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Abstract

Using point-in-time accounting data, we estimate monthly fair values of 25,000+ stocks from 36 countries. A trading strategy based on deviations from fair value earns significant risk-adjusted returns ("alpha") in most regions, especially the Asia Pacific, that are unrelated to known anomalies. The strategy's 40–70 basis point per month alpha difference between emerging and developed markets contrast with prior research findings. A country's pre-transaction-cost alpha is positively related to its trading costs, but exceeds country-specific institutional trading costs. Thus, global equity markets are inefficient, particularly in countries with quantifiable market frictions, like trading costs, that deter arbitrageurs.

JEL Classification: G11, G14, G15

Keywords: international finance, Valuation, Asset Pricing, Market Efficiency, fundamental analysis, Point-in-Time (PIT), transaction costs, principal components, instrumented principal components analy-sis (IPCA)

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1. Introduction

Because the discovery of fair prices requires some incentive to bear its cost, financial markets cannot be perfectly efficient.[1] But how inefficient are these markets and does the inefficiency differ across countries? In a well-known monograph, Ross (2005) offers a theoretical guideline for assessing whether an asset is fairly valued. According to this guideline, fairly priced assets have residuals – from the projection of their next-period payoff onto the payoff space of traded assets – that have present values and expected future payoffs of zero.[2] By contrast, in an inefficient market, buying undervalued assets and selling overvalued assets leads to risk-adjusted profits ("alpha") if prices are more likely to converge to than diverge from fair values.

Implementing Ross's insight about relative valuation and market efficiency is complex. It requires restrictions to empirically identify projection coefficients and the replicating portfolios attached to them that benchmark fair values. Moreover, if the restrictions generate residuals that correlate with the pricing kernel, risk adjustments are needed to assess efficiency. To this end, Bartram and Grinblatt (2018) estimate fair values by restricting replicating portfolio weights to be best-fit functions of the most commonly reported accounting items. Thus, according to their methodology, two firms with the same accounting data have identical fair values. Using Compustat-reported quarterly U.S. financial filings, they show that it is profitable to trade on deviations from their estimated fair values after adjusting for risk with the "usual suspects."

Our paper employs the Bartram and Grinblatt (2018) approach to study global equity market efficiency. Using accounting-based replicating portfolios, we first assign fair values to more than 25,000 firms from 36 countries in the 1993–2016 sample period. The assignment comes from "point-in-time" international accounting data, heretofore unstudied in the literature, that represent what investors knew about U.S. and non-U.S. firms' financial statements at the time. We then compute the alphas from trading on price deviations from the

[1] See, for example, Grossman (1976) and Grossman and Stiglitz (1980).

[2] Ross (1995, p. 59) states "Summing up, even in an incomplete market with an indeterminate pricing kernel, any prospective asset will have a determinate price, namely the value of its projection on the marketed assets."

estimated fair values – both before and after transaction costs. We also perform extensive tests to rule out risk-based explanations for our findings.

The use of profits from trading strategies is a long-established procedure for assessing efficiency. For example, a prominent paper in the area, Griffin, Kelly, and Nardari (2010), assesses efficiency internationally from the return spreads of long-short strategies derived from the short-term past return (week and month) reversal, momentum, and earnings surprise anomalies. These anomalies were chosen because the return spreads from them are claimed to be orthogonal to the pricing kernel, mitigating the need for risk adjustment.

Our analysis of risk-adjusted returns across the globe is primarily designed to addresses three issues. First, it speaks to the robustness of the Bartram and Grinblatt (2018) finding of risk-adjusted profits from trading on deviations of share prices from fair values. Using within-country, peer-implied norms, we find widespread economically and statistically significant differences in the risk-adjusted returns of the most under- and overpriced within-country stock quintiles, even though our data cover relatively more recent times.[3]

Second, we study cross-country heterogeneity in the risk-adjusted returns from the Bartram and Grinblatt (2018) mispricing signal and its determinants. We find that the alpha pattern across countries accord with common intuition: The pre-transaction cost alpha differences between intra-country portfolios estimated to be the most under- and over-priced are greater in emerging markets and in the Asia Pacific region (including its developed countries). In emerging markets, alphas from mispricing are higher by 40–70 basis points per month. Moreover, the decay in the signal's efficacy from delaying trade implementation is slower in emerging than developed markets. Our paper's emerging vs. developed markets results contrast with findings from two

[3] Findings are similar when the paper's fair value estimates employ another estimation technique (Theil-Sen or "TS"), implemented in a different context by Ohlson and Kim (2015), that is more robust to outliers. Moreover, we obtain similar results with two other alternative approaches: One estimates fair value by omitting the regression constant and thus does not require the market portfolio to be fairly valued; the other, inspired by the work of Frankel and Lee (1998), Liu and Thomas (2000) and Johannsson and Ohlson (2016, 2017), limits replicating portfolios to be functions of consensus earnings forecasts.

papers: The first, the Griffin, Kelly, and Nardari (2010) paper mentioned above, concludes that emerging markets have similar or smaller return spreads and thus, are *not* less efficient than developed countries' markets. The second, by Jacobs (2016), finds that profits from 11 anomalies are not more prevalent in emerging markets.

We also identify country-specific attributes that account for differences in the strategy's profitability. Specifically, trading costs significantly predict within-country pre-transaction cost profitability, even after controlling for other variables designed to capture the quality of a country's information environment, its level of economic and financial development, and its regulatory framework. Indeed, in a hypothetical country with zero transaction costs, the trading strategy's point estimate of alpha would be zero. Thus, global equity markets are inefficient, particularly in countries with quantifiable market frictions that deter arbitrageurs.

Third, and in part because transactions costs correlate with pre-transaction cost alpha, we study whether the strategy earns risk-adjusted profits after transaction costs. Risk-adjusted profits from mispricing typically exceed country-specific institutional investor transactions costs from fees, commissions and market impact. Profits from trading on mispricing exist for monthly rebalancing as well as buy-and-hold variations of the strategy that reduce turnover, and they are present for both equal- and value-weighted portfolios.

Our paper also adds to the literature on the determinants of cross-sectional expected returns more generally. We are particularly sensitive to the difficulty of distinguishing inefficiency from omitted risk attributes that might account for the strategy's abnormal returns. Our findings are based on state-of-the art adjustments for possible risk attributes that tend to eliminate most asset pricing anomalies. These adjustments employ Fama-MacBeth regressions on firm attributes known to correlate with returns, the instrumented principal components analysis (IPCA) technique developed in Kelly, Pruitt, and Su (2018) (thus representing its first application to international data), and traditional factor models using both a 50-factor model for international stocks developed from the international factors in Fama and French (2017), and our own 80-factor model for international stocks. These methods control for past returns, earnings surprises and yields, accruals, and other sources of return premiums, including country fixed effects. We also show that our strategy is relatively orthogonal to known anomalies, as it earns consistently positive alpha, even within quintiles of firms stratified by 22 other prominent alpha-generating anomalies. Thus, the signal does not proxy for something "already discovered."

