The world business cycle and expected returns

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The World Business Cycle and Expected Returns

Ilan Cooper[1] and Richard Priestley[2]

Abstract. We study the predictability of stock returns using a pure macroeconomic measure of the world business cycle, namely the world's capital to output ratio. This variable tracks variation in expected stock returns in a group of the major industrial economies in the presence of world financial market based predictor variables. The world's capital to output ratio exhibits strong out-of-sample predictive power in almost all countries studied. This is in contrast to financial market based variables that almost never have out-of-sample forecasting power. Using the stock return predictability that we uncover, we find that international versions of conditional asset pricing models perform well. The world capital to output ratio also predicts bond returns, interest rate changes and credit spreads. The results highlight the importance of world business conditions for financial markets.

JEL Classification: G12, G15, G17

1. Introduction

Recent evidence suggests that increased product and financial market integration has led to a convergence in business cycles across countries. For example, Lumsdaine and Prasad (2003) identify a world business cycle along with evidence that macroeconomic fluctuations across countries have been increasingly linked since 1973. Imbs (2006) shows that correlations in GDP fluctuations across countries rise with financial market integration. Artis and Hoffmann (2008) examine the business cycle of OECD countries and find that country specific factors become less important as globalization takes place. As financial markets have globalized and become more integrated, we expect that international, rather than country specific, measures of business conditions determine at least some of the variation in local expected stock returns and fixed income returns. While some of the current empirical evidence on international asset pricing does not support the notion of fully integrated markets, following the increased convergence of business cycles, it seems appropriate and timely to examine the relationship between expected returns and a production-based, as opposed to financial-based, measure of the world business cycle.[1]

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[1] Erb, Harvey, and Viskanta (1995, 1996) and Harvey (2000) show that country-level credit rating, variance, and co-skewness are highly significant explanatory variables in local market returns. Karolyi and Stulz (2003), Bekaert, Harvey, and Lundblad (2007),

Evidence on the predictability of stock returns in international markets and, particularly, by common predictor variables, is rather scarce, as the vast majority of evidence regarding the time variation in expected returns is based on findings regarding the predictability of U.S. stock returns using U.S. financial market based predictor variables. Ang and Bekaert (2007) provide evidence regarding the predictability of returns in four developed stock markets using local versions of the dividend yield and the risk free rate. Rangvid (2006) explores the predictability of returns across developed countries stock markets using country specific GDP scaled by price. Cooper and Priestley (2009) find that country specific measures of the output gap are predictors of country excess stock returns in the G7 countries. Notable exceptions that look at predictability using a common set of financial market based variables, as opposed to local country ones, are Harvey (1991, 1995), Bekaert and Harvey (1995) and Dumas and Solnik (1995) who predict local stock returns with a common set of predictor variables that are, with the exception of the lagged world stock market return, U.S. based financial market variables.

The paper's contribution to the stock return predictability literature is to first introduce a new measure of the business cycle based on the production side of the economy which is measured as the ratio of capital stock to output. The second contribution is to focus on the in-sample predictability of asset returns in seven developed countries plus the world stock market index using this new production based measure of the business cycle at the world level which we define as the ratio of the world's capital stock to world output, $\frac{k}{y}^w$. The third contribution of the paper is to conduct an extensive set of out-of-sample tests using strictly data and parameter estimates that are known to investors at the time the forecasts are made. The reason we examine out-of-sample predictability is because Bossaerts and Hillion (1999) caution against making inferences about predictability using in-sample evidence based on findings that the dividend price ratio cannot predict out-of-sample. Similarly, Goyal and Welch (2008) assess the out-of-sample predictability of U.S. stock returns for many variables suggested by the literature. They find that even though some of these variables have in-sample predictive power, they perform poorly out-of-sample, particularly in the past three decades.

Our major findings regarding stock returns predictability are that our measure of the world business cycle is able to predict stock returns in the presence of the dividend price ratio of the world stock market and the world (U.S.) risk free rate. Of most interest are the out-of-sample tests which show that forecasts of returns based on $\frac{k}{y}^w$ that are more accurate than forecasts based on the historic mean in almost all countries. For example, using the predictability of returns based on $\frac{k}{y}^w$, in seven of the eight markets that we consider a mean variance investor would have earned on average a positive certainty equivalent wealth of between 2% and 2.5% per annum more than using the historic mean equity return, depending on the out-of-sample forecasting period. The world dividend price ratio and the risk free rate can almost never predict out-of-sample better than the historical average.[2]

The predictability of stock returns that we uncover using $\frac{k}{y}^w$ has potential implications for conditional international asset pricing models. Therefore, our fourth contribution is

Bekaert, Hodrick, and Zhang (2009), Bekaert, Harvey, Lundblad, and Siegel (2011), Hou, Karolyi, and Kho (2011), and Lee (2011) also demonstrate the role for local factors.

[2] We also consider whether country specific versions of $\frac{k}{y}$ can predict stock returns. France and Italy are the only countries where we find in-sample predictability. In the out-of-sample tests there is no evidence of predictability for any of the countries.

to study several conditional asset pricing models. Using a cross-section of seven country level market returns and eight portfolios per country formed on high and low book-to-market, cash-flow-to-price, dividend-to-price and earnings-to-price, we find that relative to unconditional models, scaling risk factors by conditioning information helps improve the description of the cross-section of returns. For example, scaling the return on the world market portfolio by $\frac{k}{y}^w$ improves the cross-sectional performance of the international CAPM. The Fama and French (1998) international risk factors, when scaled by $\frac{k}{y}^w$ also produce higher cross sectional $\overline{R}^2$s than unconditional models and the plots of average realized and expected returns indicate that the pricing errors are smaller for conditional models than unconditional models.

In addition to examining stock return predictability using a measure of the international business cycle, we also contribute to the literature on the time variation in risk premia of fixed income securities. There is an established literature that points to the failure of the expectations hypothesis (see, for example, Fama and Bliss (1987), Campbell and Shiller (1991), and Cochrane and Piazzesi (2005)). In particular, the term spread or forward rates are able to forecast excess bond returns, a finding that is suggestive of a time-varying risk premium in the bond market. However, the finding that the term spread forecasts excess bond returns only loosely ties time varying risk premia in the bond market to business cycle risk. Theoretically, Wachter (2006) and Brandt and Wang (2003) both argue that risk premia in bond markets are driven by macroeconomic fundamentals and Ludvigson and Ng (2009) provide evidence that a common factor derived from 132 U.S. macroeconomic variables has predictive power for U.S. bond excess returns.

We show that changes in short term interest rates across the seven countries are predictable by the direct measure of the world business cycle that we propose, with the exception of the U.S. and Canada. In addition, excess U.S. bond returns with 2 to 5 years to maturity can be predicted with $\frac{k}{y}^w$ even in the presence of the Cochrane and Piazzesi (2005) domestic forward factor and the world dividend price ratio and risk free rate. Finally, we examine the predictability of three credit spreads in the U.S. and find that the riskiest spread, the difference between the yield on a long term government bond and BAA rated corporate bonds, is predictable with $\frac{k}{y}^w$. The findings regarding the predictable nature of interest rate changes, bond returns and credit spreads enhance our understanding of the economics of the time varying risk premia in fixed income markets and suggests that the markets for these types of securities are to some extent integrated internationally and integrated with the equity market in the sense that they share a common source of time varying risk premia. In addition, these results have implications for affine term structure models that have no role for macroeconomic sources of risk.

Our focus on a macroeconomic business cycle variable is related to an encouraging line of research that demonstrates that U.S. consumption based variables have predictive power for U.S. stock returns (see, for example, Lettau and Ludvigson (2001a), Santos and Veronesi (2006) Piazzesi, Schneider and Tuzel (2006), and Lustig and Van Nieuwerburgh (2005)). However, consumption, asset value, labor income and housing based variables that are employed in Lettau and Ludvigson (2001a), Santos and Veronesi (2006) Piazzesi, Schneider and Tuzel (2006) and Lustig and Van Nieuwerburgh (2005) are often unavailable in other countries and, consequently, it is not possible to test them on an independent sample or, more importantly in our context, to construct an international version of them. Furthermore, these papers do not focus on a production based macroeconomic source of predictability but focus instead on consumption related variables. Therefore, our analysis constitutes important independent evidence on the variation of equity premia over the business cycle.

Notable papers that do use production related variables are Cochrane (1991) who shows that the U.S. economy's investment to capital ratio predicts U.S. stock returns, and Lamont (2000) who demonstrates that investment plans of U.S. firms forecast stock returns. However, there are two potential problems with using aggregate investment data. First, recent findings suggest that both investment and investment plans could be affected by stock mispricing in that managers time the market in their investment decisions.[3] In contrast to investment related predictors, $\frac{k}{y}^w$ is a production based variable that is unaffected by managers' market timing and therefore predictability of stock returns through $\frac{k}{y}^w$ is unlikely to reflect stock mispricing. Second, a prominent feature of investment is time to build (and plan), see Kydland and Prescott (1982). This leads to investment being a somewhat lagging variable. It is possible that if the risk premium responds immediately to changing economic conditions, it might be captured better, especially at short horizons, by macroeconomic variables, such as output, that respond more quickly to these changes.

The article is organized as follows. The motivation for the use of the capital to output ratio as a predictor of expected returns and its construction are described in section 2. Section 3 provides results of predicting stock returns. In section 4, we examine out-of-sample predictability of stock returns. The asset pricing implications of the stock return predictability are examined in section 5. Section 6 assesses the predictability of interest rates, bond returns and credit spreads. Finally, section 7 concludes.

2. The Capital to Output Ratio, $\frac{k}{y}$

The capital to output ratio is defined as the ratio of the capital stock, k, to GDP, y, $\frac{k}{y}$. This new predictor variable is motivated by empirical studies that find that the elasticity of capital supply in the economy is low and investment is largely irreversible. Following these findings, modeling investment as irreversible has become standard in the investment and finance literatures.[4] When investment is irreversible and the economy suffers an adverse aggregate shock, output falls and the marginal product of capital declines. However, firms cannot optimally disinvest because of the irreversibility constraint and consequently $\frac{k}{y}$ rises. Hence, $\frac{k}{y}$ is countercyclical and can serve as a business cycle indicator, something that we confirm empirically in the data. The equity risk premia is also countercyclical, due to either higher risk in recessions, as in Constantinides and Duffie (1996), or higher risk aversion during recessions, as in Campbell and Cochrane (1999) and Chan and Kogan (2002). Therefore, as $\frac{k}{y}$ rises in recessions it forecasts higher stock returns in the future that are a rational compensation for higher risk or higher risk aversion.

The capital to output ratio is also related to two state variables that have implications for the equity risk premium. Market clearing conditions imply that resources are equal

[3] See, for example, Baker and Wurgler (2002), Baker, Stein and Wurgler (2003) and Polk and Sapienza (2006).

[4] See, for example, Caballero, Engel and Haltiwanger (1995) (specifically Figure 8) and Goolsbee (1998) for evidence regarding the elasticity of capital supply and irreversile investment. Dixit and Pindyck (1994), Coleman, (1997), Boldrin, Christiano and Fisher (2001) and Kogan (2004), among others, use irreversible investment in finance and investment models.

to their uses. Consequently, in equilibrium, output is equal to the sum of investment and consumption. Therefore, the capital to output ratio is the inverse of the sum of the investment to capital ratio and the consumption to capital ratio; $\frac{k}{y} = \frac{1}{\left(\frac{y}{k}\right)} = \frac{1}{\left(\frac{i}{k}\right)+\left(\frac{c}{k}\right)}$ where i is investment and c is consumption. Hence, a low investment to capital ratio and a low consumption to capital ratio correspond to a high capital to output ratio. Cochrane (1991) uses the q-theory of investment and shows that under standard assumptions regarding the production and capital adjustment technology, the economy's investment to capital ratio is negatively related to future stock market returns. Intuitively, investment to capital is low when the marginal value of capital is low, and controlling for the expected future marginal product of capital, the marginal value of capital and investment to capital are low when discount rates are high. In sum, a high capital to output ratio corresponds to a low investment to capital ratio, which in turn points to high expected stock returns. Note that output determines investment and consumption and not the other way around. Therefore the capital to output ratio is not determined by managers timing the market.

The second component in the capital to output ratio, namely the consumption to capital ratio is a procyclical variable given the low elasticity of the supply of capital. In recessions the consumption to capital ratio declines. As consumption declines, risk aversion and/or risk increases, implying higher expected excess market returns. Thus, a high capital to output ratio corresponds to a low consumption to capital ratio and high expected stock returns. Overall, the two terms in the denominator of $\frac{k}{y}$ are negatively related to future returns. Moreover, it is well known that investment and consumption are positively correlated, so that both terms in the denominator of $\frac{k}{y}$ are likely to move together and hence an increase in $\frac{k}{y}$ points to higher expected stock market returns.

The capital to output ratio, $\frac{k}{y}$, is calculated using the natural log of quarterly real capital stock of the business sector (excluding households), denominated in U.S. dollars, divided by the natural log of quarterly, dollar denominated real GDP. Both series are provided by the OECD.[5] In order to avoid problems with publication delays we always use capital and GDP measured one quarter ago: $\frac{k}{y}_t = \frac{k_{t-1}}{y_{t-1}}$. In our regressions, we regress real stock returns at time t on $\frac{k}{y}_{t-1}$ (which because of the publication delay is $\frac{k_{t-2}}{y_{t-2}}$). The world measure of $\frac{k}{y}$ is the sum of the capital stock across the countries divided by the sum of GDP across the countries. The sample period is quarter one 1970 to quarter four 2010.

The upper part of Figure 1 plots $\frac{k}{y}$ which has a strong upward trend indicating that the stock of capital has been growing at a faster rate than GDP. The strong upward trend in $\frac{k}{y}$ could, potentially, be problematic in the sense that returns were low in the early 1970s when $\frac{k}{y}$ was low and high in the 1990s when $\frac{k}{y}$ was high, resulting in a positive spurious relationship. In order to make sure that our regressions pick up more than these two observations we linearly detrended $\frac{k}{y}$ by estimating

$$\frac{k}{y}_t = \underset{(3442.7)}{1.015} + \underset{(84.83)}{0.00025} * t + u_t \qquad \overline{R}^2 = 98\% \tag{1}$$

where t is a linear time trend, u_t is the detrended $\frac{k}{y} = \frac{k}{y}^w$, and the numbers in parenthesis are t-statistics.

