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Full Length Article

Market efficiency and the capacity of stock prices to track a firm's future profitability

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Abstract

This study assesses the link between market efficiency proxies and the capacity of stock prices to anticipate a firm's future economic performance. The analysis, which covers firms from 31 countries in the period 1990−2019, reveals a strong association between the average score of market efficiency proxies and the sensitivity of current stock returns ("normalized" prices) to future profitability. These results are robust to several sensitivity tests, including different definitions of the profitability measure (earnings, cash flows, firm-specific earnings and ROA). Further analysis unveils heterogeneity in the association between popular proxies of market efficiency and the sensitivity of current stock returns ("normalized" prices) to future profitability. The signal-to-noise ratio and the partial adjustment coefficient are the market efficiency measures that display a higher association with the capacity of stock prices to track future profitability. Critically, other indicators display a weak association after controlling the effect of liquidity or the information environment.
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1. Introduction

The collection, processing, and aggregation of dispersed information about the fundamentals of the economy is an important function of financial markets. Trading in secondary markets impounds information acquired by investors into prices. Market efficiency refers to the extent to which available information is impounded into prices fully, quickly and correctly (Griffin, Kelly, and Nardari 2010). The concepts of weak-, semi-, and strong-form efficiency introduced by Fama (1970) translate the degree to which the efficient market hypothesis (EMH) can be applied to markets. Under the weak form, prices fully reflect the information implicit in the sequence of past prices, whereby future changes in stock prices are not predictable. The semi-strong (strong) form of EMH asserts that prices convey all public (public and private) available information.

Since the publication by Fama (1970), several weak and semi-strong form efficiency measures have been developed. However, little is known about how they relate to each other, both in the time series and cross-sectionally and, more crucially, whether they capture deviations of market prices from fundamental drivers. This study advances our knowledge by examining whether those indicators capture misalignment of market prices from the firm's long-term fundamentals. Specifically, we inquire whether the prices of stocks with greater market efficiency scores track future profitability more accurately. Future earnings and cash flows are key inputs of valuation models, meaning that if prices accurately reflect a firm's future economic performance, then,

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ceteris paribus, the alignment of prices with firm's intrinsic value is more plausible.

Two alternative approaches are explored to gauge the sensitivity of stock prices to future firm profitability. The first hinges on the FERC model, which emerged from the accounting literature (Collins, Kothari, Shanken, and Sloan, 1994; Lundholm & Myers, 2002). Within this setup, stock returns reflect unexpected current earnings and changes in contemporaneous expectations about future earnings. In practice, current returns are regressed against a constant, one-year lagged past earnings, current earnings, the sum of the earnings for the three-year period after the current fiscal one and three-year future stock returns. The future earnings response coefficient (FERC) corresponds to the coefficient on future earnings and quantifies the amount of forward-looking information about future earnings embedded in stock returns. The second approach is built on the framework developed by Bai, Philippon, and Savov (2016) — BPS, which explores the association between "normalized" prices and future firm profitability. At the baseline setting, the average of return on assets (ROA) for the three-year period subsequent to the current fiscal year is regressed against current "normalized" prices (Tobin's Q). A greater sensitivity of future ROA to Tobin's Q signifies higher price informativeness about future firm profitability.

Market efficiency is a latent variable, i.e., it cannot be directly observed but it can be inferred from observable variables. The concept of market efficiency comprises different facets, which is why several proxies have been developed thus far. The analysis is divided into two parts. The first addresses the association between an "aggregate" efficiency score and the capacity of stock prices to track a firm's future economic performance. In lieu of considering market efficiency proxies separately, we start by combining them into a single score that reflects the different dimensions of market efficiency. The different facets of market efficiency are considered altogether, i.e., the score summarizes the overall effect of market efficiency on the capacity of stock prices to track a firm's future profitability. This procedure also facilitates the interpretation of the results.[1]

Several proxies have been developed in the literature. We focus on those that can be measured at the stock level and rely on weekly and daily data on trading activity.[2] The "average" efficiency score is constructed using two subsets of market efficiency metrics. The first is akin to the concept of weak-form efficiency — and hence, non-predictability — of financial markets (Fama 1970, 1991) and includes the variance ratio (Fama, 1970; Lo & MacKinlay, 1988), Hasbrouck's q (Hotchkiss & Ronen, 2002), the signal-to-noise ratio (Biais et al., 1999), delay in the incorporation of market news into prices (Hou & Moskowitz, 2005) and the partial adjustment coefficient (Amihud & Mendelson, 1987). In common, they quantify pricing errors relative to a so-called efficient market benchmark or the pace with which prices converge to a new equilibrium. The second subset includes indicators mirroring the capacity of prices to assimilate new public (and private) firm-specific information, namely the measure of informed trading (Llorente, Michaely, Saar, and Wang, 2002), the overnight volatility ratio (French & Roll, 1986), and the weighted price contribution (Barclay & Warner, 1993).

The data used in the analysis covers listed firms located in 31 countries and the period 1990—2019. In the baseline approach, the efficiency score is added to the FERC model developed by Lundholm and Myers (2002) and Tucker and Zarowin (2006). More specifically, interactions of that score with covariates from the standard FERC model are introduced into the setting. If the interaction with future earnings is positive and statistically significant, then the efficiency score is associated with a rise of the sensitivity of current returns to realized future earnings. Indeed, that is exactly what we find. The estimated loading on that interaction is positive and statistically significant. Numerically, an interquartile range change of the efficiency score raises the FERC by 200%. The efficiency score is also associated with a rise of the sensitivity of future ROA to "normalized" prices.

Our interpretation is that stocks with greater efficiency score experience a smaller departure between market prices and fundamental value, manifested in the capacity of stock prices to predict a firm's future profitability. These conclusions are challenged by carrying out an extensive battery of supplementary tests. We condition most of our analyses on securities that are fairly actively traded, but to ascertain the impact of the sample selection on our inferences, other subsamples are considered when running baseline regressions. To that end, we apply alternative "price change filters" or a "trading activity filter" when defining the sample.[3] The sensitivity of the FERC to the efficiency score varies across subsamples, but it is always positive and statistically significant. Our findings are also robust with the introduction of determinants of the information environment and stock liquidity in the regressions. Moreover, similar inferences are obtained when considering cash flows or the firm-specific component of earnings as profitability metrics in the analysis. All in all, we can safely assert that the efficiency score captures the capacity of stock prices to track fundamental drivers to some extent.

We also want to learn which (individual) measures of market efficiency better capture the FERC and the sensitivity of future profitability to "normalized" prices. The second part of the analysis addresses that topic while running a horse race

[1] The composite score is also expected to provide a more accurate signal of market efficiency than individual proxies alone. Typically, single proxies are plagued with measurement error. As most of them are only modestly correlated, aggregation into a single score allows "averaging out" measurement error.

[2] We essentially cover market efficiency indicators for which data is accessible at the multi-country level and which have been employed in studies addressing the impacts on the relative efficiency of changes in regulation or similar events (e.g., short-selling prohibitions, changes in trading rules, the definition of tick sizes, index reconstitutions and derivative trading inception).

[3] The 30%, 50%, 75% and 90% "price change filters" are adopted (i.e., firm-year observations are only kept in the analysis if the proportion of non-zero price changes is above that threshold level in a given year). Alternatively, we consider the 50% "trading activity filter" (i.e., the stock trades in more than 50% of trading sessions).

between proxies of market efficiency. To that end, the empirical models are run separately for each proxy. Critically, some inferences depend on the sample filter adopted or of the introduction of liquidity and determinants of the information environment into the analysis. The association between the partial adjustment coefficient and the FERC (BPS measure) is positive and empirically very strong in all tests carried out. The same happens with the signal-to-noise ratio, although to a lesser extent. Conversely, price delay (Hou & Moskowitz, 2005) lacks correlation with both the FERC and BPS indicator, regardless of the empirical setting applied. Mixed results are obtained with regard to the other measures. After accounting for liquidity and the quality of the information environment in the analysis, the association between the FERC and these proxies becomes meaningless.

