Interpretable asset markets?

Ravi Bansal[a], Varoujan Khatchatrian[b], Amir Yaron[c,d],*

[a]*Fuqua School of Business, Duke University, Durham, NC, USA*
[b]*Department of Economics, Duke University, Durham, NC, USA*
[c]*The Wharton School, University of Pennsylvania, Philadelphia, PA 19104-6367, USA*
[d]*NBER, Cambridge, MA, USA*

Abstract

In this paper we show that measures of economic uncertainty (conditional volatility of consumption) predict and are predicted by valuation ratios at long horizons. Further we document that asset valuations drop as economic uncertainty rises—that is, financial markets dislike economic uncertainty. Moreover, future earnings growth rates are sharply predicted by current price–earnings ratios. It seems that much of the variation in asset prices can be attributed to fluctuations in economic uncertainty and expected cash-flow growth. This empirical evidence is consistent with the implications of existing parametric general equilibrium models. Hence, the channels of fluctuating economic uncertainty and expected growth seem important for interpreting asset markets.
© 2004 Elsevier B.V. All rights reserved.

1. Introduction

In this paper we provide new evidence that relates asset prices, consumption volatility and expected growth. In particular, we show that economic uncertainty

---

*Corresponding author. Tel.: +1 215 898 1241; fax: +1 215 898 6200.

E-mail addresses: ravi.bansal@duke.edu (R. Bansal), khv@duke.edu (V. Khatchatrian), yaron@savage.wharton.upenn.edu (A. Yaron).

(that is, consumption volatility) sharply predicts and is predicted by asset valuation ratios. Our evidence shows that a rise in economic uncertainty leads to a fall in asset prices, and that high valuation ratios predict low subsequent economic uncertainty. In addition, we show that there is a strong positive relation between aggregate earnings growth and asset prices. In all, our evidence suggests that fluctuations in economic uncertainty and expected growth are potentially important channels for interpreting asset markets and the variation in asset prices.

Why is this evidence important? First, this empirical evidence highlights an often discussed but not verified view that aggregate economic uncertainty (i.e., real aggregate consumption volatility) has sizable effects on asset valuations and that financial markets dislike economic uncertainty. Our empirical work for the US and foreign economies suggests that the effects of fluctuating economic uncertainty on asset valuations are sizable. Second, the evidence regarding growth rates suggests that fluctuations in expected growth directly affect asset valuations, and information regarding future expected growth is encoded in current asset valuations. Our overall evidence regarding economic uncertainty and expected growth suggests that a plausible interpretation of asset markets is based on these economic fundamentals. A rise in economic uncertainty increases expected returns and leads to a fall in asset valuations. A rise in expected growth, on the other hand leads to a rise in asset valuations. Both these effects can be interpreted from the perspective of general equilibrium models (see for example, Bansal and Yaron, 2004).

An alternative view of asset markets "shuts-off" the channels of expected growth rates and economic uncertainty, as growth rates in these models are assumed to be i.i.d. (e.g., Campbell and Cochrane, 1999; Cechetti et al., 2000). These models suggest that asset markets can be interpreted via the channels of fluctuating risk aversion and/or distorted beliefs. The empirical evidence provided in this paper does not exclude the possibility of time-varying risk-aversion; however, it does suggest that channels related to observable macroeconomic fluctuations (in expected growth and volatility) can by themselves go a long way to help interpret market movements.

Bansal and Yaron (2004) briefly discuss correlations between asset valuation and squared consumption residuals. In contrast, the main contribution of this paper is to provide a systematic and comprehensive empirical analysis of the economic uncertainty channel. By utilizing various volatility measures, alternative econometric techniques, multiple data sets, and time periods, we show that the uncertainty channel is robustly found in the data. An additional contribution is to exploit our evidence regarding volatility and predictability of cash flows to evaluate the plausibility of alternative preferences and models for asset markets.

In terms of the empirical evidence we find that consumption volatility predicts price–dividend and price–earnings ratios, with R^2 in excess of 20%. This channel is robust to using alternative measures of volatility; we use GARCH and integrated volatility measures. Interestingly, it is difficult to find comparable evidence if one replaces consumption volatility with simple measures of market volatility. Future, realized consumption volatility is predicted by current valuation ratios, and at horizons of 4–8 quarters, the R^2s from these regressions are about 6%. Current valuation ratios do not predict future realized market volatility. The slope coefficient

in the regressions that link valuation ratios to consumption volatility is always negative and significant–as predicted by our economic model. Volatility measures and valuation ratios are quite persistent, this can make inference in finite samples difficult. To account for this we also provide, monte carlo based, finite sample empirical distribution for the various parameters and test statistics of interest. Finally, we also consider data from UK, Germany, and Japan and find very similar evidence for these economies as well. The overall message is that the data strongly supports the economic uncertainty channel.

While the links between economic uncertainty and valuations highlight some new empirical evidence, the links between growth rates and valuation ratios is much explored (see for example Campbell and Shiller, 1988; Bansal and Lundblad, 2002; Hall, 2001, among others). Future cash dividend growth rates are not well predicted by current valuation ratios.[1] Future earnings growth, at horizons of 4–16 quarters are sharply predicted by current valuation ratios. The fact that at longer horizons growth rates are predictable is interesting and indicates that low frequency components in earnings growth rates contain important economic information regarding asset prices. We find that about 55% of the variation in price–earnings ratios can be explained by variations in expected growth rates and about 45% by variation in expected returns. Further, about half of the fluctuations in expected returns are due to fluctuations in economic uncertainty. In all, we argue that the evidence pertaining to the economic uncertainty and growth channels is largely consistent with the implications of Bansal and Yaron (2004) model.

The rest of the paper is organized as follows. Section 2 provides the motivation and framework of our analysis. Section 3 discusses the data. Section 4 provides our main empirical results, relating measures of volatility and valuation ratios using US data. Section 5 provides additional empirical results relating cash flows and valuation ratios as well as evidence from other countries. In Section 6 we interpret these empirical results from the perspective of existing models. Section 7 provides some concluding remarks.

2. The economy and asset valuation

To provide a framework to analyze our empirical evidence it is useful to write the log valuation ratio using the Campbell and Shiller (1988) approximation,

$$p_t - y_t = \kappa_0 + \mathrm{E}_t \sum_{j=1}^{\infty} \kappa_1^j [g_{y,t+j} - r_{t+j}]. \tag{1}$$

where p_t is the log of the stock price, y_t is the log-level of cash-flows, $g_{y,t+1}$ is the growth rate of market cash-flows, and r_{t+1} is the continuously compounded return

---

[1]Bansal and Yaron (2000) show that the connection between expected growth and asset valuations may be somewhat difficult to detect in the data as valuation ratios themselves are affected by additional factors, such as stochastic volatility of consumption, a measure of economic uncertainty. Lettau and Ludvigson (2002) also provide additional reasons for why this link may be difficult to detect.

on the market portfolio.[2] An additional accounting implication of the above present value restriction is that

$$\text{var}(p_t - y_t) = \sum_{j=1}^{\infty} \kappa_1^j [\text{cov}(g_{y,t+j}, p_t - y_t) - \text{cov}(r_{t+j}, p_t - y_t)]. \tag{2}$$

This equation says that variation in asset valuations $p_t - y_t$ can only come from variations in expected cash-flow growth and/or variations in expected asset returns.

In a variety of models, expected returns are determined by the conditional volatility of aggregate consumption, that is

$$\text{E}_t[r_{t+1}] = r_f + \gamma \sigma_{c,t}^2, \tag{3}$$

where γ capture attitudes toward risk governed by preferences and technology in the economy.[3] Substituting the expression for expected returns is Eq. (3) into Eq. (1) implies that a rise in anticipated consumption volatility should lower asset valuations, $p_t - y_t$. In other words, asset markets should dislike economic uncertainty. Following this intuition, the main focus of this paper is in exploring the links between fundamental economic uncertainty and asset valuation. Consider the following projections:

$$p_t - y_t = b_0 + b_\sigma \sigma_{c,t-1} + u_{1,t}, \tag{4}$$

where $\sigma_{c,t-1}$ is a measure of consumption volatility as of time $t-1$. A negative b_σ in the above projection indicates that financial markets dislike economic uncertainty.

Additional implications follow from substituting the expression for the expected returns (Eq. (3)) into Eq. (2). If consumption volatility is time varying and is important for explaining expected returns then $p_t - y_t$ should also predict *future* consumption volatility. Hence, consider the following additional projection:

$$|\eta_{c,t+J}| = \alpha_0 + \alpha_{1,J}(p_t - y_t) + u_{2,t+J}, \quad J \geqslant 1, \tag{5}$$

where $\eta_{c,t+J}$ is the one step-ahead innovation in the consumption growth at date $t+J$. Eq. (5) provides important information regarding the extent to which volatility is long-lasting and time-varying. That is, if volatility is long-lasting then current valuation ratios should be able to predict future realized consumption volatility, and $\alpha_{1,J}$ should be different from zero. Further, if financial markets dislike economic uncertainty, and the volatility process is persistent, then one would suspect that $\alpha_{1,J}$ should be negative as well. That is current high valuation ratios signal low future realized volatility. If, on the other hand, consumption growth is *i.i.d.* as assumed in many papers, then current valuation ratios should not predict future consumption volatility. Finally, note that any predictability of consumption volatility indicates that consumption volatility is time-varying.

---

[2] κ_1 is given by the steady-state relationship of $\exp(p-y)/(1+\exp(p-y))$, thus a number slightly lower than one. κ_0 is an approximation constant.

[3] See for example, models considered in Hansen and Singleton (1982, 1983), Mehra and Prescott (1985), Abel (1990), Kandel and Stambaugh (1991), Campbell (1993), Bansal and Yaron (2004).

Our main empirical findings, which we elaborate on below, are (i) regressing $p_t - y_t$ on to $\sigma_{c,t-1}$ produces sizeable negative slope coefficients and significant R^2s, (ii) future (realized) economic uncertainty, $|\eta_{c,t+J}|$, is predicted by $p_t - y_t$, with negative slope coefficients, and (iii) current $p_t - y_t$ predicts future growth rates, $g_{y,t+J}$, with a positive slope coefficient. This combined evidence, as discussed below, is consistent with the implications of Bansal and Yaron (2004) model.

3. Data

Our benchmark analysis for the US is based on quarterly data spanning the period 1949.1–1999.4. US consumption of nondurables and services is taken from the BEA (Bureau of Economic Analysis). Returns are based on CRSP Value Weighted Return.

To derive the price–dividend ratios we use monthly observations of returns including and excluding dividends to generate the dividend series. The quarterly price–dividend ratio is based on an arithmetic average of the dividends of the last four quarters. In addition to measures of consumption and dividend growth we also utilize evidence on aggregate earnings growth. This data is constructed from NIPA accounts. All sources and relevant data construction are given in Appendix A.

To corroborate our evidence on the US we also collected data for three other countries: Germany, Japan, and United Kingdom. All sample data starts in 1972.1 and ends in 1998.2. The consumption and CPI measures are taken from the IMF's International Financial Statistics. The financial data for these countries is collected from DataStream and Morgan Stanley Capital International stock market data. The data was kindly provided to us by John Campbell (for more details see Campbell, 1999). All the data details are provided in Appendix A.

In Table 1 we provide summary statistics of the US data. In each panel we provide the mean and volatility of the price–dividend ratio, price–earnings ratio, and consumption, dividend, and earnings growth. We provide the fourth and eighth quarter autocorrelations (corresponding to one and two years).

