gamma}{R}\right)\left[\begin{array}{c}\frac{R-1}{R}\left(R(w_t-c_t)+\theta_t M\Delta\vec{d_t}+\theta_t\mu+\theta_t\sigma_g\epsilon_{t+1}\right)+ \\ A'\Phi\Delta\vec{d_t}+A'e_{1,p}\sigma_e\epsilon_{t+1}+\left(\Phi\Delta\vec{d_t}+e_{1,p}\sigma_e\epsilon_{t+1}\right)'B\left(\Phi\Delta\vec{d_t}+e_{1,p}\sigma_e\epsilon_{t+1}\right)+q\end{array}\right]\end{array}$$

Taking expectations,

$$\begin{array}{l}E_t[\hat{c}_{t+1}] = Dc_t + \\ \left(1-\frac{\gamma}{R}\right)\left[\frac{R-1}{R}\left(R(w_t-c_t)+\theta_t M\Delta\vec{d_t}+\theta_t\mu\right)+A'\Phi\Delta\vec{d_t}+\Phi\Delta\vec{d_t}B\Phi\Delta\vec{d_t}+\sigma_e^2 e'_{1,p}Be_{1,p}+q\right]\end{array}$$

We can then write

$$\begin{array}{rcl}\hat{c}_{t+1} & = & E[\hat{c}_{t+1}]+\left(1-\frac{\gamma}{R}\right) \\ & & \left[-\sigma_e^2 e'_{1,p}Be_{1,p}+\left(\frac{(R-1)}{R}\theta_t\sigma_g+\sigma_e A'e_{1,p}+\sigma_e e'_{1,p}B\Phi\Delta\vec{d_t}+\sigma_e\Delta\vec{d_t}'\Phi'Be_{1,p}\right)\epsilon_{t+1}+\sigma_e^2 e'_{1,p}Be_{1,p}\epsilon_{t+1}^2\right].\end{array}$$

Define the following constants:

$$\begin{array}{rcl}k_t & = & \left(1-\frac{\gamma}{R}\right)\left(\frac{(R-1)}{R}\theta_t\sigma_g+\sigma_e A'e_{1,p}+\sigma_e e'_{1,p}B\Phi\Delta\vec{d_t}+\sigma_e\Delta\vec{d_t}'\Phi'Be_{1,p}\right) \\ \lambda & = & \left(1-\frac{\gamma}{R}\right)\sigma_e^2 e'_{1,p}Be_{1,p}.\end{array}$$

We can rewrite $u'(\hat{c}_{t+1})$ as

$$u'(\hat{c}_{t+1}) = e^{-\alpha\left(E[\hat{c}_{t+1}]-\lambda+k_t\epsilon_{t+1}+\lambda\epsilon_{t+1}^2\right)}.$$

We can now compute expectations.

$$E[u'(\hat{c}_{t+1})] = e^{-\alpha(E[\hat{c}_{t+1}]-\lambda)}\times\int_{-\infty}^{\infty}\frac{1}{\sqrt{2\pi}}e^{-\alpha k_t x-\alpha\lambda x^2}e^{-\frac{x^2}{2}}dx$$

Define a second variable, which is a constant,

$$s=\sqrt{\frac{1}{1+2\alpha\lambda}}$$

We can complete the square on the integral as follows:

$$-\alpha k_t x-\alpha\lambda x^2-0.5x^2 = -\frac{x^2+2\alpha k_t s^2}{2s^2} = -\frac{(x+\alpha k_t s^2)^2}{2s^2}+\frac{\alpha^2}{2}k_t^2 s^2$$

$$E[u'(\hat{c}_{t+1})] = e^{-\alpha\left(E[\hat{c}_{t+1}]-\lambda-\frac{1}{2}\alpha k_t^2 s^2\right)} s \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi s^2}} e^{-\frac{\left(x+\alpha k_t s^2\right)^2}{2s^2}} dx$$

We therefore conclude that

$$E[u'(\hat{c}_{t+1})] = e^{-\alpha\left(E[\hat{c}_{t+1}]-\lambda-\frac{1}{2}\alpha k_t^2 s^2-\frac{1}{2\alpha}\ln s^2\right)} \tag{16}$$

Next, consider the integral from the second Euler equation.

$$E[u'(\hat{c}_{t+1})\sigma_g \epsilon_{t+1}] = e^{-\alpha\left(E[\hat{c}_{t+1}]-\lambda-\frac{1}{2}\alpha k_t^2 s^2\right)} \times \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \sigma_g x e^{-\frac{\left(x+\alpha k_t s^2\right)^2}{2s^2}} dx$$

For the integral, use the following transformation:

$$u = \frac{x + \alpha k_t s^2}{s}$$

$$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \sigma_g x e^{-\frac{\left(x+\alpha k_t s^2\right)^2}{2s^2}} dx = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \sigma_g (s\,u - \alpha k_t s^2) e^{-\frac{u^2}{2}} s du = -\alpha \sigma_g k_t s^3$$

We combine 15 and the equation above to see that

$$e^{-\alpha\left(E_t[\hat{c}_{t+1}]-\lambda-\frac{1}{2}\alpha k_t^2 s^2-\frac{1}{2\alpha}\ln s^2\right)}(\mu + M\Delta\vec{d}_t) = e^{-\alpha\left(E_t[\hat{c}_{t+1}]-\lambda-\frac{1}{2}\alpha k_t^2 s^2\right)}\alpha\sigma_g k_t s^3$$

Simplifying,

$$\mu + M\Delta\vec{d}_t = \alpha\sigma_g k_t s^2$$

9.5 Solving for the policy rules

Next, we use consumption Euler equation to see that

$$\hat{c}_t = E_t[\hat{c}_{t+1}] - \lambda - \frac{1}{2}\alpha k_t^2 s^2 - \frac{1}{2\alpha}\ln s^2$$

From our conjecture about $\hat{c}_t$, we can expand $\hat{c}_{t+1}$:

$$\hat{c}_t + \lambda + \frac{1}{2}\alpha k_t^2 s^2 \frac{1}{2\alpha}\ln s^2 = \left(1-\frac{\gamma}{R}\right)\left(\frac{(R-1)}{R}E_t[w_{t+1}] + A' E_t[\Delta\vec{d}_{t+1}] + E_t[\Delta\vec{d}'_{t+1} B \Delta\vec{d}_{t+1}] + q\right) + Dc_t$$

$$\hat{c}_t + \lambda + \frac{1}{2}\alpha k_t^2 s^2 + \frac{1}{2\alpha}\ln s^2 = \left(1-\frac{\gamma}{R}\right)\left(\frac{(R-1)}{R}E_t[w_{t+1}] + A'\Phi\Delta\vec{d}_t + \lambda + \Delta\vec{d}'_t\Phi' B \Phi\Delta\vec{d}_t + q\right) + Dc_t$$

Expanding using the budget constraint,

$$\hat{c}_t - Dc_t + \frac{\gamma}{R}\lambda + \frac{1}{2}\alpha k_t^2 s^2 + \frac{1}{2\alpha}\ln s^2 = \\ \left(1-\frac{\gamma}{R}\right)\left(\frac{R-1}{R}E_t[g_{t+1}]\theta_t + (R-1)(w_t - c_t) + A'\Phi\Delta\vec{d}_t + \Delta\vec{d}_t'\Phi' B\Phi\Delta\vec{d}_t + q\right)$$

