International stock return correlation: real or financial integration? A structural present-value approach*

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Abstract

I explore the determinants of comovements between the U.S. and U.K. stock markets from an asset pricing perspective. I use a present-value model that captures the impact of time variation in both discount rates and market expectations about future cash flows embedded in stock prices. I define financial integration as the cross-country correlation in discount rate shocks and real integration as the corresponding correlation in dividend growth shocks. I find that real integration is a major determinant of stock price comovements, and it accounts for nearly 53% of the run-up in return correlation between the two countries during the last two decades. This result is consistent with the increase in the correlation of various indicators of economic activity during the same period. The relative importance of real integration is lower for domestic firms which operate just within the U.S. This evidence suggests that real integration is driven by those firms whose assets are more exposed to global shocks.

1 Introduction

Understanding what drives cross-country correlations in stock returns is of great interest to researchers in international finance. Correlations are commonly regarded as useful measures of the strength of the economic and financial linkages between two countries. They are necessary inputs for investors and mutual fund managers who want to evaluate the benefits of international diversification.

Correlations are also characterized by distinguishable patterns, like the dramatic increase in the correlation between the U.S. and U.K. stock returns during the last two decades. However, whether or not globalization has led to significant changes in the correlation between stock market valuations is still an open issue in the international finance literature. Among others, Longin and Solnik (1995) document an increase in the correlation of stock returns for various developed markets over the 1960-1990 period. Similarly, Eun and Lee (2006) find increasing convergence in international stock markets by looking at the risk-return distance among them, while Bekaert, Harvey, Lundbland, and Siegel (2008) document a decrease in segmentation in many developing countries. In contrast, Bekaert, Hodrick, and Zhang (2009) find at best weak evidence of a trend in cross-country integration using risk-based factor models which extend the standard Heston and Rouwenhorst (1994) approach.

Clearly, time-series fluctuations and trends in international correlations arise from the interplay of many factors affecting capital markets and economic integration. From an asset pricing perspective, these factors should ultimately result in changes in discount rate correlation, changes in the correlation of dividend growth, or a combination of the two. Moreover, if expected returns and investors' expectations about future dividend growth were constant over time, then the correlation in asset returns should equal the correlation in the underlying cash-flows. Yet, these correlations are empirically very different. By way of example, the correlation in aggregate dividend growth between the U.S. and U.K. has been about 0.33 during the 1966-2008 period, while the corresponding correlation in stock returns has been much higher at 0.69. Such a large difference reveals that co-movements in long-run expectations embedded in stock prices play a key role in driving international correlations. This fact is intimately related to the evidence of "excess volatility" in stock returns relative to fluctuations in underlying dividends, initially documented by Shiller (1981). Based on this evidence, several studies have investigated time variation in discount rates and in the expectation about the growth rate of dividends using valuations ratios, business-cycle indicators, or variables motivated by theoretical models (see Fama and French (1988b), Campbell and Shiller (1988), Lewellen (2004), Menzly, Santos, and Veronesi (2004), Lustig and Van Nieuwerburgh (2005) among others).

This paper explores the co-movements between the U.S. and U.K. stock markets by means of an underlying present-value model. In the model, the conditional expectations of returns and dividend growth of each country are assumed to be time-varying and are allowed to share common fluctuations. To that end, expected dividend growth is expressed as the sum of a component that is linearly related to expected returns and an orthogonal component. The system is driven by shocks to expected returns, shocks to the orthogonal component of expected dividend growth, and unexpected dividend growth. These three shocks are responsible for revisions in the price of each aggregate stock market index. Consequently, fluctuations in market returns are attributable to either revisions in discount rates, or to shocks in expected and unexpected dividend growth.

The univariate framework is then extended to take explicitly into account the correlations between these shocks across the two markets. A result of the bi-variate model is that we can write the correlation in returns as the sum of three components. One component is related to the correlation between shocks to expected returns, and is referred to as a measure of financial integration. The second component captures real integration as reflected by the correlations between shocks to unexpected dividend growth and between shocks to the component of its expectation that is unrelated to discount rates. Finally, a third component captures the cross-correlation between the two groups of shocks.

I estimate the model on U.S. and U.K. aggregate stock market data over the 1966-2008 period by relying on a generalized method of moments methodology. The findings reveal that both markets display a positive degree of co-movement between expected returns and expected dividend growth, with the U.K. exhibiting a stronger effect. The U.K. also exhibits a larger relative variability of the orthogonal component of its dividend growth process than the U.S. does. I also find that unexpected dividend growth has a variability that is one order of magnitude larger than that of the other shocks, while shocks to the orthogonal component of expected dividend growth are the least volatile. Consistent with the intuition of the model, the variability of the underlying expectations of returns and dividend growth is substantially larger than what is predicted by the dividend-yield regressions. Across the whole sample, shocks to expected returns are responsible for about two-thirds of the variance of U.S. returns, while for the U.K. the same fraction is accounted for by shocks to dividend growth. In turn, the joint correlations estimates reveal that financial integration accounts for about 48% of the 0.69 correlation in returns during the whole period, while real integration is responsible for 40% of it.

In the context of predictive regressions involving valuation ratios, it is important to take into account the possibility that structural breaks occurred during such a long sample period. Based on the findings of Lettau and Van Nieuwerburgh (2008), I adjust the dividend-yield for breaks in its conditional mean and explore the sensitivity of the results during the pre- and post-1991 break date. Looking at the behavior across different subsamples is particularly interesting in this study due to the recent run-up in the correlation between the U.S. and U.K. returns to values as high as 0.90, which were never experienced in previous periods. A similar upward trend in correlations among many developed countries has been documented by Goetzmann, Li, and Rouwenhorst (2005).

I find that expected returns and expected dividend growth have become more highly correlated and more persistent in the more recent period. I also document a decrease in the volatility of their shocks, and also in the volatility of unexpected dividend growth for the U.K. Interestingly, in the last period, shocks to dividend growth account for nearly half of the variance of U.S. returns. Taken together, all these changes in the univariate properties of the two markets during the 1992-2008 period are responsible for three effects. They imply a decrease in the volatility of returns and in their covariance. They also lead to a hypothetical increase in the return correlation from 0.62 to 0.68. However, this value is found to be much lower than the correlation of about 0.83 observed during the same period. The cross-country estimates reveal that this difference is attributable to a substantial increase in the correlations between shocks in unexpected dividend growth and between the orthogonal component of its expectation. In contrast, I find a marginal increase in the correlation of discount rate shocks across the two periods. As a consequence of this fact, real integration turns out to be the major determinant of return correlation in the recent sample period, accounting for the largest fraction (about 53%), compared to a fraction of about 38% due to the correlation in discount rate shocks.

This larger role played by real integration is consistent with the increased correlation between the growth rate of macroeconomic indicators of the two countries, such as GDP, and industrial production. These variables have been used in other studies exploring market integration (see Costello (1993)). For example, the correlation between industrial production growth has jumped from 0.32 in the 1966-1991 period to 0.62 in subsequent years. There is also some evidence that the trade activity between the two countries has been recently more pronounced, as reflected by the increased size of import/export relative to national output.

A natural question is whether this pattern at the aggregate level is representative of the whole universe of firms. In fact, there is considerable cross-sectional variability in the exposure of firms to international shocks even among large capitalization stocks. Therefore, it is interesting to investigate the implications of such heterogeneity for our measure of integration. Intuitively, we expect that real integration should play a smaller role for firms that are less exposed to economic shocks occurring in foreign markets. To test this hypothesis, I look at the degree to which firms are international as measured by the fraction of assets that are held abroad. I then construct an index of large capitalization stocks whose operations and service/sales offices are located exclusively in the U.S. and look at its joint properties with the U.K. market during the recent period. For these stocks, the correlation in discount rate shocks is larger at 0.95 than for the aggregate stock market, while the correlation in shocks to long-run dividend growth is much lower at 0.40. As a result, financial integration is responsible for the largest fraction of return correlation, about 57%, while real integration is lower at 45% . This evidence suggests that real integration at the aggregate level is mainly driven by more internationally diversified firms, and is consistent with other studies that look at the degree of internalization of companies in the context of stock market co-movements (see Brooks and Del Negro (2006)).

Our approach has several advantages. By exploiting the theoretical relations between the observed data and the data generating process, we are able to obtain estimates of the underlying properties of market participants' expectations. This goal is achieved solely using the information contained in the dividend-yield. Moreover, by estimating the univariate and joint underlying properties of the two markets our approach takes into account both the risk-return characteristics of each market as well as their co-movements in short-term shocks and long-run expectations. This allows us, for example, to separate out the effect of changes in idiosyncratic volatilities from those in the correlation among the underlying shocks.

The use of present-value models to analyze the properties of international equity markets has a long standing in the finance literature (see e.g., Fama and French (1988b), Campbell and Hamao (1992), Bekaert and Hodrick (1992), Ang and Bekaert (2007)). Ammer and Mei (1996) study the U.S. and U.K. stock markets, but rely on a VAR methodology. The point that the dividend-yield is an imperfect predictor of expected returns and expected dividend growth when these share common fluctuations has also been explored by other authors. Menzly, Santos, and Veronesi (2004) show that this co-movement is consistent with an habit formation model where the financial assets differ in the persistence of their relative share of the overall economy. Lettau and Ludvigson (2005) point at this effect to justify the ability of the *cay* variable to capture fluctuations in expected dividend growth. Koijen and Van Binsbergen (2009) rely on a Kalman filter methodology to capture expected returns and dividend growth. Similarly to them, I find that expected dividend growth is positively correlated with expected returns and its variability is largely understated by the dividend-yield.

The remainder of the paper is organized as follows. Section 2 describes the data and provides empirical evidence in support of the analysis. Section 3.1 presents the model that will be used to investigate the univariate properties of the two stock markets. Section 3.2 extends the model to the bivariate dimension, and Section 3.3 outlines the return correlation decomposition. Section 4 presents the results for the predictive regressions and underlying structural parameters for each stock market, while the joint structural parameters results are discussed in Section 4.3. Section 5 provides evidence of increased correlation in various economic indicators, and investigates the role of real integration for U.S. firms whose assets are less exposed to global shocks. In Section 6, I test the robustness of the previous findings along various dimensions such as non-dividend-paying stocks and sampling frequency. Finally, I offer concluding remarks in Section 7.

2 Data and Sample Period

2.1 Data construction

The quarterly stock market data come from two sources. For the U.S., I use the value-weighted return series from the Center for Research on Security Prices (CRSP), including NYSE/AMEX/NASDAQ. For the U.K., I rely on the U.K.-DS Index (mnemonic TOTMKUK) from Datastream, a division of Thompson Financial. This index is constructed based on a representative sample of stocks covering a minimum 75 - 80% of total market capitalization, and its performance tracks quite closely that of the FTSE 100.

Both indices are available including dividends distributions (total return index, denoted P_t) and excluding dividends distributions (price index, denoted P_t^x). Using the cum-dividend gross return R_t and the ex-dividend gross return R_t^x, I calculate the time-t implied dividend as $D_t = (R_t/R_t^x - 1) \cdot P_t^x$. To smooth out seasonality in dividends issuance, I calculate annual dividends D_t^4 by summing up dividends over the current and past three quarters, $D_t^4 = D_t + D_{t-1} + D_{t-2} + D_{t-3}$. The current dividend-price ratio, or dividend-yield, is then calculated as $DP_t = D_t^4/P_t^x$.

As is common in the international finance literature (see e.g., Bekaert, Hodrick, and Zhang (2009) and Pukthuanthong and Roll (2009)) I convert the price indexes to a common currency - U.S. dollars - to reduce the impact of exchange rate fluctuations. For the conversion of the U.K. data, I use the exchange rate provided by Datastream.[1] Finally, I work with variables measured in logs: log returns ($r_{t+1} = \ln(R_{t+1})$), log dividend growth ($\Delta d_{t+1} = \ln(D_{t+1}^4/D_t^4)$), and log dividend-yield ($dp_{t+1} = \ln(DP_{t+1})$). Returns and dividend growth are then converted to real terms by subtracting the log difference in the U.S. Consumer Price Index available from CRSP.

2.2 Sample period and summary statistics

The focus of the paper on correlations requires both series to be available for the same time period. While the U.S. series starts in 1926, the U.K. index series is available from Datastream just from the first quarter of 1965. Following the data construction method outlined above, we are left with 172 observations for returns, dividend growth, and dividend-yield beginning in the first quarter of 1966 (1966:1) and ending in the last quarter of 2008 (2008:4).

The top panel of Figure 1 plots the total real return indices for the U.S. (solid line) and U.K. (dashdot line) during the full sample. As we can see, equity returns to both countries have been positive during the 1990-2000 decade and the 2004-2007 period, with the U.K. exhibiting larger fluctuations. Both stock markets have also experienced severe downturns during the 2000-2003 period and in the recent financial crisis, with the U.K. again suffering more pronounced variations.

The bottom panel of Figure 1 shows a similar plot for the performance of an index investing in real dividend growth. U.S. real dividend growth has been relatively small but higher than for the U.K. during the first half of the sample. In the second half, the role is reversed with U.K. dividend growth being larger. The series display some common patterns, such as the

[1] Several studies examine whether exchange risk is priced in international markets by testing the restrictions of the International CAPM (see e.g., Engel and Rodrigues (1989), Dumas and Solnik (1995) and Ng (2004)). Since I work with dollar-denominated series, I do not address this question directly as exchange risk is incorporated into the expected return of the foreign country (U.K.).

decline in the early 2000s, the increase in the 2004-2007 period, and the more recent drop.

