



A Variance Decomposition for Swiss Stock Market Returns

David Rey
University of Basel/University of St. Gallen

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Author:
David Rey
University of Basel
WWZ/Department of Finance
Holbeinstrasse 12
4051 Basel
david.rey@unibas.ch
Phone: +41 (0)61 267 3307

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David Rey*

University of Basel (WWZ)

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Abstract

This paper analyzes the persistence or serial correlation of expected returns as well as the univariate time-series approach that studies the implied autocorrelation function of realized stock returns, including mean reversion and its conditions. In particular, we critically examine whether increases in expected dividend growth tend to be associated with decreases in future expected returns, a correlation that would amplify the volatility of equity returns. Based on Swiss stock market data and a number of predictive variables found important in previous studies of return predictability, we emphasize that the results are dependent on the particular specification of the information set which agents use to predict equity returns. In contrast to the standard conclusion in the literature, we do not generally find that the variance of news about future returns is greater than the variance of news about future dividends. This result rather depends on the time period under consideration, and, more importantly, whether the dividend-price ratio is included in the analysis. Our conclusions are strongly supported when we additionally introduce Bayesian model and parameter uncertainty into the analysis. The results thus pose a challenge to current conditional asset pricing theory and to the business-cycle related motivation of stock market predictability.

*Department of Finance, WWZ University of Basel, Holbeinstrasse 12, 4051 Basel, Switzerland; Phone: +41-61-267 33 07, Mail: david.rey@unibas.ch. Second preliminary version. The author thanks Manuel Ammann and Heinz Zimmermann for their valuable comments. Financial support from the National Center of Competence in Research "Financial Valuation and Risk Management" (NCCR FINRISK) is gratefully acknowledged. The NCCR FINRISK is a research program supported by the Swiss National Science Foundation.

This paper analyzes the persistence or serial correlation of expected returns as well as the univariate time-series approach that studies the implied autocorrelation function of realized stock returns, including mean reversion and its conditions. In particular, we critically examine whether increases in expected dividend growth tend to be associated with decreases in future expected returns, a correlation that would amplify the volatility of equity returns. Based on Swiss stock market data and a number of predictive variables found important in previous studies of return predictability, we emphasize that the results are dependent on the particular specification of the information set which agents use to predict stock market returns. In contrast to the standard conclusion in the literature, we do not generally find that the variance of news about future returns is greater than the variance of news about future dividends. This result rather depends on the time period under consideration, and, more importantly, whether the dividend-price ratio is included in the analysis. If it is and the sample period is from 1975 to 1988, the correlation between news about future returns and news about future dividends is negative, implied realized returns exhibit mean reversion, and the fraction of the variance of news about future returns is more important than the residual fraction of the variance of news about future dividends. Recently, however, from 1989 to 2002, even if the dividend-price ratio is included in the analysis, average correlations between news about future returns and news about future dividends are positive, and the fractions of the variance of news about future dividends is very high and much more important than the fractions of the variance of news about future returns. This result is strongly supported when we additionally introduce Bayesian model and parameter uncertainty into the analysis. The results thus pose a challenge to current conditional asset pricing theory, and, in particular, to the business-cycle related motivation of stock market predictability. The standard lesson that persistent movements in expected returns, parameterized by the dividend-price ratio and/or other business-cycle related macroeconomic variables, are a major force driving unexpected returns may be somewhat premature.

1 Introduction

As for example discussed in Rey (2003a,b), a great deal of recent research seems to have documented that rational expectations of stock market returns move systematically over time. While most of this work concentrates on the variability of expected returns, already Campbell (1990, 1991) highlights that the persistence or serial correlation of expected returns is also an important issue. Indeed, if expected returns are persistent, any variability of them is likely to have a large impact on asset prices. Consequently, any attempt to explain the volatility of realized equity returns requires information on the persistence of movements in expected returns.

To make these ideas more precise, it is necessary to have a framework that relates stock prices, stock returns, and dividends. However, the standard Gordon (1962) present value formula is only useful if expected returns are assumed to

be constant. In contrast, the log-linear approximation to the standard formula, developed by Campbell and Shiller (1987, 1988a,b) and particularly Campbell (1990, 1991), is still tractable even when expected returns vary through time.

In combination with this log-linear “dividend-ratio model”, we use a standard vector autoregressive (VAR) system to calculate the impact that innovations in expected returns will have on stock prices, holding expected future dividends constant. Campbell (1990, 1991) calls this impact the “news about future returns” component of the unexpected stock return. The “news about future dividends/cash flows” component is obtained as a residual; dividend growth rates are therefore not directly included in the analysis.¹ The relative importance of the two components (and the covariance term between them) depends not only on the predictability of stock market returns, but also on the time-series properties of the predictable components of returns. If predictable returns are highly persistent, already a small degree of return predictability may heavily influence our interpretation of realized equity returns.

We also discuss the univariate time-series approach that studies the autocorrelation function of stock returns (see, e.g., Conrad and Kaul, 1988; Fama and French, 1988a; Lo and MacKinlay, 1988; and Poterba and Summers, 1988), including mean reversion and its conditions. The univariate time-series approach attempts to decompose prices into a transitory and a permanent component. In contrast to movements of the permanent component, movements of the transitory component are usually associated with changing rational return expectations. Loosely, it is argued that if the observed autocorrelations are all zero, so that observed equity returns are white noise, then this is evidence that expected returns are constant.

Campbell (1991, p. 159), however, demonstrates that the univariate time series often delivers only weak evidence against the hypothesis that all autocorrelations are zero. This is because one loses power by predicting returns using only past returns, thus ignoring other possible predictive variables. Indeed, the autocorrelations of realized returns can disappear even when expected returns are variable and highly persistent. The reason is that innovations in expected returns cause movements in realized returns in the opposite direction; the resulting negative serial correlation in ex-post returns tends to offset the positive serial correlation coming from persistent expected returns. In fact, Campbell (1991) constructs an example in which expected returns are variable and persistent, but ex-post returns are white noise. More importantly, however, is the related difficulty that a strong assumption on the covariance of the two components is needed to identify the parameters of the model from the autocorrelations of returns.

The empirical analysis for the Swiss stock market includes includes a number of predictive variables found important in previous studies of return predictability, as well as their stochastically detrended counterparts. In contrast to the original papers of Campbell (1990, 1991) and to common beliefs (see the

¹This has the advantage that we can work with higher-frequency monthly data without having to deal with seasonals in dividend payments and other payout policy issues.

textbooks of Campbell, Lo, and MacKinlay, 1997, Ch. 7; Cochrane, 2001, Ch. 20), we do not find that the variance of news about future returns is generally greater than the variance of news about cash flows. This result rather depends on the time period under consideration, and, more importantly, whether the dividend-price ratio is included in the analysis. If it is and the sample period is from 1975 to 1988, the correlation between news about future returns and news about future dividends is negative, implied realized returns exhibit mean reversion, and the fraction of the variance of news about future returns is more important than the residual fraction of the variance of news about future dividends. This, however, is the only case where short-term predictability of returns can increase the variance of unexpected returns. Recently, from 1989 to 2002, even if the dividend-price ratio is included in the analysis, average correlations between news about future returns and news about future dividends are positive, and the predictive ability of the dividend-price ratio has largely disappeared. Moreover, the fractions of the variance of news about future dividends and even the corresponding covariance terms are very high and much more important than the fractions of the variance of news about future returns, independent of the prevailing predictive variable(s). This result is confirmed when we additionally introduce Bayesian model and parameter uncertainty into the analysis. Consequently, the role of predictable time variation in expected stock returns with respect to the observed volatility of the stock market returns (the “excess volatility” puzzle of Shiller, 1981, and LeRoy and Porter, 1981) may have been overstated. Yes, predictable returns move quite persistently when parameterized by the commonly used predictive variables, but, in general, they do not appear to fall when expected dividends rise, thereby not amplifying the response of the stock market to news about future dividends.

Overall, our results pose a challenge to current conditional asset pricing theory, and, in particular, to the business-cycle related motivation of stock market predictability. The standard lesson that persistent movements in expected returns, parameterized by the dividend-price ratio and/or other business-cycle related macroeconomic variables, are a major force driving unexpected returns may be somewhat premature, at least incomplete.

The organization of the paper is as follows. Based on Campbell (1991), the next section sets up the basic framework which will be used to calculate the relation between unexpected returns and movements in expected returns. Section 3 reviews the univariate time-series approach, mean reversion, and the VAR approach for decomposing the variance of stock returns. Section 4 reports the empirical results for our Swiss stock market data in the period from 1975 to 2002, and Section 5 concludes.

2 Expected Returns and Unexpected Returns

As in Campbell (1991), the main equation used in this paper relates the unexpected real stock return in period $t + 1$, to changes in rational expectations of future dividend growth and future stock returns. Without relying on any asset

pricing model, it can be shown that the dividend-price ratio can only vary at all if it forecasts future returns, if it forecasts future dividend growth, or if there is a bubble – if the inverse of the dividend-price ratio is non-stationary and is expected to grow explosively. In other words, if the dividend-price ratio is low, either dividends must rise, prices must decline, or the inverse of the dividend-price ratio must grow explosively. This “dividend-ratio model” is not a theory, it is simply based on the following accounting identity,

$$1 \equiv (1 + R_{t+1})^{-1} (1 + R_{t+1}) \equiv (1 + R_{t+1})^{-1} \frac{P_{t+1} + D_{t+1}}{P_t}. \quad (1)$$

Taking logs and a (first-order) Taylor approximation of the resulting last term (see, e.g., Campbell, Lo, and MacKinlay, 1997, Ch. 7, and Cochrane, 2001, Ch. 20, for accessible textbook treatments; or Rey, 2003a), the continuously compounded real stock return over period $t + 1$, r_{t+1} , can be approximated as

$$r_{t+1} \approx k + \Delta d_{t+1} + (d_t - p_t) - \rho(d_{t+1} - p_{t+1}), \quad (2)$$

where $d_t - p_t$ denotes the log dividend-price ratio and $\Delta d_{t+1} = d_{t+1} - d_t$ real dividend growth. The parameter ρ is the average ratio of the stock price to the sum of the stock price and the dividend, and the constant k is a non-linear function of ρ , a number a little smaller than one. Equation (2) says that the real return is high if the dividend-price ratio is high when the stock is purchased, if dividend growth occurs during the holding period, and if the dividend-price ratio falls during the holding period (Campbell, 1991, p. 178).

