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Demography and Fluctuations in Dividend/Price*

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Abstract

The dynamic dividend growth model (Campbell&Shiller, 1988) linking the log dividend yield to future expected dividend growth and stock market returns has been extensively used in the literature for forecasting stock returns. The empirical evidence on the performance of the model is mixed as its strength varies with the sample choice. This model is derived on the assumption of *stationary* dp_t, dividend-yield. The empirical validity of such hypothesis has been challenged in recent literature (Lettau&Van Nieuwerburgh, 2007) with strong evidence on a time varying mean, due to breaks, in this financial ratio. In this paper, we show that the slowly evolving mean toward which the dividend price ratio is reverting is determined by demographic factors. We also show that a forecasting model based on demographics and a demand factor as captured by excess consumption in the sense of Lettau and Ludvigson(2004) overperforms virtually all alternative models proposed in the empirical literature in the framework of the dynamic dividend growth model. Finally, we exploit the predictability of demographic factors to project the equity risk premium up to 2050.

KEYWORDS: dynamic dividend growth model, demographics, cointegration, forecasting stock market returns

J.E.L. CLASSIFICATION NUMBERS: G14, G19, C10, C11, C22,C53.

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1 Introduction

Stock market predictability has been an active research area in the past decades. After a long tradition of the efficient market hypothesis (Fama, 1970) that implies that returns are not predictable, the recent empirical literature has moved toward a view of predictability of returns (see, for example, Cochrane, 2007). There is, however, an ongoing debate on the robustness of the predictability evidence and its exploitability from a portfolio allocation perspective (Goyal&Welch, 2007).

Most of the available evidence on predictability can be framed within the dynamic dividend growth model proposed by Campbell&Shiller (1988).

The model of Campbell& Shiller (1988) uses a loglinear approximation to the definition of returns on the stock market. Under the assumption of stationarity of the log of price-dividend ratio pd_t, this variable is expressed as a linear function of the future discounted dividend growth, Δd_{t+j} and of future returns, h^s_{t+j} :

$$pd_t = \overline{pd} + \sum_{j=1}^{\infty} \rho^{j-1} E_t[(\Delta d_{t+j} - \bar{d}) - (h^s_{t+j} - \bar{h})] \tag{1}$$

where $\overline{pd}$, the mean of the price-dividend ratio, $\bar{d}$, the mean of dividend growth rate, $\bar{h}$, the mean of log return and ρ are constants. Once the future variables are expressed in terms of observables (1) can be used to derive an equilibrium price p^*_t as a function of present dividends and future expected dividends and returns; then a forecasting model for logarithmic return is naturally derived by estimating an *Error Correction Model* (ECM) for stock prices:

$$\Delta p^e_{t+1} = \beta_0 - \beta_1 (p_t - p^*_t) + u_t. \tag{2}$$

(2) ensures long-run convergence of stock prices to equilibrium prices allowing for the possibility of short-run disequilibria. This basic relation allows to classify different forecasting regression of stock market returns in terms of different approaches to proxy the future expected variables included in the linearized relations. The classical Gordon growth model (1962) is obtained by augmenting (1) with the hypotheses of constant dividend growth, $E_t \Delta d_{t+j} = g$, and constant expected returns, $E_t h^s_{t+j} = r$. The so-called FED model (Lander et al., 1997) proposing a long-run relation between the price-earning ratio and the long-term bond yield can be understood by substituting out the no-arbitrage restrictions in (1) $E_t h^s_{t+j} = E_t(r_{t+j} + \phi^s_{t+j})$ and then by assuming constant dividend growth, some relation between the risk premium on long-term bonds and the risk premium on stocks, and a stationary (log) earning price ratio. The extension of the FED model proposed by Asness (2003) removes the assumption of proportionality between the stock market risk premium and the bond market risk premium and augments the standard FED model by adding the ratio between the historical volatility of stock and bonds. Lettau and Lud-

vigson (2001, LL henceforth) analyze a linearized version of the consumer intertemporal budget constraint to show that excess consumption with respect to its long-run equilibrium value, a linear combination of labour income and financial wealth, may predict future return on total wealth. If future returns on total wealth are correlated with future stock market return, then excess consumption should forecast future stock market returns. They introduce the well-known cointegrating vector, *cay*, including consumption, assets and income and show empirical evidence strongly supporting their conjecture. In their proposed framework *cay* proxies p_t^* by predicting future discounted returns without concentrating on dividend growth. Julliard (2004) refines the LL contribution by observing that the total return on wealth reflect both returns on financial capital and returns on human capital, therefore the predictive power of excess consumption for stock market returns could be strengthened by controlling for returns on human capital. Labour income growth is proposed as a proxy to control for returns of human capital added to the model on top of *cay*. Ribeiro (2004) also highlights the importance of labour income in predicting future dividends and posits vector error correction model (VECM) for dividend growth and future returns with two cointegrating vectors defined as $(d_t - y_t)$ and $(d_t - p_t)$. Finally, Lamont (1998) argues that the log dividend payout ratio $(d_t - e_t)$ is the most appropriate proxy for future stock market returns and includes it in his specification. The second stage equations (2) based on all these models delivered some degree of predictability, in terms of significance of β_1. However, the degree of predictability varies with the chosen sample and so does the relative performance of different models (see Ang and Bekaert (2007)).

Such mixed evidence of predictability has been recently related to the potential weakness of the fundamental hypothesis of the dynamic dividend growth that log dividend price ratio is a stationary process (Lettau&Van Nieuwerburgh, 2007, LVN henceforth). LVN show evidence on the breaks in $\overline{pd}$ and assert that correcting for the breaks improves predictive power of the dividend yield for stock market returns. Interestingly, LVN also give some hints on possible causes for the breaks arising from economic fundamentals due to technology innovations, changes in expected return, etc. but do not explore further the possible effects of fundamentals. Breaks are modelled via a purely statistical methods without any explicit relation with economic fundamentals.

In this paper, we pursue two distinct aims.

First, we show that the predictions of the theoretical model by Geanakoplos et al.(2004) that demographic factors, along with a correction for productivity trends, explain fluctuations in the dividend yield is supported by annual US data. We then exploit stability analysis for long-run economic relationships to construct an *equilibrium* dividend-price ratio.

Second, we use our measure of disequilibrium measured as the difference between the actual dividend yield and the equilibrium dividend yield for forecasting market returns at different horizons (up to 10 years) and evaluate the forecasting performance of the model based on the corrected dividend-price ratio against different alternative specifications.

The paper is structured as follows. In the next section we provide evidence on non-stationarity of dividend yield. In section III, we introduce the cointegration framework and estimation of cointegration relations. Next we devote a section on forecasting short horizon, followed by a section on forecasting longer horizons up to 10 years. In section VI, we introduce a vector error correction (VECM) specification and provide out of sample forecasts for next few decades. The last section concludes.

2 Non-Stationarity of Dividend/Price Ratio

In this section, we consider a long sample of annual data (1909-2006), to analyze cointegration between dividends and stock prices and stationarity of the (log) dividend-yield. We report in Figure 1 the time-series of $(d_t - p_t)$.

Insert Figure 1 here

The crucial assumption for the validity of the linearized dividend growth model is that this variable is stationary, i.e. that there exists a cointegrating vector with coefficient restricted to $(1, -1)$ between d_t and p_t. The visual inspection of the time series suggest some intuitive support for the recent evidence on non-stationarity (Ribeiro, 2004; LVN, 2007). Differently from LVN (2007) we do not use recursive Chow test to identify break points but we analyse the possibility of breaks and non-stationarity by concentrating on the evidence of cointegration with a (-1,1) vector between d_t and p_t. We follow Warne et al. (2003) to study the non-zero eigenvalues of the matrix describing the long-properties of a bivariate VAR for d_t and p_t used in the Johansen (1991) approach to cointegration analysis.

We consider the following statistical model:

$$\mathbf{y}_t = \sum_{i=1}^{n} \mathbf{A}_i \mathbf{y}_{t-i} + \mathbf{u}_t \tag{3}$$

$$\mathbf{y}_t = \begin{bmatrix} d_t \\ p_t \end{bmatrix}. \tag{4}$$

This model can be re-written as follows

$$\begin{aligned} \Delta \mathbf{y}_t &= \mathbf{\Pi}_1 \Delta \mathbf{y}_{t-1} + \mathbf{\Pi}_1 \Delta \mathbf{y}_{t-2} + ... + \mathbf{\Pi} \mathbf{y}_{t-n} + \mathbf{u}_t \\ &= \sum_{i=1}^{n-1} \mathbf{\Pi}_i \Delta \mathbf{y}_{t-i} + \mathbf{\Pi} \mathbf{y}_{t-n} + \mathbf{u}_t, \end{aligned} \tag{5}$$

where:

$$\begin{aligned}\mathbf{\Pi}_i &= -\left(I-\sum_{j=1}^{i}\mathbf{A}_j\right),\\ \mathbf{\Pi} &= -\left(I-\sum_{i=1}^{n}\mathbf{A}_i\right).\end{aligned}$$

Clearly the long-run properties of the system are described by the properties of the matrix Π. There are three cases of interest:

1. rank $(\Pi) = 0$. The system is non-stationary, with no cointegration between the variables considered. This is the only case in which non-stationarity is correctly removed simply by taking the first differences of the variables;

2. rank $(\Pi) = 2$, full. The system is stationary;

3. rank $(\Pi) = 1$. The system is non-stationary but there is a cointegrating relationships among the considered variables. In this case $\mathbf{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$, where α is an (2×1) matrix of weights and $\boldsymbol{\beta}$ is an (2×1) matrix of parameters determining the cointegrating relationships.

Therefore, the rank of Π is crucial in determining the number of cointegrating vectors. The Johansen procedure is based on the fact that the rank of a matrix equals the number of its characteristic roots that differ from zero. The Johansen test for cointegration is based on the estimates of the two characteristic roots of $\mathbf{\Pi}$ matrix. Having obtained estimates for the parameters in the $\mathbf{\Pi}$ matrix, we associate with them estimates for the 2 characteristic roots and we order them as follows $\lambda_1 > \lambda_2$. If the variables are not cointegrated, then the rank of Π is zero and all the characteristic roots equal zero. In this case each of the expression $\ln(1-\lambda_i)$ equals zero, too. If, instead, the rank of Π is one, and $0 < \lambda_1 < 1$, then $\ln(1-\lambda_1)$ is negative and $\ln(1-\lambda_2) = 0$. The Johansen test for cointegration in our bivariate VAR is based on the two following statistics that Johansen derives based on the number of characteristic roots that are different from zero:

$$\begin{aligned}\lambda_{\text{trace}}(k) &= -T\sum_{i=k+1}^{2}\ln\left(1-\widehat{\lambda}_i\right),\\ \lambda_{\max}(k,k+1) &= -T\ln\left(1-\widehat{\lambda}_{k+1}\right),\end{aligned}$$

where T is the number of observations used to estimate the VAR. The first statistic tests the null of at most k cointegrating vectors against a generic alternative. The test should be run in sequence starting from the null of at most zero cointegrating vectors up to the case of at most 2 cointegrating vectors. The second statistic tests the null of at most k cointegrating vectors against the alternative of at most $k+1$ cointegrating vectors. Both statistics are small under the null hypothesis. Critical values are tabulated by Johansen (1991) and they depend on the number of non-stationary components under the null and on the specification of the deterministic component of the VAR.

The main recursive test based on the non zero-eigenvalues is the fluctuation test suggested in Hansen and Johansen (1999). The test starts from estimation of our VAR model over the full sample. After that, we re-estimate the model (the full sample estimates of all coefficients on deterministic variables and lagged first differences are used in order to reduce volatility) and computes recursive eigenvalues and β recursively extending the end point of the recursive sample, t_1, until the full sample is covered, i.e. $t_1 = T_1, T_1 + 1, ...T$ where the base period is fixed at about 35 percent of the sample, i.e. $T_1 = 0.35 * T$, as suggested in Warne et al. (2003).

Figure 2 shows the time path of the recursively calculated log transformed largest non-zero eigenvalue λ_i from the VAR(2) model together with the 95% confidence bands. We took log transformed eigenvalues to obtain a symmetrical representation of the distribution of λ_i.

$$\xi_i = \log(\lambda_i/(1 - \lambda_i))$$

The eigenvalue shows a remarkable amount of variability over the examination period with indication of three break points around 1950, 1980, 2000 and a clear possibility that null of at most zero cointegrating vectors cannot rejected for some relevant part of our sample. Interestingly, this evidence is consistent with that obtained using a different methodology by LVN (2007).

Insert Figure 2 here

Table 1 reports the results of the Johansen procedure applied to whole sample, and to two subsamples 1909-1954, 1955-2006.

Insert Table 1 here

The null of no-cointegration cannot be rejected over both whole sample and subsamples. Note that validity of the linearized model requires a stronger assumption than cointegration to be satisfied, i.e. the existence of cointegration with restricted cointegrating coefficients.