Although the aim of the paper is not to model the time-series behavior of cross-country conditional correlations, it is interesting for our subsequent analysis to look at their evolution during our sample. To this extent, Figure 2 plots the rolling correlations of returns (top panel) and dividend growth (bottom panel) to the two countries based on a 7-year window, or 28 observations.[2] Both correlations show some degree of variation. Before the 1990s, return correlation varies in a range between 0.43 and 0.74, with a decreasing trend from 1975 until the first quarter of 1982 and an increasing pattern from that point onward. In the last two decades, the correlation has been initially stable, decreasing between 1994 and 1998 to a minimum of 0.43, and then almost steadily increasing to values around 0.80-0.90 beginning in the early 2000s. Dividend growth correlation has been generally less volatile than return correlation. However, it also appears to take on larger positive values in the last two decades, reaching a value as high as 0.78 in 2004. We can also identify some common trends between the two series, such as the decrease in the mid 1990s and the sharp rise in the late 1990s and subsequent years.[3]

These fluctuations in correlations are the result of institutional and technological changes that occurred during the whole sample period. To capture permanent changes in correlations, I look at the behavior of the series across different subsamples. Lettau and Van Nieuwerburgh (2008) document a major break in the unconditional mean of the dividend-yield series and other valuation ratios in 1991. This break might be the result of either a decrease in the long-run risk premium, a persistent increase in the dividend growth rate, or a combination of the two. From an econometric viewpoint, the effect of this break is to decrease the predictive ability of the dividend-yield, as it violates the assumption of stationarity that is at the basis of the Campbell and Shiller (1988) decomposition. Ignoring this break would bias our results toward lack of return predictability, as discussed in Lettau and Van Nieuwerburgh (2008). While their analysis is based on U.S. data, I perform similar tests for the U.K. and find that we cannot reject the null of a structural break for the U.K. dividend-yield series in 1991.[4]

[2]This length is chosen to balance between consistency of the estimates and the ability to detect significant trends. The conclusions still hold whether we use a larger or smaller window, with the plot getting respectively smoother or more jagged.

[3]Pukthuanthong and Roll (2009) point out that the cross-country correlation of stock indexes is an imperfect measure of market integration. However, correlations as high as those documented between the U.K. and the U.S. undoubtedly reveal of strong economic and financial links between the two markets. Working on daily data, they also report a substantial increase in the average correlation in the early 2000s, which is line with my findings.

[4]The average log dividend-yield for the U.K. has been -3.039 in the 1966-1991 period and -3.379 during

Since the aim of the paper is to explain correlations, we don't want this break to affect the interpretation of any other change in the underlying data generating process that potentially occurred during this period. Guided by these motivations, I split the whole 1966-2008 sample period into two subsamples: 1966-1991 (104 observations) and 1992 - 2008 (68 observations).

Table 1 presents summary statistics for the return, dividend growth, and dividend-price ratio series during the whole sample and the two subsamples. For the return and dividend growth series, the average and standard deviation are multiplied by 4 and 2, respectively, to express them on an annual basis. As we can see, the unconditional real premium on U.S. equity has been about 4.1%, while for the U.K. it has been higher at 6.2%.[5] The higher premium for the U.K. comes almost entirely from the earlier period, where it has been almost twice as much as for the U.S. U.K. returns also display a larger volatility than U.S. returns. The estimates are about 22% versus 18% over the whole sample. What is especially relevant for our study is the large positive correlation in returns of about 0.69 across the whole 1966-2008 period. This value lies in between the correlation of about 0.63 in the first subsample and the larger 0.83 correlation during the second subsample. This increase in correlation is statistically significant at the 1% level based on a Chow (1960) test. To better appreciate the magnitude of this effect, the top panel Figure 3 presents the scatter plot of contemporaneous returns between the two countries during the two subperiods. As we can see, the two series are more linearly related with each other during the 1992-2008 period, as reflected by the large increase in the R^2 of the regression of U.S. returns on U.K. returns from 0.40 to 0.70. Finally, the covariance between returns is decreasing during the same last two decades. This fact is due to a decrease in the return volatility of both the U.S. (from 18.6% to 16.9%) and U.K. (from 24.2% to 18.1%).

Turning our attention to the dividend growth series, we find that its average has been higher for the U.K. (2.1%) than for the U.S. (1.2%). Similarly to what we find for returns, this difference comes entirely from the earlier period (2.4% for the U.K. versus 0.2% for the U.S.). Consistent with the evidence of Figure 1, the volatility of dividend growth is much lower than that of returns, and is larger at 7.5% for the U.K. compared to the 4.8% estimate

the 1992-2008 period. The difference of -0.340 is statistically significant at the 1% level based on a Chow (1960) test.

[5]This result is not an artifact of exchange rate fluctuations. In fact, the premium on U.K. equity has been almost the same at 6.4% in local units of consumption. The average U.S. inflation is also much higher at 5.70% during the 1966-1991 period, compared to the 2.50% average for the 1992-2008 period. The average real return to U.S. equity is much larger at 5.90% when evaluated during the whole 1925-2008 period available from CRSP.

of the U.S. The relatively high first-order autocorrelation of dividend growth of about 0.33 for the U.S. and 0.57 for the U.K. is similar in magnitude to what has been documented by other studies (see e.g., Ang and Bekaert (2007)).[6] The correlation between dividend growth is also positive, and equals 0.33. However, as was the case for returns, this correlation is increasing from 0.31 during the earlier sample to 0.43 over the 1992-2008 period. This difference is statistically significant at the 3% level based on a Chow (1960) test. As a result, with reference to the bottom panel of Figure 3, the R^2 of the regression of U.S. dividend growth on U.K. dividend growth almost doubles, passing from 0.10 to 0.19. This evidence suggests that the trend in return correlation may be partly due to a corresponding increase in the correlation between the economic activities of the two markets, as represented by the correlation in their dividend growth.

We next look at the properties of the dividend-yield, which represents our predictor. Overall, the U.K. average dividend-yield has been about 4.2%, larger than the corresponding statistic for the U.S. (3.0%). Dividend-yields are slow moving and very persistent variables, as confirmed by their close-to-unity AR(1) coefficients. However, these coefficients are quite different, especially for the U.S., whether we look at the raw series or at the series break-adjusted in 1991.[7] The raw series has an autoregressive root of 0.969 for the U.S. and 0.906 for the U.K. For the break-adjusted series, these estimates are lower at 0.911 and 0.899, respectively. These differences look substantial when converted to annual frequency. They imply a persistence for the raw series of 0.88 and 0.67, compared to a persistence of 0.69 and 0.65 for the break-adjusted series. This evidence is consistent with Lettau and Van Nieuwerburgh (2008) who document that the break-adjusted series tends to be less persistent than the unadjusted series. Since the stationarity of the forecasting variable plays a crucial role in predictive regressions, this implies that relying on the break-adjusted series would improve the efficiency of our estimates. Finally, I also report the Schwartz Information Criterion (SIC) for two candidate processes. The first is the standard first-order autoregressive AR(1), while the alternative is an ARMA(2,1). As we can see, the SIC is minimized by the more parsimonious AR(1) process for both the U.S. and the U.K. across the whole sample as well as across subsamples.

[6] This result may partly be due to the way this variable is constructed. However, I find very similar summary statistics using Robert Shiller's annual series during the same period. This suggests that the autocorrelation in dividend growth does indeed reflect the existence of a persistent component of its expectation.

[7] For consistency with the rest of the paper, the following statistics refer to the series in logarithmic form.

3 The Model

3.1 Individual stock markets

In this section, I describe the data generating process for returns, dividend-growth, and their time-varying conditional expectations. This structure is assumed to be the same for each stock market. The parameters of the model, however, are allowed to take on different values for the two indices. As a result, we will have two different sets of parameters that I denote Θ_1 (for the U.S. stock market) and Θ_2 (for the U.K. stock market).[8] A similar framework has been adopted by Lettau and Van Nieuwerburgh (2008) and Plazzi, Torous, and Valkanov (2009).

I assume that returns r and dividend growth Δd are generated by the following pair of equations:

$$r_{t+1} = \overline{r} + x_t + \xi^r_{t+1} \tag{1}$$
$$\Delta d_{t+1} = \overline{d} + \tau x_t + y_t + \xi^d_{t+1} \tag{2}$$

where ξ^r_{t+1} represents the shock to returns and ξ^d_{t+1} is the shock to dividend growth, with $E_t(\xi^r_{t+1}) = E_t(\xi^d_{t+1}) = 0$. Expected (conditional) returns and dividend-growth are time varying and equal to $E_t r_{t+1} = r + x_t$ and $E_t \Delta h_{t+1} = d + \tau x_t + y_t$, respectively. I model x_t and y_t as AR(1) processes with the same autoregressive root ϕ:

$$x_{t+1} = \phi x_t + \xi^x_{t+1} \tag{3}$$
$$y_{t+1} = \phi y_t + \xi^y_{t+1} \tag{4}$$

where ξ^x_{t+1} and ξ^y_{t+1} constitute the mean-zero innovations in expected returns and expected dividend growth, respectively.[9]

To fully characterize the model we need to specify the covariance structure of the shocks

[8]As a notational convention throughout the paper, I denote with subscripts $\{t, i\}$ the value of a variable at time t for the i-th market. The parameters have just the index subscript. To keep notation simple, in this section I omit the market subscript meaning that the equations apply equivalently to each market.

[9]This assumption facilitates the subsequent expressions and model estimation. If the autoregressive roots are different, the dividend-yield follows an ARMA(2,1) process. We saw in the previous section that the dividend-yield seems to be better described by an AR(1) process based on the SIC. While the possibility of different roots cannot be entirely ruled out, these results suggest that this issue is unlikely to be a first-order effect for our sample period and data granularity.

in $\xi_{\mathbf{t+1}} = [\xi^r_{t+1}, \xi^d_{t+1}, \xi^x_{t+1}, \xi^y_{t+1}]$, whose variances are denoted $[\sigma^2_{\xi^r}, \sigma^2_{\xi^d}, \sigma^2_{\xi^x}, \sigma^2_{\xi^y}]$, respectively. The covariances between these shocks cannot, however, be set arbitrarily. In fact, in order to be consistent with the Campbell and Shiller (1988) log-linearization, the unexpected shock in returns must satisfy the following relation (see Campbell (1991)):

$$\xi^r_{t+1} = \frac{\rho}{1-\rho\phi}\left[(\tau-1)\xi^x_{t+1} + \xi^y_{t+1}\right] + \xi^d_{t+1} \ . \tag{5}$$

Thus, unexpected news in returns are positively related to the latter two shocks, while revisions in expected returns have a partially negative impact. This restriction implies that we have just three unique shocks in $\xi_{\mathbf{t+1}}$ for which we have to specify the covariance structure. I assume that shocks to x and y are uncorrelated at all leads and lags, or that $\text{Cov}(\xi^y_{t+1}, \xi^x_{t+j}) = 0$ for all j. In addition, I assume that $\text{Cov}(\xi^d_{t+1}, \xi^x_{t+j}) = 0$ for all j, $\text{Cov}(\xi^d_{t+1}, \xi^y_{t+j}) = 0$ for all $j \neq 1$, and $\text{Cov}(\xi^d_{t+1}, \xi^y_{t+1}) = \vartheta$. Based on these assumptions, we can look at expected dividend growth as the sum of two orthogonal components. One component, τx_t, captures co-movements with expected returns. The other component, y_t, captures variation in expected dividend growth unrelated to fluctuations in discount rates.

The system of equations (1-4) is quite general and is regarded as our "structural model". It accounts for time-variation in expected returns and expected dividend growth, as well as co-movement between the two. It should be understood as the underlying (unobservable) data generating process. Econometricians observe returns, dividend growth, and the dividend-yield and try to infer the properties of the underlying state variables. This goal is usually achieved by means of the following "reduced form" VAR system:

$$r_{t+1} = const + \beta\,(dp_t) + \varepsilon^r_{t+1} \tag{6}$$

$$\Delta d_{t+1} = const + \lambda\,(dp_t) + \varepsilon^d_{t+1} \tag{7}$$

$$dp_{t+1} = const + \phi\,(dp_t) + \varepsilon^{dp}_{t+1} \ . \tag{8}$$

These three regressions can be estimated separately by ordinary least squares. An important contribution of the recent literature has been specifying the links between the regressions in this system. As Cochrane (2008) and Lettau and Van Nieuwerburgh (2008) point out, the three forecasting regressions are intimately related by the present-value constraint $\beta - \lambda = 1 - \rho\phi$, which derives from the Campbell and Shiller (1988) log-linearization. Imposing this constraint, we can estimate two out of three equations and then recover the estimates of the remaining equation in a consistent manner.