In all our empirical work we use two alternative measures of cash-flows, cash-dividends and earnings. While much of the earlier evidence has focused on cash-dividends (see for example, Cochrane, 1992), this measure is far from perfect as total payouts from corporations may include other methods of paying their stockholders (such as repurchases). Our choice of earnings (cash-dividends + undistributed profits) is similar to that used in Hall (2001), and provides a measure that is relatively less affected by financial policy. For both measures of cash-flows we construct a standard cash-flow index as in Campbell (1999), where the cash-flow index is the amount that investors would receive if they invested one dollar in the market. As a practical issue, this matters little to our results, as the earnings growth rate series and the growth rates of the earnings index have a correlation of 99%.

4. Empirical evidence—volatility implications

We start our empirical analysis by examining the US data for the quarterly sample. First we document evidence in support of conditional volatility in

Table 1
Summary statistics: USA (quarterly)

	$E(\cdot)$	$\sigma(\cdot)$	corr$(g_c, g.)$	$AC(4)$	$AC(8)$
USA (1949.1–1999.4)					
g_c	0.008	0.005		0.009	−0.128
g_d	0.005	0.017	0.11	−0.037	−0.023
g_e	0.002	0.068	0.31	−0.094	−0.159
r_m	0.021	0.078		0.002	−0.032
$(p-d)$	3.333	0.317		0.768	0.594
$(p-e)$	2.203	0.422		0.781	0.576
USA (1972.1–1998.2)					
g_c	0.007	0.005		0.034	−0.194
g_d	0.004	0.015	0.16	−0.183	0.078
g_e	0.004	0.064	0.32	0.054	−0.257
r_m	0.019	0.082		−0.016	−0.029
$(p-d)$	3.340	0.295		0.680	0.496
$(p-e)$	2.247	0.343		0.706	0.509

g_c, g_d, and g_e denote respectively the real growth rate of consumption, dividends, and earnings. r_m is the real return on the market portfolio. $p-d$ and $p-e$ denote the log price–dividend and price–earnings, respectively. $E(\cdot)$ and $\sigma(\cdot)$ denote the mean and standard deviation, and $AC(j)$ is the jth autocorrelation.

consumption growth. We then present our main results relating valuation ratios and volatility. In Section 5 we discuss the relationship between valuation ratios and growth rates. We then proceed to corroborate this evidence by examining the international data and an analogous sub-sample of the US.

4.1. Consumption dynamics and volatility

We consider two empirical measures for economic uncertainty. The first measure, motivated by Anderson et al. (2003), is $\sigma_{c,t-1,J} = \log(\sum_{j=1}^{J} |\eta_{c,t-j}|)$, where $\eta_{c,t}$ is the innovation in consumption growth. They show that such a measure provides more accurate information regarding ex-ante volatility.[4] Taking logs makes the volatility measure less sensitive to outliers and does not qualitatively affect any of our empirical results. Our second specification for volatility, denoted $\sigma_{c,t}$, is parametric and is based on modelling consumption growth as following an AR(1)-GARCH(1,1). As discussed below, our results are robust to these alternative measures of volatility.

To motivate the time-varying consumption volatility we run the following AR(1) specification for consumption growth:

$$g_{c,t} = \mu + A_1 g_{c,t-1} + \eta_{c,t}. \tag{6}$$

---

[4]While we can use squared residuals to model the variance, this matters little to our results. We choose to take absolute values to make the measure less sensitive to outliers, as argued in Davidian and Carroll (2002) and Pagan and Schwert (1990).

Table 2
Consumption growth and market return projections (quarterly)

	Growth rates/returns						Absolute residuals		
	μ	A_1	ω_0	ω_1	ω_2		$AC\,(1)$	$AC\,(4)$	$AC\,(8)$
AR(1) *estimates*									
Panel A: Consumption growth									
Estimate	0.007	0.234				Estimate	0.174	0.088	0.049
S.E.	0.001	0.080				*Q*-stat	6.20	17.73	30.76
Panel B: Market return									
Estimate	0.020	0.066				Estimate	0.108	0.071	−0.083
S.E.	0.006	0.079				*Q*-stat	2.39	9.61	16.20
AR(1)-*GARCH*(1,1) *estimates*									
Panel C: Consumption growth									
Estimate	0.007	0.310	1.63*	0.143	0.788				
S.E.	0.001	0.076	1.68*	0.073	0.091				
Panel D: Market return									
Estimate	0.002	0.090	0.002	0.139	0.541				
S.E.	0.006	0.078	0.001	0.118	0.166				

Panel A reports the parameters for the following regressions for consumption growth: $g_{c,t} = \mu + A_1 g_{c,t-1} + \eta_{c,t}$. Panel B reports analogous results for the market return, $r_{m,t} = \mu + A_1 r_{m,t-1} + \eta_{r_m,t}$. Panel C models $\sigma_{c,t}^2 = \omega_0 + \omega_1 \eta_{c,t-1}^2 + \omega_2 \sigma_{c,t-1}^2$. Panel D models the conditional volatility of the market return as $\sigma_{r_m,t}^2 = \omega_0 + \omega_1 \eta_{r_m,t-1}^2 + \omega_2 \sigma_{r_m,t-1}^2$. The sample is 1949.1–1999.4. A $*$ implies the estimate should be multiplied by 10^{-6}. All standard errors are Newey–West. The Q-stat refer to the Ljung–Box test of the null of no autocorrelations up to order J.

The results are reported in Panel A of Table 2. Our results are not sensitive to the AR(1) specification in Eq. (6). The absolute values of the residuals from the above regression, $|\eta_{c,t}|$, characterize the realized volatility of the consumption growth rate. Table 2 also presents the first, fourth and eighth autocorrelations of the absolute residuals. The autocorrelations are significantly different from zero and clearly display the persistence in conditional volatility of consumption. At all these horizons and even longer ones, the Q-stats (the Ljung–Box statistic) are large and significantly different from zero with p-values well less than 0.01. The absolute value of the residuals are autocorrelated and this is indicative of time-varying volatility in consumption. Given this persistence one measure of consumption volatility that we consider is $\sigma_{c,t-1,J} \equiv \log(\sum_{j=1}^{J} |\eta_{c,t-j}|)$, where J denotes how many lags of realized volatility are used.

For our second volatility measure we consider an AR(1)-GARCH(1,1) specification;

$$g_{c,t} = \mu + A_1 g_{c,t} + \eta_{c,t},$$
$$\sigma_{c,t}^2 = \omega_0 + \omega_1 \eta_{c,t-1}^2 + \omega_2 \sigma_{c,t-1}^2. \tag{7}$$

The estimates for this specification are given in panel C of Table 2. The estimates of ω_1 and ω_2 are both significant implying, again, consumption volatility is time varying. It is interesting to note that the correlation between the GARCH(1,1) based volatility and $\sigma_{c,t-1,J}$ (with $J = 8$) is 0.89, which indicates that they capture very similar information regarding fluctuating consumption volatility. The estimation of the consumption dynamics in Eq. (7) is conducted via MLE.

In addition to measuring economic uncertainty based on consumption volatility, we also use the more standard based market return volatility $\sigma_{r_m,t-1,J}$ as a measure of uncertainty. Estimates for the non-parametric and the AR(1)-GARCH(1,1) market volatility are provided in panel B and D of Table 2.

4.2. Economic uncertainty and asset valuations

Our first regression looks at whether lagged volatility predicts future valuation ratios as stated in Eq. (4). Columns 2–4 in Table 3 provide respectively, the estimate, t-statistic, and R^2 from the regression above. These are robust t-statistics which take into account sampling error of the first stage construction of $\sigma_{c,t-1,J}$. For constructing the standard errors for this projection we use a 2-stage GMM estimator (see Ogaki, 1993)—hence all the standard errors take account of the estimation error in estimating the consumption dynamics. The different rows provide results for $b_{\sigma,J}$ using increasing number of lags, J, in constructing the volatility measures. The results in panel A are from regressing price–dividend ratios on volatility. The results for panel B are for regressing price–earnings ratio on volatility. Finally, columns 8–10 in the table provide analogous results when we use $\sigma_{r_m,t-1,J}$ as the regressor capturing volatility.

As an additional check on our results, columns 5–7 in the table provide Monte-Carlo evidence on the finite sample properties of the t-statistics and R^2 in our environment. We simulate consumption growth (market return) based on the estimated AR(1)-GARCH(1,1) process in panel C (D) in Table 2 and discussed in (Eq. (7)). For each draw, which is of the same length as our data, we estimate an AR(1) process for consumption growth, and then construct $\sigma_{c,t-1,J}$ based on the absolute residuals. The price–earnings and price–dividend ratio are each simulated based on the AR(1) process that was fitted in the data.[5] These valuation processes are independent from the measured consumption volatility process. Consequently, the regression slope coefficient from regressing the asset valuation (consumption volatility) on the consumption volatility (asset valuation) should be zero. Our Monte-Carlo distribution is based on 20,000 draws. For each draw we estimate the parameters of interest, t-stats, and R^2s. As in the data, the t-stats correct for the two step estimation in deriving $\sigma_{c,t-1,J}$. How does one interpret these Monte-Carlo results? Our t-statistics (R^2s) in the data are larger than the bottom (top) 5% of the

---

[5]Specifically, the price–earnings ratio is simulated using an AR(1) process with the following parameters: an intercept of 0.098, an autoregressive coefficient of 0.960, and an innovation standard deviation of 0.102. The analogous parameters for simulating the price–dividend ratio are 0.085, 0.977, and 0.078, respectively.

Table 3
Economic uncertainty predicting future valuation ratios: USA

J	Regressor $\sigma_{c,t-1,J}$						Regressor $\sigma_{r_m,t-1,J}$					
	Data			Monte-Carlo			Data			Monte-Carlo		
	$b_{\sigma,J}$	t-stat	$\bar{R}^2$	t (2.5%)	t (5%)	$\bar{R}^2$(95%)	$b_{\sigma,J}$	t-stat	$\bar{R}^2$	t (2.5%)	t (5%)	$\bar{R}^2$(95%)
Panel A: Price–dividend ratio												
1	−0.084	−2.614	0.08	−1.870	−1.496	0.04	−0.049	−2.274	0.03	−1.546	−1.232	0.02
4	−0.254	−3.703	0.19	−3.873	−3.197	0.16	−0.088	−1.275	0.02	−2.733	−2.266	0.09
8	−0.358	−3.153	0.26	−4.024	−3.256	0.25	−0.135	−1.348	0.03	−2.998	−2.474	0.16
Panel B: Price–earnings ratio												
1	−0.111	−2.428	0.08	−1.826	−1.435	0.04	−0.026	−0.446	0.00	−1.521	−1.214	0.02
4	−0.364	−4.053	0.23	−3.708	−3.047	0.15	−0.000	−0.001	0.00	−2.669	−2.268	0.08
8	−0.489	−4.398	0.33	−3.778	−3.111	0.23	−0.019	−0.150	0.00	−2.913	−2.430	0.14

The panels correspond to quarterly sample of 1949.1–1999.4. The left-hand panels are regressions of future valuation ratios on consumption uncertainty. The regressor is a measure of *ex-ante* consumption volatility, $\sigma_{c,t-1,J} \equiv \log(\sum_{i=1}^{J}|\eta_{c,t-i}|)$, where consumption residuals, $\eta_{c,t}$, are obtained from $g_{c,t} = \mu + A_1 g_{c,t-j} + \eta_{c,t}$. The right-hand panels are regressions of future valuation ratios on market volatility on. The regressor is a measure of market volatility, $\sigma_{r_m,t-1,J} \equiv \log(\sum_{i=1}^{J}|\eta_{r_m,t-i}|)$, where r_m is the market return, and $\eta_{r_m,t}$ is the residual from the regression, $r_{m,t} = \mu + A_1 r_{m,t-j} + \eta_{r_m,t}$.
In the regression in Panel A, volatility predicts future price–dividend ratios, $p_t - d_t = b_0 + b_{\sigma,J}X_{t-1,J} + u_t$, for $J = 1, 4, 8$. In the regression in Panel B, volatility predicts future price–earnings ratio, $p_t - e_t = b_0 + b_{\sigma,J}X_{t-1,J} + u_t$, for $J = 1, 4, 8$, where $X_{t,J} = \{\sigma_{c,t,J}, \sigma_{r,t,J}\}$, in the left and right column blocks respectively—all standard errors are Newey–West with lag length J. The $t(2.5\%)$, $t(5\%)$ and $\bar{R}^2(95\%)$ correspond to the respective percentiles of the empirical distribution of the t-statistics and $\bar{R}^2$ based on a Monte-Carlo with 20,000 replications. The Monte-Carlo is designed so that valuation ratios are independent from volatility. Further details regarding the Monte-Carlo are given in the text in Section 4.2.

t-statistics (R^2s) of the Monte-Carlo based empirical distribution. This suggests that our test statistics in the data are very significant and support the predictions of our model.