Simplifying, and replacing c_t with $\hat{c}_t + \gamma c_{t-1}$,

$$\hat{c}_t\left(1 - D + \left(1-\frac{\gamma}{R}\right)(R-1)\right) + \left(\left(1-\frac{\gamma}{R}\right)(R-1) - D\right)\gamma c_{t-1} + \frac{\gamma}{R}\lambda + \frac{1}{2}\alpha k_t^2 s^2 + \frac{1}{2\alpha}\ln s^2 = \\ \left(1-\frac{\gamma}{R}\right)\left(\frac{R-1}{R}(M\Delta\vec{d}_t + \mu)\theta_t + (R-1)w_t + A'\Phi\Delta\vec{d}_t + \Delta\vec{d}_t'\Phi' B\Phi\Delta\vec{d}_t + q\right)$$

Let $Q = 1 - D + (1-\frac{\gamma}{R})(R-1)$. Simplifying, and expanding the terms of $\hat{c}_t$,

$$((Q-1)\gamma + QD)c_{t-1} + Q\left(1-\frac{\gamma}{R}\right)\left(\frac{R-1}{R}w_t + A'\Delta\vec{d}_t + Q\Delta\vec{d}_t' B\Delta\vec{d}_t + Qq\right) + \frac{\gamma}{R}\lambda + \frac{1}{2}\alpha k_t^2 s^2 + \frac{1}{2\alpha}\ln s^2 = \\ \left(1-\frac{\gamma}{R}\right)\left((R-1)w_t + \frac{R-1}{R}(M\Delta\vec{d}_t + \mu)\theta_t + A'\Phi\Delta\vec{d}_t + \Delta\vec{d}_t'\Phi' B\Phi\Delta\vec{d}_t + q\right)$$

We guess that $D = \frac{\gamma}{R} - \gamma$, and see that this simplifies nicely:

$$\begin{aligned} Q &= R \\ (Q-1)\gamma + QD &= 0 \end{aligned}$$

Therefore, noting that w_t cancels,

$$R\left(1-\frac{\gamma}{R}\right)\left(A'\Delta\vec{d}_t + \Delta\vec{d}_t' B\Delta\vec{d}_t + q\right) + \frac{\gamma}{R}\lambda + \frac{1}{2}\alpha k_t^2 s^2 + \frac{1}{2\alpha}\ln s^2 = \\ \left(1-\frac{\gamma}{R}\right)\left(\frac{R-1}{R}(M\Delta\vec{d}_t + \mu)\theta_t + A'\Phi\Delta\vec{d}_t + \Delta\vec{d}_t'\Phi' B\Phi\Delta\vec{d}_t + q\right)$$

Using the asset allocation Euler result, we see that

$$\frac{1}{2}\alpha k_t^2 s^2 = \frac{1}{2\alpha\sigma_g^2 s^2}\left(\mu^2 + 2\mu M\Delta\vec{d}_t + \Delta\vec{d}_t' M'M\Delta\vec{d}_t\right)$$

Expanding using the definition of s,

$$\frac{1}{2}\alpha k_t^2 s^2 = \frac{1+2\alpha\lambda}{2\alpha\sigma_g^2}\left(\mu^2 + 2\mu M\Delta\vec{d}_t + \Delta\vec{d}_t' M'M\Delta\vec{d}_t\right) \tag{17}$$

We also need to replace θ_t using the asset allocation Euler.

$$\mu + M\Delta\vec{d}_t = \alpha\sigma_g s^2 k_t = \left(1-\frac{\gamma}{R}\right)\alpha\sigma_g s^2\left(\frac{(R-1)}{R}\theta_t\sigma_g + \sigma_e A'e_{1,p} + \sigma_e e_{1,p}' B\Phi\Delta\vec{d}_t + \sigma_e\Delta\vec{d}_t'\Phi' Be_{1,p}\right)$$

Solving,

$$\theta_t = \frac{R}{R-1}\frac{1}{\sigma_g}\left(\frac{\mu + M\Delta\vec{d_t}}{(1-\frac{\gamma}{R})\alpha\sigma_g s^2} - \sigma_e A' e_{1,p} - \sigma_e e'_{1,p} B\Phi\Delta\vec{d_t} - \sigma_e \Delta\vec{d_t}'\Phi' B e_{1,p}\right)$$

To replace the term in the consumption equation,

$$\frac{R-1}{R}(M\Delta\vec{d_t} + \mu)\theta_t =$$
$$\frac{1}{\left(1-\frac{\gamma}{R}\right)\alpha\sigma_g^2 s^2}\left(\mu^2 + 2\mu M\Delta\vec{d_t} + \Delta\vec{d_t}' M' M\Delta\vec{d_t}\right) -$$
$$\frac{\mu\sigma_e}{\sigma_g}A' e_{1,p} - \frac{\sigma_e}{\sigma_g}\left(A' e_{1,p} M + \mu e'_{1,p}(B+B')\Phi\right)\Delta\vec{d_t} - \frac{\sigma_e}{\sigma_g}\Delta\vec{d_t}' M' e'_{1,p} B\Phi\Delta\vec{d_t} - \frac{\sigma_e}{\sigma_g}\Delta\vec{d_t}'\Phi' B e_{1,p} M\Delta\vec{d_t}$$

We can now substitute all of these results:

$$R\left(1-\frac{\gamma}{R}\right)\left(A'\Delta\vec{d_t} + \Delta\vec{d_t}' B\Delta\vec{d_t} + q\right) + \frac{\gamma}{R}\lambda + \frac{1}{2}\alpha k_t^2 s^2 + \frac{1}{2\alpha}\ln s^2 = \alpha k_t^2 s^2 +$$
$$\left(1-\frac{\gamma}{R}\right)\left(-\frac{\mu\sigma_e}{\sigma_g}A' e_{1,p} - \frac{\sigma_e}{\sigma_g}(A' e_{1,p} M + \mu e'_{1,p}(B+B')\Phi)\Delta\vec{d_t} - \frac{\sigma_e}{\sigma_g}\Delta\vec{d_t}' M' e'_{1,p} B\Phi\Delta\vec{d_t} - \frac{\sigma_e}{\sigma_g}\Delta\vec{d_t}'\Phi' B e_{1,p} M\Delta\vec{d_t}\right) +$$
$$\left(1-\frac{\gamma}{R}\right)\left(A'\Phi\Delta\vec{d_t} + \Delta\vec{d_t}'\Phi' B\Phi\Delta\vec{d_t} + q\right)$$

The final version of the system is:

$$R\left(1-\frac{\gamma}{R}\right)(A'\Delta\vec{d_t} + \Delta\vec{d_t}' B\Delta\vec{d_t} + q) + \frac{\gamma}{R}\lambda + \frac{1}{2\alpha}\ln s^2 =$$
$$\frac{1+2\alpha\lambda}{2\alpha\sigma_g^2}(\mu^2 + 2\mu M\Delta\vec{d_t} + \Delta\vec{d_t}' M' M\Delta\vec{d_t}) +$$
$$\left(1-\frac{\gamma}{R}\right)\left(-\frac{\mu\sigma_e}{\sigma_g}A' e_{1,p} - \frac{\sigma_e}{\sigma_g}\left(A' e_{1,p} M + \mu e'_{1,p}(B+B')\Phi\right)\Delta\vec{d_t} + \Delta\vec{d_t}'(\Phi - \frac{\sigma_e}{\sigma_g}e_{1,p} M)' B\Phi\Delta\vec{d_t}\right)$$
$$+\left(1-\frac{\gamma}{R}\right)\left(\Delta\vec{d_t}'\Phi' B(\Phi - \frac{\sigma_e}{\sigma_g}e_{1,p} M)\Delta\vec{d_t} - \Delta\vec{d_t}'\Phi' B\Phi\Delta\vec{d_t} + A'\Phi\Delta\vec{d_t} + q\right) \qquad (18)$$