Bartram and Grinblatt's (2018) methodology has several advantages over other signals used to study efficiency. First, the signal is not reverse engineered from returns as returns play no role in its construction. Second, quasi-out-of-sample tests of a relatively unstudied signal are less susceptible to the data snooping bias that (for U.S. discovered anomalies) tend to exaggerate an anomaly's true effect. Third, because the trading signal is a measure of value that is relatively devoid of discretion over specification, the signal is a more direct and natural choice for assessing efficiency. Our more agnostic, non-discretionary approach assumes that the future cash flows and their values are captured solely by projections onto spaces spanned by accounting values (or, in one robustness check, two consensus earnings forecasts). By contrast, valuation from traditional asset pricing models estimates stationary structural parameters, but within a variety of alternative specifications. The latter approach's discretion in parameters and cash flow forecasts makes its implementation complex, somewhat arbitrary, and thus subject to data snooping bias.[4]

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[4] While most anomaly studies tend to focus on U.S. equities, several analyze drivers of international stock return premiums. Fama and French (1998) show that value stocks outperform growth stocks in 12 of 13 major markets. In Rouwenhorst (1998, 1999) and Chui, Titman, and Wei (2003), momentum tends to be large in European markets, small but positive in many emerging markets, and exists in several Asian markets, while macroeconomic risk cannot explain its profits internationally (Griffin, Ji, and Martin, 2003). Chui, Titman, and Wei (2010) test whether cultural differences as well as differences in financial market development and institutional quality explain cross-country differences in momentum profits. Titman, Wei, and Xie (2013) look at asset growth's effect on return premiums across countries, finding larger effects from this attribute in more developed financial markets, but no effect from the quality of corporate governance or trading costs. Watanabe, Xu, Yao, and Yu (2013) show that the asset growth anomaly is stronger in more developed markets and those where stocks are more efficiently priced, but is unrelated to cross country differences in limits to arbitrage, investor protection, and accounting quality. Lam and Wei (2011) find that the asset growth anomaly is tied to proxies for investment frictions and limits-to-arbitrage.

2. Measurement of mispricing and market frictions

2.1. Mispricing signal

We study the profitability of Bartram and Grinblatt's (2018) mispricing signal across the world's equity markets. The signal first estimates each stock's fair market capitalization as the market price of a replicating portfolio with identical accounting data, constructed from stocks within the same country. When restricting replicating portfolio weights to be a function of accounting data, the portfolio that best fits any predicted outcome is given by the projection matrix. Residuals, which are orthogonal to the projection space by construction, are then used to generate the mispricing signal as the percentage deviation of an asset's estimated fair value from its price.

To minimize data snooping concerns, we closely mimic Bartram and Grinblatt's (2018) procedure. There are three innocuous exceptions: First, we employ annual data from Thomson Reuters' Worldscope Point-in-Time (PIT) database for international accounting data, while their study of U.S. stocks used the quarterly U.S.-only Compustat Point-in-Time database. Second, we estimate fair values from only 21 of their 28 accounting items – 11 from the balance sheet, 9 from the income statement, and 1 from the cash flow statement – because unacceptably few (or no) firms outside the U.S. report 7 of their items.[5] Third, we study international stock return data from Thomson Reuters Datastream in lieu of U.S.-only stock returns from Center for Research in Security Prices (CRSP).

As Bartram and Grinblatt (2018) show, fair values derived with their technique are equivalently obtained with hedonic linear least squares prediction of firms' fair values from accounting data. Thus, each month, fair value regressions of market capitalization on accounting data are run separately for each country having at least 30 firms with all 21 accounting regressors. Regression residuals as a fraction of market capitalization then sort firms into intra-country mispricing quintiles.

The accounting items that determine the regression's predicted fair values and residuals are known to market participants at the time of portfolio formation. This is because the study exclusively uses the Worldscope PIT database. This database details when the reported value (in local currency) for a specific accounting item

[5] Appendix A provides descriptions of the 21 accounting items and all other variables the study uses.

was made available to subscribers, known as a "point-date." Point dates conservatively estimate public release dates since press releases and other sources may reveal the same data earlier. The PIT database is free of survivorship, backfill, look-ahead, and restatement biases. To illustrate, when the PIT database contains errors, their subsequent corrections have their own separate point dates.

2.2. Transaction costs and other frictions

To investigate the impact of transactions costs, we use data from Elkins McSherry LLC on commissions, fees (include transactions taxes such as stamp duty), and market impact by country, all per U.S. dollar invested, as experienced by their typical clients, along with totals that sum the three transaction cost components. The alpha reduction from transaction costs subtracts the product of total trading costs per dollar invested by twice a portfolio's turnover. Turnover for an under- or over-priced portfolio is separately calculated: each is the average of U.S. Dollar (USD)-equivalent purchases and sales, scaled per USD-equivalent invested. Long-short spread portfolio alphas net of transaction costs are the differences between the net-of-transaction-cost alphas of the pair of portfolios in the long-short strategy. We lack data to assess the impact of short sales costs that would be borne by a long-short hedge fund that actually has to borrow shares to implement the mispricing-driven strategy. However, these net-alpha differences also capture the marginal alpha impact on an index portfolio that tilts towards stocks in the long leg and away from the short leg of the spread portfolio, which does not require short sales.

We also study the impact of trading costs on intra-country alpha spreads, controlling for other country attributes that mimic and typically are measured identically to those studied in Griffin, Kelly, and Nardari (2010). The attributes include a dummy indicating short sales are allowed (from Jain, Jain, McInish, and McKenzie, 2013), a dummy for common law legal origin (from LaPorta, López-de-Silanes, and Shleifer, 2008), total assets held by deposit money banks scaled by Gross Domestic Product (GDP) (from World Bank Financial Development Database), financial resources provided to the private sector by domestic money banks as a share of GDP (from World Bank Financial Development Database), total value of shares traded during the period divided by the average market capitalization for the period (from World Bank Financial Development Database), the Composite Country Risk Rating (from PRS Group), the logged geographical size of the country in square kilometers (from Central Intelligence Agency (CIA) Factbook), Institutional Brokers' Estimate System (IBES)'s analyst coverage ratio for the country, the annualized standard deviation of weekly market index returns for the country in the prior 52 weeks, the correlation between weekly returns of the local market index with the world market index in the prior 52 weeks, the return on the local market index, and the logged number of publically listed companies (from World Bank Financial Development Database).

2.3. *Sample definition and further data details*

The sample consists of all stocks with data from Datastream and Worldscope PIT needed to construct the mispricing signal, excluding financial firms (SIC codes 60–64), U.S. Over The Counter (OTC) Bulletin Board and 'Pink Sheet' stocks, American Depository Receipts (ADRs), secondary listings, and stocks with beginning-of-month share prices below five USD, non-positive total assets, missing country or firm identifiers, or those with share prices listed in a currency that is not legal tender in the firm's country of incorporation. [6] The portfolio formation sample period commences at the end of March 1993, the first month when all of the regions studied and most of the countries within them have the required data for at least 30 firms. [7]

International comparisons requiring common units employ U.S. Dollar equivalents. Monthly USD-translated stock returns and both local currency and USD market capitalization are from Datastream. [8] Datastream's returns require small amounts of filtering and winsorization. In particular, returns R_t and R_{t-1} are deemed missing if $|R_t| > 300\%$ or $|R_{t-1}| > 300\%$ and $R_{t-1} + R_t < 50\%$ (Ince and Porter, 2006) and are

[6] Hou, Xue, and Zhang (2017) find that 64% of 447 anomalies owe their significance to an overreliance on positions in very small firms. Our five USD share price filter, point-in-time reporting requirement (which tends to omit smaller firms), value-weighting, and other checks show that their criticism does not apply to our findings. Our results are similar if we use a USD ten million market capitalization filter.

[7] The main restriction on the sample period is point dates from Worldscope PIT, which commence in 1992. An earlier version of the paper showed similar results using accounting data from the regular Worldscope database (without re-statements) going back to 1981 using earnings announcement dates from IBES or Worldscope as release dates.

[8] Return spreads of country-neutral long/short portfolios are the same in local currency and in USD.

winsorized at the top and bottom 0.1% of the final sample.[9] Accounting variables are also winsorized (based on their ratio to total assets) at the top and bottom 5% using the variable's sample distribution from all data released prior the date of portfolio formation.

The Elkins McSherry transaction costs data are reported quarterly from Q1 1996 to Q2 2015. We employ their total cost at the monthly frequency by treating the most recent observation as constant within the quarter. For the few countries with reported costs that differ for stock purchases and sales or different exchanges in certain quarters, we conservatively take the largest of all reported costs across transaction type (buy or sell) and exchange. Lacking transaction cost data only for Croatia and Morocco, we take that quarter's maximum cost among all emerging markets countries in their respective geographic regions. We use the most recent (next) available transactions cost for the few country/quarter observations with missing costs at the end (beginning) of the sample period.