For the case of consumption uncertainty, $\sigma_{c,t-1,J}$, the sign as predicted by our economic model is negative and all estimates have significant (at 2.5%) robust t-statistics. Moreover, these t-statistic are also significant with respect to the 2.5 percentile of the distribution of t-statistics in our Monte-Carlo. The R^2 in these regression rise to 26% for price–dividend ratios, and 33% for price–earnings ratios for horizon for $J = 8$ quarters. Again, these R^2 are always larger than the 95 percentile of R^2 in the Monte-Carlo—indicating that the R^2s in the data are significant. Finally, in the upper subplot in Fig. 1 we plot the normalized measure of consumption volatility, i.e., $\log(\sum_{j=1}^{J}|\eta_{c,t-j}|)$, and the normalized price–earnings ratio. The negative correlation between these two series is visibly striking. Analogous results with market volatility are substantially weaker—the projection coefficients are negative but not significantly different from zero. Overall the evidence above
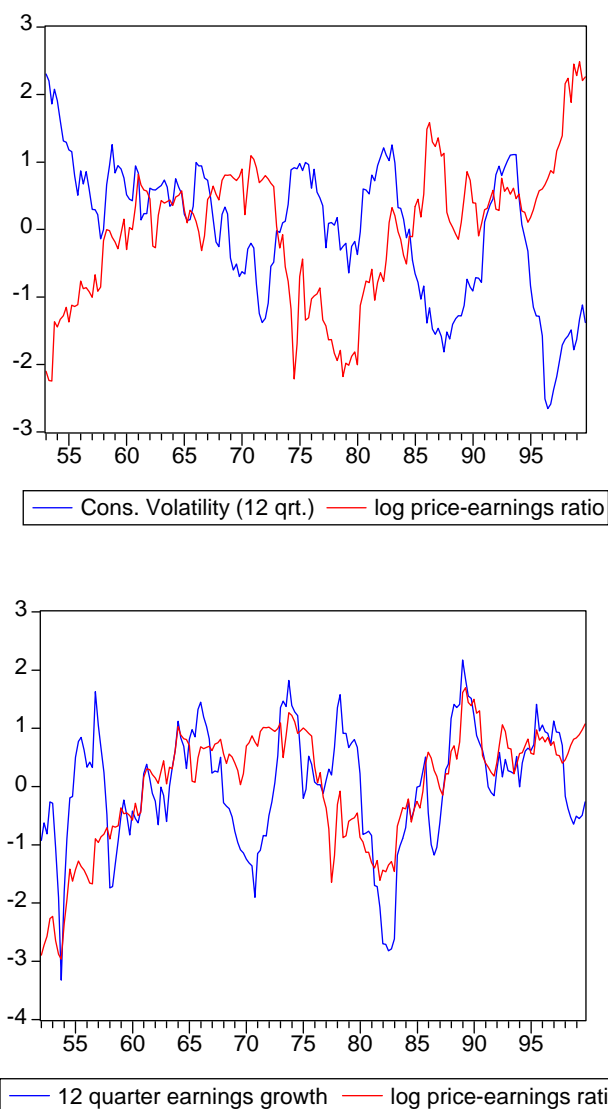
Fig. 1. Earnings growth, P/E ratios, and consumption volatility: USA. The top panel plots consumption volatility, $\sigma_{c,t-1,12}$, against log price–earnings, $(p_t - e_t)$. The bottom panel plots earnings growth $e_t - e_{t-12}$, against $p_{t-12} - e_{t-12}$. All variables are standardized (demeaned and divided by standard deviation).

suggests that fundamental measure of economic uncertainty, as captured by consumption volatility, is priced in the market. Negative slope coefficients imply that a rise in economic uncertainty leads to a fall in asset valuations—that is, financial markets dislike economic uncertainty.

Table 4
Valuation ratios predicting future economic uncertainty: USA

J	Predicting $|\eta_{c,t+J}|$						Predicting $|\eta_{r_m,t+J}|$					
	Data			Monte-Carlo			Data			Monte-Carlo		
	$a_{1,J}$	t-stat	$\bar{R}^2$	t (2.5%)	t (5%)	$\bar{R}^2$(95%)	$a_{1,J}$	t-stat	$\bar{R}^2$	t (2.5%)	t (5%)	$\bar{R}^2$(95%)
Panel A: Price–dividend ratio												
1	−1.012	−4.027	0.08	−3.200	−2.661	0.04	−0.592	−1.760	0.02	−2.322	−1.929	0.02
4	−0.788	−3.064	0.04	−3.059	−2.553	0.04	−0.194	−0.549	0.00	−2.353	−1.935	0.02
8	−0.796	−3.130	0.04	−3.035	−2.501	0.04	0.117	0.330	0.00	−2.434	−1.997	0.02
Panel B: Price–earnings ratio												
1	−0.806	−4.899	0.10	−3.121	−2.602	0.04	−0.154	−0.713	0.00	−2.378	−1.976	0.02
4	−0.629	−3.772	0.05	−3.066	−2.530	0.04	−0.034	−0.154	0.00	−2.392	−1.985	0.02
8	−0.594	−3.590	0.04	−3.062	−2.518	0.04	−0.017	−0.087	0.00	−2.465	−2.053	0.02

The panels correspond to quarterly sample of 1949.1–1999.4. The table entries provide regression results for predicting *realized* future economic uncertainty by current valuation ratios. The regressor in Panel A is the price–dividend ratio, and in Panel B is the price–earnings ratio. The measure of economic uncertainty in the left-hand panels is realized consumption volatility $|\eta_{c,t+J}|$, and market volatility $|\eta_{r_m,t+J}|$ in the right-hand panels, where consumption residuals, $\eta_{c,t}$, are obtained from $g_{c,t} = \mu + A_1 g_{c,t-1} + \eta_{c,t}$. The regressions are $Y_{t+J} = \alpha_0 + \alpha_{1,J} X_t + u_{t+J}$ for $X_t = \{p_t - d_t, p_t - e_t\}$, and $Y_{t+J} = \{|\eta_{c,t+J}|, |r_{m,t+J}|\}$, $J = 1, 4, 8$—all standard errors are Newey–West with J lags. The $t(2.5\%)$, $t(5\%)$ and $\bar{R}^2(95\%)$ correspond to the respective percentiles of the empirical distribution of the t-statistics and $\bar{R}^2$ based on a Monte-Carlo with 20,000 replications. The Monte-Carlo is designed so that valuation ratios are independent from volatility. Further details regarding the Monte-Carlo are given in the text in Section 4.3.

4.3. Valuation ratios predict economic uncertainty

Next, we document that in addition to the fact that realized volatility helps predicting future valuation ratios (price–dividend and price–earnings ratios), current valuation ratios are useful in predicting future realized volatility, $|\eta_{c,t+J}|$. This suggests that current financial valuations embody useful information for predicting future economic uncertainty—and that consumption volatility is time-varying. In Table 4 we display results for the regression in Eq. (5). The results based on consumption volatility (left columns) clearly display the fact that volatility is predicted by both price–dividend ratios (panel A) and price–earnings ratios (panel B). Again, as predicted by our model, the signs are negative and are significant at the 1% for horizons of one, four and eight quarters. Moreover, the R^2s are 4–10% for each of these horizons. It is important to realize that in these regressions the dependent variable is a single realized volatility. It is clear from the R^2s that if one would regress sums of future realized volatilities on the current valuation ratios the R^2s would further rise substantially with horizons.

Using the same Monte-Carlo set-up as described above we also provide the finite sample distribution for the test statistics—note in the Monte-Carlo, the projection coefficients should be zero. Again, this supports our claim that the t-statistic and the R^2s in the data for these projections are significant. In all, these results demonstrate

that future economic uncertainty is long-lasting and hence can be predicted by current valuation ratios. It is again important to note that once market volatility is used as the measure of economic uncertainty (right columns), the results are no longer significant. This indicates that consumption volatility is a good barometer of fundamental economic uncertainty.[6]

4.4. GARCH consumption volatility and robustness of results

An important econometric issue is that valuation ratios and consumption volatility are fairly persistent processes. This may lead to spurious regression results (e.g., Granger and Newbold, 1986; Hodrick, 1992; Stambaugh, 1999). To address this issue we use the AR(1)-GARCH(1,1) consumption dynamics to measure consumption volatility. To account for the persistence is variables we also include distributed lags of the dependent variable in our projections. Hence we consider

$$p_t - e_t = \alpha_{1,0} + \alpha_{1,1}(p_{t-1} - e_{t-1}) + \alpha_{1,2} \log \sigma_{c,t-1}^2 + \varepsilon_{1,t}, \tag{8}$$

$$\log \sigma_{c,t}^2 = \alpha_{2,0} + \alpha_{2,1}(p_{t-1} - e_{t-1}) + \alpha_{2,2} \log \sigma_{c,t-1}^2 + \varepsilon_{2,t}, \tag{9}$$

where $\log \sigma_{c,t}^2$, is the log of the conditional volatility process for consumption based on the AR(1)-GARCH(1,1) process (see Eq. (7)). Evidence based on these projections mitigate the possibility of spurious regressions. The parameter $\alpha_{1,2}$ provides information on whether volatility is important for predicting valuation ratios. This is the counterpart to Eq. (4). Similarly, the coefficient $\alpha_{2,1}$ provides information on whether valuation ratios predict future economic uncertainty. This is the counterpart to Eq. (5). All standard errors and *t*-statistics are constructed using a 2-step GMM estimator, which takes account of the estimation error in estimating the AR(1)-GARCH(1,1) process for consumption growth.

The results are given in Table 5. The first two columns of Panel A provide data estimates, while the rest provide Monte-Carlo based estimates. As before the Monte-Carlo takes the conservative view that valuation ratios are unaffected by uncertainty. To provide a Monte-Carlo distribution for our test statistics, as before, we simulate a univariate AR(1) process for the valuation ratio under consideration, which is independent of the consumption growth rate process. Further, we draw from the AR(1)-GARCH(1,1) consumption dynamics reported in Table 2 and for each draw fit an AR(1)-GARCH(1,1) model. The length of each draw is the same as our sample size in the data. We use, as in the data, a 2-step GMM estimator to construct the finite sample distribution for the *t*-stats.

Evidence in Panel A in Table 5 shows that our results are robust to the inclusion of distributed lags of the variable. As predicted by our model, the coefficient $\alpha_{1,2}$ continues to be significantly negative. Further, the data's *t*-stat of -2.08 is well below the 2.5 percentile of *t*-stats in the Monte-Carlo. Panel B provides analogous results for the projection in which price–earnings ratio predicts future volatility. As Panel B

---

[6]Using an analogous volatility measure based on GDP residuals leads to similar results as the consumption based volatility.

