Do Market Efficiency Measures Yield Correct Inferences? A Comparison of Developed and Emerging Markets

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Using data from 56 markets, we find that short-term reversal, post-earnings drift, and momentum strategies earn similar returns in emerging and developed markets. Variance ratios and market delay measures often show greater deviations from random walk pricing in developed markets. Conceptually, we show that commonly used efficiency tests can yield misleading inferences because they do not control for the information environment. Our evidence corrects misperceptions that emerging markets feature larger trading profits and higher return autocorrelation, highlights crucial limitations of weak and semi-strong form efficiency measures, and points to the importance of measuring informational aspects of efficiency. (*JEL* F30, G14, G15)

The conventional wisdom is that emerging markets are less efficient than developed markets. Highly profitable trading strategies and prices that deviate from a random walk are often what people have in mind when describing the evidence.[1] For example, in a recent speech that describes the Chinese stock

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[1] Bekaert and Harvey (2002) summarize the academic evidence for greater inefficiency in emerging markets: 1) higher serial correlations (Harvey 1995); 2) information leakage prior to public announcements (in Mexico, Bhattacharya et al. 2000); and 3) high returns to cross-sectional characteristic trading strategies (Rouwenhorst 1999; Van der Hart, Slagter, and Van Dijk 2003). We focus on aspects related to 1) and 3) as they are common academic and practitioner measures of efficiency and leave the important distinction between public and private information for future research.

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market as inefficient, Burton Malkiel states that "there is considerable serial correlation. The markets are nowhere near a random walk."[2] This article investigates this common perception across both developed and emerging markets through a comprehensive analysis of profits from trading strategies, efficiency measures, and impediments to efficient pricing, such as transaction costs. The article provides new insight into differences in stock, portfolio, and country-level efficiency measures around the world but also points to the limitations of standard notions and measures of stock market efficiency.

Our first focus is to provide a framework to quantify traditional measures of market efficiency across countries in terms of a) a practical notion of efficiency: the returns to trading strategies based on past returns and earnings announcements; and b) the deviations prices exhibit from the random walk paradigm. The trading strategies and efficiency measures we select have all been extensively used to measure stock market efficiency in the United States and, to a much lesser extent, abroad.[3] Our second focus is to examine plausible interpretations of our findings and their implications for the validity of efficiency measures. We find that building blocks of efficiency, transaction costs, and information production show much less efficiency in emerging markets. We show conceptually that traditional efficiency can yield misleading inferences when comparing securities with varying levels of information production.

The first trading strategy we examine is the well-known short-term reversal strategy (Jegadeesh 1990; Lehmann 1990) that buys last week's losing stocks and sells the prior week's winners after skipping a week to control for microstructure effects. Empirically, we find that the strategy earns profits in developed markets of 8.7% per year (16.8 bps points per week), which is similar to those found in the U.S. Perhaps more surprisingly, the profits are similar to those earned in emerging markets, 11.4% per year. This finding holds on average for a variety of formation and investment horizons and with size and volume groupings following Conrad, Hameed, and Niden (1994). It is important to note that all of our findings are prior to transaction costs. We later show that similar-sized firms in emerging markets have considerably higher transaction costs than developed markets, making actual profits from exploiting these return patterns relatively lower in emerging markets.

The second trading strategy we examine aims to exploit incomplete incorporation of earnings news into stock prices. Our international evidence indicates that post-earnings announcement drift (Ball and Brown 1968) is present in 15

[2] http://www.youtube.com/watch?v=uVcV0H4qtgw, starting at minute 34:57.

[3] This article is the first international study we are aware of that compares similar-sized emerging and developed market firms along these dimensions over a recent time period. A firm- or portfolio-level examination is important, since an analysis at the market index level may simply reflect the composition of the index (i.e., smaller cap firms in some markets). Firm-level papers examining autocorrelations include Solnik (1973), Errunza and Losq (1985), and Claessens, Dasgupta, and Glen (1993). Bae, Ozoguz, and Tan (2009) compare lead-lag effects and market delay between investable and non-investable firms in emerging markets.

of 38 markets for which we have announcement data, and, on a relative scale, abnormal returns associated with the drift are not larger in emerging markets. The third trading strategy is the well-known and applied Jegadeesh and Titman (1993) momentum strategy. Over our 1994 to 2005 period, the strategy earns high returns in developed markets, 14% per year, but considerably smaller return, 8.5% per year, in emerging markets.

Next, we turn to more traditional measures of relative efficiency. The use of autocorrelation-based measures to test efficiency dates back to early studies such as Fama (1970), who argues that large return autocorrelations reflect deviations from random walk pricing and are indicative of violations of market efficiency.[4] Following, among others, Lo and MacKinlay (1988), we use variance ratios at both the individual stock and portfolio level to study short-term autocorrelations. The results from the random walk tests suggest that individual stock and portfolio returns in emerging markets do not deviate more from a random walk than those in developed markets. These findings are similar at both daily and weekly frequencies.

The other efficiency measure we use reflects the degree to which returns respond to past market returns and is similar to the delay measure of Mech (1993) and Hou and Moskowitz (2005). This measure relies on an intuitive principle: a security price that is slow to incorporate information contained in market index movements is less efficient than a security price that instantaneously incorporates all market movements. Perhaps unexpectedly, the delay measure shows that prices in emerging markets incorporate past market returns more quickly than prices in developed markets.

In sum, both trading profits and common measures of efficiency present a consistent picture of similar or less deviation from efficiency in emerging markets using a variety of methods and over a number of time horizons. These findings are inconsistent with the conventional wisdom that emerging markets are places for more profitable trading strategies and where prices exhibit more predictability and departures from a random walk.

We next turn to interpreting our findings. Because the methods we use are conceptually simple, time-tested, and robust to various controls and return horizons, we believe that the random walk-based measures are doing what they are designed to do: they capture the predictive ability of past returns. However, we investigate whether the inferences from the findings can be generalized to suggest that "emerging stock markets are just as efficient as developed markets" or whether they imply that the concept of weak-form efficiency is too narrow or simplistic.

[4] Subsequent contributions pointed to causes of return autocorrelation other than mispricing: time-varying expected returns, non-synchronous trading, and microstructure biases. Competing evidence is presented in Lo and MacKinlay (1988), Conrad, Kaul, and Nimalendran (1991), Mech (1993), and Boudoukh, Richardson, and Whitelaw (1994), among others. We discuss these issues in Section 1.2.1. Given the relatively short (daily and weekly) time horizons we consider, the levels and the differences in autocorrelations are not likely due to time-variation in expected returns.

Two common building blocks of efficiency are transaction costs and information production. Using the Lesmond, Ogden, and Trzcinka (LOT) (1999) measure of trading costs, we find intuitive results: developed markets, like the U.S. and U.K., have some of the lowest trading costs, while smaller emerging markets have some of the highest. For similar-sized large and medium cap firms, LOT trading costs are nearly twice as large in the typical emerging market. Moreover, for most size quintiles, trading costs have decreased dramatically over our 1994 to 2005 period. Despite this decrease, neither returns to reversal strategies, delay measures, nor variance ratios seem to exhibit much change through time in either developed or emerging markets. Additionally, in most cases there is little cross-country relation between the efficiency measures and transaction costs. We use the number of analysts covering a firm and the frequency of their revisions as a rough proxy for information costs. We find that similar-sized firms in emerging markets have less of both.

Contrary to what we find in our earlier analysis, the inferences from transaction and information costs provide support for the widely held notion that emerging markets are indeed less efficient than developed markets. To reconcile the conflict, we examine some basic assumptions underlying the efficiency measures and identify three main limitations. First, empirical efficiency measures necessarily rely on partial information sets: as such, they may not yield the same inferences as their theoretical counterparts, which are typically defined in terms of all available information. Second, we show that for a given speed of information incorporation, firms with more news will appear less efficient in their return process, ceteris paribus. Third, firms with rapid, but imperfect, information incorporation can have empirical efficiency measures identical to firms with extremely slow information incorporation. In the extreme, a firm that never incorporates news into the return will only be driven by noise trading. If noise trading has no systematic correlation structure, then the firm's stock price may follow a perfect random walk even though the pricing is completely inefficient. Since emerging markets have less information production than developed markets, these biases can work to make emerging markets appear relatively more efficient.

Our analysis has several practical implications. First, given higher transaction costs in emerging markets, trading strategies that exploit information in past returns are less profitable than in developed markets. Second, our findings suggest caution in using standard efficiency measures, or even trading profits, as the sole indicators of informational efficiency. When theoretical models such as Grossman and Stiglitz (1980) discuss informational efficiency, they focus on whether information is produced and how completely it is incorporated into prices. However, the typical empirical investigation of weak- and semi-strong form market efficiency implicitly ignores the cost and quantity of information. Consistent with higher information costs, we find lower analyst

coverage and fewer forecast revisions in emerging markets. Although measuring the extent of public and private information production is a daunting task, our findings suggest that one may need to focus on measuring the informational aspects of efficiency before making meaningful statements about relative efficiency, especially for settings with large disparities in the information environment.

The portfolio strategy returns and efficiency measures we use in this article are widely used, not only historically but also in recent work examining aspects of efficiency.[5] We choose to also focus on trading profits from short-term reversal, post-earnings drift, and momentum because prior research has shown that these profits are large in the U.S. but are relatively short-term in nature and are not commonly believed to be explained by risk factors.[6] Post-earnings drift is believed to occur mainly due to investors failing to incorporate information in past earnings announcements.[7] Recently, Khandani and Lo (2007) and Kaniel, Saar, and Titman (2008) use short-term reversals as an example of a potential high-frequency strategy that traders may attempt to exploit. Our study complements this large body of research in that there has been relatively little work that undertakes a systematic global comparison of these strategies or efficiency measures across developed and emerging markets.[8] However, our work also contributes to the broader literature because it suggests that comparative examinations of relative efficiency may need to be more comprehensive than focusing on weak- or semi-strong form efficiency.

The article proceeds as follows. Section 1 describes the related literature and methodologies behind our economic and statistical efficiency measures. Section 2 describes our international sample, and Section 3 presents returns to reversal, post-earnings drift, and momentum-based trading strategies. Section 4 examines the results by size portfolio for all of the efficiency measures. Section 5 characterizes implications for possible facilitators of efficiency, transaction costs, and information production. Section 6 explores potential conceptual weaknesses in the efficiency measures, and Section 7 concludes.

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5 For example, Chordia, Roll, and Subrahmanyam (2008) and Boehmer and Kelley (2009) use variance ratios in the U.S. to measure aspects of short-term efficiency; Hou and Moskowitz (2005) use the delay measure.

6 While the literature has not reached a complete consensus on momentum, many papers provide no support for a risk-based explanation (Grundy and Martin 2001; Jegadeesh and Titman 2001; Griffin, Ji, and Martin 2003; and Cooper, Gutierrez, and Hameed 2004). Those finding some evidence for risk-based explanations, such as Ahn, Conrad, and Dittmar (2003), conclude that only part of the profits can be explained by risk.

7 Freeman and Tse (1989), Bernard and Thomas (1990), and Rangan and Sloan (1998), among others, find that drift is due to the market's failure to understand past earnings. Bartov, Radhakrishnan, and Krinsky (2000) and Battalio and Mendenhall (2005) attribute this behavior to small investors.

8 However, momentum returns have been examined more extensively internationally, as we will document in the next section. Others have examined various aspects of efficiency internationally. These include liquidity (Lesmond 2005; Bekaert, Harvey, and Lundblad 2007), allocation efficiency (Wurgler 2000; Beck, Demirguc–Kunt, and Maksimovic 2005), and the extent to which the liberalization of emerging markets changes aspects of efficiency, such as the cost of capital, beta, volatility, autocorrelations, and the information environment (Kim and Singal 2000; Bae, Bailey, and Mao 2006).

1. Background and Methodology

Information efficiency refers to the extent to which a market incorporates all available information into prices quickly and correctly. In a fully efficient and frictionless market, actual changes in stock prices are unforecastable:

$$E\left[p_t - p_{t-1} | I_{t-1}\right] = 0 \tag{1}$$

where p_t is the price and I_{t-1} is the set of all available information at time $t-1$. Since knowing what prices should be under the full information set is not possible, informational efficiency measures are typically designed to capture efficiency with respect to a smaller set of information (Z_{t-1}) observed by researchers. Additionally, efficiency measures (M) are often stated in terms of abnormal returns, where $M = 0$ if markets are efficient.[9] In this framework, efficiency measures quantify the extent by which realized returns systematically deviate from expected returns. Measures of efficiency are compared across securities to make statements about "relative" efficiency. Empirically, inefficient markets may exhibit large reversals or continuation (drift), whereas a completely efficient market will look close to a random walk, at least over short time horizons.

1.1 Trading strategies

Many of these ideas have been tested using portfolios that group stocks according to a common feature, such as past return. An advantage of forming portfolios according to such a feature is that the return spread between high and low past-return portfolios has a clear economic interpretation; it is the profit that would accrue to a long-short trading strategy in the absence of frictions. These strategies also tightly map the academic concepts of efficiency to practitioners' intuition—an inefficiency lies where someone can make money (or would in the absence of trading costs).

1.1.1 Short-term reversals. The first portfolio trading strategy we examine is the short-term reversal strategy accredited to Jegadeesh (1990) and Lehmann (1990). Any past return strategy consists of a ranking period (j weeks), over which the relative "winners" and "losers" are determined, and an investment period (k weeks), over which long and short stock positions are taken. The idea is that once stock prices are pushed in a certain direction (either due to price pressure or overreaction) they tend to revert. Hence, the reversal strategy is long in the past-loser stocks and short in the past winners. To avoid distortions induced by market microstructure, we generally adopt the common practice of

[9] For further discussion and caveats, see Campbell, Lo, and MacKinlay (1997), Chapter 1, Section 5, and Chapter 2.

skipping a week between portfolio ranking and investment periods.[10] To the best of our knowledge, this strategy, while widely used to measure inefficiencies in the U.S., has not been examined across a broad array of countries.[11]

1.1.2 Post-earnings announcement drift. One way to assess semi-strong form efficiency is to condition on a firm-specific information event. It is advantageous to have an event that is similar in nature across countries, and earnings announcements provide such an admittedly imperfect proxy. Beginning with Ball and Brown (1968), there is a large literature documenting drift following earnings announcements by U.S. firms. The international evidence, however, is sparse.[12]

1.1.3 Momentum. The Jegadeesh and Titman (1993) momentum effect is by far the most academically researched strategy based on past return and is also frequently discussed as the center piece of many quantitative investment strategies. The strategy is opposite to the previously discussed reversal strategy. It consists of buying winner stocks and selling losers, although the formation and the holding periods are much longer. We follow the most commonly adopted approach in the academic literature by focusing on a 26-week (six-month) portfolio formation and holding period. The investment rule is followed every week such that equally weighted momentum strategies of 26 varying vintages are simultaneously in effect at all times. To avoid having profits contaminated by microstructure effects, we follow the convention of skipping a week between the portfolio ranking and holding period. Returns to momentum strategies have been examined in European markets by Rouwenhorst (1998), emerging markets by Rouwenhorst (1999), and international markets by Griffin, Ji, and Martin (2003, 2005) and Chui, Titman, and Wei (2010). As with other measures, we extend this literature by focusing on the emerging and developed market differences, their importance over time, and their cross-country correlations with other dimensions of efficiency, such as transaction costs.

1.2 Common efficiency measures

Although the portfolio profit approach above provides an intuitive economic measure of efficiency, it also implicitly assumes that the grouped stocks will all behave in a homogeneous manner (e.g., move opposite to past returns in

[10] Stocks that rise in price are more likely to close at the ask price, which leads to a negative return if the stock closes at the bid price. As long as the stock trades during the week that is skipped (which is likely with stock trading filters), there should be no bid-ask bounce in the subsequent (skip-a-week) return.

[11] In addition to a number of studies examining these strategies in individual markets, Fung, Leung, and Patterson (1999) examine these strategies in six Asian markets.

[12] Hew et al. (1996), Booth, Kallunki, and Martikainen (1997), and Del Brio, Miguel, and Perote (2002) find post-earnings announcement drift in the U.K., Spain, and Finland, but Van Huffel, Joos, and Ooghe (1996) and Yang and Zhou (2004) find no drift in Belgium and China.

the case of reversals). For these reasons, and for consistency with a large literature, we turn to several previously adopted measures to assess how quickly information is incorporated into prices. These measures are: 1) firm return autocorrelations; 2) portfolio return autocorrelations (both measured by variance ratios); and 3) delay with respect to market returns. As our goal is to measure differences in relative efficiency measures across markets and avoid findings that are merely the result of the average size of firms within a market, we sort stocks into five size groupings for most of our analyses. Additional details of all of these measures are provided in Appendix A.

1.2.1 Autocorrelations and variance ratios. Much work on market efficiency has argued that informationally efficient prices follow a random walk and has tested this hypothesis using autocorrelation and variance ratio tests. In terms of international evidence related to weak-form efficiency at the firm level, Solnik (1973) examines autocorrelations of stocks in eight European markets and finds slightly more departures from a random walk in Europe (ex-U.K.) than in the U.S. An early study on emerging markets by Errunza and Losq (1985) finds that emerging market firms (from 1975 to 1981) are not as weak-form efficient as developed market firms but are comparable to firms in smaller European markets. Claessens, Dasgupta, and Glen (1993) examine 20 emerging markets and find substantial evidence for index-level autocorrelations, but small autocorrelations for portfolios of small emerging market firms.[13]

Under the null hypothesis of a random walk with uncorrelated increments, variance ratios (VRs) should equal one at all lags. VRs significantly above one indicate positive serial correlation, whereas VRs below one indicate negative autocorrelations. Because both negative and positive autocorrelation represent departures from a random walk, we use the absolute value of the VR statistic minus one (|VR-1|) as a measure of relative efficiency. This approach is advantageous in that if a market consists of stocks with both over and under reaction to past returns, then both would be captured.