The final sample consists of 25,731 stocks from 36 countries around the world with returns from 4/1993–9/2016. The largest numbers of firms come from the United States (9,112 or 35%) and Japan (4,249 or 17%), followed by Korea (7%), China (6%), France (5%), the UK (4%), Canada (4%) and Germany (4%). The sample starts with about 3,700 firms in 1993. Over time, the sample size increases rapidly with peaks before the burst of the dot-com bubble (7,784 in 2000) and the recent global financial crisis (9,839 in 2007). Because of the relative size of the U.S. and Japanese equity markets compared to other countries, subsequent analysis often reports on these two countries separately from their geographic region. Nevertheless, Asia Pacific always includes Japan, and Americas always includes the United States.

3. Empirical results

3.1. Summary statistics

At each month-end, we sort every global stock meeting the sample's criteria into intra-country mispricing quin-

[9] While Datastream lacks codes for delisting due to poor performance, evidence from Shumway (1997) for the U.S. and tests we have run that substitute –100% returns for the delisting month suggest that our results are unaffected by delisting.

tiles. The sorted trading signal is the percentage deviation of a firm's fair value estimate from its market capitalization, as described earlier. Stocks in the same quintile but in different countries are then grouped globally (sometimes with and sometimes without the United States), or by geography (Europe, Asia Pacific, Americas, and Africa/Middle East), country (specifically, United States and Japan), or economic classification (Emerging, Developed, and Developed ex-U.S.).[10] Ultimately, we relate these mispricing quintiles to returns and alphas.

Table 1 reports time series averages of monthly equal weightings of characteristics (translated into U.S. dollars) for all stocks within each of five quintiles based on the intra-country mispricing signal. It also lists time series averages of the monthly correlations between the characteristic and the mispricing signal. The top third of the table combines the United States with the rest of the world, the middle third excludes the United States, and the bottom third exclusively focuses on the United States. The quintile patterns of the characteristics for U.S. and non-U.S. firms are similar to each other, as well as to the U.S. pattern in Bartram and Grinblatt (2018).

Many characteristics of firms are known to be related to their future average returns. All three of Table 1's country groupings indicate that the most undervalued firms (Q5) tend to have higher book-to-market ratios, and lower accruals, market capitalizations, and returns over the past month and past five years (excluding the past year) – characteristics indicative of higher subsequent returns. However, Q5 firms' lower returns over the prior year and lower betas are countervailing attributes that predict lower subsequent returns. Gross profitability differences across quintiles, another return predictor, are small.

Note also that Table 1's average mispricing signals for Q1 and Q5 are extreme. For example, in the top third of the table, the most underpriced quintile of stocks is estimated to be underpriced by 1,391%. Thus, fair value estimates are clearly crude, explaining the extreme averages of the signal for Q1 and Q5 and the low

[10] The 30-firm minimum eliminates Africa/Middle East countries from most of our tables. MSCI's developed countries are Australia, Austria, Canada, Denmark, Finland, France, Germany, Israel, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and the United States; emerging markets are Brazil, Chile, China, Croatia, Czech Republic, Egypt, Greece, India, Korea, Malaysia, Morocco, Poland, Russia, South Africa, Taiwan, Thailand, and Turkey. We include MSCI "frontier" markets in our emerging category.

correlations between the characteristics and mispricing. The crudeness justifies the aggregations into quintiles. Our use of quintiles from the signal takes advantage of the quintile sort's ability to cast a wide net. While we do not pretend to have precise estimates of fair value, we believe that a Q5 stock is more likely to be truly undervalued than a Q1 stock.

The fair value estimates' high degree of noise also explains why convergence rates between market prices and estimated fair values are poor metrics of inefficiency. Large estimation errors mean revert to zero at a far greater rate than market prices plausibly converge to any target. Therefore, convergence rates of market prices to estimated fair values are not reliable indicators that prices are converging to their true fair values. By contrast, the martingale property of efficient market prices motivates the size of raw return spreads and risk-adjusted return spreads as better metrics of true convergence and efficiency.

3.2. *Is the Bartram and Grinblatt (2018) mispricing signal profitable internationally?*

3.2.1. *Raw return spreads*

With this motivation in mind, Table 2 reports time series averages of USD-translated returns for equal-weighted (Panel A) and value-weighted (Panel B) portfolios of stocks by geographic and developmental regions, stratified by quintiles formed from intra-country mispricing signals. It also reports results separately for the United States and Japan, which have the largest numbers of firms. For other countries, with far fewer firms, there is too much noise in the time series of spreads to draw meaningful conclusions about their cross-country differences.

Despite the relatively brief sample period, which commences in 1993 due to the data requirements, outlined earlier, seven of the ten average equal-weighted (EW) return spreads in Panel A of Table 2 are more than 3.3 standard errors above zero. The average value-weighted (VW) spreads in Panel B are generally smaller, but all are positive, and half are at least 1.86 standard errors from zero. Panel A's first row reports quintile-stratified average returns and quintile spreads for all firms (World): Panel A's average returns increase monotonically from the most overvalued (Q1) to the most undervalued firms (Q5), with a quintile spread of 53 basis points per month ("bp"), or 6.4% per year, and a positive spread in 62% of the months studied. This finding confirms the robustness of the Bartram and Grinblatt (2018) mispricing signal as a return-determining characteristic.

The average EW and VW monthly return spreads for the U.S., 26 bp (t = 1.46) and 23 bp (t = 0.97), are substantially smaller than the World ex-U.S. averages, 60 bp (t = 5.95) and 49 bp (t = 2.21). Europe has the smallest EW average, 8 bp (t = 0.80), but its VW average, 31 bp (t = 1.66), is a bit higher than the U.S. VW average. The best performer is Emerging, with monthly EW and VW average spreads of 123 bp (t = 6.30) and 124 bp (t = 3.76). The average spreads for Asia Pacific, which has many firms from emerging markets, including Korea and China, are also large: 109 bp (t = 6.54) and 102 bp (t = 3.38), respectively.

The U.S. results are weaker than those in Bartram and Grinblatt (2018), partly because of the switch from quarterly accounting data in Bartram and Grinblatt (2018) to annual data here. The U.S. spreads are 2.3% per year higher if we use this paper's accounting items, data sources, sample firms, and time period, but quarterly signal inputs from CRSP and Compustat. Lacking quarterly international accounting data, we cannot assess if trading in non-U.S. stocks would exhibit similar increases in spreads with more frequent signal input updating.

In sum, Table 2 shows significant return spreads from signals derived from common accounting variables. Trading profits exist for many of the equal- and valued-weighted portfolios, and they are particularly large in emerging markets, Japan, and in Asia Pacific. These extreme quintile return spreads do not control for risk. Indeed, Table 1 indicates that the trading signal is related to value, size, and past returns. For this reason, subsequent tables add controls for known drivers of returns to better assess the signal's incremental alpha.

3.2.2. Cross-sectional regressions with firm characteristics

To address whether omitted variables tied to the cross section of average returns explain Table 2's raw return differences, Table 3 regresses firm j's month t+1 return on its mispricing signal quintile and the quintile ranks of control variables known at the end of month t. It reports time series averages of the coefficients across all months along with Fama and MacBeth (1973) test statistics. Panel A studies two specifications of the regression for the entire global sample, while Panel B runs the regressions separately for subsets of stocks in given regions or countries. The two specifications are from Bartram and Grinblatt (2018). A schematic representation of the cross-sectional regression measures the mispricing signal's efficacy from the coefficient b_t in

$$R_{j,t+1} = a_t + b_t M_{j,t} + \sum_{s=1}^{S} c_{s,t} X_{j,s,t} + e_{j,t+1} \quad (1)$$

where

$R_{j,t+1}$ = month *t*+1 return of stock *j*

$M_{j,t}$ = end-of-month *t* value of stock *j*'s mispricing signal

$X_{j,s,t}$ = end-of-month *t* value of stock *j*'s control variable *s* or industry/country dummies.