Table 5
Price–earnings ratios and economic uncertainty USA

	Data			Monte-Carlo			
	Est.	t-stat	$\bar{R}^2$	t (2.5%)	t (5%)	$\bar{R}^2(95\%)$	$\bar{R}^2(97.5\%)$
Panel A: Predicting price–earnings ratio							
$p_t - e_t = \alpha_0 + \alpha_1 \log \sigma^2_{c,t-1} + \varepsilon_t$							
α_1	−0.503	−5.08	0.34	−2.93	−2.40	0.22	0.28
$p_t - e_t = \alpha_{1,0} + \alpha_{1,1}(p_{t-1} - e_{t-1}) + \alpha_{1,2} \log \sigma^2_{c,t-1} + \varepsilon_{1,t}$							
$\alpha_{1,2}$	−0.035	−2.08	0.94	−1.78	−1.50	0.96	0.97
$\alpha_{1,1}$	0.937	40.32					
Panel B: Predicting volatility							
$\log \sigma^2_{c,t-1} = \alpha_0 + \alpha_2(p_{t-1} - e_{t-1}) + \varepsilon_t$							
α_2	−0.705	−4.60	0.36	−2.45	−2.05	0.23	0.29
$\log \sigma^2_{c,t} = \alpha_{2,0} + \alpha_{2,1}(p_{t-1} - e_{t-1}) + \alpha_{2,2} \log \sigma^2_{c,t-1} + \varepsilon_{2,t}$							
$\alpha_{2,1}$	−0.128	−2.95	0.84	−1.55	−1.34	0.93	0.94
$\alpha_{2,2}$	0.856	26.67					

The consumption volatility measure is $\log \sigma^2_{c,t}$—the log of the conditional volatility estimated by an AR(1)-GARCH(1,1) in panel C of Table 2. The Monte-Carlo columns provide statistics based on 20,000 simulations. The $t(2.5\%)$ and $t(5\%)$ and $\bar{R}^2(95\%)$, $\bar{R}^2(97.5\%)$ are the respective t-stat and $\bar{R}^2$ percentiles in the Monte-Carlo's empirical distribution. The Monte-Carlo is designed so price–earnings ratio is independent of the consumption volatility—further details are given in the text in Section 4.4.

demonstrates, the inclusion of distributed lag makes no difference to our results. The t-stat of −2.95 on $\alpha_{2,1}$, is highly significant in the data.

We have also reported the regressions with the GARCH based consumption volatility where the distributed lags of the left hand variable are dropped. In Panel A of Table 5 we show that this regression produces results that strongly support our earlier evidence. The data estimate of the t-statistic is −5.08 and significant at 2.5% cutoff based on the Monte-Carlo distribution. The regression where the valuation ratio is used to predict consumption volatility is also of the right sign and highly significant in the data. In the data the t-statistic is −4.60, the 2.5% cutoff based on the Monte-Carlo empirical distribution for the t-statistic is −2.5. This GARCH volatility based evidence is similar in its content and stronger to that discussed in Sections 4.2 and 4.3. In all, Table 5 strongly confirms the previous univariate projections based on the non-parametric volatility measure.

5. Additional implications and empirical evidence

5.1. Growth rate and return predictability

It is well recognized that the variation in asset valuation is due to variation in expected growth rates and/or variation in expected returns (see Eq. (2)). In this

section we briefly provide evidence pertaining to the predictability of returns and cash flows. This evidence in conjunction with that in Section 4 is useful in interpreting asset markets from the vantage of economic models discussed below in Section 6.

We consider the following growth-rate predictability projection:

$$\sum_{l=1}^{L} g_{y,t+l} = \beta_0 + \beta_{1,L}(p_t - y_t) + u_{t+L}, \quad L \geqslant 1, \tag{10}$$

and the companion return projection

$$\sum_{l=1}^{L} r_{t+l} = a_0 + a_{1,L}(p_t - y_t) + u_{t+L}, \quad L \geqslant 1. \tag{11}$$

Given Eq. (2), these projections imply that the variance of $p_t - y_t$ attributable to growth rates is $\beta_g(L) = \beta_{1,L,\kappa}/(\beta_{1,L,\kappa} - a_{1,L,\kappa})$, and the part attributable to fluctuations in returns is $-a_{1,L,\kappa}/(\beta_{1,L,\kappa} - a_{1,L,\kappa})$, where here the explicit dependence on κ denotes scaling of the elements of the dependent variable by κ as implied by Eq. (2).[7]

The R^2s of projections (10) and (11) are important for interpreting asset markets. For example, if the R^2 in the growth rate regression is fairly small, then almost all of the variation in $p_t - y_t$ must come from variation in expected returns. In this case, the R^2s of the return projection (11) must be large. If the R^2s of the growth rate projection (10) are large, this implies that growth rates are predictable. In fact this channel is the focus of the work of Barsky and DeLong (1993), Bansal and Lundblad (2002), Bansal and Yaron (2000), and Hall (2001), who argue that fluctuations in expected growth rates are quantitatively important for understanding asset markets. In contrast, Campbell and Cochrane (1999), Barberis et al. (2001), and Shiller (1989) provide models where almost all of the variation in asset prices is due to fluctuations in expected returns.[8]

In Table 6 we provide regression results for predicting dividends and earnings growth rates by valuation ratios—this is a version of Eq. (10) for these growth rates. Our main point is that, empirically, dividends behave very differently from earnings. The results for predicting dividend growth (middle columns) replicate what is found in the literature—that is dividend growth is not predictable by price–dividend ratios. This is also true for trying to predict dividend growth using price–earnings ratio. Earnings growth, however, is predicted by price–dividend ratios, and in a sizable and significant manner by price–earnings ratios (left columns). In particular, using the

---

[7] As in Campbell and Cochrane (1999) our focus is in understanding the sources of variation of price–dividend ratios. Hence, in Eq. (11) the dependent variable is the level of returns as oppose to excess returns. As a practical matter using excess returns makes no material difference to our empirical work.

[8] Given the direct link between the parameters and the definition of R^2, and in particular assuming $\beta_{1,L} \geqslant 0$ and $-a_{1,L} \geqslant 0$, which is the typical case in the data, it follows that

$$\text{Var}(p_t - y_t) = \left\{ \text{Var}(p_t - y_t)\text{Var}\left(\sum_{l=1}^{L} g_{y,t+l}\right) R_g^2 \right\}^{1/2} + \left\{ \text{Var}(p_t - y_t)\text{Var}\left(\sum_{l=1}^{L} r_{t+l}\right) R_r^2 \right\}^{1/2},$$

where R_g^2 and R_r^2 refer to the R^2s of the projections in Eqs. (10) and (11), respectively.

Table 6
Valuation ratios predicting future growth rates and returns: USA

J	Predicting $\sum_{i=1}^{J} g_{e,t+i}$			Predicting $\sum_{i=1}^{J} g_{d,t+i}$			Predicting $\sum_{i=1}^{J} r_{m,t+i}$		
	$\beta_{1,J}$	t-stat	$\bar{R}^2$	$\beta_{1,J}$	t-stat	$\bar{R}^2$	$a_{1,J}$	t-stat	$\bar{R}^2$
Panel A: *Price–dividend ratio*									
4	0.059	0.802	0.01	0.001	0.054	0.00	−0.139	−2.071	0.06
8	0.120	0.819	0.02	−0.015	−0.462	0.00	−0.256	−2.102	0.11
12	0.237	1.366	0.07	−0.041	−1.327	0.01	−0.366	−1.931	0.15
16	0.325	1.333	0.11	−0.084	−1.941	0.03	−0.494	−1.846	0.20
Panel B: *Price–earnings ratio*									
4	0.095	1.485	0.06	−0.017	−0.971	0.01	−0.074	−1.533	0.03
8	0.195	1.650	0.14	−0.027	−0.937	0.01	−0.149	−1.646	0.07
12	0.287	2.284	0.23	−0.036	−1.310	0.02	−0.195	−1.521	0.09
16	0.350	2.071	0.31	−0.058	−1.649	0.04	−0.272	−1.586	0.15

The panels correspond to quarterly sample of 1949.1–1999.4. Table entries are for predicting future growth rates by current valuation ratios. The left-hand panels predict earnings growth $\sum_{i=1}^{J} g_{e,t+i}$, the middle panel predict dividend growth $\sum_{i=1}^{J} g_{d,t+i}$, and the right-hand panel predicts returns $\sum_{i=1}^{J} r_{m,t+i}$. The regressors are the price–dividend ratio and the price–earnings ratio. The regressions are $\sum_{i=1}^{J} g_{l,t+i} = \beta_0 + \beta_{1,J} X_t + u_{t+J}$ where $X_t = \{p_t - d_t, p_t - e_t\}$, and $g_{l,t}, l = e, d$, and analogous regression for $\sum_{i=1}^{J} r_{m,t+i}$. All standard errors are Hodrick (1992) corrected with J lags.

price–earnings ratio to predict earnings growth yields positive slope coefficients with R^2s as high as 23% at a horizon of 12 quarters, and 31% at an horizon of 16 quarters. Table 7 provides the Monte-Carlo results for earnings growth. We let earnings growth follow an AR(1) that is independent of the price–earnings ratio.[9] The table clearly shows that at least for horizons of 8 quarters or more both the t-stats and R^2s are significant (at the 90%) with respect to the Monte-Carlo empirical distribution. Finally, the bottom panel in Fig. 1 displays a tight positive link between price–earnings and earnings growth. As price–earnings ratios predict future earnings with a positive and significant slope coefficient, financial markets like higher expected growth. This is also consistent with the views and evidence documented in Bansal and Yaron (2000), Bansal and Lundblad (2002), Hall (2001), and Ang and Bekaert (2001).

Table 6 (right columns) reports results for predicting market returns using price–dividends (panel A) and price–earnings ratio (panel B). The results replicate the well known findings of return predictability by price–dividend ratios. These are significant and rise with horizon.[10] On the other hand, price–earning ratios predict returns with R^2s that are substantially smaller than when price–dividend ratios are

---

[9]Using the data estimates, earnings growth rates are generated with the following AR(1) parameters: an intercept of 0.002, an autoregressive coefficient of 0.201, and an innovation standard deviation of 0.067.

[10]See Stambaugh (1999), Goyal and Welch (2003), Torous and Valkanov (2000), for recent discussions on inference difficulties in the context of this regression.

Table 7
Price–earnings ratio and growth rates

J	Data			Monte-Carlo			
	$\beta_{1,J}$	t-stat	$\bar{R}^2$	t (90%)	t (95%)	t (97.5%)	$\bar{R}^2$(95%)
$\sum_{i=1}^{J} g_{e,t+i} = \beta_0 + \beta_{1,J}(p_t - e_t)$							
4	0.095	1.485	0.06	1.609	2.033	2.425	0.07
8	0.195	1.650	0.14	1.638	2.115	2.506	0.13
12	0.287	2.284	0.23	1.733	2.194	2.615	0.20
16	0.350	2.071	0.31	1.790	2.274	2.709	0.27

This table provides Monte-Carlo evidence for the predicting earnings growth. The t(90%), t(95%) and $\bar{R}^2$(95%) correspond to the respective percentiles of the empirical distribution of the t-statistics and $\bar{R}^2$ based on a Monte-Carlo with 20,000 replications. Both data and Monte-Carlo use Hodrick (1992) standard errors with J lags. Further details regarding the Monte-Carlo are given in the text in Section 5.1.

used. For each horizon, these R^2 are significantly smaller than the corresponding R^2s for predicting future earnings growth.