3 Demographic Trends & the Dividend/Price Ratio

The evidence of instability of the cointegrating relation between log of stock prices and dividends and therefore of the lack of stationarity of the log dividend-price ratio (Ribeiro,

2004) undermines on the validity of one of the crucial assumptions used in the loglinear approximation at the core of the dynamic dividend-growth model (Campbell and Shiller, 1988, Campbell, 1991). Geanakoplos, Magill and Quinzii.(2004) (GMQ) offer a potential solution to this problem by considering an overlapping generation model in which the demographic structure mimics the pattern of live births in the U.S. that have featured alternating twenty-year periods of boom and boost. GMQ study the equilibrium of a cyclical stochastic overlapping generations exchange economy to show that the dividend price ratio should be proportional to the ratio of middle aged to young adults. To study the effect of demographic composition on capital market prices GMQ assume that the model has been detrended so that the systematic source of dividend growths generated by population growth, capital accumulation and technical progress are filtered out. In GMQ the middle aged to young ratio, labelled as MY, and defined as the ratio of the number of agents aged 40-49 to the number of agents aged 20-29, serves as a sufficient statistic for the whole population pyramid. We find the GMQ model particularly appealing because it provides foundation for using demographic factors to explain fluctuations in the dividend price ratio. We use Total Factor Productivity (TFP) to filter out the effect of long-run trends. We take a TFP series directly from the website of Bureau of Labor Statistics (BLS) for the period 1948-2006. We then extended back the data to the period 1909-1949 by using the original series provided in the classic paper by Solow (1957)[1]. We report MY and TFP in Figure 3.

Insert Figure 3a here

Insert Figure 3b here

It is interesting to note that MY has a twin peaked behaviour with peaks roughly corresponding to the dates identified by LNV as break points for the mean of the dividend/price ratio. The whole sample correlation between MY and $(p_t - d_t)$ is as high as 0.73. This is a rather striking fact especially because the direct relation between these two variables does not take on account the potential relevance of filtering out trends explicitly cited by GMQ. We then posit the following potential cointegrating vector as directly determined by the theoretical model:

$$(d_t - p_t) = \gamma_0 + \gamma_1 MY_t + \gamma_2 TFP_t$$

Before reporting the results of estimation is important to note that the approach followed by GMQ is part of a strand of literature aimed at explaining stock market fluctuations with demographic factors . Bakshi&Chen (1994) develop two hypotheses; *life-cycle investment hypothesis* which asserts that an investor in early stage of her life allocates more wealth on housing and switches to financial assets at a later stage, and

[1] We normalized the series from BLS to bring it to the same scale with the Solow data.

life cycle risk aversion hypothesis which posits that an investor's risk aversion increases with age. The authors also test the empirical implications using fraction of people in different age ranges and average age (change in average age) in U.S. estimating an Euler equation. Using post 1945 period, they provide evidence supporting both hypotheses. Starting from this literature, Erb et al. (1996) study the population demographics in international context using population and average age growth and conjecture that it provides information about the risk exposure of a particular economy. On the other hand, Poterba (2001) using age groups finds no robust relationship between demographic structure and asset returns, but hints at the strong link between dividend-price ratio and demography variables. Goyal (2004) criticizes the use of demographic variables in levels shows evidence that changes in demographic structure in fact provide support for the traditional lifecycle models. Most of the cited papers concentrate on the slow-moving nature of the demographic variables and their ability to predict long term asset returns (Erb et al., 1996; DellaVigna&Pollet, 2006) and risk premia (Ang&Maddaloni, 2005). Overall the empirical evidence from this literature is mixed. We believe that using the GMQ model to provide foundation for a long-run cointegrating relationship between $(d_t - p_t)$ and demographic factors and then by using the derived disequilibrium to predict stock market returns within a Vector Error Correction model is a promising new avenue of empirical research to establish the importance of the interaction between the demographic structure and stock market fluctuations.

Table 2a presents summary statistics for (log) annual excess stock market returns with respect to the risk-free rate (equity premium), log dividend-price ratio, TFP, and MY for the whole sample 1909-2006. In Table 2b we also provide summary statistics for CRSP dataset spanning from 1926 to 2006. The last two tables split the whole data set into two subsamples, namely 1909-1954 and 1955-2006, and reports the summary statistics. We consider a sample split in 1954 in the light of the evidence provided by LVN (2007), and of the evidence we reported in the previous section with Eigenvalue analysis, i.e. a first break in $d_t - p_t$ series around the 50's.

In all the tables, the first panel shows the correlation matrix among the relevant variables. The panel below reports the univariate summary statistics of the variables, namely the arithmetic mean, median, mode, standard deviation, minimum, maximum and autocorrelation.

Insert here Table 2a Insert here Table 2b
Insert here Table 2c Insert here Table 2d

At a first glance, our first observation is that the technology and demographic variables have low correlation with equity premium, but relatively higher correlations with log dividend price ratio, these feature is robust to the sample choice. The correlation between TFP and $(d_t - p_t)$ and between MY and $(d_t - p_t)$ is negative, as the intuition and economic modelling suggest, and stable across different subsamples. Importantly, both technology and demography variables are quite persistent like $(d_t - p_t)$. In fact, DF residual based tests for the presence of a unit root in $(d_t - p_t)$, TFP_t, MY_t (not reported but available upon request) do not reject the null hypothesis of a unit root in these series.

Table 3 reports the results of the cointegrating analysis based on the Johansen (1991) procedure. In particular, we report the test based on the Trace statistic, critical values are chosen by allowing a linear trend in the data. The lag length in the VAR specification is chosen on the basis of standard optimal lag-length criteria.

Insert here Table 3

The trace statistics strongly rejects the null of no cointegrating relations, and does not reject the null of at most one cointegrating vector. We opt for a specification with a single cointegrating between p_t, d_t, TFP_t, MY_tvector[2], which is restricted to be $\begin{pmatrix} -1 & 1 & \beta_3 & \beta_4 \end{pmatrix}$.

The null hypothesis that the coefficient on p_t is restricted to minus one, and that the coefficient on d_t is restricted to one cannot be rejected by the test for the validity of these restrictions on the cointegrating space. The long-run coefficients describing the impact on the price-dividend ratio of TFP_t and MY_t are both positive and significant. To facilitate comparison of our cointegration based approach with the evidence based on the statistical analysis of breaks in the mean of $(d_t - p_t)$ provided by LVN (2007), we report in Figure 4a three time series: $(d_t - p_t)$, $\widetilde{dp}_t$ the dividend-price ratio corrected for exogenous breaks in LVN (2007)[3], $\left(dp_t^{TD}\right)$, i.e. $(d_t - p_t)$ adjusted for technology and demographics as in our cointegrating relation $((d_t - p_t) + 0.29 \cdot TFP_t + 1.554 \cdot MY_t + 1.318)$. The graphical evidence tells us that the cointegration based correction produces very similar results for the break-based correction in LVN (2007). We also report in Figure 5b $(p_t - d_t)$, MY_t,and MY_t corrected for the effect of technology using the appropriate coefficient in the cointegrating vectors. The Figure gives a visual impression of the strong low frequency comovement between the price-dividend ratio and its determinants in the GMQ model.

[2] We have also experimented with two cointegrating relationship. In this case the first cointegrating relations is not different from our chosen specification and the second cointegrating vector could be restricted to a simple linear relationship among the two demographic indicators that is useful only to predict these two variables. Our results should not then be affected of our choice of concentrating to unique cointegrating vector as we never use our CVAR to predict demographic trends that we will consider exogenous and take from the Bureau of Census projections.

[3] Following LVN (2007) we adopt the following definition:

$$\widetilde{dp}_t = \begin{array}{ll} dp_t - \overline{dp}_1 & \text{for } t = 1, ..., \tau_1 \\ dp_t - \overline{dp}_2 & \text{for } t = \tau_1 + 1, ..., \tau_2 \\ dp_t - \overline{dp}_3 & \text{for } t = \tau_2 + 1, ..., T \end{array}$$

where $\overline{dp}_1$ is the sample mean for 1909-1954, i.e. $\tau_1 = 1954$, $\overline{dp}_2$ is the sample mean for 1955-1994, i.e. $\tau_2 = 1994$, and $\overline{dp}_3$ is the sample mean for 1995-2006.

Insert Figure 4a-4b

Turning to the analysis of the disequilibrium correction (that we report in table 4), the α coefficients reveal that stock market returns react to disequilibrium while the restriction that α on total factor productivity and dividend growth in our CVAR is zero cannot be rejected.

Insert here Table 4a

We perform stability analysis using the recursively calculated eigenvalues and the Nyblom(1989) Stability test.

Insert here Figure 5a-5b

Our recursive analysis of the non-zero eigenvalues reveals much more stability compared to baseline case discussed in the first section of this paper, yet there is still some time variation in λ_i. There can be two sources of such time variation: time varying adjustement coefficients, $\boldsymbol{\alpha}$, or time-varying cointegrating parameters, $\boldsymbol{\beta}$. To shed more light on this issue we adopt the test of constancy of the parameters in the cointegrating space proposed by Nyblom (1989). The null hypothesis that the cointegration vectors are constant is tested against the alternative that they are not

$$H_\beta : \beta_{t_1} = \beta_0 \text{ for } t_1 = T_1.....T$$

where we use $\beta_0 = \beta_T$ (Hansen&Johansen, 1999; Warne et al., 2003). In interpreting the results it is important to note that is well known that this test has little power to detect structural change taking place at the end of the sample period (Juselius, 2006). Since we compute the Nyblom statistic for the constancy of β where its asymptotic distribution is unknown theoretically, we approximate by bootstrapping the small sample distribution (we compute 1999 bootstrap samples) using the package SVAR made available by Warne (2007). We estimate the sup-statistics to be 0.4849 (with mean-statistics = 0.2036) for a VEC model of order 1 and allowing for only one cointegration relation with the restrictions specified above. From Figure 5b we can see that the sup-statistics lies in the acceptance region of the bootstrapped distribution, hence the null hypothesis of constancy of β cannot be rejected[4].

3.1 Robustness

To assess the robustness of our cointegrating relationship in identifying the low frequency relation between stock market and demogragraphics, we evaluate the effect of augmenting

[4] We also calculated the mean-statistics, the same conclusion holds.

our baseline relation with alternative demographic factor. Research in demography has recently concentrated on the economic impact of the "demographic dividend" (Bloom et al., 2003; Mason&Lee, 2005). The demographic dividend depends on a peculiar period in the demographic transition phase of modern population in which the lack of synchronicity between the decline in fertility and the decline in mortality typical of advanced economies has an impact on the age structure of population. In particular a high support ratio is generated: i.e. a high ratio between the share of the population in working age and the share of population economically dependent. Empirical evidence has shown that the explicit consideration of the fluctuations in the support ratio delivers significant results in explaining economic perfomance (see Bloom et al., 2003). The concept of *Support Ratio (SR)* has been precisely defined by Mason and Lee (2005) as the ratio between the number of effective number of producers, L_t, over the effective number of consumers, N_t (Mason&Lee, 2005). In practice we adopt the following empirical proxy:

$$SR = a2064/(a019 + a65ov)$$

where $a2064$: Share of population between age 20-64, $a019$: Share of population between age 0-19, $a65ov$: Share of population age 65+[5].

Table 4b shows that the restrictions that the coefficient on SR is zero in the cointegrating vector cannot be rejected.

Insert HereTable 4b

4 Predictability of Stock Market Returns

The long-run analysis of the previous section has shown that there exist a stable cointegrating vector between the dividend-price ratio, total factor productivity and the ratio of the number of agents aged 40-49 to the number of agents aged 20-29. Moreover, the estimated adjustment coefficients α in the CVAR indicates that only that stock market returns adjust in presence of disequilibrium.

In this section we provide more evidence on this issue by concentrating on excess returns to provide within sample and out-of-sample evidence on predictability.

4.1 Within Sample Evidence

Our within sample evidence is constructed by comparing raw and adjusted dividend-price ratios for the sample 1909-2006, 1909-1954 and 1955-2006. We consider a sample split in

[5] We have checked robustness of our results by shifting the upper limit of the producers to the age of 75. This is consistent with the evidence on the cross-sectional age-wealth profile from Survey of Consumer Finances, provided in Table 1 of Poterba(2001), which shows that the population share between 64-74 still holds considerable amount of common stocks. Results are available upon request.