The popularity of the proxies addressed in this study stems from the availability of data (necessary for their calculation) and because they allow comparisons of market efficiency across stocks and over time. They have been used by regulators and academics to evaluate the impact of regulatory events on market quality: short-selling prohibitions (Bris, Goetzmann, and Zhu 2007; Saffi & Sigurdsson, 2011); derivative trading inception (Pereira da Silva, Vieira, & Vieira, 2018); index reconstitutions (Daya, Mazouz and Freeman 2012); and market rules (Fernandes & Ferreira, 2009; O'Hara & Ye, 2011; da Silva, 2018). Empirical studies assume that proxies of market efficiency capture the underlying concept, but inferences occasionally vary with the proxy being used. It is thus in researchers' interest to learn what exactly these empirical proxies are capturing, as well as to understand the contexts where they are more suitable.

Our work goes a step forward in that direction while clarifying the link between market efficiency proxies and long-term fundamentals and guiding researchers regarding the proxies which are more appropriate for their investigation. While the aggregate market efficiency score bolsters the capacity of prices to track future economic performance, we fail to find a similar association for most individual proxies, particularly when the effects of liquidity and the information environment are accounted for. These outcomes provide guidance on whether the different measures can be used as complements or substitutes in empirical analysis and advise the use of the synthetic score, for it captures the different dimensions of the concept of market efficiency.

The remainder of the paper is set out as follows. Section 2 develops the research hypotheses addressed in the study. Section 3 depicts the dataset and defines the variables, whereas section 4 presents the methodology and research design. The analysis and discussion of the results are shown in section 5. Finally, section 6 presents the final remarks.

2. Related literature and development of hypotheses

Market efficiency is a key concept in financial economics. There is a keen interest in assessing the extent to which financial markets or individual securities feature efficient price discovery. A survey conducted by Doran, Peterson, and Wright (2010) suggests that most professors believe the market is weak-to semi-strong efficient. However, there is no consensus in the empirical literature (and among practitioners) about the validity of that conjecture. In fact, a strand of research showed that stock returns are predictable, at least to some degree (Campbell, Lo, and MacKinlay 1997; Jegadeesh & Titman, 1993; Lehmann, 1990). Behavioral finance research documents irrational behaviors from investors (e.g., overreaction and overconfidence) that prompt predictability of returns (De Bondt and Thaler 1985). Moreover, Mandelbrot (1971), inter alia, finds a long-term memory component in series of financial returns.

Studies addressing the semi-strong form of the EMH typically rely on event studies to assess whether prices adjust quickly and in a timely manner to new public information arrival, such as, earnings, dividends and merger announcements. Ball and Brown (1968) and Fama, Fisher, Jensen and Roll (1969) constitute early illustrations regarding the application of that methodology. Fama et al. (1969) show that prices mirror direct estimates of prospective performance and information entailing more subtle interpretation, but other studies show that the adjustment to news release is often incomplete. Event study analysis focuses on price response to the arrival of new information, but it does not deliver clear indications on whether prices converge to fundamental values. The variance bounds literature (Shiller, 1981) and the noise trader literature (Black, 1986) attempted to address that issue. Shiller (1981) argues that price fluctuations are too large to be explained by (future) variability in dividend payments, but the methodology applied raised considerable controversy (Gilles & LeRoy, 1991). Black (1986) pioneered the theoretical literature of “noise” and “noise traders,” which are defined as economic agents who trade for non-information-based motives. Inter alia, Barber, Odean, and Zhu (2008) document trading by not fully rational noise traders moving prices away from fundamental values.

In a world with market frictions, where information is costly and transaction costs exist, markets cannot be fully informationally efficient. Grossman and Stiglitz (1980) noted that if markets were fully efficient, information gathering would not be profitable, and consequently, no one would trade. Thus, there must be “sufficient” profit opportunities, i.e., inefficiencies, to induce security analysis and reward investors' information-gathering and trading costs. The bottom line is that the EMH should be regarded as a limiting case: prices mirror the information for which information acquisition costs and transaction costs do not exceed the benefits of trading.

Along those lines and motivated by the empirical literature challenging the EMH, Campbell et al. (1997) set forth the concept of relative efficiency. In lieu of taking the all-or-nothing view as to whether markets are efficient, they underscore the importance of measuring the degree of efficiency or return predictability. Recent research suggests that market efficiency varies across stocks and geographies and over time (Yen & Lee, 2008). Ito and Sugiyama (2009) and Gu and Finnerty (2002) document time-varying market efficiency, with financial conditions governing the degree of efficiency. Rösch, Subrahmanyam, and Van Dijk (2017) find that the time-varying behavior of market efficiency is driven by a systematic component.

Changes in prices may stem from the arrival of unexpected information and from noise trading. The inexistence of systematic patterns or dependencies in the distribution of stock returns does not ensure that stock prices are accurately tracking the firm's intrinsic value. Griffin et al. (2010) use an extreme scenario, in which prices never assimilate new information about fundamentals and noise trading has no underlying systematic correlation structure, to illustrate that reasoning. The stock price may follow a perfect random walk, but the pricing is completely uninformative about the intrinsic value of the firm in that setting.[4]

This study asks whether the capacity of stock prices to track a firm's future profitability ("bring the future forward") is boosted by the degree of market efficiency measured through the lens of popular proxies. As market efficiency is a latent variable that encompasses multiple dimensions and is captured by various empirical proxies, the answers to the main research questions addressed herein are best determined empirically. Furthermore, the information environment — which weighs on the amount, availability and cost of relevant information about firm fundamentals, and the predominance of noise trading are likely to influence the assessment. We first center our analysis on the association of an aggregate score of market efficiency with the capacity of stock prices to track a firm's future profitability, and in the second stage we redo the same analysis using individual proxies in lieu of the aggregate score. Our research questions are the following:

RQ1: Does the (composite) market efficiency score influence the capacity of stock prices to "bring the future forward" with respect to future profitability?

RQ2: Which individual proxies exhibit greater association with the capacity of stock prices to "bring the future forward" regarding future profitability?

The next section describes the data and variables used in the assessment.

3. Data sources and sample description

The data employed in this assessment are retrieved from three different sources: Datastream, WorldScope and IBES. They cover 7370 listed firms from 31 countries in the period 1990−2019. Several data filters are applied to the initial sample. First, firms from the financial sector (SIC 6000−6999) are dropped from the assessment, given that they must usually conform to stricter transparency standards defined by regulators.[5] Second, firm-year observations with outliers with respect to earnings and returns are excluded, namely (i) if the ratio of net income before extraordinary items to lagged market capitalization is higher (lower) than 1 (−1), (ii) if the ratio of the sum of net income before extraordinary items for the years t+1, t+2, and t+3 to lagged market capitalization is higher (lower) than 3 (−3), and (iii) if the absolute value of three-year future returns exceeds 1000%. The application of the former data filters follows Lundholm and Myers (2002). Third, we drop firm-year observations when trading occurs in less than 30% of the trading sessions. Finally, firm-year observations with total assets worth below 10 million USD (measured at year 2000 constant prices), negative book equity value or net losses above the previous year's book equity value are also excluded.

The investigation is conducted in different subsamples of the main dataset. We restrict most of our analyses to securities that are fairly actively traded. In fact, the computation of market efficiency proxies could be sensitive to the number of observations available and to the trading activity and liquidity of the stock in a given period. To ensure that conclusions are not biased by measurement error in the estimation of market efficiency proxies, we introduce "price change filters" and "trading activity filters." Specifically, we exclude firm-year observations when the proportion of non-zero returns (*NZR*) is below 30%, 50%, 75% or 90%. Alternatively, it is considered a 50% "trading activity filter," i.e., a firm-year observation is dropped from the analysis if a stock trades in less than 50% of trading sessions.