Several studies (see, among others, Conrad and Kaul 1988, Conrad, Kaul, and Nimalendran 1991, Mech 1993, and Boudoukh, Richardson, and Whitelaw 1994) have demonstrated that return autocorrelations could be due to factors other than simple mispricing, such as time-varying expected returns, microstructure frictions (such as stale limit orders, inefficient market making, and bid-ask bounce), and non-synchronous trading. To reduce the likelihood of autocorrelation being the result of time-varying expected returns, we focus

[13] An interesting example, albeit only over a couple of markets, is Butler and Malaikah (1992), who look at autocorrelations in Kuwait and Saudi Arabia and find very large one-day negative autocorrelations of −0.47 in Saudi Arabia.

on short-term returns (one day to five weeks).[14] Microstructure frictions like bid-ask bounce are most problematic when focusing on one- and two-day autocorrelations at the individual firm level. To control for autocorrelations induced by microstructure effects, we a) focus on results at the weekly frequency; b) use screens where stocks are required to trade frequently; c) skip a trading day in some results, and in some cases also require that this skipped day contain trading activity, following Mech (1993).

1.2.2 Delay. Delay is an R^2-based measure of the sensitivity of current returns to past market-wide information. Delay is calculated as the difference in R^2 between an unrestricted market model with four weekly lags and a restricted model with no lags ($Delay = AdjR^2_{Unrestricted} - AdjR^2_{Restricted}$). Our measure is similar to the one used in Mech (1993). We use a local market index (rather than global) as the base case.[15]

1.2.3 Trading costs. While not a common measure of efficiency, impediments to trade are likely to impact the incorporation of information in security prices. The main trading cost measure we adopt is developed by Lesmond, Ogden, and Trzcinka (1999) (LOT) and infers the cost of trading from the occurrence of zero returns. The LOT measure calculates the size of the transaction costs by estimating the difference between what the price would have moved to in the presence of no transaction costs as compared to the zero price change that occurred in the presence of transaction costs. It is designed to capture not only direct costs of trading such as the bid-ask spread and commissions, but also, implicitly, to account for price impact and opportunity costs. Lehmann (1990) finds that the LOT measure captures emerging market trading costs better than other measures. Our findings extend this literature by performing comparisons between developed and emerging markets for similar-sized firms, and characterizing the magnitude of these costs through time. We also check our inferences using the Hasbrouck (2006) measure of transaction costs that builds upon the intuition of the Roll (1984) model.[16]

2. Data

We collect market data from 1994 through 2005 for 28 emerging markets and 28 developed markets. While data for most developed markets and many of the

[14] Ahn, Boudoukh, Richardson, and Whitelaw (2002) convincingly state that "time variation in expected returns is not a high frequency phenomenon; asset pricing models link expected returns with changing investment opportunities, which, by their nature, are low-frequency events."

[15] Griffin (2002) finds that local factors are more important than global factors for explaining time-series variation in individual stock returns. Karolyi and Stulz (2003) summarize the evidence on whether assets are best explained by local or global market returns. However, for robustness we also examine the sensitivity of portfolio returns to both local and global market information.

[16] Estimation details for both the LOT and Hasbrouck measure are provided in Appendix A.3 and A.4.

emerging markets begins prior to 1994, we wish to focus on this later period because more emerging markets are thought to have integrated with world markets by the mid-1990s. This helps mitigate the concern that our inferences may be confounded by instabilities in the dynamics we investigate. Following the World Bank's classification scheme, we rank countries according to Gross National Income (GNI) per capita and classify them as emerging if their GNI per capita in 2005 is less than USD 10,725 and developed if greater. Daily price, returns accounting for dividends and capital structure changes, and market capitalization series are from CRSP for the U.S. and from Thomson Financial's Datastream for the rest of the world. We use Datastream's value-weighted total market index returns if available; in the eight markets where they are not available, we compute our own value-weighted market index. Wednesday-to-Wednesday returns are used for weekly analyses.

We restrict our analysis to common-ordinary stocks trading in the companies' home markets with prices quoted in local currency. For the U.S., we use stocks with a CRSP share code of 10 or 11. For non-U.S. data, the distinction is substantially more complicated. We conduct an extremely extensive multistage screening process in which we eliminate preferred stock, warrants, unit or investment trusts, duplicates, GDRs or cross-listings, and other non-common equity from the sample, as described in detail in Appendix B.

Annually rebalanced size portfolios are created using U.S. market capitalization breakpoints in the following manner: at the end of each December from 1993 to 2004 we sort all stocks listed on NYSE, AMEX, and NASDAQ into five equal portfolios; each non-U.S. firm is sorted into one of the U.S.-size portfolios based on its December-end market capitalization converted into U.S. dollars using spot exchange rates from Datastream. We require at least five firms in the prior December for all of our size portfolios. In some robustness checks we use local market breakpoints as well.

We also condition most of our analyses on stocks that are fairly actively traded. While trading frictions may in fact impede the flow of information into prices, we wish to avoid capturing deviations from random walk pricing, which are solely a mechanical function of stale prices. We use non-zero price changes as a proxy for trading activity.

Table 1 presents the average December-end count of the number of firms in each size portfolio, the number of years each portfolio has at least one firm, and the average December-end U.S. dollar market capitalization for non-missing firms in each portfolio. Developed market averages are in Panel A, and emerging market averages are in Panel B. The left third of each panel presents the average number of firms (passing the 0% trading filter) and then the percentage of these firms that pass the 30% trading filters. All but the smallest emerging and developed markets have a sufficient number of firms and a long enough

Table 1
Summary statistics

Panel A: Developed Countries

		Average Yearly Firm Count with 0% Price Change Filter (Fraction Passing 30% Price Change Filter)					Year Count 0% Price Change Filter					Average Market Capitalization 0% Price Filter in U.S. $				
Country	GNI	Large	4	3	2	Small	Lrg	4	3	2	Sm	Large	4	3	2	Small
Australia	29,450	61 (0.97)	68 (0.93)	85 (0.87)	127 (0.83)	531 (0.63)	12	12	12	12	12	4491	451	141	48	8
Austria	37,180	11 (0.94)	20 (0.86)	16 (0.84)	17 (0.70)	22 (0.47)	12	12	12	12	12	2228	455	153	48	10
Belgium	36,140	23 (0.99)	18 (0.94)	23 (0.89)	24 (0.81)	26 (0.35)	12	12	12	12	12	5694	477	141	51	12
Canada	33,170	95 (0.98)	110 (0.96)	139 (0.93)	227 (0.91)	1982 (0.71)	12	12	12	12	12	4461	460	140	48	5
Cyprus	21,590	1 (1.00)	3 (0.67)	4 (0.75)	10 (0.70)	35 (0.31)	6	9	9	9	9	1466	594	148	60	11
Denmark	48,520	18 (0.98)	27 (0.95)	35 (0.75)	45 (0.59)	70 (0.25)	12	12	12	12	12	3246	449	136	50	12
Finland	38,500	16 (0.97)	29 (0.90)	19 (0.90)	25 (0.76)	31 (0.50)	12	12	12	12	12	7473	473	143	49	12
France	34,900	123 (0.93)	115 (0.83)	145 (0.79)	163 (0.75)	311 (0.53)	12	12	12	12	12	8415	455	141	49	10
Germany	34,780	114 (0.89)	123 (0.75)	133 (0.69)	138 (0.64)	248 (0.61)	12	12	12	12	12	6854	451	145	49	10
Greece	25,100	14 (0.98)	33 (0.95)	57 (0.95)	66 (0.95)	71 (0.92)	12	12	12	12	12	2629	426	139	50	15
Hong Kong	28,150	47 (0.96)	67 (0.96)	103 (0.90)	151 (0.83)	169 (0.69)	12	12	12	12	12	7289	438	138	49	14
Ireland	41,330	12 (0.97)	12 (0.79)	13 (0.47)	10 (0.37)	14 (0.14)	12	12	12	12	12	3909	477	147	48	13
Israel	19,790	10 (1.00)	19 (1.00)	27 (0.93)	59 (0.86)	222 (0.59)	12	12	12	12	12	2453	471	136	46	9
Italy	30,310	64 (0.98)	56 (0.95)	56 (0.94)	38 (0.89)	20 (0.74)	12	12	12	12	12	5600	459	147	53	16
Japan	38,930	594 (0.98)	664 (0.93)	723 (0.89)	729 (0.82)	505 (0.75)	12	12	12	12	12	5309	459	143	52	16
Luxembourg	65,140	6 (0.81)	2 (0.66)	2 (0.64)	2 (0.29)	7 (0.20)	12	12	11	12	12	7836	462	157	50	7
Netherlands	39,630	40 (0.95)	34 (0.96)	31 (0.94)	31 (0.87)	30 (0.64)	12	12	12	12	12	10334	480	148	52	13
New Zealand	23,840	4 (0.98)	13 (0.92)	16 (0.94)	22 (0.84)	39 (0.40)	12	12	12	12	12	3065	483	138	50	10
Norway	61,830	15 (0.97)	30 (0.92)	38 (0.78)	40 (0.61)	49 (0.44)	12	12	12	12	12	3606	432	145	51	13
Portugal	17,180	12 (0.93)	11 (0.88)	15 (0.86)	18 (0.70)	45 (0.25)	12	12	12	12	12	2854	472	133	50	8
Singapore	26,860	23 (0.96)	39 (0.95)	59 (0.92)	86 (0.86)	105 (0.74)	12	12	12	12	12	4698	460	140	49	16
South Korea	15,880	40 (0.95)	94 (0.94)	145 (0.94)	249 (0.93)	567 (0.91)	12	12	12	12	12	3844	448	137	47	11
Spain	25,400	46 (0.96)	36 (0.93)	24 (0.89)	13 (0.89)	7 (0.55)	12	12	12	12	12	6563	492	148	53	16
Sweden	40,950	36 (0.98)	39 (0.96)	43 (0.95)	59 (0.93)	101 (0.79)	12	12	12	12	12	5226	448	142	49	10
Switzerland	56,190	46 (0.97)	57 (0.90)	49 (0.80)	41 (0.61)	32 (0.33)	12	12	12	12	12	9900	485	148	53	12
Taiwan	14,075	77 (0.97)	140 (0.96)	151 (0.93)	158 (0.94)	144 (0.94)	12	12	12	12	12	3111	442	143	52	16
U.K.	38,140	238 (0.98)	242 (0.88)	277 (0.68)	328 (0.50)	518 (0.24)	12	12	12	12	12	7991	455	144	49	11
U.S.	43,210	1269 (0.98)	1270 (0.96)	1270 (0.95)	1270 (0.95)	1269 (0.96)	12	12	12	12	12	7951	466	145	51	13

Table 1
Continued

Panel B: Emerging Countries

		Average Yearly Firm Count with 0% Price Change Filter (Fraction Passing 30% Price Change Filter)					Year Count 0% Price Change Filter					Average Market Capitalization 0% Price Filter in U.S. $				
Country	GNI	Large	4	3	2	Small	Lrg	4	3	2	Sm	Large	4	3	2	Small
Argentina	4460	11 (0.91)	12 (0.83)	13 (0.69)	14 (0.50)	26 (0.27)	2	12	12	12	12	3164	448	146	50	10
Bangladesh	440	0 (0.00)	1 (1.00)	2 (1.00)	10 (0.80)	172 (0.70)	2	8	11	12	12	1369	493	119	46	4
Brazil	3880	24 (0.67)	28 (0.43)	39 (0.26)	33 (0.15)	73 (0.04)	11	11	11	11	11	8415	493	152	53	8
Bulgaria	3490	0 (0.00)	0 (0.00)	0 (0.00)	1 (1.00)	10 (0.20)	0	2	2	3	4	600	251	72	5	
Chile	6030	20 (0.90)	29 (0.69)	29 (0.45)	33 (0.27)	48 (0.06)	12	12	12	12	12	2256	453	143	53	10
China	1740	38 (0.95)	315 (0.95)	307 (0.95)	114 (0.98)	9 (1.00)	12	12	12	11	3	1959	407	157	63	40
Colombia	2340	3 (1.00)	10 (0.50)	10 (0.30)	10 (0.10)	25 (0.04)	9	12	12	12	12	1398	418	148	49	8
Czech Rep	11,300	2 (1.00)	2 (1.00)	5 (0.60)	6 (0.50)	9 (0.44)	10	10	10	10	10	3035	523	138	52	13
Egypt	1270	1 (1.00)	6 (0.83)	8 (0.88)	13 (0.85)	27 (0.78)	6	8	8	8	8	2375	534	187	59	12
Hungary	10,230	3 (1.00)	4 (0.75)	4 (1.00)	5 (1.00)	12 (0.58)	10	12	12	12	12	2649	377	141	49	8
India	740	36 (0.94)	70 (0.94)	111 (0.95)	175 (0.94)	491 (0.78)	12	12	12	12	12	2807	451	138	48	8
Indonesia	1250	14 (0.86)	23 (0.70)	32 (0.63)	53 (0.57)	118 (0.48)	12	12	12	12	12	2112	439	139	48	10
Kenya	530	0 (0.00)	2 (1.00)	4 (1.00)	8 (0.75)	26 (0.31)	1	8	12	12	12	445	324	158	47	8
Lithuania	7250	0 (0.00)	1 (1.00)	2 (1.00)	4 (0.50)	14 (0.36)	0	3	6	6	6		596	223	60	13
Malaysia	5080	45 (0.98)	84 (0.96)	108 (0.94)	142 (0.91)	241 (0.90)	12	12	12	12	8	2631	444	139	51	15
Mexico	7300	17 (0.82)	14 (0.64)	11 (0.45)	7 (0.29)	14 (0.14)	12	12	12	12	12	3243	455	155	49	12
Morocco	1990	3 (0.67)	8 (0.75)	6 (0.67)	9 (0.44)	10 (0.30)	11	11	11	11	11	1453	469	160	49	11
Pakistan	730	2 (1.00)	8 (0.88)	17 (0.76)	32 (0.66)	165 (0.39)	11	12	12	12	12	1837	422	138	46	7
Peru	2710	3 (0.67)	7 (0.71)	7 (0.29)	9 (0.22)	22 (0.14)	12	12	12	11	12	4915	443	137	49	9
Philippines	1270	10 (0.90)	13 (0.77)	21 (0.67)	26 (0.54)	79 (0.34)	12	12	12	12	12	1806	413	143	49	8
Poland	7280	4 (1.00)	7 (1.00)	9 (0.89)	18 (0.89)	58 (0.90)	10	10	10	10	10	2428	539	146	52	9
Romania	3830	0 (0.00)	0 (0.00)	1 (1.00)	1 (1.00)	29 (0.72)	3	4	8	6	8	2456	667	191	62	6
South Africa	4810	50 (0.84)	64 (0.72)	63 (0.70)	68 (0.66)	171 (0.37)	12	12	12	12	12	2732	454	146	50	8
Sri Lanka	1200	0 (0.00)	1 (1.00)	5 (1.00)	14 (0.79)	176 (0.35)	0	3	12	12	12		162	126	43	5
Thailand	2700	22 (0.95)	38 (0.95)	55 (0.91)	83 (0.82)	160 (0.66)	12	12	12	12	12	2245	443	141	47	11
Turkey	6150	12 (0.75)	24 (0.71)	39 (0.77)	56 (0.80)	89 (0.85)	12	12	12	12	12	2084	448	139	49	12
Venezuela	4950	2 (1.00)	3 (1.00)	3 (0.67)	4 (0.50)	8 (0.25)	8	11	11	10	10	1119	492	138	53	11
Zimbabwe	340	0 (0.00)	3 (0.67)	7 (0.86)	11 (0.73)	28 (0.68)	4	10	12	12	12	1670	398	127	46	11
Developed Avg.	34,506	109 (0.96)	120 (0.91)	132 (0.85)	148 (0.76)	256 (0.56)	12	12	12	12	12	5303	465	143	50	12
Emerging Avg.	3760	12 (0.90)	28 (0.80)	33 (0.74)	34 (0.64)	82 (0.46)	9	10	11	11	10	2504	457	152	52	10
All Average	19,133	60 (0.93)	74 (0.85)	82 (0.79)	91 (0.70)	169 (0.51)	10	11	11	11	11	3983	461	148	51	11

For December each year from 1993 through 2004, we sort all common ordinary shares from Datastream and CRSP with at least 30% or 0% days with non-zero price changes in the following 12 months into five equally weighted size portfolios using U.S. dollar NYSE/AMEX/NASDAQ breakpoints. Missing firm counts are set to zero. Year counts and average market capitalization are for all non-missing years of portfolios. In the "Average Yearly Firm Count" panel, the number to the left is the number of firms passing the 0% filter and the number in parentheses is the fraction passing the 30% price change filter. Other averages are for firms passing the 0% filter only.

time series to conduct our analyses. Interestingly, for the average market, 56% of stocks in developed markets and 46% of stocks in emerging markets trade on at least 30% of the trading days in the smallest capitalization portfolio. This indicates that most of the firms with Datastream coverage are frequently traded, though there are some countries (like Venezuela) where this is not the case.

The average market capitalization of all firms in our sample is fairly similar across countries for the same size group, indicating that the simple size groupings are effective at controlling for size differences across countries. Notably, many emerging markets have reasonable coverage in the larger cap groups. The results in table 1 show that the simple size groupings lead to market capitalizations for small cap firms that are extremely similar in developed and emerging markets. While Datastream often does not cover extremely small firms (similar to CRSP, which excludes OTC and Pink Sheet stocks), there is no reason this lack of coverage would bias our estimates since these firms likely concentrate only in the smallest cap group and likely would not pass our trading filters anyway.[17]

3. Returns to Portfolio Trading Strategies

This section details the returns to the three popular trading strategies described in Section 1.1: short-term reversal, post-earnings announcement drift, and momentum. To ensure that our results are not driven by infrequently traded stocks, unless otherwise indicated we require each country to have at least 50 firms that trade on at least 30% of trading days in the year ending in the December prior to portfolio formation. We use price changes to proxy for trading activity, so our 30% "price change filter" means that stocks have non-zero price changes on 30% or more of the trading days. To ensure that our findings are not driven by the U.S. (where the strategies were largely back tested) or any large market, we compute the developed and emerging market time-series averages as an equally weighted average of the country-level returns at any given point in time.