A standard result from the predictive system (6-8) (see, among others, Campbell and Shiller (1988), Campbell (1991), Hodrick (1992), Cochrane (2008)) is that almost all variation in dividend-yields comes from fluctuations in expected returns, while dividend growth is essentially unpredictable. While the statistical significance of the estimates in (6) is weak and suffers from well known econometric problems (see Valkanov (2003), Lewellen (2004), Torous, Valkanov, and Yan (2005)), it is ultimately the lack of dividend-growth predictability that provides stronger evidence in favor of return predictability (Cochrane (2008)).

Recently, these conclusions have been subject to an active debate in the literature. If expected returns and dividend growth share variations at the same frequency, then the dividend-yield will have difficulty in capturing this variation and will be an imperfect predictor. This common variation is consistent, for example, with the general equilibrium models proposed by Brennan and Xia (2001) and Menzly, Santos, and Veronesi (2004). It can also arise from the long-run risk model of Bansal and Yaron (2004) under some conditions on the covariance of the shocks to the system. If this is the case, distinct from that suggested by the predictive VAR, expected dividend growth may not be constant. Lettau and Ludvigson (2005) make this point to show that dividend growth indeed contains a predictable component that can be captured by the variable *cay*, the deviation in the cointegrating relationship between consumption, aggregate wealth, and labor income. These results arise from the fact that *cay* is not tightly linked to this co-movement as is the dividend-yield through the Campbell and Shiller (1988) decomposition.

In our setup, the parameter τ represents the least square projection coefficient of dividend growth on expected returns. As such, it controls in a parsimonious way for the co-movement between their conditional means, which causes the dividend-yield to be an imperfect predictor. In fact, the Campbell and Shiller (1988) decomposition in this framework implies that the log dividend-price ratio or dividend-yield dp_t can be written as:

$$dp_t = \overline{dp} + \left[\frac{(1-\tau)x_t - y_t}{1-\rho\phi} \right] \tag{9}$$

where $\rho = 1/(1+\exp(\overline{dp}))$ is a linearization constant. Provided $|\phi| < 1$, the dividend-price ratio is stationary and captures just a fraction $(1-\tau)$ of the time-varying component of returns x_t.

However, this effect is not solely responsible for the predictive regressions estimates. In fact, we can identify the impact of the various features of the model on the predictive VAR by looking at the long-run slope coefficients expressed in terms of the underlying structural parameters:[10]

$$\beta_{LR} = \frac{1}{(1-\tau) + \upsilon\frac{1}{1-\tau}} \tag{10}$$

$$\lambda_{LR} = \frac{-\left[\tau(\tau-1)+\upsilon\right]}{(1-\tau)^2+\upsilon} \ . \tag{11}$$

Here, $\upsilon \equiv \sigma^2_{\xi^y}/\sigma^2_{\xi^x}$ represents the relative variance of the shocks to the orthogonal component of expected dividend growth, ξ^y, to the variance of the shock to expected returns, ξ^x.

These expressions show that the predictive ability of the dividend-yield ultimately depends upon two characteristics of the underlying economy. The first characteristic is the degree of co-movement between expected returns and expected dividend growth, captured by τ. The coefficients, however, do not change monotonically in τ. Rather, this relation is hump-shaped for values of τ ranging between -1 and 1, with both coefficients being initially increasing and then decreasing. The predictive coefficients also depend on the magnitude of υ. This parameter acts like a noise-to-signal ratio in the return regression and, conversely, as a signal-to-noise ratio in the dividend growth regression. As a result, an increasing υ results in a smaller β and larger λ values in absolute value. Interestingly, the sign of λ can be positive for some combinations of τ and υ. Positive coefficients for the dividend growth regressions are in contradiction to the basic intuition of the Campbell and Shiller (1988) decomposition. Nevertheless, they are not uncommon in empirical studies.

The variances of expected returns and expected dividend growth implied by the model

$$\text{var}(E_t r_{t+1}) = \frac{\sigma^2_{\xi^x}}{1-\phi^2} \tag{12}$$

$$\text{var}(E_t \Delta d_{t+1}) = \tau^2\frac{\sigma^2_{\xi^x}}{1-\phi^2} + \frac{\sigma^2_{\xi^y}}{1-\phi^2} \ . \tag{13}$$

reveal that the model nests many special cases. For example, expected dividend growth may be unrelated to expected returns. This is equivalent to imposing $\tau = 0$, or $E_t\Delta d_{t+1} =$

[10]The long-run coefficients are defined as the corresponding one-period coefficients, β and λ, divided by the present-value constraint, $1-\rho\phi$. They represent, respectively, the OLS estimates in the regression of the discount rate component (weighted average of future returns) and cash flow component (weighted average of future dividend growth) on the dividend yield. Cochrane (2008) points out the importance of focusing on long-run coefficients in predictive regressions. In addition, notice that the stationarity of the dividend-yield implies that the quantity $1-\rho\phi$ is a positive factor. Thus, dividing or multiplying by this quantity does not change the interpretation of the effect of τ and υ on the sign of the coefficients.

$y_t + \xi^d_{t+1}$. If we also assume that shocks to the orthogonal component y have zero variance, or $\sigma^2_{\xi^y} = 0$, we obtain the case of constant expected dividend growth, as for example in Campbell and Cochrane (1999). Finally, the assumption that shocks to expected returns x have zero variance, or $\sigma^2_{\xi^x} = 0$, brings us to the standard Gordon (1962) model.

We can also compare the variances in equations (12) and (13) to those of the fitted values from the predictive regressions (equations (6) and (7)). The latter expressions are provided in Appendix A for brevity. What is important to notice is that the fitted variances are always lower than the actual ones, as long as $\sigma^2_{\xi^y} > 0$. Their difference depends on τ, on the variance of shocks to expected returns ($\sigma^2_{\xi^x}$) and to the orthogonal component ($\sigma^2_{\xi^y}$). This is in line with Lettau and Ludvigson (2005), who claim that expected returns may vary even more than what is captured solely by the dividend-yield. It also implies that the lack of dividend-growth predictability (a small λ in absolute value) does not per se imply that expected dividend growth is constant over time. This fact helps clarify why if any variable helps to forecast long-run dividend growth, it must also help to forecast long-run returns (Lettau and Ludvigson (2005), Cochrane (2008)).

Another implication of the model is that fluctuations in returns arise necessarily from the three structural shocks. This being the case, the Campbell (1991) decomposition implies that we can write the unconditional variance of returns as the sum of two terms:

$$\mathrm{Var}(r_t) = \mathcal{V}_x + \mathcal{V}_{yd} \tag{14}$$

The first term, $\mathcal{V}_x$, is the amount of variance that is due to revisions in expected returns, or ξ^x. The second component captures the impact of shocks to dividend growth and fluctuations in the orthogonal component of its expectation.[11]

To summarize, each of the two markets is described by its own set of structural parameters $\Theta_i = (\rho_i, \phi_i, \tau_i, \sigma_{\xi^x_i}, \sigma_{\xi^y_i}, \sigma_{\xi^d_i}, \vartheta_i)$, with $i = \{1, 2\}$.[12] The system (1-4) fully characterizes the univariate and joint dynamics of returns, dividend growth, and dividend-price ratio of a single stock market. I now discuss the link between the structural shocks of the two indices. This is necessary in order to express the correlation between their returns in terms of the correlation between the shocks to the underlying data generating process.

[11] Appendix A reports the explicit definition of $\mathcal{V}_x$ and $\mathcal{V}_{yd}$ in terms of the underlying parameters.

[12] I omit from the definition of Θ_i the unconditional returns and dividend growth averages, $\overline{r}_i$ and $\overline{d}_i$. These parameters simply equal the sample average's counterparts, and are not of particular interest for our analysis once we account for the structural break.

3.2 Cross-Markets links

There are a total of six unique shocks (three for each market) driving the data generating process of the model. Thus, in order to describe the joint dynamics of the two markets we need to specify a six-by-six covariance matrix, which I denote $\mathbf{\Sigma}$:

$$\mathbf{\Sigma} = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} .$$

Along the main diagonal, this matrix contains the three-by-three covariance matrices of the individual markets, Σ_{11} for the U.S. and Σ_{22} for the U.K. Our previous assumptions on the covariances between the shocks in the system (1-4) imply that

$$\Sigma_{11} = \begin{pmatrix} \sigma^2_{\xi^x_1} & 0 & 0 \\ 0 & \sigma^2_{\xi^y_1} & \vartheta_1 \\ 0 & \vartheta_1 & \sigma^2_{\xi^d_1} \end{pmatrix} \qquad \text{and} \qquad \Sigma_{22} = \begin{pmatrix} \sigma^2_{\xi^x_2} & 0 & 0 \\ 0 & \sigma^2_{\xi^y_2} & \vartheta_2 \\ 0 & \vartheta_2 & \sigma^2_{\xi^d_2} \end{pmatrix} .$$

The matrix Σ_{12} (or, equivalently, Σ'_{21}) represents the covariance matrix between the two groups of shocks. It is important to notice that this matrix doesn't have to be diagonal as, for example, $\text{Cov}(\xi^x_1, \xi^y_2)$ can be different from $\text{Cov}(\xi^y_1, \xi^x_2)$. Therefore, it has a total of nine distinct parameters. For ease of exposition, I denote with $(\sigma_x, \sigma_y, \sigma_d)$ the cross-covariances along the matrix main diagonal. Thus, σ_x represents the covariance between the shocks to expected returns of the two markets, or $\sigma_x \equiv \text{Cov}(\xi^x_1, \xi^x_2)$. Similarly, σ_y represents the covariance between the shocks to the orthogonal component of dividend growth, $\sigma_y \equiv \text{Cov}(\xi^y_1, \xi^y_2)$, while σ_d is the covariance between unexpected dividend growth, $\sigma_d \equiv \text{Cov}(\xi^d_1, \xi^d_2)$. These covariances will play an important role in our analysis. Intuitively, if strong links exist between two markets as reflected by their large correlations, these will likely result from common movements in the same types of shocks. The other covariances are denoted by the letter σ and a subscript that refers to the variables related to the two shocks. So, for example, σ_{x_1,y_2} represents the covariance between ξ^x_1 and ξ^y_2. As a result, the matrix $\mathbf{\Sigma}$ can be written as:

$$\mathbf{\Sigma} = \left(\begin{array}{ccc|ccc} \sigma^2_{\xi_1^x} & 0 & 0 & \sigma_x & \sigma_{x_1y_2} & \sigma_{x_1d_2} \\ 0 & \sigma^2_{\xi_1^y} & \vartheta_1 & \sigma_{y_1x_2} & \sigma_y & \sigma_{y_1d_2} \\ 0 & \vartheta_1 & \sigma^2_{\xi_1^d} & \sigma_{d_1x_2} & \sigma_{d_1y_2} & \sigma_d \\ \hline \sigma_x & \sigma_{y_1x_2} & \sigma_{d_1x_2} & \sigma^2_{\xi_2^x} & 0 & 0 \\ \sigma_{x_1y_2} & \sigma_y & \sigma_{d_1y_2} & 0 & \sigma^2_{\xi_2^y} & \vartheta_2 \\ \sigma_{x_1d_2} & \sigma_{y_1d_2} & \sigma_d & 0 & \vartheta_2 & \sigma^2_{\xi_2^d} \end{array} \right) .$$

When presenting the results, the focus will be on correlations, rather than covariances. Correlations are easier to interpret as they are unitless and vary in a finite range. The matrix $\mathcal{R}$ contains the cross-correlations between the shocks to the two markets implied by the $\Sigma_{1,2}$ estimates. The elements along its main diagonal are denoted $\varrho_x = \text{Corr}(\xi^x_{t,1}, \xi^x_{t,2})$, $\varrho_y = \text{Corr}(\xi^y_{t,1}, \xi^y_{t,2})$, and $\varrho_d = \text{Corr}(\xi^d_{t,1}, \xi^d_{t,2})$. The notation for the other correlations is similar to that of the corresponding covariances, with the letter ϱ taking the place of σ.

3.3 Real and financial integration

Once the full covariance structure within and between the two markets has been specified, we can use our model to obtain a decomposition of the correlation (covariance) between their returns. This result is made possible by the orthogonal decomposition of the expected dividend growth, which allows for separate identification of the individual sources of co-movement.

Since I did not impose any symmetry on $\mathbf{\Sigma}$, the expression for the unconditional covariance in returns involves a total of nine elements. Its formulation is reported in Appendix A. It is more convenient for the purpose of our analysis to express it as the sum of three terms:

$$\text{Cov}(r_{t,1}, r_{t,2}) \quad = \quad \mathcal{C}_x + \mathcal{C}_{yd} + \mathcal{C}_{cross} \ . \tag{15}$$

The first term, $\mathcal{C}_x$, collects the terms involving the covariance between the shocks to expected returns, σ_x. Therefore, it reflects common fluctuations in shocks to expected returns between the two markets. These would arise, for example, if expected returns in both markets depend on the same risk factors with different sensitivities. As a result, I refer to this component as capturing financial integration between the two countries.

A second term, $\mathcal{C}_{yd}$, contains the overall contribution of the covariance between shocks to the orthogonal component in dividend growth σ_y, the covariance between unexpected dividend growth σ_d, and their cross-covariances $\sigma_{d_1y_2}$ and $\sigma_{y_1d_2}$. These terms reflect the importance of common technological shocks and revisions in the growth of dividends that are unrelated to expected returns. Therefore, they capture real integration as measured by changing economic conditions and expectations about the growth rate of the economy.