The variables used in the estimation of the standard FERC model are the following: current year stock returns (R_t) calculated as the log buy-and-hold return for fiscal year t (computed over a 12-month time frame that starts three months after the beginning of fiscal year t); the log buy-and-hold return for the three-year period starting three months after the end of fiscal year t ($R3_t$); net income before extraordinary items available to common shareholders in fiscal year t scaled by lagged market capitalization (X_t); and the sum of the net income before extraordinary items available to common shareholders for the years t+1, t+2 and t+3, deflated by lagged market capitalization ($X3_t$).[6] The above-mentioned variables are winsorized at the 1% level in both tails of the distribution.

In some specifications of the FERC model, additional variables are introduced to control for the effects of liquidity and the information environment. The inverse of the Amihud illiquidity indicator (*Amihud*) and the proportion of non-zero returns (Bekaert, Harvey, and Lundblad 2007) are employed as proxies for liquidity. The relevance of the information environment is captured by means of the following controls: market capitalization at the beginning of fiscal year t (*SIZE*); asset growth (*TAG*) calculated as the percentage change in total assets from the beginning of year t-1 to the end of year t+1; analyst coverage (*ACov*) calculated as the number of analysts issuing EPS forecasts at the end of year t; earnings variability (*EarnVol*) computed as the standard deviation of earnings for fiscal years t+1 through t+3, deflated by the market capitalization of the firm at the beginning of year t;

[4] In this case, the market would essentially comprise transactions from uninformed noise traders. Noise trading would be the only determinant of stock returns. An investor is unable to develop trading rules that earn "excess" returns over time, but that does not guarantee that the stock price represents an unbiased estimate of the intrinsic value.

[5] In robustness tests, utilities (SIC 4900−4949) were also dropped from the analysis, but conclusions remained intact.

[6] Market capitalization at three months after the beginning of fiscal year t.

market-to-book ratio (M/B) at the beginning of year t; and *LOSS*, i.e., a binary variable indicating whether $X3_t$ is negative. Aside from *LOSS*, control covariates are converted into percentile ranks within country-year groups.

As for the approach put forward by Bai et al. (2016), the following variables are used: ROA_t computed as current EBIT deflated by lagged total assets; $\overline{ROA}_{t+1\to t+3}$ denoting the average of three-year future *ROA*; and *logQ* representing Tobin's Q and defined as the log ratio of the market value of equity plus debt-to-total assets. The above-mentioned variables are also winsorized at the 1% level in both tails of the distribution.

In respect to market efficiency measures, eight variables are considered: (i) the variance ratio (Lo & MacKinlay, 1988); (ii) delay in the assimilation of market news by prices (Hou & Moskowitz, 2005); (iii) Hasbrouck's q (Hotchkiss & Ronen, 2002); (iv) the signal-to-noise ratio (Biais, Hillion, and Spatt 1999); (v) the measure of informed trading (*gamma*) put forward by Llorente et al. (2002); (vi) overnight volatility divided by total volatility (French & Roll, 1986); (vii) the weighted price contribution of Barclay and Warner (1993); and (vii) the partial adjustment coefficient (Amihud & Mendelson, 1987). A detailed description of each proxy is displayed in the appendix.

Market efficiency proxies are calculated on a yearly basis for each stock. Percentile ranks within country-year cells are computed for each raw measure. Descending ranks are computed for *aVR*, *Delay*, *AMPAC*, *SNR* and *OVR*, whereas ascending ranks are calculated for *gamma*, *WPC* and *q*. In addition to the former measures, a synthetic score (*SCORE*) - corresponding to the average percentile rank of the raw measures - is also constructed. The use of *SCORE* in regression models allows us, inter alia, to pinpoint the "average" association between market efficiency and departure of market prices from fundamentals.

3.1. Summary statistics

The average (median) annual return of the firms covered by the analysis is 1.8% (5.8%). The average (median) *R*3 is 2.7% (12.5%). A first look at measures of dispersion (interquartile range and standard deviation) indicates large heterogeneity in terms of the market performance of the stocks. For instance, the interquartile range (standard deviation) of *R* hovers around 55% (52%). The average (median) of *X* is about 2.8% (5.1%), and the interquartile range is approximately 7.5%. The dispersion mounts when considering *X*3 (the interquartile range for that variable is 28.0%). The three-year earnings volatility is, on average, 7.7%.

The average market capitalization is 1903 million USD. About 25% of the firms in the sample have a market capitalization below 59 million USD, consistent with large dispersion in the size of the firms included in the analysis. On average, each firm is followed by three analysts. The average ROA is 7.3%, and the median leverage (total debt divided by total assets) is around 10.6%. Finally, the median of the log market-to-book ratio is about 48%.

Panel C of Table 1 presents the correlation matrix for market efficiency proxies. The prevalence of low correlation coefficients among them is consistent with the notion that these proxies capture different facets of the underlying concept. *WPC* and *OVR* and *aVR* and *q* are the pairs that exhibit the largest correlation (0.77 and 0.49, respectively). On the opposite side, several pairs of variables exhibit correlation coefficients close to zero. The correlations between the aggregate score and individual metrics are, by and large, high, ranging from 0.29 to 0.63.

4. Methodology

This study examines whether there is a link between (proxies of) market efficiency and the capacity of stock prices to predict a firm's future profitability, a key input of most valuation models. To that end, we focus on the relationship between returns (alternatively, Tobin's Q) and future earnings.

Table 1
— **Sample and summary statistics.** Panel A lists the countries covered by the analysis, whereas Panel B tabulates summary statistics. Panel C exhibits the correlation matrix for individual market efficiency metrics (percentile ranks) and the composite score.

Panel A

Australia	Germany	Portugal
Austria	Greece	Romania
Belgium	Hungary	Slovakia
Bulgaria	Iceland	Slovenia
Canada	Ireland	Spain
Croatia	Israel	Sweden
Czech Republic	Italy	Switzerland
Cyprus	Luxembourg	United Kingdom
Denmark	Netherlands	United States
Finland	Norway	
France	Poland	

Panel B

	Mean	S.d.	Quartile 1	Median	Quartile 3	Interquartile Range
R_t	1.8%	51.8%	−23.0%	5.8%	31.6%	54.6%
X_t	2.8%	13.5%	0.9%	5.1%	8.4%	7.5%
$R3_t$	2.7%	86.4%	−39.2%	12.5%	56.0%	95.2%
$X3_t$	8.2%	41.4%	−1.0%	15.1%	27.0%	28.0%
$EarnVol_t$	7.7%	9.9%	2.0%	4.2%	9.3%	7.3%
LnM/B_t	50.4%	78.2%	1.0%	47.6%	96.3%	95.3%
ROA_t	7.3%	13.9%	2.8%	7.3%	12.5%	9.7%
$Leverage_t$	14.1%	14.1%	1.4%	10.6%	22.4%	21.0%
$AssetGr_t$	16.8%	40.7%	−2.6%	11.7%	30.2%	32.8%
$Size_t$[a]	1903	6518	59	209	950	891
$AnalystCov_t$	2.8	1.9	0.0	3.0	8.0	8

Panel C

	aVR	Delay	OVR	SNR	AMPAC	q	WPC	gamma	Score
aVR	1.00								
Delay	0.03	1.00							
OVR	0.20	0.05	1.00						
SNR	0.06	0.04	0.14	1.00					
AMPAC	−0.02	0.00	0.00	−0.01	1.00				
q	0.49	0.03	0.20	0.07	−0.02	1.00			
WPC	0.22	0.04	0.77	−0.13	0.00	0.22	1.00		
gamma	0.12	−0.02	0.05	−0.04	−0.01	0.09	0.06	1.00	
Score	0.57	0.34	0.63	0.34	0.29	0.56	0.56	0.34	1.00

[a] Market capitalization in millions of USD.

