ESSAYS ON EMPIRICAL ASSET PRICING

by

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ABSTRACT

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Essay 1: This paper examines the time-series predictability of aggregate stock returns in 20 emerging markets. In contrast to the aggregate-level findings in US, earnings yield forecasts the time-series of aggregate stock returns in emerging markets. We consider aggregate earnings not as normalizing variables for stock price but as predictive variables in their own right. Aggregate earnings themselves covary with the market returns, hence it is not just the mean reversion of stock prices that is responsible for the forecasting power of earnings yield. These results are robust across different estimation methods and after controlling for small sample bias and macroeconomic variables. We argue that due to high levels of fundamentals' co-movement in emerging markets, the information content of firm-level earnings (unsystematic earnings) about future cash flows is not fully diversified away at the market level. Relevant literature shows that firm-level earnings are positively correlated with expected returns in US and this positive relationship remains significant only at the less diversified industry- level but disappears at the highly diversified US market level. Emerging markets are significantly less diversified compared to US. This explains the strong and robust predictive power of aggregate earnings in emerging markets.

Essay 2: This paper examines the forecasting power of earnings yield and aggregate normalized earnings in world markets. 48 countries have been ranked according to the stock price synchronicity and diversification measures, obtained by utilizing daily firm-level data for each country. There is a statistically significant relationship between aggregate earnings and one quarter ahead expected stock returns for more synchronous and less diversified countries as opposed to less synchronous and more diversified countries. We argue that due to high levels of fundamentals' co-movement in highly synchronous and less diversified markets, the information content of firm-level earnings (unsystematic earnings) about future cash flows is not fully diversified away at the aggregate level. Our results remain robust after controlling for macro variables, such as consumer price index and discount rates.

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To my family,

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Part I
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1.1 Introduction

Forecasting aggregate returns using cash-flow variables scaled by the price has been a center of attention in the asset pricing literature. Academics identify variables such as earnings yield (E/P), dividend yield (D/P), and book-to-price (B/P) as cash-flow to price ratios that are expected to identify the expected market returns. The literature starts with early studies such as Rozeff (1984), Shiller (1984), Fama and French (1988a, 1989), Campbell and Shiller (1988, 1989), and Hodrick (1992), and continues with Kothari and Shanken (1997), Pontiff and Schall (1998), Lamont (1998), and Bali, Demirtas, and Tehranian (2008).

All of these studies focus on the US market. Shiller (1984) and Fama and French (1988a, and 1988b) used both dividend yield and earnings yield as predictive variables at the aggregate level, and interestingly, they found that earnings yield has weak or no predictive power compared to the dividend yield. Their assumption was that aggregate earnings for the US market is a noisy measure of future cash flows, and therefore, this noise weakens the forecasting power of earnings yield, though they do not test this assumption explicitly. However, Lamont (1998) has a different opinion about the weak predictive power of aggregate earnings yield. Lamont (1998) argues that any cash-flow to price ratio may predict future aggregate returns either because there is mean reversion in aggregate stock market level (hence price in the denominator negatively covaries with the future stock returns) and/or cash-flow proxy in the numerator is a clean proxy for expected future cash-flows (hence it positively covaries with future stock returns). Therefore, as long as the cash-flow proxy is positively related to future returns and the price is negatively related to future returns, their predictive powers are not offsetting, hence the cash-flow to price ratio significantly positively covaries with the expected returns.

Consequently, Lamont (1998) considers the predictive power of aggregate earnings and price separately, and finds that both the level of earnings and price is negatively related to future market returns. He argues that the level of earnings is a good measure of current business conditions. Risk premia on stocks covary negatively with current economic activity: investors require high expected returns in recessions, and lower expected returns in booms. Since earnings vary with economic activity, current earnings is negatively related to future returns. Moreover, P is negatively correlated with future returns due to mean-reversion in stock prices. Therefore, Lamont (1998) concludes that earnings yield (E/P) fails to forecast aggregate stock returns because both earnings (E) and price (P) covary negatively with expected returns and their forecasting powers are offsetting.

However, Bali, Demirtas, and Tehranian (2008) reversed this seemingly basic explanation of Lamont (1998) regarding the weak or no predictive power of earnings yield. They show that the findings of Lamont (1998) are data and sample specific, and that the level of aggregate earnings has no predictive power. Since aggregate earnings act as noise, earnings yield has no predictive power in US markets, despite the strong mean-reversion in stock markets. Bali, Demirtas, and Tehranian (2008) argues that firm-level earnings have systematic and firm-specific (idiosyncratic) components. Although the firm-specific earnings is good proxy for future cash-flows (hence has a predictive power), the cash-flow information in earnings diversify away by aggregation, and all we are left with at the aggregate level is the systematic earnings which do not have much meaningful information about the expected future cash flows. Bali, Demirtas, and Tehranian (2008) backed these results by showing that the level of earnings has significantly positive predictive coefficients at the firm-level regressions and some specific industry levels, however, this predictability gets washed away at the general industry levels and at the market level.

In this paper, we examine the time-series predictability of aggregate stock returns in 20 emerging markets. We argue that at the aggregate level emerging markets would behave differently than the US market which is a developed market. In emerging markets, there are low numbers of industries and stocks are very much correlated. Therefore, the synchronicity of stocks in emerging markets prohibits the diversification of firm level cash- flow information in earnings, when these firm-level earnings are aggregated to form the market-level earnings. Thus, we argue that aggregate level earnings may still contain information about expected future cash-flows. If this is the case, we would expect earnings yield to forecast future returns in emerging markets contrary to US. Indeed, we find that in contrast to the aggregate-level findings in US, earnings yield forecasts the time-series of aggregate stock returns in emerging markets.

However, this significant forecasting power of earnings yield may very well be a result of stronger mean reversion in emerging stock markets (i.e., price in the denominator may be responsible for the forecasting power). Therefore, one of the main contribution of this study is to consider aggregate earnings not as normalizing variables for stock price but as predictive variables in their own right. Using the Campbell-Shiller log linear decomposition framework, we used normalized earnings and normalized stock price as separate right hand side variables. We show that aggregate earnings themselves covary with the market returns, hence it is not just the mean reversion in stock prices that is responsible for the forecasting power of earnings yield.

Specifically, we first use dividend yield and earnings yield in pooled panel data regressions to forecast quarterly emerging markets returns. Furthermore, we used fixed effects regressions which are effectively stacked time-series regressions. Regardless of the methodology, we showed that in contrast to the US markets, earnings yield significantly positively covaries with expected returns in emerging markets. Next, normalized variables are constructed similar to the relevant literature, and hence the predictive power of earnings yield in emerging markets is decomposed into the predictive power of aggregate earnings and that of the price. We show that aggregate earnings has predictive power in their own right and is positively related to future market returns and price is negatively related future market returns indicating the strength of mean reversion.

Moreover, these findings are robust when we control for the macroeconomic variables such as default premium, stochastically detrended riskless rate, fed rate, and the term premium. Furthermore, even though the prohibitively low number of aggregate observations in emerging markets is overcome by the use of panel setting, statistically speaking, we still may have the problem of small sample bias in predictive regressions. To overcome this problem, we further used simulations in the form of bootstrapping and randomization and showed that even after controlling for the small sample bias our findings remain intact.

The remainder of the paper is organized as follows. Section 1.2 presents the motivation and framework. Section 1.3 explains the data construction process and provides summary statistics. Section 1.4 presents the empirical results. Section 1.5 concludes the paper.

1.2 Motivation and Framework

How does one-period expected return relate to the mean reversion in stock prices as well as the discounted expected cash-flows? To answer this question, we need a framework that relates one period ahead expected returns to infinite stream of expected future cash flows, and expected future discount rates beyond the first period ahead. Log linear decomposition of stock prices by Campbell and Shiller (1988, and 1989) is a convenient framework to understand the determinants of expected returns. In the log linear approximation, we first write log stock returns as a function of the end of period price, dividend paid during the period and the beginning of the period price, such that,

$$r_{i,t+1} = \log(P_{i,t+1} + D_{i,t+1}) - \log(P_{i,t}), \tag{1}$$

where $D_{i,t+1}$ denotes dividends for firm i paid during period $t+1$, and $P_{i,t+1}$ is the stock price at the end of period *t+1*. In this setting, raw variables are represented by uppercase letters and log variables are presented in lowercase letters. After using a first-order Taylor series expansion on the return equation we obtain,

$$p_{i,t} = K + E_t\left(\sum_{j=0}^{\infty} \omega^j (1-\omega) d_{i,t+1+j}\right) - E_t\left(\sum_{j=0}^{\infty} \omega^j r_{i,t+1+j}\right), \tag{2}$$

where K is a linearization constant and ω is a constant discount factor close to one. Indeed ω is a function of aggregate dividends. As shown by Campbell and Shiller (1988, 1989) ω is specifically given by $\frac{1}{1+e^{\overline{d-p}}}$, where $\overline{d-p}$ is the average log dividend yield in the data. By using a simple algebraic move, we can write the one period expected returns as:

$$E_t\left(r_{i,t+1}\right) = -p_{i,t} + E_t\left(\sum_{j=0}^{\infty} \omega^j (1-\omega) d_{i,t+1+j}\right) - E_t\left(\sum_{j=1}^{\infty} \omega^j r_{i,t+1+j}\right) + K. \tag{3}$$

Equation (10) gives us a clear relationship between one period ahead expected returns, current price (.i.e., index for the market), expected future cash-flows, and expected future discount rates. Equation (10) makes it clear that there is an inverse relation between price and one period ahead expected returns. We denote the second term on the right hand side of equation (10) as $p^{cash-flow}$, which is the expected sum of future discounted dividends. The third term is denoted by $p^{discount}$, which is the discounted sum of future returns starting next period. In summary, we learn that controlling for the index level, one period ahead expected market returns can be explained by variables that proxy for $p^{cash-flow}$ and/or $p^{discount}$.

In the earlier literature, when academics use log dividend yield or log earnings yield as predictive variables, the inherit assumption was that earnings or dividend yield will proxy for $p^{cash-flow}$ in the above equation, and hence will be positively related to the one period ahead expected returns, moreover, the price proxy for the mean-reversion effect (i.e., it will proxy for itself), and hence will be negatively related to expected returns. Consequently, when one use earnings or dividend yield in predictive regressions, the numerator (denominator) of the cash-flow to price ratio is supposed to be positively (negatively) related to one period ahead expected returns. Of course both earnings and dividends are just imperfect proxies for $p^{cash-flow}$. Earlier literature blame earnings for the missing foracasting power of earnings yield. They argue that earnings should be a poor proxy for $p^{cash-flow}$, however, as mentioned before these earlier studies do not explicitly test for this hypothesis. Lamont (1998), on the other hand, argues a totally different explanation for the poor forecasting power of aggregate earnings yield. He presents equation (10) as:

$$E_t\left(r_{i,t+1}\right) = -(p_{i,t} - n_{i,t}) + (p_{i,t}^{cash-flow} - n_{i,t}) - p_{i,t}^{discount} + K, \qquad (4)$$

where $n_{i,t}$ is a normalization factor used to create stationary right-hand side variables. Equation (11) helps us disentangle different forecasting powers of the numerator and the denominator of a cash-flow to price ratio, by using the normalized stock price and the normalized cash flow proxy (i.e., normalized earnings or dividends) as the right-hand side variables. In the classical regression setting, where one period ahead returns are regressed on the earnings yield or the dividend yield, the coefficient estimate of the price and the cash-flow proxy is restricted to be the same. However, in the above setting, the coefficients of the stock price and the cash flow proxy are not restricted to be the same. Lamont (1998) argues that aggregate dividends proxy for $p^{cash-flow}$ and aggregate earnings are positively correlated with business cycle fluctuations. He finds that normalized earnings of the S&P Composite Index as well as the normalized price (i.e., normalized index level) have negative coefficients in predictive regressions, whereas normalized dividends have a positive coefficient. Thus, subtracting earnings from price (i.e., using earnings yield as a predictive variable) masks the relation between earnings yield and expected returns. In other words, Lamont (1998) does not argue that the aggregate earnings is a poor proxy of $p^{cash-flow}$, rather he argues that earnings move with the business cycle (i.e., earnings possibly proxy for $p^{discount}$) hence are significantly related to future returns but in a negative way. Finally, Bali, Demirtas and Tehraninan (2008) argue that results of Lamont

(1998) are a side-effect of the specific data and time-period he considers. Bali et. al. argue that aggregate earnings indeed does not contain any information about $p^{cash-flow}$, hence it masks the mean reversion effect such that aggregate earnings yield has no forecasting power. In summary, we currently know that in US markets E/P has no forecasting power even when there is a significant mean-reversion effect, and the reason is that aggregate earnings is just noise and do not contain information about future cash flows.

In this study, we examine the aggregate earnings and price in emerging markets. Although we have no specific reason to believe that there may be a different mean-reversion effect in emerging markets, we believe that aggregate earnings in emerging markets may contain more information about expected future cash flows. It is argued in the literature that firm-level earnings are strong forecasters of time-series returns. The reason is that firm level earnings contain information about expected future cash flows (i.e., they are correlated with $p^{cash-flow}$), and this information diminishes away once these earnings are aggregated to obtain market level earnings. The diversification forces are not strong enough at some industry level, hence there is still some predictability. However, at more general industry levels and at the market level, diversification of cash-flow information is at its full force, hence aggregate earnings is just noise.

In emerging markets, contrary to the US market, there are fewer number of industries and stocks' comovements are much more significant, which means that correlation between stocks are higher (i.e., idiosyncratic volatility is lower in emerging markets).[1,2] Consequently, we argue that aggregate earn-

[1]Roll(1992) and Morck et al.(2000) shows the "Herfindahl Index" which is a measure of the industry concentration in a market, is higher for emerging markets where markets are less diversified.

[2]Using several measures, Morck et al.(2000) and Jin and Myers(2006) provide evidence that there is more stock return synchronicity in emerging markets.

ings in emerging markets may contain information about $p^{cash-flow}$, which may cause earnings yield to be a significant forecaster of future returns..

However, the finding that earnings yield has stronger forecasting power in emerging markets does not necessarily mean that aggregate earnings themselves covary with expected returns in emerging markets. We may just have a stronger mean reversion in emerging markets. Therefore, by utilizing the dynamic growth model of Campbell and Shiller (1988, 1989), we use pooled and fixed-effects panel data regressions to examine the predictability at the firm-level. A predictive regression for the country returns in a fixed-effects setting can be demonstrated as:

$$r_{j,t+1} = a_j + \lambda X_{j,t} + \xi_{j,t+1}, \tag{5}$$

where $r_{j,t+1}$ is the log excess return for country j at time $t+1$ ($j = 1, 2, ..., 20$), and $X_{j,t}$ is a vector of predictive variables which are in the information set as of time t. In a fixed effects setting the intercepts (a_j) are estimated separately for each country j, which distinguishes fixed effects panel data regressions from pooled panel data regressions where the intercept is the same for each country. Therefore, pooled panel data regressions can be viewed as stacked time-series regressions as well as stacked cross-sectional regressions. However, estimating intercepts separately is equivalent to demeaning each country level data and ensures that each country's error term is orthogonal to the explanatory variables for that stock. Thus, fixed-effects panel data regressions are equivalent to stacked time-series regressions. Since our main focus will be on the time-series relation between aggregate earnings and expected returns, fixed effects regressions are important for our goal. However, even though panel regressions (fixed-effects or not) gives us bigger degrees of freedom (i.e., a larger number of observations), these regressions may still suffer from small sample bias. Coefficients may be biased and t-statistics may be inflated.[3] Hence simulations should be used to obtain unbiased p-values. We address this issue later in the paper.

