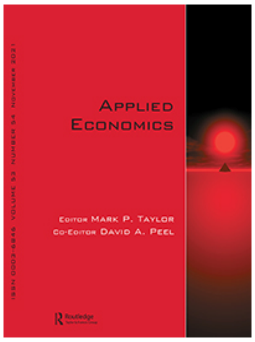



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# Decomposing the earnings-to-price ratio and the cross-section of international equity-index returns

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**ABSTRACT**
We examine whether components of the earnings-to-price (*EP*) ratio can be used to extract incremental information to better estimate future returns in the cross-section of country-industry indexes. We demonstrate that the *EP* components, such as lagged *EP*, changes in earnings, short-term momentum and long-term reversal in prices increase the accuracy of return forecasts. The *EP* decomposition matters in developed markets but is pointless in emerging countries. The results are robust to modifications in the methodology, sub-period analyses, the use of an alternative sample and remain unchanged after controlling for net share issuance, size, and fixed country and time effects.

**KEYWORDS**
International portfolio management; E/P decomposition; value effect; index-return predictability

**JEL**
G11; G12; G17

## I. Introduction

Value investing, which is a trading strategy aiming to pick underpriced assets relative to their fundamental characteristics, is one of the oldest and widely used approaches to identify profitable investment opportunities. Its formal introduction dates back to the first half of the twentieth century, when Graham and Dodd (1940) suggested investing in stocks that are believed to be traded for less than their intrinsic values. Value investing also found strong support from market practitioners. The value strategy has been applied in several different forms. It is documented that undervalued assets relative to their i) earnings (Basu 1977, 1983; Campbell and Thompson 2008); ii) book value of equity (Rosenberg, Reid, and Lanstein 1985; Griffin and Lemmon 2002); iii) dividends (Litzenberger and Ramaswamy 1979; Maio and Santa-Clara 2015); or iv) cash flow (Chan and Lakonishok 2004) outperformed their overvalued counterparts.[1]

Among these valuation ratios, the earnings-to-price (*EP*) ratio is widely used as a popular valuation metric. The *EP* ratio shows earnings generated per unit dollar of investment and is interpreted as an earnings yield on equity investment that is expressed in percentage terms. An asset with a high (low) *EP* provides a relatively high (low) return per unit of investment and can be preferred by investors. At the same time, such an asset also has a lower (higher) price-to-earnings ratio, which is the reciprocal of *EP*. The price-to-earnings ratio shows how the market values an asset given its earnings. An asset with a high (low) price-to-earnings ratio can indicate that price is relatively high (low) with respect to earnings and, thus, it can be overvalued (undervalued). So, the *EP* ratio can indirectly signal whether an asset is over- or undervalued. The extensive use of *EP* as a valuation metric is probably due to its computational ease and earlier empirical evidence in favour of its information content about returns (Basu 1977, 1983). Moreover, *EP* data is available for both stock market indexes and industry indexes. This makes it a suitable value metric for index-level studies – as

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[1]The value strategy seen in these studies is applied over different investment horizons. Basu (1977, 1983), Litzenberger and Ramaswamy (1979), as well as Griffin and Lemmon (2002), examined the investment performance of value strategy over a year. Campbell and Thompson (2008) used investment horizons from one month to one year; on the other hand, Rosenberg, Reid, and Lanstein (1985) employed a one-month investment horizon. Maio and Santa-Clara (2015) examined the predictability of one-year to twenty-year returns.

Supplemental data for this article can be accessed here.

well. Accordingly, the value effect based on *EP* has also been examined at the index level, and it is shown that there is evidence for a value premium in the returns of international indexes (Macedo 1995; Kim 2012; Angelidis and Tessaromatis 2017).

More importantly, *EP* ratios can play a special role in the context of international pricing models. Bekaert et al. (2011) assert that under the assumption of full market integration, the same industry in different countries should have the same earnings yield; this is because global factors that are common to all countries determine the profitability in that industry. This implies that industry earnings yield differentials between a country and the world market should be relatively small and fairly constant over time. However, markets may not yet be fully integrated; therefore, in addition to global factors, local factors may also influence earnings yield within an industry. In line with this conjecture, Bekaert et al. (2011) showed that the industry earnings yield differential is smaller and uniform for developed markets (which are expected to be more integrated with the world market on average) and larger and uneven for emerging markets (which are more likely to be segmented). This has an implication for the cross-section of expected returns on country-industry indexes. If the earnings yield of an industry does not exhibit cross-sectional and time-series variation in developed markets, whereas it varies across markets and through time in emerging markets, then cross-sectional Fama and MacBeth (1973) regressions of industry returns on *EP* should generate insignificant (significant) slopes for developed (emerging) markets. This is because *EP* contains no (considerable) local information for integrated (segmented) markets. In this study, we also examine whether *EP* has different roles in explaining the cross-section of expected returns in developed and emerging markets. If *EP* is noninformative for future industry returns in developed markets, then this motivates to decompose *EP* into its components in order to extract hidden information that can be used to predict returns in developed markets.

Studies on value investing have recently focused on underlying sources of the value premium. The pioneer of these studies is the work of Fama and French (2008), which examines the origins of the value effect based on the book-to-market (*BM*) ratio. Fama and French (2008) decomposed the logarithm of the *BM* ratio at time *t* ($BM_t$) into three components, which are the log of the book-to-market ratio at *t-k* ($BM_{t-k}$), change in the log of the book equity from *t-k* to *t* ($dB_{t-k}$), and change in the log of price from *t-k* to *t* ($dM_{t-k}$) as expressed in Equation (1).

$$BM_t = BM_{t-k} + dB_{t-k} - dM_{t-k} \tag{1}$$

Fama and French (2008) analyse whether these components contain additional information beyond the information contained by *BM* alone. They tested the predictive ability of the components for US stocks. Following the approach of Fama and French (2008), several studies examine whether the decomposition of *BM* matters for the estimation of stock returns in non-US G-7 countries (Bali, Cakici, and Fabozzi 2013), in China (Cakici, Chatterjee, and Topyan 2015), and in four distinct global regions (Blackburn and Cakici 2019; Atilgan et al. 2020). Interestingly, no study has yet attempted to examine the origins of the value effect based on *EP* at the index level.

In this study, we take the perspective of global investors who trade international indexes to improve their risk-return profiles through international diversification. The *EP* ratio of indexes is of particular interest for such investors, for it can signal the degree of segmentation/integration of markets – as Bekaert et al. (2011) conjectures. Although replicating international index returns may be costly, the analysis of the *EP* ratio at the index level, rather than at the stock level, can assist global investors in detecting segmented markets that can provide larger diversification opportunities. Moreover, stock-level earnings more frequently turn into negative. In such cases, the interpretation of the price-to-earnings ratios is confusing. For positive price-to-earnings ratios, a lower ratio is a good sign. However, this is the opposite for negative ratios. A more negative ratio, i.e., a lower ratio, that is indicating heavy losses could be perceived favourably. For this reason, the negative price-to-earnings ratios are usually not reported. For indexes, price-to-earnings ratios are hardly ever negative as compared to stocks. Therefore, the non-existence of price-to-earnings ratios for indexes is of a lesser concern.

This study aims to apply the *EP* decomposition at the index level for the first time in the literature. We contribute to the literature by decomposing *EP* into four components, namely, lagged *EP*, change in earnings, as well as both short-term continuation and long-term reversion in prices. We examine whether the inclusion of these components as additional explanatory variables in the cross-sectional regressions of industry-index returns enhances the predictive performance of expected return models. We also examine whether recent news is more relevant than older news in regard to predicting future returns by using various lag lengths in the *EP* decomposition. Moreover, we explore the role of *EP* decomposition in developed and emerging markets, across five size quintiles, for an alternative sample of country indexes – as well as in two sub-periods.

The results show that a significant *EP* effect exists for the full sample, and decomposing *EP* into its constituents produces powerful predictors of industry-index returns. For instance, the *EP* components such as lagged *EP*, momentum, and reversal increase the explanatory power of predictive regressions. Therefore, *EP* decomposition adds value. Splitting the sample into developed and emerging markets demonstrates that full sample results are driven by the results of developed markets. This highlights the practical implications of our results; the *EP* decomposition can be employed to forecast returns on the most liquid and actively traded exchanges. A plausible explanation for the difference in the relevancy of *EP* decomposition in emerging and developed markets can be the different degrees of market segmentation of these groups. In addition, the *EP* decomposition matters regardless of portfolio size. Momentum is the most influential component across all size quintiles. We find qualitatively similar results for the alternative sample consisting of country indexes. The use of different lags in the decomposition process indicates that *EP* components that include more recent information can be employed to obtain more accurate estimates of the expected returns – especially in developed markets. The results from the sub-period analyses provide support to the persistent relevance of *EP* decomposition in developed markets, providing further ground for decomposing *EP* in these markets. The relevancy of results for developed markets in the recent sub-period suggests that investors can currently use the incremental information arising from the decomposition in determining their trading strategies. Our main results remain unchanged even after controlling for net share issuance, size, and both fixed country and time effects.

This paper complements the literature in two ways. The value effect (based on several fundamentals) has been predominantly examined at the stock level (Basu 1977, 1983; La Porta 1996) or at the country level (Macedo 1995; Kim 2012; Angelidis and Tessaromatis 2017). First, we extend these studies by performing analyses at the industry level. International industry indexes are an important set of asset classes for global investors as international diversification across industry indexes, rather than country indexes, can be more efficient. Goetzmann, Li, and Rouwenhorst (2005) – as well as Quinn and Voth (2008) – discuss that the globalization process integrates the financial markets and increases the correlations among country indexes. Bekaert et al. (2011) argue that even in the case of full integration, industries will still have different systematic risks due to their industry-specific production technology and demand factors. Thus, it is likely that international diversification across country-industry indexes can provide more risk reduction benefits for global investors (Moskowitz and Grinblatt 1999; Ferreira and Ferreira 2006; Umutlu and Bengitöz 2021). Nevertheless, to the best of our knowledge, any similar *EP* decomposition analysis within the context of the industries has – thus far – never been performed.