[5] As GDP data are often revised ex-post by the OECD, for the out-of-sample tests we collect the unrevised data on GDP as they appear in the OECD Bulletins at the time of publication. To the best of our knowledge the capital stock data is not revised

The second graph in Figure 1 plots the linearly detrended $\frac{k}{y}^{w}$ which no longer has the upward trend but reveals clear business cycle properties. The detrended $\frac{k}{y}^{w}$ has a mean of zero and a standard deviation of 0.0018. It is also highly autocorrelated with a first order autocorrelation coefficient of 0.95, a characteristic common in most business cycle variables. Around recessions $\frac{k}{y}^{w}$ increases as output falls relative to the stock of capital, this can be observed in the 1973-1975 recession, and the recessions at the beginning of the 1980s and the 1990s. Interestingly, the run up in stock prices in the 2000s before the financial crisis corresponds to a large steady decline in $\frac{k}{y}^{w}$ followed by a steep spike around the time of the crisis as the recession took hold. An even larger spike in $\frac{k}{y}^{w}$ occurred during the recent (2007-2008) financial crisis and the ensuing recession.

3. Predicting Stock Returns

The main focus of the paper is the predictability of stock returns. We choose countries where data is available on the aggregate stock of physical capital over a reasonable time period. These countries are the U.S., U.K., Japan, Italy, France and Canada. While data on the stock of physical capital for Germany is also available it is not included because there is a large structural break in the series caused by the reunification of east and west Germany. We also examine the predictability of stock returns from Switzerland given the international nature of its economy and stock market.

The local country dividend price ratio and the risk free rate have some ability to jointly predict stock returns across four different countries in Ang and Bekaert (2007). Therefore, we examine the ability of $\frac{k}{y}^{w}$ to predict future returns along with the dividend price ratio and the risk free rate. The world dividend price ratio is obtained from the MSCI and is calculated as the sum of the last four dividend payments $(d_t + d_{t-1} + d_{t-2} + d_{t-3})$ divided by the current price, p_t. The world risk free rate is proxied by the U.S. risk free rate (three month treasury bill rate). The correlations between $\frac{k}{y}^{w}$ and the world dividend price ratio and risk free rate are 0.03 and 0.15 respectively, indicating that $\frac{k}{y}^{w}$ is capturing more of a business cycle pattern than the longer term trends evident in the dividend price ratio and the risk free rate (see the third and fourth plots in Figure 1).

All stock price and dividend data are taken from Morgan Stanley Capital International (MSCI). U.S. dollar denominated value weighted price indices which include reinvested dividends are used to measure total returns. Real stock returns are calculated by subtracting the U.S. inflation rate, measured from the CPI index, from the total returns. We also examine the predictability of the world stock market index which is the total return on the MSCI world stock market index minus the U.S. inflation rate.

We report results from estimating the following regression

$$r_{i,t} = \alpha + \delta \mathbf{Z}^{w}_{t-1} + \xi_{i,t}, \tag{2}$$

where $r_{i,t}$ is the one quarter real return on country i's aggregate stock market, α is a constant, δ is a vector of coefficient estimates, $\mathbf{Z}^{W}_{t-1}$ is a vector of international lagged predictor variables which include $\frac{k}{y}^{w}$, $\frac{d}{p}^{w}$ and r^{w}_{f}. We also estimate the above equation omitting $\frac{d}{p}^{w}$ and r^{w}_{f} from $\mathbf{Z}_{t-1}$ and then compare the $\overline{R}^{2}$ from the two regressions to find the incremental contribution of $\frac{k}{y}^w$ to stock return predictability. Newey-West robust standard errors are used to make statistical inferences.[6]

Table I presents analysis of the predictable variation in one quarter real returns using international predictor variables. The second column of the table reports the estimate of the coefficient on $\frac{k}{y}^w$ and the corresponding t-statistics in parenthesis.[7] The signs of the estimates are reassuringly positive in all cases and are statistically significant in four cases.[8] The positive sign indicates that as economic conditions worsen, returns are predicted to rise in order to compensate for the higher risk in bad times. The economic impact of $\frac{k}{y}^w$ is also important: a one standard deviation increase in $\frac{k}{y}^w$ leads to a 1.9% per quarter increase in real returns for the U.S.. Taking the average coefficient across all the countries that have a statistically significant estimate, a one standard deviation increase in $\frac{k}{y}^w$ leads to almost a 2.0% increase in real returns per quarter.

The consistency of the estimated sign, its size and the statistical significance provide evidence that $\frac{k}{y}^w$ is useful in tracking the movement in four of the local market equity returns and the world market index. This provides encouraging evidence that a direct macroeconomic measure of the world business cycle can predict stock returns in some countries. The coefficient on the world dividend price ratio, $\frac{d}{p}^w$, does have the correct sign in all countries, and it is statistically significant in Japan and marginally statistically significant in the UK and the world index. The estimated coefficients on r_f^w also have the expected sign but only in the case of Japan is the estimate statistically significant at the 5% level.

An examination of the adjusted R^2, $\overline{R}^2$ reveals they are reasonable for one quarter regressions, especially for Switzerland, U.K., U.S., and the world index. Ignoring the negative $\overline{R}^2$ in Italy, the average among the remaining countries is 2.6%. Moreover, comparing the $\overline{R}^2s$ from the regression which includes all three predictor variables to those that exclude $\frac{d}{p}^w$ and r_f^w (reported in the final column) it is evident that predictability of individual country returns by international predictor variables comes, to some extent, from $\frac{k}{y}^w$. The relative predictive power of the three predictor variables is considered further in the out-of-sample tests.

There is a concern that inferences regarding the statistical significance of predictive regressions are affected by small sample bias (see, among others, Stambaugh (1999)). We take three approaches to assess this. First, in Table I we also report the bias corrected

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[6] Alternative inference techniques that use unit-root and local-to-unity data generating processes focus on univariate regressions (see, for example, Richardson and Stock (1989), Elliot and Stock (1994), Torous, Valkanov, and Yan (2001), Valkanov (2003), Lewellen (2004), and Campbell and Yogo (2005)). As we use multivariate regressions at the one period horizon, we consider two methods of assessing the bias in estimates and t-statistics. First, we use the bias correction of Amihud and Hurvich (2004). Second, we assess the properties of the Newey-West t-statistics using a Monte-Carlo experiment.

[7] The second row for each country and for the world index reports the Amihud and Hurvich (2004) corrected estimates and t-statistics. We elaborate on this later.

[8] Considering a one sided test of the null hypothesis, we also find that Japan has a statistically significant coefficient at the 10% level. This means that that we find predictability in over 85% of the market capitalizaton of the countries that we consider. That the coefficient in Japan is marginally statiatically significnt in-sample, is consistent with the later results that stock returns in Japan are predictable out-of-sample.

estimates and t-statistics for multivariate regressions using the approach of Amihud and Hurvich (2004). Second, we run a Monte Carlo experiment that imposes the null of no predictability to assess the empirical distribution of the Newey-West t-statistics. Third, later, we perform out-of-sample tests; if a predictor variable can forecast out-of-sample then statistical issues regarding in-sample regressions become less of an issue.

For every country, we report the Amihud and Hurvich (2004) corrected estimates and t-statistics for a multivariate regression under the reported OLS estimates.[9] There is a reduction in the extent of statistical significance when applying the correction. However, if we are willing to contemplate a one-sided test (note that the alternative hypothesis is that the coefficient on $\frac{k}{y}^w$ is positive) then the coefficient on $\frac{k}{y}^w$ for Canada, Japan and Switzerland are statistically significant at the 10% level and the coefficient on $\frac{k}{y}^w$ for the U.K., U.S., and world index are significant at the 5% level. The appendix of the paper also describes a Monte Carlo experiment to investigate whether inferences on the statistical significance of the parameter estimates are affected by size distortions when using Newey-West t-statistics. The data for the Monte Carlo experiment are generated under the null hypothesis of no predictability. We compare the empirical size generated from the Monte Carlo experiment against a 5% nominal size in order to assess whether there are any size distortions with the Newey-West t-statistics using the real returns on the world stock market index. We find that the Newey-West t-statistics testing the null that $\frac{k}{y}^w$, $\frac{d}{p}^w$ and r_f^w cannot predict returns have good size properties for the 1-quarter ahead forecasting regressions (all three have a value of around 5.5% as opposed to the nominal 5% value). The empirical critical values for the t-statistics at the one quarter horizon are very close to their asymptotic counterparts. Therefore, the Newey-West t-statistics are generally fine when making statistical inference, at least at the quarterly horizon.

The results provide evidence that local stock market returns are predictable using international predictor variables. In particular, we find estimates of the coefficients on $\frac{k}{y}^w$ across the different countries that are consistent with the role of this variable as an indicator of business conditions. Therefore, the new predictor variable, $\frac{k}{y}^w$, which is a pure business cycle variable, has a role to play in local stock market predictability. Predictability with this variable is observed more often than with the financial market predictor variables. The results are important because they constitute new evidence that stock returns vary with the international business cycle.

A potential explanation for the weaker evidence of predictability in Canada, France, Italy and Japan with the international version of the capital to output ratio, both in terms of the size of the estimated coefficients and the t-statistics, is that in these countries equity markets may be driven by local business conditions. Table II reports the results from regressing country level returns on country specific versions of the three predictor variables and shows that predictability with a country specific version of $\frac{k}{y}$ is only observed in France and Italy. The inability of the local version of $\frac{k}{y}$ to predict local stock market returns reinforces the importance of considering international business conditions when assessing equity market premia.[10]

[9] We thank Yakov Amihud for providing us with the code that provides the corrected estimates and standard errors for multivariate regressions.

[10] In out-of-sample tests, which we consider in the nect section, when using the local version of $\frac{k}{y}$ there no evidence of predictability in any country. Therefore, we focus only on predictability with the world version of $\frac{k}{y}$.

4. Predicting Stock Returns Out-of-Sample

A recent area of interest in the stock return predictability literature focusses on the ability of predictor variables to predict out-of-sample. Bossaerts and Hillion (1999) and Goyal and Welch (2003) show that the dividend yield has no out-of-sample predictive power. Goyal and Welch (2008) examine the out-of-sample predictive ability of a large number of predictor variables and find little evidence that they can predict out-of-sample better than a constant. In response to this line of work, Campbell and Thompson (2008) show that sensible restrictions on forecasting models leads to the finding that a number of predictor variables have out-of-sample forecasting ability. Rapach, Strauss and Zhou (2010) find that combining forecasts from well known predictor variables leads to evidence of out-of-sample predictability. Cooper and Priestley (2009) show that the output gap can forecast stock returns out-of-sample and Ferreira and Santa Clara (2011) show that stock returns are predictable out-of-sample when individual parts of returns are forecasted. Avramov and Chordia (2006) show that individual stock returns are predictable in real time, based on macro variables.

In this section of the paper the out-of-sample tests allow us to confront the questions of whether the forecasts of returns based on $\frac{k}{y}^w$ are better than those based on using the historical average and better than those based on the dividend price ratio and the risk free rate. We also provide a metric for measuring the economic significance of the out-of-sample forecasting power of the predictor variables based on calculating utility gains to investors from employing the forecasts in a trading strategy. Finally, any evidence of out-of-sample forecasting ability goes a long way to nullifying the suggestion that the in-sample predictability is driven by small sample biases.

In order to provide out-of-sample forecasts that could actually have been made by an investor it is necessary to use only information that is available to the investor at the time the forecast is made. To this end, for each country, we hand collected data on actual GDP and the price deflator from the published issues of the OECD Economic Outlook at the time it was published. In each quarter this provides us with the actual data that the investor would have observed. We then calculate real GDP and convert it into dollars using the appropriate exchange rate. The out-of-sample tests are performed on the second half of the sample from 1990:1 to 2010:4, giving us seventy eight observations for providing the first estimate. We also perform the out-of-sample tests for the sub-sample 2000:1 to 2010:4.

Figure 2 plots $\frac{k}{y}^w$ using the vintage data before any de-trending. As in the case of the in-sample version of $\frac{k}{y}^w$ there exists an upward trend. However, closer inspection reveals that from the beginning of the sample to 1980 there is a steep trend and then from 1980 onwards a shallower trend. Given this, for the out-of-sample tests we de-trend $\frac{k}{y}^w$ at every single prediction point as follows: We estimate the trend coefficients recursively starting in 1971:1 until 1989:4 to get the first estimate of the parameters:

$$\frac{k}{y}^{wu}_t = a_\tau + b_\tau \cdot t^{1979} + c_\tau \cdot t^{1989} + v_t, \tag{3}$$

where $\frac{k}{y}^{wu}_t$ is the unadjusted world capital to output ratio, τ =1989:4, $t = 1, 2, 3, ..., \tau$, t^{1979} is a linear trend from 1971:1 to 1979:4, t^{1989} is a linear trend from 1980:1 to 1989:4, and the residual v_t is the measure of $\frac{k}{y}^w$ that is detrended over the period 1971:1 to 1989:4. Note the subscript τ for the three parameters, which indicates that they are updated with each ending quarter. Next we update the estimates of the trend by one quarter by estimating over the period 1979:1 to 1990:1:

$$\frac{k}{y}^{wu}_{t} = a_{\tau+1} + b_{\tau+1} \cdot t^{1979} + c_{\tau+1} \cdot t^{1989} + v_t, \tag{4}$$

where quarter $\tau + 1$ is 1990:1 and $t = 1, 2, 3, ..., \tau + 1$. We add on the estimate of $\frac{k}{y}^{w}$ in 1990:1 to the time series of $\frac{k}{y}^{w}$ estimated previously over the period 1971:1 to 1989:4. We then repeat this, quarter-by-quarter, estimating new trend coefficients and values of $\frac{k}{y}^{w}$ until the end of the sample. For the initial estimation period of 1971:1 to 1989:4, we then form an out-of-sample forecast of returns for 1990:1. We then add on one quarter and re-estimate, forming a new out-of-sample forecast for 1990:2. We repeat this process, quarter-by-quarter, to the end of the sample.