3.1 Reversals

Figure 1 documents the returns to a portfolio that is long on one-week losers (bottom 20%) and short on winners (top 20%) after skipping a week between the formation and investment period. Emerging market returns are in light gray, and developed markets' are in black; Newey and West (1987) heteroscedastic-

[17] To better understand the extent of our market coverage, we compare the total market capitalizations of the stocks we include in our sample from Datastream to the capitalizations reported in the World Equity Market Factbook for the period 1997-2001. Although the capitalizations in the Factbook may be inflated (the Factbook includes foreign listed firms and non-common equity that we exclude), we find that, on average, the coverage of our Datastream sample represents approximately 82% of the market capitalization available in the Factbook. This indicates that any missing firms are concentrated in the small cap portfolio. It is also important to note that our main findings are similar across small and large cap portfolios.

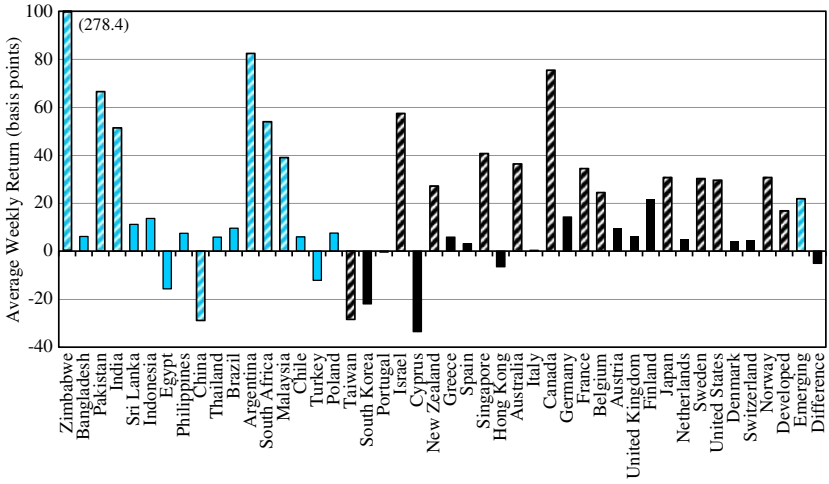


Figure 1
Average weekly contrarian profits
Profits to a weekly contrarian strategy are average weekly returns on a portfolio formed (at $t = 0$) by sorting all stocks into quintiles based on past one-week returns (calculated over $t - 1$ to t). A week is skipped and returns are calculated from $t + 1$ to $t + 2$. The portfolio, long stocks in the low return quintile and short stocks in the high-return quintile, is rebalanced weekly. Average buy-and-hold return over January 1994 through October 2005 is presented in bps/week. Differences between emerging and developed markets are calculated for each week before calculating the full period average. Stripes indicate that the average weekly return is significant at the 5% level using Newey and West (1987) corrected standard errors with optimal bandwidth selected following Newey and West (1994). To be included a stock must trade (have a non-zero price change) on at least 30% of trading days in a calendar year and the country must have at least 50 stocks that pass this criteria to be included in the sample. Trading costs are ignored in the calculation of returns. Countries are ordered from lowest (left) to highest (right) 2005 GNI per capita.

ity and autocorrelation-corrected statistical significance is indicated in stripped bars. Countries are ordered from lowest to highest 2005 GNI per capita. The returns are positive in 21 of 26 developed markets, though only significantly positive in 11 markets. As is to be expected in emerging markets, the returns are more volatile and often larger in magnitude, either positive or negative but especially on the positive side. Returns in emerging markets are positive in 14 of 17 markets, though significantly positive in only six.

Panel A of table 2 displays the summary statistics for various horizons of the short-term contrarian strategy. For the skip-a-week strategies from figure 1, Panel A1 (the top left panel of table 2) shows that on average the strategy that buys past one-week losers and sells past one-week winners (after skipping a week) earns an insignificantly different 16.76 bps per week (8.7% per year) in developed markets and 21.85 bps per week (11.4% per year) on average in emerging markets. The one-week by one-week strategy that immediately follows the ranking period (no week skipped) has profits of 122.38 bps per week (63.6% per year) in developed markets and 128.26 (66.7% per year) in emerging markets. All other strategies have a week skipped between the formation

and investment period since bid-ask bounce is often captured in the short-term effect. For the one-by-two and one-by-four-week strategies the profits drop dramatically. In both cases, emerging market returns are larger but extremely small—only by 6 bps or less. For the four-week by four-week strategy, emerging market stocks tend to earn a small positive profit of 9.17 bps per week while profits in developed markets are slightly negative.

Conrad, Hameed, and Niden (1994) show that return to reversal strategies are generally greater for securities with high volume. In Panel A2 through A5 in table 2, we examine more sophisticated contrarian strategies with volume weighting as outlined in Conrad, Hameed, and Niden and described with our

Table 2
Profits to past return, volume, and event-based trading strategies

Panel A1: Returns to contrarian strategies

	LMW	*t*-stat.	p-value	LMW	*t*-stat.	p-value
	[1 x 1] (Skip-a-week)			[1 x 1] (No skip)		
Devel. Avg.	16.76	4.20	0.000	122.38	24.33	0.000
Emerg. Avg.	21.85	5.13	0.000	128.26	23.41	0.000
Difference	−5.09	1.03	0.304	−5.88	−1.02	0.308
	[1 x 2] (Skip-a-week)			[1 x 4] (Skip-a-week)		
Devel. Avg.	8.36	2.48	0.013	1.88	0.70	0.481
Emerg. Avg.	14.08	4.08	0.000	7.03	2.42	0.016
Difference	−5.72	−1.47	0.142	−5.15	−1.72	0.085
	[4 x 4] (Skip-a-week)					
Devel. Avg.	−1.76	−0.35	0.723			
Emerg. Avg.	9.17	1.84	0.066			
Difference	−10.93	2.05	0.040			

	Small		Meduim		Large	
	Low Vol.	High Vol.	Low Vol.	High Vol.	Low Vol.	High Vol.
Panel A2: One Week LMW Return by Size and Volume						
Developed Average	104.7	180.2	18.9	45.8	44.7	40.6
Emerging Average	125.0	177.5	22.2	−20.6	35.6	11.9
Difference	−17.7	5.7	−3.3	66.4	7.8	25.6
(*t*-stat.)	(−0.60)	(0.12)	(−0.16)	(1.91)	(0.39)	(0.81)
Panel A3: One through Four Week LMW Return by Size and Volume						
Developed Average	156.8	265.7	41.3	31.6	71.9	56.3
Emerging Average	113.5	225.8	71.1	7.8	20.3	10.4
Difference	46.0	41.9	−28.8	23.8	44.9	43.9
(*t*-stat.)	(0.79)	(0.62)	(−0.78)	(0.42)	(0.98)	(0.78)
Panel A4: One Week LMW Return by Liquidity and Volume						
Developed Average	137.0	205.6	26.0	62.9	22.9	19.3
Emerging Average	158.2	170.7	34.8	78.3	18.3	52.7
Difference	−19.8	35.8	−8.8	−15.4	4.0	−33.4
(*t*-stat.)	(−0.71)	(0.75)	(−0.32)	(−0.51)	(0.19)	(−0.96)
Panel A5: One through Four Week LMW Returns by Liquidity and Volume						
Developed Average	198.7	288.6	28.8	58.2	28.5	50.9
Emerging Average	199.4	204.0	7.2	115.5	89.2	91.6
Difference	1.0	83.9	23.6	−55.9	−61.7	−41.6
(*t*-stat.)	(0.02)	(1.02)	(0.55)	(−1.32)	(−1.74)	(−0.67)

Panel B: Post-Earnings-Announcement Drift—Buy and Hold Abnormal Returns +2 to +126

	High Positive Surprise	High Negative Surprise
Devel. Avg.	163.51	250.85
Emerg. Avg.	511.48	88.54
Difference	347.97	339.39
p-value	0.101	0.059

Table 2
Continued

Panel C: Returns to Momentum Strategies

	WML	t-stat.	p-value	WML	t-stat.	p-value
	[26 x 26] (Skip-a-week)			[1 x 52] (Skip-a-week)		
Devel. Avg.	27.01	4.96	0.000	7.66	5.96	0.00
Emerg. Avg.	16.37	3.23	0.001	5.21	3.42	0.001
Difference	10.63	1.84	0.066	2.45	1.43	0.153

Presented below for emerging and developed markets are average profits in basis points to trading strategies based on past one-to-four-week returns (reversals), past one-week returns and volume, earnings surprise, and past 26-week return (momentum). These strategies are formed and held over various horizons. In Panel A1, the portfolio is long stocks in the low-return quintile and short stocks in the high-return quintile (Loser Minus Winner – LMW). A $j\times k$ strategy sorts stocks into quintiles based on past returns over $t-j$ to t and then skips a week ("Skip-a-week") or not ("No skip") and then holds the stocks for k weeks. At any time k, portfolios are held. At least 50 stocks in the prior year in a country are required for inclusion in Panels A1 and C. In Panels A2-A5 stocks with positive prior Wednesday-to-Tuesday returns are classified as winners and negative are losers. Stocks are independently sorted into three NYSE/AMEX/NASDAQ size portfolios based on prior December-end market value in Panels A2 and A3, and by average liquidity ranking in Panels A4 and A5. To calculate the liquidity ranking, we use prior year independent decile rankings for three liquidity measures: LOT, percent 0 returns, and Hasbrouck (2006) effective spread. If missing, the rank is set as the average of the remaining two (minimum two required). The three decile ranks are summed and used to sort stocks into three liquidity portfolios. Stocks are classified as high volume if the percentage change in volume from two to one week prior is positive and low volume otherwise. Returns are weighted by the one-week lag return times one plus the percentage change in volume from two to one weeks prior. For inclusion in Panels A2-A5 portfolios must have an average of at least five stocks per portfolio in the previous year. Returns are Loser Minus Winner portfolio returns. Panels A3 and A5 present non-overlapping four week LMW returns. Post-earnings announcement drift in Panel B is calculated as in figure 2. Panel C reports the returns to portfolios long winners and short losers (Winner Minus Loser – WML) calculated similarly to Panel A1. Average buy-and-hold return over January 1994 through October 2005 for all emerging markets and all developed markets is presented in the table in basis points per week. Except in Panel B, t-statistics are calculated using Newey and West (1987) corrected standard errors with optimal bandwidth selected following Newey and West (1994). Trading costs are ignored in the calculation of returns. To be included in all panels a stock must trade (have a non-zero price change) on at least 30% of trading days in a calendar year.

modifications in table 2.[18] Panel A2 shows that returns to loser-minus-winner strategies are the most pronounced among the smallest stocks. Interestingly, in developed markets LMW returns are the same or greater for high volume stocks, but in emerging markets for medium and large stocks, returns are lower for high volume stocks. Overall, returns for size/volume groups in winner stocks are similar across developed and emerging markets. The inferences are similar when moving to the four-week horizon. Because of the important role that liquidity may play, we also form portfolios with world breakpoints on three liquidity measures.[19] After grouping by liquidity, Panels A4 and A5 reinforce the conclusion that short-term reversal profits in emerging markets are not significantly larger than they are in developed markets.

[18] We also use size groupings on U.S. dollar, U.S. market capitalization breakpoints to control for important different reversal patterns across firm-size groups. We skip a day between the portfolio formation and holding period.

[19] We use three liquidity measures (LOT, percent 0 returns, and Hasbrouck 2006) to reduce estimation error noise that may be large on an individual firm basis. We use independent decile rankings on each of the three liquidity measures in the prior year. At least two measures must be present for calculation of a stock's average liquidity.

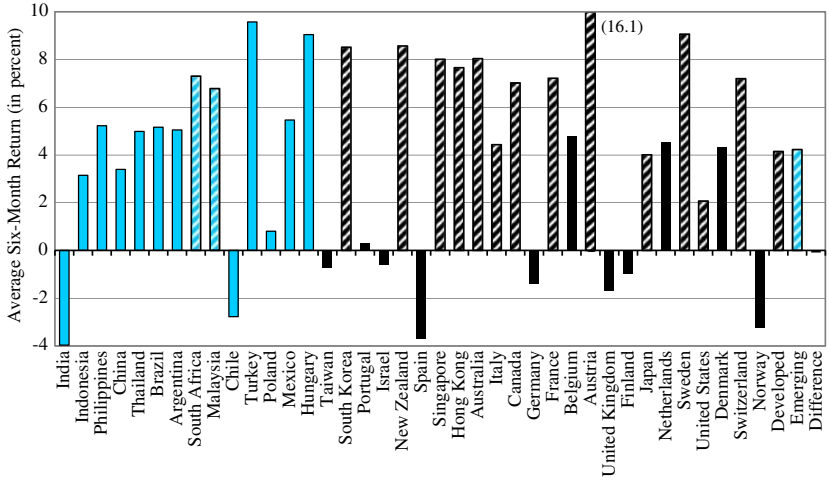


Figure 2
High minus low post-earnings drift following earnings surprises (+2 to +126)
Earnings announcement dates are from Bloomberg. Earnings surprises are calculated as the difference between the actual earnings and the mean of the last I/B/E/S earnings forecast made by each analyst covering the stock between 14 and 182 calendar days prior to the announcement. Surprise is scaled by the price at least six but not more than twelve days prior to the event. The figure displays the average six-month (+2 to +126 trading days following the announcement) buy and hold return in excess of the Datastream value-weighted total market return to stocks with an earnings surprise in the top 60% of positive surprises minus those in the bottom 60% of negative earnings surprises. We require at least 20 firm-events per portfolio for the country to be included. The averages of these abnormal returns over the 1994 to 2005 period for the two extreme surprise portfolios are presented above. Stripes indicate significance at the 5% level, where p-values are for a pooled/unpooled t-test where the null of equal averages between positive and negative surprise portfolios is tested. A pooled t-test is used when a folded F-test indicates that sample variances are insignificantly different at the 5% significance level; otherwise, an unpooled t-test is used. Countries are ordered from lowest (left) to highest (right) 2005 GNI per capita.

3.2 Post-earnings announcement drift

We now turn to examining the popular post-earnings drift strategy as a test of semi-strong form efficiency. Figure 2 presents the average buy-and-hold returns on stocks in the top 60% of earnings surprises minus those in the bottom 60% of negative surprises in the six months following earnings announcement dates.[20] In 16 out of 25 developed markets and 12 out of 14 emerging markets, portfolios with positive earnings surprises earn higher returns than those with negative unexpected earnings. The magnitudes of the post-earnings drift are extremely similar across markets. Overall, as also shown in Panel B of table 2, in the six months following earnings announcements, firms with positive unexpected earnings earn 1.6% in excess of the market in developed countries

[20] Earnings surprises are calculated as the difference between the actual reported earnings per share and the mean analyst earnings per share forecast from I/B/E/S. We include only the last forecast for each analyst made at least 14 calendar days and no more than 182 calendar days before the reporting date. In order to normalize across different firms, the earnings surprise is then scaled by the price as of six calendar days prior to the reporting date. We estimate drift following Bloomberg earnings dates as they are substantially more accurate than I/B/E/S, though clearly not perfect.

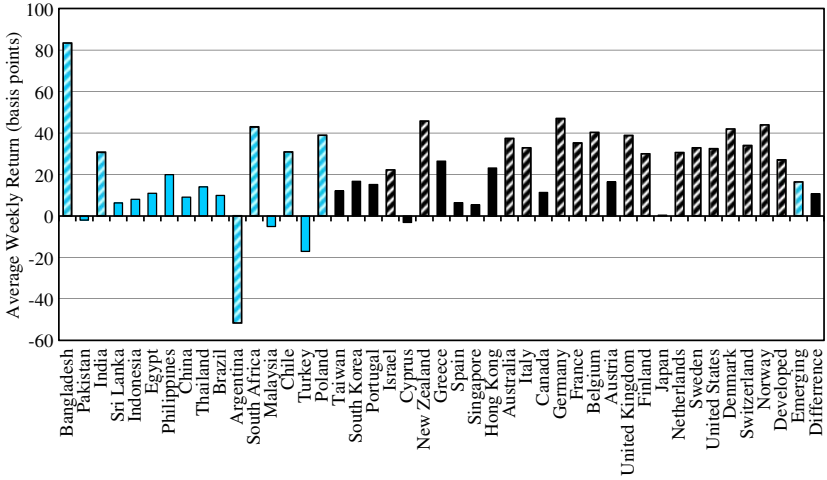


Figure 3
Momentum: Returns to a weekly rebalanced six-month strategy
Profits to a 26-by-26-week momentum strategy are average weekly returns on a portfolio formed (at $t = 0$) by sorting all stocks into quintiles based on past 26-week returns (calculated over $t - 26$ to t). A week is skipped and the portfolio, long stocks in the high return quintile and short stocks in the low return quintile, is held from week $t + 1$ to week $t + 27$. As a result, at any given time 26 overlapping portfolios are held. Average buy-and-hold returns to this strategy over January 1994 through October 2005 are presented in bps/week. Stripes indicate that the average weekly return is significant at the 5% level using Newey and West (1987) corrected standard errors with optimal bandwidth selected following Newey and West (1994). To be included a stock must trade (have a non-zero price change) on at least 30% of trading days in a calendar year and the country must have at least 50 stocks that pass this criteria to be included in the sample. Trading costs are ignored in the calculation of returns. Countries are ordered from lowest (left) to highest (right) 2005 GNI per capita.

and 5.1% in emerging markets. Firms with negative earnings surprises earn −2.5% in developed and 0.9% in emerging markets. Hence, the high minus low post-earnings drift is 4.1% (for six months) in developed markets and 4.2% in emerging markets. The differences are economically and statistically negligible. Our main conclusion is that a post-earnings drift-based trading strategy yields returns of similar magnitude in developed and emerging markets.