Second, this is the first paper to decompose the *EP* ratio and examine the role of its constituents at the index level. Anderson and Brooks (2006) examined the roles of time, size, sector, and idiosyncratic effects in their explanation of the earnings-to-price ratio of UK stocks. Our study is distinguishable from Anderson and Brooks (2006) in two ways. First, we decompose earnings yield at the index level – not at the stock level. Second, we use a completely different methodology to decompose *EP* that produces different *EP* components. Several stock-level studies decompose the book-to-market ratio and examine the predictive ability of its components for US stocks or stocks from various countries (Fama and French 2008; Bali, Cakici, and Fabozzi 2013; Cakici, Chatterjee, and Topyan 2015). Our paper complements these studies in the decomposition of the *EP* ratio rather than the *BM* ratio, as well as in the investigation of international index returns rather than stock returns. Our index-level study is also related to the study of Zaremba and Umutlu (2018), which decomposes the size effect at the international index level. This study is similar to that of Zaremba and Umutlu (2018) in the sense that both papers conduct decomposition analyses at the index level. However, our paper differs from theirs in the examination of the value effect.

The paper is organized as follows: Section 2 analytically explains the steps of *EP* decomposition. Section 3 describes the data and variables. Section 4 explains the methodology. Section 5 presents the results and the final section concludes the paper.

## II. Decomposing the earnings-to-price ratio

We aim to figure out whether the evolution of *EP* in terms of its lagged values ($EP_{t\text{-}k}$) and change in its constituents (such as earnings ($E$) and price ($P$)) reveals extra information about expected returns that is not captured by *EP* alone. For this purpose, we express $EP_t$ in the following form:

$$EP_t = \frac{E_t}{P_t} = \frac{E_{t-k}}{P_{t-k}} \frac{E_t}{E_{t-k}} \frac{P_{t-k}}{P_t} \tag{2}$$

We further split $P_{t\text{-k}}/P_t$, the last term in Equation (2), in such a way that it reflects not only the short-term changes in prices over the past year but also the long-term changes from month $t$-k to $t$-12.

$$EP_t = \frac{E_t}{P_t} = \frac{E_{t-k}}{P_{t-k}} \frac{E_t}{E_{t-k}} \frac{P_{t-12}}{P_t} \frac{P_{t-k}}{P_{t-12}} \tag{3}$$

Next, we take the logarithm of both sides of Equation (3) to express *EP* as an additive function of its components.

$$\ln(EP_t) = \ln(EP_{t-k}) + \ln\left(\frac{E_t}{E_{t-k}}\right) + \ln\left(\frac{P_{t-12}}{P_t}\right) + \ln\left(\frac{P_{t-k}}{P_{t-12}}\right) \tag{4}$$

In the final step, we use the reciprocals of the last two ratios to comply with the definitions of momentum (*MOM*) and reversal (*REV*). Note that the last two logarithmic terms turn into negative because of the use of the inverses of the ratios.

$$\ln(EP_t) = \ln(EP_{t-k}) + \ln\left(\frac{E_t}{E_{t-k}}\right) - \ln\left(\frac{P_t}{P_{t-12}}\right) - \ln\left(\frac{P_{t-12}}{P_{t-k}}\right) \tag{5}$$

We explore the effectiveness of *EP* decomposition for different lag lengths in order to compare the importance of recent news to that of older news in predicting future returns. For this purpose, we use 36-, 48- and 60-month lagged values of *EP*. That is to say, $k$ in Equation (5) takes the values of 36, 48 and 60. If the predictive ability of components decreases, as $k$ increases, it is concluded that older news is less relevant than recent news. It is noteworthy that for different values of $k$, the time horizon over which *MOM* is calculated remains unchanged. By definition, *MOM* represents the momentum performance over the previous year, which is independent of $k$.

More compactly, we express Equation (5) in the following way:

$$EP = LEP + dE - MOM - REV \tag{6}$$

where *EP* is the logarithm of the earnings-to-price ratio; *LEP* is the lagged *EP*; *dE* is the change in earnings; *MOM* is the momentum over the last 12 months; *REV* is the reversal over months $t$-$k$ to $t$-12.

## III. Data and variables

The data source is Datastream, which compiles value-weighted DS Global Indexes for local industry indexes and country indexes. We treat both country-industry and country indexes as individual international assets that are traded by international investors. We download the monthly price-to-earnings ratio and US dollar-denominated total return and price data for each country-industry and country index. All cross-sectional regressions are run over the period of January 1978 to July 2017 for a total of 475 months; however, we use data going back to January 1973, when *EP* components contain lagged information up to the previous 5 years. We use the one-month Treasury bill rate from Kenneth. R. French's data library as the monthly risk-free rate.

For the country-industry sample, we use the *supersector* definitions provided by the Industry Classification Benchmark (ICB) of the FTSE. In the ICB structure, there are 19 *supersectors* that represent broad industry classes that combine similar sectors. To track industries across countries, we collect data for 19 *supersectors* from 51 countries. Because some of the *supersectors* do not exist for some countries in Datastream, we have 885 – rather than 969 (19×51) – indexes in our country-industry sample. Table A1 in the Online Appendix overviews 19 industry indexes used in this study and provides some basic statistics. For the country sample, we use the stock market indexes of Datastream for 51 countries, of which 23 are developed and 28 are emerging. Table A2 in the Online Appendix identifies the country indexes.

The components of *EP* are used as explanatory variables in regression analyses. The lagged earnings-to-price ratio (*LEP*) represents the long-run *EP* value. *LEP* is defined as the earnings-to-price ratio in months *t*-36, *t*-48 or *t*-60, depending on the lag length used in the decomposition. The remaining components that were obtained from the decomposition are associated with well-known factors that are documented in the asset-pricing literature. For instance, the profitability effect, which is denoted as *dE* and measured as changes in earnings from month *t-k* to *t* in this study, was introduced by Fama and French (2015). It indicates that stocks with robust profitability outperform those with weak profitability. Datastream does not directly provide earnings data for country and industry indexes. Therefore, we use the Price-to-Earnings ratio (*PE*) and Price Index (*PI*) data to infer changes in the earnings value. We start with defining the *PE* value in month *t* as $X_t$ and the *PE* value in month *t-k* as $X_{t-k}$.

$$\frac{X_t}{X_{t-k}} = \frac{PE_t}{PE_{t-k}} \tag{7}$$

Then, we arrange the resulting ratios as follows:

$$\frac{X_t}{X_{t-k}} = \frac{P_t}{E_t}\frac{E_{t-k}}{P_{t-k}} = \frac{P_t}{P_{t-k}}\frac{E_{t-k}}{E_t} \tag{8}$$

If we express the earnings ratio in terms of *P* and *X*, we have the following:

$$\frac{E_t}{E_{t-k}} = \frac{P_t}{P_{t-k}}\frac{X_{t-k}}{X_t} \tag{9}$$

The price index (*PI*) can be substituted for the price (*P*) in Equation (9) because price index series in Datastream are constructed to adjust prices for capital actions such as stock splits. Therefore, the proportional change in prices will be more accurately captured by tracking the proportional change in price indexes rather than tracking the change in raw prices. As a result, the change in earnings (*dE*) from month *t-k* to month *t* is defined as follows:

$$dE = \frac{E_t}{E_{t-k}} = \frac{PI_t}{PI_{t-k}}\frac{PE_{t-k}}{PE_t} \tag{10}$$

*MOM*, which is another *EP* component, aims to capture short-term continuation in prices, i.e. momentum. The momentum effect is a pervasive phenomenon, and it is also documented in index-level studies (Bhojraj and Swaminathan 2006; Zaremba, Umutlu, and Karathanasopoulos 2019). In this study, we also investigate the predictive power of *MOM* – which is measured as the cumulative return from month *t*-12 to month *t* – for returns on international indexes.

The last *EP* component is *REV*, which denotes the long-run reversal effect. The reversal effect is known as the tendency of poorly (well) performing stocks in the previous 3–5 years to perform well (poorly) in the following period, i.e., the performance reverses in the long term. The reversal effect was not only found in stock returns but was also reported in returns of country indexes (Malin and Bornholt 2013). In this paper, we examine whether *REV* has a predictive power beyond that of *EP* for index returns. *REV* is calculated as the cumulative return from month *t-k* to month *t*-12, where *k* represents the lag lengths of 36, 48 and 60 months.

## IV. Do EP components convey independent information that is not captured by EP?

In this section, we examine whether the *EP* decomposition can reveal additional information about future returns that can be potentially embedded in the *EP* components. To determine the role of *EP* components in predictive regressions, we follow the approach of Fama and French (2008). According to this approach, if the information content of the main variable of interest and its components is the same, then there is no gain from decomposition in terms of the revelation of further information. This implies that all coefficient estimates from the regression of expected returns on the components should be equal to that of the main variable of interest. Therefore, the decomposition will not assist in achieving better estimates of future returns. Alternatively, if the decomposition discloses additional information, at least some of the slope coefficients on components should be statistically different from the slope of the main variable.

To test if the EP components contain useful information to predict future returns, we run cross-sectional regressions in the style of Fama and MacBeth (1973). Therefore, each month, we run cross-sectional predictive regressions of the next month's stock index returns on the return predicting variables, i.e., the earnings-to-price ratio and four components. In the second step, we calculate the mean of the monthly coefficient estimates (for details of the implementation, see Cochrane 2009).