For the in-sample regressions, we allowed for a one quarter publication lag. When looking at the data that is hand collected, in a number of cases there was more than one quarter publication lag. Therefore, to be conservative, we allow for a two month publication lag and regress, at each point in time:

$$r_{i,t} = \alpha + \gamma \frac{k}{y}^{w}_{t-3} + \xi_{i,t}, \tag{5}$$

We also predict out-of-sample using first, the one quarter lag of the world dividend price ratio and second, the first lag of the risk free rate. We can then assess the out-of-sample predictive power of each of the three predictor variables separately.

We conduct several out-of-sample tests. The benchmark model that we want to compare the three predictor variables to is one where real returns are regressed on a constant, quarter-by-quarter, to provide forecasts at each quarter of real returns based on the historic mean updated each quarter. This constant expected return model is a restricted, nested, version of a model of time-varying expected returns that includes a constant and one of the predictor variables. The assessment of out-of-sample predictability involves four metrics. The first statistic we report tests for the equality of the mean-squared forecasting errors of one forecast relative to another. To do this we use the MSE-F test developed by McCracken (2007) which tests the null hypothesis that the constant expected return model has a mean squared forecasting error that is less than, or equal to, that of the time-varying expected return model. The alternative hypothesis is that the time-varying expected return model has a lower MSE. The test statistic is given as:

$$MSE - F = (T - h + 1) \cdot \left(\frac{MSE_{\varepsilon} - MSE_{e}}{MSE_{e}} \right) \tag{6}$$

where MSE_{ε} is the mean squared error from the model that includes just a constant.

The second test asks if the forecasts from one model *encompass* the forecasts from another. If the forecasts from the constant expected return model do not encompass the forecasts from the time-varying expected return model, then the latter model has some information that is useful for forecasting out-of-sample. Clark and McCracken (2001) extend the encompassing test of Harvey, Leybourne and Newbold (1998) by deriving the nonstandard asymptotic distribution of a test statistic for forecast encompassing which is termed ENC-NEW. Clark and McCracken show that the encompassing test has more power than tests of the equality of mean squared forecast errors. We employ the ENC-NEW test to examine whether the forecasts from the constant expected return model encompass the forecasts from the time-varying expected return model that includes a constant and one of the predictor variables. The test is given as:

$$ENC-NEW = \frac{T-h+1}{T} \cdot \frac{\Sigma_{t=1}^{T}(\varepsilon_t^2 - \varepsilon_t \cdot e_t)}{MSE_e}, \tag{7}$$

where T is the number of observations, h is the degree of overlap and is equal to one when there is no overlap, ε_t is the vector of rolling out-of-sample errors from the historical mean model, e_t is the vector of rolling out-of-sample errors from the forecasting model including one of the predictor variables, and MSE_e is the mean squared error from the forecasting model that includes one of the predictor variables.

Further analysis of the out-of-sample performance in predicting stock returns is obtained from calculating the out-of-sample R^2, R^2_{oos}, which following Campbell and Thompson (2008) is defined as:

$$R^2_{oos} = 1 - \frac{\sum_{t=1}^{T}(r_t - \widehat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \overline{r}_t)^2} \tag{8}$$

where $\widehat{r}_t$ is the forecast of excess return based on data up to $t-1$, and $\overline{r}_t$ is the historical average excess return estimated using data up to $t-1$. The R^2_{oos} is measured in units that are comparable to the in-sample R^2. If the out-of-sample R^2 is positive, then the predictive regression has lower average mean squared prediction error than the historical average return.

As a means of measuring the economic importance of the out-of-sample performance of the predictor variables, we follow Ferreira and Santa Clara (2011) and calculate certainty equivalent gains for a mean-variance investor from using the time-varying expected returns model relative to using the historical mean return forecast. As in Campbell and Thompson (2008) and Ferreira and Santa Clara (2011), we assume that a mean variance investor calculates the optimal portfolio weight based on the forecasting model of expected returns:

$$w_t = \frac{\widehat{r}_t - r_{f,t+1}}{\gamma \widehat{\sigma}_t^2} \tag{9}$$

where w_t is the optimal weight, $\widehat{r}_t$ is the forecast of the return at time t, $r_{f,t+1}$ is the risk free return (which is known at time t), γ is the coefficient of risk aversion, and $\widehat{\sigma}_t^2$ is the variance of returns estimated up to time t. At the end of each period the portfolio return is calculated as the weighted average of the returns on the market and the return on the risk free rate. The investor's objective function is expected portfolio return less $\left(\frac{\gamma}{2}\right)$ portfolio variance, where γ can be interpreted as the coefficient of relative risk aversion to provide the certainty equivalent:

$$ce = \overline{r}_p - \frac{\gamma}{2}\sigma^2(r_p) \tag{10}$$

where $\overline{r}_p$ is the mean of the return on the portfolio and $\sigma^2(r_p)$ is its variance. As in Ferreira and Santa Clara γ is assumed to be 2.

Table III reports the results from the MSE-F, ENC-NEW tests and the R^2_{oos} and provides evidence regarding the ability of the three predictor variables to forecast out-of-sample. The left side of the Table reports the results when forecasting out of sample with $\frac{k}{y}^w$ from 1990. With the exception of Italy and Canada the R^2_{oos} is positive, indicating that the forecasts using $\frac{k}{y}^w$ outperform those of using a constant. Both the MSE-F and ENC-NEW tests show that for the U.S., U.K., Switzerland, the world stock market index and Japan the out-of-sample forecasts based on $\frac{k}{y}^w$ are statistically better than those that use a constant. The dividend price ratio can only forecast out-of-sample in the U.K. and the risk free rate can never forecast out-of-sample.

The right hand side of the Table shows that the out-of-sample predictability using $\frac{k}{y}^w$ is also present for the same set of countries when beginning the out-of-sample forecasting from 2000. So, the out-of-sample forecasting power is not confined to the 1990s. The dividend price ratio has out-of-sample forecasting power in this period in Japan and the U.K.. The risk free rate has no out-of-sample forecasting power.

The final assessment of the out-of-sample predictive ability of the variables is based on the certainty equivalent measure. In both forecasting periods and in all markets (except for Canada) the certainty equivalent from using $\frac{k}{y}^w$ as the predictor variable in a trading strategy is substantially higher than the certainty equivalent of a strategy that uses the historical average and strategies that use either $\frac{d}{p}^w$ or r_f^w. For example, when forecasting in the 1990-2010 period, the annual percentage gain from following the investment strategy relative to that of a constant varies from a low of 0.41% per annum in France to 3.53% in Switzerland and an average of 2.1% per annum, excluding Canada. In every case, using $\frac{d}{p}^w$ and r_f^w would have provided a negative certainty equivalent relative to using the historic mean.

In the shorter forecasting period of 2000-2010 the certainty equivalent gains are even greater relative to using the historic mean. For example, they range from 0.84% per annum in France to almost 4% for the world stock market with an average across all countries, except Canada, of 2.6% per annum. These certainty equivalent gains are economically large and show that an investor in each country, except Canada, would have benefited from forecasting stock returns with $\frac{k}{y}^w$.

Overall, the out-of-sample results show that there is statistical and economic evidence of predictability based in $\frac{k}{y}^w$ that would have benefited an investor in real time.

5. Asset Pricing Implications

The results regarding the ability of international predictor variables to predict local stock market returns could have important asset pricing implications. In particular, stock return predictability implies the existence of a conditional factor model for returns. Fama and French (1998) show that an unconditional asset pricing model with the world stock market factor and the high minus low book-to-market factor does a reasonable job in describing the returns on country level market portfolios and portfolios formed according to book-to-market, cash flows to assets, earning-to-price, and dividend-to-price, all portfolios that give a reasonable spread in returns. The underlying question that we want to ask is whether the predictor variables help to improve the explanation of the cross sectional differences in the returns on the test assets.

The four sets of fourteen test assets from the countries that we consider (which are a subset of the countries in Fama and French (1998)) include (i) the high and the low book-to-market portfolios for the set of countries, (ii) the high and the low cash flow to price portfolios for the set of countries, (iii) the high and the low earnings-to-price portfolios for the set of countries, and (iv) the high and the low dividend-to-prices portfolios. We augment each of these four sets of portfolio excess returns with the excess return on the market portfolio for each country providing four sets of tests assets which have a cross section of twenty one portfolios.

We consider a number of specifications of the asset pricing model, starting with the unconditional world CAPM:

$$r_{i,t} = \alpha_i + b_{i,1} * wer_t + e_{i,t} \tag{11}$$

where $r_{i,t}$ is the excess return on the ith portfolio $(i = 1, 2, ..., 21)$, wer_t is the excess return on the world stock market portfolio and $e_{i,t}$ is a residual. Introducing conditional information is straightforward and can be achieved by scaling the risk factor (see Cochrane (1996)). To provide a conditional version of the world CAPM we scale the world market portfolio excess return with either $\frac{k}{y}^w$ or $\frac{d}{p}^w$:

$$r_{i,t} = \alpha_i + b_{i,1} * wer_t + b_{i,2} * (wer_t * X^w_{t-1}) + u_{i,t} \tag{12}$$

where X^w_{t-1} is either $\frac{k}{y}^w$ or $\frac{d}{p}^w$ and $u_{i,t}$ is a residual. Next, we consider an unconditional version of the Fama and French (1998) two factor international asset pricing model:

$$r_{i,t} = \alpha_i + b_{i,1} * wer_t + c_{i,2} * wbm_t + v_{i,t} \tag{13}$$

where wbm_t is the world book-to-market factor defined as the difference between the return on the world high book-to-market portfolio and the return on the world low book-to-market portfolio, and $v_{i,t}$ is a residual. Finally, we consider a conditional version of the Fama and French (1998) two factor model which scales the two factors with either $\frac{k}{y}^w$ or $\frac{d}{p}^w$:

$$r_{i,t} = \alpha_i + b_{i,1} * wer_t + c_{i,2} * wbm_t + b_{i,2} * (wer_t * X^w_{t-1}) + c_{i,2} * (wbm_t * X^w_{t-1}) + z_{i,t} \tag{14}$$

where X^w_{t-1} is either $\frac{k}{y}^w$ or $\frac{d}{p}^w$ and $z_{i,t}$ is a residual.

We take two approaches to assessing the role of conditioning information in international asset pricing models. First, following Fama and French (1998) we employ the Black, Jensen and Scholes (1972) methodology and estimate the time series models above. We are interested in assessing the size of the pricing errors (α_i) and testing whether they are jointly zero using the Gibbons, Ross, and Shanken (1989) (GRS) F-test.

Second, we focus on the cross-sectional performance of the models using the Fama and MacBeth (1973) methodology which involves a first step in which time series regressions are used to estimate the $b's$ and $c's$ above and a second step where cross-sectional regressions are estimated by regressing the returns on each portfolio at time t on the estimated $b's$ and $c's$.[11] The cross-sectional regressions allow us to test that the average pricing errors in

[11] When data are available over a long sample period it is usual to undertake a rolling regression approach by using sixty observations up to time t in the first step to obtain the first beta; then this beta is used in the second step to estimate a cross-sectional regression of average returns at time $t + 1$ on the beta estimated until time t. The data are then rolled

the cross-section are jointly zero.[12] We also report the cross-sectional $\overline{R}^2$ which provides another metric to allow us to assess the relative performance of each model.[13] Finally, we plot the realized and expected returns from the asset pricing model. This provides a convenient way to assess the relative performance of the models and should be used in conjunction with the tests of the pricing errors since it will help us to evaluate whether we are accepting a model that prices the tests assets poorly, but does not reject the χ^2-test because the standard errors are large. The opposite is also true: we might reject statistically a good model because it has economically small pricing errors but very small standard errors (see Cochrane (1996) for a discussion of this point).

In Panel A of Table IV, we present the results from the estimation of the Black, Jensen, and Scholes (1972) regressions. Each column of the Table reports the results for a particular specification of the international asset pricing model. The rows of the Table report the average absolute pricing error (alpha) and the GRS statistic that tests whether the alpha's are jointly zero. The first set of results relates to the set of book-to-market and country level market portfolios. The unconditional international CAPM has a large average absolute pricing errors of 0.85% per quarter and we reject the null hypothesis of jointly zero pricing errors at the 8% level. The unconditional Fama and French (1998) two factor model performs somewhat better with an average pricing error of 0.64% per quarter and it is not possible to reject the null hypothesis that the pricing errors are jointly zero. In the next column, we report results from the conditional CAPM where we scale the market return with the measure of the world business cycle, $\frac{k}{y}^w$. It appears to have little effect relative to the unconditional CAPM, the pricing errors are roughly the same and the GRS test rejects the null hypothesis of zero pricing errors at the 7% level. The next column reports the results from the conditional version of the Fama and French model, where both factors are scaled by $\frac{k}{y}^w$ and shows that it performs about as well as the unconditional Fama and French (1998) model. The final two columns report the results that condition, first, the international CAPM and second the Fama and French (1998) two factor model with $\frac{d}{p}^w$. As in the case when conditioning with $\frac{k}{y}^w$, there is little improvement in estimating conditional version of the model when using $\frac{d}{p}^w$.

The remainder of Panel A reports results for the other three characteristic formed portfolios. Only in the case of the earning-to-price portfolios does conditioning with $\frac{k}{y}^w$ improve the performance of the model relative to its unconditional counterpart. When conditioning with $\frac{d}{p}^w$ the conditional Fama and French (1998) model never improves relative to its unconditional counterpart.