What are the implications of these results? A common view, driven by the focus on price–dividend ratios, is that fluctuations in cost of capital and not in cash flows are the key for explaining fluctuations in asset valuations. In fact, Cochrane (1992) and Campbell and Cochrane (1999) advocate that about 100% (or more) of the fluctuations in price–dividend ratios are attributable to cost of capital. Our evidence for dividends coincides with this. Specifically, the percentage of the variance of price–dividend ratios that is explained by dividend growth rates at a 12 quarter horizon is $\beta_g(12) = -0.13$ (see the expression for $\beta_g(L)$ below Eq. (11), where we scaled the elements of the dependent variable by $\kappa_1 = 0.9967$—as in Campbell and Shiller (1988)) with standard error 0.15, and at a 16 quarter horizon, $\beta_g(16) = -0.20$ with standard error of 0.16. Considerable caution should be exercised in interpreting this evidence; Bansal and Yaron (2000) show that in a model where dividend growth is predictable at long horizons, the current price–dividend will have considerable difficulty in detecting this predictability. The capacity of price–dividend ratios to predict future dividend growth is muted by the effects of other state variables (such as consumption volatility) on the current price–dividend ratios. Lettau and Ludvigson (2002) provide additional reasons why it may be difficult for current price–dividend ratios to predict future dividend growth rates, even if future dividend growth rates are predictable.

However our evidence based on earnings casts an important question mark regarding the economic interpretation from the dividends based evidence. About 60% of the fluctuations in price–earnings ratios are driven by earnings growth rates while the rest (about 40%) is driven by fluctuations in costs of capital. Specifically, based on the 12 quarter results, $\beta_g(12) = 0.60$ with a standard error of 0.17. The comparable results for 16 quarter horizons are $\beta_g(16) = 0.56$ with a standard error of 0.16. This indicates that if one broadens the notion of cash-flows to include earnings,

the economic conclusions are quite opposite to those based on cash-dividends. Earnings are more volatile and less managed relative to cash-dividends. Consequently, earnings may provide more valuable information regarding future growth prospects (expected growth). To us the main economic message is that current asset valuations provide information about future corporate profits (earnings).

As both parameters, $a_{1,L}$ (slope from the return regression (11)) and $b_{\sigma,J}$ (slope from regression (4)) are negative, it follows that the implied slope coefficient in the return projection in Eq. (3) is positive. For example, with J the lag length used to construct consumption volatility fixed at 8, and $L = 4$ the horizon at which the market return is predicted, the coefficient in the return regression (3) is 0.036 with standard error (0.018) and with $L = 8$ is 0.073 (0.040).[11] Hence, a rise in consumption volatility increases the expected return on the market. When consumption volatility is replaced by market volatility the slope coefficients are essentially zero. It seems that at least with simple measures of volatility, the connection between consumption volatility and expected returns is stronger. Finally, as discussed earlier about 45% of the variation in price–earnings can be attributed to fluctuations in cost of capital—our evidence suggests that about half of this can be attributed to variation in consumption volatility.[12] Hence, an economicallysignificant portion of the variability is cost of capital may indeed be due to fluctuating economic uncertainty (consumption volatility).

In summary, the evidence of a negative relationship between consumption volatility and valuation ratios, along with the finding that higher valuation ratios predict higher earnings growth, is consistent with the economic growth and the economic uncertainty channel discussed earlier. This evidence is interpreted from the perspective of economic models in Section 6 below.[13]

5.2. Evidence from other economies

To corroborate our evidence on the link between economic uncertainty, growth rates and valuation ratios we repeat our analysis above using data from the three

---

[11]Note that this approach is used because (i) measures of consumption volatility are quite persistent (ii) returns reflect almost the first difference of valuation ratios, and consequently are governed by the first difference of consumption volatility. This near first differencing makes it difficult to detect the effects of the level of consumption volatility on expected returns based solely on the projection of ex-post returns on consumption volatility. However, the level of consumption volatility directly governs the level of valuation ratios – hence the level relationship, as in projection (4), is more informative about the economic uncertainty channel.

[12]We arrive at this number by substituting for $p_t - y_t$ on the right-hand side of Eq. (11), the projection of $p_t - y_t$ onto consumption volatility in Eq. (4). Thus, $a_{1,L} * b_\sigma$ is the slope coefficient. Further, as b_σ is approximately 0.48, this implies that about half of the contribution of cost of capital variation to price–earnings is due to consumption volatility.

[13]Note that in the data expected growth of consumption and consumption volatility are virtually uncorrelated. The contemporaneous correlation is -0.09, hence the inclusion of expected growth measures in the consumption-volatility and asset valuation projections would make no difference to our empirical results. Analogously, including consumption volatility in the earnings growth projection would make no material difference either.

Table 8
Summary statistics: foreign economies

	$E(\cdot)$	$\sigma(\cdot)$	corr$(g_c, g.)$	$AC(4)$	$AC(8)$
Germany (1972.1–1998.2)					
g_c	0.005	0.012		0.154	−0.014
g_d	0.002	0.052	0.05	0.091	−0.073
g_e	0.004	0.118	0.11	−0.190	0.059
r_m	0.023	0.096		0.025	−0.082
$(p-d)$	4.580	0.361		0.754	0.593
$(p-e)$	1.601	0.460		0.712	0.534
Japan (1972.1–1998.2)					
g_c	0.008	0.014		0.100	0.189
g_d	−0.005	0.022	0.30	0.322	0.318
g_e	−0.008	0.092	−0.10	−0.086	−0.050
r_m	0.012	0.108		−0.071	−0.065
$(p-d)$	5.806	0.566		0.894	0.794
$(p-e)$	2.384	0.597		0.854	0.650
UK (1972.1–1998.2)					
g_c	0.005	0.015		0.006	0.115
g_d	0.003	0.036	0.16	0.028	0.074
g_e	0.005	0.059	0.17	−0.008	−0.253
r_m	0.021	0.108		−0.132	0.082
$(p-d)$	4.253	0.311		0.628	0.473
$(p-e)$	1.306	0.381		0.578	0.334

g_c, g_d, and g_e denote, respectively, the growth rate of real consumption, dividends, and earnings. r_m is the real return on the market portfolio. $p-d$ and $p-e$ denote the log price–dividend and price–earnings, respectively. $E(\cdot)$ and $\sigma(\cdot)$ denote the mean and standard deviation, and $AC(j)$ is the jth autocorrelation.

prominent foreign economies, Germany, Japan, and United Kingdom. The data statistics for these countries are given in Table 8. In addition to these countries, we also present results for the US for this shorter sample for comparability.

In Table 9 we present volatility results. The various panels correspond to the different countries. As each country would require its own parametric volatility model, we choose, for space considerations, to present results only with the non-parametric volatility measure $\sigma_{c,t-1,J}$. In the first two column blocks we present results for the way consumption volatility $\sigma_{c,t-1,J}$ predicts price–dividend and price–earnings ratios. The last two column blocks report results for predicting future realized volatility by price–dividend and price–earnings ratios. The results for Germany, the UK and the sub-sample of the US are broadly consistent with our previous findings. That is we find significant negative coefficients and large R^2s for economic uncertainty predicting future valuation ratios and in turn for current valuation ratios predicting future economic uncertainty. Japan is the only outlier where the results are not significant on some dimensions.

In Table 10 we report predictability results for returns, dividends and earnings growth for these international countries. Save for Japan, the results are comparable

Table 9
Valuation ratios and economic uncertainty: International

J	l.h.s: $p_t - d_t$ r.h.s: $\sigma_{c,t-1,J}$			$p_t - e_t$ $\sigma_{c,t-1,J}$			$\lvert\eta_{c,t+J}\rvert$ $p_t - d_t$			$\lvert\eta_{c,t+J}\rvert$ $p_t - e_t$		
	Est.	t-stat	$\bar{R}^2$	Est.	t-stat	$\bar{R}^2$	Est.	t-stat	$\bar{R}^2$	Est.	t-stat	$\bar{R}^2$
Panel A: Germany												
1	−0.052	−0.448	0.02	−0.080	−0.486	0.03	−0.554	−1.611	0.02	−0.794	−2.460	0.08
4	−0.279	−2.403	0.13	−0.301	−1.657	0.09	−0.507	−1.412	0.01	−0.655	−3.754	0.05
8	−0.447	−2.465	0.20	−0.385	−1.113	0.08	−0.489	−1.423	0.01	−0.539	−3.060	0.03
12	−0.586	−2.250	0.24	−0.497	−1.141	0.08	−0.534	−1.654	0.01	−0.630	−4.091	0.04
Panel B: Japan												
1	0.026	0.174	0.00	0.031	0.334	0.00	0.094	0.422	0.00	0.193	0.945	0.00
4	−0.036	−0.203	0.00	−0.064	−0.331	0.00	0.231	1.136	0.00	0.374	2.085	0.03
8	−0.231	−0.785	0.02	−0.307	−0.955	0.04	0.158	0.629	0.00	0.412	2.055	0.03
12	−0.424	−1.251	0.06	−0.540	−1.187	0.08	0.123	0.514	0.00	0.416	1.499	0.02
Panel C: UK												
1	−0.068	−0.905	0.05	−0.093	−1.070	0.06	−0.342	−1.038	0.00	−0.373	−1.489	0.01
4	−0.255	−2.842	0.20	−0.380	−3.804	0.32	−0.365	−0.830	0.00	−0.136	−0.424	0.00
8	−0.465	−7.150	0.41	−0.641	−7.966	0.55	−0.487	−1.130	0.01	−0.192	−0.570	0.00
12	−0.554	−8.736	0.55	−0.703	−5.737	0.66	−0.999	−2.204	0.06	−0.845	−3.263	0.08
Panel D: USA												
1	−0.019	−0.525	0.00	−0.039	−0.797	0.01	−0.548	−1.451	0.01	−0.699	−1.682	0.03
4	−0.220	−2.591	0.15	−0.257	−3.024	0.14	−0.380	−0.768	0.00	−0.646	−1.747	0.02
8	−0.338	−2.178	0.25	−0.372	−2.895	0.22	−0.376	−0.615	0.00	−0.562	−1.620	0.01
12	−0.366	−1.871	0.24	−0.417	−2.836	0.23	−0.425	−0.612	0.00	−0.491	−1.250	0.01

The panels correspond to quarterly sample of 1972.1–1998.2. Regressions in left column block are $p_t - d_t = b_0 + b_{\sigma,J}\sigma_{c,t-1,J} + u_t$, for $J = 1, 4, 8, 12$. Regressions in second from left panel are $p_t - e_t = b_0 + b_{\sigma,J}\sigma_{c,t-1,J} + u_t$, for $J = 1, 4, 8, 12$, where $\sigma_{c,t-1,J} \equiv \log(\sum_{i=1}^{J}\lvert\eta_{c,t-i}\rvert)$. Regressions in third from left panel are $\lvert\eta_{c,t+J}\rvert = \alpha_0 + \alpha_{1,J}(p_t - d_t) + u_{t+J}$, for $J = 1, 4, 8, 12$. Regressions in right panel are $\lvert\eta_{c,t+J}\rvert = \alpha_0 + \alpha_{1,J}(p_t - e_t) + u_{t+J}$, for $J = 1, 4, 8, 12$. The panel for the United States corresponds to the sample for the other countries. All standard errors are Newey–West with J lags.

to those that we document in the US for the entire sample. It is worth mentioning that for the shorter US sample, the return predictability results for price–dividend and price–earnings ratios become insignificant. On the other hand earnings growth during this period are significantly predictable with R^2 as large as 47% at the 12 quarter horizon. Hence in the post 1972 sample almost all of the variation in valuation ratios is determined by fluctuations in expected growth rates.