Equation (11) shows the basic Fama and MacBeth (1973) regression that includes *EP* as the only independent variable

$$R_{i,t+1} = \beta_{0,t} + \beta_{1.t}EP_{i,t} + \varepsilon_{i,t+1} \tag{11}$$

We can substitute the *EP* components for *EP* in Equation (11) to obtain Equation (12).

$$\begin{aligned} R_{i,t+1} = a_{0,t} + a_{1,t}LEP_{i,t} + a_{2,t}dE_{i,t} + a_{3,t}MOM_{i,t} \\ + a_{4,t}REV_{i,t} + \varepsilon_{i,t+1} \end{aligned} \tag{12}$$

Using Equation (12), we examine whether decomposing *EP* into its components improves the forecasting of expected returns. If the *EP* decomposition does not matter, then the true slopes on *LEP, dE, MOM* and *REV* should have the same value in magnitude. Moreover, the sign of the slopes on *LEP* and *dE* should be positive while those on *MOM* and *REV* should be negative, so that Equation (12) reduces to Equation (11) and *EP* becomes the only relevant variable in predicting expected returns. Conversely, if the *EP* decomposition matters, then this implies that the components convey independent information beyond the information content of *the EP*. Therefore, not all coefficients should be equal to one another in magnitude.

To test whether the true slopes on the components in Equation (12) are equal to the slope on *EP* in magnitude, we estimate an alternative regression that uses the most recent *EP* ratio instead of its lagged value in Equation (12) as expressed in Equation (13).

$$\begin{aligned} R_{i,t+1} = b_{0,t} + b_{1,t}EP_{i,t} + b_{2,t}dE_{i,t} + b_{3,t}MOM_{i,t} \\ + b_{4,t}REV_{i,t} + \varepsilon_{i,t+1} \end{aligned} \tag{13}$$

Inserting the *EP* components presented in Equation (6) for *EP* in Equation (13) yields Equation (14), which allows us to test whether $a_{1,t} = a_{2,t}$; $a_{1,t} = -a_{3,t}$; $a_{1,t} = -a_{4,t}$.

$$\begin{aligned} R_{i,t+1} = b_{0,t} + b_{1,t}LEP_{i,t} + (b_{1,t} + b_{2,t})dE_{i,t} \\ + (b_{3,t} - b_{1,t})MOM_{i,t} + (b_{4,t} - b_{1,t})REV_{i,t} \\ + \varepsilon_{i,t+1} \end{aligned} \tag{14}$$

When we compare the coefficients of components in Equation (12) to those in Equation (14), it is inferred that $a_{1,t} = b_{1,t}$, $a_{2,t} = b_{2,t} + b_{1,t}$, $a_{3,t} = b_{3,t} - b_{1,t}$, $a_{4,t} = b_{4,t} - b_{1,t}$. As required by the first equality ($a_{1,t} = b_{1,t}a_{1,t} = b_{1,t}$), we substitute $a_{1,t}$ for $b_{1,t}$ in other equalities. Therefore, we have the following equations, which express the coefficients $b$ in terms of coefficients $a$: $b_{2,t} = a_{2,t} - a_{1,t}$, $b_{3,t} = a_{3,t} + a_{1,t}$, $b_{4,t} = a_{4,t} + a_{1,t}$. The equations above imply that testing whether $b_{2,t} = 0$, $b_{3,t} = 0$, and $b_{4,t} = 0$ in Equation (13) are equivalent to testing whether $a_{2,t} = a_{1,t} - a_{3,t} = a_{1,t}, - a_{4,t} = a_{1,t}$; i.e. the slope of each component is equal to the slope of *EP* in magnitude.

Next, we also examine whether the slopes of components are equal to each other in magnitude, even though they can have different signs, i.e., $a_{2,t} = -a_{3,t}$; $a_{2,t} = -a_{4,t}$; and $a_{3,t} = a_{4,t}$. Using the coefficient estimates from Equation (12), we test the hypotheses that $a_{2,t} + a_{3,t} = 0$, $a_{2,t} + a_{4,t} = 0$ and $a_{3,t} - a_{4,t} = 0$.

To test the first three hypotheses ($H_1$: $b_{2,t} = 0$: $b_{3,t} = 0$: $b_{4,t} = 0$), we estimate the cross-sectional regression represented by Equation (13) for each month in the research period. Next, we test whether the time-series averages of the slopes on *dE, MOM* and *REV* are equal to zero. To test the second three hypotheses ($H_4$: $a_{2,t} + a_{3,t} = 0$, $H_5$: $a_{2,t} + a_{4,t} = 0$, and $a_{3,t} - a_{4,t} = 0$), we use the monthly individual slope coefficients of $a_{2,t}$, $a_{3,t}$, and $a_{4,t}$, which are estimated from Equation (12). We calculate the time-series average of the sums of $a_{2,t} + a_{3,t}$ and $a_{2,t} + a_{4,t}$ to find the average slopes on *dE+MOM* and *dE+REV*, respectively, as well as the average difference of $a_{3,t} - a_{4,t}$ to find the average slope on *MOM-REV*. These average slopes calculated over the months are tested against zero, using the Newey–West adjusted t-statistics. Mathematically, we simply test whether *dE +MOM* = 0, *dE+REV* = 0 and *MOM-REV* = 0.

To sum up, we test the following hypotheses:

$H_1$: $b_{2,t} = a_{2,t} - b_{1,t} = a_{2,t} - a_{1,t} = 0$

$H_2$: $b_{3,t} = a_{3,t} + b_{1,t} = a_{3,t} + a_{1,t} = 0$

$H_3$: $b_{4,t} = a_{4,t} + b_{1,t} = a_{4,t} + a_{1,t} = 0$

$H_4$: $a_{2,t} + a_{3,t} = 0$

$H_5$: $a_{2,t} + a_{4,t} = 0$

$H_6$: $a_{3,t} - a_{4,t} = 0$

If all the hypotheses are rejected, then the decomposition does not marginally add to the explanatory performance of the predictive regressions. If any of the hypothesis is not rejected, then it is concluded that decomposing *EP* into its components provides important information that is not included in *EP*.

## V. Results

### *Local industry indexes*

For the sample of local industry indexes, Table 1 shows the results of regression equations of (11), (12) and (13) in specifications (1), (2) and (3) of each panel, respectively, when *k* is 36 months.[2] Panel A presents the results for the full sample, while Panel B and Panel C depict the results for the subsamples of developed and emerging countries. Specification (1) in Panel A shows that *EP* is a strong predictor of future index returns. The coefficient estimate of the average *EP* is 0.0029, with a t-statistic of 2.93. The results for Specification (2), in which the *EP* components are included only, indicate that the average of the sum of the monthly coefficients on *dE* and *MOM* is 0.0118 and that on *dE* and *REV* is −0.0040; both of which are different from zero at 1% significance level (t-statistics are 3.59 and −2.89, respectively). So, not only *dE* and *MOM* but also *dE* and *REV* are different from each other in magnitude. The average difference between the monthly coefficients of *MOM* and *REV* is 0.0158 and it significantly differs from zero as well (t-statistic = 4.74). All these non-zero coefficient sums and the coefficient difference suggest that the slope estimates are, on average, different from each other. Moreover, the results of regression Equation (13), which is represented by Specification (3) in the table, demonstrate that the slopes of *MOM* and *REV* significantly depart from zero (t-statistics are 3.87 and −2.22, respectively). Testing the slope of *MOM* (*REV*) in Specification (3) against zero is equivalent to testing whether the sum of slopes on *MOM* (*REV*) in Specification (2) and *EP* in Specification (3) is equal to zero, i.e., whether *MOM* + *EP* = 0 (*REV* + *EP* = 0) is tested. Based on the statistically significant and positive (negative) slope on *MOM* (*REV*), it is concluded that the coefficient on *MOM* (*REV*) is not equal to that on *EP* in magnitude. Overall, the results in Specifications (2) and (3) show that the slopes on *dE, MOM* and *REV* are not statistically equal to each other; furthermore, the slopes on *MOM* and *REV* are also not equal to the slope on *EP*. These results show that the *EP* components contain independent information that can enhance the predictions of future returns for the full sample.

The results for the subsample of developed countries are presented in Panel B of Table 1. In Specification (1), *EP* does not have a significant slope and does not predict returns in developed markets. The results for Specification (2) show that the average slopes on *dE+MOM, dE+REV* and *MOM-REV* are all statistically different from zero; as is evidenced by the t-statistics of 3.97, −1.94

[2]The statistical significance of the coefficients is calculated based on the time-series averages of monthly estimates. This method builds on the Central Limit Theorem, which implies that the distribution of the sample mean will approach a normal distribution for a large enough sample size. This is true for a sample of independent random variables from any population distribution; as long as the population has a finite standard deviation. Finally, we use Matlab in order to estimate our models.