In lieu of this simplified schematic representation, Table 3's actual regressions use quintile dummies (Q2, Q3, Q4, and Q5, with Q1 omitted) for all of the non-fixed-effect regressors instead of the parametric variables themselves. For brevity, Panel A displays coefficients and test statistics only for the Q5 regressor dummies, which represents the difference in returns from being in Q5 compared to Q1. Panel B includes the same regressor dummies but only reports the coefficient for the Q5 mispricing dummy, omitting coefficients on the control dummies for brevity. All regressions include fixed effects for the stock's country and industry.[11]

To facilitate comparisons across specifications, month *t*'s regressions omit firms lacking data for both specifications. Results are highly similar without this restriction. We require the regression to have at least one hundred observations with non-missing values for all regressors to include the month's regression coefficients in the time series average, (but later explore a time series factor methodology that does not lose so many firms due to data requirements). The quintiles for all controls, like the mispricing signal, are based on intra-country sorts, except for the firm size control. Following research precedent, size quintiles both here and throughout the paper reflect NYSE breakpoints. All regressors are constructed from the latest market valuations and point-in-time accounting data available to investors at the time (Asness and Frazzini, 2013).

Both regression specifications in Panel A of Table 3 (the World sample) show a significant coefficient on the quintile 5 mispricing dummy. Quintile 5 stocks earn an average of 43 bp per month ($t = 6.55$) more than quintile 1 stocks with the narrower set of controls in column (1) and 29 bp ($t = 4.47$) more with the broader set in column (2). Except for earnings surprises (SUE), the control variables show the expected signs and are

[11] We use the Kenneth French data library, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html to classify each firm into one of 38 industries each month. The regression coefficients and test statistics without industry controls negligibly differ from those reported in Table 3.

often significant. Since the Q5 variables in Table 3 are all dummies, we can directly compare their coefficients for economic impact. The mispricing signal influences returns to about the same degree as book-to-market, and its effect is slightly weaker than momentum's effect on returns.[12]

Table 3 Panel B reports the coefficient on the quintile 5 mispricing dummy by region for the same specifications as in Panel A. The first row repeats Panel A (the World) for easy comparison. The quintile spreads remain large and significant throughout Panel B except for Europe and the United States. (The weak U.S. performance, which dominates and dilutes the Americas mispricing coefficient, masks the signal's strong non-U.S. performance.) Profits from the mispricing signal are particularly strong in Emerging Markets (83 and 63 bp), Asia Pacific (82 and 60 bp), and Japan (78 and 54 bp). Thus, throughout much of the world, and for the world as a whole, trading on the Grinblatt and Bartram (2018) mispricing signal generates large alpha, documenting the international profitability of their mispricing measure and the robustness of their U.S. results, even using different firms, sample period, and data sources.

3.3. Sources of alpha heterogeneity across the globe

3.3.1. Geography vs. economic development

Our second objective is to study the cross-country heterogeneity in alpha from the Bartram and Grinblatt (2018) mispricing signal and its causes. The alpha generating strategies analyzed above vary by region and by a country's level of economic development. Conventional wisdom once thought that emerging markets are likely to be less efficient than developed markets. Bekaert and Harvey (2002) infer the lower efficiency of emerging markets from the higher serial correlations of their returns (Harvey, 1995), information leakage prior to their public release (Bhattacharya, Daouk, Jorgenson, and Kehr, 2000) and excess returns to trading strategies formed from fundamental characteristics (Rouwenhorst, 1999; Van der Hart, Slagter, and Van Dijk, 2003). However, more recent papers focus on specific alpha-generating strategies reach the opposite conclusion that these strategies are not more profitable and sometimes are less profitable in emerging markets.

[12] We also run weighted least squares Fama-MacBeth regressions, weighting observations by market capitalization. In these, the most underpriced stocks outperform the most overpriced stocks by 22 and 32 bp (*t*-statistics are 1.94 and 2.92).

The correlation between economic and geographic region complicates assessments of whether emerging markets are less efficient than developed markets, ceteris paribus. To isolate the impact of geography and development, Table 4 reports the average cross-sectional regression coefficients of the two specifications from Table 3 Panel A, but includes geographic (with Americas the omitted dummy) and economic development (with Developed the omitted dummy) fixed effects and their interaction terms with the five mispricing quintile dummies. Country fixed effects, used in the two regressions in the table's left half, are replaced by geographic and economics region fixed effects in the table's right half. For parsimony, we report only the coefficients on the interactions terms; coefficients on the unreported controls are similar to Table 3 Panel A.

Table 4's coefficients on the Q5 interactions with the emerging markets dummy are significant in all four regressions; their magnitudes imply that the mispricing strategy produces 61–66 bp more alpha per month in emerging markets, controlling for geographic region. By contrast, Asia Pacific, the region with the largest alpha, experiences 47–50 bp additional alpha compared to the Americas (the omitted region), controlling for the state of economic development. These results indicate that less developed equity markets, as well as the Asia Pacific region, are less efficient and provide larger profit opportunities due to greater asset misvaluation.

3.3.2. Transaction costs and other country characteristics

If profits to trading strategies based on mispricing measure inefficiency, then profit variation across countries should reflect frictions that impede the forces that tie a stock's price to its fair value. These frictions include transaction costs, short sales restrictions, and other country characteristics that impose limits to arbitrage. Regions with the most profitable trading strategies, like the Emerging Markets and Asia Pacific, contain most of the markets with the highest transaction costs, as well as almost all of the markets that prohibit short sales.

Table 5 assesses whether transaction costs and other country attributes influence our strategy's pre-transaction cost alpha. It reports the average cross-sectional regression coefficients of the second specification from Table 3 Panel A, but includes interaction terms of various country attributes with the five mispricing quintile dummies. It also includes the country (and industry) fixed effects from Table 3. The first specification uses only transaction costs per dollar of purchase or sale. The second specification also employs country characteristics derived from the union of regressors used in Griffin, Kelly, and Nardari (2010), described in Appendix A. For parsimony, we report only the coefficients on the interaction terms.

The coefficients on the transaction costs interaction term indicate that transaction costs positively influence alpha. In both regressions, however, the mispricing signal coefficient does not significantly differ from zero. In the first specification, which employs transaction cost as the only country interaction, this yields an interesting insight: Based on our coefficient estimate, trading on mispricing is not predicted to be significantly profitable in a hypothetical country lacking trading costs. By contrast, for a country like Korea, where trading costs averaged about 50 basis points, the 0.75 coefficient in the left regression predicts a Q5–Q1 alpha spread of 0.375 bp per month (or about 5% per year). These conclusions are from point estimates, however, and their confidence interval is wide. Hence, other interpretations of these regression results are possible.

Table 5's "kitchen sink" specification (2) does not lend any interpretation to the mispricing Q5 coefficient since all of its many interaction terms contribute to predicted alpha. However, the regression's interaction coefficients with transaction costs are about twice as large as those without the kitchen sink controls.[13] The interpretation here is that Korea's alpha spread should be about 10% per year greater than the spread for a country with zero transaction costs. The "kitchen sink" regression also indicates that common law and market volatility inversely relate to the alpha spread. The three predictors are consistent with competition among arbitrageurs reducing mispricing. Transactions costs and lack of common law deter such competition, while market volatility may (but need not) imply greater arbitrageur competition. If the latter occurs, it would arise from sufficiently high intra-country correlations between the returns of individual stocks.[14]

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[13] Specification (2)'s coefficient in Table 5 is significant at the 5% level and about the same magnitude when using Theil-Sen version of the mispricing signal.

[14] Consider two countries, A and B, each with an undervalued and an overvalued portfolio that equally combine to form the country's market portfolio. The returns of each country's under- and over-valued portfolio pair are assumed to have equal variance, V_A and V_B, and correlations of R_A and R_B, respectively. The market return variances of countries A and

Appendix B develops a model of mispricing tied to transaction costs (or related frictions). It portrays rational arbitrageurs trading a country's mispriced stock as long as frictions or opportunity costs do not deter their trades. These arbitrageurs help tie price movements to bands, derived in closed form, that surround a stock's fair value. Countries with greater frictions have wider bands. Outside the bands, arbitrageur demand dampens sentiment's price impact, creating kinks in the mispricing demand function curve. By Jensen's inequality, the kinks create expected price movements that show up as abnormal returns.