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Specifically, we examine whether different degrees of market efficiency condition that association. Two alternative approaches are employed. The first is drawn on the future earnings-returns model of Collins et al. (1994), Gelb and Zarowin (2002) and Lundholm and Myers (2002). The second is built on the approach of Bai et al. (2016).

The future earnings-returns model emanates from the accounting literature. While investigating the returns-earnings relation (ERC model), Ball and Brown (1968) find weak predictive power of current earnings over stock returns. Collins et al. (1994) show that current stock returns contain information about future earnings, implying that investors anticipate and price future profitability. Adding future earnings as an additional covariate in a returns-earnings model (the FERC model) raised the model's explanatory power (R-squared) substantially.[7] In view of that result, the future earnings response coefficient (FERC) has been established as an indicator of the capacity of prices to track long-term fundamentals. If positive and significant, stock prices reflect accurate expectations of investors about future earnings. Prices are more informative because they embed better predictions about a firm's future profitability, thereby "bringing the future forward." Our first empirical setting is a variant of the model developed by Tucker and Zarowin (2006) and Lundholm and Myers (2002):

$$R_t = \alpha_0 + \alpha_1 {*} X_{t-1} + \alpha_2 {*} X_t + \alpha_3 {*} X3_t + \alpha_4 {*} R3_t + IND_{FE} + COUNTRY_{FE} + YEAR_{FE} + e_t \tag{1}$$

with all variables as defined in section 3. As with earlier research (Haw, Bingbing, Lee, and Wu, 2012), country, industry (two-digit SIC) and year fixed effects are included in the econometric setup to account for unobserved heterogeneity at the country and industry level, and common time-trends. Prior research found a negative (positive) estimated coefficient for X_{t-1} and $R3_t$ (X_t).[8] In this framework, the FERC equals the point estimate on $X3_t$, i.e., $\widehat{a}_3$, and is positive if a large amount of information about future earnings is contained in current prices.

To evaluate the association between proxies of market efficiency and the FERC, equation (1) is extended by adding market efficiency proxies (ME) and interactions of those variables with X_{t-1}, X_t, $X3_t$ and $R3_t$.

$$\begin{aligned} R_t = {} & \alpha_0 + \alpha_1 {*} X_{t-1} + \alpha_2 {*} X_t + \alpha_3 {*} X3_t + \alpha_4 {*} R3_t + \beta_0 {*} ME_t \\ & + \beta_1 {*} X_{t-1} {*} ME_t + \beta_2 {*} X_t {*} ME_t + \beta_3 {*} X3_t {*} ME_t \\ & + \beta_4 {*} R3_t {*} ME_t + IND_{FE} + COUNTRY_{FE} + YEAR_{FE} + e_t \end{aligned} \tag{2}$$

In some specifications, a set of controls ($CONTROLS$) is introduced in the regression with a view to capturing effects of determinants of the information environment on the FERC (Haw et al., 2012; Tucker & Zarowin, 2006). $SIZE$ and $ACov$ (to control for differences in the information environment of firms), TAG and M/B (earnings of growth firms could be harder to predict than that of value firms), and LOSS and EARNVol (future losses and volatile earnings should be more difficult to forecast) are added to equation (2). The vector of $CONTROLS$ is formed by the percentile ranks of the former variables and their interactions with X_{t-1}, X_t, $X3_t$ and $R3_t$. In another extension, we include a liquidity proxy (and interactions with X_{t-1}, X_t, $X3_t$ and $R3_t$). In the absence of additional control variables, the FERC is delivered by $\widehat{a}_3 + \widehat{\beta}_3 {*} ME_t$.

The model setting based on Bai et al. (2016) is drawn on the notion that if stock prices carry information about future profitability, then a higher current Tobin's Q (Q) should predict larger profitability in the future. In the baseline setting, three-year future ROA ($\overline{ROA}_{t+1\rightarrow t+3}$) is regressed against a constant, the log of Q_t and current ROA. Our setting extends BPS by adding a market efficiency proxy and interactions of that variable with other covariates to the model.

$$\begin{aligned} \overline{ROA}_{t+1\rightarrow t+3} = {} & \alpha_0 + \alpha_1 {*} ROA_t + \alpha_2 {*} logQ_t + \theta_0 {*} ME_t \\ & + \theta_1 {*} ME_t {*} ROA_t + \theta_2 {*} ME_t {*} logQ_t + IND_{FE} \\ & + COUNTRY_{FE} + YEAR_{FE} + e_t \end{aligned} \tag{3}$$

Here, our interest is $\alpha_2 + \theta_2 {*} ME_t$. We expect market efficiency to positively factor the association between future ROA and $logQ$.

The next section presents the empirical results.

5. Analysis and discussion of the results

The analysis of the results is divided into two parts. The first examines whether the "average" market efficiency is related to the capacity of stock prices "to bring the future forward" with respect to future profitability. In the second part, we run a horserace to identify the raw proxies that present the greatest association with the FERC (BPS measure) and whose utilization could offer advantages when conducting empirical research.

5.1. "Aggregate" relative efficiency

In this subsection, we run the regression models presented in section 4, proxying market efficiency with $SCORE$, i.e. the average of the percentile rank of the eight raw indicators presented in the appendix. Market efficiency is a latent variable that is captured by various proxies.[9] The score

[7] They show that the explanatory power of the FERC model is three to six times larger than that of the traditional ERC model. Further, they find a larger estimated loading for future earnings than for current earnings.

[8] Lundholm and Myers (2002) justify the inclusion of future returns to tackle measurement error in capturing shocks in expectations about future earnings. The choice of using up to three leads on future earnings and returns is justified by the results of Collins et al. (1994) and Lundholm and Myers (2002), who found that including further leads of those variables added little explanatory power to the model.

[9] These proxies express the multiple facets of market efficiency and are not strongly correlated.