1954 in the light of the evidence in provided by LVN (2007). In practice, we consider the following set of regressions where excess returns at different horizons (one to ten years), $r_{m,t+H} - r_{f,t+H}$, are projected on a constant and the relevant measure of the dividend-price ratio

$$\begin{aligned} r_{m,t+H} - r_{f,t+H} &= \beta_0 c + \beta_1 z_t + \varepsilon_{t+H} \\ z_t &= dp_t, \widetilde{dp}_t, dp_t^{TD} \end{aligned}$$

Insert here Table5a-5c

First we note that over the entire sample (1909-2006) dp_t^{TD}[6] is always significant and the pattern of adjusted R^2 suggests that the correction for non-stationarity improves upon in-sample predictability at all horizons. At 1-year horizon, adjusted R^2 increases to 18.9% from 3.12%, it reaches its peak 33.6% at 4-years horizon and remains above 20% until 10 years. From Table 5b, we note that before the first structural break, the log dividend price ratio has forecasting power for excess returns (t-stats in the table are always significant at 95%, except for 2 years). When we restrict our data sample to 1955-2006, we observe that dp_t loses almost all its forecasting power at very short horizons from 1 to 4 years. Instead, once we correct dp_t using the information in technology and demography, we maintain similar forecasting power exhibited in the entire sample, even at short horizons.

On the basis of these results, we proceed to compare the performance dp_t^{TD} as a predictor with that of the other financial ratios used in the framework of the dynamic dividend growth model over the sample 1955-2001[7].

We do so by first considering alternative univariate models based on the different ratios:

$$\begin{aligned} r_{m,t+H} - r_{f,t+H} &= \beta_0 c + \beta_1 z_t + \varepsilon_{t+H} \\ z_t &= dp_t^{TD}, RREL_t, de_t, term_t, default_t, cay_t, cdy_t, pe_t \end{aligned}$$

where dp_t^{TD} : (dp_t) adjusted for technology and demographics, $RREL_t$: detrended short term interest rate (Campbell, 1991; Hodrick, 1992), de_t: log dividend earningratio (Lamont, 1998), $term_t$: long term bond yield (10Y) over 3M treasury bill, $default_t$: the difference between the BAA and the AAA corporate bond rates cay_t and cdy_t coin-

[6] We follow Stock and Watson (1993) dynamic least squares (DLS) with 1 lead/lag length to estimate the cointegrating parameters.

[7] The longest sample we have data for each variable.

tegration variables introduced by LL (2001, 2005), pe_t ,log price earning ratio (Lamont, 1998).

Insert here Table 6a1

Insert here Table 6a2

Table 6 suggests that in a univariate model specification one should in all horizons include cay_t and dp_t^{TD} and both variables have substantial predictive power with in-sample $\bar{R}^2$ slightly favoring cay_t[8]. Based on the evidence of Table 6, one can also consider other potential candidates for forecasting excess return such as $RREL_t$ in very short horizons, $term_t$ up to 6-years horizon and pe_t for longer than 8-years horizon.

Finally, we also consider a forecasting model exploiting simultaneously all the available information.

$$\begin{aligned} r_{m,t+H} - r_{f,t+H} &= \beta_0 c + \beta_1 \mathbf{x}_t + \varepsilon_{t+H} \\ \mathbf{x}_t &= \begin{bmatrix} RREL_t \\ term_t \\ default_t \\ dp_t^{TD} \\ de_t \\ pe_t \\ cay_t \\ cdy_t \end{bmatrix} \end{aligned}$$

To deal with the problem of potential multicollinearity between regressors in the multivariate model we adopt Bayesian Model Averaging. The Bayesian approach allows us to account also for model uncertainty in our linear regression framework. In our analysis we follow Raftery et. al (1997)[9], instead of conditioning on a single selected model, we base our inference on averaging over a set of possible models[10]. Averaging over all possible models provides provide better predictive power than considering a single model, hence the model uncertainty problem is alleviated. Basing inferences on a single "best" model as if the single selected model were the true one underestimates uncertainty

[8] To have a conservative forecast exercise we reestimate the coefficients of dp_t, TFP_t, and MY_t with data up to the obervation points, whereas for cay_t we use the full sample coefficents (i.e. $cay_p(cay$ post) in Goyal&Welch (2007) terminology).

[9] We run the bma_g function provided in Le Sage toolbox: http://www.spatial-econometrics.com/

[10] A complete Bayesian solution would be averaging over all possible combinations of predictors, but we reduce the set of possible models to a subset of models following Raftery et.al (1997).

about excess returns. The standard Bayesian solution to this problem is

$$\Pr(r_{m,t+H} - r_{f,t+H}|\text{ Data}) = \sum_{i=1}^{K} \Pr(r_{m,t+H} - r_{f,t+H}|\text{ M}_K, \text{Data}) \Pr(\text{M}_K|\text{ Data})$$

where $M = \{\text{M}_1, \text{M}_2 ...., \text{M}_K\}$ denotes the set of all models considered. This is an average of the posterior distributions under each model weighted by corresponding posterior model probability which we call Bayesian model averaging (BMA). Below we report results

Insert here Table 7a1

Insert here Table 7a2

Insert here Table 7b1

Insert here Table 7b2

In the tables we provide the BMA posterior estimates of the coefficients of the regressors (with t-statistics in parentheses) in a multivariate regression for for 1,3,5,7,10 years horizon along with the regression R^2 statistics. In a separate table we provide the summary of model selection analysis. We report the two models with highest probability and highest number of visits among all the models considered for Bayesian analysis. We also report cumulative probability of each variables, i.e. the probability that a variable appears across all the models considered. We have used flat priors[11] and 50000 draws for the analysis. The sample considered for the analysis spans from 1952-2001[12], the longest sample we have data for each variable. We notice that consistent with the previous section on univariate analysis, both cay_t and dp_t^{TD} are the most selected variables (based on cumulative probability of entering a model visited in BMA analysis) for predicting excess returns up to 7 years, whereas in 10 years, pe_t replaces dp_t^{TD} in forecasting excess returns.

4.2 Out-of-Sample Evidence

In this section we follow Goyal and Welch (2007), and we assume that the real-world investor, who does not have access to ex-post information, would have to estimate the prediction equation only with data available strictly before the prediction point, and then make an out-of-sample prediction. Indeed we are not really conducting a true out of sample test since our out-of-sample regressions rely on the very same data points that were used in the in-sample tests to identify the proposed predictors. Therefore we call

[11] The hyperparameters ν, λ and ϕ are set 4, 0.25 and 3, respectively. See Raftery et al.(1997) for selection of prior distributions.

[12] We also report (Table 7b.1 and Table 7b.2) as robustness check results for the sample that spans the period 1955-2006, where we do not include cdy_t.We estimate our cointegrated vector dp_t^{TD} using only the data points included in the sample.

this a pseudo out-of-sample forecast exercise.

We run rolling forecasting regressions for one and five years using as an initialization sample 1952-1981, keep the rolling window of 30 data points and make the first forecast in 1982, so the forecasting period includes the anomalous period of late 90's where the sharp increase in stock market index weakens the forecasting power of financial ratios. We select predictors on the basis of our within sample evidence, therefore we focus only on cay_t and dp_t^{TD}. In particular, we consider both univariate and bivariate models and compare the forecasting performance with historical mean benchmark. In the first two columns of Table 8a we report the adjusted $\bar{\mathrm{R}}^2$ and the t-statistics using the full sample 1952-2006. Then we also report mean absolute error (MAE) and root mean square error (RMSE) calculated based on the residuals in the forecasting period, namely 1982-2006. The first column of out-of- sample panel report the out-of-sample R^2 statistics (Campbell&Thomson, 2008) which is computed as

$$R^2_{OS} = 1 - \frac{\sum_{t=t_0}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=t_0}^{T}(r_t - \bar{r}_t)^2}$$

where $\hat{r}_t$ is the forecast at $t-1$ and $\bar{r}_t$ is the historical average estimated until $t-1$. In our exercise, $t_0 = 1982$ and $T = 2006$. If R^2_{OS} is positive, it means that the predictive regression has lower mean square error than the prevailing historical mean. In the last column, we report the Diebold-Mariano (DM) t-test for checking equal-forecast accuracy from two nested models for forecasting h-step ahead excess returns.

$$DM = \sqrt{\frac{(T+1-2*h+h*(h-1))}{T}} * \left[\frac{\bar{d}}{\widehat{se}(\bar{d})}\right]$$

where we define e^2_{1t} as the squared forecasting error of prevailing mean, and e^2_{2t} as the squared forecasting error of the predictive variables, $d_t = e^2_{1t} - e^2_{2t}$, i.e. the difference between the two forecast errors, $\bar{d} = \frac{1}{T}\sum_{t=t_0}^{T} d_t$ and $\widehat{se}(\bar{d}) = \frac{1}{T}\sum_{\tau=-(h-1)}^{h-1}\sum_{t=|\tau|+1}^{T}(d_t - \bar{d}) * (d_{t-|\tau|} - \bar{d})$. A positive DM t-test statistics indicates that the predictive regression model performs better than the historical mean.

Insert here Table 8a

Insert here Table 8b

First we notice that the 1-year ahead out-of-sample performance detoriorates for the variables considered compared to the in-sample performance. Nonetheless, in the out-of-sample the relative deterioration with respect to prevailing mean becomes evident in case of dp_t while all the other candidates maintain a lower MAE and RMSE than the one of prevailing historical mean. When we move to 5-year ahead out-of-sample forecast also the exogenously corrected dp_t performs worse than the historical mean where univariate models with cay_t and dp_t^{TD} and the bivariate model continue to outperform the historical mean. The minimum MAE and RMSE is obtained when the bivariate model is used.

In the figures below we plot the cumulative squared prediction errors of prevailing mean minus the cumulative squared prediction error of dp_t and dp_t^{TD} where a positive line means that the predictive regression improves upon historical mean (the zero line is drawn in the figure to graphically detect performance).

Insert here Figure 6a

Insert here Figure 6b

In figure 6a, we use all the available data from 1909 until 1954 for initial estimation and then we recursively calculate the cumulative squared prediction errors until sample end, namely 2006. Consistent with the breaking point analysis, we notice that around the breaking points of 1954 and early 1980's and late 90's the the financial ratio dp_t predict worse than prevailing mean (note the decrease in the cumulative squared prediction error line around the points) , while the corrected dp_t , i.e. dp_t^{TD} performs as well as the historical mean around the 50's and then improves upon the benchmark, in particular during last stock market bubble. Figure 6b repeats the same exercise using a larger initial estimation period, namely 1909-1967, we notice that we we exclude the very recent data points, dp_t still performs well compared to the historical benchmark, consistent with the literature which favors this financial ratio as a major predictive regressor, but once we also include the data points around the millenium, this financial ratio loses its forecasting power (as evident in the figure), whilst dp_t^{TD} even improves its performance upon the historical benchmark, thanks to the correction mechanism driven by fundamentels which are immune to temporary bubbles.

5 Equity Premium for the period 2007-2050

One of the interesting aspects of the demographics variable is that long-forecasts for these variables are readily available. In fact, the Bureau of Census provides on its website projected data up to 2050. Having now shown that the CVAR models introduced in section 1 provides forecasts for stock market returns that are least comparable to those produced by the best available models based on financial ratios, we go back to it and use it to produce forecast for stock market equity premia over the period 2007-2050. In order to produce forecasts, we take directly the projections from Bureau of Census for our exogenous variable MY_t and we project our endogenous variables by solving a model through stochastic simulations[13], i.e. the model solution generates a distribution of outcomes for the endogenous variables in every period. Through the projected variables, both exogenous and endogenous, we construct the predictive regressors needed for equity premium forecast.

In particular we focus on three models where we augment our VEC specification with an autoregressive process for nominal risk free rate[14].

The first VEC model is already introduced in section 3 and we repeat it here for reader's convenience

$$\begin{pmatrix} \Delta p_t \\ \Delta d_t \\ \Delta TFP_t \end{pmatrix} = \Pi_0 + \Pi_1 \begin{pmatrix} \Delta p_{t-1} \\ \Delta d_{t-1} \\ \Delta TFP_{t-1} \\ \Delta MY_{t-1} \end{pmatrix} + \begin{pmatrix} \alpha_{11} \\ \alpha_{21} \\ \alpha_{31} \end{pmatrix} \begin{pmatrix} -1 & 1 & \beta_3 & \beta_4 \end{pmatrix} \begin{pmatrix} p_{t-1} \\ d_{t-1} \\ TFP_{t-1} \\ MY_{t-1} \end{pmatrix} + \begin{pmatrix} v_{1t} \\ v_{2t} \\ v_{3t} \end{pmatrix}$$

where MY_t is taken as exogenous and it assumed to take the value generated by the Bureau of census predictions over the relevant period. Moreover, we assume constant total factor productivity growth, and hence set $\alpha_{31} = 0$. Using the simulation output from our model, we construct the equity premium for 2007-2050, i.e.

$$\textit{equity premium}_t = \log\left(\frac{\tilde{P}_t + \tilde{D}_t}{\tilde{P}_{t-1}}\right) - \tilde{r}_{f,t} \tag{6}$$

where $\tilde{P}_t, \tilde{D}_t, \tilde{r}_f$ are simulated series from the model.