The model, which ties alpha to the convergence of prices to fair value from the flow of funds by arbitrageurs, is consistent with our empirical findings. It implies that we are more likely to find a large degree of mispricing and larger alphas in countries with large transaction costs. The model also implies that for a given level of mispricing, stocks in countries with low transaction costs are less likely to experience the same degree of convergence as stocks with large transaction costs.

In sum, we identify country-specific transactions costs conceptually and empirically as key driver for differences to risk-adjusted profits from mispricing, even after controlling for other variables designed to capture the quality of a country's information environment, its level of economic and financial development, and its regulatory framework. The results suggest that global equity markets are inefficient, particularly in countries with quantifiable market frictions that deter arbitrageurs.

3.4. *Mispricing vs. risk premium*

Up to this point, we have addressed two of our three main points. First, we have shown that the mispricing signal of Bartram and Grinblatt (2018) is robust. International data offer a quasi-out-of-sample test of their

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B are therefore $V_A(1 + R_A)/2$ and $V_B(1 + R_B)/2$, but their arbitrageurs' long-short portfolios have return spread variances per unit of investment equal to $2V_A(1 – R_A)$ and $2V_B(1 – R_B)$, respectively. Hence, if A has the higher market variance, it could imply that its long (or short) portfolio has higher own variance than country B's, i.e., $V_A > V_B$. Alternatively, the higher market variance of country A may imply relatively little diversification available from combining its long and short portfolios, i.e., $R_A > R_B$. If the diversification consideration dominates our cross-country comparisons, the country with the higher market volatility, here country A, would pose lower risk for arbitrageurs. That is, $2V_A(1 – R_A) < 2V_B(1 – R_B)$.

finding, and it shows results that are stronger than those found for the United States. Second, we have shown that the inefficiencies that are associated with the mispricing signal vary with common intuition. Emerging market countries and those with larger frictions such as transactions costs (typically found in Asia) tend to offer larger profits from the Bartram and Grinblatt (2018) signal.

The elephant in the room is the adjustment for risk and whether the control characteristics used in the prior tests adequately span the cross section of average returns. International risk adjustments are not as well developed as those for the United States, and most prior papers on the relative efficiency of different stock markets tend to eschew them altogether. Our cross-sectional regressions have controls that make a fair attempt to implement risk controls. However, we hope to offer some degree of comfort about this issue with an extensive set of additional risk adjustments.

3.4.1. Time-series regressions with factor portfolios for risk adjustment

As an alternative to the characteristic controls of Table 3's cross-sectional regressions, we estimate factor model alphas of quintile portfolios of firms constructed from the mispricing signal. Compared to cross-sectional regressions, factor models have the advantage of including about twice as many firms. As an example, firms that lack a data point for book value of equity or a profitability measure are excluded from Table 3's analysis; however, such firms can be included in portfolio excess returns that are regressed on the book-to-market factor, high minus low (HML), or the profitability factor, robust minus weak (RMW), which control for similar return effects. Factor models can also study value-weighted portfolios with greater ease and indicate the degree to which long and short positions contribute to the extreme quintile alpha spreads. Finally, factor models allow us to assess risk-adjusted returns, net of all transaction costs. This is the third key line of inquiry in the paper, and it will be addressed shortly.

Denote $r_{q,t+1}$ to be the USD industry-adjusted month t+1 return (which subtracts the return of an equal-weighted global industry portfolio) on quintile portfolio q based on its end of month t mispricing signal.[15] Quintile q's alpha is the intercept in the time series regression

$$r_{q,t+1} = a_q + \sum_{l=1}^{L} \beta_{q,l} F_{l,t+1} + \varepsilon_{q,t+1} , \tag{2}$$

where $F_{l,t+1}$ is the USD return difference (or excess return) of the l^{th} factor portfolio. The alphas should monotonically increase in the quintiles if the signal works; moreover, the difference in the alphas of quintiles 5 and 1 measures the mispricing signal's ability to earn risk-adjusted returns.

For the five quintile portfolios, sorted by their intra-country mispricing signal, Table 6 displays industry-adjusted returns (the top third of the table) and alphas benchmarked against two sets of factor portfolios (middle and bottom thirds of the table). Intra-country quintiles are grouped across all countries in the geographic or economic region identified by row name. We then equal weight (Panel A) or value weight (Panel B) the industry-adjusted returns of the group's stocks. Table 6 also reports the spread in alphas between the most under- and over-priced quintiles in the first column of the table.

The 80-factor alphas in the middle third of Table 6's two panels are benchmarked against eight factors – the market excess return, size, value, momentum, short-term reversal, long-term reversal, investment, and profitability factors – constructed separately for the ten (sub-)samples/regions listed in Table 6's rows. All 80 factors are used in each of the ten regions' regressions to be consistent with a literature that suggests regional and global factors improve risk adjustment[16] and for fair comparisons across regions. Thus, Europe's factor

[15] Following the literature, we subtract the return of an *equal-weighted* industry portfolio from the return of each stock. Since some industries are dominated by one firm, subtracting *value-weighted* industry portfolio returns, which may have too much firm-specific risk and not enough industry risk, is inappropriate. Roll (1992) points out the importance of industry adjustments in studying international stock returns.

[16] See Fama and French (1998, 2012), Hou, Karolyi, and Kho (2011), Bekaert, Hodrick, and Zhang (2009), and Griffin (2002).

regression includes the eight global factors and the eight European versions of the factors, but also the sets of eight factors tied to the Americas, United States, Asia Pacific, Developed Markets, Developed Markets ex. U.S., etc. [17] The 80-factor specification thus nest the Fama-French (1993) three-factor, Carhart (1997) four-factor, and Fama-French (2015) five-factor models within it.

The bottom third of Table 6 reports the alphas of the industry-adjusted quintile portfolio returns benchmarked against all 50 U.S. and international factors available in the French data library as of October 2019. [18] This 50-factor specification nests the Fama-French (1993) three-factor, Carhart (1997) four-factor, and Fama-French (2015) five-factor models, as well as the Fama and French (2017) international factor model. The 50 factors employ returns from developed and developing countries and primarily reflect larger firms.

The top third of Table 6's two panels, showing industry-adjusted returns without factor adjustment, are highly similar to the return spreads from Table 2, which lack industry adjustment. For example, Panel A's monthly return spread for the world is 55 bp, while it is 53 bp in Table 2. With Panel B's value-weighting, the spread for the world is 35 bp, whereas it is 31 bp in Table 2. As with Table 2, applying the trading signal to Emerging Markets and Asia Pacific regions is more profitable than in other regions. Moreover, while value-weighted industry-adjusted return spreads seem a bit weaker, only the United States consistently stands out as a place where the strategy (earning about 29 bp) is not extremely profitable. The relatively weaker return spreads in the U.S. dilute the performance of the developed markets at large and the Americas (particularly when value-

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[17] Following Fama and French (1993, 2017), we sort stocks each month in two size groups (split by the median) and independently into three groups (using the 30th and 70th percentiles) based on book/market, investment, operating profitability, short-term reversal, momentum and long-term reversal using NYSE breakpoints. Each factor-mimicking portfolio value weights the USD returns of the respective six portfolios' stocks for each characteristic, then differences the long and short side before averaging across the groups for the paired characteristic. The ten market factors value-weight all stocks in each region and subtract the 30-day U.S. T-bill rate. All inputs are measured as of the prior month. Results using factor models employing only global and regional factors are similar.

[18] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html for details on factor construction. Results using factor models that use the factors best corresponding to the respective geographic region are similar.

weighting). Europe's industry-adjusted return spreads are also weaker than the Asia Pacific spreads; however only Europe's industry-adjusted return spread in Panel A (equal weighting) is small and insignificant.