The six subplots in Fig. 2 display the link between price–earnings, earnings growth, and consumption volatility. The pronounced negative correlation between uncertainty and valuation seen for the US is apparent for these countries as well. In addition the positive relation between valuation ratios and future earnings growth is evident as well. Overall the message is quite clear. Our evidence for the longer US

Table 10
Valuation ratios and growth rates: International

J	l.h.s: $\sum_{j=1}^{J} g_{d,t+j}$ r.h.s: $p_t - d_t$			$\sum_{j=1}^{J} g_{e,t+j}$ $p_t - e_t$			$\sum_{j=1}^{J} r_{m,t+j}$ $p_t - d_t$			$\sum_{j=1}^{J} r_{m,t+j}$ $p_t - e_t$		
	Est.	t-stat	$\bar{R}^2$	Est.	t-stat	$\bar{R}^2$	Est.	t-stat	$\bar{R}^2$	Est.	t-stat	$\bar{R}^2$
Panel A: *Germany*												
4	0.159	2.436	0.26	0.264	1.359	0.14	0.026	0.235	0.00	0.029	0.502	0.00
8	0.267	2.066	0.30	0.452	1.490	0.22	−0.002	−0.008	0.00	0.070	0.724	0.00
12	0.316	1.743	0.27	0.527	1.450	0.20	−0.026	−0.083	0.00	0.111	0.885	0.01
16	0.324	1.321	0.22	0.310	0.853	0.04	−0.106	−0.250	0.00	−0.060	−0.237	0.00
Panel B: *Japan*												
4	0.048	3.150	0.24	0.077	1.037	0.03	−0.043	−0.510	0.00	−0.053	−0.839	0.01
8	0.088	3.052	0.29	0.110	1.201	0.02	−0.103	−0.622	0.02	−0.128	−1.019	0.04
12	0.105	2.653	0.26	0.026	0.206	0.00	−0.216	−0.877	0.08	−0.282	−1.254	0.11
16	0.105	1.998	0.18	−0.190	−1.145	0.02	−0.361	−1.144	0.16	−0.546	−1.597	0.24
Panel C: *UK*												
4	0.110	2.741	0.13	0.287	2.825	0.34	−0.238	−1.275	0.08	−0.134	−0.887	0.04
8	0.169	2.916	0.14	0.465	3.093	0.39	−0.339	−1.442	0.10	−0.230	−1.282	0.07
12	0.171	2.465	0.10	0.406	2.574	0.24	−0.458	−1.648	0.19	−0.291	−1.562	0.12
16	0.126	1.522	0.05	0.373	2.236	0.19	−0.523	−1.496	0.21	−0.349	−1.593	0.15
Panel D: *USA*												
4	0.014	1.112	0.00	0.195	2.363	0.19	−0.093	−0.869	0.01	−0.000	−0.003	0.00
8	0.014	0.539	0.00	0.376	2.443	0.34	−0.200	−0.960	0.03	−0.025	−0.130	0.00
12	−0.014	−0.334	0.00	0.520	2.328	0.47	−0.214	−0.767	0.03	0.039	0.152	0.00
16	−0.043	−0.941	0.00	0.652	2.320	0.60	−0.321	−0.890	0.07	0.060	0.187	0.00

The panels correspond to quarterly sample of 1972.1–1998.2. Regressions in first panel columns are $\sum_{j=1}^{J} g_{d,t+j} = \beta_0 + \beta_{1,J}(p_t - d_t) + u_{t+J}$, for $J = 4, 8, \ldots, 16$. Regressions in second from left panel are $\sum_{j=1}^{J} g_{e,t+j} = \beta_0 + \beta_{1,J}(p_t - e_t) + u_{t+J}$, for $J = 4, 8, \ldots 16$. Regressions in third from left panel are $\sum_{j=1}^{J} r_{m,t+j} = a_0 + a_{1,J}(p_t - d_t) + u_{t+J}$, for $J = 4, 8, 12, 16$. Regressions in right panel are $\sum_{j=1}^{J} r_{m,t+j} = a_0 + a_{1,J}(p_t - e_t) + u_{t+J}$, for $J = 4, 8, 12, 16$. The panel for the USA corresponds to the sample for the other countries. All standard errors are Hodrick (1992) corrected with J lags.

sample is generally also found in these foreign countries as well as the US subsample.

6. Interpreting the empirical evidence

In this section we provide a simple economic model that helps us interpret the empirical evidence presented in the previous sections. We do not attempt to formally test this model but rather use it as a vehicle for interpreting the data. We start by presenting an economic model (adapted from Bansal and Yaron, 2004) that
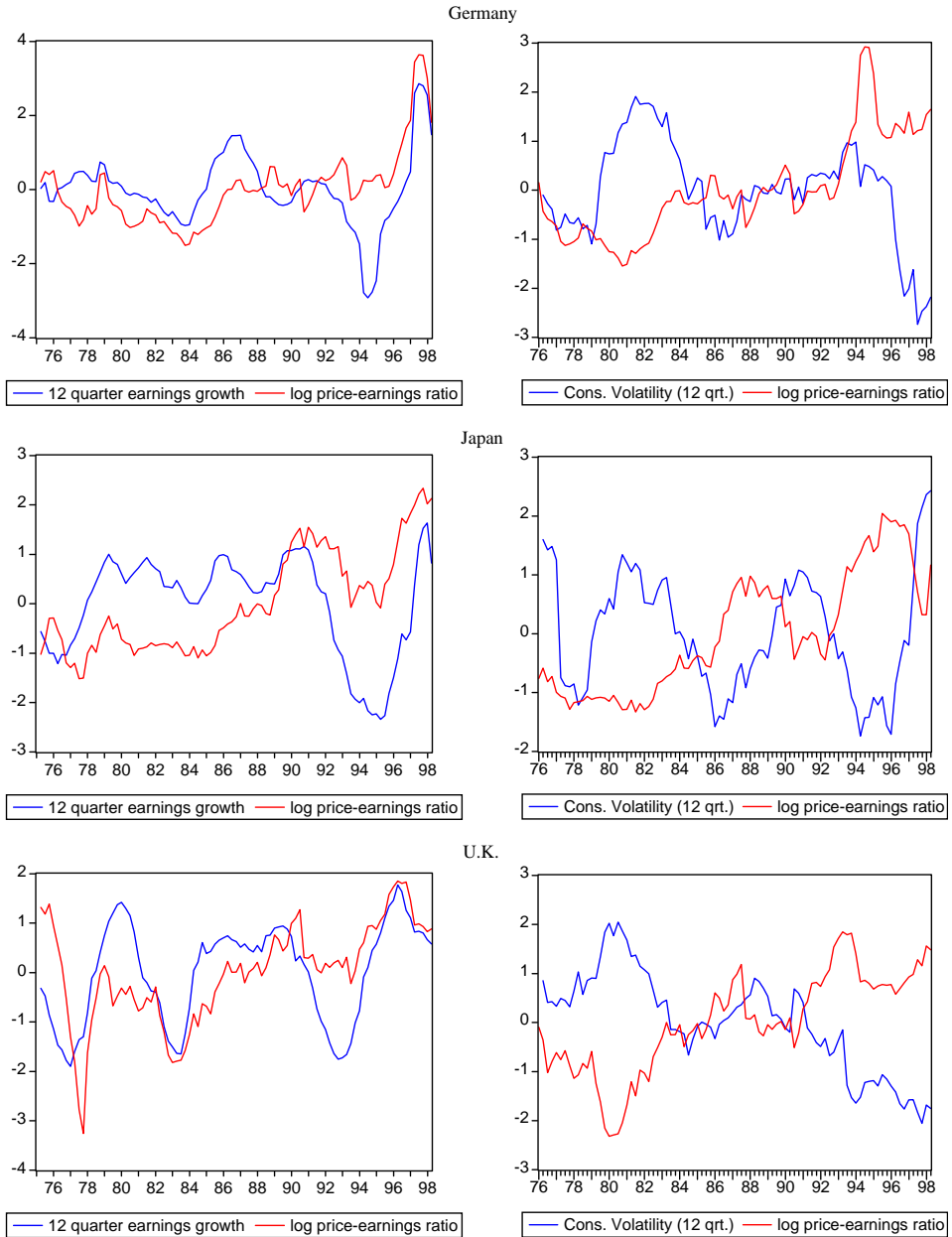
Fig. 2. Earnings growth, P/E ratios and consumption volatility: international. The right-hand plots display consumption volatility, $\sigma_{c,t-1,12}$, against log price–earnings, $(p_t - e_t)$. The left-hand plots display earnings growth $e_t - e_{t-12}$, against $p_{t-12} - e_{t-12}$. All variables are standardized (demeaned and divided by standard deviation).

highlights the importance of the channels related to fluctuating economic uncertainty and expected growth.

Let the process for aggregate consumption growth, $g_{c,t}$, follow

$$g_{c,t+1} = \mu + x_t + \sigma_{c,t}\eta_{t+1},$$
$$x_{t+1} = \rho x_t + \varphi_e \sigma_{c,t} e_{t+1},$$
$$\sigma_{c,t+1}^2 = \sigma^2 + v_1(\sigma_{c,t}^2 - \sigma^2) + \sigma_w w_{t+1}, \tag{12}$$

where x_t is the conditional expected growth rate, $\sigma_{c,t}^2$ is the conditional variance; and e_{t+1}, η_{t+1}, and w_{t+1}, are *i.i.d.* N(0, 1) shocks. Consider an endowment economy as in Lucas (1978) where the representative agent has Epstein and Zin (1989)–Weil (1990) preferences. In this economy the intertemporal marginal rate of substitution is

$$M_{t+1} = \exp\left(\theta \ln \delta - \frac{\theta}{\psi} g_{c,t+1} + (\theta - 1) r_{c,t+1}\right),$$

and the Euler condition for valuing any asset $r_{i,t+1} \equiv \log(R_{i,t+1})$ is

$$E_t\left[\exp\left(\theta \ln \delta - \frac{\theta}{\psi} g_{c,t+1} + (\theta - 1) r_{c,t+1} + r_{i,t+1}\right)\right] = 1. \tag{13}$$

The parameter ψ, is the intertemporal elasticity of substitution (IES), and $\theta = (1 - \gamma)/(1 - (1/\psi))$, with γ being the risk aversion parameter. The return, $r_{c,t+1}$, denotes the log return on wealth, which in this economy is simply the return on the claim to the consumption stream.

To make our point and keep the discussion brief we will focus on the asset valuation associated with the claim to the consumption stream. Consider $z_t = p_t - c_t$, the log price–consumption ratio, that is, the market value of the claim to the consumption stream relative to current consumption. Exploiting the Euler Equation (13), the solution for this asset valuation is $z_t = b_0 + b_x x_t + b_\sigma \sigma_{c,t}^2$, where

$$b_x = \frac{1 - (1/\psi)}{1 - \kappa_1 \rho}, \tag{14}$$

$$b_\sigma = \frac{0.5[(\theta - \theta/\psi)^2 + (\theta b_x \kappa_1 \varphi_e)^2]}{\theta(1 - \kappa_1 v_1)}. \tag{15}$$

It immediately follows that b_x is positive, that is, a rise in expected growth leads to an increase in the consumption valuation ratio only if ψ, the IES, is greater than one. In addition, if γ is also greater than one (i.e., $\theta < 0$), b_σ is negative—that is, a rise in volatility lowers the price–consumption ratio. This captures the intuition that when agents anticipate higher economic growth (all else held fixed), they buy more equity and drive up equity valuations. On the other hand when economic uncertainty rises, agents sell equity which drives down the asset valuations. Note that the CRRA power utility case (i.e., $\theta = 1$), implies that b_σ should be positive, and our empirical evidence cannot be supported by these preferences.

An implication of the above model is that current asset valuations should predict future economic uncertainty and future growth rates. These two implications are

empirically evaluated in Eqs. (5) and (10), respectively. Our empirical work shows that higher valuation ratios predict higher economic growth and lower future economic uncertainty (i.e., $b_x > 0$ and $b_\sigma < 0$). Interpreted from the perspective of the above model, this empirical evidence, is consistent with the case in which both IES and risk aversion are larger than one. Hall (1988) and Campbell (1999) argue that IES is below one, Hansen and Singleton (1982) find mixed evidence, while Attanasio and Webber (1989) estimate it to be well over one. More recently, Guvenen (2001), Vissing-Jorgensen (2002) and Attanasio and Vissing-Jorgensen (2003) also argue that the IES is above one. Our empirical evidence on the consumption-volatility and asset valuation link along with the evidence of predictability of earnings implies that the IES is larger than one.