This equation must hold for all value of $\Delta\vec{d_t}$, so we use term matching. Note that λ is actually the upper left element of B, scaled by $(1-\frac{\gamma}{R})\sigma_e^2$. Beginning with the 2nd order terms,

$$\Delta\vec{d_t}'\left(RB - \frac{1+2\alpha\lambda}{2\left(1-\frac{\gamma}{R}\right)\alpha\sigma_g^2}M' M - (\Phi - \frac{\sigma_e}{\sigma_g}M e_{1,p})' B\Phi - \Phi' B(\Phi - \frac{\sigma_e}{\sigma_g}M e_{1,p}) + \Phi' B\Phi\right)\Delta\vec{d_t} = 0$$

Define

$$\Lambda = \Phi - \hat{\Phi}$$

and note that

$$M = \frac{R}{R-1} e'_{1,p} \left[\Phi - \hat{\Phi} \left(I - \frac{1}{R} \hat{\Phi} \right)^{-1} \left(I - \frac{1}{R} \Phi \right) \right]$$
$$= \frac{R}{R-1} e'_{1,p} \left[\Lambda + \hat{\Phi} - \hat{\Phi} \left(I - \frac{1}{R} \hat{\Phi} \right)^{-1} \left(I - \frac{1}{R} \hat{\Phi} - \frac{1}{R} \Lambda \right) \right]$$
$$= \frac{R}{R-1} e'_{1,p} \left[\Lambda + \hat{\Phi} \left(I - \frac{1}{R} \hat{\Phi} \right)^{-1} \frac{1}{R} \Lambda \right]$$
$$= \frac{R}{R-1} e'_{1,p} \left(I - \frac{1}{R} \hat{\Phi} \right)^{-1} \Lambda$$

Because Λ has non-zeros only in the top row, and $e_{1,p}e'_{1,p}$ has non-zeros only in the upper left element, which is one,

$$\Lambda = e_{1,p} e'_{1,p} \Lambda$$

Therefore,

$$e_{1,p} M = \frac{R}{R-1} e_{1,p} e'_{1,p} \left(I - \frac{1}{R} \hat{\Phi} \right)^{-1} e_{1,p} e'_{1,p} \Lambda$$
$$= \frac{\sigma_g}{\sigma_e} \Lambda$$

and

$$\Phi - \frac{\sigma_e}{\sigma_g} M e_{1,p} = \Phi - \Lambda = \hat{\Phi}$$

The equation for B can be rewritten:

$$\Delta \vec{d}'_t \left(RB - \frac{1 + 2\alpha\lambda}{2\left(1 - \frac{\gamma}{R}\right)\alpha\sigma_g^2} M'M - \hat{\Phi}' B \Phi - \Phi' B \hat{\Phi} + \Phi' B \Phi \right) \Delta \vec{d}_t = 0$$

Substituting for λ and regrouping terms,

$$\Delta \vec{d}'_t \left(RB - \frac{1}{2\left(1 - \frac{\gamma}{R}\right)\alpha\sigma_g^2} M'M - \frac{\sigma_e^2}{\sigma_g^2} M' e'_{1,p} B e_{1,p} M - \hat{\Phi}' B \hat{\Phi} + \Lambda' B \Lambda \right) \Delta \vec{d}_t = 0$$

By our earlier result relating $e_{1,p}M$ and Λ, and assuming that this holds for all $\Delta \vec{d}_t$,

$$B = \frac{1}{2R\left(1 - \frac{\gamma}{R}\right)\alpha\sigma_g^2} M'M + \frac{1}{R} \hat{\Phi}' B \hat{\Phi}$$

This is a discrete time Lyapunov equation. We can apply the standard convergence results to see that, because the eigenvalues of $\frac{1}{\sqrt{R}}\hat{\Phi}$ are entirely less than 1 (no unit root), convergence is certain. Therefore,

$$B = \frac{1}{2R(1-\frac{\gamma}{R})\alpha\sigma_g^2}\sum_{k=0}^{\infty} R^{-k}\hat{\Phi}'^k M' M \hat{\Phi}^k$$

From this, we can easily solve for

$$\lambda = \left(1-\frac{\gamma}{R}\right)\sigma_e^2 e'_{1,p} B e_{1,p}$$

Moving on to the 1st order terms in equation 18, and using the symmetry of B,

$$\left(R\left(1-\frac{\gamma}{R}\right)A' - \frac{1+2\alpha\lambda}{2\alpha\sigma_g^2}2\mu M - \left(1-\frac{\gamma}{R}\right)A'\Phi + \left(1-\frac{\gamma}{R}\right)\frac{\sigma_e}{\sigma_g}(e'_{1,p}AM + 2\mu e'_{1,p}B\Phi)\right)\Delta\vec{d}_t = 0$$

Subsituting for λ, and regrouping,

$$\left(RA' - \frac{1}{2\left(1-\frac{\gamma}{R}\right)\alpha\sigma_g^2}2\mu M - \frac{2\mu\sigma_e}{\sigma_g}\frac{\sigma_e}{\sigma_g}e'_{1,p}Be_{1,p}M - A'\Phi + \frac{\sigma_e}{\sigma_g}A'e_{1,p}M + \frac{2\mu\sigma_e}{\sigma_g}e'_{1,p}B\Phi\right)\Delta\vec{d}_t = 0$$

Again using the relation between $e_{1,p}M$ and Λ,

$$\left(RA'(I-\frac{1}{R}\hat{\Phi}) - \frac{1}{2\left(1-\frac{\gamma}{R}\right)\alpha\sigma_g^2}2\mu M + \frac{2\mu\sigma_e}{\sigma_g}e'_{1,p}B\hat{\Phi}\right)\Delta\vec{d}_t = 0$$

This is solved by inversion:

$$A' = \frac{2\mu}{R\sigma_g}\left(\frac{1}{2(1-\frac{\gamma}{R})\alpha\sigma_g}M + \sigma_e e'_{1,p}B\hat{\Phi}\right)\left(I-\frac{1}{R}\hat{\Phi}\right)^{-1}$$

Finally, we solve the constants.

$$(R-1)\left(1-\frac{\gamma}{R}\right)q + \frac{\gamma}{R}\lambda - \frac{1+2\alpha\lambda}{2\alpha\sigma_g^2}\mu^2 + \left(1-\frac{\gamma}{R}\right)\frac{\mu\sigma_e}{\sigma_g}A'e_{1,p} + \frac{1}{2\alpha}\ln s^2 = 0$$

Consequently,

$$q = \frac{1+2\alpha\lambda}{2(R-1)(1-\frac{\gamma}{R})\alpha\sigma_g^2}\mu^2 - \frac{\mu\sigma_e}{\sigma_g(R-1)}A'e_{1,p} - \frac{1}{2\alpha(R-1)(1-\frac{\gamma}{R})}\ln(1+2\alpha\lambda).$$

At this point, it is worth simplifying the expression for asset allocation.

$$\theta_t = \frac{R}{R-1}\frac{1}{\sigma_g}\left(\frac{\mu + M\Delta\vec{d}_t}{\left(1-\frac{\gamma}{R}\right)\alpha\sigma_g s^2} - \sigma_e A'e - 2\sigma_e e'B\Phi\Delta\vec{d}_t\right)$$

Applying the standard substitution for s and then λ,

$$\theta_t = \frac{R}{R-1}\frac{1}{\sigma_g}\left(\frac{\mu + M\Delta\vec{d_t}}{\left(1-\frac{\gamma}{R}\right)\alpha\sigma_g} + \frac{2\mu\sigma_e^2}{\sigma_g}e'_{1,p}Be_{1,p} - \sigma_e A'e - 2\sigma_e e'_{1,p}B\hat{\Phi}\Delta\vec{d_t}\right)$$

The average value of θ (assuming $\Delta\vec{d_t} = 0$) is

$$\bar{\theta} = \frac{R}{R-1}\frac{\mu}{\left(1-\frac{\gamma}{R}\right)\alpha\sigma_g^2} + \frac{R}{R-1}\frac{2\mu\sigma_e^2}{\sigma_g^2}e'_{1,p}Be_{1,p} - \frac{R}{R-1}\frac{\sigma_e}{\sigma_g}A'e$$