Controlling for factor exposures has little effect on these conclusions.[19] Trading on the intra-country mispricing signal works worldwide. Irrespective of the row, the alpha patterns across both factor models are close to or perfectly monotonic across quintiles, and the extreme quintiles contribute about equally to the strategy's alpha. Once again, the United States and to some extent Europe are relatively weaker compared to the Asia Pacific and Emerging Markets regions.

For Europe, the 80-factor adjustment seems to improve signal performance. It is significant with Panel A's equal weighting, while Panel B's 50-factor model reduces Europe's alpha to insignificance. These appear to be the rare exceptions where risk adjustment makes a difference. Otherwise, the corresponding alpha spreads of the two factor models in Panels A and B are remarkably similar to each other and to the corresponding industry-adjusted return spreads in the top third of the panels. For example, the global spreads in Panel A are 59 and 70 bp for the 80- and 50-factor benchmarks, with the industry-adjusted return marginally lower. In Panel B, the spreads are 29 and 60 bp, respectively. The similarities of the spreads across the top, middle, and bottom thirds of Table 6's two panels, as well as their similarity to the spreads in Table 2, suggest that factor risk exposure is an unlikely driver of the success of the trading strategy.

[19]If our mispricing signal "works" because it proxies for an omitted risk factor, 80- and 50-factor models (which contain size and value factors) should generate lower abnormal return spreads than spreads without factor controls. They do not. Bartram and Grinblatt (2018) also perform other tests to refute the Berk critique of their mispricing signal, which we adopt. Moreover, when we run regressions of squared signals on the 21 accounting variables, we find that extreme (positive or negative) mispricing is strongly related to fundamental characteristics, suggesting the signal reflecting mispricing of fundamentals rather than risk. While market capitalization in the mispricing signal is measured on the second to last trading day of the month, results are also robust to lagging market capitalization in the mispricing signal by an additional seven calendar days.

Finally, both quintile 5's underpriced stocks and quintile 1's overpriced stocks generally contribute to the significant alpha spread – about equally in many instances, or with a quintile 5 magnitude that is larger. For example, with Panel A's equal weighting, World quintile 1, which would be shorted, earns significant alphas of –27 and –32 bp with its two factor benchmarks, while quintile 5 earns a significant 32 and 38 bp, respectively. By contrast, short positions are the primary drivers of significant alpha spreads for most other alpha-generating anomalies.[20] While short sales restrictions could explain why those anomalies persist, the same barrier does not exist for investment in the Q5 portfolios.[21]

3.4.2. Signal delay results support high alpha markets as being less efficient rather than poorly risk-adjusted

Overall, Table 6 indicates that the payoffs to the equal- and value-weighted strategies remain significant in various regions of the world after adjusting for broad sets of factors that nest the Fama and French (1993, 2015) and Carhart (1997) models. The existence of large misvaluations, exploitable with simple trading strategies that profit from the reversion of market prices to fair values, is a likely cause. This conclusion is also consistent with the alpha decay pattern of the mispricing signal. Fig. 1 shows risk-adjusted returns for major regions when delaying the signal by 1–36 months. The graph shows that performance deteriorates as the signal becomes older. The United States is driving the results for the world and for developed markets, with developed market performance decaying to zero for signals that are more than a year old. By contrast, the decay in the performance of stale signals in emerging markets and developed markets outside the United States is slower, approaching zero only when the signal is about three years old. The slower decay is consistent with non-U.S. equity markets, especially emerging markets, being less efficient than U.S. markets.

[20] Across 11 popular anomalies, Fama-French three-Factor alphas are larger for the short leg than the long leg of the investment strategy for all but one anomaly (Stambaugh, Yu, and Yuan, 2012).

[21] Factor model versions of Tables 4 and 5 confirm that alpha heterogeneity is explained by geographic region (higher in Asia controlling for development), development (higher in emerging markets, controlling for region), and limits to arbitrage (higher in countries with large transaction costs controlling for other country factors).

3.4.3. Other known anomalies

Table 1's analysis described underpriced firms as "beaten-up" value firms. We partly addressed this characterization of undervalued firms with controls for past returns, growth vs. value, firm size, as well as several other firm attributes. To further analyze whether the signal proxies for a previously known anomaly, Table 7 studies the World strategy's profitability within 110 groupings of global stocks that share similar amounts of one of 22 alternative characteristics known to generate alpha.

The procedure is as follows: Each month, we sort stocks into quintiles based on one of 22 characteristics that predict return. Within each quintile, stocks are then sorted into mispricing quintiles. Table 7's alpha spreads are from a long-short trading strategy in the extreme mispricing quintiles produced for each of the subgroups. If any of the 22 characteristics is masquerading as our mispricing variable, the lack of mispricing signal variation within each of 110 subgroups should greatly reduce the alpha spreads and their significance.

Panel A of Table 7 shows alpha spreads within subgroups and equal-weighted mispricing quintiles for the 80-factor model; Panel B exhibits spreads from the 50-factor model. Both panels exhibit statistically and economically significant alpha spreads in almost all the subgroups, with a few scattered exceptions to significance. To illustrate, the approximately 33 bp alpha spread for the highest one-month past return stocks is marginally insignificant with the 80-factor model. However, this is an isolated event that other past return categories lack. When many numbers are viewed, we expect a few to be insignificant by chance. Moreover, our factor model regressions control for the effect of past returns. Thus, the 22 other anomalies are unlikely to explain the alphas generated by our mispricing signal.

3.4.4. Cross-sectional regressions with IPCA factor model expected returns

To further address whether we have properly controlled for risk, we employ Instrumented Principal Component Analysis (IPCA), developed by Kelly, Pruitt, and Su (2018).[22] IPCA allows for latent factors and time-varying factor betas by introducing observable characteristics as instruments for unobservable dynamic factor betas. This new approach to modelling risk accounts for many cross-sectional anomalies as factor risk exposure.

[22] We are grateful to the authors for helpful discussion and use of their code.

For example, Kelly, Pruitt, and Su (2018) show that a five-factor IPCA model explains the cross section of U.S. stock returns significantly more accurately than the Fama and French (1993, 2015) three- and five-factor models, or even a six-factor extension of the latter that incorporates a momentum factor. Moreover, they show that only four out of 37 anomaly portfolios, constructed from firm characteristics, have IPCA alphas that significantly exceed zero. We are the first to apply this risk-adjustment methodology to international stock returns.

The IPCA technique iterates between two series of projections while imposing a constraint for factor orthogonality and rotation to pinpoint an otherwise non-unique solution. Using returns and characteristics for all stocks with data, the first projection regresses returns on factor betas each month to obtain factor realizations in the month. The second projection, using the full panel, estimates a time invariant matrix mapping (the "gamma matrix" as it is termed in IPCA) from a set of time-varying instruments to obtain a time series of factor beta vectors. The latter projection's mapping regresses returns on the product of the factors from the first set of projections and characteristics. After an initial guess for gamma and factor premiums, the iterating projections use standard algorithms to converge on a fixed point for the instrument mapping and factor realizations.

Our IPCA implementation uses 12 instruments: Tables 3's ten anomaly characteristics, the mispricing signal, and a constant. Following Kelly, Pruitt, and Su (2018), we cross-sectionally transform the scale of the instruments each month with affine functions that force each instrument to lie between –0.5 (the lowest value for the attribute) and +0.5 (the highest value) and estimate a five-factor IPCA model. Thus, our time-invariant transformation from characteristics to factor betas (i.e., gamma) is a 12×5 matrix. The model allows not only factor premiums to vary over time, but also factor betas as a function of changes in firm characteristics. Thus, with the twelve-instrument model, time-varying risk premiums associated with our mispricing signal's ability to proxy for a risk factor are fully controlled for in the analysis below.