Why are shocks to consumption volatility important for understanding risk premia? In the model with Epstein–Zin preferences volatility shocks carry a separate risk premium (details are given in Appendix B),

$$\text{E}_t[r_{c,t+1} - r_{f,t}] = \gamma\sigma_{c,t}^2 + \lambda_e B\sigma_{c,t}^2 + \lambda_w \kappa_1 b_\sigma \sigma_w^2 - 0.5\text{Var}_t(r_{c,t+1}), \tag{16}$$

where $B = \kappa_1 b_x \varphi_e$ is the asset exposure to expected growth rate news, $\lambda_e \equiv (1 - \theta)B$ is the market price of expected growth rate risk, $\lambda_w \equiv (1 - \theta)b_\sigma \kappa_1$ is the market price of volatility risk, and $\text{Var}_t(r_{c,t+1}) = (1 + B^2)\sigma_{c,t}^2 + (b_\sigma \kappa_1)^2 \sigma_w^2$ is the usual conditional variance of the return due to our use of continuous returns. The first term in the premium is the familiar *i.i.d.* case where risk aversion multiplies consumption volatility. The second term captures the exposure of the asset return to expected growth rate news, and the third term is the compensation for risk associated with fluctuating consumption volatility. It is worth noting that the compensation for volatility risk is absent in the case of power utility (when $\theta = 1$). With IES larger than one, and $\gamma > 1$, the market price for volatility risk is positive. The above discussion implies that generally risk premia is a linear affine function of consumption volatility, that is

$$\text{E}_t[r_{t+1} - r_{f,t}] = \gamma_0 + \gamma_1 \sigma_{c,t}^2 \tag{17}$$

which is the canonical equation for the risk premia as asserted in Eq. (3).[14]

6.1. Alternative interpretations

An alternative interpretation of asset markets is to rely on "stochastic risk aversion" (see for example Campbell and Cochrane, 1999; Barberis et al., 2001). Growth rates are assumed to be *i.i.d.*, but there is important time-variation in the risk preferences. That is, γ_1 is time varying (denoted as $\gamma_{1,t}$) and it approximately

---

[14]Specifically, in the example above and for the return on the consumption claim $\gamma_0 = [\lambda_w \kappa_1 b_\sigma - 0.5(b_\sigma \kappa_1)^2]\sigma_w^2$, and $\gamma_1 = \gamma + \lambda_e B - 0.5(1 + B^2)$. In Bansal and Yaron (2004) we show how to price a claim to dividends which is modelled as a levered claim on the consumption process containing additional independent shocks. Nonetheless, the general structure for the asset risk premium and its valuation ratio is analogous to the one presented in the example above.

follows a linear time-series process. In this case

$$p_t - y_t = b_0 + b_\gamma \gamma_{1,t}. \tag{18}$$

In external habit models, $\gamma_{1,t}$ could be determined by the history of past consumption growth rates.[15] Hence, valuation ratios may be related to observable past consumption growth rates. However, as the underlying cash-flow growth rates are *i.i.d.*, $b_\sigma = 0$. As there are no fluctuations in economic uncertainty, asset valuations, $p_t - y_t$, neither predict economic uncertainty nor are predicted by it. Further, current $p_t - y_t$ provides no information regarding future growth rates as growth rates are not forecastable. Consequently, conditions (i)–(iii) discussed above highlight some of the differences across these alternative interpretations for asset markets. We recognize that these differences across alternative interpretations can potentially be bridged by modifying the underlying cash-flow and/or preference processes. Nonetheless, our empirical work highlights which channels are quantitatively important for interpreting asset markets and thus can serve as a guide for any fruitful synthesis.

It is important to note that the stochastic risk aversion channel relies heavily on fluctuating expected returns to interpret asset markets—these fluctuations are related to the fluctuations in risk aversion of the agent. Fluctuations in the risk premia are also a part of the growth-uncertainty based models (see Eq. (16))—the risk premium fluctuations in this model are directly related to the fluctuating uncertainty in the economy. In both cases $p_t - y_t$ will predict the expected return of the market. Consequently, the regression of multi-horizon returns on $p_t - y_t$ (see Eq. (11)) *cannot* tell us if the sources of variation in the expected return are due to fluctuating risk-preferences or fluctuating economic uncertainty, that is $\sigma_{c,t}^2$. However, as discussed above, the link between price–cash-flow ratios and economic uncertainty is quite informative in discriminating across these alternative interpretations.

7. Conclusion

In this paper we show that measures of economic uncertainty (conditional volatility of consumption) predicts and is predicted by valuation ratios at long horizons. We show that asset valuations drop as economic uncertainty rises—that is, financial markets dislike economic uncertainty. Moreover, long horizon R^2s from predicting future economic growth (earnings growth) are fairly high for the US price–earnings ratios. Our overall evidence is consistently found across foreign economies as well. Our evidence suggests that about 55% of the variation in asset prices can be attributed to fluctuations in expected cash-flow growth and about 45% to expected return. We argue that the channels associated with fluctuating economic

---

[15]For example, in Campbell and Cochrane (1999) the intertemporal marginal rate of substitution are a function of consumption growth and the growth rate of the surplus ratio. The latter is a function of the habit level which is determined by past consumption.

uncertainty and economic growth are important for a reasonable interpretation of asset markets.

Appendix A. Data

A.1. USA

The data covers quarterly sample from 1949.1 till 1999.4. The following series are used to construct the valuation ratios, real rates of return on the market and real growth rates of dividends, earnings, and consumption:

- P: Total market value (in billions of dollars), Source: CRSP Indices (Stock File Index).
- P_{indx}: Stock price index on NYSE/AMEX. For each month, the price index is calculated as $P_{\text{indx},t} = (VWRETX_t + 1) \cdot P_{\text{indx},t-1}$ (where t is in months). The price index for a quarter is the price index for the last month of the quarter. VWRETX is the value weighted return on NYSE/AMEX excluding dividends, taken from CRSP.
- D_{indx}: Dividend index on NYSE/AMEX. Calculated as follows: the dividend yield for each month is calculated as $DY_t = (1 + VWRETD_t)/(1 + VWRETX_t) - 1$ (t is in months). The dividend for each month is calculated as $D_{\text{indx},t} = DY_t \cdot P_{\text{indx},t}$ (t is in months). The dividend for a quarter is the sum of the dividends for the 3 months comprising the quarter. VWRETD and VWRETX are, correspondingly, the value weighted return on NYSE/AMEX including and excluding dividends, taken from CRSP. The series are subsequently deseasonalized by taking a four period backward moving average of the series, i.e. $\bar{D}_{\text{indx},t} = \sum_{j=0}^{3} D_{\text{indx},t-j}$, where t is in quarters. This constructed dividend index is identical to that used by Campbell (1999).
- E: Corporate profits (earnings) after tax (in billions of dollars) = dividends in the corporate sector + undistributed profits in the corporate sector. Series includes all corporate businesses that belong to US residents. Source: NIPA Section 1, Table 1.14, line 24.
- E_{indx}: Corporate after-tax earnings index. Calculated as $E_{\text{indx},t} = P_{\text{indx},t-1} \cdot E_t/P_{t-1}$, where t is in quarters. Hence the earnings per dollar invested are E_t/P_{t-1}, and the amount invested at date $t-1$ is $P_{\text{indx},t-1}$. The present stream of

earnings E_{indx} (discounted at the rate of market return) is equal to the one dollar initial investment and is directly comparable to the D_{indx} described above. The correlation between the log growth of the earnings index and the log growth of the earnings series E is 0.99.

- C: Consumption of non-durables and services (in billions of dollars). Source: NIPA Section 1, Table 1.1, (line 4 + line 5).
- R_m: Net return on NYSE/AMEX: $R_{m,t} = (D_{\text{indx},t} + P_{\text{indx},t})/P_{\text{indx},t-1} - 1$, where t is in quarters. It is also possible to obtain the series by compounding monthly value weighted returns (including dividends).
- P_c: Deflator of non-durables consumption and services, inferred from NIPA Section 8, Table 8.7 as $P_c = (\text{line } 7 + \text{line } 8)/(\text{line } 14 + \text{line } 15) = $ (Per capita non-durable goods in current dollars + Services in current dollars)/ (Per-capita non-durable goods + services in chained (1996) dollars).

A.2. Foreign economies

The data covers quarterly sample from 1972.1 till 1998.2. The following series are used to construct the valuation ratios, real rates of return on the market and real growth rates of dividends, earnings, and consumption:

- P: Market capitalization (in local currency). Calculated as $P_t = P_t^{\$} \cdot ER_t$ using monthly data and taking the value in the last month of each quarter. ER_t is the monthly (end of period) nominal exchange rate in units of national currency per 1 US Dollar (source: IMF's International Financial Statistics CD-ROM); $P_t^{\$}$ is the market capitalization in US dollars (source: Morgan Stanley Capital International).
- P_{indx}: Stock price index (in local currency) at the end of each quarter. Source: Morgan Stanley Capital International (received from Prof. John Campbell).
- D_{indx}: Dividend index. Monthly index is calculated as $D_{\text{indx},t} = P_{\text{indx},t} \cdot DY_t$, where $P_{\text{indx},t}$ is the monthly stock price index and DY_t is the monthly dividend yield. $DY_t = \frac{R_{\text{indx},t}/R_{\text{indx},t-1}}{P_{\text{indx},t}/P_{\text{indx},t-1}} - 1$, where $R_{\text{indx},t}$ is the return index from Morgan Stanley Capital International, and time t in the equation is in months. The dividend index for a quarter, is the sum of the dividends for the three months comprising the quarter. The dividends are multiplied by 1.33 for the UK and by 1.5625 for Germany because of tax credits available to domestic investors (received from Prof. John Campbell).
- E: Corporate earnings (in local currency). Calculated as $E_t = (P_t^{\$}/PE_t) \cdot ER_t$ using monthly data and summing up over the three months of each quarter. ER_t is the monthly (end of period) nominal exchange rate in units of national currency per 1 US Dollar (source: IMF's International Financial Statistics CD-ROM); $P_t^{\$}$ is the market capitalization in US dollars (source: Morgan Stanley Capital International); PE_t is the price-to-earnings ratio (source: Morgan Stanley Capital International).

- E_{indx}: Corporate after-tax earnings index. Calculated as $E_{\text{indx},t} = P_{\text{indx},t-1} \cdot E_t / P_{t-1}$, where t is in quarters.
- C: Private consumption at current prices. This includes non-durables + services + durables. Source: IMF's International Financial Statistics CD-ROM (received from Prof. John Campbell).
- R_m: Net return on the market index. Calculated as $R_{m,t} = (D_{\text{indx},t} + P_{\text{indx},t})/P_{\text{indx},t-1} - 1$, where t is in quarters (received from Prof. John Campbell).
- P_c: Consumer price index in the last month of the quarter. Source: IMF's International Financial Statistics CD-ROM (received from Prof. John Campbell).

The resulting series are calculated as follows:

$$g_{d,t} = \log(D_{\text{indx},t}/P_{c,t}) - \log(D_{\text{indx},t-1}/P_{c,t-1}),$$
$$g_{e,t} = \log(E_{\text{indx},t}/P_{c,t}) - \log(E_{\text{indx},t-1}/P_{c,t-1}),$$
$$g_{c,t} = \log(C_t/P_{c,t}) - \log(C_{t-1}/P_{c,t-1}),$$
$$r_{m,t} = \log\left(\frac{1 + R_{m,t}}{P_{c,t}/P_{c,t-1}}\right),$$
$$(p_t - d_t) = \log(P_{\text{indx},t}/D_{\text{indx},t}),$$
$$(p_t - e_t) = \log(P_{\text{indx},t}/E_{\text{indx},t}).$$

Appendix B. Model derivation

The consumption process is given by

$$g_{c,t+1} = \mu + x_t + \sigma_{c,t}\eta_{t+1},$$
$$x_{t+1} = \rho x_t + \varphi_e \sigma_{c,t} e_{t+1},$$
$$\sigma_{c,t+1}^2 = \sigma^2 + v_1(\sigma_{c,t}^2 - \sigma^2) + \sigma_w w_{t+1}, \tag{19}$$

where x_t is the conditional expected growth rate, $\sigma_{c,t}^2$ is the conditional variance, and e_{t+1}, η_{t+1}, and w_{t+1}, are *i.i.d.* N(0, 1) shocks.