1.3 Data

1.3.1 Data Set

Our data set consists of 20 emerging markets which are listed under the Morgan Stanley Capital International (MSCI) Emerging Markets Index and the Financial Times and London Stock Exchange (FTSE) Group Emerging Markets Index as of January, 2009.[4] Our panel data includes 20 countries that are available at DataStream out of 22 emerging markets which are covered by both indices: Argentina, Brazil, Chile, China, Colombia, Czech Republic, Hungary, India, Indonesia, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, and Turkey.[5]

[3]Note that the inflation in t-statistics due to small sample bias is a different problem than the upward bias in significance levels due to contemporaneous correlation in error terms. Both of these issues will be tackled separately later in the paper.

[4]The MSCI Emerging Markets Index is a free float-adjusted market capitalization index that is designed to measure equity market performance of emerging markets. As of January, 2009 it consisted of indices in 24 emerging economies: Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Israel, Korea, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand and Turkey.

The FTSE Group lists 22 emerging markets in total. It distinguishes between Advanced and Secondary Emerging Markets on the basis of their national income and the development of their market infrastructure. Brazil, Hungary Mexico, Poland, South Africa and Taiwan are listed under Advanced Emerging markets and Argentina, Chile, China, Colombia, Czech Republic, Egypt, India, Indonesia, Malaysia, Morocco, Pakistan, Peru, Philippines, Russia, Thailand and Turkey are listed as Secondary Emerging Markets.

[5]Total market index data ($TOTMK$) for Egypt and Morocco are not available at DataStream.

The sample period ranges from 1977:Q2 to 2009:Q3, yielding an unbalanced panel data with a total of 1,176 quarters, where the last five years of data were available for each country. On average there are 59 quarters per country; South Africa has the longest sample period with 130 quarters, whereas Brazil has the shortest with 25 quarters.

1.3.2 Construction of Variables

For each market, the total market index of Datastream Global Index (*TOTMK* item of Datastream) is used as the national market index.[6] We obtain the daily returns which are continuously compounded including reinvested dividends, price index, dividend yields and earnings yield from Thompson Financial's Datastream in local currencies calculated at the index level. The *TOTMK* series of Datastream is a value-weighted index where weightings are allocated on the basis of market capitalization. We obtain the one-month Treasury bill returns for US from the Ibbotson Associates.

Quarterly returns are constructed by compounding daily returns. Quarterly price index, dividend yield and earnings yield is obtained using end of quarter values. Log excess return ($\mathbf{r}_{i,t}-\mathbf{r}_{f,t}$) is computed as the quarterly log return in excess of the one-month US Treasury bill rate compounded within quarter t. RREL_t is the stochastically detrended riskless rate defined as the end of quarter 3-month T-bill rate minus its twelve-month backward moving average. Log dividend yield ($\mathrm{d}_{i,t}-\mathrm{p}_{i,t}$) is the log of the ratio of sum of the past year's total dividends to price and log earnings yield ($\mathrm{e}_{i,t}-\mathrm{p}_{i,t}$) is the log of the ratio of sum of the past year's total earnings to price.

[6] In DataStream, indices are calculated on a representative list of stocks for each market. The number of stocks for each market is determined by the size of the market. The sample covers a minimum of 75 - 80% of total market capitalization. For more information about the construction of the market index, see the DataStream Global Equity Indices Manual.

To disentangle the individual effects of price, dividends and earnings, following Lamont (1998), we compute log normalization variables. To be able to compare our emerging market results with US studies, we use log of the average of the past five years of annual earnings per share, (calculated as the sum of the past 20 observations of quarterly earnings per share divided by five), as the normalization variable. The main goal of the normalization variable is to create stationary variables. Our choice of this specific normalization variable exactly follows the literature.[7]

1.3.3 Summary Statistics

Table I shows the descriptive statistics of the market level data. Mean, standard deviation, minimum and maximum values, quartiles, skewness and kurtosis are reported for the data set. Panel A reports the summary statistics which are computed as the averages of each country's time-series statistics. Panel B shows summary statistics, computed from the pooled panel data.

Regardless of the estimation methodology dividend yield is more volatile than the earnings yield and as shown by the standard deviations of normalized earnings and normalized dividends, higher volatility of the normalized dividend yield is due to higher volatility of dividends. This finding lowers our expectation of the predictive power of earnings. Therefore, we will see whether lower variability in normalized earnings is related to the time-varying expected returns.

[7] We should note that relevant literature shows that several other normalization variables create similar results in US.

1.4 Empirical Results

1.4.1 Forecasting Market Index Return with Value-to-Price Ratios

To test whether value-to-price ratios can predict one-quarter ahead market returns in emerging countries, we use both pooled panel data regressions and fixed effects regressions. As mentioned earlier, in pooled regressions the intercept as well as the slope coefficients are the same for each country. Since we are not demeaning the data at the country level when running pooled regressions, cross-sectional relation and the time-series relation will be reflected in the results. We use the following pooled panel data regression setting to generate the results presented in Panel A of Table II:

$$r_{m,t+1} = a + \beta X_{m,t} + \varepsilon_{m,t+1}, \tag{6}$$

where $r_{m,t+1}$ is the log raw returns on the market portfolio at time t+1, $X_{m,t}$ is the set of predictive variables such as log of earnings yield, log of dividend yield, log of dividend payout ratio, log of raw returns on the market portfolio and stochastically detrended riskless rate.

As stated by Campbell (1991) and Hodrick(1992) stochastically detrended riskless rate may be an important variable in determining the expected returns. On the other hand, the lagged dependent variable is added as a control variable, since persistent dependent variables may result in a spurious regression as addressed by Ferson, Sarkissian and Simin (2003).

In order to correct for the contemporaneous cross-sectional correlation of error terms problem, we use Rogers' (1983, 1993) method for computing standard errors in the existence of heteroscedasticity and contemporaneous cross-correlations. In a panel data setting, the variance covariance matrix of the error terms can be viewed as a combination of small variance covariance matrices of each country. And aside from the autocorrelation of the error terms within each country, there is a contemporaneous cross-sectional correlation. If this problem is uncorrected, it can inflate the t-stats by a significant amount. In the above equation, the slope coefficient (β) along with its clustered standard errors determines whether there is a significantly positive or negative relation between the value-to-price ratios and expected returns at the market level.

In Panel A of Table II, the first and third row indicates the univariate forecasting powers of earnings yield and dividend yield. Both dividend yield and earnings yield is highly significant and has a positive coefficient in predicting expected returns at the aggregate level (with a t-stat of 3.77 and 3.25 respectively). In the second and fourth row adding the lagged return and the relative T-Bill rate increase the explanatory power by a significant amount, but these two variables have no forecasting power for the total market return in emerging markets. In order to compare emerging markets findings with Lamont (1998)'s finding in US, following Lamont (1998), we also look at the univariate forecasting power of dividend payout ratio.[8] The coefficient of dividend payout ratio in row 5 is close to zero (0.011) with a t-stat of 1.1. This finding is contrary to the findings in US. The lack of predictive power of dividend payout ratio may be due to dividends and/or earnings actings as a noise. Another possible explanation is that the forecasting powers of dividends and earnings are offsetting.

[8] Lamont (1998) finds dividend payout ratio as a positive and significant predictor of excess market returns in US. He argues the positive forecasting power of dividend payout ratio is due to the negative relation between the aggregate earnings in the denominator and the expected stock returns as well as the positive relation between the aggregate dividends in the numerator and expected stock returns.

Seventh row shows that both dividend yield and earnings yield have positive and highly significant coefficients in predicting expected stock returns in a bivariate setting. Adding the control variables in the last row, does not affect the results, earnings yield and dividend yield remains as strong predictors of the market return with a t-stat of 3.33 and 2.82, respectively.

In Panel B of Table II we use fixed-effects panel data regressions:

$$r_{j,t+1} = a_j + \lambda X_{j,t} + \xi_{j,t+1}, \tag{7}$$

where $r_{j,t+1}$ is the log return for country j at time $t+1$ ($j = 1, 2, ..., 20$). Earnings yield, dividend yield, and dividend payout ratio are used as independent variables and lagged return and RREL are used as control variables. Similar control variables are used in predictive regressions by Campbell (1991), Ferson and Harvey (1991), and Bali, Demirtas, and Levy (2008, 2009). As stated previously, the distinguishing point in the equation above is that the intercepts (a_j) are estimated separately for each country j. Estimating intercepts separately is equivalent to demeaning each country level data and ensures that each country's error term is orthogonal to the explanatory variables for that country. Thus, in fixed-effects panel data regression setting, the results reflect the time-series relation between the dependent variable and the independent variables.

The first and second rows in Panel B of Table II show the univariate regressions of the one-period ahead aggregate stock returns on earnings and dividend yield. Both earnings and dividend yield are positively correlated with the time-series of future stock returns, with a t-stat of 3.53 and 3.12, respectively. The second and fourth row shows that adding the lagged return and relative T-Bill rate does not change the significance of the variables; in fact the t-stats of earnings and dividend yield rise to 4.77 and 3.93, respectively. Similar to the findings in Panel A, fixed effect regressions confirm that dividend payout ratio has no forecasting power for the aggregate stock return in emerging markets. The coefficient of dividend payout ratio in row 5 and 6 is close to zero (0.014 and 0.015) with a t-stat of 1.1. Row 7 shows that earnings yield continues to be a significant predictor of aggregate-level stock returns in the presence of dividend yield. Furthermore, in the last regression, after introducing the control variables, there is still a highly positive and significant relation between earnings yield and expected returns at the aggregate level with a t-stat of 3.00.

We find that earnings yield has a significant predictive power for expected stock returns. Either the mean-reversion in stock prices alone drives the forecasting power of earnings yield and/or aggregate earnings are positively correlated with expected stock returns in emerging markets as opposed to US. Next section examines the source of this finding by using normalized variables.

1.4.2 Forecasting Market Index Return with Aggregate Normalized Variables

In this section, we consider aggregate earnings and dividends not as normalizing variables for price but as predictive variables in their own right. Table III shows parameter estimates from the predictive regressions using scaled prices, dividends, and earnings. Panel A reports the results of pooled panel data regressions and Panel B reports the fixed effects regressions.

The first row of Panel A shows that the scaled price has a negative and significant coefficient, indicating the presence of mean-reversion at the index level in emerging markets. In Row 2, scaled price remains negative and significant after controlling for the lagged return and the relative T-Bill rate. Row

3 is one the benchmark regressions of this study, where the decomposition equation is implemented. In the classical regression setting, where one period ahead returns are regressed on the earnings yield or the dividend yield, the coefficient estimate of the price and the cash flow proxy is restricted to be the same. However, in the setting shown in equation (4), the coefficients of the stock price and the cash flow proxy are not restricted to be the same. In the third row, scaled dividends has a positive and significant coefficient with a t-stat of 2.66 and scaled aggregate earnings has a positive and significant coefficient with a t-stat of 2.89, implying that both scaled aggregate variables are proxies for expected future cash flows ($p^{cash-flow}$) in equation (4). On the other hand, scaled price has a negative and significant coefficient with a t-stat of -3.75, implying the strong mean reversion in emerging markets. The strong predictive power of scaled price, scaled dividends and scaled earnings are robust to the addition of the control variables in the last row. They remain highly significant at 1% level.

Panel B of Table III presents the slope coefficients and clustered t-statistics using the fixed effects panel data regressions. The results in the first row of Panel B indicate that scaled stock price has a negative and significant coefficient in a univariate setting. The mean reversion in emerging markets is robust to adding control variables as shown in the second row. The benchmark regression in Row 3 indicates that conditional on dividends and price, earnings are still positively correlated with future stock returns. This suggests that aggregate earnings contain information about the time-series of expected future cash flows beyond dividends. The last row shows that the results in the third row are robust to the addition of control variables. In Row 4, the scaled price has a negative coefficient with a t-stat of -5.24 implying strong mean reversion in the time-series of aggregate returns. The aggregate dividends predict the stock returns with a t-stat of 3.00. Most importantly, as opposed to US findings, aggregate earnings positively covaries with the aggregate returns in emerging markets. The positive relation between earnings and future stock returns implies that current aggregate earnings in emerging markets proxy for expected future cash flows (i.e., ($p^{cash-flow}$) in equation (4)).

Overall, the results in Panel A and Panel B show that the positive predictive power of firm level earnings can be brought to the aggregate level, if markets are less diversified as in the case of emerging markets. The market portfolios in emerging markets which are analog to Bali et al. (2008)'s less diversified 48-industry portfolios in US, are not diversified enough to wash out the information content of firm-level earnings about future cash flows.

1.4.3 Comparison to US Market

We have so far showed how earnings yield and aggregate earnings in their own right predict the expected stock returns at the market level in emerging markets. In order to have a better idea about how emerging markets differ from US, we also present the similar regressions for US.

In order to be consistent with the data source, we used *TOTMK* series of Datastream in our US analysis.[9] The sample period for the time series regressions in US is from 19977:Q2 to 2009:Q3. We used the same time period in our emerging markets analysis, therefore any difference between the results cannot be attributed to difference in sample period.

Panel A of Table IV presents the results of predictive regressions using lagged return, dividend yield, and earnings as well as the lagged return and

[9]The correlation between the value-weighted index return (with dividends) of CRSP and the *TOTMK(US)* market index return of Datastream (with dividends) is above 99%.

relative T-Bill rate as control variables. The standard errors are using Newey-West (1987) methodology. The first row of Panel A shows that earnings yield does not have a predictive power for the expected stock returns. We conclude that adding the control variables in the second row does not change the results; unlike the emerging markets dividend yield and earnings yield cannot predict future returns in US.

Lamont (1998) indicates that (E/P) fails to forecast aggregate stock returns in US because forecasting powers of earnings (E) and price (P) are offsetting. We investigate if this was the reason of the failure of earnings yield in predicting stock returns in Panel A. Panel B of Table IV shows the parameter estimates from the predictive regressions using scaled prices, dividends, and earnings. In Row 1, the scaled price has a negative coefficient indicating mean reversion, however it is statistically insignificant. Aggregate dividends can positively predict one quarter ahead stock returns at 10% significance level. As opposed to Lamont's findings in US, we find aggregate earnings has a positive coefficient but it is not statistically significant.[10] Adding the control variables in the second row, does not affect the results, aggregate earnings has no predicting power for market returns in US.

1.4.4 Small Sample Bias Correction

It is well known that there is a small sample bias in predictive regressions. Stambaugh (1999) shows that in predictive regressions, where a future re-

[10] Lamont (1998)'s sample period is 1947Q1:-1994Q4, and his market index for US is S&P 500 Composite Index. Bali et al. (2008) extends his sample period to 1947:Q1-2002:Q4, and shows that unlike Lamont (1998) the coefficient of aggregate earnings is positive and insignificant once the sample period is extended. To save space, we do not show the empirical findings obtained from the extended sample periods 1947:Q1-2009:Q3 and 1977:Q2-2009:Q3 for the S&P Composite Index. Our results are similar to Bali et al. (2008)'s results, aggregate earnings has a positive but insignificant coefficient in predicting aggragate returns in US. They are available upon request.

turn is regressed on lagged variables, the error terms of the regression are correlated with the regressors' innovations. Therefore, the expectation of the regression disturbance conditional on the future values of regressors no longer equals zero. Consequently, both the coefficient estimates and the significance levels are biased.

The small sample bias is a function of the bias of the autoregressive coefficients of the independent variables, the correlation between the error terms, and the sample size. The sign of the bias depends on the sign of the correlation between the error terms. If the regression disturbance is positively (negatively) correlated with the regressor's innovation, there is a negative (positive) bias. In this paper, we utilize regressions of returns on value to price ratios and normalization variables. Although we do not suffer from small number of observations, we do know that our explanatory variables are highly persistent (both value to price ratios and normalization variables). Hence, corrections should be done as a robustness check.