In the second VEC model, we use the cointegrated system suggested in Lettau&Ludvigson (2001)[15], namely

$$\begin{pmatrix} \Delta c_t \\ \Delta a_t \\ \Delta y_t \end{pmatrix} = \bar{\Pi}_0 + \bar{\Pi}_1 \begin{pmatrix} \Delta c_{t-1} \\ \Delta a_{t-1} \\ \Delta y_{t-1} \end{pmatrix} + \begin{pmatrix} \bar{\alpha}_{11} \\ \bar{\alpha}_{21} \\ \bar{\alpha}_{31} \end{pmatrix} \begin{pmatrix} 1 & \bar{\beta}_2 & \bar{\beta}_3 \end{pmatrix} \begin{pmatrix} c_{t-1} \\ a_{t-1} \\ y_{t-1} \end{pmatrix} + \begin{pmatrix} \bar{v}_{1t} \\ \bar{v}_{2t} \\ \bar{v}_{3t} \end{pmatrix}$$

where we augment the model with an autoregressive process for the nominal risk-free rate and a predictive regression for equity premium, i.e. $\textit{equity premium}_t = f(cay_{t-1})$. In particular, we assume that the functional relation is linear, i.e.

$$\textit{equity premium}_t = \gamma_0 + \gamma_1 * \widetilde{cay}_{t-1} + \varepsilon_t$$

[13] In fact the coefficients in our equations are estimated, rather than fixed at known values. One way to reflect this uncertainty about our coefficients in the results from our model is by using stochastic simulation.

[14] We opt for an autoregressive model AR(1) given our sample evidence.

[15] For the estimation of the model, we restricted the insignificant coeffients to zero (consistent with the evidence in LL, 2005), to keep the parameter space small given our short annual sample.

Notice the difference in forecasting the equity premia in both models. In the former, we simulate the dividend, price and risk free rate processes from the model and the equity premium accounts (in a highly non linear way) for the uncertainty in all of these random variables while in the latter we simulate the equity premium process in a univariate regression where $\gamma = \begin{bmatrix} \gamma_0 & \gamma_1 \end{bmatrix}$ is estimated in the sample 1952-2006 and the regressor, cointegrating vector $\widetilde{cay}_t$, is reconstructed with the simulated series from the second model for 2007-2050.

Finally, we combine the two VEC models, where $p_t, d_t, TFP_t, c_t, a_t, y_t$ enter as endogenous variables, MY_t as exogenous variable in the model. We augment the model again with an autoregressive process for the nominal risk-free rate and we reconstruct the equity premium according to equation (6). Given the high number of parameters to be estimated in the model, we set the following restrictions:

- the cointegrating vector cay_t only affects Δa_t
- we assume constant income growth Δy_t and constant ΔTFP_t
- as in model 2, we let only Δa_{t-1} and Δy_{t-1} affect Δc_t[16]
- we model ex-dividend return $\Delta p_t = \delta_0 + \delta_1 * \Delta p_{t-1} + \delta_2 * dp_{t-1}^{TD} + \delta_3 * cay_{t-1} + \varepsilon_t$

To calculate statistics in order to describe the distributions of our endogenous variables, namely p_t, d_t and TFP_t in the first model, c_t, a_t and y_t in the second model and p_t, d_t, TFP_t, c_t, a_t and y_t in the last model, we used a Monte Carlo approach[17], where the model is solved many times with random numbers drawn from a normal distribution with variance covariance resembling the estimation period in sample variance and substituted for the unknown errors at each repetition and then calculating statistics, namely the mean and standard deviation, over all the different outcomes. This method provides only approximate results. However, as the number of repetitions is increased, we would expect the results to approach their true values. We set the number of repetitions to be performed during the stochastic simulation to 10000 and the forecast sample is from 2007 to 2050. Since our main aim is to forecast future returns, we focus on the long-run price dynamics among other endogenous variables.

Below we report the figures of the mean equity premia (with one standard deviation band) generated from the three models along with the actual historical equity premium and in-sample fit of the models.

Insert here figure 7a

Insert here figure 7b

Insert here figure 7c

[16] We also tried different specifications but results do not change.

[17] We also solved the model bootstrapping the unknown error from estimated in sample residuals, but the results do not change.

Finally we compare the equity premia projections of three models

Insert here figure 8

Our simulation confirms the evidence in favour of the often quoted claim that the end of the baby boomers generation will cause a reduction in the equity premium. The model based on demographics and technology shows a reduction in the equity premium between 2010 and 2020 which is promptly reverted in the following years. This results are robust to the inclusion of excess consumption in the model, while the model without demographics and technology predicts a much flatter profile for the equity premium.

6 Conclusions

The intuition that demographics information should be incorporated in long-run stock return has long been assessed in finance literature. Yet, there is still controversy on the channels through which demography effects might enter stock markets and on the significance of this effect, since many other factors might be (in fact are) affecting the stock markets fluctuations. If we believe that prices are anchored by some fundamentals, even though they might deviate from these long run relations occasionally, then these economic fundamentals tend to bring prices back to their long run trend. In this paper, we follow the idea that demography, along with technology, is one of those anchors that bring prices to their long run trend. In particular, we show that demography along with technology performs well in the explanation of the breaks in the dividend price ratio and that demographics and technology capture a slowly evolving mean toward which the dividend price ratio is reverting. Correcting for non-stationarity of dividend price ratio further increases its in-sample predictive power as well as pseudo out-of sample forecasting performance for stock market returns at different horizons. We show that a forecasting model based on technology, demographics and demand factor as captured by excess consumption in the sense of Lettau and Ludvigson (2004) overperforms virtually all alternative model proposed in the empirical literature in the framework of the dynamic dividend growth model. On the basis of these results we exploit the predictability of demographic factors to project the equity risk premium up to 2050. Some decline of the equity risk premium for the next 10 years is generated by the explicit consideration of demographic variables in our model.

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APPENDIX A: TABLES

L-Max		Trace		$H_0 = r$
Test Statistics	95%CV	Test Statistics	95%CV	r =
Panel A: Whole Sample (1909-2006)				
9.73	14.26	10.44	15.49	0
0.71	3.84	0.71	3.84	1
Panel B: Subsample (1909-1954)				
14.44*	14.26	14.81	15.49	0
0.37	3.84	0.37	3.84	1
Panel C: Subsample (1951-2006)				
4.89	14.26	4.93	15.49	0
0.04	3.84	0.04	3.84	1

Table 1. Johansen Cointegration Test using log dividend and log price series. We report both L-Max and Trace test statistics with 95% critical values. The null hypothesis is that there are r cointegration relations.

Correlation Matrix (Sample 1909-2006)					
	$r_{m,t} - r_{f,t}$	dp_t	TFP	SR	MY
$r_{m,t}-r_{f,t}$	1.00	-0.24	0.01	0.08	0.10
dp_t	-0.24	1.00	-0.75	-0.21	-0.73
TFP	0.01	-0.75	1.00	0.34	0.47
SR	0.08	-0.21	0.34	1.00	0.17
MY	0.10	-0.73	0.47	0.17	1.00
Univariate Summary Statistics					
Mean	0.057	-3.217	2.278	1.290	0.793
Median	0.093	-3.133	2.143	1.294	0.752
Std	0.179	0.453	0.937	0.133	0.172
Min	-0.530	-4.450	0.983	1.048	0.550
Max	0.423	-2.287	3.976	1.509	1.149
Autocorrelation	0.081	0.880	0.972	0.974	0.967

Table 2a. Summary Statistics (whole sample, 1909-2006, using S&P500 data from Robert Shiller's website)

Correlation Matrix (CRSP: Sample 1926-2006)					
	$r_{m,t}-r_{f,t}$	dp_t	TFP	SR	MY
$r_{m,t}-r_{f,t}$	1.00	-0.03	-0.02	0.08	0.09
dp_t	-0.03	1.00	-0.72	-0.09	-0.69
TFP	-0.02	-0.72	1.00	0.17	0.29
SR	0.08	-0.09	0.17	1.00	0.01
MY	0.09	-0.69	0.29	0.01	1.00
Univariate Summary Statistics					
Mean	0.056	-3.299	2.525	1.312	0.827
Median	0.095	-3.210	2.724	1.357	0.780
Std	0.196	0.424	0.841	0.137	0.169
Min	-0.593	-4.499	1.197	1.048	0.550
Max	0.450	-2.627	3.976	1.509	1.149
Autocorrelation	0.093	0.915	0.964	0.977	0.973

Table 2b. Summary Statistics (whole sample using CRSP data, 1926-2006)

Correlation Matrix (Sample 1909-1954)					
	$r_{m,t}-r_{f,t}$	dp_t	TFP	SR	MY
$r_{m,t}-r_{f,t}$	1.00	-0.69	0.26	0.09	0.24
dp_t	-0.69	1.00	-0.04	-0.05	-0.05
TFP	0.26	-0.04	1.00	0.76	0.88
SR	0.09	-0.05	0.76	1.00	0.66
MY	0.24	-0.05	0.88	0.66	1.00
Univariate Summary Statistics					
Mean	0.063	-2.891	1.394	1.296	0.720
Median	0.085	-2.900	1.246	1.275	0.735
Std	0.208	0.235	0.325	0.107	0.082
Min	-0.530	-3.323	0.983	1.155	0.563
Max	0.423	-2.288	2.033	1.468	0.915
Autocorrelation	0.107	0.398	0.929	0.968	0.883

Table 2c. Summary Statistics (first subsample 1909-1954, using S&P500 data from Robert Shiller's website)

Correlation Matrix (Sample 1955-2006)					
	$r_{m,t} - r_{f,t}$	dp_t	TFP	SR	MY
$r_{m,t} - r_{f,t}$	1.00	-0.18	-0.03	0.08	0.10
dp_t	-0.18	1.00	-0.54	-0.42	-0.82
TFP	-0.03	-0.54	1.00	0.85	0.11
SR	0.08	-0.42	0.85	1.00	0.09
MY	0.10	-0.82	0.11	0.09	1.00
Univariate Summary Statistics					
Mean	0.052	-3.507	3.060	1.285	0.858
Median	0.093	-3.435	3.106	1.329	0.899
Std	0.151	0.402	0.500	0.154	0.202
Min	-0.365	-4.450	2.106	1.048	0.550
Max	0.285	-2.925	3.976	1.509	1.149
Autocorrelation	-0.025	0.907	0.925	0.973	0.976

Table 2d. Summary Statistics (first subsample 1955-2006, using S&P500 data from Robert Shiller's website)

L-Max		Trace		$H_0 = r$
Test Statistics	95%CV	Test Statistics	95%CV	r =
Panel A: Whole Sample (1909-2006)				
27.86*	27.58	55.10*	47.86	0
17.18	21.13	27.24	29.78	1
9.86	14.26	10.06	15.49	2
0.20	3.84	0.20	3.84	3

Table 3. Johansen Cointegration Test. We use the general model including nominal log dividends, log prices, TFP, MY.

Cointegrating Eq:	dp_{t-1}^{TD}	t-stat	χ^2	Prob.
p_{t-1}	-1		6.49	0.01
d_{t-1}	1			
TFP_{t-1}	0.290	(5.39)		
MY_{t-1}	1.554	(5.19)		
constant	1.318			
Error Correction	Δp_t	Δd_t	ΔTFP_t	ΔMY_t
dp_{t-1}^{TD}	0.315	-0.070	0.042	0.002
	(3.78)	(-1.59)	(1.81)	(0.30)
Δp_{t-1}	0.245	0.347	0.083	-0.001
	(2.27)	(6.07)	(2.78)	(-0.15)
Δd_{t-1}	-0.319	0.186	-0.036	0.017
	(-2.09)	(2.30)	(-0.84)	(1.38)
ΔTFP_{t-1}	-0.252	-0.072	-0.005	-0.061
	(-0.66)	(-0.36)	(-0.05)	(-1.97)
ΔMY_{t-1}	1.077	-0.411	-0.306	0.790
	(1.32)	(-0.95)	(-1.36)	(11.87)
constant	0.055	0.021	0.030	0.002
	(2.54)	(1.82)	(5.08)	(1.23)
Adj. R^2	0.17	0.40	0.04	0.63

Table 4a. The table reports estimated coefficients from cointegrated first order vector autoregression, where the coeffienccts on log price and log dividend are restricted to be -1,1, respectively. χ^2 along with probability is the LR test statistics for binding restrictions. The sample is annual and spans the period 1909-2006. t-statistics are reported in parentheses.