Table 2
– **Market efficiency score and the FERC.** Table 2 presents the results of the estimation of equation (2). Current returns (R_t) are regressed against a constant, X_{t-1}, X_t, $X3_t$, $R3_t$ and the interaction of the former with $SCORE_t$. Additional control variables are excluded (included) in columns [1]-[5] ([6]-[8]). To conserve space, the table does not report point estimates (and corresponding t-statistics) for CONTROLS. Country, industry (two-digit SIC) and year fixed effects are added to all the regressions. T-statistics are calculated using heteroskedastic robust standard errors clustered by firm. (***), (**), (*) indicate statistical significance at the 1%, 5% and 10% level.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
X_{t-1}	−0.235***	−0.032	0.018	−0.007	0.257*	−0.493***	−0.099	−0.172
	(-5.10)	(-0.38)	(0.26)	(-0.11)	(1.86)	(-3.42)	(-1.23)	(-1.21)
X_t	0.817***	0.434***	0.352***	0.326***	0.413**	0.787***	0.472***	0.921***
	(7.70)	(3.10)	(3.89)	(3.42)	(2.14)	(3.19)	(3.48)	(5.14)
$X3_t$	0.335***	0.022	0.007	−0.002	−0.049	0.794***	0.035	−0.046
	(12.64)	(0.46)	(0.20)	(-0.04)	(-0.62)	(9.23)	(0.63)	(-0.56)
$R3_t$	−0.055***	0.048**	0.051**	0.054**	0.112***	−0.095***	0.008	−0.008
	(-2.69)	(2.34)	(2.47)	(2.45)	(3.75)	(-2.84)	(0.47)	(-0.27)
$SCORE_t$		0.002	0.024	0.015	0.006	−0.020	0.000	0.027
		(0.02)	(0.24)	(0.16)	(0.05)	(-0.25)	(0.00)	(0.28)
X_{t-1}*$SCORE_t$		−0.352*	−0.415**	−0.384**	−0.730***	−0.257	−0.754**	−0.490**
		(-1.96)	(-2.52)	(-2.54)	(-2.76)	(-1.29)	(-2.27)	(-2.24)
X_t*$SCORE_t$		0.635**	0.775***	0.817***	0.535	0.918***	1.144***	1.087***
		(2.47)	(3.05)	(3.18)	(1.59)	(4.09)	(4.09)	(3.93)
$X3_t$*$SCORE_t$		0.537***	0.537***	0.551***	0.743***	0.391***	0.554***	0.480***
		(4.94)	(5.53)	(5.23)	(4.39)	(4.58)	(5.79)	(4.99)
$R3_t$*$SCORE_t$		−0.171***	−0.172***	−0.176***	−0.273***	−0.167***	−0.296***	−0.221***
		(-3.22)	(-3.06)	(-2.98)	(-3.74)	(-4.17)	(-4.37)	(-4.66)
LIQ_t							−0.001	−0.075
							(-0.03)	(-1.50)
Xt-1*LIQt							0.435*	0.280
							(1.78)	(1.23)
X_t*LIQ_t							−0.501***	−0.941***
							(-3.48)	(-4.84)
$X3_t$*LIQ_t							−0.028	0.130
							(-0.38)	(1.43)
$R3_t$*LIQ_t							0.151***	0.104***
							(3.93)	(3.09)
# firm-year obs.	43,609	39,064	51,805	49,516	21,403	38,028	39,064	39,064
# firms	5865	5517	6875	6674	3304	5442	5517	5517
Adj-R2	42.9%	43.5%	41.8%	41.9%	45.3%	51.9%	43.8%	43.7%
Sample	NZR>75%	NZR>75%	NZR>30%	IF>50%	NZR>90%	NZR>75%	NZR>75%	NZR>75%
Controls	No	No	No	No	No	CONTROLS	Amihud	NZR

summarizes the information about overall market efficiency and facilitates the interpretation of the results. The aggregation procedure attenuates measurement error and delivers a cleaner signal of overall market efficiency than individual proxies considered separately.[10]

A natural starting point for the analysis consists of the estimation of equation (1). We condition most of our analysis on stocks that are actively traded. While it is apparent that trading frictions impede the flow of information into prices, we also want to avoid noise into the estimation of market efficiency proxies arising from the existence of stale prices and lack of trading activity. To be included in the main analysis, a stock must have non-zero price variations on at least 75% of trading days in a given year in order to minimize measurement error prompted by the presence of stale prices. Nevertheless, in robustness tests, we apply alternative filters, namely 30%, 50% and 90% "price change filters" (*NZR*) and the "trading activity filter" (*IF*) of 50%.

Column [1] of Table 2presents the outcome of the estimation of equation (1) when adopting the 75% "price change filter." The estimated loadings on X_{t-1} and $R3_t$ are −0.235 and −0.055 (t-stats of −5.10 and −2.69), respectively. The point estimate for X_t is 0.817 (t-stat of 7.70), thereby suggesting that current prices and contemporaneous

[10] Prior finance and accounting research dealt with latent variables combining and aggregating data from different proxies. Perhaps the most striking example concerns liquidity (Lang & Maffett, 2011), which can be captured by various proxies. Many times, the choice of the proxy depends on the data available. Other examples may be found with regard to corporate governance (Larcker, Richardson, and Tuna 2007) and earnings quality (Francis et al., 2008). This procedure allows a cleaner signal to be obtained for the latent variable, as raw proxies are estimated with noise. There are more complex aggregation techniques available in the literature than the one used in this assessment, namely principal components or factor analysis. However, in our setting, those methods present the disadvantage of raw proxies being weakly correlated. Principal components (factor analysis) take advantage of common variability (correlation structure), so that proxies with the lowest commonalities would be dropped from the analysis. As such, our score is more appropriate to capture the "overall" effect of market efficiency on the FERC (BPS measure) than other measures extracted by means of more complex statistical techniques.

Table 3
– **Market efficiency score and the BPS measure.** The table presents results of the estimation of equation (3) using different sample filters. T-statistics are calculated using heteroskedastic robust standard errors clustered by firm. (***), (**), (*) indicate statistical significance at the 1%, 5% and 10% level.

	[1]	[2]	[3]	[4]	[5]	[6]
$logQ_t$	0.068***	−0.002	0.022	0.011	0.011	0.021
	(6.56)	(-0.05)	(1.00)	(0.48)	(0.32)	(0.95)
ROA_t	1.386***	1.901***	1.619***	1.745***	1.663***	1.663***
	(33.14)	(10.49)	(13.15)	(13.33)	(10.43)	(13.32)
$SCORE_t$		0.028	0.017	0.027	0.046**	0.026
		(1.22)	(0.96)	(1.36)	(2.11)	(1.43)
$SCORE_t$*$logQ_t$		0.123**	0.084*	0.101**	0.104*	0.086*
		(2.02)	(1.87)	(2.12)	(1.72)	(1.92)
$SCORE_t$*ROA_t		−0.883***	−0.446**	−0.639***	−0.516**	−0.511**
		0.028	(-2.10)	(-2.84)	(-1.98)	(-2.37)
# firm-year obs.	41,766	37,325	49,036	46,394	35,310	46,859
# firms	5648	5303	6566	6288	5208	6362
Adj-R2	35.7%	35.9%	35.7%	36.3%	36.0%	36.0%
Sample filter	NZR>75%	NZR>75%	NZR>30%	NZR>50%	NZR>90%	IF>50%

earnings move together. More pertinently, the estimated coefficient for $X3_t$ (the FERC estimate) is 0.335 (t-stat of 12.64), consistent with prices conveying information about a firm's future earnings. Non-reported results reveal that the FERC estimate is 0.29, 0.30, and 0.40, when adopting “price change filters” of 30%, 50% and 90%, respectively, and 0.30 when adopting the “trading activity filter” of 50%. The point estimate on future earnings is always statistically significant at the 1% level, irrespective of the subsample utilized.

Not surprisingly, the FERC climbs with the liquidity/trading activity of the stocks. Overall, the point estimates and statistical significance of the variables are aligned with results of previous studies (e.g., Lundholm & Myers, 2002; Tucker & Zarowin, 2006). Columns [2]-[5] of Table 2 show the results of the estimation of equation (2) using *SCORE* as a proxy for market efficiency. The table allows side-by-side comparison of results across different subsamples. Remarkably, the estimated loading on $X3$*$SCORE$ is always positive and statistically significant, irrespective of the sample filter adopted. Considering the 75% “price change filter,” an interquartile range change in *SCORE* is accompanied by a 200% increase in the FERC.