Therefore, we consider the randomization technique of Nelson and Kim (1993) to correct for the small sample bias. We run each one of our predictive regressions, record the residuals, and estimate a first-order autoregression for the independent variables (normalized earnings and value to price ratios). We then randomize the residuals of the first-order autoregression to create pseudo-independent variables and returns that have similar time-series properties as the actual series but have been generated under the null of no predictability. We should note that the pseudo stock return is generated as the unconditional mean plus the randomized error term and in each simulation, residuals from the predictive regression and the autoregressions for the independent variables are randomized simultaneously, hence the correlation that drives the Stambaugh bias is preserved. We repeat this randomization procedure 1,000 times for each regression and create the empirical distribution of the coefficient estimates. We then estimate the small sample bias adjusted coefficient estimates and p-values. Small sample bias adjusted p-values are computed as the percentage of times the simulated t-statistics are higher than the sample t-statistics. For example, p-value of 0.995 (0.005) shows that the coefficient is negative (positive) and significant at the 1% level. However, for comparability we convert p values of negative coefficients to 1 minus that value (i.e., 0.995 is presented as 0.005).

Table V shows small sample bias adjusted parameter estimates and bias adjusted one-sided p values. Panel A shows that even after bias adjustment, earnings yield is significant at the 1% level. More importantly, Panel B shows that even though bias adjustment slightly decrease the coefficient estimates, there is still a positive and significant relation between aggregate earnings and expected returns in emerging markets. Hence, we conclude that our findings are robust to small sample correction.

1.4.5 Controlling for Macro Economic Variables

Table VI uses three additional control variables. These control variables are used to make sure that our results are not affected by model misspecification, we add a set of control variables (X_t) that are expected to have an empirical relation with the market return in emerging markets. There is a large body of literature indicating that the aggregate returns can be predicted by macroeconomic variables associated with business cycle fluctuations. Merton's (1973) ICAPM also indicates that hedging demand components identify time-series of expected returns.

Following the relevant literature, we use Default Premium (DEF), Term Premium (TERM), and Federal Reserve Rate (FED) as additional controls.

DEF is the change in the default spread calculated as the daily change in the difference between the yields on BAA- and AAA-rated corporate bonds. TERM is the change in the term spread calculated as the daily change in the difference between the yields on the 10-year Treasury bond and one-month Treasury bill. As defined earlier RREL is the detrended riskless rate defined as the yield on the one-month Treasury bill minus its backward moving average.[11] Finally, we include the lagged return on the aggregate index to control for the serial correlation in quarterly index returns.

Panel A of Table VI shows estimation results for the value to price ratios and Panel B shows the estimation results for normalized variables. The first and second regressions in Panel A and Panel B are repeated for comparability purposes. As seen in these regressions, addition of control variables causes R-squares to go up. The coefficient estimates of earnings yield increase from 0.034 to 0.040 when lagged return and RREL is added to the regressions and to 0.042 when full set of controls are used. More importantly, normalized earnings do not lose any significance. There still is a positive and significant relation between aggregate earnings and expected returns.

1.5 Conclusion

We examine the relationship between aggregate earnings and expected returns in emerging markets. We consider aggregate earnings not as normalizing variables for stock price (i.e., not only in the form of earnings yield), but as predictive variables in their own right. Relevant literature argues that, in US, aggregate earnings do not contain any information about expected future cash-flows. Because any cash-flow information contained in firm-level earn-

[11] The time-series data on 10-year Treasury bond yields and BAA- and AAA-rated corporate bond yields are available in the Federal Reserve statistics release.

ings gets diversified away due to aggregation when market level earnings are formed. This is due to large number of industries that exist in US, as well as lower comovement of stocks in developed markets. Contrary to the developed markets, emerging markets contain lower number of industries. Furthermore, stocks' comovement is much higher in emerging markets, which may make the diversification of cash-flow information much harder. Hence, we argue that aggregate earnings may covary with market level expected returns.

We show that earnings yield is a significant forecaster of expected returns. Moreover, aggregate earnings themselves covary with the market returns, hence it is not just the mean reversion of stock prices that is responsible for the forecasting power of earnings yield. These results are robust across different estimation methods and after controlling for small sample bias and macroeconomic variables. We argue that due to high levels of fundamentals' co-movement in emerging markets, the information content of firm-level earnings (unsystematic earnings) about future cash flows is not fully diversified away at the market level. Thus, there exists a positive and significant relation between aggregate earnings and expected returns in emerging markets.

Table I
Summary Statistics

Panel A shows the summary statistics which are computed as the averages of each country i's time-series statistics. $\mathrm{r}_{i,t}$ is the quarterly log raw return; ($\mathrm{e}_{i,t}-\mathrm{p}_{i,t}$) is $\log(\frac{E_{i,t}}{P_{i,t}})$ where $E_{i,t}$ is the sum of the past four quarters of total earnings and $P_{i,t}$ is the market index price of country i at the end of quarter t; ($\mathrm{d}_{i,t}-\mathrm{p}_{i,t}$) is $\log(\frac{D_{i,t}}{P_{i,t}})$ where $D_{i,t}$ is the sum of the past four quarters of total dividend; $\mathrm{N}_{i,t}$ is a normalization variable, computed as the log of the average of the past five years of annual earnings, calculated as the sum of the past 20 observations of quarterly earnings divided by five.; ($\mathrm{e}_{i,t}-\mathrm{n}_{i,t}$) is $\log(\frac{E_{i,t}}{N_{i,t}})$; ($\mathrm{d}_{i,t}-\mathrm{n}_{i,t}$) is $\log(\frac{D_{i,t}}{N_{i,t}})$ and ($\mathrm{p}_{i,t}-\mathrm{n}_{i,t}$) is $\log(\frac{P_{i,t}}{N_{i,t}})$. Panel B shows similar summary statistics, computed from the pooled panel data. There are 20 countries and 1176 country-quarter observations in the data.

Panel A

	$\mathbf{r}_{i,t}$	$\mathbf{e}_{i,t}-\mathbf{p}_{i,t}$	$\mathbf{d}_{i,t}-\mathbf{p}_{i,t}$	$\mathbf{p}_{i,t}-\mathbf{n}_{i,t}$	$\mathbf{e}_{i,t}-\mathbf{n}_{i,t}$	$\mathbf{d}_{i,t}-\mathbf{n}_{i,t}$
Mean	0.036	-2.595	-3.719	2.951	0.356	-0.769
Std Dev	0.157	0.384	0.467	0.449	0.312	0.473
Min	-0.381	-3.353	-4.717	2.084	-0.369	-1.679
q1	-0.055	-2.870	-4.040	2.611	0.166	-1.109
q2	0.041	-2.620	-3.688	2.919	0.370	-0.777
q3	0.133	-2.297	-3.383	3.317	0.566	-0.397
Max	0.430	-1.754	-2.786	3.808	1.037	0.104
Skewness	-0.253	0.135	-0.112	0.029	-0.227	-0.028
Kurtosis	3.687	2.860	2.710	2.315	3.355	2.821

Panel B

	$\mathbf{r}_{i,t}$	$\mathbf{e}_{i,t}-\mathbf{p}_{i,t}$	$\mathbf{d}_{i,t}-\mathbf{p}_{i,t}$	$\mathbf{p}_{i,t}-\mathbf{n}_{i,t}$	$\mathbf{e}_{i,t}-\mathbf{n}_{i,t}$	$\mathbf{d}_{i,t}-\mathbf{n}_{i,t}$
Mean	0.035	-2.614	-3.720	2.969	0.355	-0.751
Std Dev	0.160	0.465	0.607	0.552	0.385	0.624
Min	-0.605	-4.071	-6.645	0.589	-1.679	-4.297
q1	-0.051	-2.890	-4.104	2.669	0.167	-1.081
q2	0.043	-2.639	-3.687	2.995	0.371	-0.646
q3	0.131	-2.389	-3.330	3.308	0.571	-0.403
Max	0.837	-0.531	-2.026	4.494	1.853	1.070
Skewness	-0.024	0.778	-0.404	-0.706	-0.554	-0.963
Kurtosis	4.866	5.473	4.133	4.807	5.929	6.218

Table II

Forecasting Market Index Return using Value-to-Price Ratios

This table shows the parameter estimates and standard errors from predictive regressions using value-to-price ratios. Panel A shows pooled panel regression results with clustered standard errors. Panel B shows fixed effects regression results with clustered standard errors. In each regression, dependent variable is the quarterly log raw return on the total market index of DataStream (*TOTMK*), $r_{m,t+1}$. Independent variables are $r_{m,t}$, $(d_t - p_t)$, $(e_t - p_t)$, $(d_t - e_t)$, and $RREL_t$. $RREL_t$ is the stochastically detrended riskless rate. $(d_t - p_t)$ is the log dividend yield, $(e_t - p_t)$ is the log earnings yield, and $(d_t - e_t)$ is the log dividend payout ratio. Clustered standard errors are reported in parentheses. ^{a,b,c} indicate significance at the 1%, 5% and 10% level, respectively.

Panel A. Pooled Panel Regressions

	Constant	$d_t - p_t$	$d_t - e_t$	$e_t - p_t$	$r_{m,t}$	$RREL_t$	R^2
1	0.164^a			0.049^a			2.04 %
	(0.039)			(0.013)			
2	0.182^a			0.056^a	0.070	1.010	2.99 %
	(0.034)			(0.012)	(0.069)	(1.300)	
3	0.181^a	0.039^a					2.22 %
	(0.048)	(0.012)					
4	0.196^a	0.043^a			0.057	1.056	3.04 %
	(0.040)	(0.011)			(0.069)	(1.294)	
5	0.048^a		0.011				0.16 %
	(0.016)		(0.010)				
6	0.048^a		0.011		0.039	0.774	0.59 %
	(0.015)		(0.010)		(0.071)	(1.348)	
7	0.230^a	0.029^b		0.034^a			3.03%
	(0.054)	(0.012)		(0.012)			
8	0.256^a	0.031^a		0.040^a	0.073	1.159	4.16%
	(0.045)	(0.011)		(0.012)	(0.069)	(1.273)	

Panel B. Fixed Effects Regressions

	Constant	$\mathbf{d}_t - \mathbf{p}_t$	$\mathbf{d}_t - \mathbf{e}_t$	$\mathbf{e}_t - \mathbf{p}_t$	$\mathbf{r}_{m,t}$	$\mathbf{RREL}_t$	$\mathbf{R}^2$
1	0.175^a			0.053^a			3.20 %
	(0.044)			(0.015)			
2	0.197^a			0.062^a	0.064	1.005	4.03 %
	(0.037)			(0.013)	(0.070)	(1.308)	
3	0.233^a	0.053^a					3.97 %
	(0.067)	(0.017)					
4	0.257^a	0.059^a			0.055	1.159	4.83 %
	(0.056)	(0.015)			(0.069)	(1.280)	
5	0.052^a		0.014				1.49 %
	(0.020)		(0.013)				
6	0.053^a		0.015		0.026	0.765	1.81 %
	(0.018)		(0.013)		(0.071)	(1.357)	
7	0.281^a	0.042^b		0.034^b			4.65%
	(0.073)	(0.018)		(0.014)			
8	0.322^a	0.047^a		0.042^a	0.074	1.261	5.84%
	(0.058)	(0.016)		(0.014)	(0.068)	(1.255)	

Table III

Forecasting Market Index Return using Aggregate Normalized Variables

This table shows the parameter estimates and standard errors for scaled prices, dividends, and earnings. Panel A shows pooled panel regression results with clustered standard errors. Panel B shows fixed effects regression results with clustered standard errors. In each regression, dependent variable is the quarterly log raw return on the total market index of DataStream (*TOTMK*), $r_{m,t+1}$. Independent variables are $r_{m,t}$, $(p_t - n_t)$, $(d_t - n_t)$, $(e_t - n_t)$, $RREL_t$, which are defined in Table 1. d_t is the log of total dividends paid out in the past four quarters. e_t is the log of total earnings in the past four quarters. p_t is the log of the market index level. n_t is the log of the average of the past five years of annual earnings, calculated as the sum of the past 20 observations of quarterly earnings per share divided by five. Clustered standard errors are reported in parentheses. ^{a,b,c} indicate significance at the 1%, 5% and 10% level, respectively.

Panel A. Pooled Panel Regressions

	Constant	$\mathbf{p}_t - \mathbf{n}_t$	$\mathbf{d}_t - \mathbf{n}_t$	$\mathbf{e}_t - \mathbf{n}_t$	$\mathbf{r}_{m,t}$	$\mathbf{RREL}_t$	$\mathbf{R}^2$
1	0.106^a	-0.023^c					0.66 %
	(0.040)	(0.012)					
2	0.124^a	-0.030^b			0.059	0.997	1.43%
	(0.038)	(0.012)			(0.072)	(1.327)	
3	0.221^a	-0.060^a	0.032^a	0.052^a			3.33%
	(0.054)	(0.016)	(0.012)	(0.018)			
4	0.248^a	-0.070^a	0.033^a	0.054^a	0.070	1.091	4.33%
	(0.045)	(0.014)	(0.012)	(0.018)	(0.069)	(1.286)	

Panel B. Fixed Effects Regressions

	Constant	$\mathbf{p}_t - \mathbf{n}_t$	$\mathbf{d}_t - \mathbf{n}_t$	$\mathbf{e}_t - \mathbf{n}_t$	$\mathbf{r}_{m,t}$	$\mathbf{RREL}_t$	$\mathbf{R}^2$
1	0.136^a	-0.034^b					2.29 %
	(0.050)	(0.015)					
2	0.160^a	-0.042^a			0.054	1.062	3.03%
	(0.045)	(0.014)			(0.071)	(1.318)	
3	0.275^a	-0.075^a	0.044^b	0.045^b			4.73%
	(0.074)	(0.021)	(0.018)	(0.021)			
4	0.318^a	-0.089^a	0.048^a	0.048^b	0.073	1.234	5.86%
	(0.059)	(0.017)	(0.016)	(0.020)	(0.069)	(1.259)	

Table IV

Forecasting US Total Market Index Return

Panel A of this table shows the parameter estimates and standard errors from predictive regressions using value-to-price ratios for the US total market index return. Panel B shows the predictive regressions using scaled prices dividends, and earnings. In each regression, dependent variable is the quarterly log raw return on the total market index, $r_{m,t+1}$. Independent variables are are defined in Table II and III. The sample period is 1977:Q2-2009:Q3. Newey-West (1987) standard errors are reported in parentheses. ^{a,b,c} indicate significance at the 1%, 5% and 10% level, respectively.

Panel A. Value-to-Price Ratios

	Constant	$\mathbf{d}_t-\mathbf{p}_t$	$\mathbf{d}_t-\mathbf{e}_t$	$\mathbf{e}_t-\mathbf{p}_t$	$\mathbf{r}_{m,t}$	$\mathbf{RREL}_t$
1	0.122^a	0.041		-0.019		
	(0.044)	(0.029)		(0.039)		
2	0.126^a	0.026		0.002	0.100	-0.480
	(0.044)	(0.027)		(0.039)	(0.105)	(0.624)

Panel B. Normalized Variables

	Constant	$\mathbf{p}_t-\mathbf{n}_t$	$\mathbf{d}_t-\mathbf{n}_t$	$\mathbf{e}_t-\mathbf{n}_t$	$\mathbf{r}_{m,t}$	$\mathbf{RREL}_t$
1	0.113^b	-0.016	0.061^c	0.012		
	(0.046)	(0.019)	(0.035)	(0.057)		
2	0.117^a	-0.022	0.052	0.044	0.078	-0.697
	(0.043)	(0.019)	(0.041)	(0.074)	(0.130)	(0.767)

Table V
Small Sample Bias Correction

This table shows the small sample bias adjusted parameter estimates and bias adjusted one sided p values from predictive regressions using value-to-price ratios and scaled prices, dividends, and earnings in a panel data setting. In each regression, dependent variable is the log raw return on the total market index of DataStream, $r_{m,t+1}$. Independent variables are are defined in Table II and III. The regressions employ the randomization method of Nelson and Kim (1993) to correct for small sample bias as identified in Stambaugh (1999). The first row reports the small sample bias-adjusted average slope coefficients and the second row gives the bias-adjusted one-sided p-values in square brackets. ^{a,b,c} indicate significance at the 1%, 5% and 10% level, respectively.