3.3 Momentum

Figure 3 shows that momentum returns (from 1994 to 2005) are positive in all but one developed market and statistically significant in 15 of 26 markets. Returns in all of these 15 markets are over 20 bps per week and similar in the U.S. as in other developed markets. In emerging markets, momentum strategies yield positive returns in 12 markets and negative returns in four markets. Panel C of table 2 presents summary statistics for momentum returns and shows that, other than the large return in Bangladesh, the momentum strategy seems to have larger returns in most of the richer countries. Panel C also shows the "long-lasting momentum" return from a one-week formation and 52-week

holding period documented in Gutierrez and Kelley (2007). Although the returns are much smaller than those due to the regular momentum strategy, the returns are statistically significant in both developed and emerging markets. The returns are somewhat larger in developed markets.

4. Empirical Results from Efficiency Measures

Although the portfolio returns are an economically intuitive way to measure inefficiency, we now turn to common, formal measures of efficiency, which are advantageous in that we can allow for different types of past returns (firm, portfolio, and market), and control for the size of the firms within a market. In this section, we empirically examine three measures that capture deviations from random walk pricing: averages of firm variance ratios, portfolio variance ratios, and delay with respect to market prices. In most of our results, we use U.S. dollar market capitalization breakpoints to allow comparison across similar-sized firms.

4.1 Variance ratios

We estimate autocorrelations and variance ratios at the weekly and at the daily frequency, first for individual stocks and then for portfolios.

4.1.1 Individual stocks. An advantage of using individual stocks is that one can allow correlations to switch sign across stocks. Because both negative and positive autocorrelation represent departures from a random walk, when aggregating variance ratios across stocks we compute the absolute value of the VR statistic minus one (|VR-1|) as a measure of relative efficiency for each stock return series. Based on U.S. market ($) breakpoints, we equally weight across stocks within each size, country-level grouping.

Panel A of table 3 reports average variance ratio statistics calculated from a variety of horizons with several price-change filters for individual stocks across developed and emerging markets, differences between the two averages, and the p-value from a difference-in-means test. We see that variance ratios have larger deviations from one in the small cap portfolios both in developed and emerging markets. In unreported results, these patterns are largely confirmed within most countries. More importantly, Panel A1 of table 3 shows that the differences between developed and emerging markets are quite small, though small stocks in developed markets exhibit greater departures from efficiency with either the no-price-change filter or the 30% price-change filter.[21] Only when applying the 75% price-change filter do we see similar or smaller departures from the random walk in developed markets.

[21] Internet Appendix Table A.1 reports these variance ratios on a country-by-country basis.

Table 3
Variance ratios for stocks and portfolios

Panel A: Average for Individual Stocks

	0% Price Change Filter					30% Price Change Filter					75% Price Change Filter				
	Large	4	3	2	Small	Large	4	3	2	Small	Large	4	3	2	Small
Panel A1: Five-week Variance Ratios |VR-1|															
Devel. Avg	0.129	0.150	0.159	0.180	0.218	0.129	0.150	0.159	0.180	0.220	0.128	0.140	0.154	0.172	0.192
Emerg. Avg	0.117	0.136	0.165	0.177	0.171	0.116	0.137	0.158	0.169	0.168	0.117	0.132	0.145	0.158	0.178
Diff	0.012	0.014	-0.006	0.003	0.047	0.013	0.013	0.001	0.011	0.052	0.011	0.008	0.009	0.013	0.014
p-value	0.202	0.164	0.566	0.798	0.001	0.178	0.196	0.948	0.316	0.002	0.173	0.445	0.355	0.199	0.396
Panel A2: Ten-week Variance Ratios |VR-1|															
Devel. Avg	0.179	0.205	0.220	0.237	0.289	0.179	0.205	0.219	0.237	0.292	0.178	0.195	0.212	0.227	0.252
Emerg. Avg	0.173	0.190	0.233	0.243	0.234	0.168	0.190	0.224	0.235	0.232	0.172	0.181	0.202	0.215	0.230
Diff	0.007	0.015	-0.014	-0.006	0.055	0.012	0.016	-0.004	0.002	0.060	0.006	0.014	0.010	0.012	0.023
p-valu	0.651	0.200	0.360	0.725	0.002	0.450	0.186	0.730	0.916	0.003	0.699	0.258	0.453	0.390	0.214
Panel A3: Daily Variance Ratios |VR2-1| and|VR5-1|, (30% Price Change Filter)															
Devel. Avg	0.066	0.077	0.087	0.099	0.099	0.117	0.151	0.171	0.197	0.213					
Emerg. Avg	0.062	0.064	0.073	0.075	0.087	0.117	0.122	0.153	0.154	0.186					
Diff	0.005	0.013	0.014	0.024	0.011	0.000	0.029	0.018	0.043	0.027					
p-valu	0.513	0.079	0.054	0.021	0.412	0.981	0.037	0.231	0.021	0.249					

Panel B: Portfolio

	0% Price Change Filter					30% Price Change Filter					75% Price Change Filter				
	Large	4	3	2	Small	Large	4	3	2	Small	Large	4	3	2	Small
Panel B1: Five-week Variance Ratios |VR-1|															
Devel. Avg	0.177	0.469	0.612	0.651	0.704	0.176	0.466	0.598	0.567	0.619	0.152	0.372	0.493	0.437	0.528
Emerg. Avg	0.220	0.356	0.395	0.439	0.521	0.213	0.342	0.369	0.371	0.426	0.229	0.245	0.243	0.340	0.288
Diff	-0.043	0.113	0.217	0.212	0.183	-0.037	0.124	0.229	0.196	0.192	-0.077	0.127	0.250	0.097	0.241
p-valu	0.188	0.109	0.003	0.011	0.085	0.262	0.057	0.000	0.007	0.046	0.453	0.039	0.000	0.175	0.010
Panel B2: Five-week Variance Ratios |VR-1|–Mech (1993) Adjusted															
Devel. Avg	0.114	0.313	0.415	0.432	0.522	0.111	0.316	0.414	0.407	0.500	0.133	0.271	0.341	0.367	0.508
Emerg. Avg	0.147	0.253	0.288	0.285	0.396	0.154	0.243	0.267	0.289	0.396	0.142	0.239	0.229	0.289	0.380
Diff	-0.033	0.060	0.127	0.147	0.125	-0.043	0.073	0.147	0.118	0.103	-0.009	0.032	0.111	0.078	0.129
p-valu	0.331	0.279	0.021	0.010	0.157	0.215	0.158	0.005	0.041	0.248	0.862	0.591	0.040	0.172	0.165
Panel B3: Ten-week Variance Ratios |VR-1|															
Devel. Avg	0.271	0.686	0.923	1.019	1.133	0.273	0.681	0.885	0.877	0.941	0.233	0.548	0.739	0.645	0.701
Emerg. Avg	0.272	0.538	0.590	0.725	0.852	0.246	0.492	0.540	0.599	0.673	0.337	0.367	0.355	0.495	0.513
Diff	-0.001	0.148	0.334	0.294	0.281	0.027	0.189	0.345	0.278	0.267	-0.104	0.182	0.384	0.150	0.188
p-valu	0.989	0.147	0.004	0.035	0.095	0.580	0.042	0.001	0.016	0.088	0.560	0.053	0.000	0.163	0.190

Table 3
Continued

Panel B4: Daily Variance Ratios |VR-1| (30% Price Change Filter)

Devel. Avg	0.094	0.154	0.172	0.173	0.166	0.177	0.395	0.463	0.454	0.468
Emerg. Avg	0.142	0.139	0.127	0.130	0.165	0.258	0.317	0.292	0.290	0.399
Diff	−0.049	0.014	0.046	0.043	0.002	−0.081	0.077	0.171	0.164	0.069
p-valu	0.037	0.471	0.043	0.100	0.964	0.093	0.161	0.006	0.020	0.454

Each panel reports average absolute deviations from one for variance ratios across developed and emerging markets, differences between the two averages, and the *p*-value from a difference-in-means test. In Panel A variance ratios are calculated for each stock. Next, the individual variance ratios are winsorized at the 0.5% and 99.5% levels and aggregated within size portfolios using an equally weighted scheme. In Panel B a ratio is calculated for each size portfolio. Each panel is split into three (four) subpanels to present different variance ratio specifications for stocks (portfolios). Each subpanel is further split into three subpanels, which, in panels with variance ratios calculated using weekly returns, present results with different price-change filters: the first includes all stocks (0% Price Change Filter), the second (30% Price Change Filter) contains results from using securities that traded during at least 30% of the total number of trading days over the sample period; the third (75% Price Change Filter) is based on stocks that traded during at least 75% of the total number of trading days over the sample period. In subpanels reporting statistics with variance ratios based on daily data (Panels A3 and B4), only the 30% Price Change Filter is used, and in the first subpanel, variance ratios are calculated using two-day returns and the second using five-day returns. All statistics refer to the 1994-2005 period. Under the null hypothesis of uncorrelated returns, the variance ratio equals one. Panel A reports statistics about the absolute value of (VRx - 1) where VRx (x=5 or 10) is computed as follows: a variance ratio is calculated for each stock between the variance of x week continuously compounded returns and x times the variance of one-week continuously compounded returns; next, the quantity |VRx - 1| is computed for each stock; finally, individual stock statistics are aggregated within size portfolios using an equally weighted scheme. Panel B reports statistics about the absolute value of (VRx - 1), where VRx is the ratio between the variance of x-week portfolio returns and x times the variance of one-week portfolio returns. Following Mech (1993), adjusted portfolio returns are computed as the equally weighted average of individual returns in the first four days of the week using only stocks that traded on the last day of the previous week. *p*-values are for a pooled/unpooled *t*-test where the null of equal averages between emerging and developed markets is tested. A pooled *t*-test is used when a folded *F*-test indicates that sample variances are insignificantly different at the five-percent significance level; otherwise an unpooled *t*-test is used.

We draw similar inferences from the results at the ten-week horizon in Panel A2 of Table 3 as from those at the five-week frequency. Two- and five-day variance ratios and lag-one autocorrelations are computed using daily returns and the 30% price-change filter in Panel A3.[22] These results show that differences are insignificant in most size portfolios but, where they are significantly different, developed markets have greater absolute variance ratios.

4.1.2 Portfolios. The averages for developed and emerging portfolios along with tests of differences between the two groups are displayed in Panel B of table 3. As with the individual stock variance ratios, we facilitate comparison across markets by first calculating the absolute deviation of the variance ratios from one (|VR-1|) in each country/size portfolio before aggregating across developed or emerging markets. The results for portfolio returns indicate much higher levels of average autocorrelations across almost all size quintiles for developed markets, except the largest. When these differences are statistically significant, they indicate that developed market size portfolio returns suffer greater departures from a random walk.

Non-trading and bid-ask bounce are potentially large drivers of (spurious) autocorrelations, which is a strong reason for using the trading filters throughout our analysis. Following Mech (1993), we use only stocks that traded on the last day of the previous trading week and calculate adjusted portfolio returns as the equally weighted average of individual returns in the first four days of the week. Panel B2 of table 3 shows that the relative differences between developed and emerging markets still point to slower adjustment to information in developed markets for medium-sized firms.

Panel B3 of table 3 reports portfolio variance ratios over a 10-week period. They confirm the conclusions inferred from the variance ratios computed at shorter horizons. Looking at the ratios computed from daily portfolio returns (Panel B4), it is still true that, as we found in Panel A3 for daily individual security returns, autocorrelations are lower in emerging markets, with the exception of the largest portfolios.[23]

4.2 Delay

Delay is a measure that captures the extent to which current country-size portfolio returns reflect past market-wide information. Delay with respect to the

[22] We estimate daily statistics using the 0% and the 75% price-change filters as well and they yield similar inferences.

[23] For completeness, we also examine the mean and median (non-absolute) variance ratios at the firm level by size category. Emerging markets often have slightly positive autocorrelation and stocks in developed markets have a tendency to exhibit slightly negative autocorrelations. However, in total the patterns vary considerably across countries and time such that it is unclear what we learn from such analysis other than that the sign of autocorrelation varies widely across countries but in manners inconsistent with simple notions of development. For example, similar-sized firms in the U.K. exhibit autocorrelations of the opposite sign and largely different magnitudes than those in the U.S. over the same sample period—a result also found using another framework by Gagnon, Karolyi, and Lee (2006).

Table 4
Summary measures of local and global market delay

	Large	4	3	2	Small
Panel A: Local Market Delay					
30% Price Change Filter with U.S. Market Breakpoint Size Portfolios					
Devel. Avg.	0.004	0.032	0.046	0.051	0.057
Emerg. Avg.	0.000	0.013	0.017	0.020	0.010
Diff	0.003	0.019	0.030	0.031	0.048
p-value	0.027	0.022	0.002	0.002	0.000
0% Price Change Filter					
Devel. Avg.	0.004	0.031	0.049	0.055	0.058
Emerg. Avg.	0.004	0.015	0.020	0.024	0.021
Diff	0.000	0.017	0.029	0.031	0.037
p-value	0.974	0.066	0.002	0.002	0.000
75% Price Change Filter					
Devel. Avg.	0.003	0.024	0.034	0.035	0.036
Emerg. Avg.	0.002	0.002	0.018	0.012	0.005
Diff	0.002	0.022	0.016	0.023	0.031
p-value	0.112	0.000	0.070	0.047	0.016
Panel B: Local and Global Delay					
	Large	4	3	2	Small
Devel. Avg.	0.004	0.033	0.048	0.055	0.059
Emerg. Avg.	0.002	0.013	0.025	0.021	0.015
Diff	0.003	0.020	0.023	0.034	0.044
p-value	0.058	0.017	0.023	0.001	0.001
Panel C: Local Market Delay with Local Breakpoints					
Devel. Avg.	0.011	0.042	0.051	0.054	0.055
Emerg. Avg.	0.003	0.016	0.024	0.018	−0.001
Diff	0.008	0.026	0.027	0.036	0.056
p-value	0.005	0.005	0.009	0.000	0.000
Panel D: Local Market, Hou and Moskowitz (2005) Delay					
Devel. Avg.	0.006	0.059	0.109	0.161	0.339
Emerg. Avg.	0.010	0.037	0.074	0.101	0.140
Diff	−0.004	0.022	0.035	0.059	0.199
p-value	0.489	0.163	0.390	0.072	0.001

Delay is the difference between the unrestricted and the restricted adjusted R^2 from three variations of a market model containing contemporaneous and lagged returns:

Local Market Delay: $r_{i,t} = \alpha_i + \beta_{0i} r_{m,t} + (\beta_{1i} r_{m,t-1} + \beta_{2i} r_{m,t-2} + \beta_{3i} r_{m,t-3} + \beta_{4i} r_{m,t-4}) + \varepsilon_{i,t};$

Local and Global Delay: $r_{i,t} = \alpha_i + \beta_{0i} r_{m,t} + \beta_{1i} r_{g,t} + \left(\beta_{2i} r_{m,t-1} + \beta_{3i} r_{m,t-2} + \beta_{4i} r_{m,t-3} + \beta_{5i} r_{m,t-4}\right) + \left(\beta_{6i} r_{g,t-1} + \beta_{7i} r_{g,t-2} + \beta_{8i} r_{g,t-3} + \beta_{9i} r_{g,t-4}\right) + \varepsilon_{i,t};$

where i is the size portfolio, m is the local market of the ith portfolio, and g is the global market. The terms in parentheses represent the local and global market return lags included in the unrestricted model, but not in the restricted model. Regressions are run over the full 1994-2005 period for each size portfolio. Size portfolios use U.S. market breakpoints in all panels except Panel C, which uses local market breakpoints. Delay is calculated as $(Delay = adjR^2_{unrestricted} - adjR^2_{restricted})$ except in Panel D, in which delay is calculated following Hou and Moskowitz (2005): $(Delay = 1 - R^2_{restricted}/R^2_{unrestricted})$. In Panels B, C, and D the 30% price-change filter is used. For the size quintile portfolios, common breakpoints based on U.S. equities are applied in all panels except for Panel C, where the size breakpoints are five within-country quintiles.

past four weeks of the local market return is calculated for size portfolios over the entire January 1994 to November 2005 period. Table 4 displays the magnitude of the delay measure for each of the five size portfolios averaged over the 28 developed markets and, separately, over 28 emerging markets in Panel A. Table 4 displays several interesting findings. First, delay is universally lower among large cap stocks, and, in general, it is predominantly decreasing in size. This inverse relation between size and delay is consistent with Hou and Moskowitz's (2005) U.S. study and loosely supports the use of delay as

a measure of efficiency, as one would expect that large cap stocks are more efficient than small. Second, for similar size quintiles, emerging markets have significantly less delay.

We investigate the sensitivity of these findings in a number of ways. One possibility is that delay may be influenced by the employed price-change filters. Delay may be low in emerging markets because our 30% price-change filter eliminates firms with high delay or because developed markets have more small firms that do not trade. We find in Panel A of table 4 that using a no-price-change filter (0% price-change filter) only slightly increases emerging market delay, while the more restrictive 75% price-change filter noticeably decreases delay in developed markets and nearly eliminates delay in larger emerging market portfolios.

Another possibility is that our delay measure is incomplete in that it ignores the impact of global market return. In Panel B of table 4 we examine delay with respect to both local and global market returns under our standard 30% price-change filter. The inclusion of global market returns increases the explanatory power of lagged factors in the smallest size quintile but the relative differences between developed and emerging markets remain similar.[24]

We also examine whether our findings are contingent on our application of the U.S. market size breakpoints. In Panel C of table 4 we examine our base-case delay (30% price-change filter) with respect to the local market but with portfolios formed according to local market size breakpoints. Here, because local breakpoints in most countries mean that smaller firms enter larger portfolios, the magnitude of delay increases for most portfolios, but the findings about the relative differences between developed and emerging markets remain similar.