In the following, the 75% “price change filter” is adopted, unless stated otherwise. Up to this point, additional controls have been excluded from the analysis. The information environment and liquidity could explain both the FERC and *SCORE*, which raises concerns of endogeneity.[11] Column [6] of Table 2 presents the results when *CONTROLS* are added to equation (2). The estimated loading for $X3$*$SCORE$ dips considerably in this setting, but the sign and statistical significance are preserved. Columns [7] and [8] exhibit regression results when liquidity proxies (*Amihud* and *NZR*) are added to equation (2). Previous analysis accounts indirectly for the effect of illiquidity by comparing the regression results in different subsamples of stocks. Now, liquidity is introduced directly into the model specification. The percentile rank of a liquidity indicator (*Amihud* or *NZR*) and interactions of that variable with X_{t-1}, X_t, $X3_t$ and $R3_t$ are added to equation (2). The point estimates on $X3$*$SCORE$ are 0.55 and 0.48 and statistically significant at the 1% level when liquidity is captured by *Amihud* and *NZR*, respectively.[12]

In a similar fashion, *SCORE* is used as a proxy for market efficiency in equation (3). Of most interest to the analysis, the point estimate on $logQ$*$SCORE$ is positive and statistically significant at the 5% level when considering the 75% “price change filter.” Inferences are qualitatively the same when adopting alternative sample filters (see Table 3). Taken together, these findings validate the hypothesis that the aggregate market efficiency score (*SCORE*) improves the capacity of stock prices to predict future profitability, i.e., the answer to RQ1 is affirmative. This conclusion is robust to a battery of tests, including the consideration of liquidity and determinants of the information environment in the econometric model.

To gain further insight into the association between aggregate market efficiency and the FERC, earnings figures are decomposed into (i) cash flow and accruals figures and (ii) industry-wide and firm-specific earnings components. Reported earnings are influenced by the accounting standards followed, which is why investors also factor in cash flows (which are less influenced by accounting discretionary or manipulation) when evaluating a firm's performance. We break down earnings figures into cash flow and accruals figures in subsequent analysis to

[11] Market microstructure models of market efficiency postulate that short-term deviation of prices from their efficiency levels emanates from frictions elicited by illiquidity, such as the bid-ask bounce and thin-trading (Roll, 1984). Thus, it is also natural to question whether the association between *SCORE* and the FERC derives from illiquidity.

[12] Although non-reported, inferences remain intact when considering alternative subsamples. In non-tabulated tests, we also extend equation (2) with both liquidity and *CONTROLS*, but the results remain unchanged.

check whether conclusions are affected by the profitability measure considered. For that purpose, equation (4) is estimated:

$$\begin{aligned}R_t = {} & \alpha_0 + \alpha_1{*}CF_{t-1} + \alpha_2{*}CF_t + \alpha_3{*}CF3_t + \alpha_4{*}ACC_{t-1} \\ & + \alpha_5{*}ACC_t + \alpha_6{*}ACC3_t + \alpha_7{*}R3_t + \beta_0{*}ME_t \\ & + \beta_1{*}CF_{t-1}{*}ME_t + \beta_2{*}CF_t{*}ME_t + \beta_3{*}CF3_t{*}ME_t \\ & + \beta_4{*}ACC_{t-1}{*}ME_t + \beta_5{*}ACC_t{*}ME_t + \beta_6{*}ACC3_t{*}ME_t \\ & + \beta_7{*}R3_t{*}ME_t + LIQCONTROLS + IND_{FE} \\ & + COUNTRY_{FE} + YEAR_{FE} + e_i\end{aligned} \tag{4}$$

where CF_t (ACC_t) corresponds to cash flow from operating activities (accruals) in fiscal year t divided by the market value of equity; and $CF3_t$ ($ACC3_t$) denotes the sum of cash flow from operating activities (accruals) for the year t + 1 through t + 3 divided by the market value of equity.[13]

A careful look at column [1] of Table 4 shows that both $CF3{*}SCORE$ and $ACC3{*}SCORE$ exhibit positive and statistically significant estimated coefficients. Accordingly, market efficiency—the effect of which is summarized by *SCORE*—shapes the response of current returns to shocks in future cash flows. Next, we ascertain whether *SCORE* loads positively with the amount of firm-specific information about future earnings conveyed by stock prices. To that end, we adjust the dependent variable and covariates from equation (2), and estimate the following equation:

Table 4
− Cash flows versus accruals and industry-wide versus firm-specific earnings. The panel presents the results of the estimation of equations (4) and (5). To conserve space, the table only reports point estimates (and corresponding t-statistics) for $CF3_t{*}SCORE_t$ and $ACC3_t{*}SCORE_t$ with respect to equation (4), and $FX3_t{*}SCORE_t$ and $IX3_t{*}SCORE_t$ with respect to equation (5), given that these are the variables with most interest to the assessment. The 75% "price change filter" is applied. T-statistics are calculated using heteroskedastic robust standard errors clustered by firm. (***), (**), (*) indicate statistical significance at the 1%, 5% and 10% level.

	[1]	[2]
$FX3_t{*}SCORE_t$		0.247***
		(2.78)
$IX3_t{*}SCORE_t$		0.348*
		(1.75)
$CF3_t{*}SCORE_t$	0.731***	
	(5.63)	
$ACC3_t{*}SCORE_t$	0.271***	
	(4.38)	
Equation	(4)	(5)
# firm-year obs.	34,150	39,064
# firms	5142	5517
Adj-R2	43.1%	19.3%
Sample filter	NZR>75%	NZR>75%

$$\begin{aligned}ADJR_t = {} & \alpha_0 + \alpha_1{*}IX_{t-1} + \alpha_2{*}IX_t + \alpha_3{*}IX3_t + \alpha_4{*}FX_{t-1} \\ & + \alpha_5{*}FX_t + \alpha_6{*}FX3_t + \alpha_7{*}ADJR3_t + \beta_0{*}ME_t \\ & + \beta_1{*}IX_{t-1}{*}ME_t + \beta_2{*}IX_t{*}ME_t + \beta_3{*}IX3_t{*}ME_t \\ & + \beta_4{*}FX_{t-1}{*}ME_t + \beta_5{*}FX_t{*}ME_t + \beta_6{*}FX3_t{*}ME_t \\ & + \beta_7{*}ADJR3_t{*}ME_t + IND_{FE} + COUNTRY_{FE} \\ & + YEAR_{FE} + LIQCONTROLS + e_i\end{aligned} \tag{5}$$

where the dependent variable ($ADJR_t$) is the value-weighted market-adjusted return for year t. IX_t (FX_t) is the industry-wide (firm-specific) component of a firm's earnings for year t. IX_t is computed as the median annual earnings (X_t) in the firm's country-industry group in year t less MX_t (median annual earnings (X_t) in the firm's country in year $_t$). FX_t is calculated as $X_t - IX_t - MX_t$. $IX3_t$ ($FX3_t$) is the sum of the industry-wide (firm-specific) component of a firm's earnings for fiscal year $t+1$ through $t+3$; finally, $ADJR3_t$ is the three-year future value-weighted market-adjusted return.

An inspection of column [2] of Table 4 shows that the estimated coefficients on $FX3{*}SCORE$ and $IX3{*}SCORE$ are positive and statistically meaningful. In plain words, *SCORE* shapes the capacity of current returns to predict both the firm-specific and industry-wide components of realized future earnings.

To enrich the analysis, we run supplementary regressions to see whether the sensitivity of the FERC to *SCORE* evolved over time. We estimate equation (2) using five-year rolling windows from 2000 to 2016. To save space, the results are presented in the supplementary material, available online. A visual inspection of Fig. S1 informs that although the positive association between the FERC and *SCORE* prevails over the analyzed period, it became weaker over the last decade. Because the degree of market efficiency is state-dependent, we also compare the sensitivity of the FERC to *SCORE* in bullish and bearish periods. Specifically, we split the sample of firm-year observations into two bins—a bullish partition and a bearish partition depending on whether the annual return of the local market index is above or below its median. Surprisingly, we find that *SCORE* produces larger effects on the FERC during bearish periods than in bullish ones.[14]

In a different vein, we also conduct a cross-country analysis to ascertain whether country transparency helps shape the association between market efficiency and the FERC. In fact, Griffin et al. (2010) highlight that country specific-variables influence the set of available information at the disposal of investors. So, we control for three country-specific mechanisms that ensure the flow of information in the economy: (i) the disclosure requirements index (La Porta, Lopez-De-Silanes, & Shleifer, 2006), (ii) CIFAR (Bushman, Piotroski, and Smith 2004) and (iii) newspaper circulation (Djankov, La Porta, Lopez-de-Silanes, and Shleifer, 2008). The sample is split by groups of countries considering whether they lie above or below the median with respect to these country-

[13] Market capitalization three months after the beginning of fiscal year t. *LIQCONTROLS* is a vector that comprises *Amihud* and interactions of that variable with CF_{t-1}, CF_t, $CF3_t$, $R3_t$, ACC_{t-1}, ACC_t and $ACC3_t$.