Panel A. Value-to-Price Ratios

	Constant	$\mathbf{d}_t-\mathbf{p}_t$	$\mathbf{d}_t-\mathbf{e}_t$	$\mathbf{e}_t-\mathbf{p}_t$	$\mathbf{r}_{m,t}$	$\mathbf{RREL}_t$
1	0.122^a			0.047^a		
	[0.00]			[0.00]		
2	0.142^a			0.055^a	0.071	0.993
	[0.00]			[0.00]	[0.25]	[0.27]
3	0.141^a	0.038^a				
	[0.00]	[0.00]				
4	0.156^a	0.042^a			0.061	1.012
	[0.00]	[0.00]			[0.32]	[0.28]
5	0.012		0.011			
	[0.25]		[0.10]			
6	0.012		0.011		0.042	0.810
	[0.16]		[0.18]		[0.20]	[0.37]
7	0.185^a	0.027^b		0.032^a		
	[0.00]	[0.02]		[0.00]		
8	0.213^a	0.029^a		0.040^a	0.076	1.138
	[0.00]	[0.00]		[0.00]	[0.18]	[0.16]

Panel B. Normalized Variables

	Constant	$p_t - n_t$	$d_t - n_t$	$e_t - n_t$	$r_{m,t}$	$RREL_t$
1	0.063^b	-0.021^c				
	[0.01]	[0.03]				
2	0.084^a	-0.028^b			0.060	1.038
	[0.00]	[0.01]			[0.24]	[0.31]
3	0.175^a	-0.057^a	0.031^b	0.051^a		
	[0.00]	[0.00]	[0.01]	[0.00]		
4	0.199^a	-0.065^a	0.033^b	0.052^a	0.072	1.128
	[0.00]	[0.00]	[0.01]	[0.00]	[0.17]	[0.25]

Table VI

Controlling for Macroeconomics Variables

In this we use three distinct macroeconomic variables as additional control variables. In each regression, dependent variable is the quarterly log raw return on the total market index of DataStream, $r_{m,t+1}$. Independent variables are are defined in Table II and III. The macroeconomic controls include DEF_t, $TERM_t$ and FED_t. DEF_t is the default spread calculated as the difference between the yields on Baa and Aaa-rated corporate bonds. $TERM_t$ is the term spread calculated as the difference between the yields on the 10-year Treasury bond and the 3-month Treasury bill. FED_t is the Federal Reserve rate. Clustered standard errors are reported in parentheses. [a,b,c] indicate significance at the 1%, 5% and 10% level, respectively.

Panel A. Value-to-Price Ratios w/ Macro Variables									
	Constant	$\mathbf{d_t - p_t}$	$\mathbf{e_t - p_t}$	$\mathbf{r_{m,t}}$	$\mathbf{RREL_t}$	$\mathbf{DEF_t}$	$\mathbf{TERM_t}$	$\mathbf{FED_t}$	$\mathbf{R^2}$
1	0.230^a	0.029^b	0.034^a						3.03%
	(0.054)	(0.012)	(0.012)						
2	0.256^a	0.031^a	0.040^a	0.073	1.159				4.16%
	(0.045)	(0.011)	(0.012)	(0.069)	(1.273)				
3	0.272^a	0.029^a	0.042^a	0.060	2.009	5.458	3.942	-8.087^c	5.46%
	(0.062)	(0.010)	(0.012)	(0.069)	(1.427)	(33.554)	(12.160)	(4.655)	

Panel B. Normalized Variables w/ Macro Variables										
	Constant	$\mathbf{p}_t - \mathbf{n}_t$	$\mathbf{d}_t - \mathbf{n}_t$	$\mathbf{e}_t - \mathbf{n}_t$	$\mathbf{r}_{m,t}$	$\mathbf{RREL}_t$	$\mathbf{DEF}_t$	$\mathbf{TERM}_t$	$\mathbf{FED}_t$	$\mathbf{R}^2$
1	0.124^a	-0.030^b			0.059	0.997				1.43%
	(0.038)	(0.012)			(0.072)	(1.327)				
2	0.248^a	-0.070^a	0.033^a	0.054^a	0.070	1.091				4.33%
	(0.045)	(0.014)	(0.012)	(0.018)	(0.069)	(1.286)				
3	0.097^c	-0.023^b			0.047	2.009	25.490	4.921	-5.553	2.76%
	(0.057)	(0.012)			(0.072)	(1.471)	(34.488)	(12.396)	(4.701)	
4	0.262^a	-0.069^a	0.033^a	0.064^a	0.054	1.990	5.711	4.469	-8.929	5.86%
	(0.062)	(0.013)	(0.010)	(0.019)	(0.069)	(1.434)	(33.828)	(12.107)	(4.798)	

Part II

Stock Price Synchronicity, Diversification and Predictability of Aggregate Stock Returns in International Markets

2.1 Introduction

Predicting market returns using value-to-price variables has been one of the central topics in financial economics. Variables such as earnings yield (E/P), dividend yield (D/P), and book-to-price (B/P) ratio are shown to explain the expected market returns. There have been many studies in the literature with contradicting findings, such as Rozeff (1984), Shiller (1984), Fama and French (1988a, 1989), Campbell and Shiller (1988, 1989), and Hodrick (1992), Kothari and Shanken (1997), Pontiff and Schall (1998), Lamont (1998), and Bali, Demirtas, and Tehranian (2008). All of these studies focus on US market.

Shiller (1984) and Fama and French (1988a, and 1988b) used both dividend yield and earnings yield as predictive variables at the aggregate level, and they found that earnings yield has weak or no predictive power compared to the dividend yield. They assumed aggregate earnings is a nosier proxy for the future cash flows compared to dividends, however they did not test this assumption explicitly. Lamont (1998) on the hand, had a different explanation about the weak predictive power of aggregate earnings yield. Lamont (1998) examines the predictive power of aggregate earnings and price separately, and finds that both the level of earnings and price is negatively related to future market returns. Hence he concludes that earnings yield (E/P) fails to forecast aggregate stock returns because both earnings (E) and price (P) covary negatively with expected returns and their forecasting powers are offsetting.

However, Bali, Demirtas, and Tehranian (2008) show that the findings of Lamont (1998) are data and sample specific, and that the level of aggregate earnings has no predictive power. Bali, Demirtas, and Tehranian (2008) argues that firm-level earnings have systematic and firm-specific (idiosyncratic) components. Although the firm-specific earnings is a good proxy for future cash-flows, the cash-flow information in earnings diversify away by aggregation, and all we are left with at the aggregate level is the systematic earnings which do not contain information about the expected future cash flows. They supported their argument by showing explicitly that the level of earnings has significant and positive coefficients at the firm-level predictive regressions, they also demonstrate that this predictability remain intact in more specific industry level regressions (using Fama and French (1997) 48 industry portfolios); however it gets washed away at the more general industry levels (using Fama and French (1997) 17 industry portfolios) and at the US market level. Hence, they conclude that aggregate earnings may contain information about unsystematic earnings if cash flow news is not fully diversified away by aggregation.

Recently, stock market synchronicity and diversification levels of the market index in international markets have been intensely studied by researchers. Morck et al. (2000) argues that stock price synchronicity is higher in emerging markets with relatively low per-capita GDP and less developed financial systems as opposed to developed countries. The extent to which individual stock prices move independently and the level of diversification vary both across countries and over time. French and Roll (1986) and Roll (1988) argue that a well informed market generate low stock synchronicity. Roll (1992) shows that some national market indices are more diversified than others and argues that technical aspects of index construction might lead different diversification levels for different country indices. In addition, synchronicity in the price movement declines over time within U.S. as well as internationally (Li, Morck, Yang and Yeung (2003), Campbell, Lettau, Malkiel and Xu (2001), Jin and Myers (2006)). In general, the debates focus on whether the markets are efficient or not.[12] The patterns of price synchronicity and diversification levels across countries have never been utilized to explain the difference in the predictive power of yield variables or earnings yield more specifically.

In this paper, we utilize stock price synchronicity and diversification level in a given country, to examine the predictive power of aggregate earnings. We argue that high synchronicity of stocks prohibits the diversification of firm level cash-flow information when earnings are aggregated to form the market-level earnings. Therefore, we argue that aggregate level earnings may still contain information about expected future cash-flows in less diversified or highly synchronous markets. If this is the case, we would expect earnings yield to forecast future returns in highly synchronous and less diversified countries. Indeed, we find that in contrast to the findings in highly diversified and less synchronous countries, earnings yield is a significant predictive variable in more synchronous countries.

The price in the denominator may be responsible for the forecasting power of earnings yield in highly synchronous and less diversified countries. Following Lamont (1998) and Bali, Demirtas, and Tehranian (2008), we consider aggregate earnings not as normalizing variables for stock price but as predictive variables in their own right. Using the Campbell-Shiller log linear decomposition framework, we used normalized earnings and normalized stock price as separate right hand side variables. We show that aggregate

[12] Longin and Solnik (2001) documented that co-movement in stock prices is higher in down markets. Durnev, Morck, Yeung and Yu (2001) found higher association between current return and future earnings among the firms and industries with low market synchronicity supporting the idea that low synchronicity is indicative of information efficiency in the market. In contrast, West (1988) argued that rapid information incorporation reduces idiosyncratic volatility, thereby raising synchronicity. Consistent with West (1988), Chan and Hameed (2006) find that low R2 stocks are smaller and younger with lower institutional ownership, analyst coverage, and liquidity than their high R2 counterparts. These findings suggest that low R2 (high synchronicity) could be indicative of a poor information environment with greater impediments to informed trade.

earnings themselves covary with the market returns in portfolios that consist of highly synchronous and less diversified countries. Hence, it is not just the mean reversion in stock prices that is responsible for the forecasting power of earnings yield.

We specifically compute two measures: Classical price synchronicity measure of Morck et al. (2000) and a Diversification measure of Roll (1992). The classical synchronicity measure determines the percentage of the stocks that are moving in the same direction for each country in a weekly time setting. The diversification measure (the Herfindahl-Firm Index) quantifies the level of firm dominance in the market index on a daily basis. High values of the Herfindahl-Firm Index indicate that the total market index is dominated by a few large firms. For each country, these two distinct measures are formed using a moving window of daily data. Therefore a daily time series diversification and a weekly time series synchronicity measures are formed for each country. Then, we compute the time-series mean of these measures and rank countries according to this mean. The low synchronous (high synchronous) portfolio consists of the countries that have the lowest (highest) 25 percent synchronicity means of our total sample. The high diversification (low diversification) portfolio consists of the countries that have the highest (lowest) 25 percent synchronicity means of our total sample. After constructing our portfolios, we use fixed-effects panel regressions which are effectively stacked time-series regressions for each portfolio.

We show that, earnings yield significantly positively covaries with expected returns *only* in our high synchronous portfolio. Next, normalized variables are constructed similar to the relevant literature, and hence the predictive power of earnings yield in synchronous markets is decomposed into the predictive power of aggregate earnings and that of the price. We demonstrate that aggregate earnings has predictive power in their own right and is positively related to future market returns in high synchronous and less diversified markets as opposed to more diversified and less synchronous markets. Price is negatively related with future market returns in both portfolios indicating the strength of mean reversion. Moreover, these findings are robust when we control for the macroeconomic variables such as interest rate and consumer price index.

The remainder of the paper is organized as follows. Section 2.2 presents the motivation and framework. Section 2.3 explains the data construction process and provides summary statistics. Section 2.4 presents the empirical results. Section 2.5 concludes the paper.

2.2 Motivation and Framework

Bali, Demirtas, and Tehranian (2008) shows that the relation between earnings and expected returns is positive and highly significant at the firm-level. They argue that firm-level earnings consists of systematic earnings (aggregate earnings) and unsystematic earnings (firm-specific earnings) and it is the unsystematic component that is positively correlated with expected stock returns, whereas the systematic portion has no correlation with expected stock returns. They demonstrate that earnings has positive predictive power at the more specific industry level when 48 industry portfolios of Fama and French (1997) are used. However, the predictive power of earnings weakens in more diversified industry level when 17 industry portfolios of Fama and French (1997) are used. And eventually when firm-level earnings are aggregated to generate the market level earnings in highly diversified United States market, the information content of firm-level earnings about future cash flows diversifies away. Hence, the aggregate-level earnings do not have any explanatory power for the market returns in the United States.

Our motivation is to examine the predictive power of earnings at the aggregate level in international markets, where markets are more synchronous and less diversified. To test our argument, following the literature we construct two measures: one stock market synchronicity measure (Morck et al. (2000)) and one diversification measure (Herfindahl-Firm Index (Roll (1992))) for each country. We group countries into high versus low synchronous, as well as high versus low diversification portfolios. We show that earnings yield and aggregate earnings can predict expected market returns in highly synchronous and less diversified markets.

Log linear decomposition of Campbell and Shiller (1988, and 1989) provides insight regarding the cash flow and expected return news components of stock price. In the log linear approximation, we first write log stock return as a function of the end of period price, dividend paid during the period and the beginning of the period price, such that,

$$r_{i,t+1} = \log(P_{i,t+1} + D_{i,t+1}) - \log(P_{i,t}), \tag{8}$$

where $D_{i,t+1}$ denotes dividends for firm i paid during period $t+1$, and $P_{i,t+1}$ is the stock price at the end of period *t+1*. In this setting, raw variables are represented by uppercase letters and log variables are presented in lowercase letters. After using a first-order Taylor series expansion on the return equation we obtain,

$$p_{i,t} = K + E_t\left(\sum_{j=0}^{\infty} \omega^j (1-\omega) d_{i,t+1+j}\right) - E_t\left(\sum_{j=0}^{\infty} \omega^j r_{i,t+1+j}\right), \tag{9}$$

where K is a linearization constant and ω is a constant discount factor close to one. Indeed ω is a function of aggregate dividends. ω is specifically given by $\frac{1}{1+e^{\overline{d-p}}}$, where $\overline{d-p}$ is the average log dividend yield in the data. By using a simple algebraic move, we can write the one period expected returns as:

$$E_t\left(r_{i,t+1}\right) = -p_{i,t} + E_t\left(\sum_{j=0}^{\infty} \omega^j (1-\omega) d_{i,t+1+j}\right) - E_t\left(\sum_{j=1}^{\infty} \omega^j r_{i,t+1+j}\right) + K. \tag{10}$$

Equation (10) gives us a clear relationship between one period ahead expected returns, current price (.i.e., index for the market), expected future cash-flows, and expected future discount rates. Equation (10) makes it clear that there is an inverse relation between price and one period ahead expected returns. We denote the second term on the right hand side of equation (10) as $p^{cash-flow}$, which is the expected sum of future discounted dividends. The third term is denoted by $p^{discount}$, which is the discounted sum of future returns starting next period. In summary, we learn that controlling for the index level, one period ahead expected market returns can be explained by variables that proxy for $p^{cash-flow}$ and/or $p^{discount}$. Lamont (1998) presents equation (10) as:

$$E_t\left(r_{i,t+1}\right) = -(p_{i,t} - n_{i,t}) + (p_{i,t}^{cash-flow} - n_{i,t}) - p_{i,t}^{discount} + K, \tag{11}$$

where $n_{i,t}$ is a normalization factor used to create stationary right-hand side variables. Equation (11) helps us disentangle different forecasting powers of the numerator and the denominator of a cash-flow to price ratio, by using the normalized stock price and the normalized cash flow proxy (i.e., normalized earnings or dividends) as the right-hand side variables. In the classical regression setting, where one period ahead returns are regressed on the earnings yield or the dividend yield, the coefficient estimate of the price and the cash-flow proxy is restricted to be the same. However, in the above setting, the coefficients of the stock price and the cash flow proxy are not restricted to be the same.