Recall that

$$\mu = \frac{R\alpha}{(1-\frac{\gamma}{R})(R-1)}\hat{\sigma}_c^2$$
$$\hat{\sigma}_c = \frac{R-1}{R}(1-\gamma/R)\frac{\hat{\sigma}_e}{\sigma_e}\sigma_g$$

We can rewrite the average asset allocation as

$$\bar{\theta} = \frac{\hat{\sigma}_e^2}{\sigma_e^2} + \frac{R}{R-1}\frac{2\mu\sigma_e^2}{\sigma_g^2}e'_{1,p}Be_{1,p} - \frac{R}{R-1}\frac{\sigma_e}{\sigma_g}A'e \tag{19}$$

9.6 Inter-temporal Budget

It will be helpful to solve for an inter-temporal budget constraint. The transversality condition is

$$\lim_{k\to\infty} E_t[R^{-k}w_{t+k}] = 0$$

Seeing that

$$\begin{aligned} E[w_{t+2}] &= E[R(w_{t+1} - c_{t+1} + y) + \theta_{t+1}M\Delta\vec{d}_{t+1} + \theta_{t+1}\mu] \\ &= E[R^2(w_t - c_t + y) + R(-c_{t+1} + y)\theta_{t+1}M\Delta\vec{d}_{t+1} + \theta_{t+1}\mu + R\theta_t M\Delta\vec{d_t} + R\mu] \end{aligned}$$

We conjecture that

$$E_t[R^{-k}w_{t+k}] = w_t + \frac{1}{R}\sum_{j=0}^{k} R^{-j}E_t[\theta_{t+j}M\Delta\vec{d}_{t+j} + \theta_{t+j}\mu - Rc_{t+k} + Ry]$$

This holds trivially for $k = 0$ and $k = 1$. Assume it holds for k.

$$\begin{aligned} E[R^{-k-1}w_{t+k+1}] &= E[R^{-k}w_{t+k} - R^{-k}c_{t+k} + R^{-k}y + R^{-k-1}\theta_{t+k}M\Delta\vec{d}_{t+k} + R^{-k-1}\theta_{t+k}\mu] \\ &= w_t + \frac{1}{R}\sum_{j=0}^{k+1} R^{-j}E_t[\theta_{t+j}M\Delta\vec{d}_{t+j} + \theta_{t+j}\mu - Rc_{t+k} + Ry] \end{aligned}$$

By induction, it holds in the limit, and therefore the inter-temporal budget constraint is

$$\sum_{j=0}^{\infty} E_t[R^{-j} c_{t+j}] = w_t + \frac{1}{R-1} y + \sum_{j=0}^{\infty} E_t[R^{-j} \theta_{t+j} M \Delta \vec{d}_{t+j} + R^{-j} \theta_{t+j} \mu]$$

We can rewrite the sum of c_{t+j} in terms of $\hat{c}_{t+j} = c_{t+j} - \gamma c_{t+j-1}$.

$$\begin{aligned}
\sum_{j=0}^{\infty} E_t[R^{-j} c_{t+j}] &= \sum_{j=0}^{\infty} E_t[R^{-j}(\hat{c}_{t+j} + \gamma c_{t+j-1})] \\
&= \gamma c_{t-1} + \sum_{j=0}^{\infty} E_t[R^{-j} \hat{c}_{t+j}] + \frac{\gamma}{R} \sum_{j=1}^{\infty} E_t[R^{-j+1} c_{t+j-1}] \\
&= \gamma c_{t-1} + \sum_{j=0}^{\infty} E_t[R^{-j} \hat{c}_{t+j}] + \frac{\gamma}{R} \sum_{k=0}^{\infty} E_t[R^{-k} c_{t+k}]
\end{aligned}$$

We can then solve to see that

$$\sum_{j=0}^{\infty} E_t[R^{-j} c_{t+j}] = \frac{1}{1 - \frac{\gamma}{R}} (\gamma c_{t-1} + \sum_{j=0}^{\infty} E_t[R^{-j} \hat{c}_{t+j}])$$

Rewriting the inter-temporal budget constraint,

$$\sum_{j=0}^{\infty} E_t[R^{-j} \hat{c}_{t+j}] = -\gamma c_{t-1} + (1 - \frac{\gamma}{R}) \left(w_t + \frac{1}{R-1} y + \sum_{j=0}^{\infty} E_t[R^{-j} \theta_{t+j} M \Delta \vec{d}_{t+j} + R^{-j} \theta_{t+j} \mu] \right) \tag{20}$$

Table 1
Estimated coefficients from AR(p)

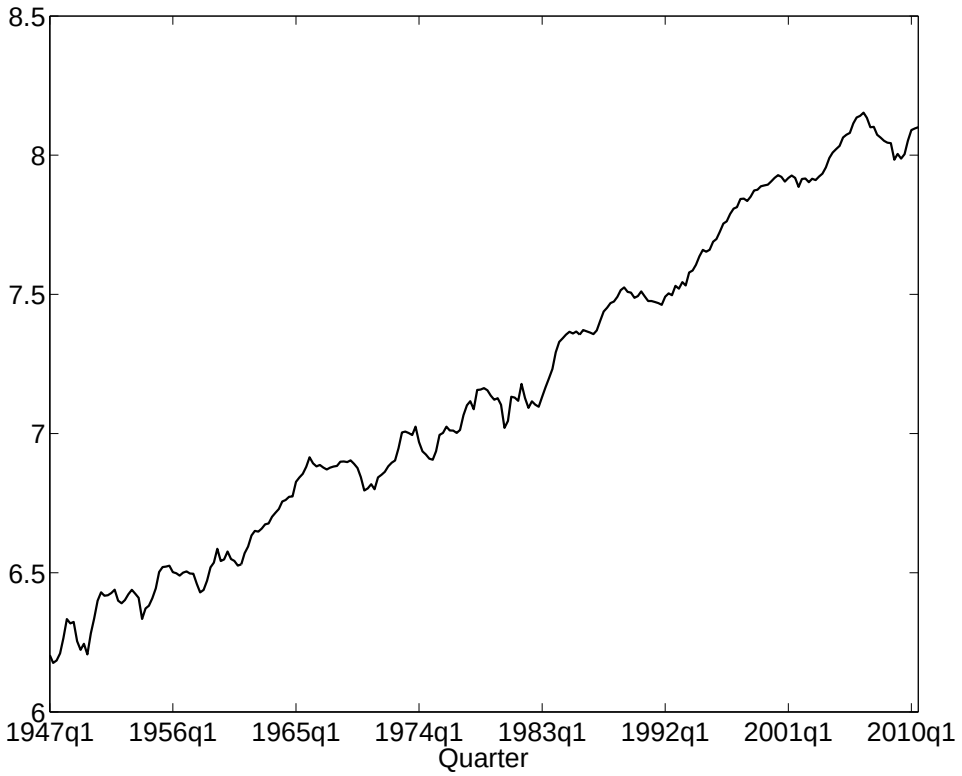
	AR(1)		AR(10)		AR(20)		AR(30)		AR(40)	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t	Coef.	t
1st lag	0.2011	3.27	0.1841	2.83	0.1894	2.80	0.18	2.57	0.2113	2.79
2nd lag			0.0319	0.48	0.0159	0.23	0.01	0.15	-0.0493	-0.64
3rd lag			0.1242	1.93	0.1121	1.64	0.16	2.19	0.1969	2.57
4th lag			-0.1009	-1.57	-0.0801	-1.16	-0.08	-1.11	-0.1282	-1.64
5th lag			-0.1487	-2.31	-0.1622	-2.36	-0.19	-2.68	-0.1057	-1.35
6th lag			-0.0904	-1.41	-0.0276	-0.40	-0.04	-0.62	-0.0880	-1.13
7th lag			0.1181	1.86	0.0626	0.90	0.05	0.68	0.0682	0.87
8th lag			-0.1318	-2.04	-0.1718	-2.42	-0.15	-2.03	-0.2069	-2.59
9th lag			0.0853	1.31	0.0432	0.62	0.04	0.55	0.0755	0.94
10th lag			-0.0130	-0.20	0.0144	0.21	-0.05	-0.69	-0.0826	-1.02
11th lag					-0.0158	-0.23	-0.02	-0.27	-0.0047	-0.06
12th lag					-0.1696	-2.48	-0.15	-2.07	-0.1831	-2.32
13th lag					-0.0227	-0.33	0.00	0.05	0.0327	0.41
14th lag					-0.0099	-0.15	-0.03	-0.43	-0.0642	-0.82
15th lag					-0.0573	-0.85	-0.03	-0.34	-0.0231	-0.30
16th lag					0.0208	0.31	-0.03	-0.35	-0.0592	-0.75
17th lag					-0.0580	-0.89	-0.07	-0.99	-0.0873	-1.12
18th lag					0.0877	1.34	0.01	0.19	0.0039	0.05
19th lag					-0.0231	-0.35	-0.05	-0.74	-0.0624	-0.81
20th lag					-0.0908	-1.41	-0.06	-0.88	-0.0705	-0.92
21st lag							-0.01	-0.08	-0.0062	-0.08
22nd lag							-0.10	-1.48	-0.1343	-1.76
23rd lag							0.06	0.81	0.0944	1.23
24th lag							-0.04	-0.58	-0.0541	-0.70
25th lag							-0.05	-0.68	-0.0352	-0.46
26th lag							-0.06	-0.90	-0.0876	-1.15
27th lag							0.02	0.29	0.0317	0.41
28th lag							0.05	0.71	-0.0012	-0.02
29th lag							-0.02	-0.31	-0.0109	-0.15
30th lag							-0.17	-2.62	-0.2144	-2.95
31st lag									0.0547	0.74
32nd lag									-0.1021	-1.39
33rd lag									0.0556	0.78
34th lag									-0.0994	-1.39
35th lag									0.1435	2.01
36th lag									-0.1413	-1.95
37th lag									-0.0149	-0.21
38th lag									-0.1210	-1.71
39th lag									0.0858	1.20
40th lag									-0.0630	-0.90
N	253		244		234		224		214	
R squared	0.0407		0.1244		0.1658		0.2071		0.2483	
Root MSE	0.0249		0.0236		0.0228		0.0225		0.0227	