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forward one month and the procedure is repeated. This results in a time-series of cross-section estimates of the price of risk. However, this rolling procedure is not appropriate with quarterly time series data over a relatively short sample. Instead, we estimate the beta coefficients over the entire sample and we use them in all of the T cross-sectional regressions. This is the method recommended and employed by Lettau and Ludvigson (2001b) for quarterly data over a relatively short time series sample such as ours, and discussed in Cochrane (2005).

[12] This is a Chi-sq test, $\widehat{\alpha}' cov(\widehat{\alpha})^{-1}\widehat{\alpha}$, where $\widehat{\alpha}$ is the vector of average pricing errors across the twenty one portfolios and cov is the covariance matrix of the pricing errors.

[13] Following Jagannathan and Wang (1996) and Lettau and Ludvigson (2001b), we calculate the $\overline{R}^2$ as $\left[Var_c(\overline{r}_i) - Var_c(\overline{e}_i)\right]/Var_c(\overline{r}_i)$, where Var_c is the cross-sectional variance, $\overline{r}_i$ is the average return and $\overline{e}_i$ is the average residual.

Overall, the results from the time-series analysis of the asset pricing models indicate that conditioning on either $\frac{k}{y}^w$ or $\frac{d}{p}^w$ does little to improve the time series description of the portfolio excess returns. Panel B of Table IV reports the results from the cross-sectional analysis and tells an altogether different story. First, the results for the book-to-market and country portfolios produces a cross-sectional $\overline{R}^2$ of 2% for the unconditional international CAPM, however the χ^2 test cannot reject the null hypothesis that the pricing errors are zero. This either implies that the test lacks power or there is little spread in the average realized returns. To assess which one of these is correct, in Figure 3 we plot the average realized returns and expected returns given by the model. The first figure in the top left hand corner refers to the unconditional international CAPM. It is clear that there is a decent spread in average realized returns, however the CAPM is unable to explain this as is evident from the distance between the points on the graph and the 45° line. Therefore, the power of the test to reject the null hypothesis is very weak and caution should be taken when assessing the performance of asset pricing models using only pricing error tests statistics.

The next column in Panel B of Table IV reports the results for the unconditional Fama and French (1998) two factor model where the $\overline{R}^2$ now increases to 32% and the χ^2 test is somewhat smaller. The better performance of the unconditional Fama and French model (1998) is reflected in Figure 3, top right hand side, where the plots of the average realized and expected returns lie closer to the 45° line.

Our main interest is in the role of the conditioning information and we see that when conditioning the international CAPM on $\frac{k}{y}^w$ that there is a major improvement relative to the unconditional international CAPM with a reported $\overline{R}^2$ of 19%. This is somewhat larger than the $\overline{R}^2$ when the international CAPM is conditioned on $\frac{d}{p}^w$ which produces a $\overline{R}^2$ of only 5%. The largest differences in model performance are obtained when conditioning the Fama and French two factor model with $\frac{k}{y}^w$ where the $\overline{R}^2$ rises to 52%. The corresponding $\overline{R}^2$ for the Fama and French model conditioned on $\frac{d}{p}^w$ is 34%. These differences in the $\overline{R}^2$ across models are reflected in the remaining plots of the average realized and expected returns in Figure 3. When conditioning with $\frac{k}{y}^w$ the plots always lie closer to the 45° line when compared with unconditional models indicating smaller pricing errors. When scaling the Fama and French risk factors with $\frac{d}{p}^w$ there is very little improvement relative to the unconditional Fama and French two factor model.

The next set of results in Panel B of Table IV refers to the cash flow to asset and country portfolios. We see similar results here. In particular, the unconditional CAPM and the conditional CAPM scaled with $\frac{d}{p}^w$ is unable to explain the cross-sectional spread in average realized returns, again evident from the $\overline{R}^2s$ which are zero and the plots of average realized and expected returns depicted in the top left hand corner of Figure 4 (unconditional CAPM) and the bottom left hand corner (conditional CAPM scaling the market return by $\frac{d}{p}^w$). In contrast, scaling the market return by $\frac{k}{y}^w$ increases the $\overline{R}^2$ to 20% and scaling the Fama and French (1998) two risk factors by $\frac{k}{y}^w$ leads to a rise in the $\overline{R}^2$ from 30% to 42%. In the case of the Fama and French (1998) two risk factor model scaled by $\frac{d}{p}^w$ the $\overline{R}^2$ increase to 58%. The plots on the right hand side of Figure 4 show the different versions of the Fama and French (1998) model and indicate a much better performance when scaling the risk factors.

The results for the earnings to price and country portfolios are presented in the next part of Panel B and once again show that conditioning the Fama and French (1998) two factor model on either $\frac{k}{y}^w$ or $\frac{d}{p}^w$ leads to a large increase in the $\overline{R}^2$s to 68% and 69% respectively, compared to 23% for the unconditional Fama and French (1998) model. Figure 5 confirms the improved performance of these conditional versions of the model by showing that these models provide plots of average realized and expected returns that are closer to the 45° line.

The final part of Panel B provides the results for the dividend to price and country portfolios. In this case, the best performing model is the Fama and French (1998) two factor model that conditions on $\frac{k}{y}^w$ where the $\overline{R}^2$ is 75% as opposed to 43% when conditioning this model on $\frac{d}{p}^w$ and 24% for the unconditional Fama and French (1998) two factor model. Note that for these portfolios, we always reject the null hypothesis that the cross sectional pricing errors are jointly zero. However, as Figure 6 shows, the size of the pricing errors are small because the plots of average realized and expected returns fall close to the 45° line, especially when conditioning the Fama and French (1998) two factor model on $\frac{k}{y}^w$.

Overall, from the cross-sectional Fama and MacBeth (1973) regressions there is evidence that the conditional version of the international CAPM provides a better description of the cross-sectional pattern in average returns than the unconditional CAPM. When we estimate a conditional version of the Fama and French (1998) two factor model, there is a further improvement in the cross-sectional description of average returns. Our plots of the average actual and expected returns show that relying on tests that pricing errors are jointly zero can be severely misleading and indicates that they have low power to reject the null hypothesis of zero cross-sectional pricing errors in relatively small samples such as ours. In summary, the empirical tests indicate that there is often a role for conditioning information in standard one and two factor international asset pricing models.

6. Predicting Fixed Income Security Returns

Under the expectations hypothesis, when changes in short-term rates are regressed on the term spread the estimated coefficient should be equal to two (Mankiw and Miron (1986)). In unreported results, we confirm earlier findings that the term spread in each country cannot forecast the change in the short term rates: in every country it is not possible to reject the null hypothesis that the coefficient on the term spread is zero. The point estimates are small and a long way from the expectations theory's predictions that the coefficient should be two.[14] One explanation of this apparent failure of the expectations hypothesis is that there exists a time-varying risk premium which is an important determinant of changes in short term rates. To assess whether this may be a possibility, we consider if the world measure of the business cycle can predict short term rates. We run the following regression:

$$\Delta s_{i,t} = \alpha + \delta \mathbf{Z}_{t-1}^{w} + \xi_{i,t}, \tag{15}$$

where $\Delta s_{i,t}$ is the change in country i's short-term interest rate from time $t-1$ to time t, α is a constant, δ is a vector of coefficient estimates, $\mathbf{Z}_{t-1}^{W}$ is a vector of international

[14] The average estimated coefficient on the term spread across the seven countries is 0.097.

lagged predictor variables which include $\frac{k}{y}^w$, $\frac{d}{p}^w$ and r_f^w and $\xi_{i,t}$ is an error term. The risk free rates of return for the U.S., U.K., France and Canada are three month treasury bill rates. For Italy we use the 3 month interbank rate. Money market rates are used in Japan and Switzerland. Table V reports the results and shows that $\frac{k}{y}^w$ has predictive power for France, Italy, Japan, Switzerland and marginally for the U.K.. The estimated signs are negative across all countries which implies that as international business conditions worsen short term rates in all six countries subsequently fall. The $\overline{R}^2$s range from 0% in the U.S. and Canada to 14% in Japan. The lagged U.S. risk free rate has predictive power for the changes in the short-term rates in all cases except the U.S. and Canada and $\frac{d}{p}^w$ does have predictive power in three countries.

Evidence of a time-varying risk premium in bond markets is also suggested in studies that find bond excess returns are predictable with yield and forward spreads (see, for example, Fama and Bliss (1987), Campbell and Shiller (1991) and Cochrane and Piazzesi (2005)). This evidence only loosely ties time varying risk premia in the bond market to business cycle risk. Ludvigson and Ng (2006) provide a more direct approach by forming a common factor from 132 U.S. macroeconomic variables. They show that this factor has predictive power for U.S. bond excess returns. Theoretically, Brandt and Wang (2003) and Wachter (2006) both show that risk premia in bond markets are driven by macroeconomic fundamentals.

We assess the presence of a time-varying risk premium in the bond market by examining the predictability of excess bond returns. Due to data availability, we can only assess U.S. excess bond return predictability. Following Cochrane and Piazzesi (2005) we use the Fama and Bliss data from CRSP to calculate annual excess bond returns at a quarterly frequency over the sample 1971:2 to 2003:4.[15] We obtain the annual return in a given quarter by borrowing at the one year rate and buying either a two, three, four, or five year bond and then selling it after one year. We estimate the following:

$$b_{n,t} = \alpha + \delta \mathbf{Z}_{t-1}^w + \xi_{n,t}, \tag{16}$$

where $b_{n,t}$ is the bond return at horizon n in excess of the one year bond return, where $n = 2, .., 5$. The results regarding excess bond returns are presented in Table VI using various combinations of predictor variables. In the first instance we use $\frac{k}{y}^w$, $\frac{d}{p}^w$, r_f^w and f, the forward rate predictor variable of Cochrane and Piazzesi (2005). $\frac{k}{y}^w$ predicts excess bond returns for all of the maturities and the coefficient estimates increase monotonically with the time to maturity from 3.085 for the excess return on the two year bond to 7.322 for the five year bond. This indicates that international business cycle risk has a larger economic impact on longer term bonds, consistent with the findings in Cochrane and Piazzesi (2005) and Ludvigson and Ng (2006) that use U.S. based predictor variables. When including all four predictor variables in the predictive regression, the $\overline{R}^2$s range from 23% for the two year bond to 19% for the five year bond.

We also report three more sets of results that predict the bond returns using only $\frac{k}{y}^w$, only the forward rate variable, and only $\frac{d}{p}^w$ and r_f^w. For all of the four bonds, when $\frac{k}{y}^w$ is included on its own it is highly statistically significant and we observe the increase in the estimated coefficient with time to maturity. In these cases, the $\overline{R}^2$s range from a half to a quarter of the $\overline{R}^2$s when all four variable are included. When included on its own, over

[15] We thank John Cochrane for making this data available.

the sample period we study, the Cochrane and Piazzesi (2005) factor is only statistically significant at conventional levels for the two year bond, but is significant at the 10% level for the three and four year bond. While the dividend price ratio has no predictive power for the bond returns, the risk free rate is a strong predictor and the $\overline{R}^2$s are around a half of the $\overline{R}^2$s that employ all four predictor variables. These findings indicate that a measure of the world business cycle predicts U.S. excess bond returns as well as, and has a role in addition to that of financial market based variables and the forward rate that is employed in Cochrane and Piazzesi (2005).

Credit spreads have also been related to macroeconomic fundamentals in Tang and Yan (2006) and Amato and Luisi (2006). These papers present general equilibrium models that illustrate how macroeconomic variables affect credit spreads. However, they do not examine the predictability of credit spreads with macroeconomic variables. Krishnan, Rictchken and Thomson (2010) show that the current credit spread slope predicts future credit spreads, clearly rejecting the expectations hypothesis. Krishnan, Ritchenken and Thomson (2010) find no evidence that U.S. macroeconomic factors help to predict firm level credit spreads using U.S. data.

We consider the predictability of three U.S. credit spreads: AAA minus BAA corporate bonds, long term government bonds minus AAA corporate bonds, and long term government bonds minus BAA corporate bonds. Table VII presents the results from the regression:

$$cs_{k,t} = \alpha + \delta \mathbf{Z}^w_{t-1} + \xi_{k,t}, \tag{17}$$

where $cs_{k,t}$ is the credit spread and $k = AAA - BAA$, $Govt - AAA$, $Govt - BAA$. Due to the strong persistence in the credit spreads we also include the first lag of the spread in the forecasting equation. The coefficients on $\frac{k}{y}^w$ are all positive indicating a slowdown in international economic activity predicts higher spreads. Reassuringly, the coefficient estimate is largest and statistically significant for the $Govt - BAA$ spread, that is, the riskiest spread. The estimate on $\frac{k}{y}^w$ is marginally statistically significant for the $AAA - BAA$ spread. There is a marginal role for the dividend price ratio in predicting spreads, however its sign is not consistent across all spreads.

In summary, there is evidence that $\frac{k}{y}^w$ has predictive power for short term rates, excess bond returns, and the riskiest credit spread. These results are novel and suggest two important implications. First, a measure of the international business cycle plays a role in the determination of interest rate changes, bond returns and credit spreads indicating some level of integration of fixed income markets and equity markets in the sense that their risk premium shares a common international measure of business conditions. Second, affine term structure models are unlikely to be successful descriptions of interest rate movements in the presence of macroeconomic sources of risk premia.

7. Conclusion

In this paper, we start by investigating the predictability of stock returns with a new macroeconomic measure of the world business cycle, namely the world's capital to output ratio, $\frac{k}{y}^w$, along with the world stock market index's dividend price ratio and the world (U.S.) risk free rate. The most striking results regarding stock return predictability are that in all but one country there is evidence of out-of-sample predictability when forecasting with $\frac{k}{y}^w$. This is important since doubt has been cast on the ability of predictor variables to forecast out-of-sample even if they have in-sample forecasting power (Bossaerts and Hillion (1999) and Goyal and Welch (2008)). We find statistical evidence that $\frac{k}{y}^w$ can forecast out-of-sample. This statistical evidence is economically important because certainty equivalent measures show that an investor would have benefited from following a trading strategy of forecasting returns with $\frac{k}{y}^w$ when compared with forecasting strategies based on the historical average, the world dividend-to-price ratio and the world risk free rate. These results indicate that some proportion of the variation in country level equity risk premia is related to international business conditions and therefore points to the possibility that these stock markets are to some extent integrated internationally.