We have no priori belief that the mean reversion effect (price effect) would differ accross countries with different synchronicity levels. However, we expect aggregate earnings to contain more information about the cash flow news ($p_{i,t}^{cash-flow}$) in more synchronous and less diversified markets.

2.3 Data

2.3.1 Data Set

The data for daily market returns, price index, dividend yield and earnings yield are obtained from the DataStream Global Equity Indices database. There are 52 countries for which DataStream provides market level information. To be included in our sample, a country must have data for at least 50 firms available at DataStream as of September 2011.[13] We also require more than 30 observations per country in our quarterly regressions.[14] Our final sample consists of 48 countries after applying all of the restrictions.[15] The sample period for index level regressions ranges from 1977:Q2 to 2011Q2,

[13] DataStream has valid stock return data for 18 firms for Czech Republic, 46 firms for Ireland and 30 firms for Luxembourg as of September 2011. Hence these countries are dropped from our sample.

[14] Data for Bulgaria starts on October, 2000. We use log of the average of the past five years of annual earnings as our normalization variable. Therefore the data for Bulgaria in our quarterly regressions is limited between 2005:Q2 and 2011:Q2, resulting in 25 observations. For this reason, Bulgaria has also been dropped from our sample.

[15] Final sample consists of Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Cyprus, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Israel, Italy, Japan, Korea, Malaysia, Mexico, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Romania, Russia, South Africa, Singapore, Slovenia, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom, United States and Venezuela.

yielding an unbalanced panel data with a total of 4,557 quarters, where the last five years of data were available for each country. On average, there are 95 quarters per country[16] the longest sample period is 137 quarters for most of the developed countries, whereas the shortest is Brazil with 32 quarters.

In order to calculate the synchronicity and diversification measures, we obtain daily with-dividend stock returns and firm-level market value data also from DataStream. Our total cross section for 2011 thus contains 28,344 firms spanning 48 countries.

2.3.2 Construction of Variables

For each market, the total market index of DataStream Global Index (TOTMK) is used as the national market index.[17] The TOTMK series of DataStream is a value-weighted index where weightings are allocated on the basis of market capitalization. Log raw return ($\mathrm{r}_{i,t}$) is the log of quarterly returns that are constructed by compounding daily returns. Quarterly price index, dividend yield and earnings yield are obtained using end of quarter values. Log dividend yield ($\mathrm{d}_{i,t}-\mathrm{p}_{i,t}$) is the log of the ratio of sum of the past year's total dividends to price and log earnings yield ($\mathrm{e}_{i,t}-\mathrm{p}_{i,t}$) is the log of the ratio of sum of the past year's total earnings to price.

The log normalization variable is computed in order to analyze the individual effects of price, dividends and earnings, following Lamont (1998) and Bali et al. (2008). We use log of the average of the past five years of

[16]These statistics are for the full sample when all 48 countries are together. For high synchronicity and low diversification portfolios that consist of 12 countries, total numbers of quarters are approximately 1,100 and the average number of quarters per country never falls below 60.

[17]In DataStream, indices are calculated on a representative list of stocks for each market. The number of stocks for each market is determined by the size of the market. The sample covers a minimum of 75% - 80% of total market capitalization.

annual earnings per share, as the normalization variable. The main goal of the normalization variable is to create stationary variables. Our choice of this specific normalization variable exactly follows the literature.

As for our first synchronicity measure, we compute the classical synchronicity measure advocated by Morck et al. (2000). This measure analyses market-wide price movements in a week and focuses on the tendency of stocks that move in the same direction across in one market. The following equation illustrates the synchronicity measure,

$$f_{jt} = \frac{\max\left[n_{jt^{up}}, n_{jt^{down}}\right]}{n_{jt^{up}} + n_{jt^{down}}}, \tag{12}$$

where $n_{jt^{up}}$ is the number of stocks in country j whose prices rise in week t, and $n_{jt^{down}}$ is the number of stocks whose prices fall. We drop stocks whose prices do not move to avoid bias due to non-trading. This measure is bounded to lie between 0.5 and 1.0 by construction. A maximum of 1.0 would mean a perfectly synchronized market, where all shares are moving in the same direction within that week. On the other hand, a minimum of 0.5 would indicate the least possible synchronized market. Our synchronicity measure is calculated for 48 countries, covering the period between January 1973[18] and December 2010. In terms of the classical synchronicity measure, it is the longest time-series as well as the widest cross-sectional one in the literature.[19]

Before ranking each country according to its synchronicity measure, we calculate

[18]The beginning date for each country differs, depending on the introduction of the stock market date in one country and data availability in DataStream. For most of the developed countries this is January 1973, whereas for emerging markets it is around late 1980s. Brazil has the shortest period in our sample starting January 1992.

[19]Note that Morck et al. (2000) covered 40 countries for the year of 1995.

$$f_j = \frac{1}{T}\sum_{t=1}^{T}\frac{\max\left[n_{jt^{up}}, n_{jt^{down}}\right]}{n_{jt^{up}} + n_{jt^{down}}} = \frac{1}{T}\sum_{t=1}^{T} f_{jt}, \tag{13}$$

where T is the total number of weeks country j has in our sample. f_j is defined as the average value of f_{jt}, across weeks.

As for our second measure, we calculate the Herfindahl-Firm index, following Roll (1992).[20] If w_{ijt} is the market value proportion of country j's index represented by stock i on day t, the Herfindahl measure is given by

$$H_{jt} = \sum_{i=1}^{n} w_{ijt}^2. \tag{14}$$

As a result, we obtain an H_{jt}, that represents the firm dominance of the market index for each country j on each day t. The minimum value of H_{jt} is 1/n where n is the total number of stocks in country j on day t. The maximum possible value of H_{jt} is 1.0, which would imply that the total market index consists of one stock, and hence dominated only by one firm. The higher the H_{jt} is, the lower the diversification of the market index is in one country. As the number of stocks increase over time, H_{jt} mostly[21] has a decreasing trend in time-series for each country, indicating higher levels of diversification over time.

Before ranking each country according to its diversification measure, we calculate

[20] For a general discussion of the Herfindahl measure, see Stigler (1968), Chapter 4.

[21] H_{jt} does not have to decrease each time the number of stocks increase. As stated in the computation of H_{jt}, it depends on the concentration of market value of each firm in the index, therefore it does not decrease on a steady basis, however if we compare the first day H_{jt} of each country with the most recent date in our sample, it is becoming lower for each country, indicating higher levels of diversification over time.

$$H_j = \sum_{t=1}^{T}(\sum_{i=1}^{n} w_{ijt}^2) = \frac{1}{T}\sum_{t=1}^{T} H_{jt}. \qquad (15)$$

where T is the total number of days country j has in our sample. H_j is defined as the average value of H_{jt}, across days (which is time-series mean).

2.3.3 Summary Statistics

Table 1 shows the time-series statistics of our stock market synchronicity and diversification measures for each country. Mean, standard deviation, quartiles, skewness, kurtosis and total number of observations are reported for the data set. Panel A reports the summary statistics for the synchronicity measure and Panel B reports the summary statistics for Herfindahl-Firm Index which is our diversification measure.

In Panel A, countries are sorted according to the time-series mean of their synchronicity measure which is calculated weekly.[22] Canada is the least synchronous country in our sample, where on average only 60.43 percent of the total stock market in a week is moving in the same direction. It is followed by other developed markets such as Australia, Germany and United States, with 62.37 percent, 62.57 percent and 63.06 percent stocks comovement in an average week. As we can see in Panel A, most developed markets happen to be less synchronous than most of the emerging markets, which was first documented by Morck et al. (2000). The most synchronous country is China in our sample, with an average of 76.54 percent stock price synchronicity in a week. The synchronicity measure difference between the mean of Canada and China is 16.11 percent, even though this may not seem to be a large

[22] Sorting countries according to the median does not change the results in a significant way.

difference economically, note that this measure is bounded to lie between 50 percent (zero synchronicity) and 100 percent (fully synchronous behavior). Another reason for the seemingly low difference across countries is that most of the variation is lost during the process of taking the time-series average of the weekly values.

Our stock price synchronicity measure in Panel A is more volatile in more synchronous countries. The standard deviations tend to increase with the level of average synchronicity; it is only 8.41 percent for Canada, where it gets as high as 14.66 percent for the most synchronous country China. The time-series median values are very close to the mean values for each country; Canada has the lowest median of 58.37 percent synchronicity, where China has the highest median of 76.33 percent.[23] Finally the last column gives the total number of weeks for each country in our sample. For most of the developed countries, the sample period contains 1992 weeks where their firm level information is available at DataStream starting in January 1973.

Panel B shows the countries that are sorted according to the time-series mean of their diversification measure which is calculated daily.[24] Japan is the most diversified country in our sample, which has a Herfindahl-Firm Index of 0.0091. It is followed by United States, with a average Herfindahl-Firm Index of 0.0135 on a daily basis. As can be seen in Panel B, most of the developed markets have higher diversification levels measured by the firm dominance of the market index. The least diversified country is Norway in our sample, with an average of 0.3684 Herfindahl Index.

Identical to our synchronicity measure, the standard deviations tend to in-

[23]Note that the difference between the lowest and highest synchronicity countries is 17.96 percent when the medians are compared.

[24]Sorting countries according to the median does not change the results in a significant way.

crease with the level of average Herfindahl-Index; it is only 0.0051 for Japan, where it gets as high as 0.2826 for the least diversified country Norway. Herfindahl Index in Panel B is more volatile in countries whose market index is the least firm dominated. The time-series median values are very close to the mean values for each country; Japan has the lowest median of 0.0072, where Norway has the second highest median of 0.2672 percent. Finally the last column gives the total number of daily observations for each country in our sample. For most of the developed countries, the sample period has 9903 days where their firm level information is available at DataStream starting in January 1973.

2.4 Empirical Results

2.4.1 Forecasting Market Index Return in Full Sample

To test whether one-quarter ahead market returns can be predicted with value-to-price ratios in our full sample which consists of 48 countries, we use panel fixed effects regressions:

$$r_{j,t+1} = a_j + \lambda X_{j,t} + \xi_{j,t+1}, \tag{16}$$

where $r_{j,t+1}$ is the log return for country j at time t+1 (j=1,2,...,48). Earnings yield and dividend yield are used as independent variables and lagged return, interest rate, nominal effective exchange rate and log of gross domestic product are used as control variables.

As stated by Ferson, Sarkissian and Simin (2003), since persistent dependent variables may result in a spurious regression, the lagged dependent variable is added as a control variable. In order to correct for the contemporaneous cross-sectional correlation of error terms problem, we use Rogers' (1983, 1993) method for computing standard errors in the existence of heteroskedasticity and contemporaneous cross-correlations. In a panel data setting, the variance covariance matrix of the error terms can be viewed as a combination of small variance covariance matrices of each country. And aside from the autocorrelation of the error terms within each country, there is a contemporaneous cross-sectional correlation. If this problem is uncorrected, it can inflate the t-stats by a significant amount. In the above equation, the slope coefficient (λ) along with its clustered standard errors determines whether there is a significantly positive or negative relation between the value-to-price ratios and expected returns at the market level.

The distinguishing point in the panel fixed effects regressions defined above is that the intercepts (a_j) are estimated separately for each country j. Estimating intercepts separately is equivalent to demeaning each country level data and ensures that each country's error term is orthogonal to the explanatory variables for that country. Thus, in fixed-effects panel data regression setting, the results reflect the time-series relation between the dependent variable and the independent variables.

In Panel A of Table 2, the first and second row indicates the univariate forecasting power of earnings yield and dividend yield in the presence of lagged return. Both dividend yield and earnings yield are highly significant and has a positive coefficient in predicting expected returns at the aggregate level (with a t-stat of 3.21 and 3.20 respectively). Third row shows that using both the dividend yield and the earnings yield in a bivariate setting, dividend yield still has positive and significant coefficient and the earnings yield becomes marginally significant (with a t-stat of 2.68 and 1.86 respectively). Adding the control variables in the last five rows, does not affect the results.

We find that dividend yield has a significant predictive power for expected stock returns whereas earnings yield is marginally significant. It may be the mean-reversion in stock prices alone driving the forecasting power of yield variables in our full sample. Next section examines the source of this finding by using normalized variables.

In Panel B of Table 2, we consider aggregate earnings and dividends not as normalizing variables for price but as predictive variables in their own right. Following the method in Panel A, we use fixed effect regressions to show the parameter estimates and the clustered t-statistics from the predictive regressions using scaled prices, dividends, and earnings.

The first row of Panel B shows that the scaled price has a negative and highly significant coefficient (with a t-stat of -2.99), indicating the presence of mean-reversion at the index level in our full sample. In Row 2, when aggregate earnings is used in a univariate setting, we see that the marginal predictive power of earnings yield was actually a result of the mean reversion of the price in the denominator, since aggregate earnings has no predictive power at the market level in our full sample of 48 countries. Row 3 is showing one of the benchmark regressions of this study, where the decomposition equation is implemented. In the classical regression setting in Panel A, where one period ahead returns are regressed on the earnings yield or the dividend yield, the coefficient estimate of the price and the cash flow proxy is restricted to be the same. However, in the setting shown in equation (4), the coefficients of the stock price and the cash flow proxy are not restricted to be the same. The scaled price has a negative and significant coefficient with a t-stat of -3.38, implying the strong mean reversion as in the univariate setting. Yet, scaled aggregate earnings still has no predictive power (with a t-stat of 0.62). The results remain the same after including the control variables, scaled price is strongly negatively correlated with one quarter ahead market returns (with a t-stat of -3.19), dividends are positively correlated (with a t-stat of 1.99) and aggregate earnings has no predictive power in our full sample where both developed countries and emerging markets are pooled in the same panel data. In the next sections, we will examine whether the results remain the same once we group countries according to their synchronicity and diversification level.

2.4.2 Forecasting Market Index Return in High vs. Low Synchronous Portfolios

We have so far provided evidence in Panel B of Table 2, that there is no significant relation between aggregate earnings and expected returns at the market level in our full sample. In this section, we analyze the predictive power of earnings yield and aggregate earnings at the market level once we group countries into low versus high synchronous portfolios according to their average stock market synchronicity.

Previous literature shows that the relation between earnings and expected returns is positive and highly significant at the firm-level (Bali, Demirtas, and Tehranian (2008)). The question is whether the positive predictive power of firm level earnings can be brought to the aggregate level, if markets are more synchronous. In countries where stock price synchronicity is higher, we expect the fundamentals' comovement to be higher.[25] If this is the case, the information content of firm-level earnings about future cash flows is not fully diversified away and higher aggregate earnings forecasts higher returns in highly synchronous countries. To test this, we first calculate:

[25] Morck et al. (2000) shows that the high stock price synchronicity in low income countries can be partially explained by the higher fundamentals' comovement, according to their sample in 1995.

$$f_j = \frac{1}{T}\sum_{t=1}^{T}\frac{\max\left[n_{jt^{up}}, n_{jt^{down}}\right]}{n_{jt^{up}} + n_{jt^{down}}} = \frac{1}{T}\sum_{t=1}^{T} f_{jt}, \tag{17}$$

where T is the total number of weeks country j has in our sample. f_j is defined as the average value of f_{jt}, across weeks (which is time-series mean). Thus, we have an average synchronicity measure for each country. 48 countries are ranked according to this measure, which ranges from 60.4 percent to 76.54 percent in our full sample.

The low synchronous portfolio consists of 12 countries, which rank in the bottom 25 percent of our full sample with their average synchronicity measures.[26] Our stock price synchronicity measure ranges between 60.43 percent (Canada) and 65.08 percent (Chile) in our portfolio that is named as low synchronous portfolio. The high synchronous portfolio also consists of 12 countries, which rank in the top 25 percent of our full sample with their average synchronicity measures.[27] The lowest average synchronicity in our high synchronous portfolio is 70.12 percent (Austria) and the highest is 76.54 percent (China), implying that at least 70.12 percent of the stocks are moving in the same direction on an average week in our high synchronous portfolio. Once we group the countries into different synchronicity portfolios, we repeat the analysis in Part A and run the fixed effects panel regressions for each of these portfolios.