Cointregrating Eq:	dp_{t-1}^{TD}	t-stat	χ^2	Prob.	
p_{t-1}	-1		5.40	0.07	
d_{t-1}	1				
TFP_{t-1}	0.196	(4.09)			
MY_{t-1}	2.083	(7.49)			
SR_{t-1}	0				
constant	1.114				
Error Correction	Δp_t	Δd_t	ΔTFP_t	ΔMY_t	ΔSR_t
dp_{t-1}^{TD}	0.297	-0.122	0.045	0.002	-0.006
	(2.95)	(-2.38)	(1.68)	(0.24)	(-1.28)
Δp_t	0.254	0.307	0.085	-0.001	0.002
	(2.11)	(5.02)	(2.67)	(-0.07)	(0.36)
Δd_t	-0.272	0.171	-0.032	0.018	-0.013
	(-1.74)	(2.14)	(-0.77)	(1.46)	(-1.90)
ΔTFP_t	-0.256	-0.060	-0.022	-0.057	0.046
	(-0.65)	(-0.30)	(-0.21)	(-1.84)	(2.67)
ΔMY_t	1.502	-0.680	-0.372	0.825	0.019
	(1.61)	(-1.43)	(-1.50)	(11.14)	(0.47)
ΔSR_t	1.534	-1.338	-0.097	0.102	0.841
	(0.92)	(-1.57)	(-0.22)	(0.77)	(11.35)
constant	0.045	0.029	0.031	0.001	-0.001
	(1.80)	(2.32)	(4.71)	(0.72)	(-0.48)
Adj. R^2	0.13	0.42	0.05	0.63	0.77

Table 4b. The table reports estimated coefficients from cointegrated first order vector autoregression, where the coeffiencts on log price, log dividend and supportratio are restricted to be -1,1 and 0, respectively. χ^2 along with probability is the LR test statistics for binding restrictions. The sample is annual and spans the period 1909-2006. t-statistics are reported in parentheses.

$z_t =$	Horizon h (in years)				
	1	2	3	4	5
dp_t	0.053	0.142	0.190	0.275	0.368
	(1.22)	(1.98)	(2.09)	(2.61)	(3.15)
	[0.74]	[4.60]	[6.06]	[9.56]	[14.3]
$\tilde{dp}_t$	0.182	0.463	0.531	0.664	0.749
	(2.37)	(4.04)	(2.91)	(2.95)	(3.05)
	[4.04]	[13.6]	[13.2]	[15.7]	[16.9]
dp_t^{TD}	0.259	0.568	0.688	0.885	1.025
	(3.80)	(5.78)	(4.77)	(5.32)	(6.36)
	[11.1]	[25.9]	[28.6]	[35.5]	[40.3]

$z_t =$	Horizon h (in years)				
	6	7	8	9	10
dp_t	0.423	0.461	0.522	0.568	0.633
	(3.04)	(2.81)	(2.55)	(2.28)	(2.12)
	[16.5]	[16.5]	[17.4]	[16.7]	[16.7]
$\tilde{dp}_t$	0.723	0.689	0.789	0.771	0.772
	(2.73)	(2.68)	(3.38)	(3.0)	(2.71)
	[14.6]	[12.0]	[14.4]	[12.7]	[11.3]
dp_t^{TD}	1.028	1.017	1.051	0.986	0.951
	(6.556)	(6.999)	(7.53)	(6.12)	(5.36)
	[37.7]	[34.2]	[33.0]	[26.9]	[22.3]

Table 5a. This table reports the results of h-period regressions of returns on the S&P500 index in excess of a 3-month Treasury bill rate. For each regression, the table reports OLS estimates of the regressors, Newey-West (1987) corrected t-statistics (in parentheses) and adjusted R^2 statistics in square brackets. The sample is annual and spans the period 1909-2006.

$z_t =$	Horizon h (in years)				
	1	2	3	4	5
	0.129	0.462	0.604	0.898	1.022
dp_t, $\tilde{dp}_t$	(1.10)	(3.45)	(2.26)	(2.78)	(3.21)
	[0.18]	[10.2]	[12.8]	[22.5]	[26.3]
	0.184	0.446	0.610	0.885	1.068
dp_t^{TD}	(2.50)	(5.80)	(4.19)	(4.96)	(6.10)
	[5.35]	[17.2]	[22.6]	[34.7]	[42.3]

$z_t =$	Horizon h (in years)				
	6	7	8	9	10
	0.892	0.814	0.850	0.758	0.819
dp_t, $\tilde{dp}_t$	(2.99)	(3.07)	(3.78)	(3.22)	(3.09)
	[20.5]	[17.1]	[18.6]	[15.1]	[15.3]
	1.046	1.059	1.148	1.075	1.104
dp_t^{TD}	(6.11)	(7.20)	(8.38)	(5.64)	(4.24)
	[40.0]	[40.4]	[46.0]	[42.5]	[41.3]

Table 5b. This table reports the results of h-period regressions of returns on the S&P500 index in excess of a 3-month Treasury bill rate. For each regression, the table reports OLS estimates of the regressors, Newey-West (1987) corrected t-statistics (in parentheses) and adjusted R^2 statistics in square brackets. The sample is annual and spans the period 1909-1954.

$z_t =$	Horizon h (in years)				
	1	2	3	4	5
dp_t	0.061	0.123	0.151	0.193	0.270
	(1.08)	(1.24)	(1.26)	(1.71)	(3.18)
	[0.73]	[3.42]	[4.25]	[5.61]	[9.24]
$\tilde{dp}_t$	0.275	0.475	0.436	0.381	0.342
	(3.04)	(2.43)	(1.77)	(1.45)	(1.18)
	[12.2]	[19.6]	[12.9]	[6.91]	[3.56]
dp_t^{TD}	0.583	1.042	1.086	1.129	1.245
	(5.25)	(6.67)	(5.22)	(4.70)	(4.82)
	[32.3]	[53.7]	[47.8]	[40.4]	[38.4]

$z_t =$	Horizon h (in years)				
	6	7	8	9	10
dp_t	0.341	0.364	0.388	0.485	0.639
	(4.32)	(4.02)	(2.97)	(2.11)	(1.80)
	[11.6]	[10.3]	[7.84]	[8.44]	[10.9]
$\tilde{dp}_t$	0.347	0.344	0.474	0.643	0.784
	(0.92)	(0.83)	(1.25)	(1.54)	(1.71)
	[2.76]	[2.21]	[5.26]	[9.87]	[14.0]
dp_t^{TD}	1.312	1.197	1.016	0.952	0.847
	(5.10)	(5.11)	(4.12)	(2.40)	(1.64)
	[35.0]	[24.2]	[13.1]	[8.68]	[5.22]

Table 5c. This table reports the results of h-period regressions of returns on the S&P500 index in excess of a 3-month Treasury bill rate. For each regression, the table reports OLS estimates of the regressors, Newey-West (1987) corrected t-statistics (in parentheses) and adjusted R^2 statistics in square brackets. The sample is annual and spans the period 1955-2006.

$z_t =$	Horizon h (in years) 1	2	3	4	5
dp_t^{TD}	0.544	0.978	0.957	0.993	1.217
	(5.04)	(5.32)	(3.74)	(3.49)	(3.76)
	[29.2]	[47.7]	[36.9]	[27.7]	[29.4]
de_t	0.003	0.097	0.130	0.207	0.335
	(0.04)	(0.55)	(0.55)	(0.90)	(1.49)
	[-2.04]	[-1.17]	[-0.99]	[-0.12]	[2.01]
pe_t	-0.050	-0.084	-0.037	0.001	-0.004
	(-0.95)	(-1.06)	(-0.40)	(0.00)	(-0.02)
	[-0.74]	[-0.00]	[-2.01]	[-2.44]	[-2.50]
$TERM_t$	0.339	1.036	4.219	7.168	6.606
	(0.23)	(0.44)	(1.72)	(1.88)	(1.22)
	[-2.2]	[1.93]	[3.07]	[11.1]	[5.81]
$DEFAULT_t$	4.922	4.152	2.060	5.529	12.149
	(1.24)	(0.81)	(0.30)	(0.63)	(1.44)
	[0.42]	[-1.19]	[-1.96]	[-1.26]	[1.28]
$RREL_t$	-3.180	-4.307	-1.819	-3.701	-4.677
	(-2.61)	(-2.65)	(-1.53)	(-2.19)	(-2.98)
	[5.56]	[5.60]	[-1.05]	[1.80]	[2.40]
cay_t	5.706	10.110	11.092	12.326	14.211
	(3.53)	(4.70)	(4.12)	(4.36)	(4.73)
	[25.6]	[45.6]	[47.3]	[42.1]	[40.1]
cdy_t	0.242	5.727	5.086	5.727	6.832
	(0.13)	(3.05)	(1.85)	(1.70)	(1.74)
	[-2.21]	[11.7]	[7.90]	[7.41]	[7.41]

Table 6a. This table reports the results of h-period regressions of returns on the S&P500 index in excess of a 3-month Treasury bill rate. For each regression, the table reports OLS estimates of the regressors, Newey-West (1987) corrected t-statistics (in parentheses) and adjusted R^2 statistics in square brackets. The sample is annual and spans the period 1955-2001.

$z_t =$	Horizon h (in years) 6	7	8	9	10
dp_t^{TD}	1.346	1.166	1.037	0.958	0.820
	(3.42)	(3.58)	(3.36)	(2.30)	(1.67)
	[28.9]	[18.8]	[11.2]	[7.59]	[3.88]
de_t	0.447	0.389	0.135	-0.205	-0.557
	(1.36)	(0.87)	(0.28)	(-0.47)	(-1.42)
	[3.87]	[1.47]	[-2.01]	[-1.71]	[2.11]
pe_t	-0.004	-0.038	-0.073	-0.343	-0.532
	(-0.02)	(-0.15)	(-0.25)	(-1.27)	(-1.99)
	[-2.50]	[-2.42]	[-2.15]	[4.96]	[12.82]
$TERM_t$	7.148	8.105	6.252	6.883	8.383
	(1.31)	(1.48)	(1.16)	(1.28)	(1.38)
	[5.26]	[6.36]	[1.84]	[1.59]	[2.60]
$DEFAULT_t$	16.300	19.039	22.734	29.906	37.051
	(1.95)	(2.25)	(2.55)	(2.46)	(2.75)
	[3.06]	[4.37]	[5.97]	[10.3]	[14.9]
$RREL_t$	-4.523	-6.113	-6.808	-5.454	-6.200
	(-1.86)	(-2.34)	(-1.89)	(-1.45)	(-1.94)
	[1.14]	[3.48]	[3.80]	[0.86]	[1.37]
cay_t	17.549	18.122	19.359	20.849	21.326
	(5.25)	(4.60)	(4.28)	(4.09)	(4.37)
	[49.0]	[45.1]	[40.3]	[39.1]	[35.7]
cdy_t	8.673	6.934	6.871	6.908	7.942
	(1.59)	(1.10)	(1.23)	(1.06)	(1.19)
	[10.02]	[4.64]	[3.11]	[2.28]	[3.16]

Table 6b. This table reports the results of h-period regressions of returns on the S&P500 index in excess of a 3-month Treasury bill rate. For each regression, the table reports OLS estimates of the regressors, Newey-West (1987) corrected t-statistics (in parentheses) and adjusted R^2 statistics in square brackets. The sample is annual and spans the period 1955-2001.

Bayesian Model Averaging (BMA) Posterior Estimates (Sample:1952-2001)									
$r_{m,tt}-r_{f,tt-1}$	$const$	dp_{t-1}^{TD}	de_{t-1}	pe_{t-1}	cay_{t-1}	cdy_{t-1}	$RREL_{t-1}$	$Term_{t-1}$	$Default_{t-1}$
H:1 Year (R^2= 0.42)									
coefficient	-0.005	0.540	-0.007	0.005	0.369	0.003	-1.360	0.127	1.288
t-statistics	(0.78)	(4.82)	(-0.06)	(0.08)	(0.24)	(0.00)	(-0.97)	(0.08)	(0.30)
H:3 Years (R^2= 0.64)									
coefficient	0.031	0.991	-0.014	0.001	2.326	0.304	-0.122	5.262	1.093
t-statistics	(1.32)	(6.42)	(-0.10)	(0.02)	(1.04)	(0.17)	(-0.07)	(2.72)	(0.21)
H:5 Years (R^2= 0.66)									
coefficient	-0.192	1.428	0.008	0.022	2.186	0.162	-0.149	11.039	19.480
t-statistics	(-1.02)	(6.83)	(0.04)	(0.20)	(0.65)	(0.07)	(-0.06)	(4.28)	(2.84)
H:7 Years (R^2= 0.59)									
coefficient	0.228	1.048	0.167	-0.043	7.525	0.184	-0.140	9.517	19.188
t-statistics	(1.61)	(3.78)	(0.46)	(-0.18)	(1.90)	(0.06)	(-0.04)	(2.76)	(2.10)
H:10 Years (R^2= 0.49)									
coefficient	1.052	0.358	0.159	-0.245	16.627	0.423	-0.024	5.551	12.478
t-statistics	(3.52)	(0.91)	(0.22)	(-1.00)	(3.02)	(0.10)	(-0.01)	(1.07)	(1.02)

Table 7a1. Bayesian Posterior Estimates. We report the BMA posterior estimates of the coefficients of the regressors (with t-statistics in parentheses) in a multivariate regression for for 1,3,5,7,10 years horizon along with the regression R^2 statistics.