Table 2: Bootstrap confidence intervals under the null of no predictability

Moment	US data	*Bootstrap* Mean	90% C.I.	95% C.I.
1) corr(XR_τ, $XR_{\tau+2\to\tau+5}$)	-0.220	-0.049	$[-0.249, 0.165]$	$[-0.284, 0.206]$
2) corr($(P/E_{10})_\tau$, $XR_{\tau+2\to\tau+5}$)	-0.377	-0.141	$[-0.432, 0.192]$	$[-0.478, 0.249]$
3) corr($ln(c_\tau) - ln(c_{\tau-1})$, $XR_{\tau+2\to\tau+5}$)	-0.297	-0.009	$[-0.267, 0.254]$	$[-0.313, 0.297]$
4) corr($(P/E_{10})_\tau$, $ln(c_{\tau+6}) - ln(c_{\tau+2})$)	-0.167	-0.022	$[-0.424, 0.388]$	$[-0.493, 0.450]$
5) corr($ln(c_\tau) - ln(c_{\tau-1})$, $ln(c_{\tau+6}) - ln(c_{\tau+2})$)	-0.245	0.008	$[-0.237, 0.257]$	$[-0.283, 0.302]$

Note: Sources for empirical moments and bootstrap procedures are described in the text.

Figure 1: Log of Real Net Operating Surplus ("Earnings") of U.S. Private Enterprises from 1947Q1 to 2010Q3



Source: U.S. National Income and Product Accounts (Bureau of Economic Analysis), Table 1.10, line 12. Adjusted for inflation using the GDP deflator.

Figure 2: Estimated Impulse Response Function for Earnings, for Different AR(p) Models

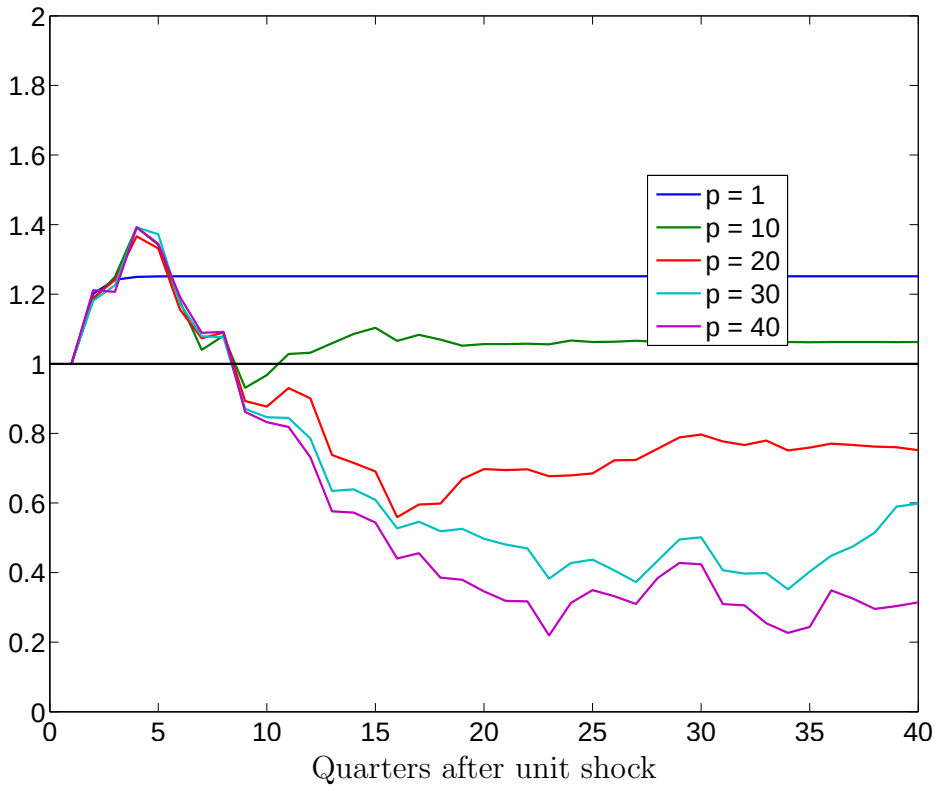


Figure 3: Cumulative Impulse Response Function for Gains, for Different AR(p) Models of Earnings Growth