Campbell (1991) shows that equation (2) can be thought of as a difference equation relating $d_t - p_t$ to $d_{t+1} - p_{t+1}$, Δd_{t+1} and r_{t+1} . Solving forward (and imposing the terminal condition that $\lim_{j \rightarrow \infty} \rho^j (d_{t+j} - p_{t+j}) = 0$), we obtain

$$d_t - p_t \approx -c + \sum_{j=1}^{\infty} \rho^{j-1} (r_{t+j} - \Delta d_{t+j}). \quad (3)$$

The log dividend-price ratio can thus be written as a discounted value of all future returns, r_{t+j} , and dividend growth rates, Δd_{t+j} , discounted at the constant rate ρ less a constant c , $c \equiv k / (1 - \rho)$. Consequently, if the dividend-price ratio is high today, this will give high future returns unless dividend growth is low in the future. Since the approximate identity in equation (3) holds ex-post, we can take conditional expectations and relate the dividend-price ratio to ex-ante dividend growth and return forecasts as

$$d_t - p_t \approx -c + E_t \sum_{j=1}^{\infty} \rho^{j-1} (r_{t+j} - \Delta d_{t+j}). \quad (4)$$

Using equation (4) to substitute $d_t - p_t$ and $d_{t+1} - p_{t+1}$ out of equation (2), we obtain for the unexpected component of the stock return, $\nu_{r,t}$ (Campbell, 1991, eq. 1):

$$\nu_{r,t} \equiv r_t - E_{t-1} r_t \approx (E_t - E_{t-1}) \left(\sum_{j=0}^{\infty} \rho^j \Delta d_{t+j} - \sum_{j=1}^{\infty} \rho^j r_{t+j} \right). \quad (5)$$

Thus, a positive shock to real returns must either come from a positive shock to future dividend growth or from a negative shock to expected future stock returns. Equation (5) is best thought of as a consistency condition for expectations. If the unexpected stock return is positive, then either expected future dividend growth must be higher, or expected future stock returns must be lower, or both.

2.1 Real Returns

Similar to Campbell (1991), we simplify the notation in equation (5) as follows. Define $\eta_{d,t}$ to be the term in equation (5) which represents news about future dividends (or cash flows),

$$\eta_{d,t} \equiv (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+j}. \quad (6)$$

Similarly, define $\eta_{r,t}$ to be term in equation (5) which represents news about future real returns,

$$\eta_{r,t} \equiv (E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j r_{t+j}. \quad (7)$$

Trivially, equation (5) can then be rewritten as (Campbell, 1991, eq. 2)

$$\nu_{r,t} \approx \eta_{d,t} - \eta_{r,t}. \quad (8)$$

2.2 Excess Returns

So far, the discussion has been based on real stock returns, r_t . For our purposes, however, it is more natural to work with (continuously compounded) excess stock returns, $e_t = r_t - r_{f,t}$, where $r_{f,t}$ denotes the log real interest rate.

Campbell (1991, eq. 7 and 8) shows that

$$\begin{aligned} \nu_{e,t} &\equiv e_t - E_{t-1}e_t \\ &\approx (E_t - E_{t-1}) \left(\sum_{j=0}^{\infty} \rho^j \Delta d_{t+j} - \sum_{j=0}^{\infty} \rho^j r_{f,t+j} - \sum_{j=1}^{\infty} \rho^j e_{t+j} \right), \end{aligned} \quad (9)$$

or, in more compact notation,

$$\nu_{e,t} \approx \eta_{d,t} - \eta_{i,t} - \eta_{e,t}, \quad (10)$$

with news about future interest rates

$$\eta_{i,t} \equiv (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j r_{f,t+j} \quad (11)$$

and news about future excess returns

$$\eta_{e,t} \equiv (E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j e_{t+j}. \quad (12)$$

Note that $\eta_{i,t} = 0$ and $\nu_{e,t} = \nu_{r,t}$ if the the log real interest rate is assumed to be constant, $r_{f,t} = r_f$.

3 Alternative Approaches to Variance Decomposition

Return predictability can only be interpreted in conjunction with an intertemporal equilibrium model of the economy. However, the choice of a particular model for the time-varying behavior of expected returns is, by nature, somewhat arbitrary. At best, an equilibrium model should specify both the stochastic process for and the underlying economic determinants of expected returns. But existing asset pricing theories do hardly ever specify any particular a priori restrictions on the variation through time in expected returns. For example, one reasonable restriction is that equilibrium in an efficient market never implies predictable price declines (negative expected nominal or even real returns). Yet, even the models by Merton (1973), Lucas (1978), Breeden (1979), and Cox, Ingersoll, and Ross (1985) do not rule out negative expected returns. At least, there are good reasons to think that expected stock returns may be persistent. In the Gordon growth model, for example, both investment and dividends rise when earnings increase. In practice, investment is generally a sequential process that involves various stages of planning and execution over time. Once the initial costs are sunk, the firm often has an economic incentive to follow through with additional investment, even in the face of lowered expectations about future benefits. As a result, changes in investment should have a significant predictable component. Asset pricing models like the consumption model of Lucas (1978) describe expected stock returns as functions of expected economic growth rates. Merton (1973) and Cox, Ingersoll, and Ross (1985) propose real interest rates as candidate state variables, driving expected returns in intertemporal models. Such variables are likely to be highly persistent. Consequently, already the early empirical studies for stock return dynamics by Conrad and Kaul (1988), Fama and French (1988b), Lo and MacKinlay (1988), and Huberman and Kandel (1990) involve persistent, autoregressive expected returns. However, it is important to note that this process does not restrict the size of the market's information set. In particular, there is no presumption that the relevant information set contains only the history of past asset returns. It is quite possible that a very large number of variables is useful in predicting the asset return over the next period; the univariate autoregression assumption merely restricts the way in which the next period's forecast is related to past forecasts. In what follows, we show that persistence in the expected return process increases the variability of realized returns, and that small but persistent changes in expected returns may have large effects on prices and thus on realized returns.

3.1 The Univariate Time-Series Approach and Mean Reversion

Consider the following useful special case in which the expected real stock return follows a first-order autoregressive (AR(1)) process,

$$r_t = \alpha + \beta x_{t-1} + \xi_t, \quad (13)$$

where x_t is a (stationary) predetermined predictive variable, known at the beginning of the return period, and

$$x_t = \gamma + \delta x_{t-1} + \eta_t. \quad (14)$$

When the AR coefficient δ is close to (but strictly less than) one, the process for the predictive variable is highly persistent but still stationary.

Consequently, if the expected return is described by equations (13) and (14), it is easy to see that $\eta_{r,t}$ is an exact function of η_t ,

$$\eta_{r,t} \equiv (E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j r_{t+j} = \frac{\rho\beta}{1 - \rho\delta} \eta_t, \quad (15)$$

and $\text{Corr}(\eta_{r,t}, \eta_t) = 1$. Since ρ is a number close to one, equation (15) says that for $\beta = 1$, a 1% increase in the expected return today ($\eta_t = 1\%$) is associated with a capital loss of about 2% if the AR coefficient δ is 0.5, a loss of about 4% if the AR coefficient is 0.75, and a loss of about 10% if $\delta = 0.9$ (Campbell, 1991, p. 161).

Campbell (1991, eq. 5) shows that equation (15) can be used to calculate the ratio of the variance of news about future returns to the overall variance of unexpected returns. If the AR(1) model holds, this ratio satisfies

$$\begin{aligned} \frac{\text{Var}(\eta_{r,t})}{\text{Var}(\nu_{r,t})} &= (1 - \delta^2) \left(\frac{\rho}{1 - \rho\delta} \right)^2 \left(\frac{R^2}{1 - R^2} \right) \\ &\approx \left(\frac{1 + \delta}{1 - \delta} \right) \left(\frac{R^2}{1 - R^2} \right), \end{aligned} \quad (16)$$

where

$$R^2 = \frac{\text{Var}(E_{t-1}r_t)}{\text{Var}(r_t)} = \frac{\beta^2}{1 - \delta^2} \frac{\text{Var}(\eta_t)}{\text{Var}(r_t)}. \quad (17)$$

If, for example, R^2 is 2.5% and $\delta = 0.9$ (these estimates are not unreasonable for monthly stock returns; see, e.g., Rey, 2004a), then the share of news about future expected returns in the variance of unexpected returns may be as high as 49%. The predictive regression specification in equations (13) and (14) with δ near one is only a natural consequence in this regard, and, as shown for example in Campbell (1991), Campbell, Lo, and MacKinlay (1997, Ch. 7), and Cochrane (2001, Ch. 20), sufficient (and, in this setting, necessary) to explain the “excess volatility” puzzle of Shiller (1981) and LeRoy and Porter (1981).

This example thus shows that movements in expected returns can be very important in explaining stock price volatility, even if the predictable component of the monthly stock return is small. Indeed, persistence in the expected return process increases the variability of realized returns, and small but persistent changes in expected returns may have large effects on prices and thus on realized returns. On the other hand, however, recent theoretical results in the econometric literature indicate that the standard approaches to statistical inference fail to provide an asymptotically valid method of statistical inference in regression models in which the predictive variable has a near unit root, i.e., $\delta \approx 1$. Rather, statistical inference in predictive regressions depends critically on the predictive variable's stochastic properties one is willing to consider, notably its order of integration ($\delta < 1$ for stationarity versus $\delta = 1$ for a non-stationary unit root or "random walk"). Incorporating information about the predictive variable's order of integration can result in large efficiency gains and therefore have a significant effect on inferences drawn in predictive regressions (Campbell and Yogo, 2002; Torous, Valkanov, and Yan, 2002; Lewellen, 2003).

Mean Reversion... One way to decompose the variance of real stock returns is to examine the serial correlation of returns. Recall that the (unconditional) variance ratio statistic, $VR(q)$, is defined as the ratio of the variance of q -period returns to the variance of 1-period returns, divided by q . This ratio will be one for white noise (independently and identically distributed, i.i.d.) returns; it will exceed one for returns which are predominantly positively autocorrelated (mean aversion), and it will be below one when negative autocorrelations dominate (mean reversion). It is now well-known that the variance ratio statistic can be calculated directly from the autocorrelations of 1-period returns by using the fact that

$$VR(q) \equiv \frac{Var(r_{t \rightarrow q})}{qVar(r_t)} = 1 + 2 \sum_{j=1}^{q-1} \left(1 - \frac{j}{q}\right) Corr(r_t, r_{t+j}) \quad (18)$$

with $r_{t \rightarrow q} \equiv r_t + r_{t+1} + \dots + r_{t+q-1}$ and $Corr(r_t, r_{t+j})$ the j th-order autocorrelation coefficient of $\{r_t\}$.