Finally, the third component $\mathcal{C}_{cross}$ collects the cross-terms which arise from correlations between expected returns of one market and expected and unexpected dividend growth of the other market. These are represented by the terms involving $\sigma_{x_1d_2}$, $\sigma_{x_1y_2}$, $\sigma_{d_1x_2}$ and $\sigma_{y_1x_2}$.

Clearly, these three sources have very different economic interpretations and implications. One way of succinctly measuring the relative importance of each term is to calculate its percentage contribution to the overall covariance: $\mathcal{C}_x/\text{Cov}(r_{t,1}, r_{t,2})$, $\mathcal{C}_{yd}/\text{Cov}(r_{t,1}, r_{t,2})$, and $\mathcal{C}_{cross}/\text{Cov}(r_{t,1}, r_{t,2})$. This decomposition is unchanged whether we define it with respect to covariances or correlations.

The empirical facts that we documented in the previous section raise important questions that can be addressed with our model. First, the large positive correlation in returns implies that one or more of the correlations in $\mathcal{R}$ must be statistically and economically large. The fact that the unconditional correlation in dividend growth is also positive suggests that part of this correlation is likely to come from the cash flow component. The decomposition above can be used to identify which term is the primary source of co-movements in returns between the two markets.

Second, correlations have not been stable over time but have increased substantially over the last two decades. This suggests that the properties of the underlying data generating process have changed during this period. However, this evidence does not necessarily imply that the relative contribution of the three components in equation (15), or the matrix $\mathcal{R}$, or both, have changed. In fact, holding $\mathcal{R}$ fixed, any variation in the univariate structural parameters Θ_1 and Θ_2 can have sizeable effects on the unconditional correlation in returns. Without estimates of the parameters of the model, we cannot understand which effect is responsible for such an increase. We explore this estimation in the next section.

4 Empirical Results

4.1 Univariate Predictive Regressions

Table 2 reports the OLS estimates of the predictive regressions of quarterly returns and dividend growth on a constant and the dividend-yield, for the U.S. and the U.K. stock markets. For the full sample period, the regressor is break-adjusted in 1991 following the approach of Lettau and Van Nieuwerburgh (2008). For each regression, I also show the corresponding in-sample R^2 statistic and the standard deviation of the fitted values, denoted by $\mathrm{std}(\widehat{E}_t r_{t+1})$ and $\mathrm{std}(\widehat{E}_t \Delta d_{t+1})$, respectively.

As we can see, the slope coefficients of the return regression β are positive, suggesting that higher relative prices today reflect lower future returns. During the full sample period, the estimates are 0.084 for the U.S. and 0.093 for the U.K. These values are statistically different from zero at the 1% and 10% level, with standard errors of 0.033 and 0.051, respectively. The R^2 statistics show that a fraction of about 4% for the U.S. and around 3% for the U.K. of the overall return variance is captured by the dividend-yield. Looking at the predicted returns, these estimates imply a 1.9% quarterly volatility for both countries. Finally, return predictability appears to be stronger in the early sample, as reflected by the larger coefficients and R^2 statistics. In the last two decades, the coefficients are positive but more imprecisely estimated, most likely reflecting the reduced sample size.

Turning our attention to the dividend-growth regression, we find that the λs are much smaller in absolute value than the corresponding βs. For the U.K., the estimate has the theoretical negative sign (-0.019) while for the U.S. it is positive at 0.011. The standard errors are, however, quite large, and none of the coefficients are statistically different from zero at conventional levels. The R^2 statistics are rather small, in the range of 1% to 2.5% depending on the market and time period. As a result, time variation in predicted dividend growth almost never exceeds 0.4%.[13]

In the last three rows, I also report the volatility and correlation of the residuals, as they play an important role for the identification of the structural parameters. The volatility of shocks to the return regression, σ_{ϵ^r}, is around 9% for the U.S. and 11% for the U.K. As we saw for the raw series, the volatility of shocks to returns is decreasing for both markets in

[13]The only exception is for the U.K. in the early sample, where the coefficient is -0.03 and the implied volatility of predicted dividend growth equals 0.7%. This is in line with the relatively large corresponding R^2 of about 2.5%.

the later sample. The volatility of the shocks in the dividend growth regression, σ_{ϵ^r}, is much smaller and varies between 2 to 4%. The correlation between the two shocks is positive but not large. The estimates are 0.102 for the U.S. and 0.183 for the U.K. during the whole sample period.

Taken together, the results from Table 2 suggest the presence of a predictable component in returns that is positively related to the dividend-yield. There is a considerable amount of variation in returns that is left unexplained, as reflected by the high residual standard deviation. However, the coefficients are statistically significant and the in-sample quarterly R^2 that we find are indeed large and economically relevant.[14] Dividend-growth, on the contrary, is not predictable by the dividend-yield.

4.2 Structural parameters for individual markets

The next step is to investigate the properties of the underlying data generating process implied by the estimates of Table 2. That is, we obtain estimates of the univariate structural coefficients in Θ_1 and Θ_2, and their corresponding standard errors. Unlike other studies, I rely on a GMM-type estimator, which exploits the present value constraint, the OLS estimates of Table 2, and some other relevant moments of the data to identify the model parameters. The approach is similar in spirit to that of Lettau and Van Nieuwerburgh (2008) and Plazzi, Torous, and Valkanov (2009), and is described in detail in Appendix B.

Table 3 presents the estimates for the structural parameters of the individual markets. Focusing our attention on the full sample results, we find that both markets are characterized by a positive co-movement in their expected returns and expected dividend growth, as captured by the parameter τ. The estimates are 0.345 for the U.S. and 0.601 for the U.K. Both values are statistically significant at the five percent level with standard errors of 0.150 and 0.277, respectively. The degree of persistence of the dividend-yield series, as implied from the present value constraint, is seen to be higher for the U.S. (0.933) than for the U.K. (0.898). These value are in line with the AR(1) coefficients estimated for the break-adjusted series reported in Table 1.

Shocks to dividend growth display a much larger variability compared to the other shocks

[14]Campbell and Thompson (2008) show that the R^2 should be compared to the squared Sharpe Ratio to judge the economic significance of a predictor. In our data, the quarterly Sharpe Ratio is 0.114 for the U.S. and 0.140 for the U.K. These numbers imply, for example, that a mean-variance investor with a risk aversion coefficient of five would increase her portfolio return by 0.90% in the U.S. and 0.61% in the U.K. on a quarterly basis when conditioning on the dividend-yield.

of the system. The estimates are rather similar, 2.10% for the U.S. and 2.41% for the U.K. The volatility of shocks to expected returns is lower at 0.80% for the U.S. compared to the corresponding 1.53% estimate for the U.K. market. Shocks to the orthogonal component in dividend growth are the least volatile, as reflected by their volatilities of 0.30% and 0.87%. Finally, the covariance ϑ is found to be positive but not significantly different from zero for both markets.

Looking at the estimates across subsamples, the persistence of the dividend-yield appears to be increasing in the last two decades. The difference between the two subperiods is quite substantial for the U.K., where the value of ϕ rises from 0.874 to 0.950. The estimates of τ are also higher in the later period. The difference is substantial for the U.S. (from 0.213 to 0.534) but less pronounced for the U.K. (from 0.536 to 0.690). On the other hand, the volatility estimates display a clear decline in the later period. For example, the volatility of shocks to expected returns is seen to be about half as large for both markets. The estimates for the two markets change from 1.09% and 1.81% during the 1966-1991 period to 0.54% and 0.89% during the 1992-2008 period. Only in the case of the U.S. for the volatility of unexpected dividend growth do we find an increase across the two subsamples from 1.64% to 2.69%. This decreasing trend in volatilities is responsible for the similar trend that we document in Section 2 for the unconditional return volatilities.

To better understand the economic implications of these estimates, Panel A of Table 4 reports some relevant moments as implied by the estimates of Table 3 and their GMM standard errors. The parameter υ was previously defined as the ratio of the variance of the shock to the orthogonal component of expected dividend growth to that of the shock to expected returns, or $\upsilon \equiv \sigma^2_{\xi^y}/\sigma^2_{\xi^x}$. By combining its estimates with those of the other structural parameters we can provide an economic interpretation of the predictive regressions results. To that end, Figure 4 shows the behavior of the predictive coefficients β and λ for values of τ ranging from -1 and 1. These plots are obtained by inputting the corresponding values of ϕ, ρ, and υ as seen in Table 3. Focusing on the slope coefficient in the return regressions, it is readily apparent that the larger value that we document for the U.K. stems from the larger co-movement τ when compared to that of the U.S. Turning to the dividend growth coefficient λ, we clearly see for the U.K. that its negative value is entirely due to the relatively strong signal in the dividend growth regression, as reflected by $\upsilon = 0.320$. To the contrary, the noisiness in the dividend growth regression is larger for the U.S., for which $\upsilon = 0.143$. This fact, coupled with the small positive value of τ, is responsible for the positive slope coefficient.

The properties of the underlying conditional means are also of great interest. The volatility of expected returns is about 2.2% for the U.S. and 3.5% for the U.S. These estimates are found to be higher than those reported in Table 2, confirming the claim that variability in expected returns is higher than what is predicted solely by the dividend-yield. Dividend growth is also characterized by fluctuations in its conditional mean, albeit to a lesser extent than returns. During the full sample, the underlying volatility of U.S. expected dividend growth is 1.14% compared to a fitted volatility of just 0.20% when relying on the OLS estimates. In light of this result, it is not surprising that some variables detect a predictable component in U.S. dividend growth. For the U.K., expected dividend growth exhibits a large 2.87% volatility in comparison with a fitted volatility of 0.4%.

To further evaluate the link between expected returns and expected dividend growth, I also report their degree of correlation. Interestingly, its value is about 0.7 for both markets and is increasing from about 0.6 in the first period to about 0.8 in the later sample. Finally, the volatility of unexpected returns varies in the range of 8% to 12% and is roughly one order of magnitude larger than the volatility of shocks to their conditional mean.

Panel B of Table 4 shows the relative weight of the two components of the returns variance (equation (14)) as implied by the estimated parameters. As we can see, 68% of the total variance of U.S. returns is due to revisions in expected returns while the remaining 32% is due to cash-flow shocks. For the U.K. these percentages are almost exactly reversed, with the cash-flow component now being larger. Interestingly, while for the U.K. these proportions remain unchanged across subsamples, for the U.S. the cash-flow component increases substantially from 19% to 50%. Thus, in spite of the decrease in unconditional variance in the later sample, a larger fraction of it arises from shocks to dividend growth.

4.3 Cross-country Results

Before presenting the results for the underlying model, it is interesting as a preliminary analysis to explore cross-predictability between the U.S. and U.K. markets. To that end, I regress the domestic dividend-yield on foreign returns and growth in dividends. Across the whole sample period, the domestic dividend-yield series are positively and statistically significantly related to foreign country returns. The estimated slope coefficients are 0.078 for the U.K. dividend-yield (standard error of 0.033) and 0.069 for the U.S. dividend-yield (standard error of 0.031). This evidence reinforces the view of the existence of strong cross-country links between the underlying shocks. The dividend-yield slope coefficients are also positive in the predictive regression of dividend growth, but they are not statistically significant. The estimate is 0.009 for the U.S dividend-yield (standard error of 0.022) and is larger at 0.027 for the U.K. series (standard error of 0.012).

Armed with this evidence, we next look at the joint properties of the underlying structural shocks as summarized by the three-by-three correlation matrix $\mathcal{R}$. Table 5 reports its GMM estimates based on joint moments of the data, as described in Appendix B. Focusing on the full sample results, it can be seen that the correlation between shocks to expected returns and to the orthogonal component of dividend growth are positive and large at 0.71 and 0.73, respectively. The correlation between unexpected dividend growth is also positive, but is rather small and not statistically significant. Shocks to dividend growth seem to be positively correlated across markets, while shocks to expected returns display a negative correlation with unexpected dividend growth. However, all off-diagonal elements are quite small in absolute value and rather imprecisely estimated. This evidence validates our previous claim that the correlation to the same type of shocks is the major source of comovements between the two markets.

When comparing the results across the two subsamples, a few interesting comments arise. First, the correlation in shocks to expected returns shows just a small increase, from 0.72 to 0.74. This is quite surprising given the large increase in return correlation during the later sample that we documented in Section 2. Second, the correlations between shocks to dividend growth are both increasing during the 1992-2008 period. The correlation in unexpected dividend growth increases from 0.11 to 0.30, while that of shocks to the orthogonal component moves from 0.63 to 0.76.

Panel B reports the decomposition of the correlation in returns into its three elements (equation (15)) as implied by the estimates of $\mathcal{R}$. As we can see, during the whole sample the co-movement in shocks to expected returns $\mathcal{C}_x$ is responsible for the largest fraction, about 48%, of the overall correlation. The correlation in shocks to dividend growth accounts for nearly 40%, while the component capturing cross-correlations explains the remaining 12%. However, the relative importance of the first two components changes dramatically across the two subsamples. In the early 1966-1991 period, the co-movement of shocks to expected returns is the most important source of common fluctuations, accounting for about 60% of the total. However, during the last two decades, common fluctuations in dividend growth account for about 53% of returns correlation, compared to a fraction of 38% due to expected returns. Finally, the component related to cross-correlations always accounts for the least amount.