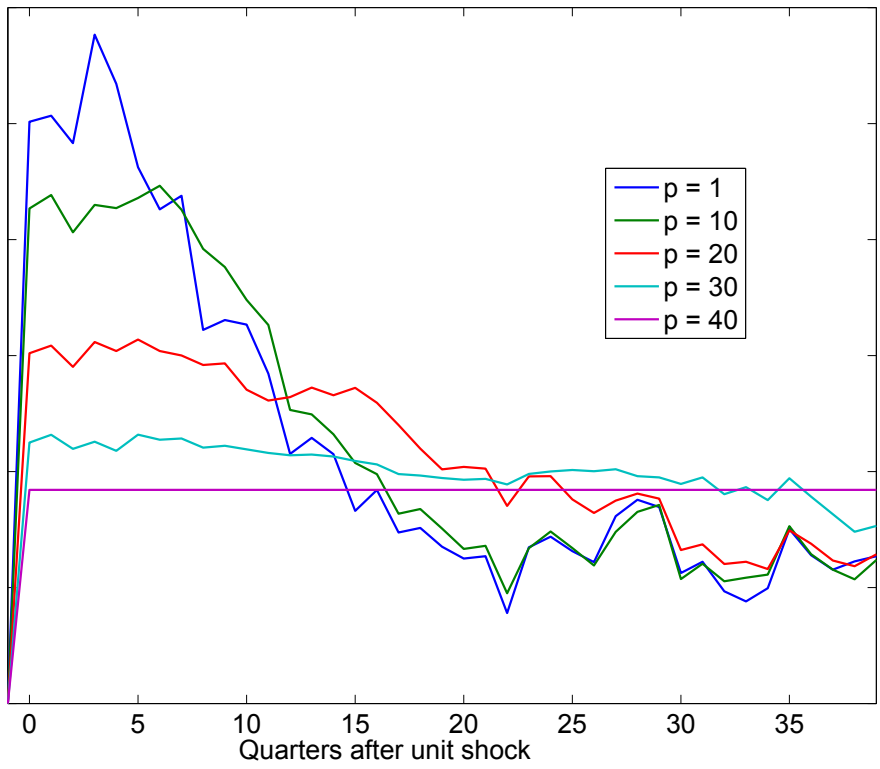


Figure 4: Impulse Response Function for Consumption, for Different AR(p) Models of Earnings Growth

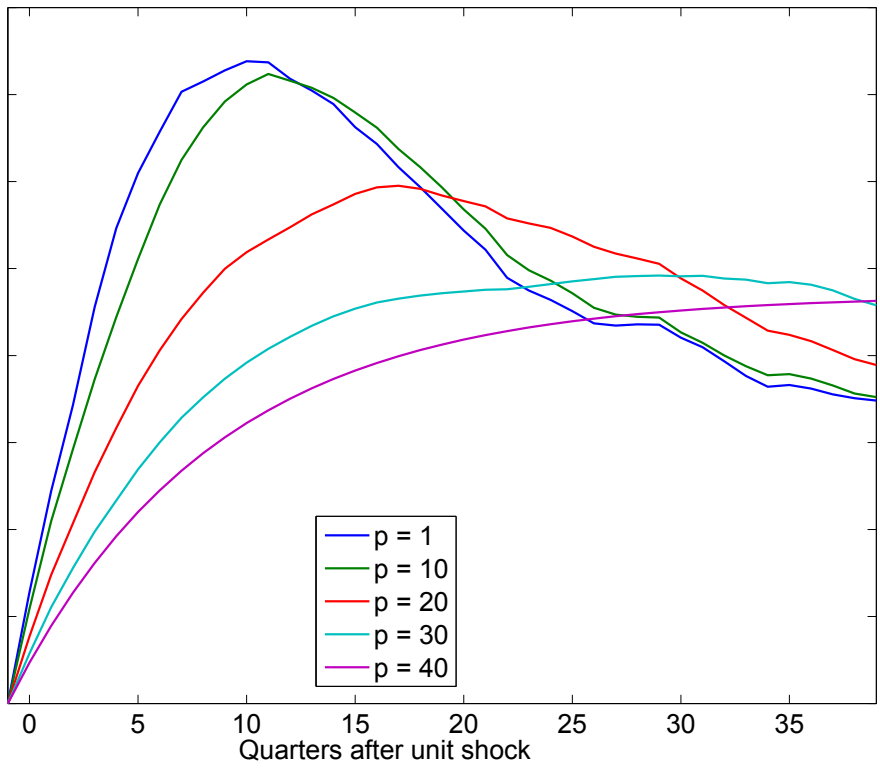
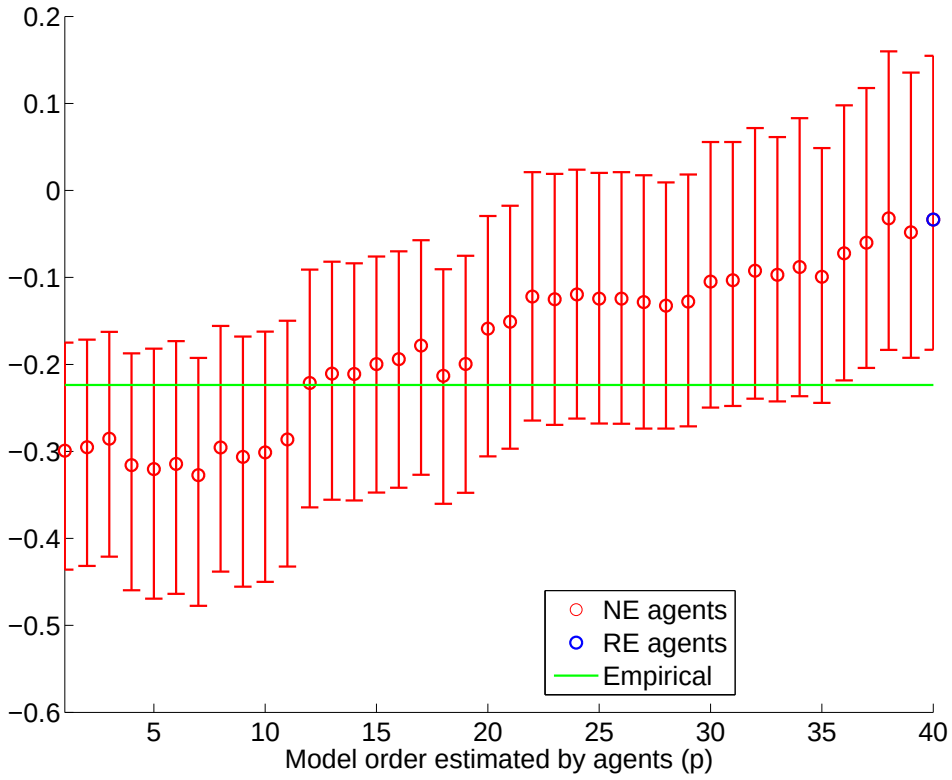
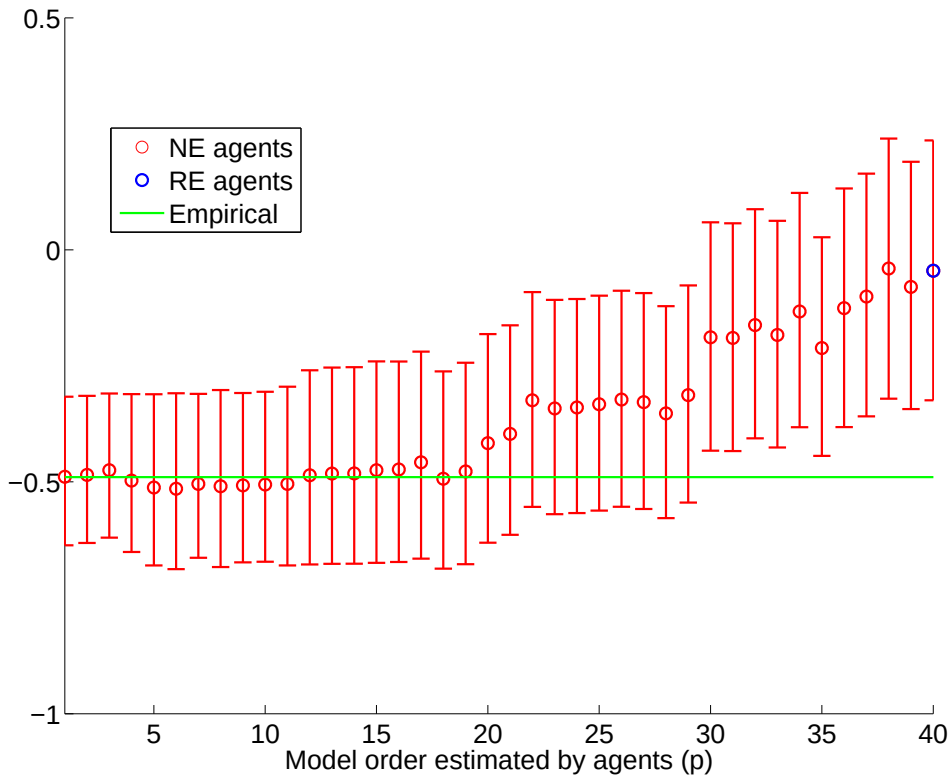