In this economy the intertemporal marginal rate of substitution is

$$M_{t+1} = \exp\left(\theta \ln \delta - \frac{\theta}{\psi} g_{c,t+1} + (\theta - 1) r_{c,t+1}\right),$$

and the Euler condition for valuing any asset $r_{i,t+1} \equiv \log(R_{i,t+1})$ is

$$E_t\left[\exp\left(\theta \ln \delta - \frac{\theta}{\psi} g_{c,t+1} + (\theta - 1) r_{c,t+1} + r_{i,t+1}\right)\right] = 1. \tag{20}$$

The parameter ψ, is the intertemporal elasticity of substitution (IES), and $\theta = (1 - \gamma)/(1 - \frac{1}{\psi})$, with γ begin the risk aversion parameter. The return, $r_{c,t+1}$, denotes the log return on the claim to the consumption stream.

B.1. The return on consumption portfolio, R_c

We conjecture that the log price–consumption ratio follows, $z_t = b_0 + b_x x_t + b_\sigma \sigma_t^2$. Armed with the endogenous variable z_t we substitute the approximation $r_{c,t+1} = \kappa_0 + \kappa_1 z_{t+1} - z_t + g_{c,t+1}$ into the Euler equation (20).

Since g_c, x and $\sigma_{c,t}^2$ are conditionally normal, $r_{c,t+1}$ and $\ln M_{t+1}$ are also normal. Exploiting the normality of $r_{c,t+1}$ and $\ln M_{t+1}$, we can write down the Euler equation (20) in terms of the state variables x_t and $\sigma_{c,t}$. As the Euler condition has to hold for all values of the state variables, it follows that all terms involving x_t must satisfy the following:

$$-\frac{\theta}{\psi} x_t + \theta[\kappa_1 b_x \rho x_t - b_x x_t + x_t] = 0. \tag{21}$$

It immediately follows that

$$b_x = \frac{1 - 1/\psi}{1 - \kappa_1 \rho} \tag{22}$$

which is (14) in the main text.

Similarly, collecting all the $\sigma_{c,t}^2$ terms leads to the solution for b_σ,

$$\theta[\kappa_1 v_1 b_\sigma \sigma_{c,t}^2 - b_\sigma \sigma_{c,t}^2] + \frac{1}{2}\left[\left(\theta - \frac{\theta}{\psi}\right)^2 + (\theta b_x \kappa_1 \varphi_e)^2\right]\sigma_{c,t}^2 = 0, \tag{23}$$

which implies that

$$b_\sigma = \frac{0.5[(\theta - \theta/\psi)^2 + (\theta b_x \kappa_1 \varphi_e)^2]}{\theta(1 - \kappa_1 v_1)}, \tag{24}$$

the solution given in (15).

Given the solution for z_t it is possible to derive the innovation to the return r_c as a function of the evolution of the state variables and the parameters of the model.

$$r_{c,t+1} - E_t(r_{c,t+1}) = \sigma_{c,t}\eta_{t+1} + B\sigma_{c,t}e_{t+1} + b_\sigma \kappa_1 \sigma_w w_{t+1}, \tag{25}$$

where $B = \kappa_1 b_x \varphi_e = \kappa_1 \varphi_e/(1 - \kappa_1 \rho)(1 - \frac{1}{\psi})$. Further it follows that the conditional variance of $r_{c,t+1}$ is

$$\text{Var}_t(r_{c,t+1}) = (1 + B^2)\sigma_{c,t}^2 + (b_\sigma \kappa_1)^2 \sigma_w^2. \tag{26}$$

B.1.1. IMRSs

Now substituting for $r_{c,t+1}$ and the dynamics of $g_{c,t+1}$, we can re-write the IMRS in terms of the state variable—referring to this as the pricing kernel. Suppressing all the constants in the pricing kernel,

$$m_{t+1} \equiv \ln M_{t+1} = \theta \ln \delta - \frac{\theta}{\psi} g_{c,t+1} + (\theta - 1)r_{c,t+1},$$

$$E_t[m_{t+1}] = m_0 - \frac{x_t}{\psi} + b_\sigma(\kappa_1 v_1 - 1)(\theta - 1)\sigma_{c,t}^2,$$

$$m_{t+1} - E_t(m_{t+1}) = \left(-\frac{\theta}{\psi} + \theta - 1\right)\sigma_{c,t}\eta_{t+1} + (\theta - 1)(b_x\kappa_1\varphi_e)\sigma_{c,t}e_{t+1}$$
$$+ (\theta - 1)b_\sigma\kappa_1\sigma_w w_{t+1}$$
$$= \lambda_\eta\sigma_{c,t}\eta_{t+1} - \lambda_e\sigma_{c,t}e_{t+1} - \lambda_w\sigma_w w_{t+1}, \tag{27}$$

where $\lambda_\eta \equiv [-\theta/\psi + (\theta - 1)] = -\gamma$, $\lambda_e \equiv (1 - \theta)B$, $\lambda_w \equiv (1 - \theta)b_\sigma\kappa_1$, and B and b_σ are defined above. Note that the λ's represent the market price of risk for each source of risk, namely η_{t+1}, e_{t+1}, and w_{t+1}.

B.1.2. Risk premia for $r_{c,t+1}$

The risk premium for any asset is determined by the conditional covariance between the return and m_{t+1}. Thus the risk premium for $r_{c,t+1}$ is equal to

$$E_t(r_{c,t+1} - r_{f,t}) = -\text{cov}_t[m_{t+1} - E_t(m_{t+1}), r_{c,t+1} - E_t(r_{c,t+1})] - 0.5\text{var}_t(r_{c,t+1}).$$

Exploiting the innovations in (25) and (27) it follows that

$$E_t[r_{c,t+1} - r_{f,t}] = \gamma\sigma_{c,t}^2 + \lambda_e B\sigma_{c,t}^2 + \kappa_1 b_\sigma\lambda_w\sigma_w^2 - 0.5\text{Var}_t(r_{c,t+1}) \tag{28}$$

where $\text{Var}_t(r_{c,t+1})$ is defined in Eq. (26).

References

Abel, A., 1990. Asset prices under habit formation and catching up with the Joneses. American Economic Review 80, 38–42.

Anderson, T., Bollerslev, T., Diebold, F., 2003. Parameteric and non-parameteric volatility measurement. In: Ait Sahalia, Y., Hansen, L.P. (Eds.), Handbook of Financial Econometrics. North-Holland, Amsterdam.

Ang, A., Bekaert, G., 2001. Stock return predictability: Is it there? Working paper, Columbia University.

Attanasio, O., Vissing-Jorgensen, A., 2003. Stock market participation, intertemporal substitution and risk aversion. American Economic Review, Papers and Proceedings 93, 383–391.

Attanasio, O., Webber, W., 1989. Intertemporal substitution, risk aversion and the Euler equation for consumption. Economic Journal 99, 59–73.

Bansal, R., Lundblad, C., 2002. Market efficiency, asset returns, and the size of the risk premium in global equity markets. Journal of Econometrics 109, 195–237.

Bansal, R., Yaron, A., 2000. Risks for the long run: A potential resolution of asset pricing puzzles. NBER Working Paper 8059, December 2000.

Bansal, R., Yaron, A., 2004. Risks for the long run: A potential resolution of asset pricing puzzles. Journal of Finance 59, 1481–1509.

Barberis, N., Huang, M., Santos, T., 2001. Prospect theory and asset pricing. Quarterly Journal of Economics 1–53.

Barsky, R.B., DeLong, B., 1993. Why does the stock market fluctuate? Quarterly Journal of Economics 108, 291–311.

Campbell, J.Y., 1993. Intertemporal asset pricing without consumption data. American Economic Review 83, 487–512.

Campbell, J.Y., 1999. Asset prices, consumption and the business cycle. In: Taylor, B., Woodford, M. (Eds.), Handbook of Macroeconomics, vol. 1. Elsevier Science, New York, North-Holland, Amsterdam, pp. 1231–1303 (Chapter 19).

Campbell, J.Y., Cochrane, J.H., 1999. By force of habit: A consumption-based explanation of aggregate stock market behavior. Journal of Political Economy 107, 205–251.

Campbell, J.Y., Shiller, R., 1988. The dividend – price ratio and expectations of future dividends and discount factors. Review of Financial Studies 1, 195–227.

Cochrane, J.H., 1992. Explaining the variance of price dividend ratios. Review of Financial Studies 5, 243–280.

Davidian, M., Carroll, R., 2002. Variance function estimation. Journal of the American Statistical Association 82, 1079–1091.

Epstein, L.G., Zin, S., 1989. Substitution, risk aversion and the temporal behavior of consumption and asset returns: A theoretical framework. Econometrica 57, 937–969.

Goyal, A., Welch, I., 2003. Predicting the equity premium with dividend ratios. Management Science 49, 639–654.

Granger, C., Newbold, P., 1986. Forecasting Economic Time Series. Academic Press, San Diego, CA.

Guvenen, F., 2001. Mismeasurement of elasticity of substitution: The role of limited stock market participation. Working paper, University of Rochester.

Hall, R., 1988. Intertemporal substitution in consumption. Journal of Political Economy 96, 339–357.

Hall, R., 2001. Struggling to understand the stock market. American Economic Review 91, 1–11.

Hansen, L.P., Singleton, K., 1982. Generalized instrumental variables estimation of nonlinear rational expectations models. Econometrica 50, 1269–1286.

Hansen, L.P., Singleton, K., 1983. Stochastic consumption, risk aversion and the temporal behavior of stock returns. Journal of Political Economy 91, 249–265.

Hodrick, R., 1992. Dividend yields and expected stock returns: Alternative procedures for inference and measurement. Review of Financial Studies 5, 357–386.

Kandel, S., Stambaugh, R., 1991. Asset returns and intertemporal preferences. Journal of Monetary Economics 27, 39–71.

Lettau, M., Ludvigson, S., 2002. Expected return and expected dividend growth. Unpublished manuscript, Stern Business School, New York University.

Lucas, R., 1978. Asset prices in an exchange economy. Econometrica 46, 1429–1445.

Mehra, R., Prescott, E., 1985. The equity premium: A puzzle. Journal of Monetary Economics 15, 145–161.

Ogaki, M., 1993. Generalized method of moments: Econometric applications. In: Maddala, G.S., Rao, C.R., Vinod, H.D. (Eds.), Handbook of Statistics. Elsevier Science Publisher, New York, North-Holland, Amsterdam, pp. 455–488 (Chapter 17).

Pagan, A.R., Schwert, G.W., 1990. Alternative models for conditional stock volatility. Journal of Econometrics 45, 267–290.

Shiller, R.J., 1989. Market Volatility. MIT Press, Cambridge, MA.

Stambaugh, R., 1999. Predictive regressions. Journal of Financial Economics 54, 375–421.

Torous, W., Valkanov, R., 2000. Boundaries of predictability: Noisy predictive regressions. Unpublished manuscript, UCLA.

Vissing-Jorgensen, A., 2002. Limited stock market participation and the elasticity of intertemporal substitution. Journal of Political Economy 110, 825–853.

Weil, P., 1990. Nonexpected utility in macroeconomics. Quarterly Journal of Economics 105, 29–42.