To better understand the economic magnitude of these effects, it is interesting to disentangle the effect of changes in the correlation matrix $\mathcal{R}$ from changes in the univariate parameters (Θ_1, Θ_2) on the correlation in returns. To do so, I calculate a theoretical correlation by combining the estimates of $\mathcal{R}$ for the 1966-1991 period and the estimates of (Θ_1, Θ_2) for the 1992-2008 period. The goal is to evaluate the correlation that would have resulted in the later period holding fixed the value of $\mathcal{R}$. The resulting correlation equals 0.68, compared to an actual correlation of 0.83 from Table 1. Considering that the correlation in shocks to expected returns displays just a very modest increase across the two periods, this evidence further confirms the view that the increased correlation in dividend growth is responsible for a large fraction of the return correlation during the last two decades.

5 Understanding the source of integration

In the previous section, we document that real integration constitutes a major source of stock prices co-movements. An interesting question is whether other economic variables reveal increasing economic linkages between the two countries in the more recent period. To this extent, Table 6 shows univariate and joint summary statistics for several indicators of economic activity for both countries at the aggregate level. A detailed description of the data source for each variable is provided in Appendix C.

The first three variables are GDP growth, growth in consumption of nondurable goods and services, and industrial production growth. As we can see, all variables are characterized by an increased correlation from the pre- to the post-1991 period. The difference is substantial for industrial production growth (from 0.32 to 0.64) and GDP growth (from 0.26 to 0.54), but less pronounced for consumption growth (from 0.17 to 0.28). The larger correlation in output compared to consumption between the two countries is a well-known fact in the literature testing real business cycle models (see e.g., Backus, Kehoe, and Kydland (1992)). Interestingly, the volatility of these variables has been substantially lower in the more recent period for both countries. This decrease in volatility is in line with what we document for returns and for dividend-growth in the case of the U.K. Another indicator of the degree of integration between countries is represented by their trade activity, as measured by the import/export volume between the two countries expressed as a fraction of domestic GDP. As we can see, there is some evidence of increased import/export activity in the more recent period. U.S. exports to the U.K. have been on average about 3% during the 1966-1991 period and 3.7% during the 1992-2008 period. During the same periods, average U.K. exports have been about 2.2% and 2.5%, respectively. The difference in the average exports across periods is statistically significant at the 5% level for both countries.

Taken together, these results reveal an increased correlation between the underlying aggregate economic shocks to the two countries during the 1992-2008 period. The impact of global shocks is not likely, however, to be the same for all companies. In fact, there is considerable evidence that firms differ in their degree of exposure to international shocks (see e.g., Brooks and Del Negro (2006)). Ceteris paribus, it is more likely that a firm is more subject to domestic rather than foreign changes in economic conditions (such as employment or population shocks) if its assets are geographically located in its home country. As a result, we expect that real integration should play a lesser role for those firms whose assets are internationally less diversified.

To test this hypothesis, I construct an index of large capitalization companies whose segments have operations and/or significant sales/service offices just within the U.S. Appendix D provides a detailed explanation of the index construction. I focus on large stocks to reduce the impact of changes in the index composition. In addition, there is evidence that cross-country correlation has been substantially increasing for large capitalization companies (see Bekaert, Hodrick, and Zhang (2009)). I then apply the same methodology as I do for the aggregate index and look at the relative importance of real and financial integration with respect to the U.K. during the 1992-2008 period. Table 7 reports the correlation matrix between the underlying structural shocks of domestic U.S. firms and the U.K., and the corresponding return correlation decomposition. As we can see, the correlation in discount rates shocks equals 0.95 and is substantially larger than the correlation of about 0.40 and 0.35 in expected and unexpected dividend growth, respectively. These estimates, in turn, imply that financial integration is largely responsible for the 0.72 correlation between the two indices, accounting for 57% of it compared to a fraction of 45% explained by real integration. This result suggests that the increase in real integration that we document at the aggregate level is mostly attributable to firms that are more exposed to global shocks due to international diversification in their assets and operations.

6 Robustness checks

Excluding NASDAQ stocks

Some authors have documented a negative trend in the fraction of dividend-paying stocks (see e.g., Fama and French (2001), Grullon and Michaely (2002)). This evidence is particularly relevant in the U.S. stock market, where share repurchases have benefited from a relatively more favorable tax treatment at the shareholders' level compared to dividend issuance.[15] In contrast, in the U.K., dividend issuance had a tax advantage versus retained earnings until 1997. While changes in payout policy or dividends smoothing do not violate the present-value relation between returns and dividends (see Cochrane (2008)), it is interesting to investigate whether our results are sensitive to the inclusion of non-dividend paying stocks. To that end, I follow Lettau and Van Nieuwerburgh (2008) and exclude NASDAQ stocks from the universe of CRSP stocks by relying on the NYSE/AMEX value-weighted index.[16] When using this series, the main conclusions of the paper remain unchanged. For example, the estimate of τ for the U.S. during the whole period is now 0.337 and the corresponding volatility of expected returns and expected dividend growth equal 2.1% and 1.1%, respectively. The fraction of return correlation attributable to real integration is again the highest at 69% during the most recent sample, where the impact of NASDAQ stocks should be larger.

Annual series for the 1927-2008 period

A natural question is whether our previous results are specific of the 1966-2008 sample period and quarterly frequency. Indexes with and without dividend distributions are available from C.R.S.P. beginning in December of 1925. Unfortunately, the U.K. data start in only 1965. Therefore, I rely on the Europe price series from Global Financial Data (GFD). This index is constructed as a weighted average of European developed country indices and it essentially extends the most widely used Morgan Stanley Capital International (MSCI) Europe Index back to 1925. I use the annual series and construct annual dividend growth as $\Delta d_{t+1} = dp_{t+1} - dp_t + r^x_{t+1}$, where $DP_t = R_t/R^x_t - 1$ and lowercase letters denote logs. The sample then consists of 82 observations for real returns, dividend growth, and dividend-yield

[15]This relative advantage has been recently partially eliminated. However, financial executives seem to prefer share repurchases primarily for their greater flexibility and ability to time the equity market, while tax reasons are just of second-order importance (see Brav, Graham, Harvey, and Michaely (2005)).

[16]This approach is motivated by the evidence in DeAngelo, DeAngelo, and Skinner (2004) who document an increase in aggregate real dividends in the most recent period. They find that dividends have concentrated among larger companies, while firms that paid very small dividends are largely responsible for the recent reduction in the number of dividend-payers companies.

spanning the 1927-2008 period. Interestingly, the dividend-yield of the European series is also decreasing during the more recent period. Its average value during the 1927-1991 period equals 0.0415, and is statistically higher than the 0.0265 average for the 1991-2008 sample. Thus, it appears that the decline in dividend-yields has been a phenomenon common to all E.U. countries as well. Consequently, I use the break-adjusted series in the predictive regressions.

Table 8 presents the model estimates across the full sample obtained following the same empirical approach as in Section 3. By comparing the U.S. estimates with those previously documented, a few remarks are in order. First, the value of τ is slightly higher at 0.480 compared to the 0.345 value reported for the 1966-2008 period, but is more imprecisely estimated, probably reflecting the reduced sample size. Second, the estimated volatilities of the structural shocks are much larger than the corresponding annualized parameters from Table 3. This fact is justified by the higher volatility of returns and dividend growth during the whole 1927-2008 period of about 20% and 14%, respectively.[17] Not only do we find a comparable value for τ but also the implied υ estimate during this extended sample is very similar at 0.159. In contrast, the annual volatilities of expected returns and expected dividend growth are much higher than the corresponding 1966-2008 estimates, and equal 8.23% and 5.14% respectively. Their correlation is also larger at 0.77, but smaller than what is documented by Koijen and Van Binsbergen (2009). Finally, expected returns shocks are responsible for almost half of the variance in returns.

Turning our attention to the E.U., it can be seen that the estimates are quantitatively very similar to those of the U.S. and U.K. market. The persistence of the dividend-yield is comparable at 0.827 and the τ estimate is slightly higher at 0.593, but is close to that documented for the U.K. Unexpected shocks to dividend growth exhibit the larger volatility, about 16%, compared to shocks to the conditional means. Similarly to what we documented for the U.K., about two-thirds of the variance in returns is attributable to fluctuations in dividend growth.

These results should, however, be interpreted with some degree of caution. The European capital market was not homogeneous until the recent convergence of E.U. countries that are now part of the Euro. In addition, fluctuations in exchange rates may be playing

[17] The volatility of dividend growth during the 1927-2088 period is about 10% higher than the 4.8% value reported in Table 1 for the 1966-2008 period. This large difference arises partly because in CRSP dividends paid out during the year are reinvested in the market portfolio, and partly because dividend growth has been indeed more volatile during the pre-1966 sample. In fact, when calculating dividend growth using quarterly data its volatility during the 1927-1965 sample is about 9% on an annual basis.

an important role due to the absence of a common currency. Notwithstanding these considerations, the fact that the model estimates are so comparable is rather encouraging, and suggests that the characteristic of the underlying data generating processes are common across the various developed stock markets.[18]

Inclusion of other variables

One concern with our empirical approach might be that variables other than the dividend-yield have been shown to predict returns and dividend growth. These include, among others, standard macroeconomic variables like the term spread, the relative T-bill, and the default spread (see e.g., Fama and French (1988a), Campbell (1991)), the value spread (Campbell and Vuolteenaho (2004)), the dividend-earning ratio (Lamont (1998)), and the *cay* variable of Lettau and Ludvigson (2005).

However, I decided against including these predictors in the analysis for a number of reasons. First, the theoretical relations that enable the model's estimation are valid only for solely including the dividend-yield, as they are derived from the present-value relation. Extending the model to account for other variables would require modeling their joint behavior, thus increasing the risk of model misspecification. Second, break-adjusting the dividend-yield series enhances its predictive ability. In fact, I find that none of the macroeconomic variables are significant in the return regression for the whole 1966-2008 sample period when including the break-adjusted dividend-yield. I also find that the *cay* variable and the default spread capture future variation in dividend growth. More importantly, the evidence that other variables in the investor's opportunity set are significant predictors does not contradict, but rather reinforces our previous arguments. In fact, it confirms the claim that the dividend-yield alone is not a sufficient statistics for capturing variations in expected returns and expected dividend growth. Our structural approach allows us to infer the properties of expected returns and expected dividend growth from the dividend-yield alone.

Other robustness checks

Our analysis relies on the assumption that the Campbell and Shiller (1988) decomposition provides an accurate description of the relation between returns, dividend growth, and

[18] I also investigated the results pre- and post-1991. The results are quantitatively similarly to those previously documented, with a decreasing trend in the volatilities of the underlying shocks in the more recent period. However, the model estimation is rather imprecise. This is to be expected given the limited sample size.

dividend-yields. However, this result is just an approximation as it derives from a first-order Taylor expansion. To investigate its accuracy in our context, I construct log-linearized returns for both markets.[19] In doing this for the full sample, it is important to take into account the structural break in the dividend-yield. This implies using different linearization constants for the pre- and post-break periods. I find that the raw and log-linearized series are almost indistinguishable, with correlations above 0.999 across all periods. As a result, the structural parameters estimated using the log-linearized returns are very similar to those previously reported.

I also tested the model using dividend growth and excess returns, as opposed to real variables. The results are in line with those documented in Table 2 and 3, thus confirming the view that predictability is mainly the result of time-series fluctuations in risk premia, rather than real rates.

7 Conclusions

In this work, I investigate the joint properties of the U.S. and U.K. equity markets by modeling their underlying data generating processes. I find that increasing economic linkages, as reflected by the correlation in shocks to dividend growth, are major determinants of the recent increase in the correlation between the countries' stock returns. Real integration, however, is much lower for firms whose assets are less internationally diversified and therefore are less exposed to global shocks. The results also show that both countries are characterized by a positive comovement in the conditional means of returns and dividend growth. These cross-country differences may be related to the persistence of the relative share of each aggregate stock market as in Menzly, Santos, and Veronesi (2004).

The model has been used to explore the properties of international capital markets, but its structure is quite general. It could be also used, for example, to investigate the source of cross-sectional links across portfolios or across different industry sectors. Another interesting extension of the model would be to take into account time variation in the conditional variance-covariance matrix. This can be done, for example, following the literature on dynamic conditional correlation models (see Engle (2002)) or using Bayesian based methods (as in Nardari and Scruggs (2005)).

[19] Log-linearized returns are defined as $r_{t+1} = \kappa - \rho\, dp_{t+1} + \Delta d_{t+1} + dp_t$, where $\kappa = -\log(\rho) - (1-\rho)\log(1/\rho - 1)$.