Figure 5: Correlation of Excess Returns in Year τ with Cumulative Excess Returns for Years $\tau + 2$ to $\tau + 5$, for Different AR(p) Models of Earnings Growth



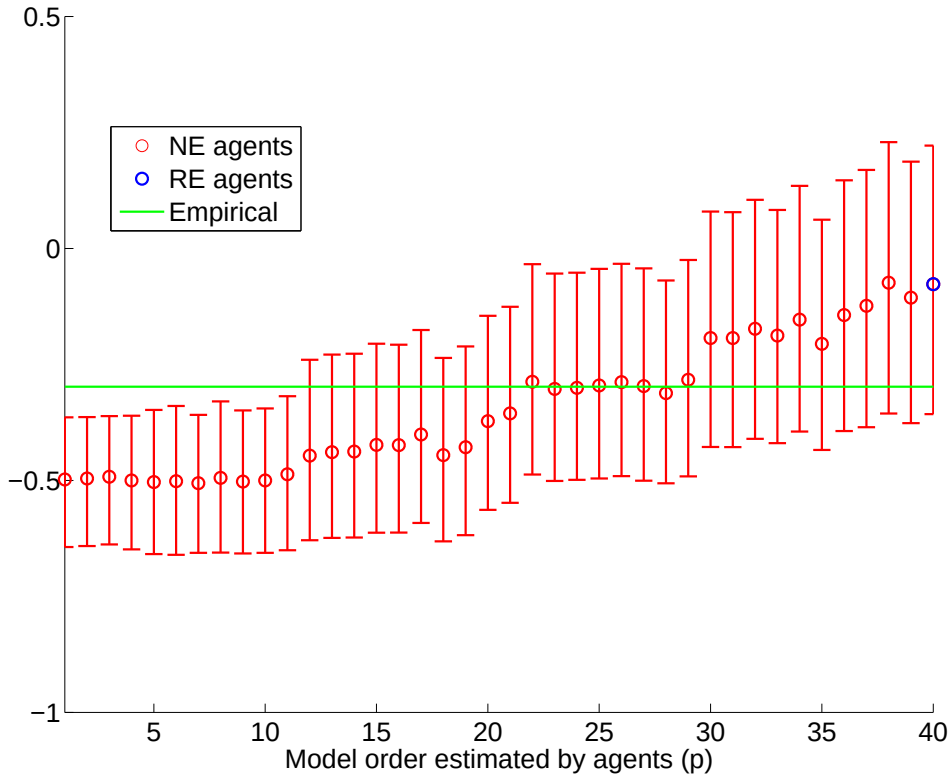
Note: Circles depict mean correlations over 200 simulations of length equal to the empirical sample, while bars depict the 5th and 95th percentile of simulated values. "NE agents" use models with too few lags (AR(1) to AR(39)) while "RE agents" use the correct (AR(40)) model for earnings growth.

Figure 6: Correlation of the P/E_{10} Ratio in Year τ with Cumulative Excess Returns for Years $\tau + 2$ to $\tau + 5$, for Different AR(p) Models of Earnings Growth



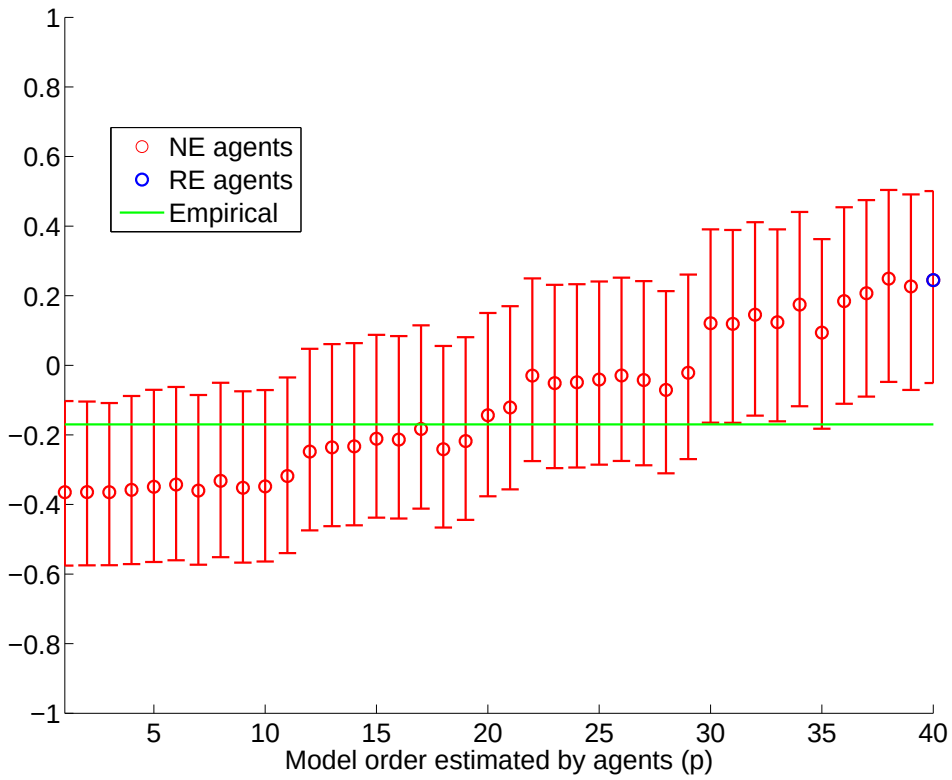
Note: Circles depict mean correlations over 200 simulations of length equal to the empirical sample, while bars depict the 5th and 95th percentile of simulated values. "NE agents" use models with too few lags (AR(1) to AR(39)) while "RE agents" use the correct (AR(40)) model for earnings growth. *GREEN LINE SHOULD BE AT* -0.377*; TO BE FIXED.*

Figure 7: Correlation of Consumption Growth in Year τ with Cumulative Excess Returns for Years $\tau + 2$ to $\tau + 5$, for Different AR(p) Models of Earnings Growth