[14] Non-tabulated tests indicate that the coefficient on $X3{*}SCORE$ is statistically different in the two analyzed periods.

Table 5
− **Market efficiency and the FERC: a horserace.** Panels A, B and C present the results of the estimation of variants of equation (2). Panel D presents the results of the estimation of equation (3). Market efficiency proxies are introduced separately in the regressions. Country, industry (two-digit SIC) and year fixed effects are added to all the regressions. The sample includes firm-year observations with proportion of non-zero returns (NZR) above 75%. To conserve space, only point estimates (and corresponding t-statistics) for $X3_t$*ME_t and ME_t*$LogQ_t$ are reported. T-statistics are calculated using heteroskedastic robust standard errors clustered by firm. (***), (**), (*) indicate statistical significance at the 1%, 5% and 10% level.

A − Estimation of equation (2) with no CONTROLS *and no liquidity variables*

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	aVR	Delay	OVR	SNR	AMPAC	q	WPC	gamma
$X3_t$*ME_t	0.013	−0.001	0.133***	0.071***	0.408***	−0.023	0.134**	0.019
	(0.38)	(-0.04)	(2.66)	(2.67)	(8.80)	(-0.72)	(2.57)	(0.50)
# firm-year obs.	43,599	42,675	40,905	40,879	43,599	43,599	40,879	42,138
# firms	5863	5797	5659	5655	5863	5863	5655	5753
Adj-R2	43.0%	42.9%	43.4%	43.4%	44.4%	43.0%	43.4%	43.1%

B − Estimation of equation (2) *with* CONTROLS, *but no liquidity variables*

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	aVR	Delay	OVR	SNR	AMPAC	q	WPC	gamma
$X3_t$*ME_t	−0.017	0.005	0.075**	0.015	0.344***	−0.041**	0.067**	0.031
	(-0.59)	(0.17)	(2.01)	(0.72)	(7.36)	(-2.39)	(2.00)	(0.97)
# firm-year obs.	42,450	41,535	39,841	39,817	42,450	42,450	39,817	41,021
# firms	5781	5715	5584	5580	5781	5781	5580	5673
Adj-R2	51.3%	51.3%	51.7%	51.7%	52.3%	51.3%	51.7%	51.4%

C − Estimation of equation (2) *with liquidity variables, but no* CONTROLS

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	aVR	Delay	OVR	SNR	AMPAC	q	WPC	gamma
$X3_t$*ME_t	−0.036	−0.006	0.090*	0.059**	0.409***	−0.071***	0.085	0.009
	(-1.24)	(-0.16)	(1.74)	(2.41)	(8.84)	(-2.80)	(1.24)	(0.24)
# firm-year obs.	42,549	41,724	40,170	40,144	42,549	42,549	40,144	42,138
# firms	5783	5724	5599	5595	5783	5783	5595	5753
Adj-R2	43.2%	43.1%	43.5%	43.5%	44.6%	43.2%	43.5%	43.3%

D − Estimation of equation (3)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	aVR	Delay	OVR	SNR	AMPAC	q	WPC	gamma
ME_t*$logQ_t$	0.043*	0.026	−0.009	0.037**	0.059***	0.035	0.029	−0.036*
	(1.83)	(1.38)	(-0.36)	(1.98)	(3.42)	(1.49)	(1.17)	(-1.86)
# firm-year obs.	41,756	40,849	39,135	39,109	41,756	41,756	39,109	40,322
# firms	5646	5581	5446	5441	5646	5646	5441	5535
Adj-R2	35.8%	35.7%	35.7%	35.8%	35.8%	35.8%	35.7%	35.9%

specific variables. Fig. S2—available in the supplementary material—shows a larger effect of *SCORE* on the FERC in countries which display greater newspaper circulation, lower accounting quality and below-median disclosure requirement index, but these differences are not statistically meaningful (non-reported statistical tests indicate no difference of coefficients in the contrasting groups).[15]

5.2. Horserace of raw market efficiency proxies

In what follows, we check whether raw market efficiency proxies capture the sensitivity of price changes to variation in a firm's fundamental value. Columns [1]− [8] of panel A of Table 5 report the results of the estimation of equation (2) when raw proxies are added to the baseline setting. The 75% "price change filter" is adopted, unless stated otherwise. Raw proxies and corresponding interactions with X_{t-1}, X_t, $X3_t$ and $R3_t$ are introduced into equation (2). As before, the main interest lies in the point estimate for ME_t*$X3_t$. Interestingly, *AMPAC**$X3$, *OVR**$X3$, *SNR**$X3$ and *WPC**$X3$ display positive and statistically meaningful estimated loadings, which is consistent with the idea that *AMPAC*, *OVR*, *SNR* and *WPC* go hand in hand with the FERC. Other raw proxies do not seem to influence the FERC. The impact of an interquartile range variation of *ME* on the FERC ranges from 0% (*Delay*) to 91% (*AMPAC*).[16]

[15] We conducted similar procedures with respect to other country-specific transparency variables retrieved from Bushman et al. (2004). However, we also did not find meaningful differences in these groups with respect to the association between the FERC and the efficiency score.

[16] The FERC of a firm with AMPAC in the first quartile hovers around 0.222, whereas the FERC of a firm with AMPAC in the third quartile is about 0.426.

In non-tabulated robustness tests, other sample filters are considered. Interestingly, when stocks lacking liquidity are added to the sample (e.g., when the 30% and 50% "price change filters" are adopted), all proxies, apart from *Delay*, influence the FERC. Nevertheless, the statistical significance of $aVR*X3$ and $q*X3$ vanishes when *CONTROLS* are considered in equation (2), despite the inclusion of illiquid stocks in the sample. Panels B and C report results when equation (2) is extended with the vector of *CONTROLS* and a liquidity measure (*Amihud* and interactions with X_{t-1}, X_t, $X3_t$ and $R3_t$), respectively. With regard to panel B, the magnitude of the estimated loadings for $AMPAC*X3$, $OVR*X3$, and $WPC*X3$ drops considerably, but statistical significance is retained. As for panel C, *AMPAC*, *OVR* and *SNR* conserve their (statistically meaningful) association with the FERC after the inclusion of the liquidity measure in equation (2). The inclusion of *CONTROLS* and liquidity in tandem does not alter the main inferences.

The empirical setting of BPS constitutes an alternative to the FERC model. The results from regressions on equation (3) are presented in panel D. As expected, the sensitivity of future ROA to market valuation does not climb along with all raw proxies. Only *AMPAC*, *SNR*, and *aVR* exhibit a positive and meaningful association with the BPS measure (point estimates on $logQ*AMPAC$, $logQ*SNR$, and $logQ*aVR$ are positive and statistically significant; see columns [1], [4] and [5]).

In light of the results, *AMPAC*, *SNR*, *OVR* and *WPC* appear to weigh on the FERC, irrespective of the liquidity/trading activity exhibited by the stock. *aVR*, *q* and *Gamma* do not influence the FERC when stocks lacking liquidity are excluded from the sample, or when the information environment and liquidity are considered in the main regression. *Delay* is unable to influence the FERC regardless of the sample filter adopted. In reality, this outcome is not so surprising: Griffin et al. (2010) point out the weakness of *Delay* while showing that prices in emerging markets incorporate past market returns faster than prices in developed markets.[17] These results point to large heterogeneity in the association of market efficiency proxies with the capacity of stock prices to predict future profitability.