In Panel A of Table 3, we test whether one-quarter ahead market returns can be predicted with value-to-price ratios in our low synchronous portfolio. The panel fixed effects regression (in Equation 9) is applied where the dependent variable, $r_{j,t+1}$, is the one quarter ahead market return and the

[26] The low synchronous portfolio includes Canada, Australia, Germany, United States, Belgium, France, Japan Portugal, Israel, Brazil, Holland and Chile.

[27] The high synchronous portfolio consists of Austria, Slovenia, Poland, Denmark, Singapore, Argentina, Venezuela, Malaysia, Turkey, Taiwan, Phillipines and China.

independent variables are dividend yield and earnings yield. The current quarter's market return is added as a control variable. The first row shows the predictive power of earnings yield in a univariate setting controlling for the lagged return. Earnings yield is positively and significantly correlated with one quarter ahead market returns with a t-stat of 2.06. However, in the second row, once we include the dividend yield, the positive forecasting power of earnings yield diminishes away, and the dividend yield is only marginally significant (with a t-stat of 1.75) in predicting the expected returns. To better see the predictive power of aggregate earnings, and dividends in the low synchronous portfolio, we consider them not as normalizing variables for price but as predictive variables in their own right in the next section.

Panel B of Table 3, presents the results of the panel fixed effects regression in low synchronous portfolio where the independent variables are scaled prices, dividends, and earnings and the dependent variable is one quarter ahead market return. The first row of Panel B, illustrates that scaled price is negatively and significantly correlated with expected returns (with a t-stat of -2.02) whereas normalized aggregate earnings has no predictive power at all in the low synchronous portfolio. This finding proves that the positive predictive power of earnings yield in the first row of Panel A, was solely a result of the price in the denominator, which is the mean reversion. In the second row, after including the dividends, results remain the same, there is strong mean reversion (t-stat of -2.08), however there is no correlation between aggregate earnings and expected returns at the market level in our low synchronous portfolio.

In Panel C of Table 3, one quarter ahead market return is regressed on value-to price ratios in our high synchronous portfolio using panel fixed effects regression (in Equation 9). The independent variables are dividend yield and earnings yield; and lagged return is used as a control variable. In the first row of Panel C, earnings yield is a statistically significant (with a t-stat of 3.26) predictor of expected returns in a univariate setting. The second row of Panel C shows that earnings yield remains to be highly statistically significant (t-stat of 2.63) even after controlling for the dividend yield. This very last result is the evidence that earnings yield contains information about future cash flows above and beyond dividend yield in countries where markets are highly synchronous. However, this may very well be the result of stronger mean reversion in synchronous markets.

Panel D of Table 3, shows the fixed effects regression (in Equation 9) results, where scaled price, dividends and earnings are used as independent variables in predicting expected market returns in high synchronous portfolio. Thus, we can see whether it is merely the stronger mean reversion in the denominator, or both the aggregate earnings and the price have played a role in the strong predictive power of earnings yield in the Panel C of Table 3 results. The first row of Panel D reveals that there is the strong mean reversion (scaled price has a t-stat of -3.26) as well as the strong positive predictive power of aggregate earnings (normalized earnings has a t-stat of 2.37) in highly synchronous markets. The second row shows that our results remain robust after adding the normalized dividends to the regression. In our high synchronous portfolio, which consists 12 countries that has the highest synchronicity levels among 48 markets, aggregate earnings can significantly predict one quarter ahead market returns (with a t-stat of 2.19) as opposed to the case in low synchronous portfolio. Scaled price is negatively correlated with expected returns with a t-stat of -3.34, whereas normalized dividends has no correlation with expected returns at all. Second row of Panel D is the evidence that aggregate earnings itself contain information about expected market returns above and beyond dividends in highly synchronous markets. Overall, the results in Panel A through Panel D of Table 3 show that the positive predictive power of firm level earnings can be brought to the aggregate level, if markets are more synchronous.

2.4.3 Forecasting Market Index Return in Portfolios with High vs. Low Diversification Levels

As stated earlier, previous literature (Bali, Demirtas, and Tehranian (2008)) shows that firm-level earnings consists of systematic earnings (aggregate earnings) and unsystematic earnings (firm-specific earnings). And it is the unsystematic component that is positively correlated with expected stock returns, whereas the systematic portion has no correlation. Bali, Demirtas, and Tehranian (2008) also states that when firm-level earnings are aggregated to generate the market level earnings, the information content of firm-level earnings about future cash flows diversifies away. Hence, the aggregate-level earnings do not have any explanatory power for the market returns in the United States.

In this section, we examine whether the unsystematic portion of firm level earnings, which contains information about future cash flows, can be brought to the aggregate level in international markets if markets are less diversified. To analyze the predictive power of earnings yield and aggregate earnings in high versus low diversification portfolios, first we calculate:

$$H_j = \sum_{t=1}^{T}(\sum_{i=1}^{n} w_{ijt}^2) = \frac{1}{T}\sum_{t=1}^{T} H_{jt}. \tag{18}$$

where T is the total number of days country j has in our sample. H_j is defined as the average value of H_{jt}, across days (which is time-series mean).

Thus, a Herfindahl-Firm Index which quantifies the degree of firm dominance is computed for each country. The smaller the Herfindahl-Index, the higher the level of diversification of the market index is. 48 countries are ranked according to this measure, which takes on values between 0.0091 (Japan) and 0.3684 (Norway) in our full sample.

The high diversification portfolio consists of 12 countries, which have the lowest Herfindahl-Index, ranking in the bottom 25 percent of our full sample with.[28] Our diversification measure ranges between 0.0091 (Japan) and 0.0676 (Germany) in our high diversification portfolio. The low diversification portfolio also consists of 12 countries, which have the highest Herfindahl-Index (hence have the highest firm dominance, and therefore the lowest diversification), ranking in the top 25 percent of our full sample.[29] The lowest average Herfindahl-Index in our low diversification portfolio is 0.2059 (Peru) and the highest is 0.3684 (Norway). Once we group the countries into high versus low diversification portfolios, we repeat the analysis in Part A and Part B and run the fixed effects panel regressions.

In Panel A of Table 4, we test whether one-quarter ahead market returns can be predicted with value-to-price ratios in our high diversification portfolio. The panel fixed effects regression (in Equation 9) is applied where the dependent variable, $r_{j,t+1}$, is the one quarter ahead market return and the independent variables are dividend yield and earnings yield. The lagged market return is added as a control variable. The first row shows the predictive power of earnings yield in a univariate setting. Earnings yield can predict one quarter ahead market returns with a t-stat of 2.88. However, once we

[28] The high diversification portfolio includes Japan, United States, Taiwan, Thailand, China, United Kingdom, France, Canada, Sri Lanka, Indonesia, Hong Kong and Germany.

[29] The low diversification portfolio consists of Peru, Argentina, Turkey, Poland, Finland, India, New Zealand, Hungary, Romania, Brazil, Philippines and Norway.

include the dividend yield in the second row, the positive forecasting power of earnings yield no longer exists, and the dividend yield becomes significant (with a t-stat of 2.00) in predicting the expected returns. In order to be able to analyze whether this versatile predictive power of the yield variables is actually driven by the price in the denominator, we consider scaled price, dividends and earnings as predictive variables in their own right in the next section.

Panel B of Table 4, shows the results of the fixed effects regression in high diversification portfolio where one quarter ahead market return is regressed on normalized prices, dividends, and aggregate earnings. The first row of Panel B, presents that scaled price is negatively and significantly correlated with expected returns (with a t-stat of -3.12) whereas normalized aggregate earnings has no predictive power at all in our high diversification portfolio. This finding is the evidence that the positive predictive power of earnings yield in the first row of Panel A, was merely a result of the price in the denominator. In the second row, after including the dividends, scaled price continues to predict expected market returns with a t-stat of -3.12; however there is no correlation between aggregate earnings and expected returns at the market level in our high diversification portfolio.

In Panel C of Table 3, one quarter ahead market return is regressed on value-to price ratios in our low diversification portfolio using fixed effects regression (in Equation 9). The independent variables are dividend yield and earnings yield; and the lagged return is used as a control variable. In the first row of Panel C, earnings yield is a statistically significant predictor of expected returns with a t-stat of 3.86 in a univariate setting. The second row of Panel C shows that earnings yield remains to be highly statistically significant (t-stat of 3.66) even after controlling for the dividend yield. This preceding finding is the evidence that earnings yield contains information about future cash flows above and beyond dividend yield in countries where markets are significantly less diversified.

Panel D of Table 3, shows the fixed effects regression (in Equation 9) results, where scaled price, dividends and earnings are used as independent variables in predicting expected market returns in our low diversification portfolio. Therefore, it can be better seen whether it is purely the stronger mean reversion in the denominator which is responsible for the strong predictive power of earnings yield in the Panel C of Table 4 results. The first row of Panel D confirms that there is the strong mean reversion (scaled price has a t-stat of -3.37) as well as the very strong positive predictive power of aggregate earnings with a t-stat of 2.45 in less diversified markets. The second row shows that our results remain intact after adding the normalized dividends to the regression. In our low diversification portfolio, which consists 12 countries with the lowest diversification levels (measured by the degree of firm dominance of the index) among 48 markets, aggregate earnings can significantly predict one quarter ahead market returns (with a t-stat of 2.39) as opposed to the case in highly diversified markets. Scaled price is negatively correlated with expected returns with a t-stat of -3.22, whereas normalized dividends are only weakly correlated with expected returns (with a t-stat of 1.81). Second row of Panel D is the second evidence that the positive predictive power of firm level earnings can be brought to the aggregate level, if markets are less diversified.

2.4.4 Controlling for Macro Economic Variables

Table 5 uses two additional control variables. These control variables are used to make sure that our results are not affected by model misspecification; we add a set of control variables (X_t) that are expected to have an empirical relation with the market return in international markets. There is a large body of literature indicating that the aggregate returns can be predicted by macroeconomic variables associated with business cycle fluctuations. Merton's (1973) ICAPM also indicates that hedging demand components identify time-series of expected returns.

Following the relevant literature, we use the interest rate (INT) and Consumer Price Index (CPI) as additional controls. We obtained INT and CPI from the International Financial Statistics (IFS). INT is the quarterly discount rate (available money market rate) which is constructed by compounding daily discount rates for each country. Quarterly CPI data is computed as the end of quarter values which measures the rate at which the prices of consumer goods and services are changing over time. Finally, we include the lagged return in our regressions to control for the serial correlation in quarterly index returns.

Panel A and Panel B of Table 5 show estimation results for normalized variables in low synchronous and high synchronous portfolios, respectively. As seen in these regressions, addition of control variables causes R-squares to go up. The scaled price remains to be the only predictor of expected returns in low synchronous portfolio (aggregate earnings has no predictive power) as in Panel B of Table 3. Whereas in high synchronous portfolio (in Panel B of Table 5), besides the mean reversion, there is the robust predictive power of normalized earnings even after adding the control variables.

In Panel C of Table 5, scaled price continues to be the only predictor of expected returns in high diversification portfolio and aggregate earnings has no predictive power, confirming our previous results (in Panel D of Table 4). And Panel D reveals that in low diversification portfolio, aggregate earnings maintains to be positively and significantly correlated with one quarter ahead returns at the market level even after we control for the macroeconomic variables. [30] The robustness of our results show that at the aggregate-level, if the markets are significantly less diversified or if the markets are highly synchronous, the information content of firm-level earnings about future cash flows is not fully diversified away and higher aggregate earnings forecast higher returns.

2.5 Conclusion

We examine the explanatory power of earnings yield and aggregate earnings in forecasting market level expected returns in international markets. Relevant literature argues that, in US, aggregate earnings do not contain any information at the market level about expected future cash-flows. Because any cash-flow information contained in firm-level earnings gets diversified away due to aggregation when market level earnings are formed. This is due to lower comovement of stocks (low stock price synchronicity) and highly diversified nature of the US market index. In this paper, we show that in contrast to low synchronous and highly diversified markets, earnings yield significantly positively covaries with expected returns in high synchronous and less diversified countries. Next, normalized variables are constructed similar to the relevant literature, and hence the predictive power of earnings yield in synchronous and highly diversified markets is decomposed into the predictive power of aggregate earnings and that of the price. We prove that aggregate earnings has predictive power in their own right and is positively related to future market returns in high synchronous and less diversified mar-

[30] To save space, in Table 5 only normalized variables is presented. The results remain robust also for value-to-price ratio regressions and can be provided upon request.

kets as opposed to low synchronous and more diversified markets. Price is negatively related with future market returns in both portfolios indicating the strength of mean reversion.

Our results indicate that when firm-level earnings are aggregated to generate the market-level earnings, whether the information content of firm-level earnings about future cash flows diversifies away depends on the level of the synchronicity and diversification in one market. We argue that due to high levels of fundamentals' co-movement in synchronous markets, the predictive component of the firm-level earnings (unsystematic earnings) is not fully diversified away at the market level. Thus, there exists a positive and significant relation between aggregate earnings and expected returns. Moreover, these findings are robust when we control for the macroeconomic variables such as interest rate and consumer price index.

Table I
Summary Statistics

Panel A shows the descriptive statistics of the price synchronicity measure for each country. We calculate $f_{jt} = \frac{\max\left[n_{jt^{up}}, n_{jt^{down}}\right]}{n_{jt^{up}} + n_{jt^{down}}}$ following Morcket. al. (2000), where $n_{jt^{up}}$ is the number of stocks in country j whose prices rise in week t, and $n_{jt^{down}}$ is the number of stocks whose prices fall. We drop stocks whose prices do not move to avoid bias due to non-trading. Panel B shows the descriptive statistics of our diversification measure for each country. It is calculated following Roll (1992). We calculate$H_{jt} = \sum_{i=1}^{n} w_{ijt}^2$ w_{ijt} is the market value proportion of country j's index represented by stock i on day t. Column 1 is the mean. Column 2 is the standard deviation. Column 3 is the first quartile. Column 4 is the median. Column 5 is the third quartile. Column 6 is the maximum value. Column 7 is the skewness. Column 8 is the kurtosis. And the last column (N) gives the total number of weeks (Panel A)/days (Panel B) in our sample.