Model: $r_{m,t+1}-r_{f,t+1}$	dp_{t-1}^{TD}	de_{t-1}	pe_{t-1}	cay_{t-1}	cdy_{t-1}	$RREL_{t-1}$	$Term_{t-1}$	$Default_{t-1}$	Prob.	Visit
H:1 Year										
Model 1	1	0	0	0	0	0	0	0	28.14	3418
Model 2	1	0	0	0	0	1	0	0	25.76	2208
Cum. Probability	0.97	0.07	0.08	0.15	0.05	0.42	0.08	0.17		
H:3 Years										
Model 1	1	0	0	0	0	0	1	0	29.18	2083
Model 2	1	0	0	1	0	0	1	0	18.22	2150
Cum. Probability	0.99	0.09	0.06	0.43	0.13	0.08	0.82	0.15		
H:5 Years										
Model 1	1	0	0	0	0	0	1	1	45.63	1116
Model 2	1	0	0	1	0	0	1	1	9.39	1973
Cum. Probability	0.99	0.07	0.15	0.28	0.08	0.08	0.93	0.83		
H:7 Years										
Model 1	1	0	0	0	0	0	1	1	30.47	354
Model 2	0	0	0	1	0	0	0	0	13.64	1655
Cum. Probability	0.72	0.24	0.15	0.49	0.08	0.07	0.68	0.61		
H:10 Years										
Model 1	0	0	0	1	0	0	0	0	21.26	2727
Model 2	0	0	1	1	0	0	0	0	15.73	2213
Cum. Probability	0.27	0.18	0.42	0.79	0.10	0.06	0.37	0.32		

Table 7a2. Model selection analysis. We report the two models with highest probability and highest number of visits among all the models considered for Bayesian analysis. 1's in the cells denote that the variable is included in the model, whereas 0's indicate that those variables no not enter the model. We report cumulative probability of each variables, i.e. the probability that a variable appears across all the models considered and two models with highest probability. We have used flat priors and 50000 draws for the analysis. The sample considered for the analysis spans from 1952-2001.

Bayesian Model Averaging (BMA) Posterior Estimates (Sample:1955-2006)								
$r_{m,H}-r_{f,H-1}$	$const$	dp_{t-1}^{TD}	de_{t-1}	pe_{t-1}	cay_{t-1}	$RREL_{t-1}$	$Term_{t-1}$	$Default_{t-1}$
H:1 Year (R^2=0.37)								
coefficient	0.011	0.564	-0.006	0.004	0.414	-0.579	0.195	0.298
t-statistics	(1.24)	(4.71)	(-0.07)	(0.08)	(0.28)	(-0.43)	(0.14)	(0.07)
H:3 Years (R^2=0.67)								
coefficient	0.063	0.807	-0.005	0.007	6.174	-0.078	3.075	0.029
t-statistics	(2.86)	(4.95)	(-0.04)	(0.11)	(3.35)	(-0.05)	(1.80)	(0.01)
H:5 Years (R^2=0.65)								
coefficient	-0.254	1.094	-0.000	0.104	6.172	-0.210	5.629	10.613
t-statistics	(1.70)	(4.78)	(0.00)	(1.07)	(2.32)	(-0.09)	(2.26)	(1.45)
H:7 Years (R^2=0.54)								
coefficient	0.157	0.392	0.030	0.014	12.383	-0.145	3.174	9.051
t-statistics	(3.98)	(1.33)	(0.13)	(0.09)	(4.232)	(-0.05)	(0.98)	(1.05)
H:10 Years (R^2=0.55)								
coefficient	1.162	-0.004	0.028	-0.327	18.174	-0.022	1.377	14.662
t-statistics	(2.81)	(-0.01)	(0.06)	(-2.07)	(5.11)	(-0.01)	(0.34)	(1.41)

Table 7b1. We report the BMA posterior estimates of the coefficients of the regressors (with t-statistics in parentheses) in a multivariate regression for for 1,3,5,7,10 years horizon along with the regression R^2 statistics. The sample period is 1955-2006.

Model: $r_{m,t}-r_{f,t-1}$	dp^{TD}_{t-1}	de_{t-1}	pe_{t-1}	cay_{t-1}	$RREL_{t-1}$	$Term_{t-1}$	$Default_{t-1}$	Prob.	Visit
H:1 Year									
Model 1	1	0	0	0	0	0	0	44.17	2778
Model 2	1	0	0	0	1	0	0	14.06	3131
Cum. Probability	0.99	0.07	0.08	0.17	0.23	0.11	0.08		
H:3 Years									
Model 1	1	0	0	1	0	1	0	46.14	2195
Model 2	1	0	0	1	0	0	0	25.49	2862
Cum. Probability	1.00	0.06	0.10	0.94	0.06	0.66	0.05		
H:5 Years									
Model 1	1	0	0	1	0	0	0	25.08	1590
Model 2	1	0	1	0	0	1	1	24.44	484
Cum. Probability	0.96	0.07	0.39	0.65	0.09	0.62	0.45		
H:7 Years									
Model 1	0	0	0	1	0	0	0	32.85	2376
Model 2	0	0	0	1	0	0	1	8.85	2873
Cum. Probability	0.39	0.11	0.16	0.85	0.07	0.32	0.39		
H:10 Years									
Model 1	0	0	1	1	0	0	0	29.55	1629
Model 2	0	0	0	1	0	0	1	17.98	1385
Cum. Probability	0.10	0.12	0.67	0.99	0.07	0.20	0.50		

Table 7b2. Model selection analysis. We report the two models with highest probability and highest number of visits among all the models considered for Bayesian analysis. 1's in the cells denote that the variable is included in the model, whereas 0's indicate that those variables no not enter the model. We report cumulative probability of each variables, i.e. the probability that a variable appears across all the models considered and two models with highest probability. We have used flat priors and 50000 draws for the analysis. The sample considered for the analysis spans from 1955-2006.

$z_t =$	In-Sample				Out-Of-Sample			
	R^2	t-stat	MAE	RMSE	R^2_{OS}	MAE	RMSE	DM
dp_t	0.74	1.22	12.47	14.90	-5.12	13.37	15.80	-2.53
$\tilde{dp}_t$	4.04	2.37	11.38	14.09	11.48	11.36	14.50	19.65
dpp_t^{TD}	21.50	4.17	9.71	11.29	9.90	11.97	14.63	3.31
cay	17.15	3.27	10.61	12.91	-7.25	11.19	14.10	-2.04
cay,dpp_t^{TD}	37.05	1.56,4.33	9.02	11.16	16.73	10.00	12.42	5.01
Historical Mean	-	-	10.82	12.92	-	11.62	13.61	-

Table 8a. This table presents statistics on 1-year ahead forecast errors (in-sample and out-of-sample) for stock returns. The sample starts in 1952 and we construct first forecast in 1982. All numbers are in percent. RMSE is the root mean square error, MAE is the mean absolute error. DM is the Diebold and Mariano (1995) t-statistic for difference in MSE of the unconditional forecast and the conditional forecast. The out-of-sample R^2 compares the forecast error of the historical mean with the forecast from predictive regressions.

$z_t =$	In-Sample				Out-Of-Sample			
	$\bar{R}^2$	t-stat	MAE	RMSE	R^2_{OS}	MAE	RMSE	DM
dp_t	6.06	2.09	18.72	24.55	-9.76	22.59	28.84	-0.15
$\tilde{dp}_t$	13.23	2.91	17.66	23.30	-0.38	21.42	27.58	-0.02
dpp_t^{TD}	28.64	4.77	14.80	19.51	32.66	16.89	22.59	0.74
cay	36.16	3.91	13.78	17.19	53.28	17.03	20.05	2.56
cay,dpp_t^{TD}	62.71	2.60,4.79	11.60	14.59	54.24	17.46	19.84	1.88
Historical Mean	-	-	17.26	24.72	-	23.33	29.34	-

Table 8b. This table presents statistics on 3-year ahead forecast errors (in-sample and out-of-sample) for stock returns. The sample starts in 1952 and we construct first forecast in 1982. All numbers are in percent. RMSE is the root mean square error, MAE is the mean absolute error. DM is the Diebold and Mariano (1995) t-statistic for difference in MSE of the unconditional forecast and the conditional forecast. The out-of-sample R^2 compares the forecast error of the historical mean with the forecast from predictive regressions.

$z_t =$	In-Sample $\bar{R}^2$	t-stat	MAE	RMSE	Out-Of-Sample R^2_{OS}	MAE	RMSE	DM
dp_t	14.35	3.15	21.91	30.05	-3.60	28.98	37.13	-0.03
$\tilde{dp}_t$	16.97	3.05	24.39	32.45	-22.93	33.90	40.45	-0.39
dpp_t^{TD}	40.27	6.36	19.47	24.79	39.84	22.85	28.29	0.74
cay	38.78	5.57	15.81	20.38	60.97	21.63	25.64	4.21
cay,dpp_t^{TD}	57.05	3.73,4.72	14.38	17.95	58.03	22.31	26.59	1.92
Historical Mean	-	-	23.13	30.89	-	36.08	41.04	-

Table 8c. This table presents statistics on 5-year ahead forecast errors (in-sample and out-of-sample) for stock returns. The sample starts in 1952 and we construct first forecast in 1982. All numbers are in percent. RMSE is the root mean square error, MAE is the mean absolute error. DM is the Diebold and Mariano (1995) t-statistic for difference in MSE of the unconditional forecast and the conditional forecast. The out-of-sample R^2 compares the forecast error of the historical mean with the forecast from predictive regressions.

APPENDIX B: FIGURES

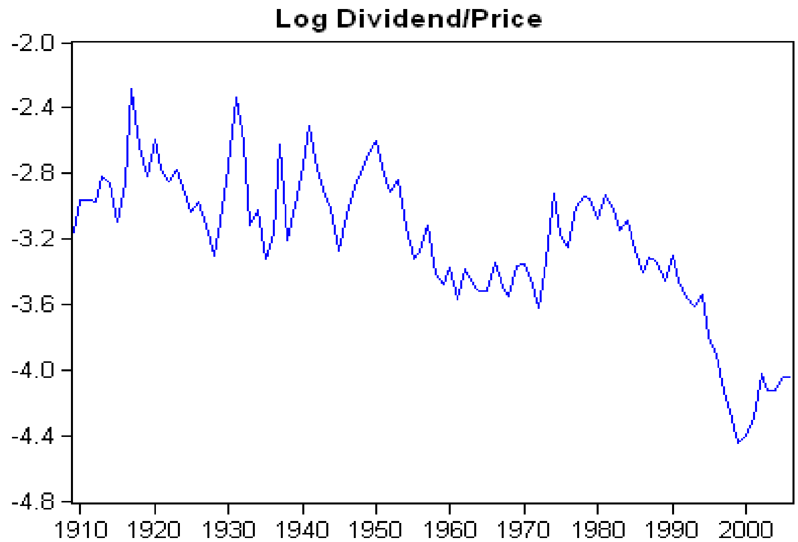

Figure 1. The time series of log dividend price ratio ($d_t - p_t$). Annual data from 1909 to 2006.

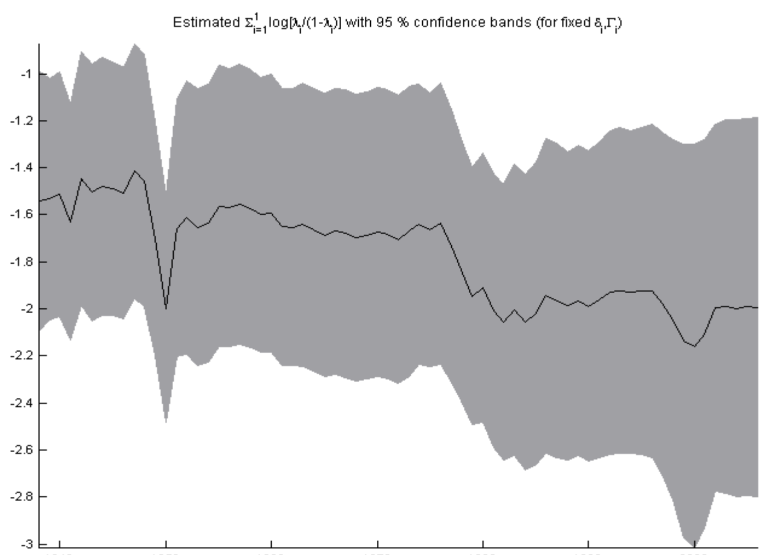

Figure 2. Recursive Eigenvalue Test using log nominal prices and log nominal dividends.