**Table 1.** Cross-sectional regressions for country-industry indexes.

| Panel A: Full Sample | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
| (1) | 0.0172[a] | 0.0029[a] | | | | | | | | 0.0165 | 199911 |
| | (4.99) | (2.93) | | | | | | | | | |
| (2) | 0.0174[a] | | 0.0036[a] | 0.0028[a] | 0.0091[a] | −0.0067[a] | 0.0118[a] | −0.0040[a] | 0.0158[a] | 0.0875 | 199911 |
| | (4.33) | | (3.33) | (3.12) | (2.76) | (−4.60) | (3.59) | (−2.89) | (4.74) | | |
| (3) | 0.0165[a] | | 0.0034[a] | −0.0007 | 0.0125[a] | −0.0032[b] | | | | 0.0878 | 199911 |
| | (4.27) | | (3.29) | (−1.24) | (3.87) | (−2.22) | | | | | |
| **Panel B: Developed Markets** | | | | | | | | | | | |
| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
| (1) | 0.0142[a] | 0.0020 | | | | | | | | 0.0247 | 127726 |
| | (3.21) | (1.51) | | | | | | | | | |
| (2) | | 0.0135[a] | 0.0026[b] | 0.0022[a] | 0.0126[a] | −0.0054[a] | 0.0148[a] | −0.0032[c] | 0.0180[a] | 0.1109 | 127726 |
| | | (3.19) | (2.25) | (2.63) | (3.34) | (−2.91) | (3.97) | (−1.94) | (4.78) | | |
| (3) | 0.0132[a] | 0.0026[b] | | −0.0004 | 0.0152[a] | −0.0027[c] | | | | 0.1113 | 127726 |
| | (3.24) | (2.32) | | (−0.62) | (4.45) | (−1.69) | | | | | |
| **Panel C: Emerging Markets** | | | | | | | | | | | |
| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
| (1) | 0.0351[a] | 0.0099[a] | | | | | | | | 0.1196 | 72185 |
| | (3.86) | (2.71) | | | | | | | | | |
| (2) | 0.0188[b] | | 0.0037 | 0.0030[b] | 0.0013 | −0.0059[a] | 0.0043 | −0.0030 | 0.0073[c] | 0.1431 | 71303 |
| | (2.31) | | (1.30) | (2.05) | (0.32) | (−3.05) | (0.96) | (−1.50) | (1.76) | | |
| (3) | 0.0109 | 0.0009 | | 0.0015 | 0.0022 | −0.0034 | | | | 0.1431 | 71303 |
| | (1.51) | (0.38) | | (0.61) | (0.39) | (−0.79) | | | | | |

This table shows the average slopes and their *t*-statistics from cross-sectional regressions of one-month ahead country-industry index returns on *EP*, as well as its components, for the period between January 1978 and July 2017. Panel A shows the results for the full sample of industry indexes, while Panel B and Panel C focus on industry indexes from developed and emerging markets, respectively. *EP* is the log of the earnings-to-price ratio at month *t; LEP* is the log of the earnings-to-price ratio at month *t*-36; *dE* is the log of the change in earnings from month *t*-36 to *t; MOM* is the cumulative log return from month *t*-12 to *t*; and *REV* is the cumulative log return from month *t*-36 to *t*-12. *dE+MOM* (*dE+REV*) shows the monthly average value of the sum of the slopes on *dE* and *MOM* (*dE +REV*); *MOM-REV* shows the monthly average value of the difference of the slopes on *MOM* and *REV*. Lastly, *Nobs* shows the total number of index-month observations for each regression specification. The Newey–West (1987) adjusted *t*-statistics are reported in parentheses. [a], [b] and [c] indicate significance at 1%, 5% and 10% levels, respectively.

and 4.78, respectively. This means that the *EP* components are not equal to each other, and thus, they have different effects on expected returns. The results for Specification (3), in the same panel, demonstrate that the slope of *MOM* has a t-statistic of 4.45 and that the slope of *REV* has a t-statistic of −1.69. This implies that the slope of *MOM* and that of *REV* are not equal to the slope of *EP*. So, decomposing *EP* into its constituents reveals incremental information to predict future returns. Hence, the results regarding the relevancy of the decomposition for the sample of developed countries are qualitatively the same as those for the full sample.

However, the results for the sample of emerging countries presented in Panel C fail to provide evidence in favour of the relevancy of the *EP* decomposition. The results for Specification (2) indicate that the equality of the slopes on *EP* components cannot be rejected except for the equality of the slopes on *MOM* and *REV*, which is only marginally rejected (*MOM-REV* = 0.0073, t-stat = 1.76). Moreover, the results for Specification (3) demonstrate that none of the slopes on *EP* components are different from the slope on *EP*. Therefore, there is no consistent evidence for the relevancy of the *EP* decomposition in emerging countries. Consequently, the results for the full sample are driven by the results of the developed-markets subsample. These results indicate that the *EP* decomposition is important in developed markets but not in emerging markets. Lastly, the significant slope of *EP* in Specification (1) (0.0099 with a t-statistic of 2.71) suggests that *EP* alone has a stronger predictive ability than its components in emerging markets. Moreover, the slope on *EP* is also economically significant. One unit increase in *EP* causes expected returns to increase by 0.99% per month. Therefore, rather than decomposing *EP* and trying to forecast returns with its components, using *EP* itself in predictive regressions will be more meaningful within emerging markets.

A plausible explanation for the difference in the relative importance of the *EP* decomposition in developed and emerging markets can be provided in the framework of market segmentation/integration studies (Errunza and Losq 1985; Umutlu, Altay Salih, and Akdeniz 2010). Bekaert et al. (2011) offer a novel model-independent measure of market segmentation, which is the absolute difference between the *EP* ratios of a country and the global market. The intuition behind using this measure as a proxy for market segmentation rests on the fact that the earnings yield for a specific industry should be similar across countries under the null hypothesis of full financial and economic integration. If a country is not fully integrated with the global market, the earnings yield of a segmented country will be more heavily influenced by local factors and will deviate from the earnings yield of the world market, which is the weighted average of earnings yields of all countries. The higher (lower) the deviation is, the more the country is segmented (integrated). Bekaert et al. (2011) also showed that the market segmentation measure is low (high) and exhibits little (large) cross-country and time-series variation in developed (emerging) markets, on average. These findings support the view that developed markets are more integrated with the world market, whereas emerging markets are relatively more segmented.[3]

If this view is true, then it has some implications for the Fama–MacBeth regressions. We should observe an insignificant coefficient on *EP* in the Fama–MacBeth regressions of developed market industry returns on *EP*; this is because earnings yield in developed markets depicts no considerable cross-sectional and temporal variations. In other words, *EP* does not contain country-specific information across markets that can be used to capture the cross-sectional variation in expected returns on developed market industries. Naturally, another implication is that *EP* predicts future returns on emerging market industries, as it varies both across countries and through time; therefore, it contains both local market and time-specific information. The results for Specification (1), in which *EP* is the only explanatory variable, indicate an insignificant coefficient estimate on *EP* in developed markets and a significant slope in emerging markets, supporting the argument above. As *EP* does not predict country-industry returns in developed markets, searching for *EP* components that can help to reveal additional information becomes more important in these markets. Indeed, our decomposition analysis in developed markets shows that the *EP* components are more powerful than *EP* itself in predicting industry returns. Oppositely, as *EP* itself does predict future industry returns in emerging markets, the motivation for decomposing *EP* to seek other variables that contain extra information diminishes. Moreover, when *EP* has some information content, *EP* components should contain information that marginally adds to the existing information content of *EP* so that they can improve return estimates. If the information content of *EP* is large enough, i.e., *EP* has a strong predictive ability, then finding alternative variables that complement the large information set of *EP* can be harder. This can explain why the decomposition of *EP* in emerging markets does not lead to components that have predictive ability.

### Local stock-market indexes

So far, we have used the local industry indexes from 51 countries as the basic test assets. In this subsection, we check whether the results obtained are robust to the use of an alternative sample of local stock-market indexes.

A comparison of the results from the stock-market indexes in Table 2 to the results from the local industry indexes in Table 1 points out some important similarities. First, the full sample results are influenced by the results of developed markets for both stock-market indexes and local industry indexes. Second, *MOM* is the most important component that increases the predictive performance of regressions in developed markets for both samples. Third, *EP* itself, rather than its components, is a sufficient measure to explain returns in emerging markets. There is only one difference between the results found in Tables 1 and 2; while *REV* is a crucial component for local industry indexes from developed markets as can be seen in Table 1, it does not contribute to return estimation for stock-market indexes of both developed and emerging markets – as is evidenced in Table 2. Overall,

[3]The heterogeneity in the relevancy of *EP* decomposition in emerging and developed markets might be potentially attributed to differences in the degree of market efficiency of these markets; for it is expected that emerging (developed) markets are less (more) efficient. However, the results do not lend support towards a market-efficiency explanation. *EP* contains information about future returns in emerging markets, whereas price-based variables – such as *MOM* and *REV* – have no predictive power. These results are in line with the view that emerging markets are weak-form efficient. However, *MOM* and *REV* capturing past price information end up predicting future returns in developed markets; this suggests that developed markets are not efficient – even in weak form.

**Table 2.** Results for an alternative sample consisting of local stock-market indexes.

| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Full Sample | | | | | | | | | | | |
| (1) | 0.0225$^{a}$ | 0.0053$^{a}$ | | | | | | | | 0.0576 | 15778 |
| | (4.01) | (3.23) | | | | | | | | | |
| (2) | 0.0271$^{a}$ | | 0.0074$^{a}$ | 0.0041 | 0.0061 | −0.0057$^{c}$ | 0.0102$^{c}$ | −0.0016 | 0.0118$^{b}$ | 0.2712 | 15778 |
| | (3.31) | | (3.35) | (1.39) | (1.26) | (−1.67) | (1.89) | (−0.59) | (2.13) | | |
| (3) | 0.0214$^{a}$ | 0.0057$^{a}$ | | −0.0022 | 0.0120$^{a}$ | 0.0008 | | | | 0.2708 | 15778 |
| | (2.71) | (2.74) | | (−0.74) | (2.66) | (0.25) | | | | | |
| Panel B: Developed Markets | | | | | | | | | | | |
| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
| (1) | 0.0165$^{b}$ | 0.0033 | | | | | | | | 0.0929 | 9604 |
| | (2.25) | (1.45) | | | | | | | | | |
| (2) | 0.0192$^{a}$ | | 0.0047$^{b}$ | 0.0017 | 0.0117$^{b}$ | −0.0028 | 0.0134$^{b}$ | −0.0011 | 0.0145$^{a}$ | 0.3624 | 9604 |
| | (2.78) | | (2.33) | (0.55) | (2.46) | (−0.70) | (2.55) | (−0.32) | (2.67) | | |
| (3) | 0.0185$^{a}$ | 0.0047$^{b}$ | | −0.0029 | 0.0164$^{a}$ | 0.0020 | | | | 0.3639 | 9604 |
| | (2.93) | (2.48) | | (−0.93) | (3.92) | (0.54) | | | | | |
| Panel C: Emerging Markets | | | | | | | | | | | |
| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
| (1) | 0.0360$^{a}$ | 0.0092$^{b}$ | | | | | | | | 0.0797 | 5957 |
| | (2.91) | (2.54) | | | | | | | | | |
| (2) | 0.0489$^{a}$ | | 0.0161$^{a}$ | 0.0068$^{c}$ | −0.0081 | −0.0091$^{c}$ | −0.0013 | −0.0023 | 0.0009 | 0.3164 | 5853 |
| | (2.72) | | (2.79) | (1.67) | (−0.92) | (−1.77) | (−0.18) | (−0.55) | (0.11) | | |
| (3) | 0.0294$^{c}$ | 0.0091$^{b}$ | | −0.0060$^{b}$ | 0.0020 | 0.0025 | | | | 0.3158 | 5853 |
| | (1.95) | (2.03) | | (−2.19) | (0.25) | (0.63) | | | | | |