Panel A

Country	Mean	Std Dev	q1	q2	q3	Skewness	Kurtosis	N
Canada	0.6043	0.0841	0.5423	0.5837	0.6468	1.2253	4.4658	1992
Australia	0.6237	0.1004	0.5426	0.5984	0.6835	0.9932	3.3934	1992
Germany	0.6257	0.0974	0.5455	0.6034	0.6878	0.9054	3.2687	1992
United States	0.6306	0.0907	0.5561	0.6141	0.6908	0.7500	3.1071	1992
Belgium	0.6331	0.0990	0.5556	0.6111	0.6889	0.9310	3.5218	1992
France	0.6379	0.1081	0.5500	0.6136	0.7021	0.9254	3.1760	1992
Japan	0.6441	0.1064	0.5593	0.6214	0.7138	0.8706	3.3856	1992
Portugal	0.6447	0.1020	0.5600	0.6279	0.7143	0.6230	2.6688	1203
Israel	0.6482	0.1030	0.5624	0.6317	0.7152	0.6461	2.7958	1310
Brazil	0.6487	0.1090	0.5613	0.6372	0.7143	0.9887	4.1569	887
Holland	0.6498	0.1074	0.5591	0.6304	0.7222	0.6834	2.7567	1992
Chile	0.6508	0.1029	0.5641	0.6364	0.7253	0.5651	2.6635	1126
New Zealand	0.6519	0.1329	0.5556	0.614	0.7143	1.2472	3.9242	1285
Switzerland	0.6524	0.1067	0.5633	0.6364	0.7225	0.6933	2.8780	1992
United Kingdom	0.6555	0.1138	0.5602	0.6321	0.7321	0.6442	2.4847	1992

Table 1-Continued

Panel A

Country	Mean	Std Dev	q1	q2	q3	Skewness	Kurtosis	N
S. Africa	0.6560	0.1189	0.5576	0.6307	0.7333	0.7964	2.9049	1992
Indonesia	0.6590	0.1085	0.5669	0.6456	0.7345	0.5541	2.5602	1076
Thailand	0.6624	0.1045	0.5795	0.6495	0.7303	0.5621	2.7821	1256
Sweden	0.6642	0.1148	0.5667	0.6462	0.7404	0.5972	2.5911	1517
Pakistan	0.6651	0.1130	0.5735	0.6522	0.7313	0.7425	3.2372	1003
Italy	0.6705	0.1154	0.5762	0.6538	0.7560	0.4925	2.4123	1992
Finland	0.6714	0.1273	0.5672	0.6517	0.7434	0.8033	3.0679	1256
Cuprus	0.6784	0.1306	0.5714	0.6582	0.7500	0.8111	2.9757	939
Sri Lanka	0.6793	0.1186	0.5811	0.6632	0.7561	0.5984	2.7717	1255
Hong Kong	0.6836	0.1217	0.5808	0.6678	0.7778	0.4260	2.2280	1992
Romania	0.6837	0.1292	0.5778	0.6667	0.7576	0.6766	2.8669	781
Mexico	0.6845	0.1152	0.5938	0.6738	0.7692	0.3800	2.4060	1204
Hungary	0.6847	0.1384	0.5779	0.6667	0.7619	0.7560	2.7987	1044
Spain	0.6854	0.1316	0.5769	0.6667	0.7679	0.6389	2.7164	1308
Norway	0.6859	0.1572	0.5577	0.6471	0.7778	0.7629	2.4685	1989
Greece	0.6886	0.1215	0.5848	0.6793	0.7806	0.3399	2.1970	1204
India	0.6953	0.1422	0.5750	0.6706	0.7788	0.6894	2.5988	1196
Russia	0.6975	0.1458	0.5714	0.6687	0.7895	0.5950	2.4329	792
Colombia	0.6977	0.1259	0.5862	0.6923	0.7931	0.3340	2.2402	995
Korea	0.6990	0.1477	0.5749	0.6687	0.7878	0.6540	2.4470	1581
Peru	0.7011	0.1160	0.6082	0.7020	0.7846	0.2188	2.3968	1046
Austria	0.7012	0.1555	0.5714	0.6667	0.8333	0.6636	2.2554	1991

Table 1-Continued

Panel A

Country	Mean	Std Dev	q1	q2	q3	Skewness	Kurtosis	N
Slovenia	0.7059	0.1454	0.6000	0.7000	0.8000	0.4576	2.2436	686
Poland	0.7077	0.1630	0.5741	0.6667	0.8174	0.6628	2.1673	1019
Denmark	0.7096	0.1613	0.5741	0.6628	0.8421	0.6037	2.0065	1990
Singapore	0.7126	0.1369	0.5991	0.7006	0.8168	0.3034	2.0872	1992
Argentina	0.7213	0.1466	0.6000	0.7021	0.8286	0.3984	2.1339	1199
Venezuela	0.7215	0.1467	0.6000	0.7143	0.8333	0.3811	2.1041	1100
Malaysia	0.7223	0.1512	0.6040	0.6807	0.8333	0.4575	2.1602	1992
Turkey	0.7310	0.1316	0.6185	0.7324	0.8411	0.0458	1.9359	1191
Taiwan	0.7432	0.1473	0.6105	0.7382	0.8727	0.1016	1.7882	1221
Philippines	0.7485	0.1723	0.5971	0.7143	0.9091	0.2958	1.6833	1557
China	0.7654	0.1466	0.6436	0.7633	0.8951	-0.0366	1.8504	1025

Table I -Continued

Panel B

Country	Mean	Std Dev	q1	q2	q3	Skewness	Kurtosis	N
Japan	0.0091	0.0051	0.0066	0.0072	0.0093	3.1842	14.4166	9903
United States	0.0135	0.0115	0.0077	0.0107	0.0177	3.2620	36.3790	9903
Taiwan	0.0314	0.0289	0.0197	0.0227	0.0303	4.0164	20.1653	6072
Thailand	0.0325	0.0407	0.0192	0.0206	0.0243	4.9133	29.5621	6249
China	0.0415	0.1131	0.0061	0.0118	0.0262	4.7988	26.0747	5206
United Kingdom	0.0427	0.0162	0.0285	0.0384	0.0551	0.7108	2.7161	9903
France	0.0443	0.0144	0.0330	0.0406	0.0510	0.9885	3.1351	9903
Canada	0.0518	0.0379	0.0206	0.0434	0.0713	1.3116	5.2401	9903
Sri Lanka	0.0534	0.1218	0.0266	0.0306	0.0473	7.5122	58.4158	6243
Indonesia	0.0541	0.0181	0.0416	0.0511	0.0624	1.5464	7.7572	5403
Hong Kong	0.0661	0.0244	0.0397	0.0692	0.0854	0.1528	2.0237	9903
Germany	0.0676	0.0310	0.0464	0.0610	0.0719	1.1690	3.6573	9903
Sweden	0.0732	0.0329	0.0465	0.0703	0.0885	1.5398	6.8235	7553
Australia	0.0749	0.0333	0.0466	0.0710	0.0971	0.3163	2.1567	9903
Greece	0.0754	0.0426	0.0481	0.0543	0.0923	1.6129	4.8322	5988

Table 1-Continued

Panel B

Country	Mean	Std Dev	q1	q2	q3	Skewness	Kurtosis	N
S. Africa	0.0759	0.0479	0.0329	0.0414	0.1223	0.4989	1.7644	9903
Singapore	0.0837	0.0318	0.0573	0.0836	0.1135	-0.0170	1.8369	9903
Switzerland	0.0920	0.0263	0.0766	0.0872	0.0976	1.9822	7.7198	9903
Mexico	0.0924	0.0402	0.0639	0.0731	0.1131	1.4246	4.3825	5988
Denmark	0.0963	0.0308	0.0739	0.0874	0.1103	1.4563	5.4267	9903
Belgium	0.1004	0.0252	0.0771	0.1006	0.1188	0.4158	2.3621	9903
Pakistan	0.1017	0.0848	0.0472	0.0697	0.1260	2.0560	6.3952	5729
Colombia	0.1048	0.0485	0.0660	0.0835	0.1432	0.9317	2.6923	4945
Italy	0.1115	0.0468	0.0647	0.1062	0.1505	0.4939	2.2599	9903
Spain	0.1276	0.1914	0.0750	0.0838	0.0980	4.2951	19.6505	6504
Malaysia	0.1297	0.1489	0.0246	0.0308	0.2737	0.9585	2.2270	9903
Portugal	0.1366	0.0308	0.1059	0.1390	0.1626	-0.0457	1.6990	5987
Chile	0.1390	0.1967	0.0304	0.0345	0.2357	1.5212	3.7562	5988
Austria	0.1473	0.0898	0.0814	0.1109	0.2126	1.0332	2.8996	9903
Venezuela	0.1609	0.0889	0.0767	0.1429	0.2160	0.7121	2.7435	5467
Korea	0.1669	0.3090	0.0259	0.0468	0.0592	2.0439	5.2546	8074
Slovenia	0.1821	0.0970	0.1358	0.1682	0.1875	5.2335	36.4151	3432
Holland	0.1983	0.0941	0.1110	0.1889	0.2779	0.4055	2.0876	9903
Israel	0.2000	0.2008	0.0788	0.1293	0.2674	2.7647	11.0202	6512
Russia	0.2018	0.1218	0.1104	0.1696	0.2791	1.9152	9.1527	3987
Cyprus	0.2024	0.0717	0.1517	0.1811	0.2559	0.8106	3.4280	4698
Peru	0.2059	0.2391	0.0562	0.0864	0.3392	1.6073	4.3778	5206

Table 1-Continued

Panel B

Country	Mean	Std Dev	q1	q2	q3	Skewness	Kurtosis	N
Argentina	0.2073	0.0717	0.1430	0.2062	0.2702	0.1581	1.7591	5988
Turkey	0.2085	0.2363	0.0376	0.1344	0.2684	1.7493	5.4405	5988
Poland	0.2110	0.2440	0.0592	0.0952	0.2377	2.0781	6.7271	5132
Finland	0.2237	0.1819	0.0970	0.1481	0.3095	1.3709	3.6610	6248
India	0.2251	0.3441	0.0132	0.0183	0.3518	1.2165	2.7328	7814
New Zealand	0.2808	0.2587	0.0944	0.1539	0.4148	1.4863	4.6927	6501
Hungary	0.2951	0.1527	0.2169	0.2320	0.2990	2.3978	7.8801	5206
Romania	0.2986	0.1030	0.2247	0.2792	0.3289	1.3223	4.4952	3933
Brazil	0.3382	0.3986	0.0361	0.0663	0.8351	0.8459	1.9097	6243
Philippines	0.3683	0.4334	0.0509	0.0699	0.8469	0.7518	1.6011	8898
Norway	0.3684	0.2826	0.1352	0.2672	0.4868	0.9376	2.3276	9903

Table 2

Forecasting Market Index Return in Full Sample

Panel A shows the parameter estimates and t-statistics from predictive regressions using value-to-price ratios for the full sample consisting of 48 countries. We used fixed effects regressions with clustered standard errors in our panel data. In each regression, dependent variable is the quarterly log raw return on the total market index of DataStream (TOTMK), $r_{m,t+1}$. Independent variables are $r_{m,t}$, $(d_t - p_t)$, $(e_t - p_t)$. $(d_t - p_t)$ is the log dividend yield, $(e_t - p_t)$ is the log earnings yield. Panel B shows the parameter estimates and t-statistics for scaled prices, dividends, and earnings for the full sample consisting of 48 countries. We used fixed effects regressions with clustered standard errors in our panel data. In each regression, dependent variable is the quarterly log raw return on the total market index of DataStream (TOTMK), $r_{m,t+1}$. Independent variables are $r_{m,t}$, $(p_t - n_t)$, $(d_t - n_t)$, $(e_t - n_t)$. $r_{m,t}$ is current quarter's log of raw return. $E_{i,t}$ is the sum of the past four quarters of total earnings; $P_{i,t}$ is the market index price of country i at the end of quarter t; $D_{i,t}$ is the sum of the past four quarters of total dividend; $N_{i,t}$ is a normalization variable, computed as the log of the average of the past five years of annual earnings, calculated as the sum of the past 20 observations of quarterly earnings divided by five.; $(e_{i,t} - n_{i,t})$ is $\log(\frac{E_{i,t}}{N_{i,t}})$; $(d_{i,t} - n_{i,t})$ is $\log(\frac{D_{i,t}}{N_{i,t}})$ and $(p_{i,t} - n_{i,t})$ is $\log(\frac{P_{i,t}}{N_{i,t}})$. int_t is the current quarter's interest rate as the discount rate obtained from IFS, cpi_t is the current quarter's consumer price index obtained from IFS. [a,b,c] indicate significance at the 1%, 5% and 10% level, respectively.

Panel A. Value-to-Price Ratios

	Constant	$d_t - p_t$	$e_t - p_t$	$r_{m,t}$	int_t	cpi_t	R^2	# obs
1	0.122^a		0.037^a	0.111			1.6 %	4281
	(3.78)		(3.2)	(1.82)				
2	0.174^a	0.041		0.111			3.3 %	4281
	(3.66)	(3.21)		(1.81)				
3	0.186^a	0.033	0.016^c	0.117			3.4 %	4281
	(3.72)	(2.68)	(1.86)	(1.92)				
4	0.203^a	0.032	0.022^b	0.108	0.015		3.8 %	3484
	(3.90)	(2.9)	(2.1)	(1.85)	(0.1)			
5	0.189^a	0.033	0.016^c	0.117		-0.011	3.4 %	4266
	(3.77)	(2.67)	(1.86)	(1.92)		(-0.68)		
6	0.206^a	0.032	0.022^b	0.108	0.013	-0.010	3.8 %	3484
	(3.97)	(2.9)	(2.1)	(1.85)	(0.12)	(-0.66)		

Table 2-Continued

Panel B. Normalized Variables

	Constant	$p_t - n_t$	$e_t - n_t$	$d_t - n_t$	$r_{m,t}$	int_t	cpi_t	R^2	# obs
1	0.131^a	-0.036^a			0.108^c			2.9 %	4281
	(3.6)	(-2.99)			(1.75)				
2	0.028^a		-0.011		0.083			1.6 %	4281
	(2.83)		(-0.9)		(1.34)				
3	0.192^a	-0.051^a	0.007	0.028^b	0.118^c			3.6 %	4281
	(3.77)	(-3.38)	(0.62)	(2.35)	(1.93)				
4	0.210^a	-0.057^a	0.013	0.028^b	0.109^c	0.015		3.9 %	3484
	(3.96)	(-3.89)	(0.96)	(2.57)	(1.87)	(0.1)			
5	0.194^a	-0.051^a	0.007	0.028^b	0.118^c		-0.011	3.6 %	4266
	(3.82)	(-3.37)	(0.64)	(2.34)	(1.93)		(-0.68)		
6	0.212^a	-0.057^a	0.013	0.028	0.109^c	0.013	-0.010	3.9 %	3484
	(4.02)	(-3.89)	(0.97)	$(2.56)^b$	(1.88)	(0.12)	(-0.66)		

Table 3

Forecasting Market Index Return in Low versus High Synchronous Portfolios

48 countries in our sample are sorted according to their mean of synchronicity measure. In Panel A and Panel B, low synchronous portfolio consists of 12 countries that have the lowest price synchronicity mean of our sample. In Panel C and Panel D, high synchronous portfolio consists of 12 countries that have the highest price synchronicity mean of our sample. We used fixed effects regressions with clustered standard errors in our panel data. In Panel A and Panel C, dependent variable is the quarterly log raw return on the total market index of DataStream (TOTMK), $r_{m,t+1}$. Independent variables are $r_{m,t}$, $(d_t - p_t)$, $(e_t - p_t)$. $(d_t - p_t)$ is the log dividend yield, $(e_t - p_t)$ is the log earnings yield. In Panel B and Panel D, dependent variable is $r_{m,t+1}$. Independent variables are $r_{m,t}$, $(p_t - n_t)$, $(d_t - n_t)$, $(e_t - n_t)$. $r_{m,t}$ is current quarter's log of raw return. $(e_{i,t} - n_{i,t})$ is the log of normalized earnings; $(d_{i,t} - n_{i,t})$ is the log of normalized dividends; $(p_{i,t} - n_{i,t})$ is the log of normalized price. [a,b,c] indicate significance at the 1%, 5% and 10% level, respectively.