In particular, if the expected real return follows the AR(1) process given in equations (13) and (14), then Campbell (1991, eq. 9) shows that the ex-post return follows an ARMA(1,1) process whose j th autocovariance is given by

$$Cov(r_t, r_{t+j}) = \delta^{j-1} \left[\beta Cov(\eta_{d,t}, \eta_t) + \left(\frac{\beta^2 \delta}{1 - \delta^2} - \frac{\rho \beta^2}{1 - \rho \delta} \right) Var(\eta_t) \right]. \quad (19)$$

Obviously, the autocovariances of realized returns are all of the same sign and die off at rate δ ; this is a property of the ARMA(1,1) which is already emphasized by Poterba and Summers (1988).²

²Trivially, the autocovariances are zero if one of the following is true: $\beta = 0$ (returns are white noise, "random walk"), $\delta = 0$ (expected returns are white noise, not persistent at all), or $Var(\eta_t) = 0$ (constant expected returns).

...and its Conditions Campbell (1991, p. 163), however, emphasizes two difficulties with the univariate time-series approach and particularly with equation (19).

First, if not all of the autocovariances are zero, they only identify δ and the term in square brackets. This, however, is not enough to identify the innovation variance of expected returns, $Var(\eta_t)$. For that we need an assumption about the covariance $Cov(\eta_{d,t}, \eta_t)$ between news about future dividends and shocks to expected returns, or, given that

$$Cov(\eta_{d,t}, \eta_{r,t}) = \frac{\rho\beta}{1 - \rho\delta} Cov(\eta_{d,t}, \eta_t), \quad (20)$$

about the covariance between news about future dividends and news about future returns, and, of course, the sign of β .

The assumption generally made is that the covariance is zero (see, e.g., Fama and French, 1988b), $Cov(\eta_{d,t}, \eta_t) = Cov(\eta_{d,t}, \eta_{r,t}) = 0$. In this case, the autocorrelation of stock returns is determined by the balance of two opposing effects. On the one hand, expected stock returns are positively autocorrelated, and this creates positive autocorrelation in realized stock returns. On the other hand, however, innovations in expected future stock returns are negatively correlated with current unexpected stock returns, and this creates negative autocorrelation and hence mean reversion in realized stock returns. The latter effect dominates when $\delta < \rho$, i.e., when expected returns are not too persistent.

However, the assumption that news about future dividends and news about future returns are uncorrelated is quite arbitrary, and does not really correspond to the common and intuitively appealing business-cycle argumentation that expected returns rise during an economic slow-down and fall during periods of economic growth, so that the equity premium and business conditions (dividends or cash flows) move in opposite directions, such that $Corr(\eta_{d,t}, \eta_{r,t}) < 0$ (e.g., Fama and French, 1989; Chen, 1991; Fama, 1991; Ferson and Harvey, 1991).

The intuition behind mean reversion is the following. Suppose, for example, that expected returns are parameterized by the dividend-price ratio and that the dividend-price ratio falls unexpectedly, $\eta_t < 0$. Given the evidence in Rey (2004a, Table 2), for Swiss stock market data from 1975 to 1988 that $\beta > 0$ and $Cov(\xi_t, \eta_t) < 0$, this is likely to be accompanied by a contemporaneous positive shock to returns, $\xi_t > 0$. However, since the dividend-price ratio is lower, returns are expected to be lower in the future, $\eta_{r,t} < 0$. This rise, followed by a fall in returns, generates a component of negative serial correlation in realized returns which slows the evolution of the variance of cumulative returns as the horizon grows. Indeed, there is a strong economic intuition behind the general idea that time variation in expected returns induces mean reversion in realized returns. If there is a positive shock to expected returns, it is very reasonable that realized returns should suffer a contemporaneous negative shock since the discount rate for discounting future cash flows has suddenly increased. This negative shock to current realized returns, followed by the higher returns predicted for the future, are the source of mean reversion. Put it differently, since $\nu_{r,t} = \xi_t = \eta_{d,t} - \eta_{r,t}$

and $\eta_{r,t} < 0$, we need $\eta_{d,t} > \eta_{r,t}$ such that $\xi_t > 0$. This is trivially the case if $\eta_{d,t} > 0$, i.e., a positive shock to news about (current or) future cash flows such that $Corr(\eta_{d,t}, \eta_{r,t}) < 0$.

Secondly, even in the case that expected returns are variable and persistent, it is possible that all autocovariances disappear. In this case, the univariate time-series approach would completely break down. Campbell (1991, eq. 10) shows that the condition for this is

$$\beta Cov(\eta_{d,t}, \eta_t) = \left(\frac{\rho\beta^2}{1-\rho\delta} - \frac{\beta^2\delta}{1-\delta^2} \right) Var(\eta_t). \quad (21)$$

Trivially, equation (21) may be satisfied with zero covariance $Cov(\eta_{d,t}, \eta_t)$ between shocks to cash flows and shocks to expected returns, if the expected return follows a highly persistent process with $\delta = \rho$. Alternatively, it may be satisfied with a positive covariance between shocks to cash flows and shocks to expected returns, and a less persistent expected return process with $\delta < \rho$. In general, thus, if the covariance between news about future dividends and innovations to future returns is large enough (and $\beta > 0$), the first term in equation (19) can dominate the others, giving positive return autocovariances.

After all, we may express the conditions for mean reversion in terms of the parameters in equations (13) and (14), i.e., α , β , γ , δ , $Var(\xi_t)$, $Var(\eta_t)$, and $Corr(\xi_t, \eta_t)$, and, where appropriate, ρ . Given equation (19), it is easy to see that $Cov(r_t, r_{t+j}) < 0$ is equivalent to

$$\beta Cov(\eta_{d,t}, \eta_t) < \left(\frac{\rho\beta^2}{1-\rho\delta} - \frac{\beta^2\delta}{1-\delta^2} \right) Var(\eta_t). \quad (22)$$

Since, in addition,

$$Cov(\eta_{d,t}, \eta_t) = Cov(\xi_t + \eta_{r,t}, \eta_t) = Cov(\xi_t, \eta_t) + \frac{\rho\beta}{1-\rho\delta} Var(\eta_t), \quad (23)$$

we have for $\beta > 0$

$$Cov(\xi_t, \eta_t) < -\frac{\beta\delta}{1-\delta^2} Var(\eta_t) \quad (24)$$

such that $Cov(\xi_t, \eta_t) < 0$, and for $\beta < 0$

$$Cov(\xi_t, \eta_t) > -\frac{\beta\delta}{1-\delta^2} Var(\eta_t) \quad (25)$$

such that $Cov(\xi_t, \eta_t) > 0$. In terms of correlations, the conditions for mean reversion are

$$Corr(\xi_t, \eta_t) < -\frac{\beta\delta}{1-\delta^2} \sqrt{\frac{Var(\eta_t)}{Var(\xi_t)}} \quad (26)$$

for $\beta > 0$ and

$$Corr(\xi_t, \eta_t) > -\frac{\beta\delta}{1-\delta^2} \sqrt{\frac{Var(\eta_t)}{Var(\xi_t)}} \quad (27)$$

for $\beta < 0$. Thus, if $\beta > 0$ ($\beta < 0$), the correlation between innovations to returns and to the predictive variable parameterizing expected returns must be lower (higher) the higher β , δ , and $Var(\eta_t)/Var(\xi_t)$, respectively, i.e., the more variable and persistent expected returns are.

Put it differently, namely in terms of the covariance $Cov(\eta_{d,t}, \eta_{r,t})$ between news about future dividends and news about future returns, mean reversion is equivalent to

$$Cov(\eta_{d,t}, \eta_{r,t}) < \left(\frac{\rho^2 \beta^2}{(1 - \rho\delta)^2} - \frac{\rho\beta^2\delta}{(1 - \delta^2)(1 - \rho\delta)} \right) Var(\eta_t). \quad (28)$$

In general, thus, to ensure that realized real returns mean revert, we do not necessarily need that $Cov(\eta_{d,t}, \eta_{r,t}) < 0$. However, equation (28) gives an upper bound to $Cov(\eta_{d,t}, \eta_{r,t})$: the correlation between news about future dividends and news about future returns cannot be too high to be consistent with mean reversion.

Finally, we may be interested to express the conditions for $Corr(\eta_{d,t}, \eta_{r,t}) < 0$ in terms of the parameters in equations (13) and (14), too. The case of $Corr(\eta_{d,t}, \eta_{r,t}) < 0$ is therefore interesting as it corresponds to the common and intuitively appealing business-cycle argumentation that expected returns rise during an economic slow-down and fall during periods of economic growth, so that the equity premium and business conditions (dividends or cash flows) move in opposite directions. Since

$$Cov(\eta_{d,t}, \eta_{r,t}) = \frac{\rho\beta}{1 - \rho\delta} Cov(\xi_t, \eta_t) + \frac{\rho^2\beta^2}{(1 - \rho\delta)^2} Var(\eta_t), \quad (29)$$

it is straightforward to see that the condition for $Corr(\eta_{d,t}, \eta_{r,t}) < 0$ is

$$Corr(\xi_t, \eta_t) < -\frac{\rho\beta}{1 - \rho\delta} \sqrt{\frac{Var(\eta_t)}{Var(\xi_t)}} \quad (30)$$

in the case that $\beta > 0$, and

$$Corr(\xi_t, \eta_t) > -\frac{\rho\beta}{1 - \rho\delta} \sqrt{\frac{Var(\eta_t)}{Var(\xi_t)}} \quad (31)$$

for $\beta < 0$. Once again, thus, if $\beta > 0$ ($\beta < 0$), the correlation between innovations to returns and to the predictive variable must be lower (higher) the higher β , δ , and $Var(\eta_t)/Var(\xi_t)$, i.e., the more variable and persistent expected returns are.

To sum up, if expected returns are represented by the standard process given in equations (13) and (14), realized returns are characterized by an ARMA(1,1) process. Accordingly, autocorrelated expected returns and the opposite response of prices to expected return shocks (the “discount-rate effect”, Fama and French, 1988a) can combine to produce mean-reverting components of stock

prices. Fama and French (1988b) and Poterba and Summers (1988) show that mean-reverting price components tend to induce negative autocorrelation in long-horizon returns. But a mean-reverting, positively autocorrelated expected return does not necessarily imply negative autocorrelated returns or a mean-reverting component of prices. If shocks to expected returns and expected dividends are positively correlated, the opposite response of prices to expected return shocks can disappear. In this case, the positive autocorrelation of expected returns will imply positively autocorrelated returns, and time-varying expected returns will not generate mean-reverting price components (the MA part stems from news about future dividends; if the roots cancel, realized returns are white noise). However, as Cochrane (2001, Ch. 20) puts it, any positive correlation between dividend growth and expected return shocks is difficult to reconcile with the business cycle, consumption smoothing explanation of a time-varying risk premium. If anything, since expected returns are assumed to rise in “bad times” when risk or risk aversion increases, one should see a positive shock to expected returns associated with a negative shock to current or future dividend growth. Of course, changes through time in the autocorrelation of expected returns, or in the relation between shocks to expected returns and expected dividends, can change the time-series properties of returns and obscure tests of forecast power based on autocorrelation (e.g., Campbell, 1991, 2001; Campbell, Lo, and MacKinlay, 1997, Ch. 7; Cochrane, 2001, Ch. 20).