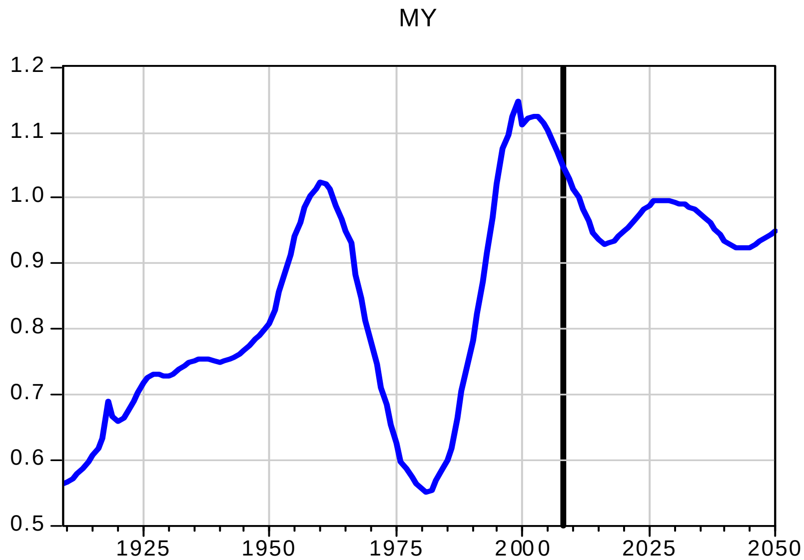

Figure 3a. Middle/young (MY) ratio from 1909 to 2006 and Bureau of Census projections from 2007-2050.

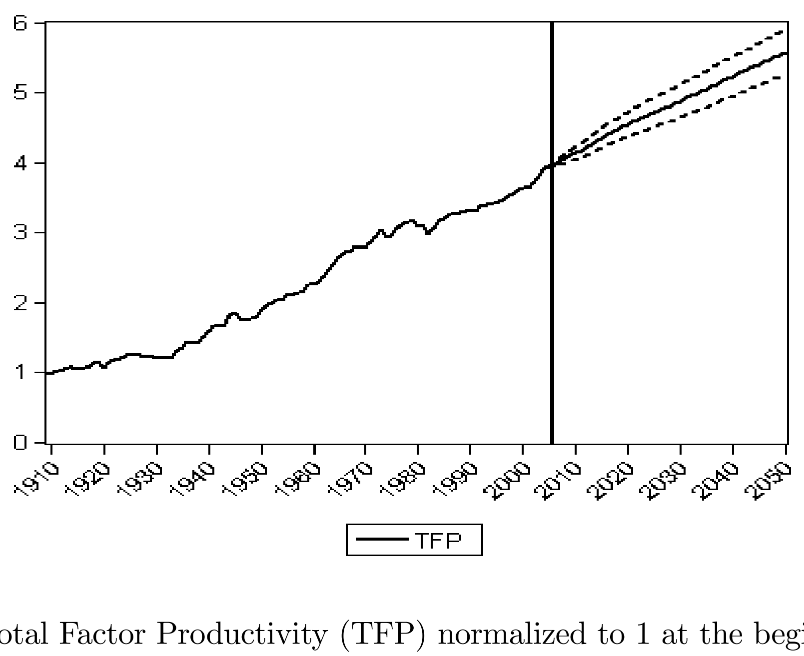

Figure 3b. Total Factor Productivity (TFP) normalized to 1 at the beginning of our sample and projections out-of-sample (with one standard deviation band) obtained from stochastic simulation of VECM model for the period 2007-2050.

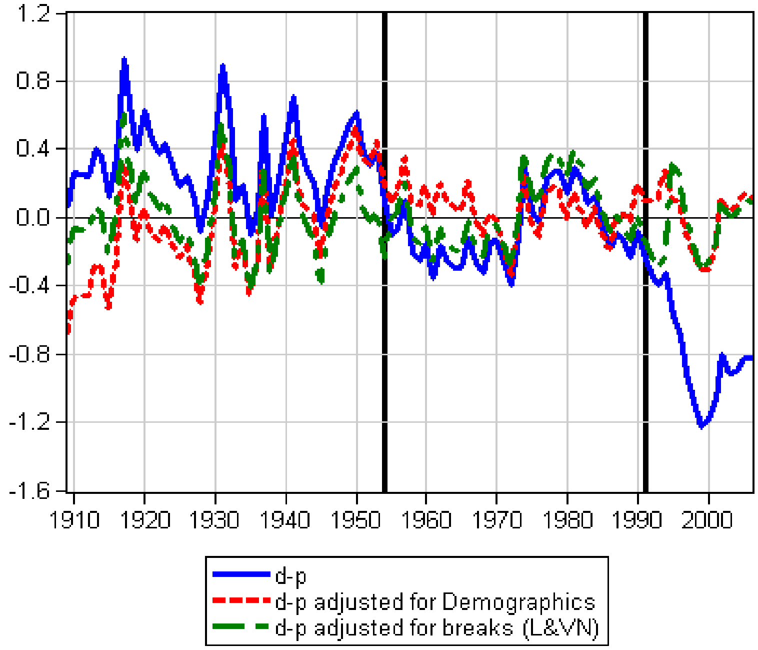

Figure 4a. log dividend price ratio, log dividend price ratio adjusted for exogenous breaks (LVN, 2007) and log dividend price ratio adjusted for demography.

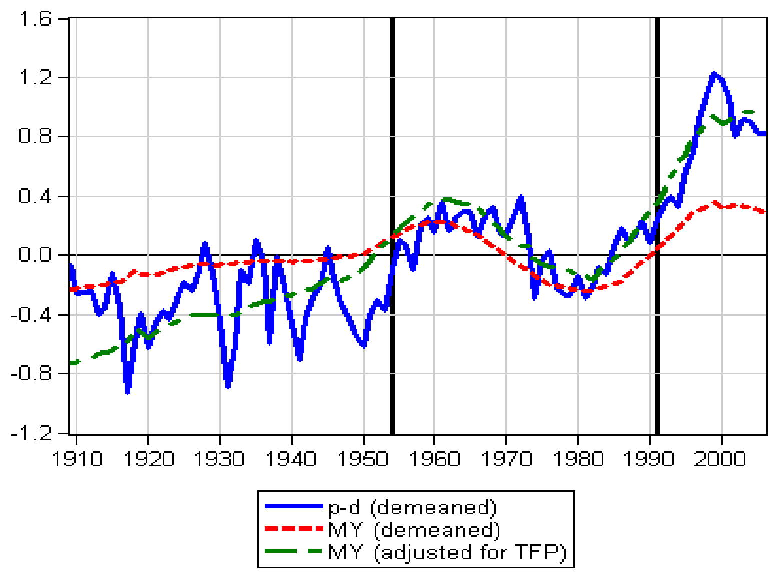

Figure 4b. Log of the price dividend ratio, MY , and MY adjusted for TFP using coefficient in our cointegrating vector. All variables demeaned

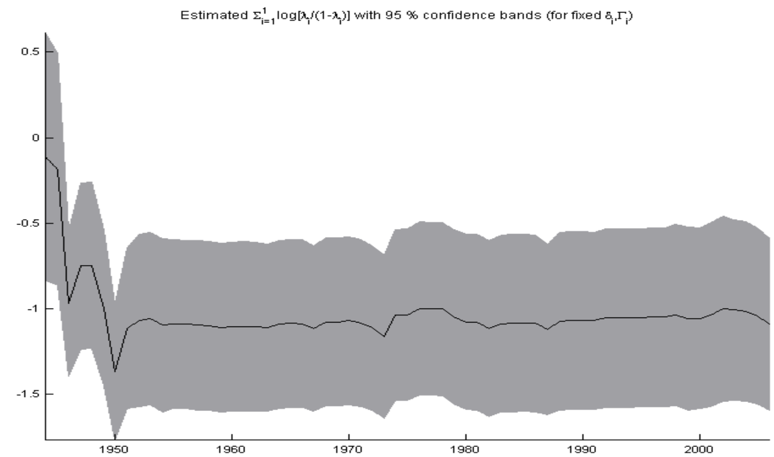

Figure 5a. Recursive Eigenvalue test using the general model. We include nominal log dividends, log prices, TFP, MY and SR.

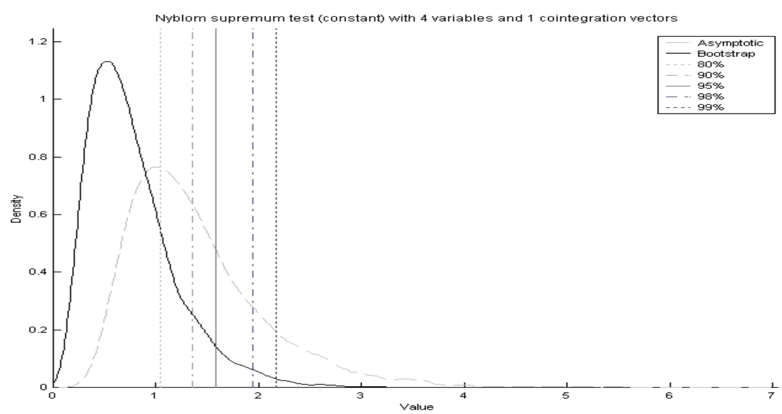

Figure 5b. Nyblom Bootstrap Test for a our model. The sup-statistics is 0.4849 (with mean-statistics = 0.2036) for a VEC model of order 1 allowing for only one cointegration relation

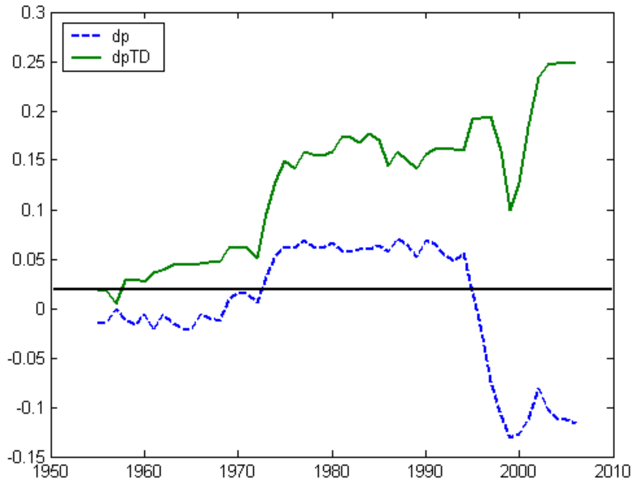

Figure 6a. Out-of sample performance for annual predictive regression. Difference between cumulative squared forecast errors based on a linear regression incuding just a constant and a linear regression including the predictive variable (dp^{TD} or dp). The units are in percent. First forecast in 1955.

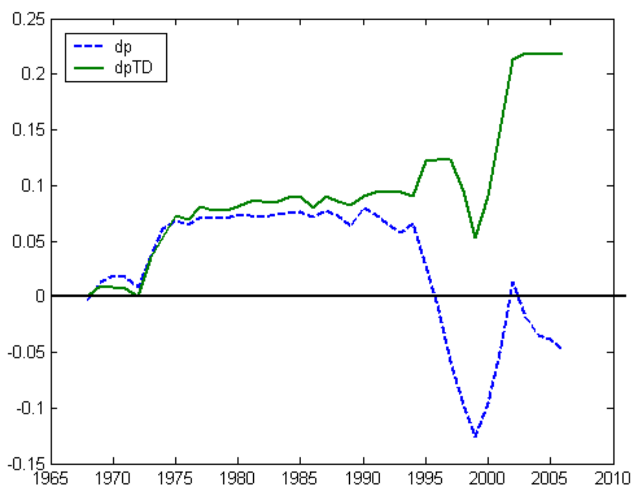

Figure 6b. Out-of sample performance for annual predictive regression. Difference between cumulative squared forecast errors based on a linear regression incuding just a constant and a linear regression including the predictive variable (dp^{TD} or dp). The units are in percent. First forecast in 1968.

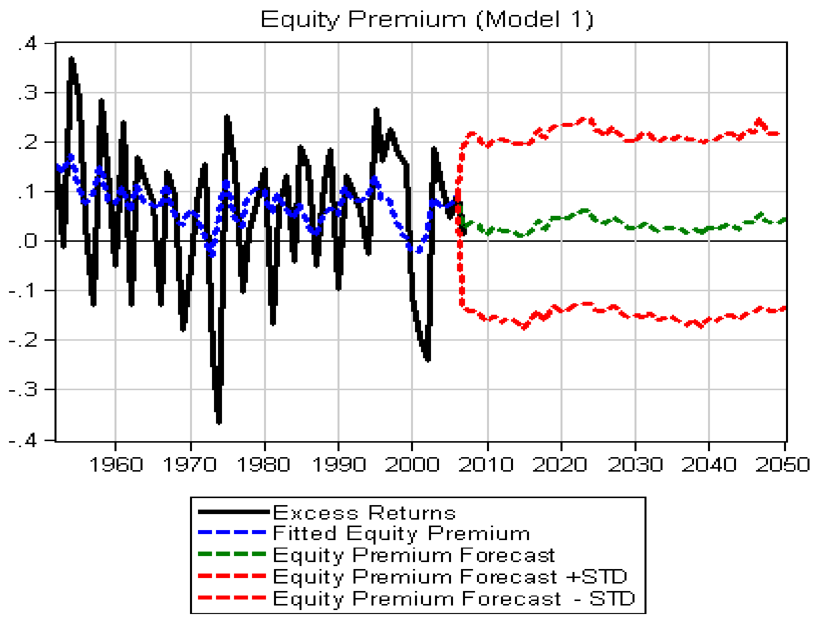

Figure 7a. Stochastic Simulation of Equity Premium using the specification with p_t, d_t, TFP_t as endogenous variables and MY_t as exogenous variable.