Panel A. Low Synchronous Portfolio-Value-to-Price Ratios

	Constant	$d_t - p_t$	$e_t - p_t$	$r_{m,t}$	R^2	# obs	#countries
1	0.100^a		0.029^b	0.114	2.37%	1325	12
	(2.74)		(2.06)	(1.50)			
2	0.147^a	0.034^c	0.001	0.117	2.97%	1325	12
	(2.68)	(1.75)	(0.08)	(1.52)			

Panel B. Low Synchronous Portfolio-Normalized Variables

	Constant	$p_t - n_t$	$e_t - n_t$	$d_t - n_t$	$r_{m,t}$	R^2	# obs	#countries
1	0.122^b	-0.035^b	0.009		0.116	2.78%	1325	12
	(2.48)	(-2.02)	(0.56)		(1.52)			
2	0.146^a	-0.036^b	-0.001	0.027^c	0.117	3.01%	1325	12
	(2.72)	(-2.08)	(-0.06)	(1.65)	(1.52)			

Table 3-Continued

Panel C. High Synchronous Portfolio-Value-to-Price Ratios

	Constant	$d_t - p_t$	$e_t - p_t$	$r_{m,t}$	R^2	# obs	#countries
1	0.182^a		0.058^a	0.121^b	4.42%	972	12
	(3.50)		(3.26)	(1.98)			
2	0.121^a	0.020	0.044^a	0.125^b	4.82%	972	12
	(3.55)	(1.61)	(2.63)	(2.07)			

Panel D. High Synchronous Portfolio-Normalized Variables

	Constant	$p_t - n_t$	$e_t - n_t$	$d_t - n_t$	$r_{m,t}$	R^2	# obs	#countries
1	0.194^a	-0.060^a	0.048^b		0.123^b	4.49%	972	12
	(3.45)	(-3.26)	(2.37)		(2.00)			
2	0.223^a	-0.064^a	0.042^b	0.019	0.125^b	4.82%	972	12
	(3.54)	(-3.34)	(2.19)	(1.42)	(2.05)			

Table 4

Forecasting Market Index Return in Low versus High Diversification Portfolios

48 countries in our sample are sorted according to their mean of their Herfindahl-Index. In Panel A and Panel B, high diversification portfolio consists of 12 countries that have the lowest Herfindahl-Index mean, ranking in the bottom 25 percent of our full sample. In Panel C and Panel D, low diversification portfolio consists of 12 countries that have the highest Herfindahl-Index mean, ranking in the top 25 percent of our full sample. We used fixed effects regressions with clustered standard errors in our panel data. In Panel A and Panel C, dependent variable is the quarterly log raw return on the total market index of DataStream (TOTMK), $r_{m,t+1}$. Independent variables are $r_{m,t}$, $(d_t - p_t)$, $(e_t - p_t)$. $(d_t - p_t)$ is the log dividend yield, $(e_t - p_t)$ is the log earnings yield. In Panel B and Panel D, dependent variable is $r_{m,t+1}$. Independent variables are $r_{m,t}$, $(p_t - n_t)$, $(d_t - n_t)$, $(e_t - n_t)$. $r_{m,t}$ is current quarter's log of raw return. $(e_{i,t} - n_{i,t})$ is the log of normalized earnings; $(d_{i,t} - n_{i,t})$ is the log of normalized dividends; $(p_{i,t} - n_{i,t})$ is the log of normalized price. ^{a,b,c} indicate significance at the 1%, 5% and 10% level, respectively.

Panel A. High Diversification Portfolio-Value-to-Price Ratios

	Constant	$d_t - p_t$	$e_t - p_t$	$r_{m,t}$	R^2	# obs	#countries
1	0.156^a		0.048^a	0.042	2.07%	1348	12
	(3.50)		(2.88)	(0.68)			
2	0.204^a	0.039^b	0.012	0.039	2.76%	1348	12
	(3.77)	(2.00)	(0.56)	(0.65)			

Panel B. High Diversification Portfolio-Normalized Variables

	Constant	$p_t - n_t$	$e_t - n_t$	$d_t - n_t$	$r_{m,t}$	R^2	# obs	#countries
1	0.185^a	-0.055^a	0.016		0.043	2.59%	1348	12
	(3.65)	(-3.12)	(0.72)		(0.71)			
2	0.210^a	-0.055^a	0.003	0.030	0.041	2.90%	1348	12
	(3.81)	(-3.12)	(0.13)	(1.35)	(0.67)			

Table 4-Continued

Panel C. Low Diversification Portfolio-Value-to-Price Ratios

	Constant	$d_t - p_t$	$e_t - p_t$	$r_{m,t}$	R^2	# obs	#countries
1	0.172^a		0.054^a	0.134^c	4.54%	773	12
	(4.12)		(3.86)	(1.87)			
2	0.264^a	0.030^c	0.047^a	0.148^b	5.51%	773	12
	(3.29)	(1.78)	(3.66)	(2.09)			

Panel D. Low Diversification Portfolio-Normalized Variables

	Constant	$p_t - n_t$	$e_t - n_t$	$d_t - n_t$	$r_{m,t}$	R^2	# obs	#countries
1	0.173^a	-0.054^a	0.054		0.135^c	4.54%	773	12
	(3.48)	(-3.37)	(2.45)		(1.85)			
2	0.259^a	-0.075^a	0.052^a	0.031^c	0.147^b	5.53%	773	12
	(3.16)	(-3.22)	(2.39)	(1.81)	(2.04)			

Table 5

Controlling for Macroeconomics Variables

In Panel A, low synchronous portfolio consists of 12 countries that have the lowest price synchronicity mean of our sample. In Panel B, high synchronous portfolio consists of 12 countries that have the highest price synchronicity mean of our sample. In Panel C, high diversification portfolio consists of 12 countries that have the lowest Herfindahl-Index mean, ranking in the bottom 25 percent of our full sample. In Panel D, low diversification portfolio consists of 12 countries that have the highest Herfindahl-Index mean, ranking in the top 25 percent of our full sample. In each regression, dependent variable is the quarterly log raw return on the total market index of DataStream (TOTMK), $r_{m,t+1}$. Independent variables are $r_{m,t}$, $(p_t - n_t)$, $(d_t - n_t)$, $(e_t - n_t)$. $r_{m,t}$ is current quarter's log of raw return. $E_{i,t}$ is the sum of the past four quarters of total earnings; $P_{i,t}$ is the market index price of country i at the end of quarter t; $D_{i,t}$ is the sum of the past four quarters of total dividend; $N_{i,t}$ is a normalization variable, computed as the log of the average of the past five years of annual earnings, calculated as the sum of the past 20 observations of quarterly earnings divided by five.; $(e_{i,t} - n_{i,t})$ is $\log(\frac{E_{i,t}}{N_{i,t}})$; $(d_{i,t} - n_{i,t})$ is $\log(\frac{D_{i,t}}{N_{i,t}})$ and $(p_{i,t} - n_{i,t})$ is $\log(\frac{P_{i,t}}{N_{i,t}})$. int_t is the current quarter's interest rate as the discount rate obtained from IFS, cpi_t is the current quarter's consumer price index obtained from IFS. ^{a,b,c} indicate significance at the 1%, 5% and 10% level, respectively.

Panel A. Low Synchronous Portfolio-Normalized Variables

	Constant	$p_t - n_t$	$e_t - n_t$	$d_t - n_t$	$r_{m,t}$	int_t	cpi_t	R^2	# obs	#countries
1	0.146^a	-0.036^b	-0.001	0.027^c	0.117			3.01%	1325	12
	(2.72)	(-2.08)	(-0.06)	(1.65)	(1.52)					
2	0.172^a	-0.047^b	0.021	0.013	0.084	-0.000		3.23 %	1021	12
	(2.67)	(-2.39)	(1.19)	(0.73)	(1.21)	(-0.28)				
3	0.163^a	-0.030	-0.004	0.018	0.107		-0.004	3.39 %	1325	12
	(3.23)	(-1.53)	(-0.29)	(1.01)	(1.43)		(-1.44)			
4	0.211^a	-0.040^c	0.021	-0.004	0.067	0.001	-0.003^c	4.24 %	1021	12
	(3.53)	(-1.9)	(1.17)	(-0.18)	(1.00)	(0.96)	-1.81			

Table 5-Continued

Panel B. High Synchronous Portfolio-Normalized Variables

	Constant	$p_t - n_t$	$e_t - n_t$	$d_t - n_t$	$r_{m,t}$	int_t	cpi_t	R^2	# obs	#countries
1	0.223[a]	-0.064[a]	0.042[b]	0.019	0.125[b]			4.82	972	12
	(3.54)	(-3.34)	(2.19)	(1.42)	(2.05)					
2	0.242[a]	-0.077[a]	0.042[b]	0.017	0.127[b]	0.002		6.12%	807	12
	(3.97)	(-4.12)	(2.22)	(1.25)	(2.17)	(1.49)				
3	0.233[a]	-0.072[a]	0.045[b]	0.022	0.132[b]		0.000	4.93 %	972	12
	(3.38)	(-2.90)	(2.24)	(1.51)	(2.2)		(0.76)			
4	0.251[a]	-0.083[a]	0.045[b]	0.019	0.132[b]	0.001	0.000	6.19 %	807	12
	(3.69)	(-3.46)	(2.23)	(1.28)	(2.26)	(1.21)	(0.55)			

Table 5-Continued

Panel C. High Diversification Portfolio-Normalized Variables

	Constant	$p_t - n_t$	$e_t - n_t$	$d_t - n_t$	$r_{m,t}$	int_t	cpi_t	R^2	# obs	#countries
1	0.210^a	-0.055^a	0.003	0.030	0.041			2.90%	1348	12
	(3.81)	(-3.12)	(0.13)	(1.35)	(0.67)					
2	0.229^a	-0.061^a	0.013	0.0316	0.057	-0.000		3.10%	1138	12
	(2.98)	(-2.92)	(0.47)	(1.23)	(0.86)	(-0.13)				
3	0.213^a	-0.054^a	0.002	0.030	0.040		-0.000	2.90 %	1333	12
	(4.14)	(-2.79)	(0.08)	(1.32)	(0.66)		(-0.36)			
4	0.243^a	-0.059^a	0.011	0.031	0.053	-0.000	-0.000	3.20 %	1138	12
	(3.21)	(-2.73)	(0.39)	(1.20)	(0.81)	(-0.17)	(-1.15)			

Table 5-Continued

Panel D. Low Diversification Portfolio-Normalized Variables

	Constant	p_t-n_t	e_t-n_t	d_t-n_t	$r_{m,t}$	int_t	cpi_t	R^2	# obs	#countries
1	0.259^a	-0.075^a	0.052^a	0.031^c	0.147^b			5.53%	773	12
	(3.16)	(-3.22)	(2.39)	(1.81)	(2.04)					
2	0.264^a	-0.078^a	0.041^b	0.036^c	0.139^b	0.001		6.44%	729	12
	(3.16)	(-3.39)	(1.97)	(2.21)	(1.96)	(0.75)				
3	0.276^a	-0.073^a	0.053^b	0.029^c	0.144^b		-0.000	5.62 %	773	12
	(3.63)	(-2.93)	(2.46)	(1.66)	(2.01)		(-0.82)			
4	0.276^a	-0.075^a	0.043^b	0.035^b	0.136^c	0.001	-0.000	6.51 %	729	12
	(3.51)	(-3.05)	(2.06)	(2.01)	(1.92)	(0.76)	(-0.74)			

References

[1] Bali, Turan G., Demirtas, K. Ozgur, and Hassan Tehranian, 2008, Aggregate Earnings, Firm-Level Earnings and Expected Stock Returns, Journal of Financial and Quantitative Analysis 43(3), 657-684.

[2] Bali, Turan G., Demirtas, K. Ozgur and Haim Levy, 2008, Nonlinear Mean Reversion in Stock Prices, Journal of Banking and Finance 32(5), 767-782.

[3] Bali, Turan G., Demirtas, K. Ozgur and Haim Levy, 2009, Is There an Intertemporal Relation between Downside Risk and Expected Returns, Journal of Financial and Quantitative Analysis 44(4), 883-909.

[4] Campbell, John Y., 1991, A Variance Decomposition for Stock Returns, Economic Journal 101, 157-179.

[5] Campbell, John Y., and Robert J. Shiller, 1988, Stock Prices Earnings, and Expected Dividends, Journal of Finance 43, 661-676.

[6] Campbell, John Y., and Robert J. Shiller, 1989, The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors, Review of Financial Studies 1, 195-228.

[7] Campbell, J., Lettau, M., Malkiel, B., Xu, Y., 2001. Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. Journal of Finance 56, 1–43.

[8] Chan, K and A. Hameed (2006), Stock price synchronicity and analyst coverage in emerging markets, Journal of Financial Economics 80, 115-147.

[9] Durnev, A., Morck, R., Yeung, B., Zarowin, P., 2003. Does greater firm-specific return variation mean more or less informed stock pricing? Journal of Accounting Research 41, 797–836.

[10] Durnev, A., Morck, R., Yeung, B., 2004. Value-enhancing capital budgeting and firm-specific stock return variation. Journal of Finance 59, 65–105.

[11] Fama, Eugene F., and Kenneth R. French, 1988a, Dividend Yields and Expected Stock Returns, Journal of Financial Economics 22, 3-25.

[12] Fama, Eugene F., and Kenneth R. French, 1988b, Permanent and Transitory Components of Stock Prices, Journal of Political Economy 96, 246-273.

[13] Fama, Eugene F., and Kenneth R. French, 1989, Business Conditions and Expected Returns on Stocks and Bonds, Journal of Financial Economics 25, 23-49.

[14] Fama, E. F., and K. R. French. "Industry Costs of Equity." Journal of Financial Economics, 43 (1997), 153-193

[15] Ferson, Wayne E., and Campbell R. Harvey, 1991, The Variation of Economic Risk Premiums, Journal of Political Economy 99, 385-415.

[16] Ferson, Wayne E., Sarkissian, Sergei, and Simin Timothy, 2003, Spurious Regressions in Financial Economics? Journal of Finance 58, 1393-1414.

[17] Hodrick, Robert J., 1992, Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement, Review of Financial Studies 5, 357-386.

[18] Jin, Li, Myers, Stewart C., 2006, R2 Around the World: New Theory and New Tests, Journal of Financial Economics 79, 257–292.

[19] Kothari, S.P., and Jay Shanken, 1997, Book-to-market, Dividend Yield, and Expected Market Returns: A Time-Series Analysis, Journal of Financial Economics 44, 169-203.

[20] Lamont, Owen, 1998, Earnings and Expected Returns, Journal of Finance 53, 1563-1587.

[21] Li, Kan, Randall Morck, Fan Yang, and Bernar d Yeung (2003). "Firm-Specific Variation and Openness in Emerging Markets." Review of Economics and Statistics 86(3, August): 658-69.

[22] Longin, F., Solnik, B., 2001. Extreme correlation of international equity markets. Journal of Finance 56 (2), 649-676.

[23] Merton, Robert C., 1973, An Intertemporal Capital Asset Pricing Model, Econometrica 41, 867-887.

[24] Morck, Randall, Yeung, Bernard and Wayne Yu, 2000, The Information Content of Stock Markets: Why Do Emerging Markets Have Synchronous Stock Price Movements? Journal of Financial Economics 58,215–260.

[25] Nelson, Charles R., and Myung J. Kim, 1993, Predictable Stock Returns: The Role of Small Sample Bias, Journal of Finance 48, 641-661.

[26] Newey, Whitney K., and Kenneth D. West, 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, Econometrica 55, 703-708.

[27] Pontiff Jeffrey, and Lawrence D. Schall, 1998, Book-to-market Ratios as Predictors of Market Returns, Journal of Financial Economics 49, 141-160.

[28] Rogers, William H., 1983, Analyzing Complex Survey Data, Rand Corporation Memorandum, Santa Monica, CA.

[29] Rogers, William H., 1993, Regression Standard Errors in Clustered Samples, Stata Technical Bulletin Reprints STB-13, STB-18, 88-94.

[30] Roll, R., 1988. R-squared. Journal of Finance 43, 541–566.

[31] Roll, Richard, 1992, Industrial Structure and the Comparative Behavior of International Stock Market Indices, Journal of Finance 47, 3–42.

[32] Rozeff, Michael S., 1984, Dividend Yields Are Equity Risk Premiums, Journal of Portfolio Management 11, 68-75.

[33] Shiller, Robert J., 1984, Stock Prices and Social Dynamics, The Brooking Papers on Economic Activity 2, 457-510.

[34] Stambaugh F. Robert, 1999, Predictive Regressions, Journal of Financial Economics 54, 375-421.

[35] West, Kenneth (1988), Dividend innovations and stock price volatility, Econometrica 56, 3761.