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Appendix

A Derivations

Actual and fitted conditional means' volatilities

The expressions for the variance of predicted returns and dividend growth are obtained by combining the expressions for β and λ from equations (10) and (11) with the variance of the dividend-yield implied by the Campbell and Shiller (1988) decomposition:

$$\text{var}(dp_t) = \frac{(1-\tau)^2\sigma^2_{\xi^x} + \sigma^2_{\xi^y}}{(1-\rho\phi)^2(1-\phi^2)}$$

Thus, for returns we have:

$$\text{var}(\widehat{E}_t r_{t+1}) = \text{var}(\beta\, dp_t) = \frac{(1-\tau)^2\sigma^2_{\xi^x} + \sigma^2_{\xi^y}}{(1-\phi^2)\left[1-\tau+\frac{\upsilon}{1-\tau}\right]^2}$$

and similarly for dividend growth:

$$\text{var}(\widehat{E}_t \Delta d_{t+1}) = \text{var}(\lambda\, dp_t) = \frac{[\tau(\tau-1)+\upsilon]^2[(1-\tau)^2\sigma^2_{\xi^x} + \sigma^2_{\xi^y}]}{(1-\phi^2)\left[(1-\tau)^2+\upsilon\right]^2}$$

It can be shown that the difference between the actual and predicted variances is the same for both equations, and equals:

$$\text{var}(E_t r_{t+1}) - \text{var}(\widehat{E}_t r_{t+1}) = \text{var}(E_t \Delta d_{t+1}) - \text{var}(\widehat{E}_t \Delta d_{t+1}) = \frac{\sigma^2_{\xi^y}}{\left[(1-\tau)^2+\upsilon\right](1-\phi^2)}$$

This quantity is positive provided $|\phi| < 1$, $\sigma^2_{\xi^y} > 0$, and $\sigma^2_{\xi^x} < \infty$.

Returns variance decomposition

If we combine the definition of returns from equation (1), the Campbell (1991) decomposition of equation (9), the AR(1) structure of x_t, and the covariance structure of the shocks we obtain:

$$\begin{aligned}
\text{Var}(r_{t+1}) &= \text{Var}(x_t + \xi^r_{t+1}) \\
&= \text{Var}\left(x_t + \frac{\rho}{1-\rho\phi}\left[(\tau-1)\xi^x_{t+1} + \xi^y_{t+1}\right] + \xi^d_{t+1}\right) \\
&= \text{Var}(x_t) + \text{Var}\left(\frac{\rho}{1-\rho\phi}\left[(\tau-1)\xi^x_{t+1} + \xi^y_{t+1}\right] + \xi^d_{t+1}\right) \\
&= \mathcal{V}_x + \mathcal{V}_{yd}
\end{aligned} \tag{16}$$

where

$$\mathcal{V}_x \equiv \left[\frac{1}{1-\phi^2} + \frac{\rho^2(\tau-1)^2}{(1-\rho\phi)^2}\right]\sigma^2_{\xi^x}$$
$$\mathcal{V}_{yd} \equiv \frac{\rho^2}{(1-\rho\phi)^2}\sigma^2_{\xi^y} + \sigma^2_{\xi^d} + 2\frac{\rho}{(1-\rho\phi)}\ .\vartheta$$

Returns covariance decomposition

The returns covariance can be written as:

$$\begin{aligned}
\text{Cov}(r_{1,t+1}, r_{2,t+1}) &= \text{Cov}(x_{1,t} + \xi^r_{1,t+1}, x_{2,t} + \xi^r_{2,t+1}) \\
&= \text{Cov}(x_{1,t},, x_{2,t}) + \text{Cov}(\xi^r_{1,t+1}, \xi^r_{2,t+1}) \\
&= \text{Cov}(x_{1,t}, x_{2,t}) + \qquad (17) \\
&\quad \text{Cov}\left(\frac{\rho_1}{1-\rho_1\phi_1}\left[(\tau_1-1)\xi^x_{1,t+1} + \xi^y_{1,t+1}\right] + \xi^d_{1,t+1}, \frac{\rho_2}{1-\rho_2\phi_2}\left[(\tau_2-1)\xi^x_{2,t+1} + \xi^y_{2,t+1}\right] + \xi^d_{2,t+1}\right)
\end{aligned}$$

For the first term, the AR(1) expression for x implies that:

$$\begin{aligned}
\text{Cov}(x_{1,t}, x_{2,t}) &= \text{Cov}(\phi_1 x_{1,t-1} + \xi^x_{1,t}, \phi_2 x_{2,t-1} + \xi^x_{2,t}) \\
&= \phi_1\phi_2\text{Cov}(x_{1,t-1}, x_{2,t-1}) + \text{Cov}(\xi^x_{1,t}, \xi^x_{2,t}) \\
&= \phi_1\phi_2\text{Cov}(x_{1,t-1}, x_{2,t-1}) + \sigma_x
\end{aligned}$$

The stationarity of expected returns implies that $\text{Cov}(x_{1,t}, x_{2,t}) = \text{Cov}(x_{1,t-1}, x_{2,t-1})$. Using this fact, we obtain:

$$\text{Cov}(x_{1,t}, x_{2,t}) = \frac{\sigma_x}{1-\phi_1\phi_2}$$

Given that the matrix $\mathbf{\Sigma}$ is full, the second term of equation (17) consists of nine elements. Collecting all the elements, we obtain the following decomposition:

$$\text{Cov}(r_{1,t+1}, r_{2,t+1}) = \mathcal{C}_x + \mathcal{C}_{yd} + \mathcal{C}_{cross}$$

where

$$\mathcal{C}_x \equiv \left[\frac{1}{1-\phi_1\phi_2} + \frac{\rho_1\rho_2(\tau_1-1)(\tau_2-1)}{(1-\rho_1\phi_1)(1-\rho_2\phi_2)}\right]\sigma_x$$
$$\mathcal{C}_{yd} \equiv \frac{\rho_1\rho_2}{(1-\rho_1\phi_1)(1-\rho_2\phi_2)}\sigma_y + \frac{\rho_1}{1-\rho_1\phi_1}\sigma_{y_1d_2} + \frac{\rho_2}{1-\rho_2\phi_2}\sigma_{d_1y_2} + \sigma_d$$
$$\mathcal{C}_{cross} \equiv \frac{\rho_1\rho_2(\tau_1-1)}{(1-\rho_1\phi_1)(1-\rho_2\phi_2)}\sigma_{x_1y_2} + \frac{\rho_1\rho_2(\tau_2-1)}{(1-\rho_1\phi_1)(1-\rho_2\phi_2)}\sigma_{y_1x_2} + \frac{\rho_1(\tau_1-1)}{1-\rho_1\phi_1}\sigma_{x_1d_2} + \frac{\rho_2(\tau_2-1)}{1-\rho_2\phi_2}\sigma_{d_1x_2}\ .$$

B Estimation of Structural Parameters

Univariate Parameters

The vector of structural parameters for each market consists of six elements, $\Theta = [\phi, \tau, \sigma_{\xi^x}, \sigma_{\xi^y}, \sigma_{\xi^h}, \vartheta]$, plus the loglinearization constant ρ. From the predictive regressions (Table 2) we obtain estimates of the slope coefficients $(\widehat{\beta}, \widehat{\lambda})$ and of the variance-covariance matrix of residuals $(\widehat{\sigma}^2_{\varepsilon^r}, \widehat{\sigma}^2_{\varepsilon^d}, \widehat{\sigma}_{\varepsilon^r,\epsilon^d})$. Note also that estimating the autoregression of the dividend-yield does not provide additional moments for the estimation of the structural parameters. In fact, the present value constraint implies that $\beta - \lambda = 1 - \rho\phi$ and $\rho\varepsilon^{dp} = \varepsilon^d - \varepsilon^r$, so that one equation of the system (6 - 8) is fully redundant. The assumptions on the covariance of the structural shocks implies the following system of five equations in six unknowns:

$$
\begin{cases}
\widehat{\beta} = \frac{(1-\rho\phi)(1-\tau)\sigma^2_{\xi^x}}{(1-\tau)^2\sigma^2_{\xi^x} + \sigma^2_{\xi^y}} \\
\widehat{\beta} - \widehat{\lambda} = 1 - \rho\phi \\
\widehat{\sigma}^2_{\epsilon^d} = \sigma^2_{\xi^d} + \frac{\sigma^2_{\xi^x}}{1-\phi^2} \cdot \left(\frac{\tau\beta - \lambda}{1-\rho\phi}\right)^2 + \frac{\sigma^2_{\xi^y}}{1-\phi^2} \cdot \left(\frac{\beta}{1-\rho\phi}\right)^2 \\
\widehat{\sigma}^2_{\epsilon^r} = \sigma^2_{\xi^d} + \frac{\sigma^2_{\xi^x}}{1-\phi^2} \cdot \left(\frac{\tau\beta - \lambda}{1-\rho\phi}\right)^2 + \frac{\sigma^2_{\xi^y}}{1-\phi^2} \cdot \left(\frac{\beta}{1-\rho\phi}\right)^2 + \frac{\rho^2(1-\tau)^2}{(1-\rho\phi)^2}\sigma^2_{\xi^x} + \frac{\rho^2}{(1-\rho\phi)^2}\sigma^2_{\xi^y} + \frac{2\rho}{1-\rho\phi}\vartheta \\
\widehat{\sigma}_{\epsilon^r,\epsilon^d} = \sigma^2_{\xi^d} + \frac{\sigma^2_{\xi^x}}{1-\phi^2} \cdot \left(\frac{\tau\beta - \lambda}{1-\rho\phi}\right)^2 + \frac{\sigma^2_{\xi^y}}{1-\phi^2} \cdot \left(\frac{\beta}{1-\rho\phi}\right)^2 + \frac{\rho}{1-\rho\phi}\vartheta
\end{cases}
$$

In order to identify the structural parameters, further restrictions must be imposed. Therefore, I require the model to fit the following additional moments: $\text{Cov}(r_t, \Delta d_{t+1})$, $\text{Cov}(r_{t+1}, \Delta d_t)$, $\text{Cov}(r_{t+1}, r_t)$, and $\text{Cov}(\Delta d_{t+1}, \Delta d_t)$. This implies that we have a total of nine equations (five from the OLS estimates plus the four covariances) in six unknowns (the structural parameters). I then rely on the following GMM estimator

$$
\widehat{\Theta}_T = \underset{\Theta}{\text{argmin}} \left[(1/T)\sum_{t=1}^{T} \mathbf{h}(\Theta; Y_t)\right]' W \left[(1/T)\sum_{t=1}^{T} \mathbf{h}(\Theta; Y_t)\right]
$$

where $\mathbf{h}(\Theta; Y_t)$ represents the orthogonality condition for the t-th observation. The weighting matrix W is diagonal, with a large value (10^3) associated to the first five moments, and unitary weight for the remaining four moments. This specification of W is preferred to the standard optimal GMM because it allows the estimator to match closely the predictive regressions estimates.[20] In the estimation, I make sure the resulting covariance matrix for each individual country is positive definite. Standard asymptotic theory implies that the variance of $\widehat{\Theta}$ equals

$$
\widehat{V_T(\widehat{\Theta})} = (\widehat{D}'_T W \widehat{D}_T)^{-1} \widehat{D}'_T W \widehat{S}_T W \widehat{D}_T (\widehat{D}'_T W \widehat{D}_T)^{-1}/T
$$

where $\widehat{D}_T$ is the Jacobian matrix of the moments with respect to the parameters evaluated at $\widehat{\Theta}$, and

[20] As long as W converges in probability to a positive definite matrix, as it is the case for our choice, the resulting estimator is a consistent estimate of the true Θ_0.

$\widehat{S}_T = (1/T)\sum_{t=1}^{T}[\mathbf{h}(\widehat{\Theta}_T;Y_t)][\mathbf{h}(\widehat{\Theta}_T;Y_t)]'$. The estimate of ρ is obtained from the average dividend-yield during each sample, while implied structural parameters are calculated by exploiting the theoretical relationships of the model. Standard errors for standard deviations and implied estimates are calculated through the delta-method.

Joint Parameters

For the estimation of the joint parameters, I proceed in a similar way as for the univariate ones. The vector of unknown parameters is now represented by the nine joint correlations, which I denote with $\varrho = \text{vec}(\mathcal{R}_{1,2})$. To identify them, I use the following joint moments of the data: $\text{Cov}(r_{1,t+1}, r_{2,t+1})$, $\text{Cov}(\Delta d_{1,t+1}, \Delta d_{2,t+1})$, $\text{Cov}(r_{1,t+1}, r_{2,t})$, $\text{Cov}(r_{1,t}, r_{2,t+1})$, $\text{Cov}(r_{1,t+1}, \Delta d_{2,t})$, $\text{Cov}(\Delta d_{1,t}, r_{2,t+1})$, $\text{Cov}(dp_{1,t}, r_{2,t+1})$, $\text{Cov}(r_{1,t+1}, dp_{2,t})$, $\text{Cov}(dp_{1,t}, \Delta d_{2,t+1})$, $\text{Cov}(\Delta d_{1,t+1}, dp_{2,t})$, $\text{Cov}(r_{1,t+1}, \Delta d_{2,t+1})$, $\text{Cov}(\Delta d_{1,t+1}, r_{2,t+1})$, $\text{Cov}(\Delta d_{1,t+1}, \Delta d_{2,t})$, $\text{Cov}(\Delta d_{1,t}, \Delta d_{2,t+1})$. As a result, we have a total of fourteen moments in nine unknowns. I then use the following GMM estimator

$$\widehat{\varrho}_T = \underset{\varrho}{\text{argmin}} \left[(1/T)\sum_{t=1}^{T}\mathbf{g}(\varrho;Y_t)\right]' W \left[(1/T)\sum_{t=1}^{T}\mathbf{g}(\varrho;Y_t)\right]$$

where $\mathbf{g}(\varrho;Y_t)$ represents the orthogonality condition for the t-th observation. The weighting matrix W is diagonal, with a large value (10^5) associated to the first two moments, and unitary weight for the remaining moments. In the estimation, I fix the value of (Θ_1, Θ_2) to their sample values and make sure that the resulting overall variance-covariance matrix $\widehat{\Sigma}$ is positive definite.[21]

The sampling variation in the univariate estimates needs to be taken into account when making statistical inference on $\widehat{\varrho}$. To do so, I rely on the following Monte Carlo simulation. First, I simulate a time series of returns, dividend growth, and dividend-yield for both markets based on equations (1-9) assuming normality of the shocks. There, I use the estimates $(\widehat{\Theta}_1, \widehat{\Theta}_2)$ as population parameters and impose the null hypothesis $\mathcal{R}_{12} = \mathbf{0}$. The sample size is set equal to that of the corresponding series across each period. Second, I estimate the univariate and joint parameters using the same GMM procedure as I do for the actual data and store the resulting joint estimates. I repeat this procedure 5,000 times and calculate the standard error of the joint estimates as their standard deviation across the simulated samples. [22]

C Economic Data

The economic data used in Section 6 are obtained from the following sources: Quarterly seasonally adjusted data on GDP and consumption expenditures in nondurable goods and services in chained 2005 dollars

[21]Due to the high dimensionality of the parameters vector, I perform the minimization along a grid of starting points using a simulated annealing algorithm and then select the value that minimizes the objective function in order to ensure that a global minimum has been achieved. Fixing the value (Θ_1, Θ_2) considerably reduces the sample space in this second estimation as opposed to estimating the univariate and joint parameters together. This comes at the cost of losing efficiency in the estimates of the univariate parameters.