Table 8 Panel A parallels Table 3 Panel A. Using our full sample of global stocks, it cross-sectionally regresses returns on four dummies for mispricing quintiles 2–4, as well as the predicted return of the stock in a month from the five-factor IPCA. The "Unconstrained" column places no constraints on the regression coefficients; the "Constrained" column forces the coefficient on the IPCA return prediction to be 1. The constrained results are equivalent to stepwise regression in which we first subtract the IPCA predicted return from the stock return and then regress the difference (a return residual) on the mispricing signal dummies and fixed effects. All regressions include fixed effects for industry and country, as in Table 3 Panel A.

The unconstrained regression's high *t*-statistic in Table 8 Panel A indicates that the IPCA-predicted returns are important for explaining the cross section of returns. What is telling, however, is that the mispricing signal yields highly significant spreads between the IPCA-controlled return of the most under- and overpriced quintiles of global stocks. In particular, the unconstrained regression yields a highly significant spread of 41 bp per month between the two extreme quintiles of the mispricing signal. Moreover, the quintile spreads with the signals are larger than the coefficients from Specification (2) of Table 3 Panel A, which uses quintile dummies for the ten characteristics as controls. Table 8 Panel A's unconstrained regression also illustrates that the coefficients on the mispricing quintile dummies are monotonic. (That monotonicity also existed in Table 3 Panel A but was not apparent because of the need to shorten what Panel A displayed.) In Table 8 Panel A, however, the monotonicity with the unconstrained regressions supports claims that we are identifying pricing inefficiencies as we now control for factor risk associated with mispricing. The constrained regression also exhibits a significant and nearly monotonic effect from mispricing – separate from the effect of the mispricing signal on factor betas. The coefficients on the mispricing quintiles are smaller than those in the unconstrained regression.

Table 8 Panel B reports the coefficient on the quintile 5 mispricing dummy by region for Panel A's specifications, thus mirroring Table 3 Panel B. The quintile spreads in the unconstrained regressions remain large and significant for all of Panel B's rows except for Europe and the United States. As in Table 3 Panel B, they are particularly strong in Emerging Markets (85 bp), Asia Pacific (90 bp), and Japan (67 bp).[23] In sum, the lessons from Table 3 are unchanged with the expected return controls from the five-factor IPCA model, even though we additionally control for the factor risk premiums implicit in the mispricing signal. This was a tall

[23] While results in Table 8 Panel B are weaker in the constrained regressions for the Developed Markets (and Americas), they are economically and statistically significant with TS mispricing signals.

hurdle for our mispricing signal given that the IPCA estimation makes use of this same characteristic, along with 10 others, for a best in-sample fit. Jumping over that hurdle is compelling evidence that our findings of profitable trades from mispricing are not due to some omitted risk variable.

In summary, our findings on market efficiency and its heterogeneity across countries and regions are robust to state-of-the art adjustments for possible risk attributes that tend to eliminate most asset pricing anomalies. These include Fama-MacBeth regressions with firm characteristics, 50- and 80-factor models for international stocks, as well as instrumented principal components analysis. The mispricing signal's alpha effect is also incremental to return effects of 22 other prominent alpha-generating anomalies.

3.5. Turnover and risk-adjusted profits net of transactions costs

The third and final key issue we investigate is whether transaction costs negate trading profits from mispricing. Since high transaction costs often require a lower turnover strategy, we first compare the pre-transaction cost profitability of a low turnover version of the mispricing strategy we have studied until now, which rebalances every month. We then analyze both the monthly and low turnover strategy's alphas after netting out transaction costs.

3.5.1. Buy-and-hold portfolios

While the mispricing signal is based on annual accounting data, trades take place every month as new market valuations become known and (for some firms) new accounting data is released to the public. However, (gross) performance from the mispricing signal does not account for the transactions costs incurred by this monthly rebalancing strategy. Sophisticated traders tend to reduce its turnover when optimizing performance in practice. To assess turnover's effect on profitability, we study the alphas of a trading strategy that is closer to what investors might do in practice; specifically, we build a long-short portfolio each month and hold it for the following 12 months. Averaging the returns of the 12 overlapping portfolios at each month yields the payoff of a strategy with lower rebalancing frequency. The monthly returns from averaging the 12 portfolio returns do not overlap and lend themselves to standard statistical analysis as developed in Jegadeesh and Titman (1993, 2001).

Table 9, which reports industry-adjusted (top third), 80- (middle third), and 50- factor (bottom third) alphas along with test statistics, shows that the reduced turnover strategy is less profitable, as one might expect. However, except for the Asia Pacific region and Japan, a comparison with Table 6 Panel A indicates an average reduction in 80-factor alphas of less than 22 bp per month. The reductions in alphas are particularly small in the United States and Europe, which have low performance to begin with, and the Emerging Markets. The United States and Europe, in turn, influence the lower drop in spreads in the Americas and Developed regions. The reduction in alpha spreads compared to Table 6 is large in Japan, with the more sizable Asia Pacific reduction largely due to Japan. However, alpha spreads from the buy-and-hold strategy remain significant if they were previously significant with Table 6's monthly rebalancing strategy.

The relatively greater alpha reduction with the buy-and-hold strategy in Japan – and the possible need to incur the transaction costs of a higher turnover strategy – could deter arbitrageurs. This fact could explain why the profits from the mispricing signal in Tables 3 and 6 are larger in Japan than in other developed countries. Similarly, the arbitrage-deterring effect of higher trading costs in emerging markets could account for the larger alphas generated by the emerging markets mispricing signal.

3.5.2. Alpha after transactions costs

Neoclassical finance contends that competition among arbitrageurs eliminates profitable trading opportunities based on public information. However, arbitrageurs face frictions, particularly trading costs, that could deter arbitrage. Negative performance net of trading costs for each country is sufficient (but, not necessary, as the paper's conclusion discusses) for such deterrence. The netting here subtracts the product of the per dollar trading costs for each country with our strategy's country-specific turnover in each month, as described in Section 2. Table 10 reports the effect of these trading costs in the Q1 (most overpriced) and Q5 (most underpriced) portfolios. The top half of Table 10 focuses on the effect of transaction costs on the monthly rebalancing strategy studied in Table 6; the bottom half shows the impact for Table 9's buy-and-hold strategy.

According to Table 10's first row, turnover for the world strategy is 29% per month, with about half of the turnover coming from the underpriced (Q5) and half from the overpriced (Q1) leg of the spread strategy. Table 10's remaining rows show nearly equal turnover for the long and short legs of the strategy for the other regions in the table. Generally, Q1's sell turnover exceeds Q5's buy turnover, but the difference never exceeds 2% in the table's top half or 1% in its bottom half.

With monthly rebalancing, the associated transaction costs from the world strategy's turnover ratio amount to more than 30% of the alpha spread, reducing the pre-transaction cost 80-factor alpha spread from 59 to 40 bp per month. The largest trading costs are in emerging markets, with a 53 bp per month reduction in the alpha spread, in part because they have the highest turnover, at 36% per month. However, dividing the 53 bp by 36% and analogously computing this ratio for the other rows indicates that trading costs per dollar of trading are twice as high in emerging markets compared to the other nine regions we study. U.S. transaction costs are lowest, both because the U.S. strategy has the lowest turnover and the lowest trading costs per dollar of trading.

All of the 80-factor alpha spreads in the "Net Performance" column for the spread portfolio (Q5–Q1) in Table 10's top half are positive; all of the regions that were significantly positive before transaction costs remain so after transaction costs, except for Emerging, Americas, and Europe. Moreover, investors can mitigate these costs by reducing turnover, as the annually rebalanced buy-and-hold strategy does in the lower half of Table 10. The associated reduction in turnover leads to trading costs that are about one-fifth of the costs in the table's top half. Except for Europe, the United States, and the Americas (with mostly U.S. firms), the resulting net performance alpha spreads are positive and statistically significant at the 5% level. In most cases, the buy-and-hold strategy's reduction in transaction costs approximately offsets the signal's loss of efficacy from deployment delay. However, in Emerging Markets, where signal delay is less detrimental to profitability and where transaction costs are high when rebalancing monthly, the net-of-trading-cost alpha is substantially larger with the buy-and-hold strategy. In Japan, the cost of signal delay outweighs the trading cost reduction, cutting its net-of-transaction cost monthly alpha by 35 bp, and explaining the lower buy-and-hold Asia-Pacific alpha after transaction costs.