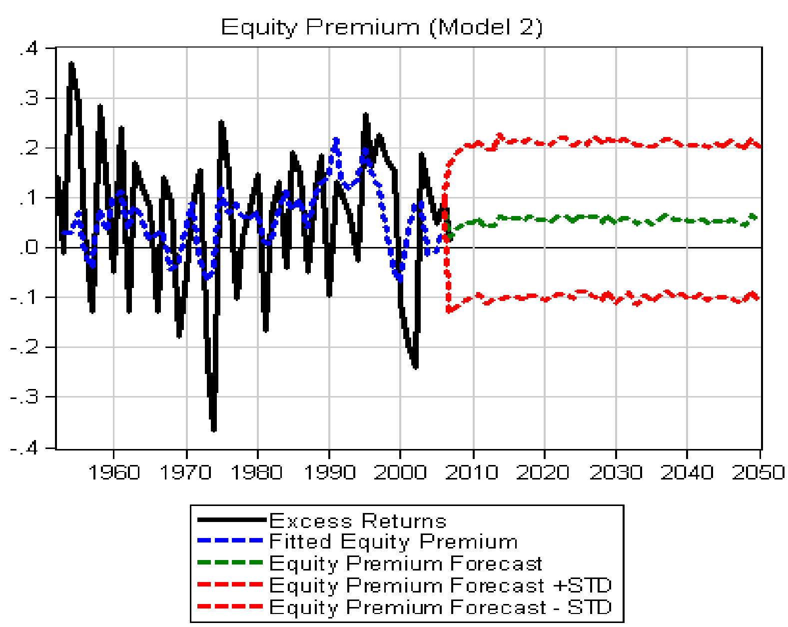

Figure 7b. Stochastic Simulation of Equity Premium using the specification with c_t, a_t, y_t as endogenous variables and without any exogenous variables.

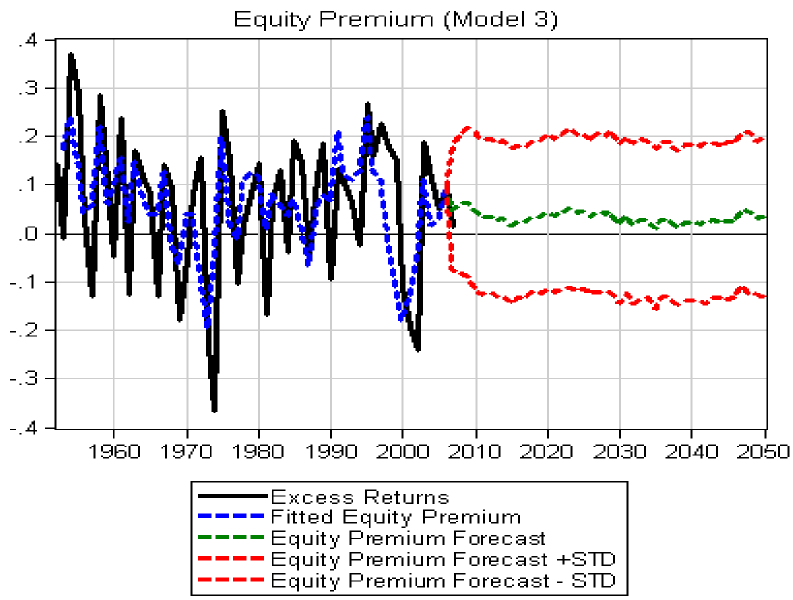

Figure 7c. Stochastic Simulation of Equity Premium using the specification with $p_t, d_t, TFP_t, c_t, a_t$ and y_t as endogenous variables and MY_t as exogenous variable.

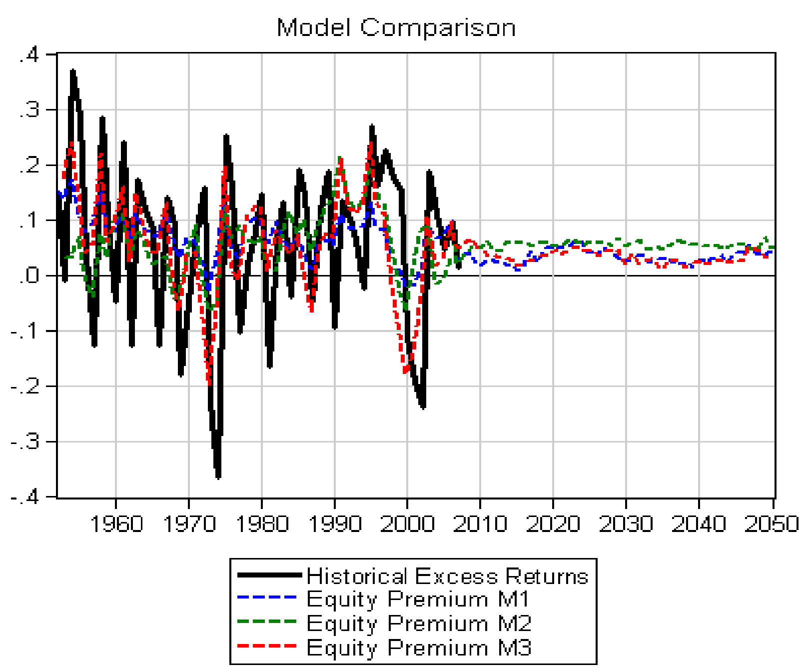

Figure 8. Model Comparison. We graph from 1952 to 2006 the fitted values from three alternave model we consider in this section and from 2007 to 2050 we also graph model forecasts.

APPENDIX C:

In Appendix C, we describe our data construction and provide the links to the data sources. We report results with annual data, but we also cross-check the results using quarterly data. We opt for annual frequency for several reasons; first, the demography variables move slowly and do not change much in quarterly frequency (in that case we interpolate the series), second we are mainly concerned with long term prediction (up to 10 years!) and thus we correct for overlapping data. This way, we also remove the seasonality effects of the data, mainly the dividends. But these advantages come with the tradeoff of few data points, which might be particular concern for estimation. Below, we describe the main series we have constructed;

First, the dependent variable, the excess return over the risk free rate:

Stock Prices: S&P 500 index yearly prices from 1909 to 2006 are from Robert Shiller's website, but we took the last month's observation for each year. Alternatively, we also use CRSP annual end-of-year data for value-weighted market (NYSE+AMEX+NASDAQ) index (cum dividend) from 1926 to 2006.

Stock Returns: For S&P 500 index, to construct the continously compounded return r_t, we take the ex-dividend price P_t add dividend D_t[18] over P_{t-1} and take the natural logarithm of the ratio. On the other hand, for CRSP value-weighted market return, we directly download the cum-dividend market return (*retd*) add 1 and take the natural logarithm to construct the continously compounded market return.

Risk-free Rate: We download secondary market 3-Month Treasury Bill rate from St.Louis (FRED) from 1934-2006. The risk-free rate for the period 1920 to 1933 is from New York City from NBER's Macrohistory data base. Since there was no risk-free short-term debt prior to the 1920's, we estimate it following Goyal&Welch (2007). We obtain commercial paper rates for New York City from NBER's Macrohistory data base. These are available for the period 1871 to 1970. We estimate a regression for the period 1920 to 1971, which yielded

$$T - billRate = -0.004 + 0.886 \times \ CommercialPaperRate.$$

Therefore, we instrument the risk-free rate for the period 1909 to 1919 with the predicted regression equation.

Hence we build our dependent variable which is the equity premium $(r_{m.t} - r_{f,t})$, i.e., the rate of return on the stock market minus the prevailing short-term interest rate in the year $t-1$ to t.

Second, we construct the independent variables commonly used in the long horizon stock market prediction literature; namely

[18] In Robert Shiller's database, Prices are beginning of period, i.e. January prices, whereas dividends are distributed at the end of the period. In the last section, we simulated our models with december prices.

Log Dividend-Price Ratio (dp_t): is the difference between the log of dividends and the log of prices. For S&P 500 index, i.e. data taken from Robert Shiller's website, we take the natural logarithm of D_t over P_t, in the case of CRSP data we construct dividends D_t by substracting vwretx_t from $vwretd_t$ and multiplying it by $vwindx_{t-1}$.Then dp_t is constructed by taking the natural logarithm of D_t over $P_t(vwindx_t)$. This variable is one of the best candidates for long horizon stock market prediction and is extensively used in the litarature (Rozeff (1984), Shiller (1984), Campbell (1987), Campbell and Shiller (1988), Campbell and Shiller (1989), Fama and French (1988a), Hodrick (1992), Barberis (2000), Campbell and Viceira (2002), Campbell and Yogo (2003), Lewellen (2004). See Cochrane (1997) for a survey on dividend price ratio prediction literature).

Log Dividend-Earnings (payout) ratio: Both annual dividend and earning series are taken from Robert Shiller's website. The variable is constructed by taking the natural logarithm of D_t over E_t (Lamont,1998).

Log Earnings Price ratio: Both annual price and earning series are taken from Robert Shiller's website. The variable is constructed by taking the natural logarithm of E_t over P_t (Lamont,1998).

RREL: This variable, the stochastically detrended riskless rate, is constructed using monthly 3-Month Treasury Bill yield data from NBER Macrohistory Data Base (from 1920 to 1933) and 3-Month Treasury Bill: Secondary Market Rate from FRED St. Loius (1934-2006); i.e. we define RREL for month t, $RREL_t$ is r_t minus the average of r_t from months $t-12$ to $t-1$. Yearly $RREL_t$ is the last observation at the end of the year (Campbell,1991; Hodrick,1992). The data is available from 1921-2006.

TERM: is the difference between the long-term govenment bond yield (10year) from Robert Shiller's Website and 3-Month T-Bill yield from NBER Macrohistory Data Base (from 1920 to 1933) and 3-Month Treasury Bill: Secondary Market Rate from FRED St. Loius (1934-2006) and available from 1920 to 2006.

DEFAULT: is the difference between the BAA and the AAA corporate bond rates. Both series are collected from St.Louis (FRED) and available from 1919 to 2008.

Consumption, wealth, income ratio (cay): is suggested in Lettau and Ludvigson (2001). Data for its construction is available from Sydney Ludvigson's website at annual frequency from 1948 2001. Lettau-Ludvigson estimate is described in equation (4) in their paper, where two lags are used in annual estimation (k = 2). This variable is named as $cayp(post)$ by Goyal&Welch (2007), which they claim contains look-ahead bias, we also consider their variable $caya(ante)$ that eliminates the bias, but report the results using $cayp$, since this gives us a more conservative benchmark. We also use their updated quarterly cay (1952-2006, last quarter as annual obervation) for BMA analysis.

Consumption, dividend, income ratio (cdy): is suggested in LL (2005). Data for its construction is available from Sydney Ludvigson's website at annual frequency from 1948 2001. Lettau-Ludvigson estimate is described in equation (4) in their paper, where two lags are used in annual estimation (k = 2).

In addition to the independent variables commonly used in the literature, we also use demography and technology variables in a cointegration framework to explain the long run movement of prices driven by fundamentals.

Demography Variables

The U.S annual population estimates series are collected from U.S Census Bureau and the sample covers estimates from 1900-2050.

Technology Variable

Among other candidates such as Industrial production[19] , number of patents or a variable extracted from a large dataset using principal component, we first focus on a single technology variable, total factor productivity (TFP), which is typically the only source of randomness in standard Real Business Cycle models (RBC, Kydland & Prescott, 1982).

Total Factor Productivity (TFP): This series is available on the website of Bureau of Labor Statistics(BLS) from 1948-2006. In order to have a longer time series, we merged this series with the TFP data from 1909 to 1949 provided in the original paper by Solow (1957). We normalized the series from BLS to bring it to the same scale with Solow data.

DATA SOURCES

Robert Shiller's Website

http://www.econ.yale.edu/~shiller/

NBER Macrohistory Data Base

http://www.nber.org/databases/macrohistory/contents/chapter13.html.

Sydney Ludvigson's Website

http://www.econ.nyu.edu/user/ludvigsons/

Martin Lettau's Website

http://faculty.haas.berkeley.edu/lettau/

WRDS

http://wrds.wharton.upenn.edu/

US Census Bureau

http://www.census.gov/popest/archives/1990s/ST-99-08.txt

Andrew Mason's Website

http://www2.hawaii.edu/~amason/

Bureau of Labor Statistics Webpage

http://www.bls.gov/data/

FRED

http://research.stlouisfed.org/fred2/

[19] We have also run tests with log IP (data collected from St. Louis FRED from 1919-2007) and the results did not change significantly.