3.2 The VAR Approach

As in Campbell (1991), instead of focusing solely on the autocovariances of stock returns, we may model the stock return as one element of a vector autoregression (VAR).

3.2.1 Real Returns

Let us first define a vector \mathbf{z}_t with $n + 1$ elements, the first of which is the real stock return, r_t , and the other elements are the n predictive variables, \mathbf{x}_t . We then assume that the vector \mathbf{z}_t follows a first-order VAR as in Campbell (1991), Hodrick (1992), Barberis (2000), and Rey (2004a,b). It takes the form

$$\mathbf{z}_t = \mathbf{a} + \mathbf{B}\mathbf{x}_{t-1} + \boldsymbol{\xi}_t, \quad (32)$$

with $\mathbf{z}'_t = [r_t \ \mathbf{x}'_t]$, $\mathbf{x}_t = [x_{1,t} \cdots x_{n,t}]'$, and $\boldsymbol{\xi}_t \sim \text{i.i.d. } N(\mathbf{0}, \boldsymbol{\Sigma})$. This VAR framework neatly summarizes the dynamics we are trying to model: the first equation in the system specifies expected returns as a function of the predictive variables, the other equations specify the stochastic evolution of the predictive variables.

Further, we define a $(n + 1, 1)$ -element vector \mathbf{e}_1 , whose first element is 1 and whose other elements are all 0. This vector picks out the real stock return r_t from the vector \mathbf{z}_t , $r_t = \mathbf{e}'_1 \mathbf{z}_t$, and $\nu_{r,t} \equiv r_t - E_{t-1} r_t = \mathbf{e}'_1 \boldsymbol{\xi}_t$. Note that since $\mathbf{z}_t = \mathbf{a} + \mathbf{B}\mathbf{x}_{t-1} + \boldsymbol{\xi}_t$, we can write $\mathbf{z}_t = \mathbf{a} + \mathbf{B}_0 \mathbf{z}_{t-1} + \boldsymbol{\xi}_t$ with $\mathbf{B}_0 = [\mathbf{0} \ \mathbf{B}]$, where $\mathbf{0}$

is an $(n + 1, 1)$ vector of zeros. Therefore, the first-order VAR generates simple multi-period forecasts of future returns,

$$E_{t-1}r_{t+j} = \mathbf{e}'_1 \left(\mathbf{a} + \mathbf{B}_0\mathbf{a} + \mathbf{B}_0^2\mathbf{a} + \dots + \mathbf{B}_0^j\mathbf{a} + \mathbf{B}_0^{j+1}\mathbf{z}_{t-1} \right). \quad (33)$$

It is easy to see that the discounted sum of revisions in forecast returns can then be written as

$$\begin{aligned} \eta_{r,t} &\equiv (E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j r_{t+j} \\ &= \mathbf{e}'_1 \sum_{j=1}^{\infty} \rho^j \mathbf{B}_0^j \boldsymbol{\xi}_t = \mathbf{e}'_1 \rho \mathbf{B}_0 (\mathbf{I} - \rho \mathbf{B}_0)^{-1} \boldsymbol{\xi}_t \equiv \boldsymbol{\lambda}' \boldsymbol{\xi}_t, \end{aligned} \quad (34)$$

where $\boldsymbol{\lambda}'$ is defined to equal $\mathbf{e}'_1 \rho \mathbf{B}_0 (\mathbf{I} - \rho \mathbf{B}_0)^{-1}$, a non-linear function of the VAR coefficients (Campbell, 1991, eq. 13).

Because $\nu_{r,t}$ is the first element of $\boldsymbol{\xi}_t$, $\mathbf{e}'_1 \boldsymbol{\xi}_t$, equations (8) and (34) imply that

$$\eta_{d,t} \equiv (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+j} = (\mathbf{e}'_1 + \boldsymbol{\lambda}') \boldsymbol{\xi}_t. \quad (35)$$

These expressions can then be used to decompose the variance of the unexpected stock return, $\nu_{r,t}$, into the variance of the news about cash flows, $\eta_{d,t}$, the variance of the news about expected return, $\eta_{r,t}$, and the corresponding covariance term,

$$Var(r_t - E_{t-1}r_t) = Var(\eta_{d,t}) + Var(\eta_{r,t}) - 2Cov(\eta_{d,t}, \eta_{r,t}). \quad (36)$$

As noted in Campbell (1991, p. 164), there is no single measure of the persistence of expected returns in the VAR context. He therefore suggests to summarize persistence by the variability of the innovation in the expected present value of future returns, relative to the variability of the innovation in the one-period-ahead expected return. Accordingly, he defines the VAR persistence measure P_r as

$$P_r \equiv \sqrt{\frac{Var(\eta_{r,t})}{Var(\mathbf{e}'_1 \mathbf{B}_0 \boldsymbol{\xi}_t)}}. \quad (37)$$

In words, a typical 1% positive innovation in the expected return will cause a $P_r\%$ capital loss on the stock. In the univariate AR(1) case described above, P_r would just equal $\rho / (1 - \rho\delta) \approx 1 / (1 - \delta)$.

3.2.2 Excess Returns

Of course, the VAR approach can also be used to analyze continuously compounded excess returns instead of real returns. In this case, the vector \mathbf{z}_t must include the excess return e_t as its first element, and the real interest rate $r_{f,t}$ as its second element, $\mathbf{z}'_t = [e_t \ r_{f,t} \ \mathbf{x}'_t]$. When \mathbf{e}_2 is defined as a $(n + 2, 1)$ -element vector whose second element is 1, with all other elements zero, and $\mathbf{B}_0 = [\mathbf{0} \ \mathbf{B}]$,

where $\mathbf{0}$ is an $(n+2, 2)$ matrix of zeros, news about future excess returns is given by $\eta_{e,t} = \boldsymbol{\lambda}'\boldsymbol{\xi}_t$, with $\boldsymbol{\lambda}'$ defined as before. News about future real interest rates is

$$\begin{aligned}\eta_{i,t} &\equiv (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j r_{f,t+j} \\ &= \mathbf{e}'_2 \mathbf{B}_0 (\mathbf{I} - \rho \mathbf{B}_0)^{-1} \boldsymbol{\xi}_t \equiv \boldsymbol{\mu}' \boldsymbol{\xi}_t,\end{aligned}\tag{38}$$

where $\boldsymbol{\mu}'$ is defined to equal $\mathbf{e}'_2 \mathbf{B}_0 (\mathbf{I} - \rho \mathbf{B}_0)^{-1}$ (Campbell, 1991, eq. 16). The residual news about future dividends, $\eta_{d,t}$, is then trivially given by

$$\eta_{d,t} = (\mathbf{e}'_1 + \boldsymbol{\lambda}' + \boldsymbol{\mu}') \boldsymbol{\xi}_t.\tag{39}$$

As above for P_r , we follow Campbell (1991, eq. 18) and define a persistence measure for the real interest rate, P_i , as follows

$$P_i \equiv \sqrt{\frac{\text{Var}(\boldsymbol{\mu}' \boldsymbol{\xi}_t)}{\text{Var}(\mathbf{e}'_2 \mathbf{B}_0 \boldsymbol{\xi}_t)}},\tag{40}$$

while the persistence measure for the excess return, P_e , is given by equation (37).

These expressions can be used to decompose the variance of the unexpected excess return, $\nu_{e,t}$, into the variance of the news about future cash flows, $\eta_{d,t}$, the variance of the news about expected excess return, $\eta_{e,t}$, and the variance of the news about future real interest rates, and the respective covariance terms,

$$\begin{aligned}\text{Var}(e_t - E_{t-1}e_t) &= \text{Var}(\eta_{d,t}) + \text{Var}(\eta_{i,t}) + \text{Var}(\eta_{e,t}) \\ &\quad - 2\text{Cov}(\eta_{e,t}, \eta_{d,t}) - 2\text{Cov}(\eta_{i,t}, \eta_{d,t}) \\ &\quad + 2\text{Cov}(\eta_{e,t}, \eta_{i,t}).\end{aligned}\tag{41}$$

4 Empirical Results

For the sake of comparability with Rey (2004a,b), we use the same data from the Swiss stock market here.

4.1 The Data

Our investment universe consists of monthly observations on continuously compounded excess stock market returns over January 1975 through December 2002 (336 observations). The continuously compounded real monthly risk-free interest rate, $r_{f,t}$, is the one-month Swiss interbank rate. To obtain continuously compounded real returns, total returns are deflated using monthly rates of change in the Consumer Price Index (CPI), provided by the Swiss National Bank. The stock market data is summarized in Appendix A.

In deciding which predictive variables to include, attention was given to those variables found important in previous studies of return predictability. Of course, there is a natural concern about return predictability uncovered through collective “data-snooping” by a series of researchers (Lo and MacKinlay, 1990; Foster, Smith, and Whaley, 1997; Ferson, Sarkissian, and Simin, 2003, 2004). However, most of this research is based on U.S. data and, to our knowledge, there is no study for the Swiss stock market that uses data covering the period starting in 1975 and that includes the recent bear market.

Each of the 2^M competing predictive regression specifications considered retains a unique subset of the following $M = 7$ predictive variables:

- (i) Dividend-price ratio, log (DPR),
- (ii) Earnings-price ratio, log (EPR),
- (iii) Term spread (TERM),
- (iv) Nominal one-month Swiss interbank rate (IR),
- (v) Realized stock market volatility, log (VOLA),
- (vi) U.S. TED spread (TED), and, finally,
- (vii) U.S. default risk spread (DEF).³

The dividend-price ratio/earnings-price ratio is measured as the sum of dividends/earnings paid on the index over the previous year, divided by the current level of the index. The term spread is the difference between the (log) nominal yield on long-term government bonds provided by IMF and the (log) nominal three-month Swiss interbank rate. In the same way as Goyal and Santa-Clara (2003), we compute the monthly realized variance of the real stock market returns using within-month daily return data for each month as

$$Var_t^{Market} = \sum_{d=1}^{D_t} r_{m,d}^2 + 2 \sum_{d=2}^{D_t} r_{m,d} r_{m,d-1},$$

where D_t is the number of days in month t and $r_{m,d}$ is the continuously compounded real stock market return on day d . The second term on the right-hand side adjusts for the autocorrelation in daily returns using the approach proposed by French, Schwert, and Stambaugh (1987). The U.S. TED spread is calculated as the difference between (log) three-month Eurodollar rates and (log) three-month Treasury Bill rates, provided by the Federal Reserve Board of Governors. Finally, the U.S. default risk spread is formed as the difference in annualized (log) yields of Moody’s Baa and Aaa rated bonds.