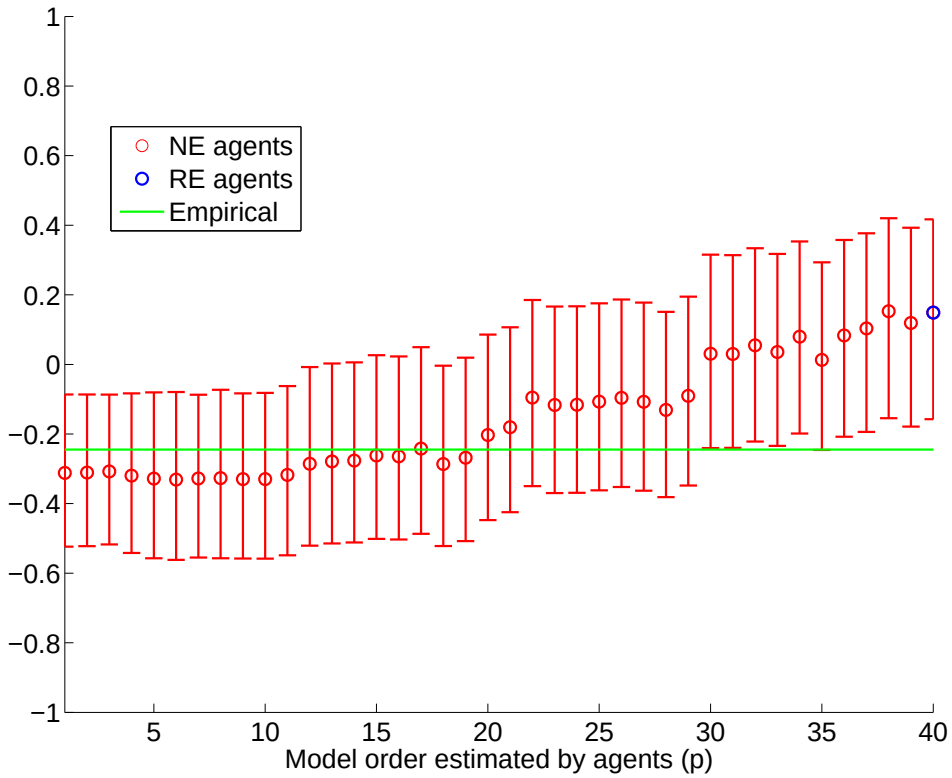
Note: Circles depict mean correlations over 200 simulations of length equal to the empirical sample, while bars depict the 5th and 95th percentile of simulated values. "NE agents" use models with too few lags (AR(1) to AR(39)) while "RE agents" use the correct (AR(40)) model for earnings growth.

Figure 8: Correlation of the P/E_{10} Ratio in Year τ with Consumption Growth from Year $\tau + 2$ to $\tau + 6$, for Different AR(p) Models of Earnings Growth



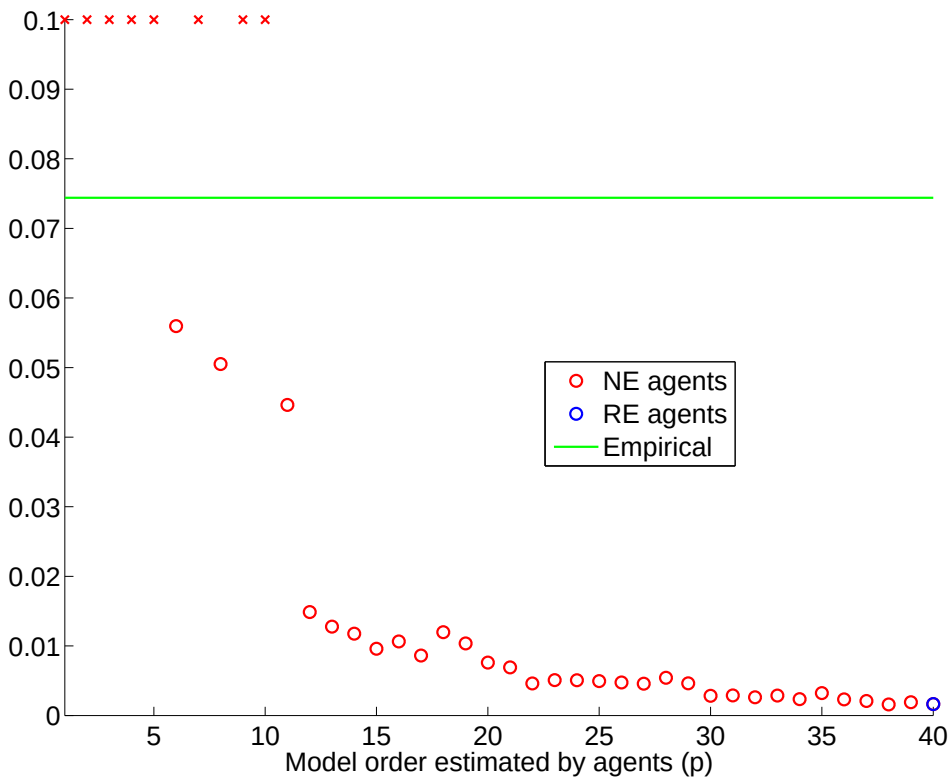
Note: Circles depict mean correlations over 200 simulations of length equal to the empirical sample, while bars depict the 5th and 95th percentile of simulated values. "NE agents" use models with too few lags (AR(1) to AR(39)) while "RE agents" use the correct (AR(40)) model for earnings growth.

Figure 9: Correlation of Consumption Growth in Year τ with Consumption Growth from Year $\tau + 2$ to $\tau + 6$, for Different AR(p) Models of Earnings Growth



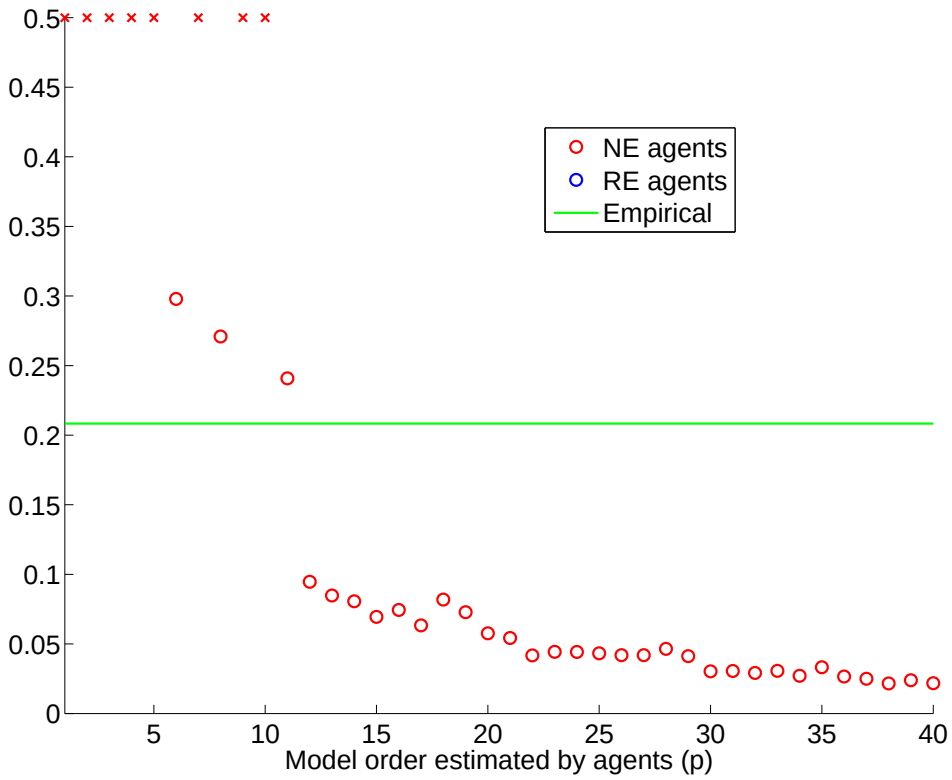
Note: Circles depict mean correlations over 200 simulations of length equal to the empirical sample, while bars depict the 5th and 95th percentile of simulated values. "NE agents" use models with too few lags (AR(1) to AR(39)) while "RE agents" use the correct (AR(40)) model for earnings growth.

Figure 10: Equity Premium (= Mean Excess Return of Equity over the Riskfree Rate) for Different AR(p) Models of Earnings Growth



Note: "x" denote equity premia above 10%. "NE agents" use models with too few lags (AR(1) to AR(39)) while "RE agents" use the correct (AR(40)) model for earnings growth.

Figure 11: Standard Deviation of Excess Returns for Different AR(p) Models of Earnings Growth



Note: "x" denote standard deviations above 50%. "NE agents" use models with too few lags (AR(1) to AR(39)) while "RE agents" use the correct (AR(40)) model for earnings growth.

Figure 12: Standard Deviation of Consumption Growth for Different AR(p) Models of Earnings Growth