Another relevant point pertains to the analysis of whether raw measures affect the FERC after accounting for the effect of the market efficiency score. Previous regression results indicate that the point estimate on $X3*SCORE$ is always larger than that obtained for the interaction of $X3$ with raw proxies. This outcome informs that the aggregation of proxies mitigates measurement error, thereby delivering a better signal of market efficiency. We probe deeper into this issue by re-running an extension of equation (2) that includes a raw market efficiency measure, the set of *CONTROLS*, the proxy for liquidity and the synthetic score (all of them interacted with X_{t-1}, X_t, $X3_t$ and $R3_t$). Here, the synthetic score ($Score_{t,(-k)}$) consists of the average score of all proxies excluding the one added to the regression. For instance, when evaluating the impact of *aVR* on the FERC, the synthetic score ($Score_{t,(-aVR)}$) is calculated as the average percentile rank of *AMPAC*, *OVR*, *WPC*, *gamma*, *SNR*, *delay*, and *q*.

The results are reported in Table S1 of the supplementary material available online. Strikingly, one feature which is common to all the regression outcomes is that the estimated coefficient for $Score_{t,(-k)}*X3_t$ is always positive and statistically significant. Therefore, the sensitivity of the FERC to *SCORE* is not being driven by a specific market efficiency proxy. Moreover, after accounting for the impact of $Score_{t,(-k)}$, only *AMPAC* and *SNR* produce effects on the FERC. Overall, *SCORE* appears to do a better job in capturing the FERC than individual measures considered separately, corroborating the advantages of the aggregation procedure in empirical work.

6. Final remarks

This study evaluates the link between market efficiency proxies and the capacity of stock prices to predict a firm's future economic performance. Our sample covers firms located in 31 countries and the time frame ranging from 1990 to 2019. Based on a set of popular market efficiency proxies, a synthetic score is constructed. Strikingly, that score correlates positively with the sensitivity of current returns (or market valuations) to future profitability shocks. To put it another way, aggregate market efficiency bolsters the capacity of stock prices to predict a firm's future earnings. However, the results for raw proxies considered individually are not so clear-cut. While the partial adjustment coefficient and the signal-to-noise ratio enhance the sensitivity of current returns (or market valuations) to future profitability shocks, we obtain mixed findings for other measures.

The conclusions of this study are important to empirical researchers, regulators, the financial industry (namely stock exchanges) and policymakers. Indeed, many studies employ market efficiency proxies when assessing the impacts of regulation and laws on market quality. Typically, these studies overlook the association of market prices with fundamentals and focus on weak-form market efficiency indicators, such as returns predictability. Our findings suggest that an aggregate market efficiency score captures the capacity of stock prices to track long-term fundamentals to some extent, but most market efficiency proxies alone do not.

Declaration of competing interest:

The author declares that there are no conflicts of interest regarding the publication of this paper.

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Appendix A. Supplementary data

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[17] In non-tabulated regressions, we re-run equations (4) and (5) considering raw market efficiency indicators. *AMPAC* and *SNR* are the market efficiency metrics that present the greatest association with the sensitivity of stock returns to future cash flows and firm-specific earnings.

Appendix. Additional information on the estimation of market efficiency measures

All the measures are calculated for each firm on a yearly basis. We apply data filters from Griffin et al. (2010) when cleaning stock prices series.

Hasbrouck's q	The following regression is run: $r_t = a \times e_{t-1} + e_t$. r_t respects to the daily stock return in t. An annual estimate of q bounded between 0 and 1 is obtained. Larger q values portend better market quality. $q = \frac{\sigma_e^2 - 2a \times cov(e_t,\ e_{t-1})}{\sigma_e^2 \times (1+a) - 2a \times cov(e_t,\ e_{t-1})}$	Hotchkiss and Ronen (2002).
Gamma	The following regression is run: $r_t = a + \theta \times r_{t-1} + \gamma \times r_{t-1} \times V_{t-1} \times +e_t$. r_t respects to the weekly stock return in t; V_{t-1} is log turnover detrended by subtracting a 26-week moving average. Higher $\widehat{\gamma}$ (the gamma estimate) hints at more information-based trading (as opposed to noise or liquidity trading).	Llorente et al. (2002)
Weighted price contribution (WPC)	The *WPC* is the proportion of return determined during trading hours. The WPC of the ith trading period is expressed as: $WPC_i = \sum_{t=1}^{T} \frac{r_{i,t}}{r_t} \times \left(\frac{\lvert r_t \rvert}{\sum_{s=1}^{T} \lvert r_s \rvert} \right)$, and $r_t = \sum_{t=1}^{T} r_{i,t}$ The ratio $\frac{r_{i,t}}{r_t}$ indicates the proportion of return on day t credited to period i. $\frac{\lvert r_t \rvert}{\sum_{s=1}^{T} \lvert r_s \rvert}$ measures the proportion of the annual return attributed to day t. The flow of private information is stronger during trading hours than non-trading hours since informed investors speculate using their private information while trading. The WPC corresponds to the share of information incorporated on stock returns during the trading period.	Barclay and Warner (1993); Cao, Ghysels, and Hatheway (2000)
Partial adjustment coefficient (AMPAC)	Stock returns are influenced by both noise and the failure of observed prices to adjust to intrinsic values instantly. p_t denotes the log of market prices, v_t is the log of the intrinsic value, and e_t and ε_t are white noises. The estimation is undertaken via Kalman filter approach $p_t - p_{t-1} = g(v_t - p_{t-1}) + e_t$ $v_t = \delta + v_{t-1} + \varepsilon_t$ $var(e_t) = \sigma_e^2$ AMPAC equals $\lvert 1-g \rvert$. *AMPAC* reflects the speed and accuracy of the adjustment of market prices to equilibrium prices.	Amihud and Mendelson (1987); Chelley-Steeley (2008) and Daya et al. (2012)
Signal-to-noise ratio (SNR)	This is extracted from the output of the regression of close-to-close returns against a constant and close-to-open returns. SNR equals the absolute value of one minus the coefficient on close-to-open returns. If SNR converges to zero, then markets are perfectly efficient.	Luo, Chen, and Yan (2014)
Overnight volatility ratio (OVR)	OVR is computed as the ratio between the variance of close-to-open returns and the variance of close-to-close returns. If private information is progressively unveiled through trading, then higher volatility should be observed during trading hours, not overnight.	French and Roll (1986)
Delay	Delay consists of the R2 difference from two market model regressions: the unconstrained regression and the constrained regression. With respect to the unconstrained regression, weekly stock returns are regressed against a constant, the contemporaneous returns of a domestic market index (Datastream country indexes), and one lead and one lag of the domestic market index return (Dimson, 1979). In the constrained regression, the lag of the market index returns is suppressed. Delay indicates the share of return variation being captured by lagged market returns. Higher values signify more time to assimilate new market information.	Hou and Moskowitz (2005)
Variance ratio (aVR)	aVR is computed as the absolute value of the variance of five-day (non-overlapping) stock returns divided by five times the variance of daily stock returns, minus one (assuming no drift in the computation of the variance). [We undertake a battery of tests to check whether conclusions are affected by the definition employed. Thus, we also run regression models using definitions of the variance ratio in that (i) the indicator is the variance of two-day stock returns divided by two times the variance of daily stock returns, (ii) overlapping returns are utilized in the computation of the variance of five- and two-day returns, and (iii) assuming a drift in returns when computing variances. As a whole, the results are insensitive to the definition of the variance ratio utilized.]	Lo and MacKinlay (1988); Poterba and Summers (1988)

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