Again, monthly data are used throughout, spanning 336/337 months from December 1974 to November/December 2002.

Motivated by the recent contributions of Ferson, Sarkissian, and Simin (2003, 2004), a second subset includes the same $M = 7$ predictive variables, but now transformed in the following simple way. We transform the predictive variables by subtracting off a trailing moving average of its own past values,

$$\mathbf{x}_{t-1}^* = \mathbf{x}_{t-1} - \frac{1}{12} \sum_{\tau=1}^{12} \mathbf{x}_{t-1-\tau}.$$

³A full list of references is provided in Rey (2003a,b).

In words, we subtract a backward one-year moving average of past values from the prevailing value of the predictive variable to get a “stochastically detrended” time series that is equivalent to a triangularly weighted moving average of past changes in the predictive variable, where the weights decline as one moves back in time. Accordingly, the detrended time series is stationary if changes in the predictive variable are stationary. While this stochastic detrending method has already been used by Campbell (1991) and Hodrick (1992), only recently Ferson, Sarkissian, and Simin (2003, 2004) show that this is the most practically useful insurance against spurious regression bias (and therefore data mining). Since most of the above predictive variables are either manifestly non-stationary (realized stock market volatility is the exception), or, if not, their behavior is close enough to unit-root non-stationarity for small-sample statistics to be affected, it is interesting to compare the characteristics of the two data subsets.

Finally, we use sample means to set $\rho = 0.9783$ for the full sample, $\rho = 0.9725$ and $\rho = 0.9828$ for the first and second subsample, respectively. As expected, our results are not sensitive to variation in ρ within any plausible range.

4.2 Univariate Implications and Mean Reversion

Let us start to calculate the univariate time-series implications of the AR(1) process in equations (13) and (14). Figure 1 and 2 show implied (unconditional and conditional) variance ratio and R^2 statistics for horizons out to ten years, when the predictive variable, x_t , is the dividend-price ratio and the term spread, respectively. These statistics are computed from the respective parameter estimates, and not directly from the original return data. All statistics are shown for the periods 1975 to 1988 and 1989 to 2002.

In the case of the dividend-price ratio, the general pattern is quite different in the two subperiods. From 1975 to 1988, the variance ratios decline steadily and approach a limit below 0.3. Thus, the corresponding implied autocorrelations are negative, indicating strong mean reversion. Of course, as discussed in Rey (2004a), conditional variance ratios are lower than the corresponding unconditional variance ratios. Recently, however, Figure 1 shows that the variance ratios differ from the earlier ones in that they are approximately one for all horizons, indicating no return predictability by the dividend-price ratio and thus white noise returns.

Fama and French (1988a) characterize the univariate behavior of stock returns by regressing the q -period stock return on the lagged q -period return. Campbell (1991, eq. 20) shows that the resulting regression coefficient, $\beta(q)$, is related to the variance ratio statistic by

$$\beta(q) \equiv \frac{VR(2q)}{VR(q)} - 1. \quad (42)$$

The unconditional R^2 of the q -period regression is then simply the square of $\beta(q)$. For comparison, we also show the corresponding implied conditional R^2 s,

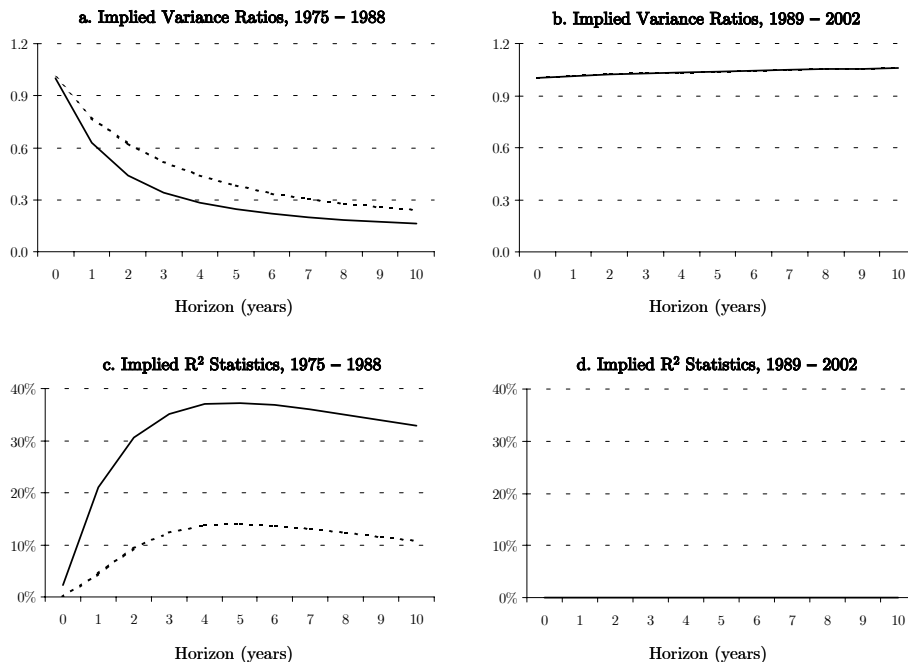


Figure 1:
Dividend-price ratio. Implied variance ratios and implied R^2 statistics.

The two graphs on the top show implied variance ratio statistics, the ones below implied RSquares. The solid lines correspond to conditional statistics, the dotted lines to the respective unconditional statistics. In all cases, expected real returns are parameterized by the dividend-price ratio. The parameters are estimated using data from 1975 to 1989 (graphs on the left), and 1989 to 2002 (graphs on the right). The time horizon is measured on the horizontal axis (in years).

calculated as

$$R^2(q) = 1 - \frac{Var_t(r_{t \rightarrow q})}{Var(r_{t \rightarrow q})}, \quad (43)$$

where $Var_t(r_{t \rightarrow q})$ denotes the conditional variance of long-horizon returns (see Rey, 2004a).

Figure 1 also shows the implied R^2 s for horizons out to ten years when expected real returns are parameterized by the dividend-price ratio. In the first subperiod, the dividend-price ratio predicts real returns and the conditional R^2 statistics rise steeply from their initial values at a one-month horizon to a peak at about 36% at a horizon of four to five years. This is a result of the fact that the dividend-price ratio as predictive variable is highly persistent. On the other hand, the unconditional Fama-French R^2 s peak at about 16%, indicating that the conditional R^2 statistics are about twice as high as the unconditional Fama-French R^2 s. As emphasized in Campbell (1991, p. 172), this is an indication of

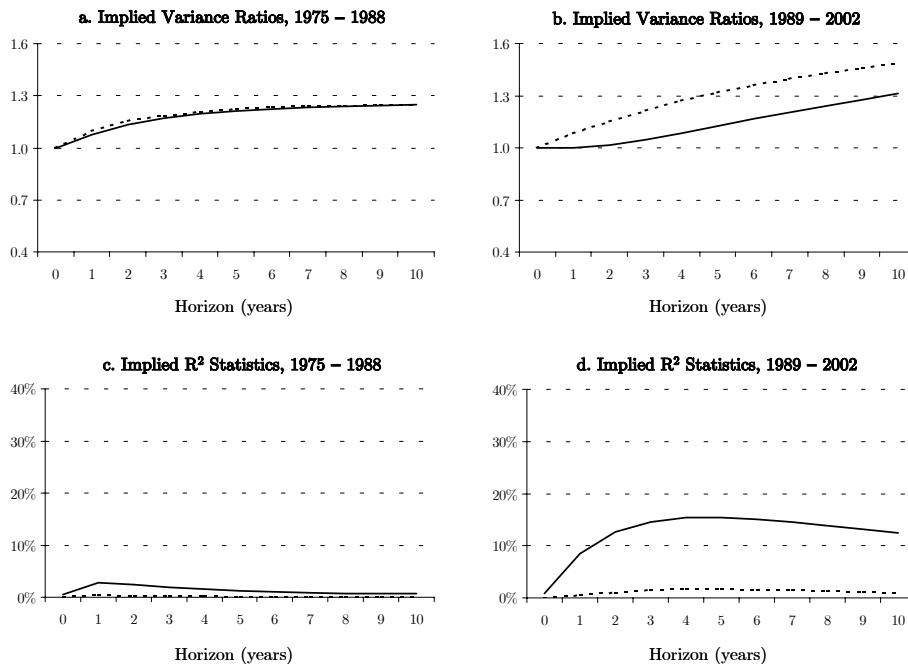


Figure 2:
Term spread. Implied variance ratios and implied R^2 statistics.

The two graphs on the top show implied variance ratio statistics, the ones below implied R^2 s. The solid lines correspond to conditional statistics, the dotted lines to the respective unconditional statistics. In all cases, expected real returns are parameterized by the term spread. The parameters are estimated using data from 1975 to 1989 (graphs on the left), and 1989 to 2002 (graphs on the right). The time horizon is measured on the horizontal axis (in years).

the benefits obtainable from a multivariate rather than a univariate approach to stock returns. In the recent subsample, however, the dividend-price ratio does not predict real returns. The corresponding implied regression coefficients and R^2 statistics do not rise with the forecast horizon.

Figure 2 shows the respective statistics when expected real returns are parameterized by the term spread. In comparison to the dividend-price ratio, the general pattern is quite different. Instead of mean reversion, real returns exhibit mean aversion, i.e., unconditional and conditional variance ratios exceed one, indicating that returns are predominantly positively autocorrelated. This is true for both subperiods. With respect to the R^2 statistics, only conditional R^2 s rise from their initial values at a one-month horizon to a peak at about 16% at a horizon of four to five years. This result, however, is restricted to the recent subperiod, unconditional R^2 s and the corresponding R^2 s from 1975 to 1988 are merely flat over the horizon.

Overall, it is important to note that the resulting general pattern for the term

spread is representative for the other predictive variables introduced above: real returns do hardly ever show mean reversion, and the implied R^2 statistics do not significantly rise over the horizon. These results thus confirm the findings in Rey (2004a). Moreover, the major role of the dividend-price ratio in the first subperiod, including return data from the mid-70s, is evident once again.

4.3 VAR and Real Returns

Tables 1 and 2 calculate the implications of the VAR estimates for the variance of unexpected real returns over the full sample from 1975 to 2002 and the two subsamples, respectively. When $M = 7$ predictive variables are suspected relevant, there are $2^M = 128$ competing linear regression specifications (see Rey (2004b) for a more thorough discussion). Thus, each of these competing predictive regression specifications considered retains a unique subset of the predictive variables introduced above.