Another possible explanation for our findings is that it is simply a reflection of the strong explanatory power of the (contemporaneous) market model in emerging markets. Thus we also calculate delay as a scaled measure in the same manner as Mech (1993) and Hou and Moskowitz (2005), which scales the restricted model R^2 by the unrestricted R^2, as shown in Appendix Equation (A.4). Nonetheless, the results reported in Panel D in table 4 are qualitatively similar.

5. Discussion of Findings, Transaction Costs, and Information Production

5.1 Possible interpretations

If one looks across size portfolios at the results presented in the previously discussed tables and figures, one sees that within countries we do generally find what we would expect: greater returns to reversal strategies and greater

[24] In addition, we examine the incremental explanatory power of local and global market returns after controlling for lagged own-portfolio returns. The magnitude of delay between developed and emerging markets is similar, although both magnitudes are considerably less than the delay in Panel B.

departures from a random walk for small firms with higher trading costs than for large firms. On the other hand, the findings across countries are counterintuitive. Trading strategies designed to exploit market inefficiencies generate no larger returns in emerging markets. Variance ratios at the firm level indicate comparable degrees of autocorrelation, whereas portfolio variance ratios and delay measures indicate that emerging markets are often more efficient than developed markets.

There are three possible ways to interpret our counterintuitive cross-country findings. One, the measures do not accurately capture the manner in which past returns are incorporated into prices. Two, the inferences from the common, autocorrelation-based efficiency measures are correct and similarly sized firms in emerging markets are indeed just as or even more efficiently priced than in developed markets. Three, the measures do what they were designed to do: reflect the degree to which prices incorporate the information contained in past returns. But this concept of efficiency has important limitations: as a consequence, it is problematic to make broad assessments of efficiency and comparisons based on these measures. Restated, interpretation two sticks more to the traditional view, often implied in many empirical papers, that weak-form efficiency is essentially what matters when assessing stock market efficiency. Interpretation three states that the very measurement of weak-form efficiency has important limitations.

We find interpretation one unlikely for several reasons. First, the measures are conceptually intuitive and straightforward—they directly measure the ability of past returns to predict future prices. Second, since the impact of past returns could vary importantly with the observation frequency, we have examined a variety of horizons in tables 2, 3, and 4. Third, we have examined the impact of different aspects of past returns—individual stock, portfolio, and market level. In sum, while we can never completely rule out the possibility that the measures fail to capture relevant associations between past and current returns, especially in emerging markets, this possibility seems unlikely given the large array of widely accepted techniques, data, time periods, and robustness checks that we have applied to the problem.

This leaves us to distinguish between the two remaining possibilities for interpreting the empirical findings. Namely, are emerging markets just as efficient as developed markets (interpretation two), or are weak-form and semi-strong-form efficiency conceptually insufficient to capture the most salient features of efficiency in a market (interpretation three)? To distinguish between these two competing explanations, it is useful to reconsider the notion of informational efficiency. Fama (1970) states:

> First, it is easy to determine *sufficient* conditions for capital market efficiency. For example, consider a market in which (i) there are no transaction costs in trading securities, (ii) all available information is costlessly available to all market participants, and (iii) all agree

> on the implications of current information for the current price and distributions of future prices of each security. In such a market, the current price of a security obviously "fully reflects" all available information.[25]

We examine two potential sources of efficiency (or lack thereof) related to (i) and (ii)[26] above—transaction costs and the amount and cost of information produced. Bid-ask spreads, trading commissions, and lack of liquidity undermine the ability of arbitrageurs to exploit deviations from efficient pricing. Hence, while theoretically possible, it is in practice hard to imagine a market with high transaction costs that is just as efficient as a market with low costs. We first use the estimate of round-trip transaction costs developed in Lesmond, Ogden, and Trzcinka (1999) (LOT). One way to quantify the amount and, possibly, the cost of information acquisition is to examine the extent and frequency of analyst activity within a market, under the rationale that the main purpose of analysts' activity is to collect and disseminate value-relevant information to their clients. Competition among analysts may speed up the dissemination of information. These proxies are not without their limitations, but they are readily available and have intuitive appeal.[27]

If these impediments to efficiency produce a picture consistent with our efficiency measures findings (i.e., similar trading costs and analyst coverage across markets), then these features support the notion that emerging markets are just as efficient as developed markets. But, if the inferences from these measures indicate that emerging markets have higher impediments to trade or higher information acquisition costs, then they present a conflicting picture of relative (weak-form) efficiency and, possibly, cast doubts on the validity of commonly used efficiency measures.

5.2 Transaction costs

Figure 4 displays the average LOT measure for each of the top four size portfolios in each country.[28] Most emerging market countries have much higher transaction costs in all but the smallest quintile (unreported). It is hard to place

[25] Fama then goes on to note that while these sufficient conditions "are not necessarily sources of market inefficiency, they are potential sources."

[26] The third component, investors' agreement on the implications of current market information, is problematic to measure empirically.

[27] There are several caveats as analysts might: 1) be better at generating some types of information but not others (Piotroski and Roulstone 2004; Chan and Hameed 2006); 2) revise estimates without new information; or 3) not revise estimates, even if they do have information; or 4) have no real skill in generating or disseminating information. In addition, to the extent there is herding among analysts, analyst estimates may be a noisy proxy for information generation.

[28] As with most of our results, we require stocks to trade on 30% of days in the prior year before being included with at least five stocks per size portfolio, which are formed on the U.S. market, U.S. dollar breakpoints. Trading costs are averaged across stocks at the portfolio level in each country, and then cross-country averages are computed across countries for each size portfolio.

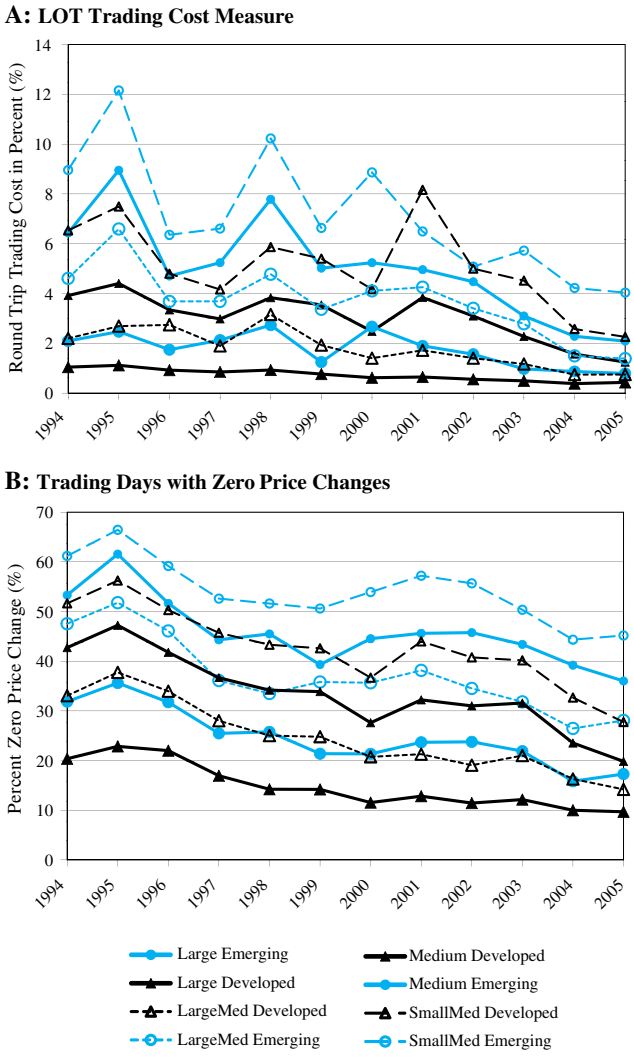


Figure 4
Average trading costs by year for emerging and developed markets
Panel A presents round-trip (buy plus sell) transaction costs as a percentage of price. Transaction costs are calculated for each calendar year following Lesmond, Ogden, and Trzcinka (1999) for each stock in the sample that has price changes on at least 30% of all trading days in the calendar year prior to portfolio formation with at least five stocks per country, size, and year portfolio. Trading costs are averaged across all stocks passing these criteria each year for each U.S. market, U.S. dollar size portfolio. The chart reports the cross-country average of average size portfolio trading costs for each year. Panel B presents the percentage of trading days on which the average stock in an emerging or developed size portfolio has a zero price change from the trading day before. In Panel B all stocks are included even if they do not have price changes on at least 30% of all trading days in the calendar year prior to portfolio formation.

emphasis on the very small cap firms since inferences might change simply as a function of the database adding new firms in a market and hence the size controls are unlikely to be effective here.[29] In the largest three portfolios, trading costs are close to twice as large in emerging markets as they are in developed.

Examining the time-series changes in trading costs, Panel A in Figure 4 shows that for the largest four quintiles there has been a large decrease in round-trip transaction costs.[30] For example, in the largest cap stocks in developed markets, transaction costs have decreased from 1% in 1994 to 38 bps in 2005. These decreases in transaction costs are dramatic for medium and large emerging market firms as well. For example, medium-sized emerging market trading costs were just over 6% in 1994 but fell to about 2% in 2005. Interestingly, Lesmond (2005) examines LOT and other trading costs through time from 1993 to 2000 in emerging markets but finds a slight increase in transaction costs over this period. In addition to our extended time period, this emphasizes the importance of the size ranks as they provide a simple metric that controls for the composition of the market.[31]

We also examine our inferences with two alternative trading costs measures. Panel B in figure 4 shows the percentage of observations with a zero return. The percentage of zero returns is the main measure used by Bekaert, Harvey, and Lundblad (2007) and has the same intuition as the LOT measure but is less subject to problems in estimation. Here, unlike many other analyses in the article, we require no filters on the percentage of zero returns in the prior year. Panel B of figure 4 shows that emerging markets generally have more zero return days, and the percentage of zero price-change days decreases across the sample in every size/development category. In unreported results, we calculate the Hasbrouck (2006) measure of the effective spread. Here, the decrease in transaction costs occurs from 2001 to 2005. Conceptually, we prefer the LOT measure as it is a more inclusive measure designed to incorporate the effective spread, commissions, and price impact, whereas the Hasbrouck (2006) measure is designed to capture the effective spread.

[29] For example, developed markets like the U.S. could have extremely tiny small-cap firms that are thinly traded and hence one might erroneously conclude that the market is illiquid just because these firms are allowed to list and/or are covered by Datastream. For this reason, we focus on the top four quintiles when presenting summary statistics for size portfolios in subsequent analysis in figures 4 through 6.

[30] It is worth noting that Table 1 shows that, except in the largest size quintile, the market caps of emerging and developed markets are similar.

[31] Lesmond did not use size controls in the time-trend analysis. Consistent with the importance of this difference in approach, the only quintile that did not experience a dramatic decrease in trading costs is the smallest size quintile (not graphed). These increasing costs for small firms seem likely to be due to the dramatically increasing coverage in Datastream for small-cap firms rather than any true increase in costs. One related potential problem is that since U.S. dollar breakpoints are used, LOT may appear to be decreasing in emerging markets mainly as a function of increasing U.S. breakpoints. Therefore, we also examine inferences with 1994 U.S. breakpoints that are adjusted for U.S. (CPI) inflation. We find similar inferences.

In sum, using three leading methods for estimating trading costs, we find that trading costs are consistently lower in developed markets. Additionally, trading costs in both emerging and developed markets have been decreasing dramatically over time.

5.3 Information

As a proxy for information gathering and costs, we examine analyst coverage, the number of forecasts, and the frequency of analyst revisions. While a number of papers use analysts' estimates internationally, we did not locate a study that compares coverage between similar-sized developed and emerging market firms.[32]

Table 5 presents the percentage of firms in the five size portfolios covered by I/B/E/S analysts. Across markets we see that a sizable percentage of firms covered by Datastream have analyst coverage and, more importantly, we see more analyst coverage in developed than in emerging markets, particularly among small and medium firms. The middle panel shows that, among firms with coverage, the average number of analysts is roughly the same across emerging and developed markets, except among the largest firms, where there are just under 50% more analysts in developed markets (19.8 vs. 13.6). The right most panel of table 5 shows that among stocks with analyst coverage, the average large firm in a developed market has 70% more estimates (60 vs. 35) than a firm in an emerging market, suggesting a higher level of information gathered in developed markets. The disparity between emerging and developed markets is increasing in market capitalization.

Figure 5 plots the I/B/E/S analyst coverage (Panel A) and analyst estimates and revisions (Panel B) through time. The figure shows two interesting findings. First, for firms of similar size, it is generally the case that the developed market firms have more firms covered and more estimates per firm. Second, in developed markets, analyst coverage and the number of estimates per firm have been increasing throughout the sample period. However, in emerging markets, the frequency has actually dropped off since 2001 for many size portfolios. These findings are consistent with the notion that there is greater information gathered and lower information costs in developed markets.

5.4 The relation between transaction costs, analyst coverage, and efficiency through time and across countries

The analyses in the previous two sections yield the intuitive finding that emerging markets have higher transaction costs and less (or more costly) information

[32] The closest is Chang, Khanna, and Palepu (2000), who with a sample of 30 firms per country find fewer analysts per firm in countries with less developed capital markets.

Table 5
Information generation by country: average analyst activity

Panel A: Developed Countries

	Average Percentage of Firms in Market with Analyst Coverage					Average Number of Analysts per Company (only if covered)					Average Number of Estimates and Revisions per Company (only if covered)				
Country	Large	4	3	2	Small	Large	4	3	2	Small	Large	4	3	2	Small
Australia	95	89	78	48	6	17.9	10.4	6.1	3.0	1.8	74.9	35.1	17.4	7.4	3.6
Austria	88	62	69	45	18	13.1	6.8	4.1	2.9	2.3	33.5	15.3	8.8	5.7	4.1
Belgium	80	62	58	43	7	21.4	9.2	5.8	3.9	1.6	59.8	24.8	13.2	8.2	3.0
Canada	53	45	39	30	3	30.6	16.7	10.3	6.3	3.6	111.3	53.7	29.7	16.4	7.8
Cyprus	33	44	4	11	1	1.0	1.4	1.5	1.3	1.1	1.0	1.5	1.5	1.3	1.1
Denmark	82	82	63	46	14	20.8	9.6	4.6	2.7	1.7	63.9	27.9	11.4	6.0	3.1
Finland	89	75	73	63	36	25.8	12.8	7.4	4.6	3.1	83.8	35.8	18.5	10.7	6.0
France	80	65	53	39	11	31.9	14.0	7.2	3.3	1.7	95.2	35.8	16.9	6.8	3.1
Germany	71	59	49	35	13	29.4	11.9	6.4	3.0	1.7	77.2	27.1	13.9	6.0	2.9
Greece	9	6	2	0	1	11.7	4.9	3.2		1.4	32.8	12.2	5.5		2.7
Hong Kong	91	79	52	25	6	31.8	15.0	6.1	2.7	1.7	93.8	35.1	12.2	4.5	2.5
Ireland	90	90	84	57	38	11.7	5.8	4.4	3.7	2.4	30.0	12.4	8.8	7.1	4.3
Israel	69	41	15	1	0	5.7	4.0	1.9	1.1		3.0	8.5	3.7	1.4	
Italy	92	77	64	32	12	21.0	9.3	5.0	2.3	1.6	50.7	20.0	10.0	4.1	3.6
Japan	87	77	67	57	43	11.1	4.3	2.3	1.7	1.5	25.6	8.6	4.4	3.2	3.0
Luxembourg	14	0	6	0	0	6.1		1.0			12.4		1.0		
Netherlands	78	87	84	70	41	37.8	19.1	11.7	6.0	2.6	110.6	45.2	26.7	12.6	4.2
New Zealand	98	78	86	62	14	12.6	10.1	6.6	3.7	1.9	53.8	37.7	23.0	11.3	4.3
Norway	85	78	71	47	18	24.6	11.2	6.0	3.2	1.8	95.1	39.1	21.2	9.0	4.3
Portugal	91	81	75	33	4	15.3	7.7	5.7	3.5	2.2	36.5	18.0	11.3	6.7	3.7
Singapore	87	86	68	41	10	29.9	14.3	6.6	3.2	1.8	96.7	35.1	13.2	5.6	2.9
South Korea	41	50	53	49	23	19.1	11.1	7.4	4.0	2.1	62.8	34.1	20.2	9.5	3.9
Spain	88	74	68	56	27	28.0	14.0	7.2	4.4	2.3	68.4	29.2	13.2	7.7	4.0
Sweden	87	78	70	56	25	25.3	9.4	4.7	2.6	1.6	86.0	29.4	14.1	7.2	3.6
Switzerland	83	79	65	48	16	23.0	9.7	6.7	3.0	1.4	67.7	22.3	14.0	5.5	2.5
Taiwan	81	71	47	20	3	11.1	4.5	2.2	1.7	1.4	30.7	10.5	4.2	3.1	1.6
U.K.	93	91	81	62	32	20.1	8.4	4.1	2.3	1.4	55.9	19.4	8.6	4.5	2.4
U.S.	98	92	79	51	16	17.2	7.2	4.1	2.4	1.4	57.1	22.4	11.5	5.9	3.0