We assess the asset pricing implications of the stock return predictability results by estimating a conditional version of the international CAPM and international Fama and French (1998) two factor model. Our results show that scaling the CAPM risk factor as well as the two Fama and French (1998) world risk factors with conditioning information results in a better description of the cross-sectional pattern in average returns for country level portfolios and portfolios formed on firm characteristics, reinforcing the role of $\frac{k}{y}^w$ in equity market risk premia.

The final part of the paper examines the predictability of short term interest rate changes, bond excess returns and credit spreads which are also shown to be related to $\frac{k}{y}^w$ in several countries. These findings that a common measure of the world business cycle predicts fixed income securities and equity returns suggests that fixed income markets are to some extent integrated across countries and integrated with equity markets.

In summary, under the plausible assumption that investment is irreversible and capital adjustment costs prevent firms from disinvesting, the capital to output ratio moves in a counter-cyclical fashion. In the presence of higher risk aversion and/or risk in recessions, the capital to output ratio tracks variations in expected returns on financial securities. We find empirical evidence in support of this proposition.

References

Amato, J.D. and Luisi, M. (2006) Macro factors in the term structure of credit spreads. BIS Working Paper No. 203.

Amihud, Y. and Hurvich, C.M. (2004) Predictive regressions: a reduced-bias estimation method, *Journal of Financial and Quantitative Analysis* **39**, 813-841.

Ang, A. and Bekaert, G. (2007) Stock return predictability: is it there?, *Review of Financial Studies* **20**, 651-707.

Artis, M.J. and Hoffmann, M. (2008) Financial globalization, international business cycles and consumption risk sharing, *Scandinavian Journal of Economics* **110**, 447-471.

Avramov, D. and Chordia, T. (2006) Predicting stock returns, *Journal of Financial Economics* **82**, 387-415.

Baker, M. and Wurgler, J. (2002) Market timing and capital structure, *Journal of Finance* **57**, 1-32.

Baker, M., Stein J., and Wurgler, J. (2003) When does the market matter? stock prices and the investment of equity-dependent firms, *Quarterly Journal of Economics* **118**, 969-1006.

Bekaert, G., and Harvey, C.R. (1995) Time-varying world market integration, *Journal of Finance* **50**, 403-444.

Bekaert, G., Harvey C.R., and Lundblad, C. (2007) Liquidity and expected returns: lessons from emerging markets, *Review of Financial Studies* **20**, 1783-1831.

Bekaert, G., Hodrick R., and Zhang, X. (2009) International stock return comovements, *Journal of Finance* **64**, 2591-2626.

Bekaert, G., Harvey, C.R., Lundblad C., and Siegel, S. (2011) What segments equity markets?, *Review of Financial Studies*, forthcoming.

Black, F., Jensen, M., and Scholes, M. (1972) The capital asset pricing model: some empirical tests," in Michael C.J. (ed), Studies in the Theory of Capital Markets, Praeger, New York pp. 79-121.

Boldrin, M., Christiano, L.T., and Fisher, J.D.M. (2001) Habit persistence, asset returns, and the business cycle, *American Economic Review* **91**, 149-166.

Bossaerts, P. and Hillion, P. (1999) Implementing statistical criteria to select return forecasting models: what do we learn? *Review of Financial Studies* **12**, 405-428.

Brandt, M.W. and Wang, K.Q. (2003) Time-varying risk aversion and unexpected inflation, *Journal of Monetary Economics* **50**, 1457-1498.

Caballero, R.J., Engel, E.M.R.A., and Haltiwanger, J.C. (1995) Plant-level adjustment and aggregate investment dynamics, *Brookings Papers on Economic Activity* **2**, 1-54.

Campbell, J.Y. and Cochrane, J.H. (1999) By force of habit: a consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* **107**, 205-251.

Campbell, J.Y. and Shiller, R. (1991) Yield spreads and interest rate movements; a bird's eye view, *Review of Economic Studies* **58**, 495-514.

Campbell, J.Y. and Yogo, M. (2006) Efficient tests of stock return predictability, *Journal of Financial Economics* **81,** 27-60.

Campbell, J.Y. and Thompson, S.B. (2008) Predicting excess stock returns out of sample: can anything beat the historical average?, *Review of Financial Studies* **21**, 1509-1531.

Chan, Y. and Kogan, L. (2002) Catching up with the Joneses: heterogeneous preferences and the dynamics of asset prices, *Journal of Political Economy* **110**, 1255-1285.
Clark, T.E. and McCracken, M.W. (2001) Tests of forecast accuracy and encompassing for nested models, *Journal of Econometrics* **105**, 85-110.
Cochrane, J.H., (1991) Production-based asset pricing and the link between stock returns and economic fluctuations, *Journal of Finance* **46**, 209-237.
Cochrane, J.H., (2005) Asset Pricing, Princeton University Press.
Cochrane, J.H., (1996) A cross-sectional test of an investment-based asset pricing model, *Journal of Political Economy* **104**, 572-621.
Cochrane, J.H., and Piazzesi, M. (2005) Bond risk premia, *American Economic Review* **95**, 138-160.
Constantinides, G.M., and Duffie, D. (1996) Asset pricing with heterogeneous consumers, *Journal of Political Economy* **104**, 219-240.
Cooper, I. and Priestley, R. (2009) Time-varying risk premia and the output gap, *Review of Financial Studies* **22**, 2801-2833.
Coleman, W.J. (1997) Behavior of interest rates in a general equilibrium multisector model with irreversible investment, *Macroeconomic Dynamics* **1**, 206-227.
Dixit, A. and Pindyck, R. (1994) Investment under uncertainty, Princeton University Press, Princeton, NJ.
Dumas, B. and Solnik, B. (1995) The world price of foreign exchange risk, *Journal of Finance* **50**, 445-480.
Elliot, G. and Stock, J.H. (1994) Inference in time series regressions when the order of integration of a regressor is unknown, *Econometric Theory* **10**, 672-700.
Elliot, G., Rotherberg, T.J., and Stock, J.H. (1996) Efficient tests for an autoregressive unit root, *Econometrica* **64**, 813-736.
Erb, C.B., Harvey, C.R., and Viskanta, T.E. (1995) Country risk and global equity selection, *Journal of Portfolio Management* **21**74-83.
Erb, C.B., Harvey, C.R., and Viskanta, T.E. (1996) Expected returns and volatility in 135 countries, *Journal of Portfolio Management* **22** 46-58.
Fama, E. and Bliss, R.B. (1987) The information in long-maturity forward rates, *American Economic Review* **77**, 680-692.
Fama, E. and French, K. (1998) Value versus growth: the international evidence, *Journal of Finance* **53**, 1975-2000.
Fama, E. and MacBeth, J.D. (1973) Risk return and equilibrium: empirical tests, *Journal of Political Economy* **71**, 607–636.
Ferreira, M.A. and Santa-Clara, P. (2011) Forecasting stock market returns: the sum of the parts is more than the whole, *Journal of Financial Economics* **100**, 514-537.
Gibbons, M., Ross, S., and Shanken, J. (1989) A test of the fffiiciency of a given portfolio, *Econometrica* **57**, 1121-1152.
Goolsbee, A. (1998) Investment tax incentives, prices and the supply of sapital goods, *Quarterly Journal of Economics* **113**, 121-148.
Goyal, A. and Welch, I. (2003) Predicting the equity premium with dividend ratios, *Management Science* **49**, 639–54.
Goyal, A. and Welch, I. (2008) A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* **21**, 1455-1508.
Harvey, C.R. (1991) The world price of covariance risk, *Journal of Finance* **47**, 111-157.
Harvey, C.R. (1995) Predictable risk and return in emerging markets, *Review of Financial Studies* **8**, 773-816.

Harvey, C.R. (2000) The drivers of expected returns in international markets, *Emerging Markets Quarterly* **1**, 32-49.
Harvey, D., Leybourne, S., and Newbold, P. (1998) Tests for forecast encompassing, *Journal of Business and Economic Statistics* **16**, 254-259.
Hou, K,G., Karolyi A., and Kho, B.C. (2011) What factors drive global stock returns?, *Review of Financial Studies* **24**, 2527-2574.
Imbs, J. (2006) The real effects of financial integration, *Journal of International Economics* **68**, 296-324.
Karolyi, A.G. and Stulz, R.M. (2003) Are assets priced locally or globally? in George Constantinides, Milton Harris, and Rene M. Stulz (eds), Handbook of the Economics of Finance, North Holland.
Kogan, L. (2004) Asset prices and real investment, *Journal of Financial Economics* **73**, 411-431.
Krishnan, C.N.V., Ritchken, P.H., and Thomson, J.B. (2010) Predicting credit spreads, *Journal of Financial Intermediation* **19**, 529-563.
Kydland, E.F. and Prescott, E.C. (1982) Time to build and aggregate fluctuations, *Econometrica* **50**, 1345-1370.
Lamont, O. (2000) Investment plans and stock returns, *Journal of Finance* ***55,*** 2719-2755.
Lee, K.H. (2011) The world price of liquidity risk, *Journal of Financial Economics* **99**, 136-161.
Lettau, M. and Ludvigson, S.C. (2001a) Consumption, aggregate wealth, and expected stock returns, *Journal of Finance* **56**, 815-849.
Lettau, M. and Ludvigson, S.C. (2001b) Resurrecting the (C)CAPM: a cross-sectional test when risk premia are time-varying, *Journal of Political Economy* **109**, 1238–1287.
Lewellen, J. (2004) Predicting returns with financial ratios, *Journal of Financial Economics* **74**, 209-235.
Ludvigson, S.C. and Ng, S. (2009) Macro factors in bond risk premia, *Review of Financial Studies* **22**, 5027-5067.
Lumsdaine, R. and Prasad, E. (2003) Identifying the common component of international economic fluctuations: a new approach, *Economic Journal* **113**, 101-127.
Lustig, H.N. and Van Nieuwerburgh, S.G. (2005) Housing collateral, consumption insurance, and risk premia: an empirical perspective, *Journal of Finance* **60**, 1167-1219.
Mankiw N.G. and Miron, J.A. (1986) The changing behavior of the term structure of interest rates, *Quarterly Journal of Economics* **101**, 211-228.
Mankiw N.G. and Shapiro, M.D. (1986) Do we reject too often? small sample properties of tests of rational expectations models, *Economics Letters* **20**, 139-145.
McCracken, M.W. (2007) Asymptotics for out-of-sample tests of Granger causality. *Journal of Econometrics* **140**, 719–52.
Piazzesi, M., Schneider M., and Tuzel, S. (2006) Housing, consumption, and asset pricing, *Journal of Financial Economics* **83**, 531-569.
Polk, C. and Sapienza, P. (2009) The stock market and corporate investment: a test of catering theory, *Review of Financial Studies* **22**, 187-217.
Rangvid, J. (2006) Output and expected returns, *Journal of Financial Economics* **81**, 595-624.
Rapach, S. and Zhou, G. (2010) Out-of-sample equity premium prediction: combination forecasts and links to the real economy, *Review of Financial Studies* **23**, 821-862.

Richardson M. and Stock, J. (1989) Drawing inferences from statistics based on multi-year asset returns, *Journal of Financial Economics* **25** 323-348.

Sanots, T. and Veronesi, P. (2006) Labor income and predictable stock returns, *Review of Financial Studies* **19**, 1-44.

Stambaugh, R.F. (1999) Predictive regressions, *Journal of Financial Economics* **54**, 375-421.

Tang, D.Y. and Yan, H. (2006) Macroeconomic conditions, firm characteristics, and credit spreads, *Journal of Financial Services Research* **29**, 177-210.

Torous, W., Valkanov, R., and Yan, S. (2005) On predicting stock returns with nearly integrated variables, *Journal of Business* **77**, 937-966.

Valkanov, R. (2003) Long-horizon regressions: theoretical results and applications, *Journal of Financial Economics* **68**, 201-232.

Wachter, J.A. (2006) A consumption based model of the term structure of interest rates, *Journal of Financial Economics* **79**, 365-399.

8. Appendix: A Monte Carlo Experiment

It is well known that the reliance on asymptotic distribution theory in interpreting statistical significance of predictor variables can be misleading, especially when the regressor used to do the predicting is persistent and its errors from an autoregressive regression are highly correlated with the variable being predicted (see, for example, Mankiw and Shapiro (1986) and Stambaugh (1999)). Torous, Valkanov, and Yan (2001), Valkanov (2003), Lewellen (2004), and Campbell and Yogo (2007) all note that the problems are severe when the predictor variables are financial variables that are scaled by price. This is because the innovation in the autoregressive model of the predictor regression will be highly correlated with returns by construction. Of course, this should be less of a problem for $\frac{k}{y}$.[16]

Work on local-to-unit root processes have been used to provide a more accurate approximation to the actual finite distribution of t-statistics (see Elliot and Stock (1994)). Using this framework Torous, Valkanov and Yan (2001) Lewellen (2004), Valkanov (2003) and Campbell and Yogo (2007) provide inference techniques that correct for this problem in a univariate setting. When examining a multivariate setting Ang and Bekaert (2007) use a Monte Carlo experiment under the null of no predictability to assess the power of t-statistics. They show substantial size distortions with the Newey-West t-statistics when forecasting stock returns at long horizons using the dividend yield and the risk free rate, both highly persistent regressors. They show that the empirical size of the Newey-West t-statistic is somewhat larger than a nominal 5% value and hence there is an obvious tendency to over reject the null of no predictability.