To save space, however, Panel A of Table 1 reports only the results of the following models: the seven univariate predictive regression specifications that include only one of the seven predictive variables and the all-inclusive model. In addition, we also report the mean values over all models, as well as the results of Avramov's (2002) Bayesian model averaging approach. The Bayesian procedure first computes posterior probabilities for the collection of all 128 competing models, as described in Rey (2004b) and Avramov (2002). It then uses these probabilities as weights on the individual models to obtain one composite weighted forecasting model, which summarizes the dynamics of real returns. The Bayesian weighted model is then employed to investigate the sample evidence on return predictability and the variance decomposition of unexpected real returns. Finally, Panel B of Table 1 and Table 2 reports the average values for each of the seven predictive variables. They are computed as $\mathbf{A}'\mathbf{P}$, where \mathbf{A} is a $(2^M, M)$ matrix representing all forecasting models by zeros and ones, designating exclusions and inclusions of predictive variables, respectively, and \mathbf{P} is a $(2^M, 1)$ vector containing the respective statistics for each of the forecasting models. The resulting quantity is then divided by $2^M/2$ to get the average value for each predictive variable.

Consider first Table 1, presenting results over the full sample. In general, only a very small part of the variance of unexpected real returns is attributed to the variance of news about future returns. For the Bayesian weighted model, for example, the fraction of $Var(\eta_{r,t})$ is only 8.30%. Instead, most of the variance of unexpected real returns is attributed to the variance of news about future dividends (86.79% for the Bayesian weighted model), and the remainder is due to the covariance term. The correlation between shocks to expected real returns and shocks to cash flows is strongly negative only when the dividend-price ratio and the earnings-price ratio are included in the analysis. In general, however, $Corr(\eta_{d,t}, \eta_{r,t})$ is rather around zero, indicating that news about fundamental value are uncorrelated with news about expected future real returns. This means that it is difficult to judge whether stock prices move less or more in response to cash flows news than they would if expected returns were constant (or negatively

	Var (η_r)	Var (η_d)	-2Cov (η_r, η_d)	Corr (η_r, η_d)	P_r
A: 1975:01–2002:12					
DPR	0.0244	0.7537	0.2219	-0.8181	25.8660
EPR	0.0190	0.8027	0.1783	-0.7216	21.7335
TERM	0.0672	1.1169	-0.1841	0.3361	13.7304
IR	0.0118	1.0351	-0.0469	0.2123	15.7292
VOLA	0.0106	1.0616	-0.0722	0.3407	2.1713
TED	0.0081	0.9726	0.0192	-0.1079	9.7223
DEF	0.0001	0.9991	0.0009	-0.0473	16.2282
ALL	0.1238	0.8037	0.0726	-0.1150	3.6974
Mean	0.0746	0.8520	0.0734	-0.1874	8.4127
Bayes	0.0830	0.8679	0.0492	-0.1288	7.4918
B: 1975:01–2002:12, Average Values					
DPR	0.0827	0.7546	0.1627	-0.3784	9.2182
EPR	0.0816	0.7853	0.1331	-0.3180	8.7531
TERM	0.1055	0.8756	0.0189	-0.0391	6.9404
IR	0.0802	0.8544	0.0654	-0.1384	7.1811
VOLA	0.0794	0.8706	0.0500	-0.1241	5.2496
TED	0.0774	0.8513	0.0713	-0.1913	7.9522
DEF	0.0823	0.8448	0.0730	-0.1654	7.9551

Table 1:
Variance decomposition for real stock returns (full sample).

The variance and covariance terms are given as ratios to the variance of the unexpected real stock return. Panel A shows the results based on a number of return-generating processes and the Bayesian weighted forecasting model (BAYES). The former set includes the seven predictive models that include only one of the following variables: dividend-price ratio (DPR), earnings-price ratio (EPR), term spread (TERM), one-month Swiss interbank rate (IR), realized stock market volatility (VOLA), U.S. TED spread (TED), and U.S. default spread (DEF), and the all-inclusive model (ALL). Panel A also reports the mean values over all models. Panel B reports the average values for each of the seven variables. The time period is from January 1975 to December 2002.

correlated with news about future dividends).

Table 2 reports the average values for each of the seven predictive variables, as well as the mean values over all models and the results of the Bayesian weighted model for the subperiods from 1975 to 1988 (Panel A) and 1989 to 2002 (Panel B), respectively. There is evidence of parameter instability between the subperiods. Consider the average values for the dividend-price ratio and the earnings-price ratio. From 1975 to 1988, 46.24% and 58.51% of the variance of unexpected real returns are attributed to the variance of news about future returns and 33.75% and 44.61% are attributed to the variance of news about cash flows. In fact, this is the only specification where the fraction of $Var(\eta_{r,t})$ is more important than the fraction of $Var(\eta_{d,t})$. As in Campbell (1991), however, the inclusion of the dividend-price ratio is necessary. When the dividend-price ratio is excluded from the analysis (or the predictive variables are stochastically detrended), the variance of unexpected real returns attributed to the variance of news about future returns is much smaller than the variance of news about future cash flows. On average, the correlations between shocks to expected real returns and shocks to cash flows are negative, indicating that good news about fundamental value tends to be associated with declines in expected future real returns. This means that stock prices move more in response to cash flows news than they would if expected returns were constant. However, as the results below show, this is entirely due to the inclusion of the dividend-price ratio. The 64 model specifications that do not include the dividend-price ratio would, on average, display a positive correlation between news about future returns and news about future dividends. The same is true for the more recent subperiod (Panel B of Table 2). Even if the dividend-price ratio is included in the analysis, average correlations between news about future returns and news about future dividends are positive; the predictive ability of the dividend-price ratio has largely disappeared recently. Moreover, the fractions of $Var(\eta_{d,t})$ and even $-2Cov(\eta_{d,t}, \eta_{r,t})$ are very high and more important than the fractions of $Var(\eta_{r,t})$, independent of the prevailing predictive variable(s). This result does not change when the predictive variables are stochastically detrended.

4.4 VAR and Excess Returns

Table 3 reports the variance decomposition for excess returns, using equations (38) through (41). The variance of unexpected excess returns is decomposed into the variance of news about future excess returns, $Var(\eta_{e,t})$, the variance of news about real interest rates, $Var(\eta_{i,t})$, the variance of news about future dividends, $Var(\eta_{d,t})$, and covariances among these shocks. Overall, the results for excess returns are similar in magnitude to the ones for real returns presented in Tables 1 and 2. In particular, average correlations between shocks to expected excess returns and shocks to future cash flows are reliably negative only from 1975 to 1988 and when the dividend-price ratio is included in the analysis. The 64 model specifications that do not include the dividend-price ratio would, on average, display a positive correlation between news about future returns and

	Var (η_r)	Var (η_d)	-2Cov (η_r, η_d)	Corr (η_r, η_d)	P_r
A: 1975:01–1988:12					
DPR	0.4624	0.3375	0.2001	-0.3365	8.0532
EPR	0.5851	0.4461	-0.0312	0.0250	6.1092
TERM	0.3944	0.5797	0.0259	-0.0517	6.2398
IR	0.3755	0.5738	0.0507	-0.0829	6.0425
VOLA	0.4037	0.5781	0.0182	-0.0440	6.1462
TED	0.4111	0.5744	0.0146	-0.0261	6.4254
DEF	0.3950	0.5708	0.0342	-0.0732	6.8091
Mean	0.3928	0.5661	0.0411	-0.0722	6.6893
Bayes	0.5548	0.4570	-0.0118	-0.0059	6.2727
B: 1989:01–2002:12					
DPR	0.7693	1.4903	-1.2597	0.4297	8.6236
EPR	0.7037	1.6053	-1.3090	0.5468	9.2809
TERM	0.6895	1.5397	-1.2292	0.4926	9.1769
IR	0.6896	1.5659	-1.2555	0.4937	9.4553
VOLA	0.6698	1.5675	-1.2374	0.5157	8.1962
TED	0.8957	1.7894	-1.6850	0.5809	7.9146
DEF	1.0636	2.0349	-2.0984	0.6979	11.6680
Mean	0.6666	1.5582	-1.2248	0.4982	9.8555
Bayes	0.9624	1.8195	-1.7819	0.5910	8.6083

Table 2:
Variance decomposition for real stock returns (subsamples).

The variance and covariance terms are given as ratios to the variance of the unexpected real stock return. Both panels show the average values for each of the following seven variables: dividend-price ratio (DPR), earnings-price ratio (EPR), term spread (TERM), one-month Swiss interbank rate (IR), realized stock market volatility (VOLA), U.S. TED spread (TED), and U.S. default spread (DEF). The table also report the mean values over all models and the results of the Bayesian weighted model (BAYES). Panel A uses data from 1975 to 1988, Panel B from 1989 to 2002.

news about future dividends. The same is true for the more recent subperiod (Panel B of Table 3). Even if the dividend-price ratio is included in the analysis, average correlations between news about future excess returns and news about future dividends are positive; the predictive ability of the dividend-price ratio has largely disappeared recently. Moreover, the fractions of $Var(\eta_{d,t})$ and even $-2Cov(\eta_{e,t}, \eta_{d,t})$ are very high and more important than the fractions of $Var(\eta_{e,t})$, independent of the prevailing predictive variable(s).

As in Campbell (1991), the variance of news about future real interest rates is very small. The covariances between news about real interest rates and news about other variables are also small. It seems that news about real interest rates cannot account for large movements in stock prices. However, while the persistence measure P_e is quite similar to the respective measure for real returns, P_r , the persistence measure P_i for the expected real interest rate is, in contrast to Campbell (1991), quite large.

4.5 Robustness of the Results

While Campbell (1991) shows that the variance decomposition for stock returns is quite robust to changes in VAR lag length and data frequency, he also notes that it is quite sensitive to changes in the predictive variables which are used. The critical variable appears to be the dividend-price ratio. When this variable is included in the VAR, the variance decomposition is much the same even if the stochastically detrended short rate is dropped from the system or replaced by the term spread. But when the dividend-price ratio is excluded from the system, the variance of news about future cash flows is given a more important role while the variance of news about future returns becomes less important and the covariance term is imprecisely estimated (Campbell, 1991, p. 172).

Our results in Tables 1 through 3 seem to support Campbell's (1991) findings. In what follows, we extend the above analysis and additionally introduce parameter and model uncertainty in the same way as in Rey (2004a,b). In particular, we first draw a model M_j with posterior probability, $p(M_j | \mathbf{z})$, where \mathbf{z} stands for the data. Second, the model-specific parameters \mathbf{a} , \mathbf{B} , and Σ are drawn from their joint posterior distribution as described in Rey (2004a,b). Repeating this many times (our 10,000 draws provide a high degree of accuracy) gives an accurate representation of the Bayesian weighted (predictive) model which we can use to compute the variance decomposition when taking stock market predictability, parameter uncertainty, and model uncertainty into account.