Table 5
Continued

Panel B: Emerging Countries

	Average Percentage of Firms in Market with Analyst Coverage					Average Number of Analysts per Company (only if covered)					Average Number of Estimates and Revisions per Company (only if covered)				
Country	Large	4	3	2	Small	Large	4	3	2	Small	Large	4	3	2	Small
Argentina	89	82	69	57	22	14.8	11.0	5.9	3.2	1.8	32.6	22.8	12.0	6.4	3.0
Bangladesh	0	0	0	0	0										
Brazil	24	18	7	5	2	20.4	9.0	6.2	4.8	5.6	49.9	17.7	10.8	9.0	8.9
Bulgaria		0	0	0	0										
Chile	86	65	42	19	3	8.2	4.1	2.5	2.0	1.8	20.5	9.2	5.3	3.7	2.8
China	17	9	3	0	0	4.0	2.4	2.1	1.3	1.0	8.0	4.0	2.8	1.9	1.0
Colombia	93	48	29	8	1	4.2	2.7	4.0	3.5	1.1	9.4	4.7	8.3	6.2	2.4
Czech Republic	100	100	28	14	6	19.1	9.2	5.0	3.8	1.3	41.5	17.1	10.5	6.0	2.8
Egypt	72	48	24	9	1	4.9	3.1	1.5	1.1	1.3	8.0	5.2	2.0	1.3	1.5
Hungary	100	78	86	66	24	20.7	12.6	10.7	6.5	2.5	49.4	27.0	20.7	11.8	4.0
India	95	83	49	18	2	15.1	9.0	4.0	2.2	1.2	38.2	20.3	7.3	3.2	1.6
Indonesia	95	87	65	39	14	20.4	14.0	7.2	3.6	2.6	66.0	41.8	18.8	8.8	4.9
Kenya	0	0	0	0	0										
Lithuania		33	8	2	1		2.0	1.0	1.0	2.0		2.0	4.0	1.0	2.0
Malaysia	92	78	48	23	6	28.9	14.4	6.2	2.8	1.9	81.5	36.7	13.8	5.1	3.1
Mexico	75	63	49	28	9	17.9	12.6	8.3	5.2	3.3	47.4	33.2	21.0	13.6	8.3
Morocco	29	38	34	20	10	1.1	1.4	1.1	1.2	1.0	1.7	1.9	1.5	1.5	1.1
Pakistan	95	80	55	33	6	4.4	3.9	3.6	2.5	1.7	9.5	8.3	7.0	4.6	3.2
Peru	31	32	14	9	6	12.5	5.7	5.7	4.9	1.7	23.2	10.8	9.8	9.5	2.7
Philippines	81	79	55	32	10	20.9	14.3	9.5	5.0	2.7	59.5	34.4	20.5	8.6	4.7
Poland	92	84	71	42	17	12.6	9.2	6.6	3.6	2.6	24.7	16.3	11.8	5.6	3.5
Romania	0	0	63	11	7			3.8	5.5	2.5			8.7	9.0	4.4
South Africa	88	75	61	36	7	10.5	6.4	4.1	2.2	1.7	31.8	16.0	9.4	4.4	4.2
Sri Lanka		100	62	57	14		6.6	4.2	3.6	2.2		12.6	9.5	7.4	3.8
Thailand	97	88	83	62	39	23.6	14.8	8.0	3.8	2.2	80.8	45.3	21.9	9.3	4.4
Turkey	100	97	89	83	76	14.0	11.8	8.5	6.2	4.8	33.2	28.7	18.9	12.7	9.1
Venezuela	96	71	44	32	26	7.7	3.7	2.1	2.1	1.7	18.8	9.0	4.4	6.2	3.2
Zimbabwe	0	0	0	0	0										
Developed Average	76	68	58	4	16	19.8	9.7	5.4	3.2	1.9	60.0	25.8	12.8	6.8	3.5
Emerging Average	66	55	41	25	11	13.6	8.0	5.1	3.4	2.2	35.0	18.5	10.9	6.5	3.8
Dvlp – Emerg.	10	13	17*	15*	5	6.2*	1.7	0.3	−02	−03	25.*	7.3*	1.9	0.3	0.3

For each year from 1994 through 2005 we count the number of unique brokers/analysts making fiscal year-end earnings forecasts and the number of estimates and revisions made for each company with analyst forecasts on I/B/E/S. Panels A and B present for developed and emerging markets, the average percentage of firms listed on Datastream over 1994-2005 in that size portfolio that have at least one analyst making a fiscal year-end forecast during the year, the average number of analysts per firm with coverage, and the average number of estimates and revisions made per company with analyst coverage. * next to the difference indicates statistical significance ($\alpha = .05$).

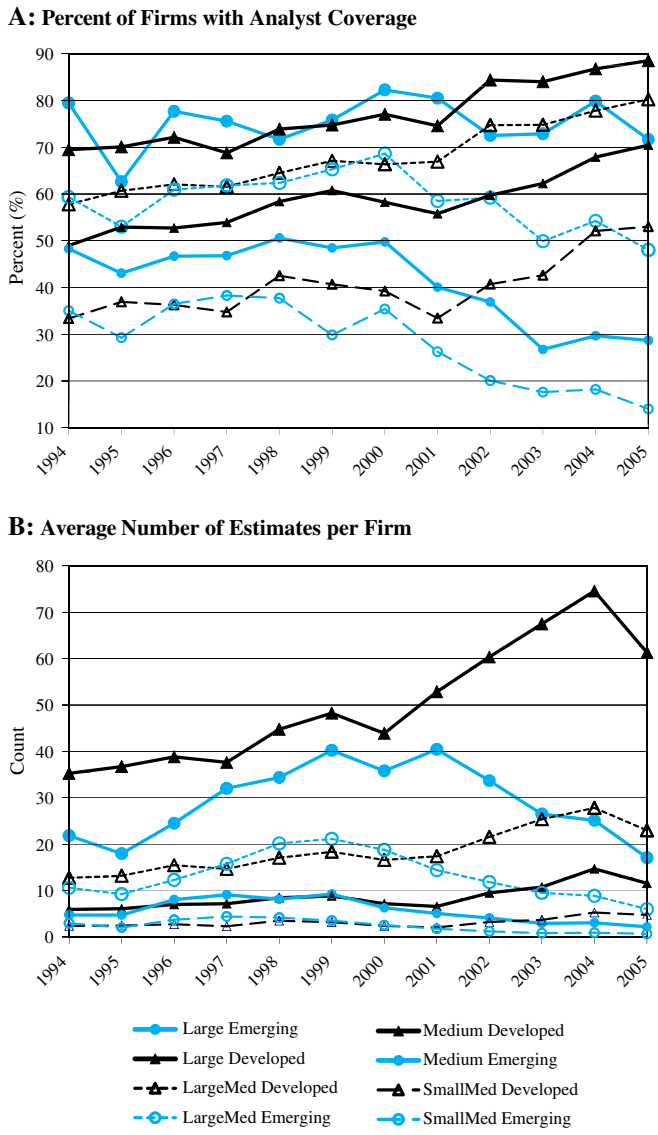


Figure 5
Average percentage of firms covered and average number of estimates per firm
For each year from 1994 through 2005, we count the number of firms with broker/analysts making fiscal year-end earnings forecasts and the number of estimates and revisions made during the year for each company with analyst forecasts on I/B/E/S. The percentage of firms with coverage and the average number of estimates and revisions are presented for each year.

gathered.[33] Our findings on returns from strategies exploiting apparent weak- and semi-strong-form inefficiencies and transaction costs complement this literature and suggest that trading strategies in emerging markets are likely to generate substantially lower returns. The findings have an even more important implication in terms of efficiency assessment. Since transaction costs are a major impediment to correcting inefficiencies, the rapidly decreasing patterns of transaction costs should be accompanied by lower trading profits over time and higher efficiency, as indicated by variance ratios and delay measures.

Panel A of figure 6 plots the time-series of reversal-strategy returns. We do this for strategies with and without a week skipped between the formation and holding period. We also display the U.S. reversal returns for comparison. Consistent with Khandani and Lo (2007), Panel A shows a clear pattern of U.S. reversal returns falling over the 1994 to 2005 period, particularly for the strategy without a week skipped in the formation period. Interestingly, for both developed (other than the U.S.) and emerging markets, no such pattern is shown over the same period.[34]

Panels B and C of figure 6 present post-earnings drift and momentum returns and show no consistent pattern of increasing or decreasing returns. Average absolute variance ratios and levels of the delay measure in Panels D and E present little consistent trend, except that the average absolute variance ratio increased in many size quintiles in the volatile 2000 to 2002 period, but fell thereafter.

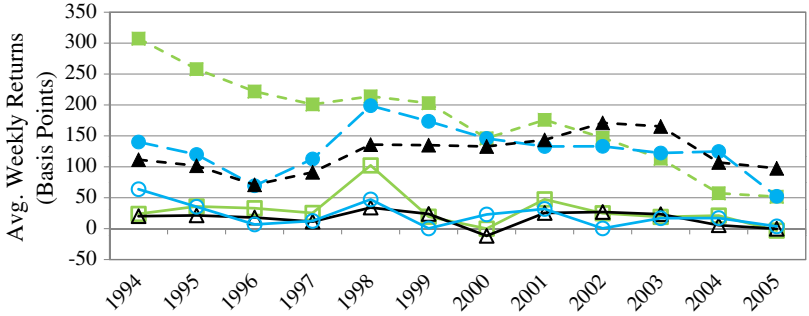
Table 6 looks at simple cross-country correlations between the trading returns/efficiency measures and measures of financial and economic development. We also include LOT trading costs, as well as a summary measure of analyst coverage. Across countries, we find that neither the return from strategies designed to exploit inefficiencies nor any of the traditional efficiency measures have statistically significant relations with commonly used measures of development. Conversely, we find a negative and statistically significant correlation with the development measures for LOT transaction costs and for analyst coverage.[35] We also see little positive relation between trading strategy returns and efficiency measures except that returns to reversal strategies are positively related to transaction costs.

[33] Previous literature has shown that, in the U.S., gross profits from strategies based on past reversals (Conrad, Gultekin, and Kaul 1997) and momentum (Lesmond, Schill, and Zhou 2004) tend to be positively related to transaction costs.

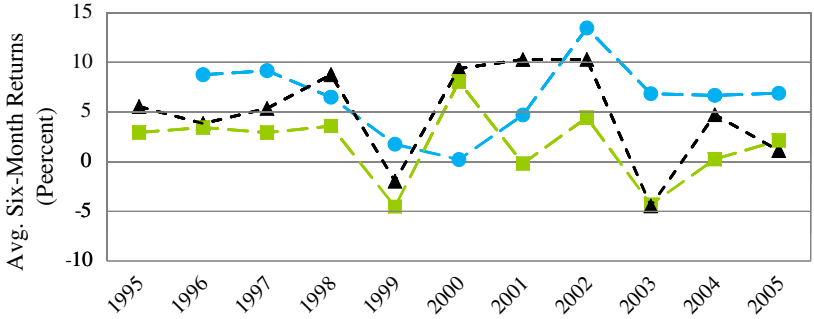
[34] Although the returns seemed to have decreased since 2002, the differences are economically small. In unreported results, we also go back and estimate returns for tercile size portfolios from 1986 through 2005. There is no discernable trend even with the longer period and after controlling for U.S. size breakpoints. Developed markets typically exhibit larger returns.

[35] In unreported results we also investigated the relation between the random walk pricing measures and transaction costs in multivariate regressions but generally fail to find any consistent relation even after inclusion of a host of other cross-country variables.

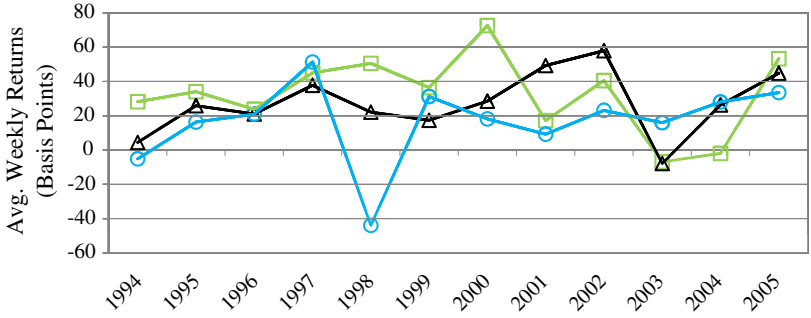
A: Average Weekly Contrarian Profits (1×1)



B: Post-earnings Drift



C: Average Weekly Momentum Profits (26×26, skip a week)



U.S. (No Skip) — Emerg. Avg. (No Skip) — Devel. Avg. (No Skip)
U.S. (With Skip) — Devel. Avg. (With Skip) — Emerg. Avg. (With Skip)

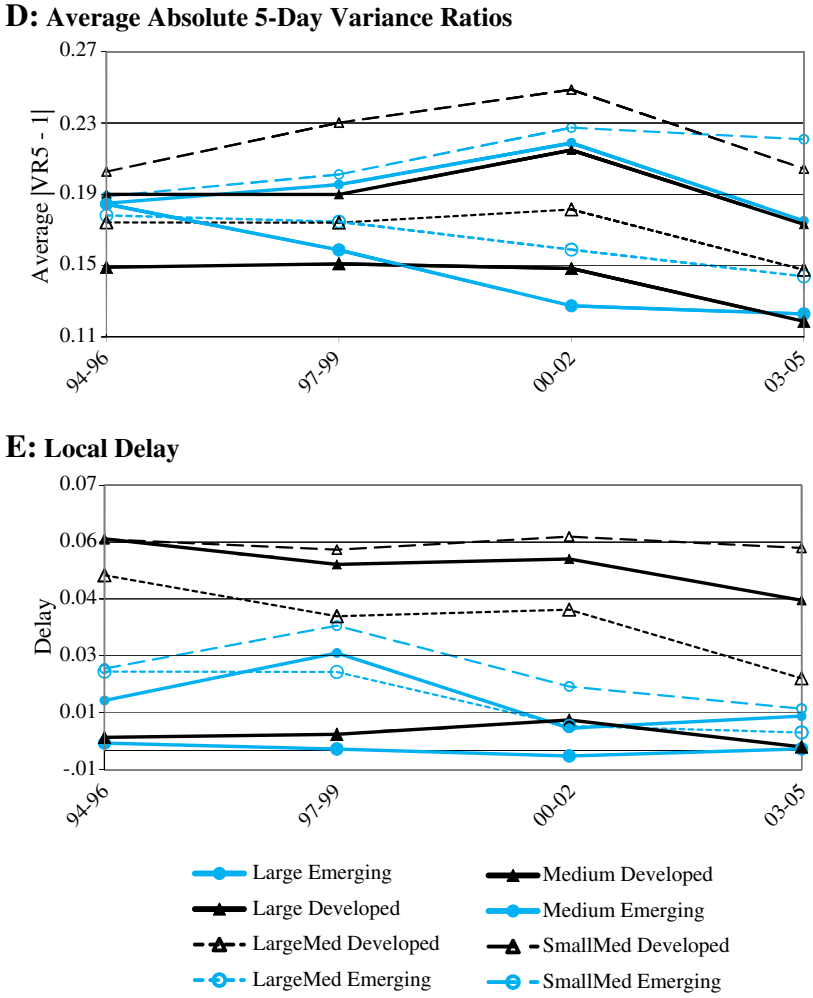


Figure 6

Average weekly contrarian, post-earnings drift, momentum profits, delay, and |VR5-1|

Average weekly profits to the contrarian, post-earnings drift, and momentum trading strategies in Panels A, B, and C are calculated as in figures 1, 2, and 3, respectively, except the averages are presented by year. Panel D presents the average absolute normalized five-day variance ratio calculated as described in table 3 for individual stocks over three-year periods. The variance ratios are winsorised at the 0.5% and 99.5% levels before calculating the absolute values and averaging. Delay is calculated for each three-year subperiod as described in table 4 and the average of delay over emerging and developed markets for the five size portfolios is presented in Panel E.

It may be that the emerging/developed classification is not the relevant criterion for discerning differences in efficiency. There are a multitude of cross-country variables that may be related to our measures of stock market efficiency. Following Griffin, Nardari, and Stulz (2007) and Bekaert, Harvey, Lundblad, and Siegel (2008), we use a broad set of variables that have intuitive appeal for characterizing various facets of stock market activity. The variables can be roughly grouped into the following categories: regulatory, economic/financial development, information environment, trading costs, and characteristics of the equity markets, such as volatility and correlations with world returns. Although it would be too lengthy to motivate the choice of each of the 19 variables, the general motivation is that stock market efficiency may be increasing in the presence of a better regulatory structure, higher economic/financial development, better information environment, and lower trading costs. Because the possible combinations are endless, to determine the best model that characterizes the data we use a procedure from PCGive, which is an econometric package implementing an automatic general-to-specific reduction of variables, as outlined by Hendry (1995, ch. 9) and applied in finance by Bekaert, Harvey, Lundblad, and Siegel (2008).[36] We apply this procedure through cross-sectional regressions in separate specifications with each efficiency measure as the dependent variable.

Panel B of table 6 displays the best-fitting model for each efficiency indicator. All variables are included as possible correlates of our measures.[37] However, we present only the coefficients on the variables that are in the best-fitting model as selected by PCGive. For the trading return measures, we find little consistent evidence linking them to intuitive drivers of efficiency. Delay is related to sensible measures (short sales and trading costs) but the positive coefficient on short sales is counterintuitive as it indicates that the ability to short is associated with more delay. Post-earnings drift is not displayed because the best model was a constant.

5.5 Summary and interpretation

The inference from our analysis of trading strategies and weak-form efficiency measures is that emerging markets are at least as efficient as developed. This is quite different from that suggested by our evidence on transaction costs, information generation/cost measures. While these characteristics may play an important role in exploiting arbitrage opportunities of the sort examined here,

[36] Variables are constructed as the average of the annual values from 1994 to 2005 when possible, but, when taken from other papers, they are limited to the sample period therein. We estimate these cross-sectional regressions using the PCGive (formerly called PCGets) software, which cannot handle missing observations. We start with a set of variables that are available in at least 50 countries; however, some dependent variables are not available for all markets and we perform additional tests, with a smaller cross-section that includes these variables.

[37] Variables that do not have complete coverage for all markets covered by the dependent variable are excluded in some specifications to avoid the reduction of countries.