Although we have reported the Amihud and Hurvich (2004) bias corrected estimates and t-statistics, we want to further ensure that the predictability uncovered in this paper is not spurious in the sense that Newey-West t-statistics indicate statistical significance when it is not there. To this end, we perform a Monte Carlo experiment to investigate whether inferences on the statistical significance of the parameter estimates are affected by size distortions when using Newey-West t-statistics. The data for the Monte Carlo experiment are generated under the null hypothesis of no predictability:

$$r_t = \gamma_0 + \upsilon_t. \tag{A1}$$

We use the variance-covariance matrix of returns and the predictor variables to generate the data. Finally, to complete the data generation process, we need to specify a data generating equation for the predictor variables $\frac{k}{y}^w$, $\frac{d}{p}^w$ and r_f^w. We start by specifying a first order VAR:

$$\mathbf{z}_t = \gamma + \rho \mathbf{z}_{t-1} + \eta_t, \tag{A2}$$

where υ and η are draws from a normal distribution and $\mathbf{z}$ is a vector including $\frac{k}{y}^w$, $\frac{d}{p}^w$ and r_f^w. From this specification we set to zero any coefficients that are not statistically significant and then run the Monte Carlo experiment.

[16] With regard to this issue we calculated the Campbell and Yogo (2005) pre-test regarding the applicability of asymptotic $t-$statistics in predictability regressions. We found that $\frac{k}{y}$ passed this test and hence the $t-$statistics should be fine asymptotically. In fact, the only predictor variable to fail the Campbell and Yogo (2005) test is the dividend price ratio. These results are available on request.

We generate 100,000 samples with $100+T$ observations, where T is the sample size (156 in our case) for the relevant regression. The first 100 observations are discarded and, subsequently, we estimate equation (2) 100,000 times with the remaining T observations. This gives us the distribution of the t-statistics testing the null hypothesis that $\delta = 0$ in (2). We compare the empirical size generated from the Monte Carlo experiment against a 5% nominal size in order to assess whether there are any size distortions with the Newey-West t-statistics using the real returns on the world stock market index.[17] The empirical size is the percentage of times the relevant null hypothesis is rejected at the 5% level of significance. If the empirical size of the t-statistic is greater than 5%, the Newey-West t-statistics have a tendency to over-reject the null hypotheses finding predictability when it is not there.

Table III reports the results of the Monte Carlo experiment for the Newey-West t-statistics. We report the empirical size of the tests and the t-statistics that reject at the 5% level. Looking at the size properties for all three predictor variables, we find the Newey-West t-statistics testing the null that $\frac{k}{y}^w$, $\frac{d}{p}^w$ and r_f^w cannot predict returns have good size properties for the 1-quarter ahead forecasting regressions (all three have a value of around 5.5% as opposed to the nominal 5% value). To assess how important the size distortions are in terms of assessing if there really is any predictability in the data, the next row of the Table reports the Monte Carlo-generated critical values for the t-statistic testing $\delta = 0$. The usual asymptotic critical values for a two-sided t-statistic are ± 1.96 at all horizons. The empirical critical values for the t-statistics at the one quarter horizon are very close to their asymptotic counterparts. Taken together the results show that for a one quarter horizon inference in predictive regressions using Newey-West t-statistics are generally fine when making statistical inference. That is, the results in Table III do not alter our conclusions about predictability with $\frac{k}{y}^w$ reached on the basis of the findings in Tables 1.

Table A1 Newey-West Size Properties, t-statistics and $\overline{R}^2$ with Simulated Unpredictable Returns

This table reports the results of a Monte Carlo experiment to investigate the empirical size of the Newey-West t-statistics for a nominal size of 5% for the predictive regression that regresses the real return on the world stock market index on the three international predictor variables, $\frac{k}{y}^w$, $\frac{d}{p}^w$ and r_f^w, and the Monte Carlo-generated critical values for the Newey-West t-statistics. The data are generated under the null hypothesis of no predictability. The parameters in the data generation process are their empirical counterparts. We use the moments of the real returns on the MSCI world stock market index to simulate the unpredictable returns. The row "Size" reports the percentage of times H_0:$\gamma =$ 0 is rejected against a nominal significance level of 5%. The row "t-statistic" reports the Monte Carlo-generated 5% t-statistics testing H_0: $\gamma = 0$ against H_1:$\gamma \neq 0$.

Size Properties		t-statistics	
$\frac{k}{y}^w$	5.570	$\frac{k}{y}^w$	2.033
$\frac{d}{p}^w$	5.530	$\frac{d}{p}^w$	1.995
r_f^w	5.491	r_f^w	2.044

[17] Unreported results, which are very similar to the ones we report for the world stock index, are found for the individual countries' real returns. These results are available on request.

Table I. Predicting Real Stock Returns with International Predictor Variables

This table reports results from predicting real stock returns using international predictor variables. Stock returns are calculated from the MSCI country indices. $\frac{k}{y}^w$ is the measure of the world business cycle defined as the ratio of capital stock to output. $\frac{k}{y}^w$. $\frac{d}{p}^w$ is the dividend price ratio on the world stock market index (MSCI), r_f^w is the world risk free rate of return proxied by the U.S. risk free rate. $\overline{R}^2$ is the adjusted R^2. t-statistics are in parentheses and are calculated from Newey-West standard errors adjusted for the serial correlation induced by the use of overlapping observations with a lag length that is two times k-1 where k is the horizon of the return observations. "$\overline{R}^2$ no $\frac{d}{p}^w$ or rf" is the $\overline{R}^2$ calculated from a regression of real returns on $\frac{k}{y}^w$ only. The second row for each country reports the bias-corrected estimates and t-statistics using the approach of Amihud and Hurvich, (2004). CD is Canada, FR is France, IT is Italy, JP is Japan, SZ is Switzerland and WD is the world portfolio. The data are sampled from 1971Q1 to 2010Q4.

	$\frac{k}{y}^w$	$\frac{d}{p}^w$	r_f^w	$\overline{R}^2$	$\overline{R}^2$ no $\frac{d}{p}^w$ or rf
CD	7.118	0.012	−2.691	0.02	0.00
	(1.52)	(1.11)	(1.73)		
CD_C	4.970	0.008	−2.458		
	(1.09)	(0.88)	(1.83)		
FR	7.735	0.012	−2.162	0.00	0.00
	(1.30)	(1.03)	(1.09)		
FR_C	3.357	0.010	−1.358		
	(0.57)	(0.88)	(0.79)		
IT	6.273	0.002	−0.598	-0.01	0.00
	(1.05)	(0.17)	(0.28)		
IT_C	3.544	−0.001	−0.003		
	(0.53)	(0.09)	(0.12)		
JP	7.706	0.027	−3.403	0.03	0.00
	(1.53)	(2.43)	(2.14)		
JP_C	6.000	0.022	−3.030		
	(1.53)	(2.01)	(1.86)		
SZ	9.699	0.013	−2.855	0.03	0.01
	(2.40)	(1.35)	(1.92)		
SZ_C	7.305	0.011	−2.875		
	(1.57)	(1.22)	(2.12)		
U.K.	11.273	0.024	−2.707	0.03	0.01
	(2.22)	(1.72)	(1.62)		
U.K._C	9.878	0.018	−2.307		
	(1.82)	(1.66)	(1.45)		
U.S.	10.675	0.008	−1.143	0.03	0.03
	(3.10)	(1.02)	(0.98)		
U.S._C	9.072	0.004	−0.878		
	(2.40)	(0.56)	(0.79)		
WD	10.037	0.014	−2.026	0.04	0.03
	(2.89)	(1.66)	(1.57)		
WD_C	8.198	0.009	−1.741		
	(2.20)	(1.28)	(1.57)		

Table II. Predicting Real Stock Returns with Country Specific Predictor Variables

This table reports results from predicting real stock returns using country specific predictor variables. Stock returns are calculated from the MSCI country indices. $\frac{k}{y}^i$ is the measure of country $i's$ business cycle defined as the ratio of capital stock to output in each given country. $\frac{d}{p}^i$ is the dividend price ratio on country $i's$ stock market index (MSCI), r_f^i is the risk free rate of return in country i. $\overline{R}^2$ is the adjusted R^2. t-statistics are in parentheses and are calculated from Newey-West standard errors adjusted for the serial correlation induced by the use of overlapping observations with a lag length that is two times k-1 where k is the horizon of the return observations. "$\overline{R}^2$ no $\frac{d}{p}$ or rf" is the $\overline{R}^2$ calculated from a regression of real returns on $\frac{k}{y}^i$ only. CD is Canada, FR is France, IT is Italy, JP is Japan, SZ is Switzerland and WD is the world portfolio. The data are sampled from 1971Q1 to 2010Q4.

	$\frac{k}{y}^i$	$\frac{d}{p}^i$	r_f^i	$\overline{R}^2$	$\overline{R}^2$ no $\frac{d}{p}$ or rf
CD	0.735 (0.27)	0.013 (1.17)	−4.778 (1.50)	0.00	0.00
FR	8.351 (2.16)	0.009 (1.25)	−7.205 (1.82)	0.03	0.02
IT	17.513 (2.43)	−0.001 (0.10)	−2.178 (0.95)	0.03	0.03
JP	4.567 (1.73)	0.029 (1.92)	−1.342 (0.45)	0.02	0.00
SZ	3.584 (1.41)	0.017 (1.04)	−1.994 (1.30)	0.01	0.00
U.K.	−5.644 (0.57)	0.028 (0.95)	−1.895 (0.78)	0.03	0.03
U.S.	−1.365 (0.38)	0.061 (2.04)	−2.314 (1.69)	0.00	0.01

Table III. Out-of-Sample Tests
This table reports the results of out-of-sample forecast comparisons. The comparisons are of forecasts of real returns based on a constant (the restricted model) and forecasts based on a constant and a predictor variable (the unrestricted model). We report comparisons based on forecasting one quarter ahead. The row labelled "ENC-NEW" provides the Clark and McCracken (2001) encompassing test statistic. The row labelled "MSE-F" gives the F-test of McCracken (2004) that tests the null hypothesis of equal MSEs against the alternative that the MSE from the unrestricted model is smaller. The row labeled R^2_{oos} is the out-of-sample R^2. The row headed "CE" reports the certainty equivalent an investor would have obtained from using the predictability results or from using the historical mean excess returns when forming portfolio weights. CD is Canada, FR is France, IT is Italy, JP is Japan, SZ is Switzerland and WD is the world portfolio. Asterisks denote the tests rejects the null hypothesis at the 5% level.

		1990:1-2010:4				2000:1-2010:4			
	Test	$\frac{k}{y}^w$	$\frac{d}{p}^w$	r_f^w	Constant	$\frac{k}{y}^w$	$\frac{d}{p}^w$	r_f^w	Constant
CD	MSE-F	-0.408	-0.937	0.233		-0.039	-0.382	0.171	
	ENC_NEW	-0.081	-0.020	0.404		0.011	-0.159	0.281	
	R^2_{OOS}	<0.0	<0.0	0.3		<0.0	<0.0		
	CE (%)	1.118	0.909	0.881	1.248	0.964	0.876	0.399	1.124
FR	MSE-F	0.608	-0.980	-3.476		0.725	-0.351	-2.159	
	ENC-NEW	0.621	-0.387	-1.012		0.452	-0.164	-0.844	
	R^2_{OOS}	0.7	<0.0	<0.0		1.6	<0.0	<0.0	
	CE(%)	0.944	0.663	0.339	0.842	0.050	-0.321	-1.485	-0.161
IT	MSE-F	-1.400	-1.250	-1.238		-0.106	-0.653	-0.938	
	ENC-NEW	-0.621	-0.543	-0.576		-0.033	-0.304	-0.439	
	R^2_{OOS}	<0.0	<0.0	<0.0		<0.0	<0.0	<0.0	
	CE(%)	1.311	0.523	0.202	0.647	0.482	-0.312	-1.840	-0.448
JP	MSE-F	3.702*	-0.312	-5.385		4.679*	2.425*	-3.114	
	ENC-NEW	3.089*	0.182	-1.875		3.453*	1.498*	-1.245	
	R^2_{OOS}	4.5	<0.0	<0.0		9.6	5.3	<0.0	
	CE(%)	0.097	-1.375	-1.886	-0.763	0.423	0.223	-1.305	-0.330
SZ	MSE-F	4.513*	-0.997	-2.947		2.175*	-0.385	-3.418	
	ENC-NEW	5.138*	-0.436	-0.168		2.578*	-0.138	-1.004	
	R^2_{OOS}	5.1	<0.0	<0.0		4.6	<0.0	<0.0	
	CE(%)	2.353	1.212	1.266	1.470	0.793	0.110	-1.131	0.376
U.K.	MSE-F	2.419*	0.760**	-2.529		3.481*	1.696*	-1.372	
	ENC-NEW	3.316*	1.240**	-1.035		2.656*	1.077*	-0.641	
	R^2_{OOS}	3.3	0.8	<0.0		7.3	3.7	<0.0	
	CE(%)	1.085	0.744	0.709	0.890	0.468	0.326	-0.471	-0.021
U.S.	MSE-F	2.662*	-1.132	-1.077		2.777*	-0.342	-1.276	
	ENC-NEW	1.952*	-0.407	-0.480		1.675*	-0.150	-0.610	
	R^2_{OOS}	3.0	<0.0	<0.0		5.9	<0.0	<0.0	
	CE(%)	1.004	0.340	0.452	0.739	-0.119	-1.283	-1.746	-0.941
WD	MSE-F	3.045*	-0.221	-1.671		2.524*	0.322	-1.549	
	ENC-NEW	2.537*	0.002	-0.591		1.715*	0.202	-0.691	
	R^2_{OOS}	3.5	<0.0	<0.0		5.4	0.7	<0.0	
	CE (%)	1.235	0.435	0.136	0.579	0.127	-0.646	-2.143	-0.856

Table IV. Asset Pricing Tests

This table reports results from time series regressions (Panel A) of excess returns from four sets of portfolios based on four different characteristics, namely the book-to-market ratio, cash flows, earnings to price ratio and dividend to price ratio. Each set contains a high and low value of the characteristic from each of the seven countries (CD, FR, IT, JP, SZ, U.K. and U.S.) as well as the seven country portfolios for a total of 21 portfolios. a.a.p.e is the average absolute pricing error. GRS tests whether the intercepts are jointly zero. Panel B reports Fama MacBeth quarter-by-quarter cross-sectional regression results for each of the four sets of test assets, using the full sample to estimate the first step. $\overline{R}^2$ is the cross-section adjusted r-squared. χ^2 is a test that the cross-sectional pricing errors are jointly zero. The sample period is 1975:1 to 2007:4 except Canada where the sample period is 1977:1 to 2007:4. Probability values are in parentheses.