Figures 3 through 5 show the resulting distributions of the correlations between news about future excess returns, news about future dividends, and news about future interest rates, respectively. The graphs on the left-hand side are for the first subperiod from 1975 to 1988, the ones on the right for the recent time period 1989 to 2002.

Consider first the distribution of the correlations between news about future excess returns and news about future cash flows, $Corr(\eta_{e,t}, \eta_{d,t})$, given in

	Var (η_e)	Var (η_i)	Var (η_d)	2Cov (η_e, η_i)	-2Cov (η_e, η_d)	-2Cov (η_i, η_d)	P_e	P_i
A: 1975:01–1988:12								
DPR	0.5213	0.0129	0.3318	-0.0668	0.2833	-0.0826	8.4743	11.1966
EPR	0.6205	0.0112	0.4346	-0.0397	0.0401	-0.0667	6.2242	9.7008
TERM	0.4508	0.0126	0.5738	-0.0648	0.0666	-0.0391	6.5866	8.7777
IR	0.4283	0.0129	0.5669	-0.0618	0.1043	-0.0506	6.3454	9.1951
VOLA	0.4471	0.0100	0.5721	-0.0488	0.0614	-0.0419	6.3924	8.9030
TED	0.4484	0.0116	0.5695	-0.0443	0.0687	-0.0539	6.7565	7.4030
DEF	0.4401	0.0100	0.5646	-0.0509	0.0765	-0.0404	7.0381	8.4629
Mean	0.4365	0.0101	0.5600	-0.0495	0.0851	-0.0422	6.9398	9.0394
Bayes	0.5900	0.0089	0.4450	-0.0385	0.0436	-0.0491	6.4240	9.5937
B: 1989:01–2002:12								
DPR	0.7966	0.0099	1.4980	-0.0321	-1.2894	0.0170	8.9341	17.4725
EPR	0.7393	0.0089	1.6126	-0.0401	-1.3674	0.0467	9.6442	16.1684
TERM	0.7136	0.0102	1.5460	-0.0293	-1.2463	0.0057	9.5334	16.5493
IR	0.7093	0.0126	1.5742	-0.0272	-1.2559	-0.0130	9.7933	20.8476
VOLA	0.6917	0.0097	1.5750	-0.0273	-1.2679	0.0188	8.6138	14.6452
TED	0.9078	0.0099	1.7995	-0.0149	-1.7162	0.0138	7.8389	13.9881
DEF	1.0346	0.0111	2.0469	0.0253	-2.0807	-0.0372	11.5842	17.4480
Mean	0.6874	0.0099	1.5650	-0.0265	-1.2543	0.0183	10.1728	17.5781
Bayes	0.9695	0.0101	1.8126	-0.0191	-1.7791	0.0060	8.4793	15.4308

Table 3:
Variance decomposition for excess stock returns (subsamples).

The variance and covariance terms are given as ratios to the variance of the unexpected excess stock return. Both panels show the average values for each of the following seven variables: dividend-price ratio (DPR), earnings-price ratio (EPR), term spread (TERM), one-month Swiss interbank rate (IR), realized stock market volatility (VOLA), U.S. TED spread (TED), and U.S. default spread (DEF). The table also reports the mean values over all models and the results of the Bayesian weighted model (BAYES). Panel A uses data from 1975 to 1988, Panel B from 1989 to 2002.

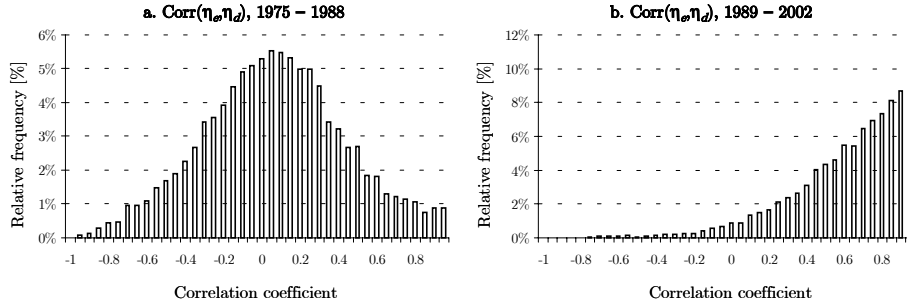


Figure 3:
Distribution of implied correlations between news about future dividends and future expected returns.

The graph on the left shows the distribution (relative frequency) of implied correlations between news about future dividends and future expected excess returns, using data from 1975 to 1988. The graph on the right is based on data from 1989 to 2002. The distributions result from a Monte Carlo simulation experiment that endogenously accounts both for Bayesian model and parameter uncertainty.

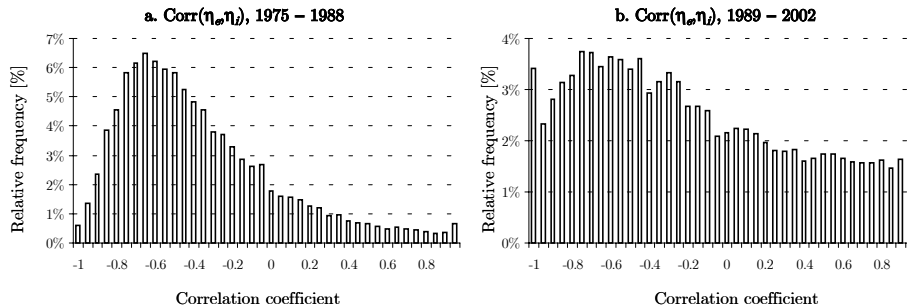


Figure 4:
Distribution of implied correlations between news about future interest rates and future expected returns.

The graph on the left shows the distribution (relative frequency) of implied correlations between news about future interest rates and future expected excess returns, using data from 1975 to 1988. The graph on the right is based on data from 1989 to 2002. The distributions result from a Monte Carlo simulation experiment that endogenously accounts both for Bayesian model and parameter uncertainty.

Figure 3. The general pattern is quite different between the two subperiods. From 1975 to 1988, relative frequencies are highest around zero and the distribution is quite symmetric around zero correlations. Recently, from 1989 to 2002, even if the dividend-price ratio is included in the analysis, correlations between news about future excess returns and news about future dividends are predominantly positive. This means that stock prices move less in response to cash flows news than they would if expected returns were constant (or negatively correlated with news about future dividends), actually reinforcing the “excess volatility” puzzle of Shiller (1981) and LeRoy and Porter (1981). Worse, as Cochrane (2001, Ch. 20) puts it, any positive correlation between dividend growth and expected return shocks is difficult to reconcile with the business cycle, consumption smoothing explanation of a time-varying risk premium. If anything, since expected returns are assumed to rise in “bad times” when risk or risk aversion increases, one should see a positive shock to expected returns associated with a negative shock to current or future dividend growth! After all, as first emphasized by Fama and French (1989) and Fama (1991), it is widely accepted that expected returns vary over business cycles; it takes a higher risk premium to get people to hold stocks at the bottom of a recession. Our results are hard to reconcile with this view, however. Exactly those variables that are most correlated to macroeconomic activity do not show the postulated negative correlations between news about future expected returns and news about future cash flows. Unfortunately, the fact that the inclusion of the dividend-price ratio does create the negative correlations (of course, only in the early subsample), is not of great help. The dividend-price ratio has a special status since the risk-based business-cycle argumentation is not explicitly needed to explain its predictive power. Our results, as well as those of Ang and Bekaert (2003), Engstrom (2003), Goyal and Welch (2003a,b), and Lettau and Ludvigson (2003), suggest that the standard conclusion in the literature, namely that the bulk of the variance of dividend-price ratios must be accounted for by changing forecasts of discount rates over business cycles, is probably somewhat premature, at least incomplete. In addition, if studies such as those of Goetzmann and Jorion (1995) and particularly Goyal and Welch (2003a,b), who show that the predictive power of the dividend-price ratio is entirely due to the volatile markets in the mid-70s, are right, it would not really strengthen our beliefs that the correlation between news about future excess returns and future cash flows is reliably negative!

The distributions of $Corr(\eta_{e,t}, \eta_{i,t})$ and $Corr(\eta_{i,t}, \eta_{d,t})$ are shown in Figures 4 and 5, respectively. As expected, the results are less interesting than those for the distribution of $Corr(\eta_{e,t}, \eta_{d,t})$. While relative frequencies of $Corr(\eta_{e,t}, \eta_{i,t})$ exhibit peaks around correlation coefficients of -0.6 over both sample periods, the respective distributions are rather flat, particularly so in the recent time period. The latter is also true for the distribution of the correlations between news about future interest rates and future dividends, $Corr(\eta_{i,t}, \eta_{d,t})$; the correlations, however, are, on average somewhat positive from 1975 to 1988, and somewhat negative only recently. These results, while not very strong, are

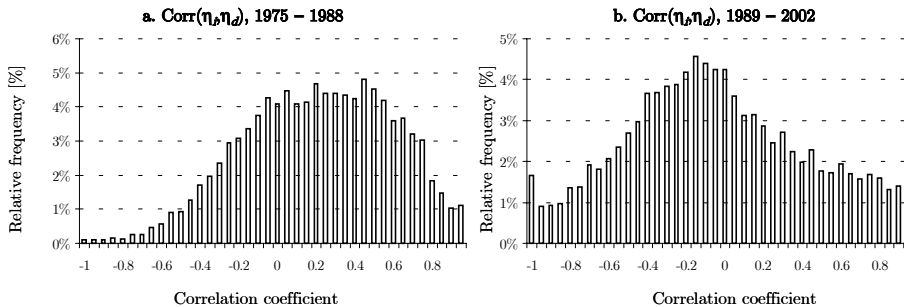


Figure 5:
Distribution of implied correlations between news about future interest rates and future dividends.

The graph on the left shows the distribution (relative frequency) of implied correlations between news about future dividends and future interest rates, using data from 1975 to 1988. The graph on the right is based on data from 1989 to 2002. The distributions result from a Monte Carlo simulation experiment that endogenously accounts both for Bayesian model and parameter uncertainty.

nevertheless quite in line with the business-cycle argumentation briefly discussed above. Note that since discount rates consist of a risk-free and risk premium component, $r_t = r_{f,t} + e_t$, equation (4) might be rewritten as

$$d_t - p_t \approx -c + E_t \sum_{j=1}^{\infty} \rho^{j-1} (e_{t+j} - r_{f,t+j} - \Delta d_{t+j}). \quad (44)$$

Thus, the variation of dividend-price ratios should not only be attributed to the variation of expected future excess returns and dividend growth, but also to the variation of expected future interest rates. Ang and Bekaert (2003) is one of the few studies that examine the fraction of the variation in dividend-price ratios that reflects the predictability of future interest rates as well. Indeed, they find that the dividend-price ratio significantly predict interest rates. The role of the dividend-price ratio with respect to the riskless interest rate and the role of the short rate for the variation in expected real stock market returns should therefore not be neglected, see Ang and Bekaert (2003) and the respective discussion in Rey (2003a).