This table shows the average slopes and their *t*-statistics from cross-sectional regressions of one-month ahead stock-market index returns on *EP*, as well as its components, for the period between January 1978 and July 2017. Panel A shows the results for the full sample of country indexes, while Panel B and Panel C focus on country indexes from developed and emerging markets, respectively. *EP* is the log of the earnings-to-price ratio at month *t; LEP* is the log of the earnings-to-price ratio at month *t*-36; *dE* is the log of the change in earnings from month *t*-36 to *t; MOM* is the cumulative log return from month *t*-12 to *t*; and *REV* is the cumulative log return from month *t*-36 to *t*-12. *dE+MOM* (*dE+REV*) shows the monthly average value of the sum of the slopes on *dE* and *MOM* (*dE* and *REV*); *MOM-REV* shows the monthly average value of the difference of the slopes on *MOM* and *REV*. Lastly, *Nobs* shows the total number of index-month observations for each regression specification. The Newey–West (1987) adjusted *t*-statistics are reported in parentheses. [a], [b] and [c] indicate significance at 1%, 5% and 10% levels, respectively.

using the alternative sample of stock-markets indexes does not materially change our main results.

## Size portfolios

The relevancy of *EP* decomposition may not be the same for all size portfolios; moreover, the relationship between both *EP* components and returns may not be linear across size portfolios. The decomposition may not produce return predicting variables for portfolios of a certain size, and/or only some of the components may have predictive ability across all size quintiles. To check these issues, we split the sample into five quintiles that are based on market capitalization. Local industry indexes are sorted on the previous month's market capitalization and then quintile portfolios are formed for each month of the research period. Portfolio *MV*1 includes the industry indexes with the lowest market capitalization values, while portfolio *MV*5 includes the ones with the highest values. Then, the Fama–MacBeth regressions are estimated for each size portfolio for each month in the usual manner and the results are reported in Table 3.

The results show that *MOM* is the most important *EP* component across all size quintiles. For small size quintiles, *REV* and *dE* play an important role in predicting returns. However, as the market capitalization of portfolios increases, *MOM* remains as the only influential *EP* component. These results suggest that the pertinence of *EP* decomposition is pervasive across size quintiles.

## Further tests

### Changes in EP at different lags

We are also interested in the question whether recent news is more relevant about expected returns than older news. Answering this question has substantial implications for the importance of the *EP* decomposition, as the *EP* components include past changes in earnings and prices, which contain more recent information than the lagged value of *EP*, which captures more distant

**Table 3.** Results for size portfolios.

| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Low *MV*1 | | | | | | | | | | | |
| (1) | 0.0179[a] | 0.0011 | | | | | | | | 0.0551 | 21905 |
| | (2.62) | (0.48) | | | | | | | | | |
| (2) | 0.0258[a] | | 0.0045 | 0.0058[c] | 0.0137[a] | −0.0121[b] | 0.0195[a] | −0.0063[b] | 0.0258[a] | 0.2244 | 21887 |
| | (2.69) | | (1.40) | (1.83) | (2.87) | (2.31) | (3.80) | (−2.05) | (3.83) | | |
| (3) | 0.0240[c] | 0.0040 | | 0.0015 | 0.0181[a] | −0.0079[b] | | | | 0.2239 | 21887 |
| | (1.78) | (1.40) | | (0.75) | (4.03) | (−2.00) | | | | | |
| Panel B: *MV*2 | | | | | | | | | | | |
| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
| (1) | 0.0175[a] | 0.0021[b] | | | | | | | | 0.0352 | 34986 |
| | (4.37) | (2.20) | | | | | | | | | |
| (2) | 0.0185[a] | | 0.0037[a] | 0.0022[b] | 0.0128[a] | −0.0059[a] | 0.0150[a] | −0.0037[b] | 0.0187[a] | 0.1622 | 34986 |
| | (3.42) | | (3.01) | (2.16) | (3.15) | (−3.27) | (3.44) | (−1.99) | (4.05) | | |
| (3) | 0.0168[a] | 0.0033[a] | | −0.0013 | 0.0163[a] | −0.0023 | | | | 0.1624 | 34986 |
| | (3.22) | (2.73) | | (−1.20) | (3.62) | (−1.53) | | | | | |
| Panel C: *MV*3 | | | | | | | | | | | |
| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
| (1) | 0.0207[a] | 0.0043[a] | | | | | | | | 0.0316 | 42289 |
| | (4.87) | (3.10) | | | | | | | | | |
| (2) | 0.0236[a] | | 0.0057[a] | 0.0033[b] | 0.0069[c] | −0.0077[a] | 0.0102[b] | −0.0044[b] | 0.0146[a] | 0.1614 | 42289 |
| | (4.92) | | (3.99) | (2.21) | (1.80) | (−3.35) | (2.50) | (−1.99) | (3.49) | | |
| (3) | 0.0211[a] | 0.0051[a] | | −0.0020[b] | 0.0123[a] | −0.0022 | | | | 0.1617 | 42289 |
| | (4.48) | (3.54) | | (−2.36) | (3.12) | (−1.02) | | | | | |
| Panel D: *MV*4 | | | | | | | | | | | |
| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
| (1) | 0.0079[c] | −0.0001 | | | | | | | | 0.0316 | 47849 |
| | (1.94) | (−0.06) | | | | | | | | | |
| (2) | 0.0108[b] | | 0.0022[c] | 0.0014 | 0.0127[a] | −0.0016 | 0.0141[a] | −0.0002 | 0.0144[a] | 0.1662 | 47849 |
| | (2.37) | | (1.82) | (1.28) | (3.51) | (−0.80) | (3.72) | (−0.11) | (3.42) | | |
| (3) | 0.0096[b] | 0.0018 | | −0.0005 | 0.0147[a] | 0.0004 | | | | 0.1660 | 47849 |
| | (2.23) | (1.59) | | (−0.54) | (4.00) | (0.20) | | | | | |
| Panel E: High *MV*5 | | | | | | | | | | | |
| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
| (1) | 0.0143[a] | 0.0025 | | | | | | | | 0.0835 | 52834 |
| | (2.85) | (1.52) | | | | | | | | | |
| (2) | 0.0124[b] | | 0.0022 | 0.0023[c] | 0.0063 | −0.0058[b] | 0.0086[b] | −0.0035 | 0.0120[a] | 0.2413 | 52834 |
| | (2.43) | | (1.24) | (1.76) | (1.44) | (−2.13) | (2.02) | (−1.43) | (2.74) | | |
| (3) | 0.0119[b] | 0.0021 | | 0.0002 | 0.0084[c] | −0.0036 | | | | 0.2417 | 52834 |
| | (2.54) | (1.27) | | (0.12) | (1.81) | (−1.28) | | | | | |

This table shows the average slopes and their *t*-statistics from cross-sectional regressions of one-month ahead country-industry index returns on *EP* and its components for different size quintiles. *MV*1(5) indicates the portfolio of country-industry indexes with the lowest (highest) market capitalization. Panels A-E show the results for each size portfolio. *EP* is the log of the earnings-to-price ratio at month *t; LEP* is the log of the earnings-to-price ratio at month *t*-36; *dE* is the log of the change in earnings from month *t*-36 to *t; MOM* is the cumulative log return from month *t*-12 to *t*; and *REV* is the cumulative log return from month *t*-36 to *t*-12. *dE+MOM* (*dE+REV*) shows the monthly average value of the sum of the slopes on *dE* and *MOM* (*dE* and *REV*); *MOM-REV* shows the monthly average value of the difference on the slopes for *MOM* and *REV*. Lastly, *Nobs* shows the total number of index-month observations for each regression specification. The Newey–West (1987) adjusted *t*-statistics are reported in parentheses. [a, b] and [c] indicate significance at 1%, 5% and 10% levels, respectively.

information. If the *EP* decomposition makes sense, then more recent news contained in *EP* components, such as *dE, MOM* and *REV*, should be more relevant than older news contained in *LEP*. To test this conjecture, we examine the change in slopes of *EP* components with respect to *k* and compare the magnitude of the slope on *LEP* to the magnitudes of slopes on *dE, MOM* and *REV*. If the slopes on *EP* components decay as lag *k* increases; and/or the slope on *LEP* (which contains more distant news) is closer to zero than at least one of the slopes on *EP* components, which contains more recent news; it is concluded that recent information is more relevant than the old information. Therefore, it will show that *EP* decomposition matters.