Panel A: Black-Jensen-Scholes

	CAPM	FF	CAPM$\frac{k}{y}^w$	FF$\frac{k}{y}^w$	CAPM$\frac{d}{p}^w$	FF$\frac{d}{p}^w$
Book-to-Market and Country Portfolios						
aape	0.849	0.638	0.835	0.641	0.831	0.680
GRS	1.553	1.148	1.576	1.148	1.542	1.138
	(0.08)	(0.32)	(0.07)	(0.24)	(0.08)	(0.23)
Cash Flow and Country Portfolios						
aape	0.869	0.616	0.852	0.630	0.841	0.647
GRS	1.277	0.986	1.279	1.056	1.261	0.983
	(0.21)	(0.48)	(0.21)	(0.41)	(0.22)	(0.49)
Earnings to Price and Country Portfolios						
aape	0.931	0.669	0.926	0.608	0.904	0.695
GRS	1.484	1.034	1.500	1.200	1.464	1.244
	(0.10)	(0.43)	(0.09)	(0.27)	(0.11)	(0.24)
Dividend to Price and Country Portfolios						
aape	0.895	0.587	0.885	0.599	0.870	0.613
GRS	1.606	1.268	1.604	1.343	1.586	1.300
	(0.06)	(0.22)	(0.06)	(0.17)	(0.07)	(0.17)

Panel B: Fama and MacBeth

	CAPM	FF	$\text{CAPM}\frac{k}{y}^w$	$\text{FF}\frac{k}{y}^w$	$\text{CAPM}\frac{d}{p}^w$	$\text{FF}\frac{d}{p}^w$
Book-to-Market and Country Portfolios						
$\overline{R}^2$	0.017	0.323	0.190	0.520	0.058	0.343
χ^2	26.940	20.332	27.296	18.467	26.267	15.757
	(0.14)	(0.44)	(0.13)	(0.36)	(0.09)	(0.54)
Cash Flow and Country Portfolios						
$\overline{R}^2$	0.000	0.296	0.199	0.418	0.000	0.575
χ^2	26.694	20.007	24.942	22.067	25.942	21.321
	(0.16)	(0.39)	(0.16)	(0.18)	(0.13)	(0.21)
Earnings to Price and Country Portfolios						
$\overline{R}^2$	0.000	0.231	0.010	0.680	0.000	0.687
χ^2	29.694	30.221	29.967	18.441	29.219	14.387
	(0.07)	(0.05)	(0.07)	(0.26)	(0.08)	(0.64)
Dividend to Price and Country Portfolios						
$\overline{R}^2$	0.000	0.237	0.085	0.746	0.000	0.434
χ^2	32.271	30.271	31.799	28.916	31.289	29.297
	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.03)

Table V. Predicting Changes in the Short Rate

This table reports results from predicting changes in quarterly risk free rates using international predictor variables. $\frac{k}{y}^{w}$ is the measure of the world business cycle defined as the ratio of capital stock to output. $\frac{d}{p}^{w}$ is the dividend price ratio on the world stock market index (MSCI), r_f^w is the world risk free rate of return proxied by the U.S. risk free rate. $\overline{R}^2$ is the adjusted R^2. t-statistics are in parentheses and are calculated from Newey-West standard errors. The data are sampled from 1971Q1 to 2010Q4.

	$\frac{k}{y}^{w}$	$\frac{d}{p}^{w}$	r_f^w	$\overline{R}^2$
CD	−0.591	−0.001	0.125	0.00
	(1.47)	(1.16)	(0.84)	
FR	−1.062	−0.002	0.379	0.08
	(3.07)	(2.72)	(2.90)	
IT	−1.267	−0.001	0.393	0.05
	(2.53)	(1.21)	(2.73)	
JP	−1.425	−0.001	0.300	0.14
	(4.31)	(2.70)	(2.77)	
SZ	−1.101	−0.003	0.385	0.06
	(2.24)	(2.74)	(2.71)	
U.K.	−0.676	−0.001	0.259	0.02
	(1.71)	(1.46)	(1.95)	
U.S.	−0.117	0.0000	−0.095	0.00
	(0.31)	(0.08)	(0.86)	

Table VI. Predicting Bond Excess Returns

This table reports results from predicting quarterly bond excess returns using international predictor variables. $\frac{k}{y}^{w}$ is the measure of the world business cycle defined as the ratio of capital stock to output. $\frac{d}{p}^{w}$ is the dividend price ratio on the world stock market index (MSCI), r_f^w is the world risk free rate of return proxied by the U.S. risk free rate, f is the forward rate predictor variable of Cochrane and Piazzesi (2005). $\overline{R}^2$ is the adjusted R^2. t-statistics are in parentheses and are calculated from Newey-West standard errors. The data are sampled from 1971Q2 to 2003Q4.

	$\frac{k}{y}^{w}$	$\frac{d}{p}^{w}$	r_f^w	f	$\overline{R}^2$
U.S. 2 Year	3.085 (2.56)	0.002 (1.12)	−1.149 (3.89)	0.176 (2.03)	0.23
U.S. 2 Year	4.228 (4.61)				0.11
U.S. 2 Year				0.228 (2.60)	0.07
U.S.. 2 Year		0.001 (0.70)	−1.021 (3.66)		0.09
U.S. 3 Year	4.700 (2.03)	0.002 (0.71)	−2.289 (4.22)	0.258 (1.65)	0.21
U.S. 3 Year	6.585 (3.82)				0.07
U.S. 3 Year				0.313 (1.89)	0.04
U.S. 3 Year		0.001 (0.36)	−2.096 (4.10)		0.12
U.S. 4 Year	6.516 (2.02)	0.003 (0.74)	−3.174 (4.27)	0.308 (1.47)	0.20
U.S. 4 Year	8.799 (3.69)				0.07
U.S. 4 Year				0.386 (1.68)	0.03
U.S. 4 Year		0.002 (0.38)	−2.920 (4.11)		0.12
U.S. 5 Year	7.322 (1.83)	0.004 (0.64)	−3.950 (4.14)	0.334 (1.30)	0.19
U.S. 5 Year	9.920 (3.36)				0.05
U.S. 5 Year				0.406 (1.41)	0.02
U.S. 5 Year		0.002 (0.31)	−3.668 (4.03)		0.13

Table VII. Predicting Credit Spreads

This table reports results from predicting quarterly credit spreads using international predictor variables. $\frac{k}{y}^w$ is the measure of the world business cycle defined as the ratio of capital stock to output. $\frac{d}{p}^w$ is the dividend price ratio on the world stock market index (MSCI), r_f^w is the world risk free rate of return proxied by the U.S. risk free rate. Spread is the one-quarter lagged spread. $\overline{R}^2$ is the adjusted R^2. t-statistics are in parentheses and are calculated from Newey-West standard errors. The data are sampled from 1971Q1 to 2010Q4.

	$\frac{k}{y}^w$	$\frac{d}{p}^w$	r_f^w	Spread	$\overline{R}^2$
Govt - BAA	45.593	0.035	−9.934	0.878	0.69
	(2.07)	(1.02)	(1.65)	(12.58)	
Govt - AAA	17.860	0.044	−2.341	0.859	0.77
	(1.44)	(1.86)	(0.62)	(12.90)	
AAA - BAA	22.736	−0.042	−5.588	0.769	0.74
	(1.65)	(1.90)	(1.27)	(11.59)	

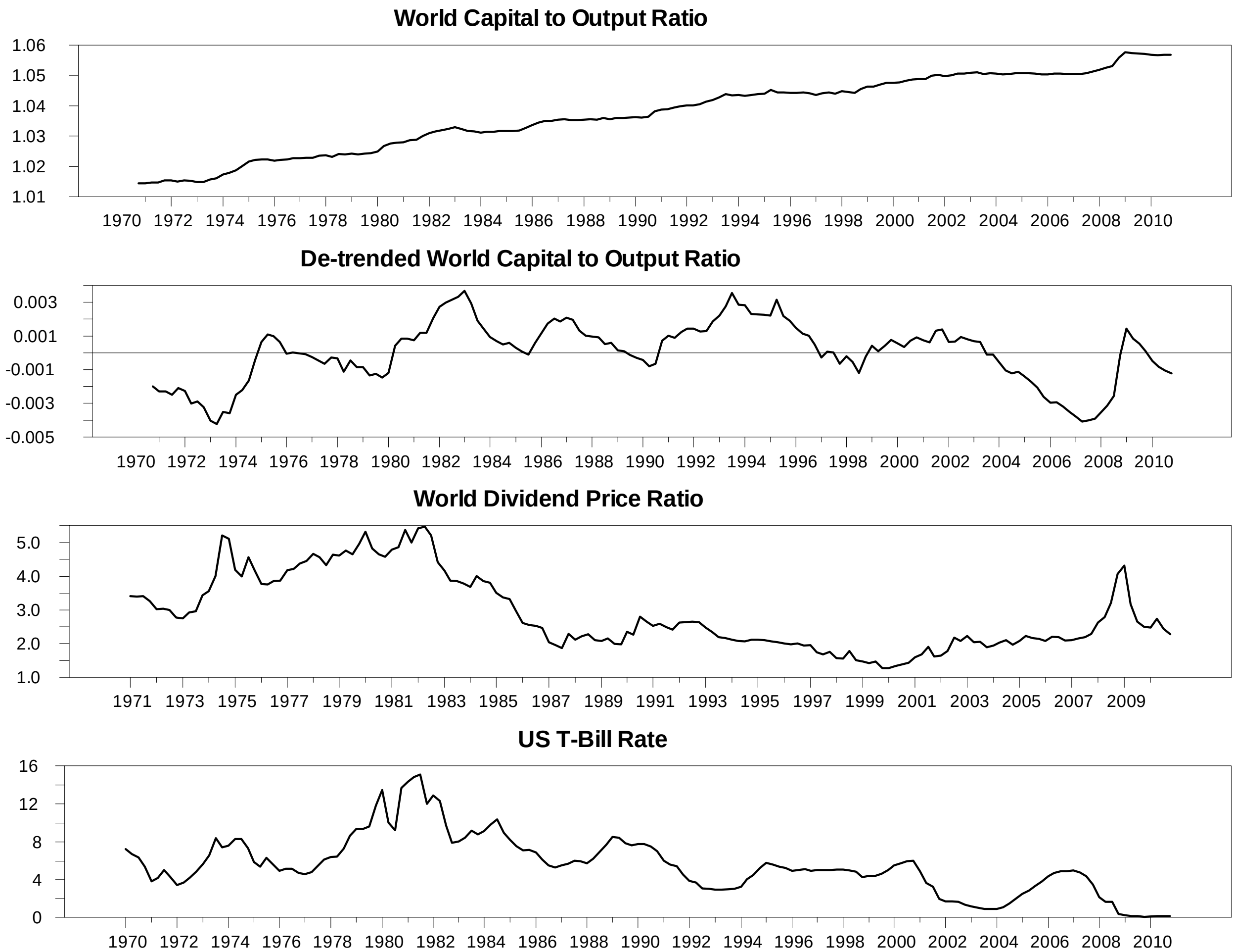

Fig. 1. Predictor Variables**:** This figure plots the unadjusted world capital to output ratio, the detrended capital to output ratio, the world dividend price ratio andthe world (U.S.) risk free rate.

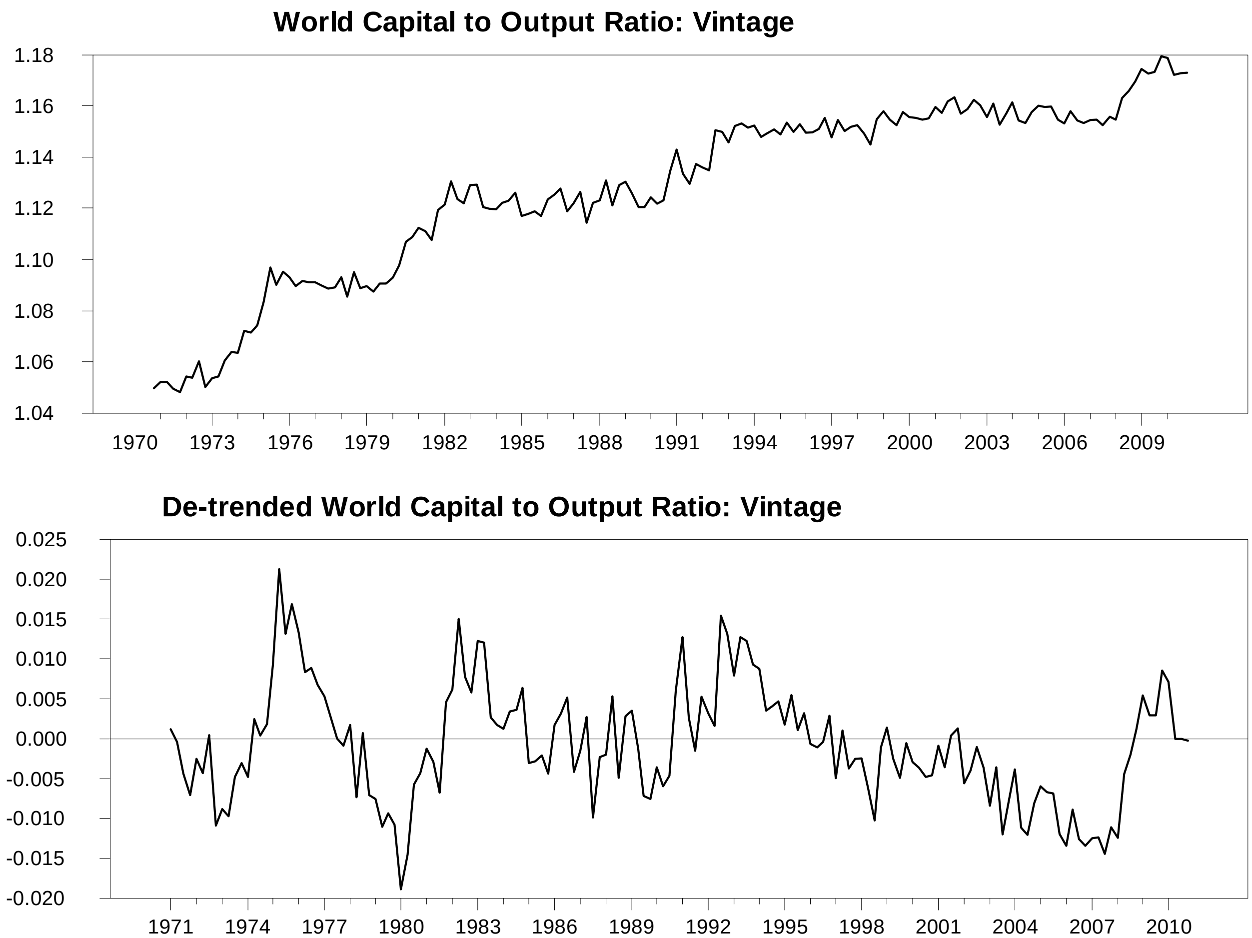

Fig. 2. Vintage Data**.** This figure plots the unadjusted and detrended world capital to output ratio based on vintage data.