Table 6
Information generation and efficiency: cross-country correlations

Panel A: Correlation Matrix

	Traditional Efficiency Measures													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Contrarian profits														
(2) Pos. - Neg. PEAD	0.07													
(3) Momentum	0.07	−0.11												
(4) |VR5-1|	0.03	0.19	0.02											
(5) Delay	0.02	0.01	0.38*	0.32*										
(6) LOT Trading Cost	0.50*	0.14	0.01	0.21	0.20									
(7) Analyst Coverage	0.08	0.22	0.07	0.19	0.58*	0.10								
(8) GNI per Capita	0.00	0.00	0.36*	0.29*	0.61*	−0.13	0.49*							
(9) Market Cap. / GDP	0.15	0.02	0.16	0.23	0.58*	0.06	0.47*	0.62*						
(10) Deposit Bank Assets	−0.14	−0.02	0.41*	0.30*	0.33*	−0.11	0.26	0.59*	0.35*					
(11) Liquid Liabilities / GDP	−0.09	0.02	−0.02	0.35*	0.45*	−0.09	0.32*	0.58*	0.69*	0.43*				
(12) Private Credit / GDP	−0.17	0.03	0.08	0.42*	0.56*	−0.01	0.39*	0.67*	0.72*	0.53*	0.93*			
(13) Allocational Efficiency	−0.07	0.17	0.44*	0.13	0.56*	0.00	0.32*	0.69*	0.44*	0.48*	0.46*	0.57*		
(14) Country Risk	−0.29	−0.15	0.07	0.24	0.25	−0.31*	0.14	0.16	0.31*	0.31*	0.27	0.27	−0.03	
(15) Insider Trade	0.14	0.08	0.39*	0.13	0.58*	0.09	0.30*	0.73*	0.50*	0.45*	0.47*	0.58*	0.49*	0.14

Table 6
Continued

Panel B				
Dependent	|VR5-1|	Delay	Rev.	Mom.
Intercept	0.15	−3.53	14.48	−119.97
	(0.00)	(0.01)	(0.25)	(0.03)
Regulatory				
Short Sales Dummy		2.47 (0.00)		
Insider Trading Dummy				
UK Law			27.70 (0.00)	
Economic & Financial Development				
Market Cap./GDP				
Market Turnover/GDP				
GNI per Capita				
Deposit Bank Assets				232 (0.00)
Private Credit/GDP	0.03 (0.00)			−30.21 (0.00)
Market Turnover	−0.02 (0.05)			
Country Risk			−0.45 (0.01)	
Geographical Size(ln)				
Informational Environment				
Analyst Coverage(÷100)				
Corruption				
Trading Costs				
Hasbrouck Trading Cost				
LOT Trading Cost		0.19 (0.06)		
Characteristics of Equity Market				
Market Volatility				−11.82 (0.00)
Corr/ w/ World Market			88.55 (0.00)	−56.51 (0.03)
Company Herfindahl				
No. of Firms (ln)		0.75 (0.00)		
No. of Obs.	49	49	38	38
Adjusted R^2	0.19	0.47	0.36	0.39

Panel A presents cross-country Spearman rank correlations for country-level averages of the efficiency, trading cost, and information generation measures. Contrarian profits, Positive - Negative PEAD, and Momentum are calculated as in figures 1, 2, and 3 respectively. |VR5-1| is calculated as in table 3, Panel A1, averaging the absolute value of the five-week stock level variance ratio minus one for all stocks with at least 30% price changes in the previous year. Delay is calculated as in table 4. LOT Trading Costs presented in Figure 4, Panel A, are averaged across the five size portfolios for each country, then over time (1994-2005). To calculate the analyst coverage measure we use the same data as in Table 5. We rank each country by the average percentage of firms covered in each country, the average number of analysts per company (setting missing values to zero), and the average number of estimates (setting missing values to zero). The sum of these three ranks is used in the analysis below. GNI per Capita is from World Bank's Financial Development and Structure Database and is the average over 1994-2005. The following variables are from World Bank's Financial Structure Dataset developed by Beck, Demirgüç-Kunt, and Levine (2000) and are annual observations averaged over 1994 to 2005: Market Cap. / GDP - the annual market capitalization divided by the GDP, Deposit Bank Assets are Deposit Money Bank Assets divided by Deposit Money Bank and Central Bank Assets, Liquid Liabilities / GDP is M3 divided by GDP, Private Credit / GDP is Private Credit by Deposit Money Banks to GDP, as well as Market Turnover/GDP and Market Turnover used in Panel B. Allocational Efficiency comes from Wurgler (2000). Country Risk is the average over the period 1994-2005 of the country risk index published by Euromoney. Insider Trade is the Prevalence of Insider Trade from the Executive Opinion Survey in the Global Competitiveness Report (GCR) and is the average of the 98–99, 99–00, and 02–03 GCR responses. The question asks if "Insider trading in your country's stock markets is (1=pervasive, 7=extremely rare)." Additional variables are used in Panel B. Insider Trading (from Bhattacharya and Daouk 2002) is a dummy variable that equals one if insider trading laws exist and are enforced as of the end of 1998. Short Sales (from Bris, Goetzmann, and Zhu 2007) is a dummy variable that equals one if short sales are allowed as of the end of 1998. UK Law is a dummy variable for whether the legal system in a country is based on common law. Country Risk is the average over the period 1994–2005 of the country risk index published by Euromoney. Higher values indicate lower risk. The natural log of the Geographical Size is from the CIA Factbook. Corruption is the average for the 1993–2003 period of the Corruption Perception Index published by Transparency International: higher values of the Index indicate less corruption. Hasbrouck Trading Cost is calculated in the following manner. Bayesian (Gibbs sampler) estimates of effective trading costs (log-effective spread) are calculated annually for each stock based on daily returns, following Hasbrouck (2006). Each year at the end of December, stocks are sorted into five size portfolios using breakpoints based on U.S. equities, and trading costs are averaged across all stocks in each portfolio. The average effective trading cost for each portfolio over the 1994–2005 period is reported. Market Volatility is the sample standard deviation in percent of weekly equity market local currency returns over the period 1993–2003.

at the country level we find no relation between returns from trading strategies, efficiency measures and our measures of transaction costs, information generation, and information cost, with the exception of the reversal strategy. Furthermore, the 1994 to 2005 period saw a tremendous decrease in transaction costs in both developed and emerging markets and some increases in information gathering in developed markets that were not met by comparable improvements in any of the efficiency indicators we consider.

The combination of higher impediments to trade and more costly information strongly suggests that equity pricing in emerging markets is less efficient. The finding that these broadly accepted aspects of efficiency, as well as measures of financial development, are largely unrelated to common efficiency measures highlights limitations in the concepts of weak- and semi-strong-form efficiency.

The empirical work on weak-form market efficiency tends to focus on how quickly past returns are, or are not, reflected in prices. Similarly, studies of semi-strong-form efficiency investigate how quickly prices return to a random walk following value-relevant public news, such as earnings surprises. In comparing securities and/or markets, it is implicitly assumed that past prices and public news contain information and that the weak-form and semi-strong-form efficiency measures detail how rapidly that information is incorporated into prices. And, as Fama (1970) suggests, while it is plausible that readily available sources of information (such as past prices or earnings news) can be reflected into prices despite high transaction costs, it seems less plausible that private information can be rapidly reflected into prices with the presence of large transaction costs. Hence, while, by definition, we cannot observe the extent of private information, it is hard to think of a high transaction costs market that could easily incorporate "all available" information. Thus, our findings from transaction costs suggest that private information may not be impounded into prices in emerging markets as much as it is in developed. The analyst coverage findings suggest that emerging markets have less public information as well.

Table 6
(continued)

The correlation with the world market is computed for the period 1994–2005 between country equity returns and returns on the Datastream world market index. For the major markets (US, UK, JP, GER, FRA), the world index excludes the country for which the correlation is being calculated. Company Herfindahl is squared December-end market capitalizations summed over all companies within a country each year and then averaged over all years. Number of Firms is the log of the December-end count of listed firms averaged over all years. In panel A, coefficients marked with asterisks indicate significance at the five-percent level. In Panel B, we run a model selection program, PCGive, to select the variables that best fit the data. If a variable is selected (using default target size, $\alpha = 0.05$, and the default diagnostic test p-value, 0.01), we report the coefficient with its p-value in parentheses; otherwise, we leave the coefficient blank.

6. Limitations of Common Efficiency Measures

Why do weak-form and semi-strong-form efficiency tests yield different inferences from transaction costs and information production estimates? We believe the answer lies in the key limitations of those efficiency tests. First, as pointed out in our conceptual discussion of equation (1), stock market efficiency denotes prices "fully reflecting all available information" (call this information set I). Unfortunately, the full information set is unknowable and the empiricist must rely on a limited observable information set, Z.

$$M^I = E\left[r_t | I_{t-1}\right] \neq E\left[r_t | Z_{t-1}\right] = M^Z \tag{2}$$

Stated simply, theoretical efficiency measures that use all available information may not yield the same inferences as empirical efficiency measures that rely on partial information. This is important when making a statement about relative efficiency, because, in a setting where there are large differences in the information in I not captured in Z (as might be the case across markets), the empiricist may obtain misleading inferences about differences in efficiency. For instance, a well-functioning market incorporates information from a broad array of sources in addition to Z, but a poorly functioning market only incorporates Z into prices. The empiricist only makes statements about efficiency with respect to Z, and thus ignores both the extent of information gathering, and the extent to which the additional information is or is not incorporated into prices.

A second and potentially more serious problem is also related to information content. Consider a generic form of empirical efficiency measure (M^E) that captures stock return serial dependence as measured by its autocovariance:[38]

$$M^E = |Cov(r_{t+1}, r_t)|, \tag{3}$$

where returns (r) are driven by an expected return (μ), innovations due to news (η), and noise (e).

$$r_1 = \mu + \delta\eta_1 + e_1 \tag{4}$$

$$r_2 = \mu + (1-\delta)\eta_1 + \delta\eta_2 + e_2, \tag{5}$$

where δ is the fraction of the news that is incorporated into prices instantaneously while the remainder is incorporated in the next period. As $\delta \to 1$, news is instantaneously incorporated. The subscripts denote a simple two-period model, where time 2 is the terminal period and all information is incorporated into prices by time-period two. With the simplifying assumption

[38] Empirical efficiency measures are typically restated to test the notion of whether returns are uncorrelated through time. This is the basic version of the efficiency statement presented in Chapter 2 of Campbell, Lo, and MacKinlay (1997).

that news is not autocorrelated and is uncorrelated with noise, the empirical efficiency measure becomes

$$M^E = |\delta(1-\delta)Var(\eta_1) + Cov(e_1, e_2)|\,. \tag{6}$$

In this formulation, more news is reflected in a greater variance of η_t. Depending on the trading patterns of uninformed traders, noise may or may not be autocorrelated. If noise is autocorrelated, it may result in a higher M and hence less efficiency.[39] When noise trading is uncorrelated, M^E reduces to

$$M^E = |\delta(1-\delta)Var(\eta_t)|\,. \tag{7}$$

This formulation makes transparent the problems with the standard empirical efficiency measure: empirically measured inefficiency is not only a function of the speed of information incorporation (δ), but it is a function of how much news (η) is made known to the market.

We graph this tradeoff between speed of information incorporation, the quantity of news, and the efficiency measure (covariance) in Figure 7 for illustrative purposes. We observe three simple but interesting points. First, both immediate ($\delta = 1$) and no information incorporation ($\delta = 0$) result in an efficiency measure (M^E), which equals zero and suggests perfectly efficient pricing, even though in one case all information is incorporated and in the other none is. Second, slower news incorporation leads to greater departures from measured efficiency, but this is only true for $\delta > 0.5$. For values less than 0.5, measured efficiency is actually "improving" as the speed of news incorporation decreases. Third, ceteris paribus, markets with more news will exhibit seemingly worse efficiency [except when there is no information incorporation ($\delta = 0$) or complete and instantaneous information incorporation ($\delta = 1$)]. The intuition is that as long as there is some slow information incorporation, a market with more news will have more information to work into prices and, as a result, more autocovariance.

In an Internet Appendix, we show that variance ratios, delay, profits for reversals/momentum, and post-earnings drift all map into formulas similar to M^E above. We show that all are a function both of news and of the speed of its incorporation. In particular, all else equal, the variance of news always increases the level of inefficiency.

In summary, we see several potential difficulties with the commonly used weak- and semi-strong-form efficiency tests. First, statements about efficiency are made with respect to a limited information set, and hence empirical efficiency measures are capturing neither the depth of the information environment nor the way information outside that available to the researcher is incorporated into prices. Relative statements about weak- or semi-strong-form

[39] In focusing on this noise component of prices, Summers (1986) makes the point that, even if there are behavioral traders persistently moving prices, correlation tests will not have enough power to detect these deviations. Our findings indicate that the tests do constantly have power to reject the random walk, but, nevertheless, the point is relevant that it will be difficult to detect a highly persistent mispricing that only slowly reverts.

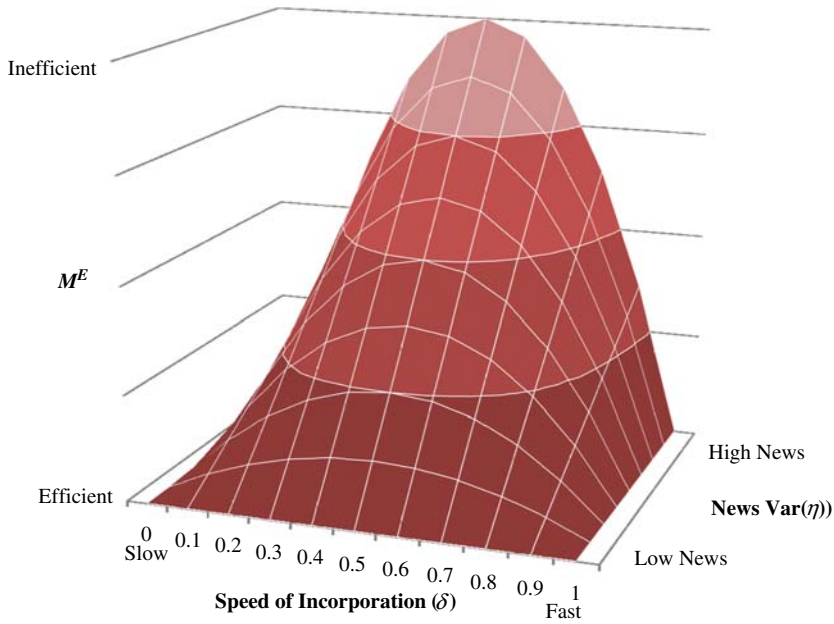


Figure 7
Empirically measured efficiency, news, and speed of incorporation
This figure plots how measured efficiency, $M^E = |\delta(1-\delta)Var(\eta_t)|$, is affected by differences in the quantity of information production (News or $Var(\eta_t)$) and the speed of its incorporation (δ) into prices. Higher M^E means prices are less efficient. Speed of information incorporation is on the x-axis ($\delta = 0$ means no news is incorporated, and $\delta = 1$ means that news is immediately and fully incorporated), news production is on the y-axis, and measured efficiency, M^E, is on the z-axis.

efficiency can be misleading to the extent that the researcher is unable to control for the amount and cost of information gathered. Second, as illustrated by our simple two-period example, a market with extremely slow information incorporation can yield similar levels of measured efficiency as a market with rapid information incorporation. Third, since empirical efficiency measures do not control for the level of information in these returns, markets with more information will appear less efficient for the same speed of information incorporation, all else equal. To the extent that there is less information produced in emerging markets (as shown in table 5), empirical efficiency measures are biased toward finding that emerging markets are more weak or semi-strong form efficient relatively to developed markets than they truly are.

Empirically, tests of market efficiency will provide a valid comparison only in settings where two conditions are true: information differences are small and news is incorporated rather rapidly (in our example, $\delta > 0.5$). Conversely, caution must be exercised when comparing efficiency in settings where large informational differences and widely varying speeds of information incorpo-

ration exist, such as when making comparisons across markets internationally, as these differences make efficiency comparisons rather complex.

While these considerations are important for the empirical researcher, variables like the level and the cost of information production are, unfortunately, exceedingly difficult to measure. Hence, we think the challenge in measuring and controlling for these crucial aspects of efficiency makes reliable statements about relative market weak or semi-strong form efficiency extremely difficult. One avenue that has been pursued in the literature is to use idiosyncratic volatility as a measure of information production. Concerns regarding this interpretation of firm-specific idiosyncratic variance have been raised by Kelly (2007) and Dasgupta, Gan, and Gao (2009). In an earlier version of the article, we found evidence that idiosyncratic volatility is an unreliable measure of informational efficiency.[40]

7. Conclusion

Emerging equity markets are widely thought to be places of substantial trading profits and weak- and semi-strong-form market inefficiencies when compared to developed markets. We examine the extent to which this is true using a variety of methodologies and data from 28 developed and 28 emerging markets. As an intuitive measure of the economic magnitude of inefficiencies, we use returns to short-term reversal and post-earnings drift strategies and find similar returns across emerging and developed markets. Return momentum is substantially larger (though insignificantly so) in developed markets. To more formally investigate weak-form information efficiency, we examine the ability of equity returns to capture information contained in past individual stock, portfolio, and local market returns. Emerging markets exhibit similar autocorrelation in firm returns, suggesting that they are not under- or overreacting to news contained in past returns any more than in developed markets. Emerging markets incorporate past market and portfolio returns into prices slightly better than developed markets.

To measure how well the return-based and random walk pricing measures map to impediments to trade, we investigate their relation with the Lesmond, Ogden, and Trzcinka (1999) transaction costs measure both across countries and through time. For similar-sized firms, LOT transaction costs are higher in emerging markets, but not cross-sectionally related to trading revenue or random walk pricing measures across countries. Additionally, trading costs have been decreasing dramatically through time in both developed and emerging markets but these decreases do not correspond to changes in trading profits or random walk pricing measures. To further assess the validity of the infer-

[40] We found that a country's market-model R^2 is not related to the standard good government or measures of investor protection but most consistently related to market volatility, as shown in Internet Appendix table B.1. Bartram, Brown, Stulz (2009) provide a comprehensive examination of what drives idiosyncratic volatility (i.e., $1 - R^2$) across countries.

ences provided by the random walk pricing measures, we correlate them with several measures of economic and financial development and find negligible associations.