The results from predictive regressions of monthly returns of local industry indexes that are estimated for lags of forty-eight and 60 months are presented in Table 4. The relative importance of old versus recent news is not clearly deduced from the full sample results, which are shown in Panel A. Although the slope on *LEP* is economically less influential for expected returns, i.e., closer to zero than the slopes on *MOM* and *REV*, the slopes on some *EP* components do not decrease monotonically as lag *k* increases. Note that, unlike the other *EP* components, we do not track the evolution of

**Table 4.** Decomposition with alternative lag lengths.

| | | $\alpha_0$ | EP | LEP | dE | MOM | REV | dE+MOM | dE+REV | MOM-REV | $R^2$ | Nobs |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Full Sample | | | | | | | | | | | | |
| (2) | $k = 48$ | 0.0183$^{a}$ | | 0.0038$^{a}$ | 0.0028$^{a}$ | 0.0088$^{a}$ | −0.0060$^{a}$ | 0.0116$^{a}$ | −0.0033$^{a}$ | 0.0148$^{a}$ | 0.0879 | 199911 |
| | | (4.72) | | (3.39) | (3.30) | (2.76) | (−3.93) | (3.57) | (−2.59) | (4.53) | | |
| (3) | $k = 48$ | 0.0173$^{a}$ | 0.0036$^{a}$ | | −0.0009 | 0.0124$^{a}$ | −0.0024 | | | | 0.0884 | 199911 |
| | | (4.65) | (3.38) | | (−1.60) | (3.95) | (−1.56) | | | | | |
| (2) | $k = 60$ | 0.0178$^{a}$ | | 0.0036$^{a}$ | 0.0026$^{a}$ | 0.0086$^{a}$ | −0.0062$^{a}$ | 0.0112$^{a}$ | −0.0036$^{a}$ | 0.0148$^{a}$ | 0.0878 | 199911 |
| | | (4.68) | | (3.61) | (3.02) | (2.70) | (−4.40) | (3.51) | (−3.20) | (4.59) | | |
| (3) | $k = 60$ | 0.0169$^{a}$ | 0.0035$^{a}$ | | −0.0009$^{c}$ | 0.0120$^{a}$ | −0.0027$^{b}$ | | | | 0.0884 | 199911 |
| | | (4.67) | (3.70) | | (−1.92) | (3.82) | (−2.13) | | | | | |
| Panel B: Developed Markets | | | | | | | | | | | | |
| | | $\alpha_0$ | EP | LEP | dE | MOM | REV | dE+MOM | dE+REV | MOM-REV | $R^2$ | Nobs |
| (2) | $k = 48$ | 0.0147$^{a}$ | | 0.0027$^{b}$ | 0.0023$^{a}$ | 0.0119$^{a}$ | −0.0049$^{a}$ | 0.0142$^{a}$ | −0.0026$^{c}$ | 0.0168$^{a}$ | 0.1106 | 127726 |
| | | (3.40) | | (2.28) | (2.73) | (3.20) | (−2.66) | (3.88) | (−1.70) | (4.60) | | |
| (3) | $k = 48$ | 0.0142$^{a}$ | 0.0027$^{b}$ | | −0.0003 | 0.0145$^{a}$ | −0.0022 | | | | 0.1112 | 127726 |
| | | (3.48) | (2.36) | | (−0.49) | (4.32) | (−1.36) | | | | | |
| (2) | $k = 60$ | 0.0143$^{a}$ | | 0.0026$^{b}$ | 0.0020$^{b}$ | 0.0118$^{a}$ | −0.0047$^{a}$ | 0.0138$^{a}$ | −0.0027$^{b}$ | 0.0165$^{a}$ | 0.1101 | 127726 |
| | | (3.22) | | (2.25) | (2.38) | (3.11) | (−2.88) | (3.77) | (−2.10) | (4.55) | | |
| (3) | $k = 60$ | 0.0138$^{a}$ | 0.0026$^{b}$ | | −0.0006 | 0.0143$^{a}$ | −0.0021 | | | | 0.1108 | 127726 |
| | | (3.29) | (2.34) | | (−0.87) | (3.99) | (−1.61) | | | | | |
| Panel C: Emerging Markets | | | | | | | | | | | | |
| | | $\alpha_0$ | EP | LEP | dE | MOM | REV | dE+MOM | dE+REV | MOM-REV | $R^2$ | Nobs |
| (2) | $k = 48$ | 0.0050 | | −0.0006 | −0.0015 | −0.0001 | 0.0016 | −0.0015 | 0.0002 | −0.0017 | 0.1443 | 71303 |
| | | (0.54) | | (−0.25) | (−0.76) | (−0.01) | (0.42) | (−0.33) | (0.04) | (−0.27) | | |
| (3) | $k = 48$ | 0.0051 | −0.0005 | | −0.0001 | −0.0005 | −0.00004 | | | | 0.1446 | 71303 |
| | | (0.55) | (−0.22) | | (−0.04) | (−0.09) | (−0.02) | | | | | |
| (2) | $k = 60$ | 0.0094 | | 0.0055$^{a}$ | 0.0164 | 0.0051 | −0.0118$^{b}$ | 0.0215$^{c}$ | 0.0046 | 0.0169$^{a}$ | 0.1421 | 71303 |
| | | (1.29) | | (2.85) | (0.84) | (1.31) | (−2.18) | (1.74) | (0.64) | (3.08) | | |
| (3) | $k = 60$ | 0.0139$^{b}$ | 0.0086$^{a}$ | | 0.0121 | 0.0180$^{a}$ | −0.0076 | | | | 0.1421 | 71303 |
| | | (2.25) | (4.40) | | (0.74) | (3.96) | (−0.99) | | | | | |

This table shows the average slopes, as well as their *t*-statistics from cross-sectional regressions of one-month ahead country-industry index returns on *EP* components calculated with alternative lag lengths. Panel A shows the results for the full sample of industry indexes, while Panel B and Panel C focus on industry indexes from developed and emerging markets, respectively. *EP* is the log of the earnings-to-price ratio at month *t; LEP* is the log of the earnings-to-price ratio at month *t-k; dE* is the log of the change in earnings from month *t-k* to *t; MOM* is the cumulative log return from month *t*-12 to *t*; and *REV* is the cumulative log return from month *t-k* to *t*-12. *k* represents the alternative lag lengths of 48 and 60 months. *dE+MOM* (*dE+REV*) shows the monthly average value of the sum of the slopes on *dE* and *MOM* (*dE* and *REV*); *MOM-REV* shows the monthly average value of the difference of the slopes on *MOM* and *REV*. Lastly, *Nobs* shows the total number of index-month observations for each regression specification. The Newey–West (1987) adjusted *t*-statistics are reported in parentheses. $^{a,}$ $^{b}$ and $^{c}$ indicate significance at 1%, 5% and 10% levels, respectively.

the slope on *MOM* with respect to different levels of *k*; this is because *MOM* persistently measures the change in price over the last 12 months by definition, and thus, the information captured by *MOM* is independent of *k*. A closer look at the developed markets seen in Panel B demonstrates that recent news is far more relevant in developed markets, as the slope magnitudes of *MOM* and *REV* are much larger than that of *LEP* in Specification (2); moreover, the slopes of *LEP*, *dE* and *REV* decay as *k* increases. For emerging markets, there is no evidence that recent news is more relevant than older news for expected returns. None of the slopes for *EP* components in Panel C are getting closer to zero as *k* gets larger.

The finding that recent news is more relevant than older news in developed markets, but not in emerging markets, is consistent with the results of Table 1, which indicate that *EP* decomposition only matters for developed markets. Recall that a change in *EP* can be expressed as the summation of lagged changes in earnings (*dE*) and price (*MOM* and *REV*), as well as the lagged value of *EP* (*LEP*). If recent news is more relevant than distant news in predicting future returns, as documented in Table 4, then the *EP* components such as *dE, MOM* and *REV* that contain more recent information than the remaining *EP* component, *LEP*, which has the oldest information, should have statistically different slopes than the slope of *LEP*. This is exactly what we have found in Table 1 for developed markets. Hence, the results in Table 4, which suggest that recent news is more relevant in developed markets and that *EP* decomposition only matters for developed markets, confirm the results in Table 1.

## *Sub-period analyses*

We further test whether the relevancy of the *EP* decomposition changes over time. If *EP* decomposition helps track useful information to predict returns, especially in the recent past, then this can determine the current trading strategies of investors. To check this issue, we perform a sub-period analysis and split the research period into two halves. The first half extends from 1978 to 1997, and the second half covers the period between 1998 and 2017.

The results in Panel A and Panel B of Table 5 show that the *EP* decomposition is a persistently important issue for developed markets. In both the early sub-period (Panel A) and the recent sub-period (Panel B), *MOM* is significantly distinguished from other components; this is evidenced by the significant slopes on *dE+MOM* and *MOM-REV* in Specification (2) and also from *EP* as evidenced by the significant slope on *MOM* in Specification (3). However, in the recent period, both the economic and statistical significance of the above-mentioned slopes diminish, as can be seen in Panel B. This suggests that the decomposition reveals relatively less information in the recent period when compared to the early period. Nevertheless, in both periods, decomposing *EP* into its constituents is a worthwhile effort in developed markets. In emerging markets, the results for the first and second halves of the sample period are very similar to those for the full sample period. In both sub-periods, *EP* decomposition does not work to obtain incremental information.