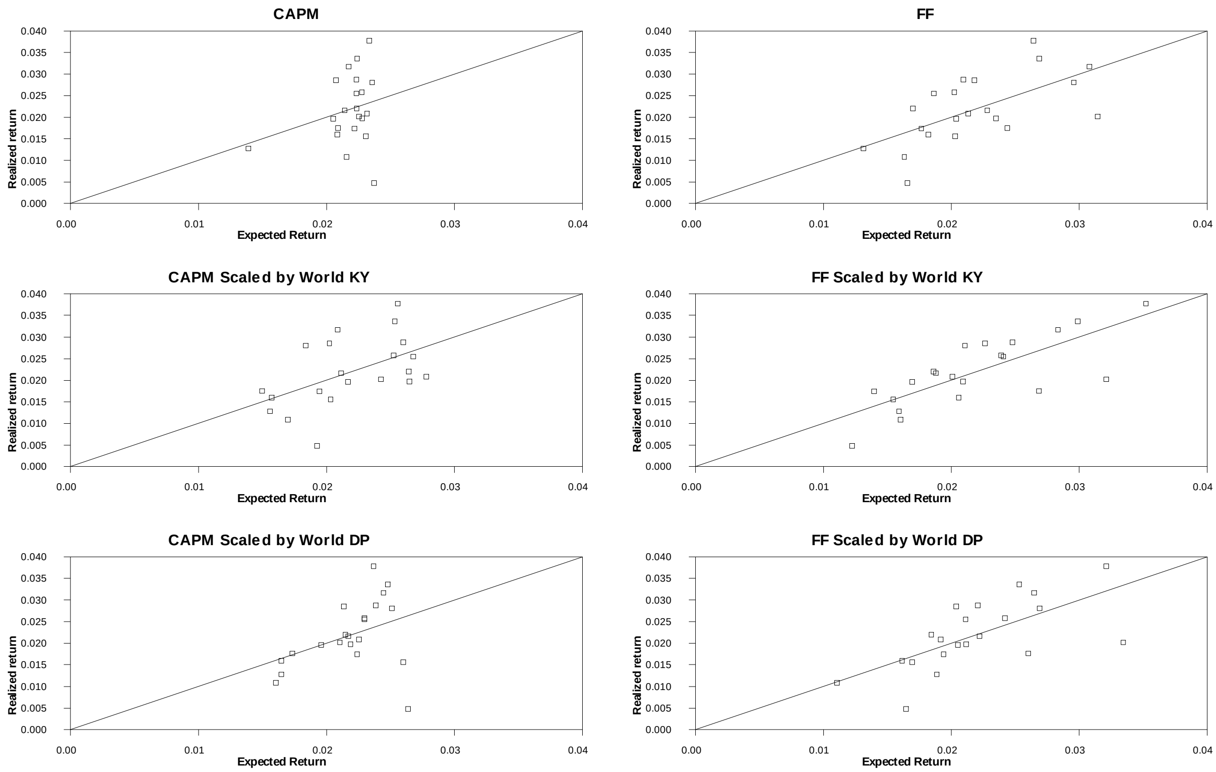

Fig. 3. Plots of expected and actual returns using Book-to-Market and Country market portfolios.

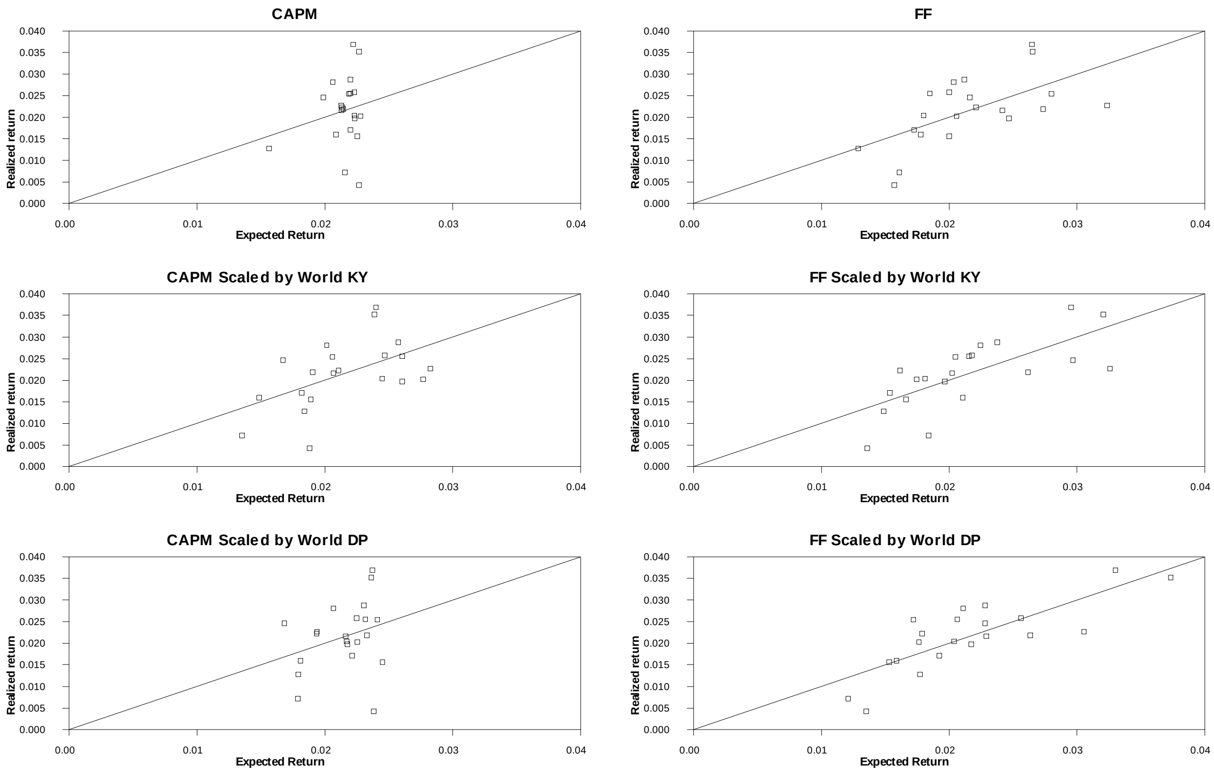

Fig. 4. Plots of expected and actual returns using Cash Flow and Country market portfolios.

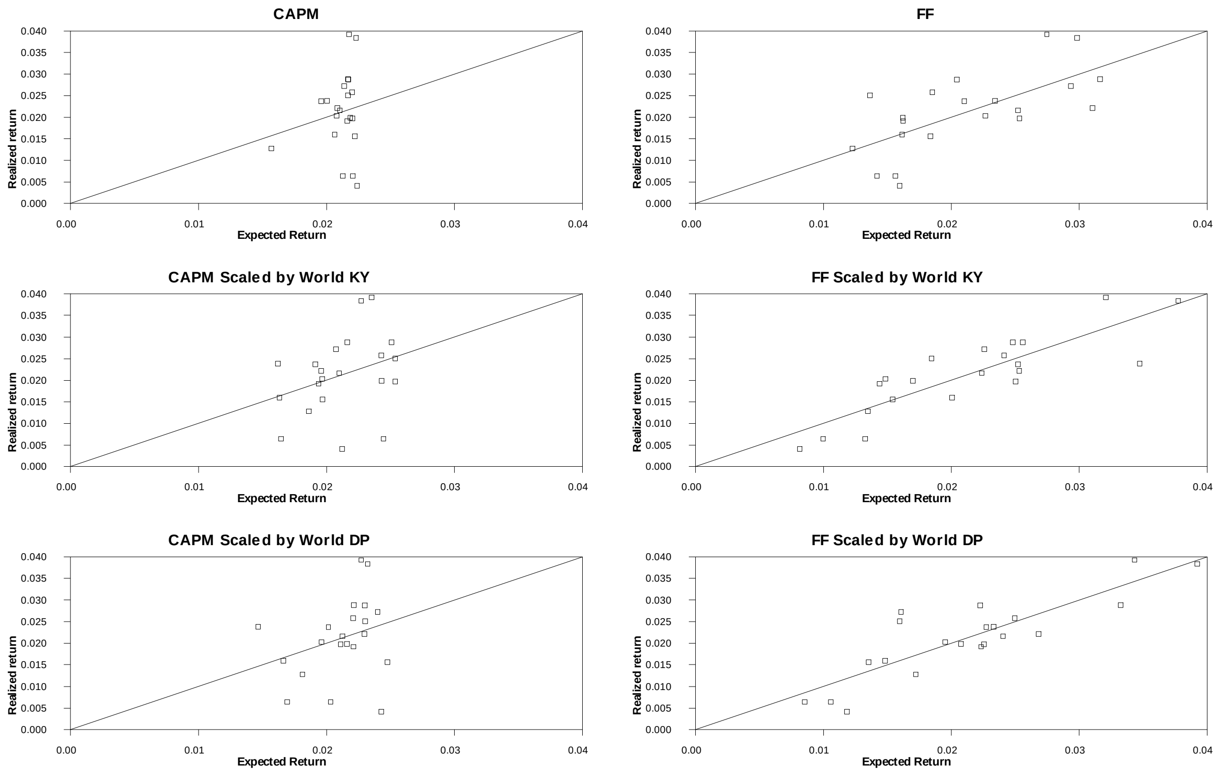

Fig. 5. Plots of expected and actual returns using Earnings to Price and Country market portfolios.

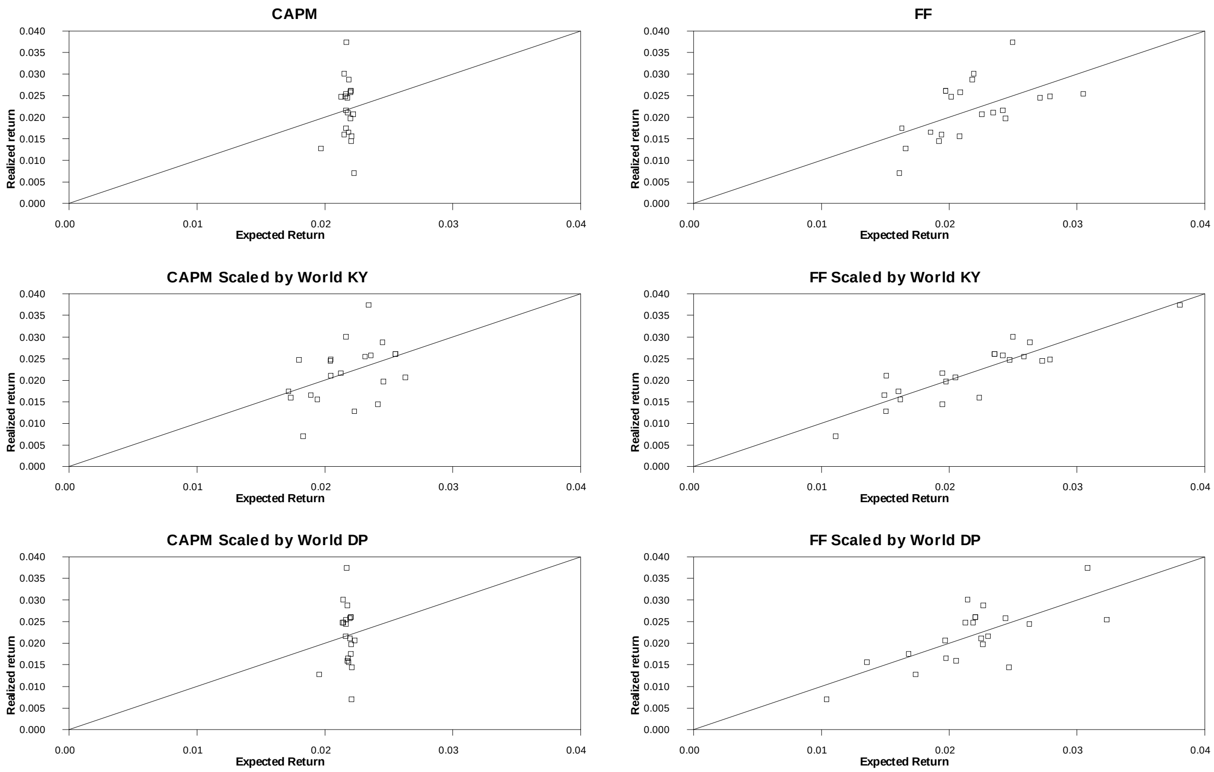

Fig. 6. Plots of expected and actual returns using Dividend to Price and Country market portfolios.