Given this lack of association with essential drivers of efficiency, we conjecture that commonly used measures of efficiency may have limitations that are featured in our international setting. We show conceptually that efficiency measures indeed have key limitations that are related to information generation. First, empirical efficiency measures rely on incomplete information sets and, across markets, such sets may represent substantially different proportions of the entire information set. As a consequence, statements about relative overall efficiency that do not account for this differential incompleteness of the information sets become problematic. Second, all else constant, a firm with little news will have stock prices that more closely follow a random walk than a firm with relatively more news anytime information incorporation is less than instantaneous. Additionally, for the same level of information, a firm with slow information incorporation can have an efficiency measure similar to a firm with rapid incorporation. Since we show that firms in emerging markets have less public information, this would bias one toward finding greater measured efficiency in emerging markets even if they were actually less efficient.

Our overall findings present a challenge to academics and practitioners alike, as 1) they cast serious doubt on common perceptions regarding the relative weak- and semi-strong-form efficiency of emerging and developed markets; 2) they bring bad news to quantitative investors seeking profits in emerging markets through common strategies based on past returns and earnings; and 3) they point to potential problems when gauging efficiency through the lens of weak- or semi-strong-form efficiency. Empiricists must control for the extent of information generation before making meaningful statements about relative efficiency. Nevertheless, precisely measuring the information environment is a difficult task, but an important one for future research. Our findings also suggest the potential benefits of analyzing market efficiency from a broader perspective rather than merely focusing on the information arbitrage component in returns.[41] We hope to see additional research examining the importance of the private and public information environment across international markets.

Appendix A. Methodology Description

A.1 Variance ratios

We follow Lo and MacKinlay (1988) and Campbell, Lo, and MacKinlay (1997) in the construction of variance ratio (VR) statistics and of their heteroscedasticity consistent significance tests.[42] To

[41] Tobin (1987) labels four aspects of efficiency: information arbitrage, fundamental valuation, full insurance, and functional efficiency. The majority of finance papers relate to the information arbitrage component of efficiency (otherwise known as weak- and semi-strong-form efficiency), while Tobin suggests that more focus on "functional" efficiency or the ability to which financial markets facilitate decisions in the real economy is warranted.

[42] For the relevant test statistics, see Campbell, Lo, and MacKinlay (1997), Chapter 2, equation 2.4.44.

improve the small sample properties of the tests, in all reported VR analysis, we use overlapping observations, also following Campbell, Lo, and MacKinlay (1997). We first estimate autocorrelation coefficients of order one, five, and ten for the daily and weekly return series both for individual stocks and size-ranked portfolio returns and then compute VR statistics. If returns are uncorrelated over time, their variance is a linear function of the time interval over which they are computed. So, for instance, the variance of five-week returns should be equal to five times the variance of one-week returns and a VR of order five is obtained by dividing the former by five times the latter.

A.2 Delay

For each size portfolio in each country, we estimate the restricted and the unrestricted models below over the entire July 1994 to June 2005 sample period. The unrestricted model uses four lags of weekly market returns and is

$$r_{i,t} = \alpha_i + \beta_{0i} r_{m,t} + \beta_{1i} r_{m,t-1} + \beta_{2i} r_{m,t-2} + \beta_{3i} r_{m,t-3} + \beta_{4i} r_{m,t-4} + \varepsilon_{i,t}, \tag{A1}$$

where $r_{i,t}$ is the weekly portfolio return at time t and $r_{m,t}$ is the local market return. The restricted model constrains the coefficients on the lagged market returns to zero:

$$r_{i,t} = \alpha_i + \beta_{0i} r_{m,t} + \varepsilon_{i,t}. \tag{A2}$$

The adjusted R^2s from these regressions are used to calculate delay as follows:[43]

$$Delay = Adj.R^2_{unrestricted} - Adj.R^2_{restricted}. \tag{A3}$$

To control for increased explanatory power simply due to a higher number of regressors, we use adjusted R^2s. Like Hou and Moskowitz (2005), we find that delay on individual firms is extremely noisy, but the use of size portfolios substantially reduces estimation error.However, our measure of delay is slightly different from the scaled measure calculated by Mech (1993) and Hou and Moskowitz (2005), which is

$$Delay = 1 - \frac{R^2_{restricted}}{R^2_{unrestricted}}. \tag{A4}$$

We prefer measuring delay as the difference in adjusted R^2s, because with the scaled version of delay in (A4), small unrestricted R^2s can result in large, yet economically insignificant, values for the delay measure in cases where total explanatory power is low. Nevertheless, we check the robustness of our findings using the scaled measure.

A.3 LOT trading costs

A limited dependent variable model is estimated by maximizing a likelihood function for each firm, each year: the details are provided in Lesmond, Ogden, and Trzcinka (1999). The measure is estimated through the use of an iterative non-linear estimation procedure. The procedure requires starting values for each of the estimated parameters, α_{Ni}, α_{Pi}, β_i, and σ_i. We use −.01, .01, 1, and .1, respectively. If the procedure fails to converge, we change the starting values to −.1, .1, 1, and .1 and re-estimate. All estimations converge using this procedure.

[43] One should note that, even though our measure is labeled as delay, we do not restrict our lagged betas to be strictly positive. In practice most coefficients are positive, but a negative coefficient can simply be interpreted as overreaction and, thus, still as a violation of market efficiency.

A.4 Hasbrouck trading costs

The measure developed by Hasbrouck (2004, 2006) is based on the Roll (1984) model and is designed to proxy for the log effective spread, defined for a trade at time t as

$$c = \begin{cases} p_t - m_t\,, & for\ a\ buy\ order \\ m_t - p_t\,, & for\ a\ sell\ order \end{cases} \tag{8}$$

where m_t is the (log) efficient price and p_t is the (log) observed price. To estimate c, we use the following variant of the Roll model, as adopted by Hasbrouck (2004):

$$\begin{aligned} m_t &= m_t - 1 + u_t \\ p_t &= m_t + cq_t \end{aligned} \tag{9}$$

where q_t is the trade direction indicator, with +1 indicating a purchase and −1 indicating a sale and u_t a Gaussian i.i.d. error term. Therefore, depending on q_t, the log transaction price is either at the bid or at the ask. Because intra-day signed-order flow, transaction prices, and quotes are unavailable, the unobserved efficient price and the trade direction need to be treated as latent and estimated from the daily series of prices. This is the primary motivation for us to rely on the Bayesian approach proposed by Hasbrouck (2004 and 2006). In this approach, the latent variables are treated as parameters and estimated using the Gibbs sampler. We use daily prices for international stocks and closely follow the implementation proposed by Hasbrouck (2006)). Hasbrouck (2006) shows that, in the U.S., despite possible model misspecifications in the simple framework above, the Bayesian estimate of the log effective spread has a 0.94 correlation with the log effective spread calculated using microstructure data. This strong association with actual trading costs further motivates the use of the Bayesian measure in our study.

Appendix B. Data Description

Stock data for non-U.S. companies are from Thomson Financial's Datastream and for U.S. companies are from CRSP. We restrict our analysis to common stocks that trade in the companies' home markets and in local currency. For the U.S., these restrictions are trivial; we choose stocks with the CRSP share code of 10 or 11. For non-U.S. data, the distinction is substantially more complicated as Datastream tracks security-type information predominantly though the addition of text in the security's name field.

In order to eliminate non-common equity, we search the name fields of all securities using both automated and manual methods. We eliminate securities that represent cross listings, duplicates, mutual funds, unit trusts, certificates, notes, rights, preferred stock, and other non-common equity. When a firm has multiple classes of stock, we include a class of stock if it began trading at least three months earlier than all other classes. For China, Mexico, and the Philippines, we first choose the stock that can be traded by local residents. For cases in which two or more classes of stock are first listed on Datastream within three months of each other, we choose the more actively traded stock, which is determined to be the class that has greater volume in the first calendar year of trading. If volume is missing, we choose the stock that has the greater number of trading days as proxied by non-zero returns during the trading day. These filter rules are listed in Panel A of table B.1.

B.1 Filters applied to all stocks

Datastream maintains lists of active and delisted (dead) stocks traded in each country (and in rare cases each market). These lists include a security type, the home country and industry of the underlying company, and the currency in which the security is traded. We include only stocks Datastream classifies as equity (TYP=EQ). We eliminate cross-listed stocks by requiring that the home country and the country in which the security is traded are the same. Because Datastream

does not separate country/market lists for Asian and Latin American dead stocks, we assume that the home country of the company behind the dead security is the market in which the stock is traded. We require that each security trade in the local currency.

Through the industry code Datastream identifies mutual funds, unit trusts, and other "firms" for which the underlying asset is not typical of that underlying common equity. Securities with the industry codes listed in Panel B of table B.1 are eliminated.

B.2 Country-specific identifier filters

In addition to the filters described above, which are applied to all assets in all countries, we use country-specific filters as well. They are listed in table B.2. The process was as follows. First, based on prior knowledge of Datastream including filters previously applied in previous papers by the authors, firm screens were applied. Second, for all of our firms that made it past our filters, the entire list was checked for duplicate names or suspicious identifiers by hand. These suspicious identifiers were flagged and researched later using predominantly newswires and Internet searches. This led to the creation of some new filters (which appear in the list above) and the exclusion of a list of duplicate or non-equity firms. A firm needed to trade for at least 90 days to be examined. Similarly named firms were researched to confirm (or not) if they were indeed the same. If the same firm traded its common equity under the same name with no distinguishing characteristics, we choose the firm with the earliest coverage in Datastream. We believe that the end result of the screening is a sample of common equity firms that is virtually free of duplicates and non-common equity.

B.3 Return filters

Due to concern over data errors, we ran the following return filters. For daily returns, if r_t or $r_{t-1} > 100\%$ and $(1 + r_{t-1})(1 + r_t) - 1 < 20\%$, then both r_t and r_{t-1} are set equal to a missing value. Additionally, any daily return greater than 200% is set to missing. For weekly returns, if r_t or $r_{t-1} > 100\%$ and $(1 + r_{t-1})(1 + r_t) - 1 < 20\%$, then both r_t and $r_{t-1}$are set equal to a missing value. Additionally, any weekly return greater than 200% is set to missing.

B.4 Earnings dates

A comprehensive set of annual earnings dates is available from Bloomberg. We randomly select five firms for each country and check the accuracy of these firms for as many earnings years as they are in the sample. If a firm is identified on Factiva and we can find the earnings event date, then we count the number of firms where the event day is represented.

Table B.1
Generic Filter Rules for Excluding non-Common Equity Datastream Securities

Panel A: Non-Common Equity Security Codes

Non-common equity	Words searched
Duplicates	DUPLICATE DUPL DUP DUPE DULP DUPLI 1000DUPL XSQ XET[a]
Depository Receipts	ADR GDR
Preferred Stock	PREFERRED PF PFD PREF 'PF'
Warrants	WARRANT WARRANTS WTS WTS2 WARRT
Debt	DEB DB DCB DEBT DEBENTURES DEBENTURE
Unit Trusts (2 word phrases)	RLST IT, INVESTMENT TRUST, INV TST, UNIT TRUST, UNT TST, TRUST UNITS, TST UNITS, TRUST UNIT, TST UNIT
Unit Trusts (single words)	UT IT. .IT[b]
Recommended by Ince and Porter (2006)	500 BOND DEFER DEP DEPY ELKS ETF FUND FD IDX INDEX LP MIPS MITS MITT MPS NIKKEI NOTE PERQS PINES PRTF PTNS PTSHP QUIBS QUIDS RATE RCPTS RECEIPTS REIT RETUR SCORE SPDR STRYPES TOPRS UNIT UNT UTS WTS XXXXX YIELD YLD
Expired securities	EXPIRED EXPD EXPIRY EXPY

Panel B: Industry Codes for Investment Vehicles

Code	Number	Industry Name
ITSPL	73	SPLIT CAPITAL INV.TST
ITVNT	76	INV.TST.VENTURE + DEV
INVNK	77	INVESTMENT COS.(6)
ITGSP	88	INV.TST.GEOG.SPECLSTS
IVTUK	89	INVESTMENT TRUST UK
	96	INVESTMENT TRUST – OLD
ITINT	109	INV.TST INTERNATIONAL
UNITS	110	AUTH. UNIT TRUSTS
RLDEV	112	REAL ESTATE DEV.
CURFD	121	CURRENCY FUNDS
INVCO	124	INVESTMENT COS. (UK)
INSPF	125	INS.+ PROPERTY FUNDS
OFFSH	136	OFFSHORE FUNDS
INVTO	137	OTHER INV. TRUSTS
ITEMG	145	INV.TST.EMERGING MKTS
OEINC	148	OPEN ENDED INV. COS.
ITVCT	149	VENTURE CAPITAL TRUST
	154	REAL ESTATE
EXTRF	159	EXCHANGE TRADED FUNDS

This table lists words used in a screen to identify Datastream securities for which the underlying asset is not common equity. Panel A lists non-common equity security codes, and Panel B lists industry codes for investment vehicles. In Panel A, the left column lists securities excluded from the study, and the right column lists words in the security name that indicate it is of the type in the left column. If part of a security name is matched to a word in the right column, it is excluded from the study. Similarly, all securities with industry codes listed in Panel B are excluded. These filters were applied to all securities from all countries in the initial sample.

[a]XSQ (an international electronic stock exhchange)and XET (XETRA – a German electronic trading system) are indicators of electronic exchanges and their presence indicates that the prices for this security come from the alternate exchange. Hence, stocks with XSQ and XET in the name represent duplicates.

[b]These were examined for false positives due to picking up companies with "IT" as part of the company name. In all instances of "IT" representing an investment trust, the word IT either began or ended with a period.

Table B.2
Country-Specific Identifiers for Excluding non-Common Equity Datastream Securities

Country	Words searched
Brazil	(preferred and ETFs - Portfolio Receipts): PN PNA PNB PNC PND PNE PNF PNG RCSA RCTB PNDEAD PNADEAD PNBDEAD PNCDEAD PNDDEAD PNEDEAD PNFDEAD PNGDEAD
Columbia	(preferred, privileged): PFCL, PRIVILEGIADAS, PRVLG.
China	For separate analysis lag stocks as A shares (for Chinese citizens) and B shares (until February 18, 2001) for foreigners only – we do not delete these.
Sri Lanka	(Non-voting and rights): RTS RIGHTS and Two-word filter for NON VTG and NON VOTING
Greece	(preferred registered and preferred bearer): PR PB
Hungary	(non-ordinary): törzsrészvény (T) is ordinary share osztalékelsbbségi (OE)
Indonesia	(foreign-board-listed stocks and rights): FB FBDEAD RTS RIGHTS
India	XNH
Israel	(preferred): P1 1 5 (1 & 5 refer t the par values of preferred stock)
South Korea	(preferred): 1P 2P 3P 1PB 2PB 3PB 4PB 5PB 6PB 1PFD 1PF PF2 2PF
Lithuania	(preferred): PREFERENCE
Mexico	(convertible shares): ACP and BCP (no voting rights): C, L, CPO, O
Malaysia	(stocks for foreigners only): A 'A' FB FB. (Electronic exchange that results in duplicates): XCO (XCO) XCODEAD (other papers have also deleted) : SES (SES) (non-common equity): RIGHTS
Peru	(inversion (i.e. Investment) shares have no voting rights and are similar to preferred shares): INVERSION INVN INV
Philippines	(deposit receipts): PDR
Portugal	(registered stock can have sales restricted by the firm): R 'R'
South Africa	(restricted voting shares): N (certificate of participation): CPF (Options): OPTS
Singapore	(non-redeemable convertible preference shares): NCPS NCPS100 (non-ranking for dividend): NRFD (foreign board): FB FBDEAD
Taiwan	(Deposit Receipts): TDR 'TDR'
Thailand	(foreign board stocks): FB FBDEAD
Australia	(Rights): RTS (Deferred): DEF DFD DEFF (Fully and Partially Paid): PAID PRF
Germany	GENUSSCHEINE or GSH are securities, which are hybrid securities between a loan and equity: GENUSSCHEINE GSH
Belgium	(conversion): CONV (VVPR strips are coupons which reduce taxes in Belgium and are separately tradable): VVPR STRIP
Canada	(Rights, Shares, Voting, subordinated voting): RTS SHS VTG SBVTG SUBD (Series): SR SER (Receipts are rights to receive stocks or options at a future date): RECPT Receipt (Exchangeable): EXH EXCHANGEABLE (Split Share Corporations a derivative of common stock): SPLIT
Denmark	(VXX and CSE appear to be alternate exchanges, which result in multiple listings for the same stock): VXX CSE
Finland	(the word USE is always used with a Datastream code and the reference code always appears to be primary): USE
France	(certificates of investment or investment trusts): ADP CI CIP ORA ORCI OBSA OPCSM SGP SICAV FCP FCPR FCPE FCPI FCPIMT OPCVM
Italy	(risparmio non convertibili which is a Non-convertible saving share and is distinct from azioni ordinarie - ordinary shares): RNC RIGHTS (PV is Privileged and RP is Risparmio - neither are common shares): PV RP
Netherlands	(Profit-sharing certificates): CERT CERTS (preferred or other non-common share): STK – except DSCD= 927654
New Zealand	(Rights): RTS
Austria	(Participation Certificate): PC (Genussscheine = non-voting equity securities): GSH Genussscheine
Sweden	(alternate, non-primary stock exchange): VXX (the word USE and converted is always used with a Datastream code and the reference code always appears to be primary): USE CONVERTED CONV
Switzerland	(the word USE and converted is always used with a Datastream code and the reference code always appears to be primary):USE CONVERTED CONV CONVERSION
United Kingdom	(ranking for dividend): ranking for dividend (book-keeping entry): PAID (Non-voting): NV

The names of all securities from each country in the left column were screened for the words in the corresponding row in the right column. These country-specific words identify non-common equity Datastream securities. If a security's name includes one of these words, it is excluded from the sample.

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