Another interesting point in Table 5 is the time variation in the slope of *EP* in Specification (1). In developed markets, *EP* has a significant slope in Specification (1) in the first half of the sample; however, the significant impact of *EP* disappears in the second half. Bekaert et al. (2011) state that developed markets have been effectively integrated since 1993, whereas emerging markets remained segmented. This suggests that in the first half when developed markets were also relatively segmented, *EP* predicts future returns. When

**Table 5.** Sub-period analyses.

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Developed Markets 1978–1997 | | | | | | | | | | | |
| | $a_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
| (1) | 0.0185[a] | 0.0033[a] | | | | | | | | 0.0225 | 51669 |
| | (4.65) | (2.60) | | | | | | | | | |
| (2) | 0.0180[a] | | 0.0037[a] | 0.0031[a] | 0.0139[a] | −0.0067[a] | 0.0170[a] | −0.0035[c] | 0.0206[a] | 0.1008 | 51669 |
| | (4.58) | | (2.79) | (2.81) | (3.33) | (−3.72) | (3.75) | (−1.86) | (4.73) | | |
| (3) | 0.0173[a] | 0.0036[a] | | −0.0005 | 0.0175[a] | −0.0030 | | | | 0.1015 | 51669 |
| | (4.66) | (2.83) | | (−0.67) | (4.31) | (−1.38) | | | | | |
| Panel B: Developed Markets 1998–2017 | | | | | | | | | | | |
| | $a_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
| (1) | 0.0118 | 0.0014 | | | | | | | | 0.0205 | 84377 |
| | (1.58) | (0.63) | | | | | | | | | |
| (2) | 0.0111 | | 0.0022 | 0.0017 | 0.0095[c] | −0.0040 | 0.0113[b] | −0.0023 | 0.0135[a] | 0.0996 | 84377 |
| | (1.53) | | (1.28) | (1.40) | (1.94) | (−1.27) | (2.51) | (−0.84) | (2.89) | | |
| (3) | 0.0110 | 0.0022 | | −0.0004 | 0.0117[a] | −0.0018 | | | | 0.0997 | 84377 |
| | (1.56) | (1.32) | | (−0.61) | (2.76) | (−0.68) | | | | | |
| Panel C: Emerging Markets 1978–1997 | | | | | | | | | | | |
| | $a_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
| (1) | 0.0609[a] | 0.0206[a] | | | | | | | | 0.1920 | 10582 |
| | (5.05) | (4.06) | | | | | | | | | |
| (2) | −0.0448 | | −0.0157 | −0.0722 | 0.1589[b] | 0.0183 | 0.0867 | −0.0538 | 0.1406 | 0.6357 | 10582 |
| | (−0.47) | | (−0.75) | (−0.99) | (2.26) | (0.22) | (1.42) | (−1.28) | (1.56) | | |
| (3) | 0.1425 | 0.0242 | | 0.0906 | 0.0390 | −0.1251 | | | | 0.6364 | 10582 |
| | (1.29) | (1.20) | | (0.89) | (0.47) | (−1.22) | | | | | |
| Panel D: Emerging Markets 1998–2017 | | | | | | | | | | | |
| | $a_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
| (1) | 0.0230[a] | 0.0039[a] | | | | | | | | 0.0110 | 73859 |
| | (4.94) | (3.59) | | | | | | | | | |
| (2) | 0.0181[a] | | 0.0037[a] | 0.0030[a] | −0.0008 | −0.0073[a] | 0.0023 | −0.0042[c] | 0.0065[b] | 0.0696 | 73859 |
| | (2.79) | | (3.37) | (2.74) | (−0.20) | (−3.69) | (0.55) | (−1.88) | (2.11) | | |
| (3) | 0.0160[b] | 0.0031[b] | | −0.0003 | 0.0024 | −0.0039 | | | | 0.0697 | 73859 |
| | (2.43) | (2.55) | | (−0.47) | (0.57) | (−1.60) | | | | | |

This table shows the average slopes, as well as their *t*-statistics from cross-sectional regressions of one-month ahead country-industry index returns of developed and emerging markets on *EP* and its components for two sub-periods. Panels A and B (C and D) show the results of developed (emerging) markets for the sub-periods of 1978 to 1997 and 1998 to 2017, respectively. *EP* is the log of the earnings-to-price ratio at month *t*; *LEP* is the log of the earnings-to-price ratio at month *t*-36; *dE* is the log of the change in earnings from month *t*-36 to *t*; *MOM* is the cumulative log return from month *t*-12 to *t*; and *REV* is the cumulative log return from month *t*-36 to *t*-12. *dE+MOM* (*dE+REV*) shows the monthly average value of the sum of the slopes on *dE* and *MOM* (*dE* and *REV*); *MOM-REV* shows the monthly average value of the difference on the slopes for *MOM* and *REV*. Lastly, *Nobs* shows the total number of index-month observations for each regression specification. The Newey–West (1987) adjusted *t*-statistics are reported in parentheses. [a], [b] and [c] indicate significance at 1%, 5% and 10% levels, respectively.

developed markets were integrated with the global markets in the second half, *EP* lost its significance. This is consistent with our previous interpretation that *EP* does not contain local information for integrated markets. In emerging markets, both the economic and statistical significance of the slope on *EP* in Specification (1) decrease in the second half, as is evidenced by a lower slope coefficient and a t-statistic. This is also in line with the view that the local information content of *EP* diminishes, as emerging markets get more and more integrated through time.[4]

### Inclusion of control variables

Last, we examine the robustness of our results after controlling for both net share issuance and size effects. We regress one-month ahead returns of country-industry indexes on *EP* and its components along with net share issue and size in different combinations. The size variable (*MV*) is the market capitalization of a country-industry index. Fama and French (2008) define net share issue (*NSI*) as the change in the log of split-adjusted shares outstanding, which is equal to the difference between continuously compounded growth in total market equity and continuously compounded capital gain.

We report the results for regression specifications, including *MV* and *NSI*, in Table 6. This table presents the average slope coefficients of regression Equations (11)–(13) when 36-months lagged value of *EP* is used. The results in Table 6 are qualitatively the same as the results in Table 1. Hence, our results are robust even after accounting for the size and net share issue effects.

### Panel regressions

As a robustness check, we switch our methodology from the Fama and MacBeth (1973) cross-sectional regressions to panel regressions. The strong side of panel regressions is its ability to accommodate both fixed country and time effects in analyses. The weak side is that the panel estimation procedure that is used requires a balanced panel with the same number of time-series observations for every cross-sectional unit. This causes a loss of time-series observations, especially for the cross-sectional units that have time-series data that go relatively far back in time. On the other hand, cross-sectional regressions employ all data, at a point in time, for the available cross-sectional units. In contrast to panel regressions, the Fama and MacBeth regressions allow the number of cross-sectional units to change through time; therefore, they incorporate a larger amount of information within the analysis. As shown in Table 7, the main results from panel regressions for both developed and emerging country indexes still hold after controlling for fixed country and time effects. In short, the decomposition matters for developed markets but is irrelevant for emerging markets.

The full sample results for panel regressions are similar to those of the emerging subsample, suggesting that the full sample is dominated by the emerging subsample. This is not surprising, as in the balanced panel, the number of emerging markets outweighs the number of developed markets. Hence, emerging markets' share in the full sample increases. However, note that this is not the case for cross-sectional regressions. For a long time within the early periods, the full sample almost entirely consisted of developed markets because many of the emerging stock exchanges were established in the late 1980s or early 1990s. The dominance of developed markets, especially in early periods, is reflected in the full sample results, which are similar to those of developed markets.

## VI. Conclusion

We examine whether the components of the earnings-to-price (*EP*) ratio can be used to extract incremental information to better estimate future returns of international indexes. Cross-sectional regressions of industry-index returns on *EP* components (such as lagged *EP*, changes in earnings, short-term momentum, and long-term reversal in

[4]We perform another sub-period analysis that is based on the pre- and post-Global Financial Crisis periods to check whether the results are sensitive to the choice of sub-period dates. The pre-crisis period is defined as the period between 1978 and 2006; and the post-crisis period is defined as the period starting from 2007 and extending to 2018. The results for new sub-period definitions are presented in Table A3 of the Online Appendix and are qualitatively similar with the results from the former sub-period analysis.

**Table 6.** Cross-sectional regressions with control variables.

Panel A: Full Sample

| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *NSI* | *MV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | 0.0273$^{a}$ | 0.0025$^{b}$ | | | | | 0.0000 | −0.0013$^{a}$ | | | | 0.0390 | 199680 |
| | (5.30) | (2.40) | | | | | (0.07) | (−3.94) | | | | | |
| (2) | 0.0260$^{a}$ | | 0.0031$^{a}$ | 0.0026$^{a}$ | 0.0095$^{a}$ | −0.0059$^{a}$ | 0.0000 | −0.0012$^{a}$ | 0.0121$^{a}$ | −0.0033$^{b}$ | 0.0154$^{a}$ | 0.1087 | 199680 |
| | (4.87) | | (2.75) | (3.01) | (2.82) | (−4.16) | (−0.29) | (−4.08) | (3.62) | (−2.46) | (4.63) | | |
| (3) | 0.0250$^{a}$ | 0.0029$^{a}$ | | −0.0003 | 0.0124$^{a}$ | −0.0029$^{b}$ | 0.0000 | −0.0012$^{a}$ | | | | 0.1089 | 199680 |
| | (4.81) | (2.66) | | (−0.56) | (3.79) | (−2.09) | (−0.29) | (−4.07) | | | | | |

Panel B: Developed Markets

| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *NSI* | *MV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | 0.0224$^{a}$ | 0.0017 | | | | | 0.0000 | −0.0010$^{a}$ | | | | 0.0535 | 127655 |
| | (3.98) | (1.22) | | | | | (−0.16) | (−3.05) | | | | | |
| (2) | 0.0198$^{a}$ | | 0.0022$^{c}$ | 0.0021$^{b}$ | 0.0130$^{a}$ | −0.0049$^{a}$ | −0.0001 | −0.0009$^{a}$ | 0.0151$^{a}$ | −0.0028$^{c}$ | 0.0179$^{a}$ | 0.1368 | 127655 |
| | (3.57) | | (1.83) | (2.40) | (3.31) | (−2.79) | (−0.72) | (−2.94) | (3.92) | (−1.85) | (4.75) | | |
| (3) | 0.0195$^{a}$ | 0.0022$^{c}$ | | −0.0001 | 0.0152$^{a}$ | −0.0026$^{c}$ | −0.0001 | −0.0009$^{a}$ | | | | 0.1371 | 127655 |
| | (3.58) | (1.89) | | (−0.18) | (4.31) | (−1.75) | (−0.72) | (−2.93) | | | | | |