[22]I use simulation rather than bootstrap as it allows us to impose this null hypothesis on the structural shocks. It is impossible to impose such a null on the predictive VAR system.

are from the Department of Commerce, Bureau of Economic Analysis for the U.S., and from the Office of National Statistics for the U.K. Quarterly seasonally adjusted indices of Industrial Production are taken from Datastream, whose source is the International Monetary Fund (IMF). Finally, annual data on import/export between the US. and U.K. are from the IMF Direction of Trade Statistics.

D Domestic Index

The index of domestic U.S. firms is constructed as follows: First, I obtain data on the geographic operating segment of each firm from the CRSP/Compustat Merged Segment file for the 1991-2007 period. I then select the set of firms trading at the NYSE/AMEX/NASDAQ whose segments are only operationally active within the U.S. (using to the SGEOTP variable available from CRSP). Stocks with missing PERMNO are excluded from the sample. Second, at the end of December of each year $t-1$ beginning in 1991, I rank stocks based on their market capitalization and keep those in the top two deciles. For these stocks, I obtain from CRSP monthly holding period returns with and without distributions during year t and construct a value-weighted index where weights are based on the market capitalization at the end of the previous year. If a stock disappears from the sample during that year, I rescale the weights to sum up to one based on the market capitalization of that month, and keep these weights constant throughout the remaining months. The index is rebalanced at the end of each year. The quarterly return series is finally obtained as sum of the corresponding log returns within that quarter. Real returns and dividend growth are then constructed using the same methodology as in Section 2.1.

Table 1: Summary statistics

This table reports summary statistics for the U.S. and U.K. data at quarterly frequency across various samples. Returns and dividend growth are continuously compounded and measured in real units of U.S. consumption. Their sample average and standard deviation (Std) are multiplied by 4 and 2, respectively. The first-order autocorrelation coefficient ($AR(1)$), the covariance (Cov), and autocorrelation (Cor) between the series are also displayed. For the dividend-yield, the average and standard deviation refer to the variable in levels. To the contrary, the autocorrelation coefficient for the raw series ($AR(1)\,unadj$) and for the break-adjusted series ($AR(1)\,adj$) as well as the Schwartz Information Criterion are calculated on the variable in logs.

	1966-2008		1966-1991		1992-2008	
	U.S.	U.K.	U.S.	U.K.	U.S.	U.K.
			returns			
Average	0.041	0.062	0.041	0.079	0.041	0.035
Std	0.179	0.220	0.186	0.242	0.169	0.181
$AR(1)$	0.058	0.114	0.074	0.104	0.030	0.137
Cov	0.00675		0.00707		0.00636	
Corr	0.685		0.627		0.829	
			dividend growth			
Average	0.012	0.021	0.002	0.024	0.027	0.017
Std	0.048	0.075	0.037	0.083	0.060	0.061
$AR(1)$	0.329	0.567	0.203	0.537	0.379	0.646
Cov	0.0003		0.0002		0.0004	
Corr	0.333		0.309		0.434	
			dividend-price ratio			
Average	0.030	0.042	0.037	0.048	0.019	0.034
Std	0.011	0.012	0.007	0.011	0.005	0.007
$AR(1)\,unadj$	0.969	0.906	0.903	0.875	0.960	0.951
$AR(1)\,adj$	0.911	0.899	0.903	0.875	0.960	0.951
SIC AR(1)	-2.079	-1.804	-1.994	-1.632	-2.179	-2.068
SIC ARMA(2,1)	-2.020	-1.770	-1.918	-1.599	-2.056	-2.067

Table 2: Forecasting Regressions of Returns and Dividend Growth

This table reports the OLS estimates of returns and dividend growth on a constant and lagged dividend-yield for the U.S. and U.K. across various samples. The table shows the slope coefficient for the dividend-yield, the R^2 goodness-of-fit measure, and the volatility of the predicted series (std($\widehat{E}_t r_{t+1}$) and std($\widehat{E}_t \Delta d_{t+1}$)). The bottom panel shows the volatility of the residuals in the return (σ_{ϵ_r}) and dividend-growth (σ_{ϵ_d}) regression, and their correlation ($\sigma_{\epsilon_r \epsilon_d}$). Newey-West standard errors based on four lags are displayed in parentheses below the estimates.

	1966-2008		1966-1991		1992-2008	
	U.S.	U.K.	U.S.	U.K.	U.S.	U.K.
			return regression			
β	0.084	0.093	0.120	0.106	0.051	0.064
	(0.030)	(0.051)	(0.041)	(0.063)	(0.044)	(0.075)
R^2	0.043	0.029	0.063	0.035	0.023	0.016
std($\widehat{E}_t r_{t+1}$)	0.019	0.019	0.023	0.023	0.013	0.012
			dividend growth regression			
λ	0.011	-0.019	0.014	-0.030	0.007	0.006
	(0.010)	(0.025)	(0.010)	(0.030)	(0.021)	(0.048)
R^2	0.010	0.010	0.021	0.025	0.004	0.001
std($\widehat{E}_t \Delta d_{t+1}$)	0.002	0.004	0.003	0.007	0.002	0.001
			residuals			
σ_{ϵ_r}	0.088	0.109	0.091	0.120	0.084	0.090
σ_{ϵ_d}	0.024	0.037	0.018	0.041	0.030	0.031
$\sigma_{\epsilon_r,\epsilon_d}$	0.102	0.183	0.079	0.196	0.141	0.153

Table 3: Structural Parameters

This table reports the GMM estimates of the vector of model parameters Θ for both the U.S. and U.K. across various samples. The moments are the slope coefficients from the return and dividend growth regressions, the volatility of the residuals, their covariance, and additional moments of the data as described in Appendix B. GMM standard errors are reported in parentheses below the estimates.

	1966-2008		1966-1991		1992-2008	
	U.S.	U.K.	U.S.	U.K.	U.S.	U.K.
ρ	0.9932	0.9900	0.9910	0.9886	0.9955	0.9918
	(0.0008)	(0.0008)	(0.0007)	(0.0009)	(0.0006)	(0.0007)
ϕ	0.9326	0.8975	0.9019	0.8739	0.9601	0.9503
	(0.0284)	(0.0653)	(0.0436)	(0.0905)	(0.0371)	(0.0650)
τ	0.3448	0.6010	0.2125	0.5356	0.5338	0.6898
	(0.1495)	(0.2772)	(0.1845)	(0.3975)	(0.2297)	(0.2140)
σ_{ξ^x}	0.0080	0.0153	0.0109	0.0181	0.0054	0.0089
	(0.0024)	(0.0059)	(0.0036)	(0.0082)	(0.0034)	(0.0062)
σ_{ξ^y}	0.0030	0.0087	0.0030	0.0112	0.0023	0.0038
	(0.0008)	(0.0036)	(0.0018)	(0.0046)	(0.0016)	(0.0036)
σ_{ξ^d}	0.0210	0.0241	0.0164	0.0281	0.0269	0.0200
	(0.0036)	(0.0068)	(0.0042)	(0.0096)	(0.0062)	(0.0060)
$\vartheta \times 10^4$	0.1630	0.8772	0.3311	1.5416	0.0457	0.1781
	(0.1262)	(0.7606)	(0.2311)	(1.5381)	(0.1173)	(0.2346)

Table 4: Implied Structural Parameters

This table shows the properties of the underlying data generating process as implied from Table 3. Panel A shows the υ parameter, defined as $\upsilon \equiv \sigma^2_{\xi^y}/\sigma^2_{\xi^x}$, the implied volatility of expected returns (std($E_t r_{t+1}$)) and expected dividend growth (std($E_t \Delta d_{t+1}$)), their correlation (corr($E_t r_{t+1}, E_t \Delta d_{t+1}$)), and the volatility of unexpected shocks to returns (σ_{ξ^r}). Their GMM standard errors are obtained through the delta method. Panel B shows the resulting decomposition of the variance in returns into the expected return ($\mathcal{V}_x$) and dividend growth ($\mathcal{V}_{yd}$) components, as defined in Appendix A.

Panel A: Implied Structural Parameters

	1966-2008		1966-1991		1992-2008	
	U.S.	U.K.	U.S.	U.K.	U.S.	U.K.
υ	0.1433	0.3197	0.0769	0.3822	0.1851	0.1825
	(0.0678)	(0.0726)	(0.1171)	(0.1043)	(0.0948)	(0.1388)
std($E_t r_{t+1}$)	0.0223	0.0347	0.0253	0.0373	0.0193	0.0285
	(0.0028)	(0.0040)	(0.0036)	(0.0057)	(0.0052)	(0.0045)
std($E_t \Delta d_{t+1}$)	0.0114	0.0287	0.0088	0.0305	0.0133	0.0231
	(0.0032)	(0.0056)	(0.0064)	(0.0087)	(0.0046)	(0.0043)
corr($E_t r_{t+1}, E_t \Delta d_{t+1}$)	0.6735	0.7284	0.6081	0.6548	0.7786	0.8502
	(0.1150)	(0.1669)	(0.1333)	(0.2610)	(0.1609)	(0.1355)
σ_{ξ^r}	0.0872	0.1049	0.0901	0.1158	0.0831	0.0869
	(0.0069)	(0.0108)	(0.0094)	(0.0146)	(0.0102)	(0.0110)

Panel B: Return Variance Decomposition

	1966-2008		1966-1991		1992-2008	
	U.S.	U.K.	U.S.	U.K.	U.S.	U.K.
$\mathcal{V}_x$	68.34%	34.01%	80.76%	34.69%	49.47%	36.69%
$\mathcal{V}_{yd}$	31.66%	65.99%	19.24%	65.31%	50.53%	63.31%

Table 5: Cross-Markets Structural Parameters

This table shows the cross-countries structural parameters. Panel A shows the three-by-three correlation matrix between the shocks to each stock market. Its estimation is based on the GMM procedure described in Appendix C. Standard errors are reported in parentheses below the estimates. Panel B displays the resulting returns correlation decomposition into its three components: expected returns ($\mathcal{C}_x$), dividend-growth ($\mathcal{C}_{yd}$), and cross-term ($\mathcal{C}_{cross}$) as defined in Appendix A.

	Panel A: joint correlation matrix								
		1966-2008			1966-1991			1992-2008	
	0.7062	-0.1324	-0.2296	0.7158	-0.1803	-0.0677	0.7380	-0.1324	-0.1656
	(0.0653)	(0.0546)	(0.0693)	(0.0701)	(0.0597)	(0.0726)	(0.1047)	(0.0926)	(0.1168)
$\mathcal{R}$	0.1468	0.7327	0.1854	0.2079	0.6339	-0.1818	0.1500	0.7593	0.2618
	(0.0773)	(0.0569)	(0.0722)	(0.1016)	(0.0628)	(0.0790)	(0.0978)	(0.0724)	(0.0866)
	-0.0127)	0.0862	0.1209	0.0435	0.4449	0.1141	-0.2052	0.1991	0.3051
	(0.0925)	(0.0699)	(0.1791)	(0.1262)	(0.0821)	(0.2486)	(0.0966)	(0.0772)	(0.2276)
	Panel B: return correlation decomposition								
$\mathcal{C}_x$		48.18%			59.14%			37.67%	
$\mathcal{C}_{yd}$		39.91%			27.74%			53.37%	
$\mathcal{C}_{cross}$		11.90%			13.12%			8.95%	

Table 6: Economic Variables

This table shows summary statistics for GDP growth, growth in consumption expenditures of nondurable goods and services, industrial production growth for the U.S. and U.K. across various periods. The table also shows the volume of export from one country to the other as a fraction of the former country GDP. All variables are expressed in real terms. Means and standard deviations are annualized.