5 Conclusion

It is often argued that the variability and persistence of expected stock market returns account for a considerable degree of volatility in realized returns. Using monthly data on the Swiss stock market index over the period from 1975 to 2002 and two subsamples of equal length, respectively, we critically examine whether increases in future expected cash flows tend to be associated with decreases in future expected returns, a correlation that would amplify the volatility of equity

returns. We emphasize that the results are dependent on the particular specification of the predictive variables. In contrast to the standard conclusion in the literature, we do not generally find that the variance of news about future returns is greater than the variance of news about future dividends. This result rather depends on the time period under consideration, and, more importantly, whether the dividend-price ratio is included in the analysis. If it is and the sample period is from 1975 to 1988, the correlation between news about future returns and news about future dividends is negative, implied realized returns exhibit mean reversion, and the fraction of the variance of news about future returns is more important than the residual fraction of the variance of news about future dividends. Recently, from 1989 to 2002, even if the dividend-price ratio is included in the analysis, average correlations between news about future returns and news about future dividends are positive, and the fractions of the variance of news about future dividends is very high and much more important than the fractions of the variance of news about future returns, independent of the prevailing predictive variable(s). This result is not only confirmed when we additionally introduce Bayesian model and parameter uncertainty into the analysis, but also when we stochastically detrend the predictive variables, irrespective of the underlying sample period.

Consequently, the role of predictable time variation in expected stock returns with respect to the observed volatility of the stock market returns may have been overstated. Of course, predictable returns move quite persistently when parameterized by the commonly used predictive variables, but, in general, they do not appear to fall when expected dividends rise. This means that stock prices move less in response to cash flows news than they would if expected returns were constant (or negatively correlated with news about future dividends), actually reinforcing the “excess volatility” puzzle of Shiller (1981) and LeRoy and Porter (1981). Worse, as Cochrane (2001) puts it, any positive correlation between dividend growth and expected return shocks is difficult to reconcile with the business cycle, consumption smoothing explanation of a time-varying risk premium. Indeed, our results are hard to reconcile with this view. Exactly those variables that are most correlated to macroeconomic activity do not show the postulated negative correlations between news about future expected returns and news about future cash flows. Unfortunately, the fact that the inclusion of the dividend-price ratio does create the negative correlations (of course, only in the early subsample), is not of great help. The dividend-price ratio has a special status since, first, the risk-based business-cycle argumentation is not explicitly needed to explain its predictive power, and, second, it is not unlikely that the predictive power of the dividend-price ratio is entirely due to one or two outlier return observations during the volatile markets in the mid-70s.

Overall, thus, although the variance decomposition cannot give an unambiguous structural interpretation, the standard lesson that persistent movements in expected returns, parameterized by the dividend-price ratio and/or other business-cycle related macroeconomic variables, are a major force driving unexpected returns may be somewhat premature, at least incomplete. Interestingly, while based on a simpler and static framework, Zimmermann (2004) comes to

a similar conclusion. It would be interesting to reconcile Zimmermann's (2004) static and our dynamic analysis in another piece of research.

A Description of Data

Appendix A describes the Swiss stock market data used throughout the paper.

A.1 The Stock Market Index

The empirical results in this paper are based on Swiss stock market data. Monthly data are used throughout, spanning 336 months from January 1975 to December 2002. We also investigate two subsamples of equal length (each 168 months). The first subsample uses data from January 1975 to December 1988, covering the first half of the total time period, the second subsample is based on data from January 1989 to December 2002, covering the second half of the full sample.

The Swiss stock market index is a value-weighted aggregate of the following industry sector indices:

- Airlines and Transportation (*Datastream Mnemonic: AIRLNBV*),
- Financials (*BANKSBV, INSURBV*),
- Food (*FOODSBV, BREWSB*),
- Industrials (*GENINBV*),
- Pharma (*PHARMBV*),
- Retailers (*MULTIBV, FDRETBV*),
- Utilities (*UTILSBV*), and
- Other Businesses (*OTHBUBV, LESURBV*).

All return series include dividends (total returns). To obtain continuously compounded real returns, total returns are deflated using monthly rates of change in the Consumer Price Index (CPI), provided by the Swiss National Bank. Continuously compounded excess returns are less the prevailing one-month Swiss interbank rate (*SWIBK1M*) at the beginning of the month.

Figure 6 shows the nominal price index (January 1975 = 100) and the respective continuously compounded return series.

Table 4 presents summary statistics for the continuously compounded excess and real returns.

Mean Reversion in Stock Market Returns An interesting and important sidestep is to consider whether the stock market returns exhibit mean reversion over the respective sample periods. In particular, we calculate the q -period variance ratio statistic $VR(q)$ as

$$VR(q) \equiv \frac{Var(e_{t \rightarrow q})}{qVar(e_t)} = 1 + 2 \sum_{j=1}^{q-1} \left(1 - \frac{j}{q}\right) Corr(e_t, e_{t+j}), \quad (45)$$

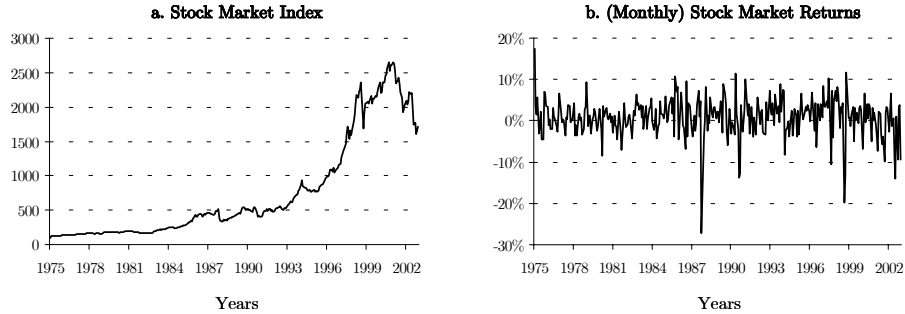


Figure 6:
The Swiss stock market.

The graph on the left shows the time series of the aggregated nominal price index (January 1975 = 100). The graph on the right plots the respective continuously compounded return series. Monthly data are used from January 1975 to December 2002.

	1975:01–2002:12		1975:01–1988:12		1989:01–2002:12	
	Exc. ret.	Real ret.	Exc. ret.	Real ret.	Exc. ret.	Real ret.
Mean	6.02%	7.40%	6.65%	7.44%	5.39%	7.35%
Median	0.86%	0.86%	0.51%	0.62%	1.43%	1.59%
Max.	16.81%	16.95%	16.81%	16.95%	11.65%	11.77%
Min.	-27.57%	-27.72%	-27.57%	-27.72%	-19.92%	-20.06%
Volatility	16.14%	16.19%	14.75%	14.82%	17.45%	17.49%
Skewness	-1.13	-1.14	-1.42	-1.43	-0.93	-0.95
Kurtosis	8.25	8.36	14.44	14.53	4.76	4.85
J.-Bera	457.6	476.0	971.8	987.9	45.9	49.2
Prob.	***0.00	***0.00	***0.00	***0.00	***0.00	***0.00
Obs.	336	336	168	168	168	168

Table 4:
Summary statistics of the Swiss stock market data.

The table presents summary statistics of continuously compounded real and excess monthly Swiss market stock returns. These include mean (ann.), median, maximum and minimum value, volatility (ann.), skewness, and kurtosis. The table includes the Jarque and Bera (1980) test of normality. Estimates are given for three different time periods: 1975 to 2002 (full sample), 1975 to 1988, and 1989 to 2002. */**/** indicate p-values less than 0.1/0.05/0.01.

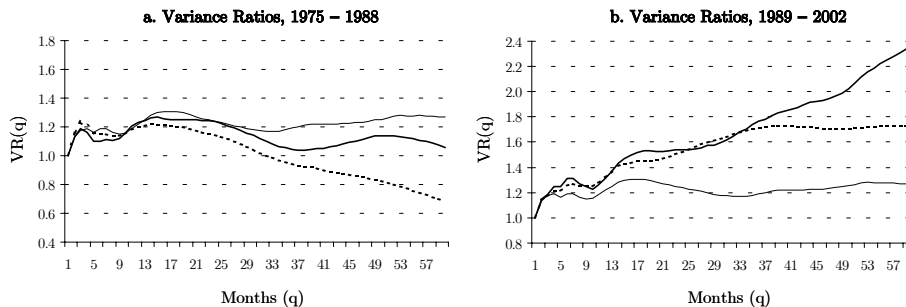


Figure 7:
Mean reversion and variance ratio statistics.

The graphs show variance ratio statistics for time horizons varying from one to 60 months. A variance ratio below one indicates mean reversion, a ratio above one mean aversion. The graph on the left is based on data from 1975 to 1988. The graph on the right uses monthly data from 1989 to 2002. The fine lines plot variance ratios calculated based on the full sample (1975 to 2002). The dotted lines are based on the standard approach given in equation (29). Bold lines correspond to efficient and bias-adjusted variance ratio statistics (Lo and MacKinlay, 1988, 1989).

with $e_{t \rightarrow q} \equiv e_t + e_{t+1} + \dots + e_{t+q-1}$ and $Corr(e_t, e_{t+j})$ is the j th-order autocorrelation coefficient of $\{e_t\}$. If returns are positively autocorrelated, variances grow faster than linearly and the variance ratio is above one for $q > 1$, $VR(q) > 1$. Alternatively, in the presence of negative autocorrelation, the variance of the sum of one-month returns is smaller than the sum of the one-month return's variances; hence $VR(q) < 1$, variances grow slower than linearly. This is the case of mean reversion. If returns are i.i.d., $VR(q) = 1$.

Figure 7 shows variance ratio statistics for time horizons, q , varying from one to 60 months. The results reveal an interesting pattern. Based on the data covering the first half of the total time period (1975 to 1988), continuously compounded excess returns seem to mean revert. The variance ratio statistic is well below one for long horizons. Recently, however, the mean reversion pattern has completely disappeared. Rather than mean reversion, the Swiss stock market exhibits strong mean aversion since 1989. However, if the estimates of the variance ratio statistics are based on overlapping q -period returns and corrected for the bias in the variance estimators (Lo and MacKinlay, 1988, 1989), the evidence on mean reversion over the first subsample vanishes. Over the recent subsample, the tendency of mean aversion is even amplified.

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