Panel C: Emerging Markets

| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *NSI* | *MV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | 0.0634$^{a}$ | 0.0095 | | | | | 0.0031$^{c}$ | −0.0017$^{b}$ | | | | 0.3447 | 72025 |
| | (3.64) | (1.47) | | | | | (1.78) | (−2.34) | | | | | |
| (2) | 0.0239$^{a}$ | | −0.0020 | −0.0031$^{c}$ | −0.0016 | 0.0015 | 0.0003 | −0.0022$^{a}$ | −0.0047 | −0.0016 | −0.0031 | 0.1790 | 71143 |
| | (3.10) | | (−1.34) | (−1.81) | (−0.32) | (0.55) | (0.72) | (−4.87) | (−0.85) | (−0.64) | (−0.57) | | |
| (3) | 0.0058 | −0.0088$^{a}$ | | 0.0007 | −0.0155$^{a}$ | −0.0020 | 0.0002 | −0.0020$^{a}$ | | | | 0.1789 | 71143 |
| | (0.67) | (−4.32) | | (0.53) | (−2.58) | (−0.52) | (0.63) | (−4.25) | | | | | |

This table shows the average slopes, as well as their *t*-statistics from cross-sectional regressions of one-month ahead country-industry index returns on *EP* and its components for the period between January 1978 and July 2017. Panel A shows the results for the full sample of industry indexes, while Panel B and Panel C focus on industry indexes from developed and emerging markets, respectively. *EP* is the log of the earnings-to-price ratio at month *t; LEP* is the log of the earnings-to-price ratio at month *t*-36; *dE* is the log of the change in earnings from month *t*-36 to *t; MOM* is the cumulative log return from month *t*-12 to *t; REV* is the cumulative log return from month *t*-36 to *t*-12; *NSI* is the log of the net share issuance from *t*-12 to *t*; and *MV* is the log of the market capitalization in month *t. dE+MOM* (*dE+REV*) shows the monthly average value of the sum of the slopes on *dE* and *MOM* (*REV*); *MOM-REV* shows the monthly average value of the difference of the slopes on *MOM* and *REV*. Lastly, *Nobs* shows the total number of index-month observations for each regression specification. The Newey–West (1987) adjusted *t*-statistics are reported in parentheses. $^{a,\ b}$ and $^{c}$ indicate significance at 1%, 5% and 10% levels, respectively.

**Table 7.** Panel regression results.

Panel A: Full Sample

| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | 0.0365$^{a}$ | 0.0108$^{a}$ | | | | | | | | 0.3761 | 18838 |
| | (5.98) | (4.72) | | | | | | | | | |
| (2) | 0.0539$^{a}$ | | 0.0168$^{a}$ | 0.0105$^{a}$ | −0.0063 | −0.0148$^{a}$ | 0.0042 | −0.0042 | 0.0084 | 0.4235 | 16866 |
| | (7.42) | | (6.33) | (4.16) | (−1.02) | (−3.77) | (0.64) | (−1.21) | (1.27) | | |
| (3) | 0.0473$^{a}$ | 0.0148$^{a}$ | | −0.0051$^{b}$ | 0.0090 | 0.0011 | | | | 0.4232 | 16866 |
| | (7.15) | (5.96) | | (−2.51) | (1.42) | (0.36) | | | | | |

Panel B: Developed Markets

| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | 0.0204$^{a}$ | 0.0051$^{b}$ | | | | | | | | 0.5353 | 10984 |
| | (2.90) | (1.97) | | | | | | | | | |
| (2) | 0.0338$^{a}$ | | 0.0097$^{a}$ | 0.0059$^{b}$ | 0.0087 | −0.0126$^{a}$ | 0.0147$^{b}$ | −0.0066$^{c}$ | 0.0213$^{a}$ | 0.5664 | 10151 |
| | (4.67) | | (3.75) | (2.54) | (1.41) | (−3.30) | (2.37) | (−1.95) | (3.16) | | |
| (3) | 0.0324$^{a}$ | 0.0095$^{a}$ | | −0.0035 | 0.0182$^{a}$ | −0.0029 | | | | 0.5665 | 10151 |
| | (4.75) | (3.78) | | (−1.54) | (2.95) | (0.84) | | | | | |

Panel C: Emerging Markets

| | $\alpha_0$ | *EP* | *LEP* | *dE* | *MOM* | *REV* | *dE+MOM* | *dE+REV* | *MOM-REV* | $R^2$ | *Nobs* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | 0.0586$^{a}$ | 0.0188$^{a}$ | | | | | | | | 0.3418 | 7854 |
| | (5.59) | (4.71) | | | | | | | | | |
| (2) | 0.0796$^{a}$ | | 0.0260$^{a}$ | 0.0174$^{a}$ | −0.0251$^{a}$ | −0.0238$^{a}$ | −0.0076 | −0.0064 | −0.0012 | 0.3999 | 6715 |
| | (5.69) | | (4.92) | (3.59) | (−2.69) | (−3.99) | (−0.79) | (−1.32) | (−0.12) | | |
| (3) | 0.0648$^{a}$ | 0.0212$^{a}$ | | −0.0060$^{c}$ | −0.0023 | 0.0002 | | | | 0.3989 | 6715 |
| | (5.18) | (4.34) | | (−1.82) | (−0.23) | (0.04) | | | | | |

This table shows the slopes, as well as their *t*-statistics from panel regressions of one-month ahead stock-market index returns on *EP* and its components for the period between January 1978 and July 2017. Panel A shows the results for the full sample of country indexes, while Panel B and Panel C focus on country indexes from developed and emerging markets, respectively. *EP* is the log of the earnings-to-price ratio at month *t; LEP* is the log of the earnings-to-price ratio at month *t*-36; *dE* is the log of the change in earnings from month *t*-36 to *t; MOM* is the cumulative log return from month *t*-12 to *t*; and *REV* is the cumulative log return from month *t*-36 to *t*-12. *dE+MOM* (*dE+REV*) shows the sum of the slopes on *dE* and *MOM* (*REV*); *MOM-REV* shows the difference of the slopes on *MOM* and *REV*. Lastly, *Nobs* shows the total number of index-month observations for each regression specification. The Newey–West (1987) adjusted *t*-statistics for individual slope coefficients are reported in parentheses. The numbers in parentheses, for the sum and difference of slopes (*dE+MOM, dE+REV* and *MOM-REV*), indicate t-statistics from Wald Test that examines whether coefficient sums and differences are equal to zero. $^{a,\ b}$ and $^{c}$ indicate significance at 1%, 5% and 10% levels, respectively.

prices) show that the *EP* decomposition increases the explanatory power of predictive regressions for developed markets but not for emerging markets. Momentum and reversal turn out to be the components that contain information beyond the information content of *EP* in developed markets. The results from an alternative sample that consists of country indexes confirm our previous result that the *EP* decomposition is more important in developed markets.

Moreover, we further decompose *EP* using 48- and 60-months lagged information, in addition to using a default lag length of 36 months. The results demonstrate that the *EP* components that contain more recent information have better predictive abilities in developed markets, suggesting that recent news is more relevant than older news in regard to estimating future returns. In addition, the sub-period analyses indicate that the *EP* decomposition in developed markets produces significant estimators of returns in both periods, providing further ground for decomposing *EP* in developed markets. Although more information is extracted in the former period, the significant results that are obtained in the recent period can be more interesting for investors who can form their current trading strategy based on the current return patterns. The irrelevancy of the decomposition in emerging markets is also verified by the sub-period analyses. Finally, our main results still hold after controlling for net share issuance, size, as well as fixed country and time effects.

Overall, the results show that decomposing *EP* into its components unlocks the buried information in *EP* in international markets – especially from developed markets. However, *EP* itself is more informative for emerging markets. The difference in the degree of market segmentation between developed and emerging markets can be an explanation for why the *EP* decomposition matters in developed markets but is pointless in emerging markets. Bekaert et al. (2011) conjecture that the *EP* ratio contains information about the degree of segmentation/integration of industries and countries. This conjecture suggests that earnings yields deviate from that of the world market and contain market-specific information for segmented markets; however, they are similar to the earnings yield of the world market and contain no local information for developed markets. One of the testable implications of this conjecture, in the context of international asset-pricing models, is that the *EP* ratio has predictive power in the cross-section of expected returns for emerging markets that are anticipated to be relatively more segmented, whereas it has no predictive ability for developed markets that are likely to be more integrated. Our results from predictive cross-sectional regressions lend support to this conjecture; furthermore, they have implications for global investors who aim to attain efficient international portfolio diversification. Emerging markets with *EP* ratios that depart from the *EP* ratio of the world market are characterized as segmented markets and, therefore, provide larger diversification opportunities.

Examining the existence of a value effect and its origins in alternative markets or in the cross-section of stock returns can be an interesting direction for future research. Consideration of transaction costs can also be another direction for future research. This study examines the predictability of returns via cross-sectional regressions; it does not aim to develop a trading strategy based on the portfolio sorting procedure. In such a portfolio analysis, the changes in portfolio weights over a month multiplied by a presumed fixed per trade cost can be used to estimate transaction costs. However, there is ambiguity on how to incorporate transactions costs into cross-sectional regressions. Since this paper is solely focused on the cross-sectional predictability of returns via regression analysis as in Fama and French (2008), and not on constructing a trading strategy based on portfolio sorts, the examination of transactions costs is left for a future study that contains the portfolio analysis.

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