	1966-2008		1966-1991		1992-2008	
	U.S.	U.K.	U.S.	U.K.	U.S.	U.K.
GDP growth						
Avg	0.029	0.023	0.030	0.022	0.029	0.025
Std	0.017	0.019	0.019	0.023	0.011	0.009
Corr	0.291		0.255		0.543	
Consumption Growth						
Avg	0.030	0.025	0.032	0.030	0.028	0.018
Std	0.009	0.020	0.009	0.023	0.007	0.013
Corr	0.209		0.170		0.283	
Industrial Production Growth						
Avg	0.024	0.010	0.024	0.014	0.024	0.003
Std	0.029	0.035	0.034	0.042	0.021	0.020
Corr	0.367		0.324		0.624	
Export						
Avg	0.033	0.023	0.030	0.022	0.037	0.025
Std	0.007	0.004	0.007	0.005	0.004	0.002

Table 7: Cross-country results for domestic U.S. firms

This table shows the cross-countries structural parameters between the index of U.S. firms whose assets are domestic and the U.K. during the 1992-2008 period. Panel A shows the three-by-three correlation matrix between the shocks to each stock market. Its estimation is based on the GMM procedure described in Appendix C. Standard errors are reported in parentheses below the estimates. Panel B displays the resulting returns correlation decomposition into its three components: expected returns ($\mathcal{C}_x$), dividend-growth ($\mathcal{C}_{yd}$), and cross-term ($\mathcal{C}_{cross}$) as defined in Appendix A.

Panel A: joint correlation matrix			
	0.9530	0.2239	0.0181
	(0.2825)	(0.2682)	(0.3394)
$\mathcal{R}$	-0.1004	0.3918	-0.0557
	(0.2652)	(0.2475)	(0.3015)
	-0.1244	0.1379	0.3469
	(0.3120)	(0.2835)	(0.2266)
Panel B: return correlation decomposition			
$\mathcal{C}_x$		57.15%	
$\mathcal{C}_{yd}$		45.14%	
$\mathcal{C}_{cross}$		-2.29%	

Table 8: Structural model for U.S. and E.U. - Annual data

Panel A of this table shows the structural parameters for the U.S. and E.U. obtained using the methodology described in Appendix B. Panel B reports the implied moments of the data generating process. Panel C reports the return variance decomposition, as described in Appendix A. GMM standard errors are reported in parentheses below the estimates. The sample is annual observations for the 1927-2008 period.

Panel A: structural model estimates

	U.S.	E.U.
ρ	0.9650	0.9643
	(0.0016)	(0.0011)
ϕ	0.8229	0.8268
	(0.0833)	(0.0725)
τ	0.4803	0.5928
	(0.2249)	(0.1498)
σ_{ξ^x}	0.0468	0.0541
	(0.0184)	(0.0203)
σ_{ξ^y}	0.0187	0.0177
	(0.0113)	(0.0101)
σ_{ξ^d}	0.1312	0.1607
	(0.0209)	(0.0269)
$\vartheta \times 10^4$	-3.2177	-7.3295
	(5.8021)	(7.5112)

Panel B: implied structural parameters

	U.S.	U.K.
υ	0.1592	0.1074
	(0.1123)	(0.0897)
$\text{std}(E_t r_{t+1})$	0.0823	0.0962
	(0.0206)	(0.0246)
$\text{std}(E_t \Delta d_{t+1})$	0.0514	0.0652
	(0.0276)	(0.0270)
$\text{corr}(E_t r_{t+1}, E_t \Delta d_{t+1})$	0.7692	0.8752
	(0.1463)	(0.0870)
σ_{ξ^r}	0.1866	0.1922
	(0.0098)	(0.0115)

Panel C: return variance decomposition

	U.S.	E.U.
$\mathcal{V}_x$	47.48%	43.81%
$\mathcal{V}_{yd}$	52.52%	56.19%

Table continued from previous page.

Figure 1: Returns and dividend growth

This figure plots the total return indices (top panel) and dividend growth indices (bottom panel) for the U.S. and U.K. from the first quarter of 1966 (1966:1) to the last quarter of 2008 (2008:4). All indices are dollar denominated and expressed in real terms.

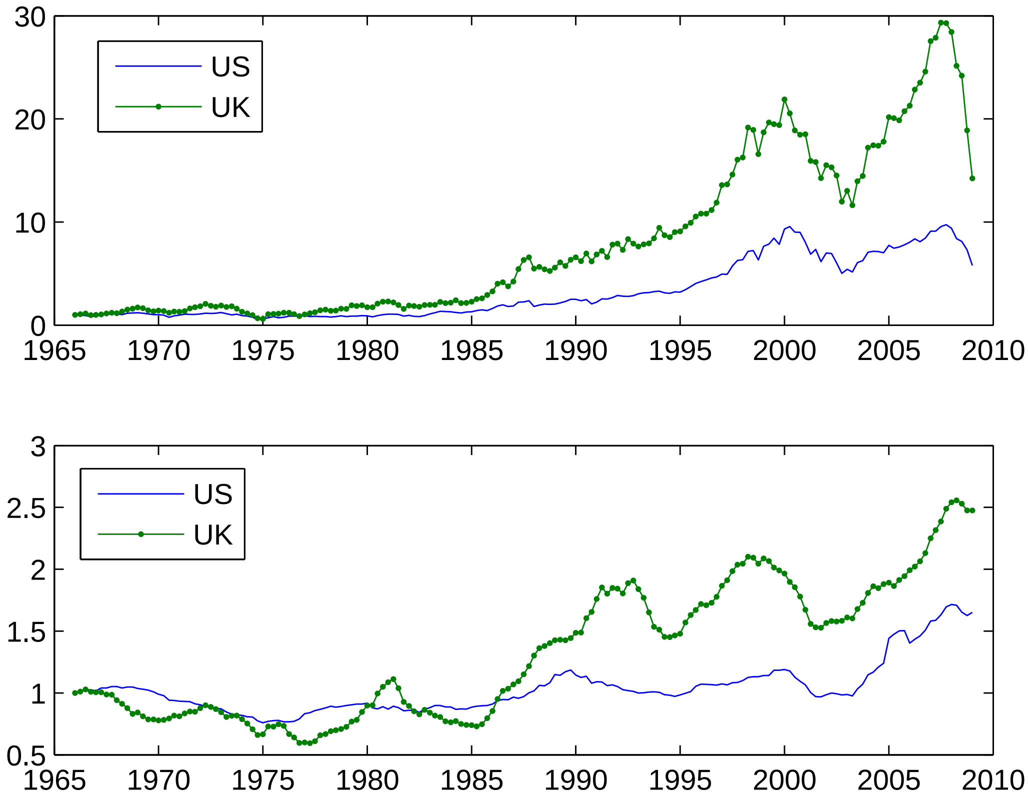

Figure 2: Correlation in returns and dividend growth

This figure reports the rolling correlation in returns (top panel) and dividend growth (bottom panel) based on a 7-year window, or 28 quarterly observations during the 1966:1 - 2008:4 period.

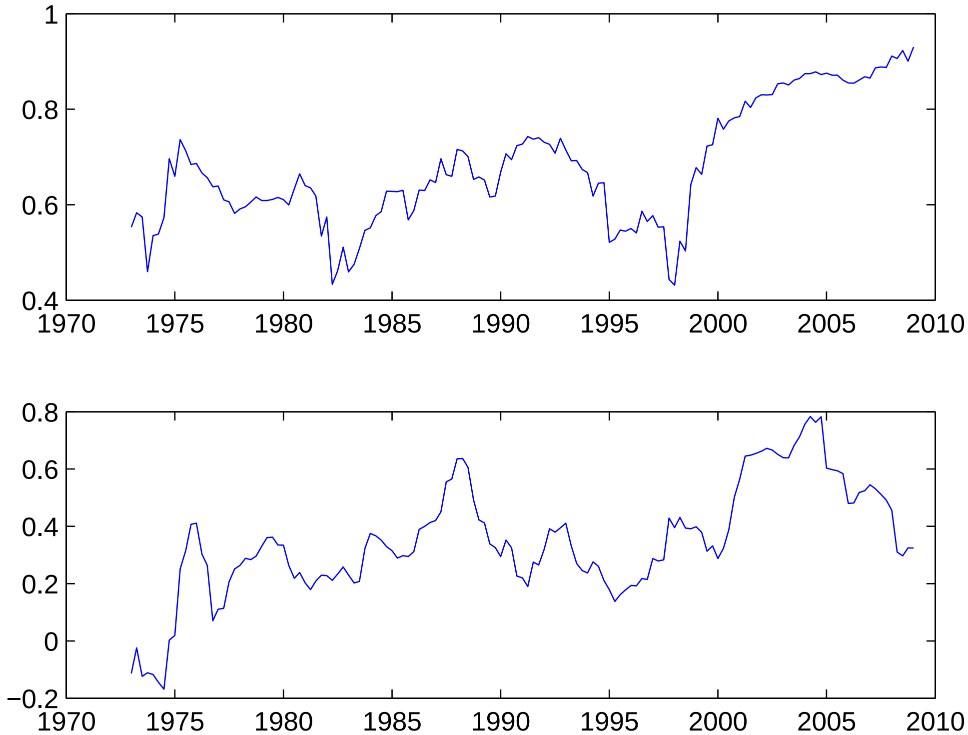

Figure 3: Scatter plot of returns and dividend growth

The figure reports the scatter plot of returns (top two plots) and dividend growth (bottom two plots) for the U.S. and U.K. during the 1966-1991 period (left figure) and 1992-2008 period (right figure). Superimposed is also a linear regression function and its associated R^2 statistic.

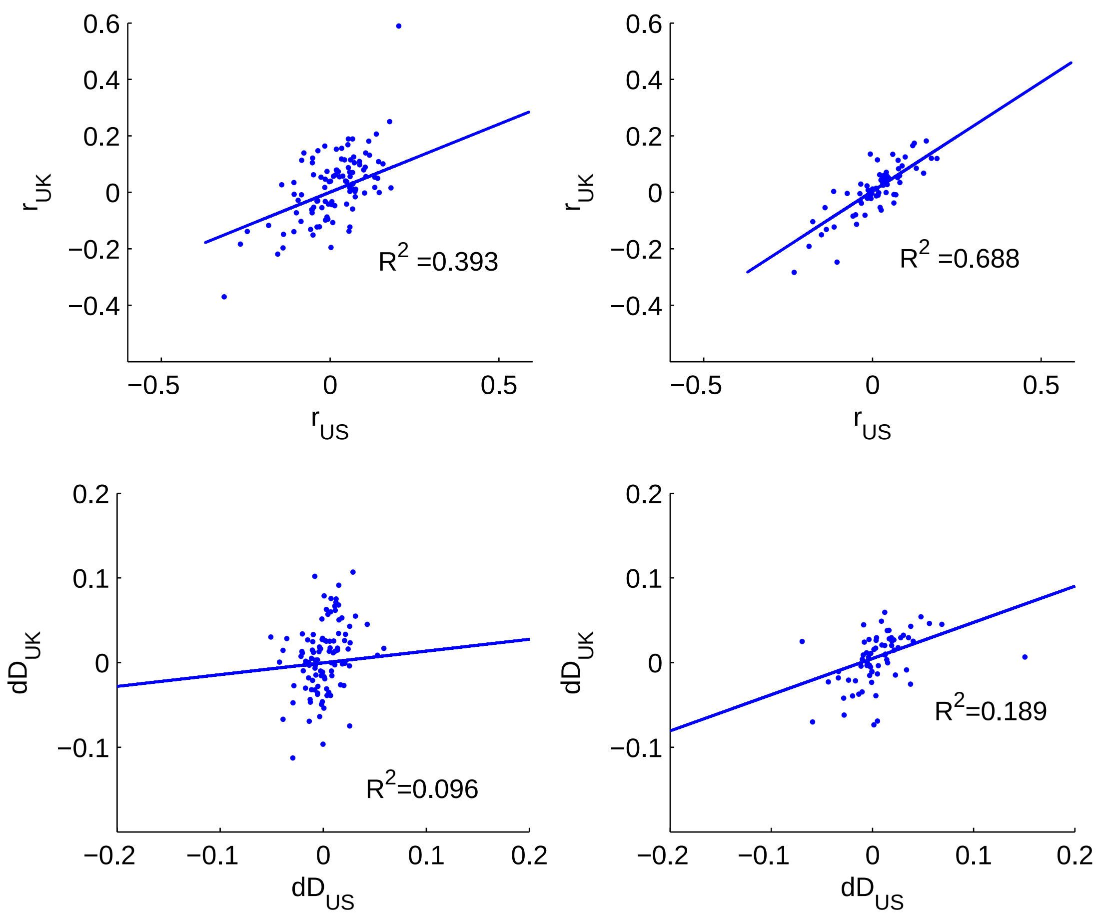

Figure 4: Predictive coefficients

The figure reports the slope coefficients in the regression of returns on lagged dividend-yield (β) and dividend growth on lagged dividend-yield (λ) of the U.S. and U.K. as a function of the parameter τ. The plot is obtained by inputting the value of the structural parameters (ρ, ϕ, υ) from Table 3 and 4 into the theoretical expressions of the coefficients.