4. Conclusion

In a semi-strong form efficient market, investors cannot earn alpha by trading on public information about mispricing (Fama 1970). When alphas are non-zero, moving a unit of capital out of a low-alpha opportunity to a high-alpha one enhances the overall risk reward (or Sharpe) ratio of an investor's portfolio in the absence of transaction costs. Of course, transaction costs and other frictions void this calculation and can explain why alphas (before netting out frictions) exist to begin with. However, because prices still fail to fully reflect information in these cases, pre-transaction cost alpha is a long-accepted inefficiency metric. If transaction costs are the major friction allowing this alpha to persist, higher cost countries exhibit higher alphas if there is limited supply of investable "smart money" that is mobile across countries.

With this motivation in mind, we have used international point-in-time accounting data to show that stock price deviations from their accounting-implied fair value predicts their future returns. These returns, even risk-adjusted, are significantly larger in emerging than developed markets, suggesting that emerging markets are less efficient at incorporating basic, widely available fundamental information. Profits are also large in Asia Pacific's developed markets, notably Japan. The strategy's performance is modestly lower when value-weighted, but is profitable within groups of stocks that share similar amounts of 22 "anomaly characteristics" known to predict returns. Buy-and-hold strategies that reduce transaction costs, as well as alternative fair value specifications, risk adjustment techniques, and estimation approaches do not eliminate the strategy's profitability. However, reduced turnover strategies tend to modestly lower profitability measured before netting out trading costs.

These findings support the thesis that the signal's profitability is more likely to reflect the relative efficacy of fundamental analysis in uncovering mispriced stocks than other explanations like an omitted risk variable. We have been sensitive to the need for extensive adjustments for risk – using Fama-MacBeth (1973) regressions on a host of characteristics, instrumented principal components analysis that allows for dynamic factor betas derived from numerous return-related firm characteristics (including mispricing), and two international factor models. However, in the absence of a universally accepted asset pricing theory, it is always possible to argue that some heretofore undiscovered risk attribute explains our findings. In the end, the reader will have to decide for herself whether our discovery represents one more anomaly, awaiting the magic bullet of a new theory of risk to shoot it down, or an insightful look at the relative efficiency of stock markets around the globe.

Mispricing in international equity markets could be tied to differences in market frictions across countries. To this end, we investigate the degree to which transaction costs and other country attributes explain cross-country differences in profitability. We establish that some differences across countries influence the strategy's profitability, depending on the specification. However, transaction costs consistently affect a country's pre-transaction cost alpha. Our study of turnover and transactions costs also shows that the strategy's positive alpha survives transactions costs from fees, commissions, and market impact. Moreover, simple adaptations of the strategy that reduce turnover can improve net alpha in emerging markets.

One of our more interesting findings here is that, in a hypothetical country with zero trading costs, the mispricing signal predicts no significant alpha. Why then do profits after trading costs persist? Tautologically, arbitrageurs who could earn profits after transaction costs are deterred from fully exploiting the inefficiency. Either other costs, such as the costs of information acquisition and processing, legal compliance in a foreign country, or the opportunity costs of organizational effort and capital deter trades by these arbitrageurs. If other alpha opportunities are more lucrative uses of scarce organizational resources, the foregone alpha is the cost of engaging in the mispricing strategy outlined here.

It would be useful to understand the costs of short sales and their role as drivers of alpha. To date, international data on short sales costs, like stock lending fees, is not available to researchers. A clear understanding of the role that short sales costs play for the profits and entry deterrence of sophisticated arbitrageurs would aid our understanding of how inefficient stock prices arise and persist. There are intriguing results about short sales prohibition that we have not discussed because they apply to few firms and only a handful of countries, often over a limited time period. For example, the 80-factor alpha spread in countries with a short sale prohibition is a significant 166 bp per month – more than three times the World's alpha spread. However, there are few countries and firms that experience this performance, and these firms have almost four times the trading costs of the "World strategy". Moreover, these firms have no influence on the rest of our results because they contribute a trivial percentage of firms to the World strategy and or its sub-regions.

In sum, our paper's portrait of market efficiency offers a middle ground, supporting both the view that prices reflect fundamentals and that sentiment drives price movements. In this portrait, which we formalized in a simple linear reduced-form model, deviations from fair value are within bounds set by frictions. As the frictions vary, so do the bounds. If sentiment moves prices, but only within bounds set by the deployment of arbitrage capital, then it is important to understand what drives the deployment of arbitrage capital. In this view, asset pricing should be more centered on the objective functions of the arbitrageurs. For example, the average covariance between stock pairs within a small country has little bearing on asset prices for worldwide diversified portfolios. For portfolios that concentrate in a country, high average covariance is generally unattractive to a long-only portfolio manager as it tends to increase the return variance of the portfolio. However, it could have a very different effect on the risk of long-short strategies, other things equal. Hence, if arbitrage capital deployment reduces sentiment's influence, we may be interested in average covariance, the average R-squared of within-country factor models, short sales costs, or other determinants of long-short arbitrageur risk – even if these factors play no role in neoclassical asset pricing.

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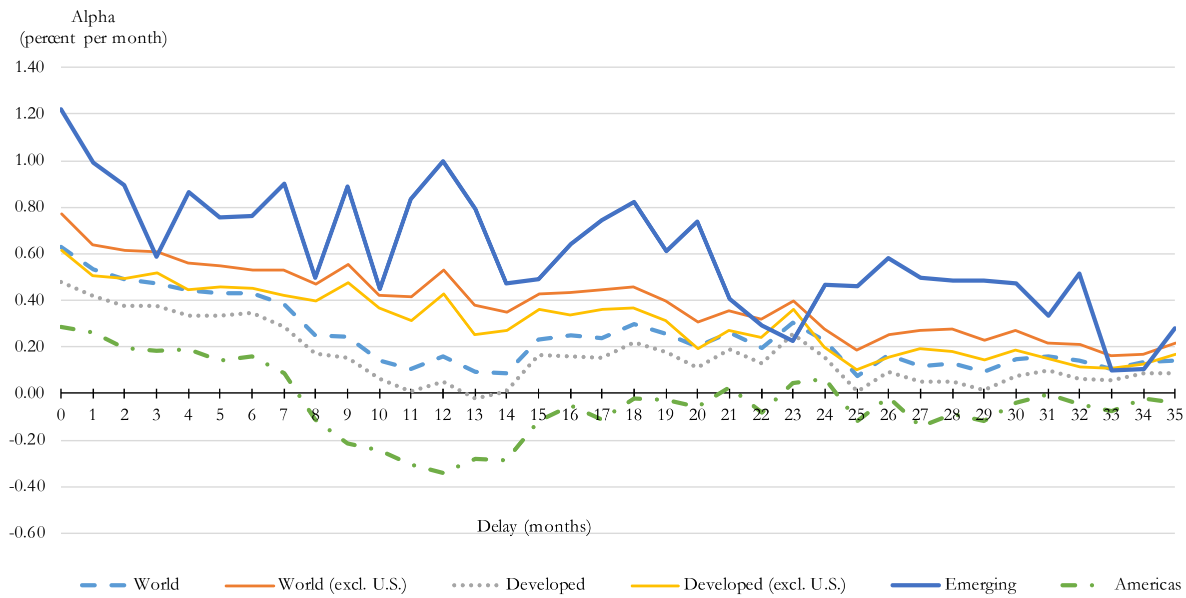

Fig. 1. Lagged signals. The figure shows results from factor model time series regressions. Stocks are sorted each month into quintiles by country based on the mispricing signal, and their industry-adjusted returns are combined into equal-weighted portfolios by region. The signal is lagged between 0 and 35 months. A spread portfolio is formed as the difference between the returns of the portfolios of the most undervalued and the most overvalued stocks, adjusted for industry portfolios based on 38 Fama French industry classifications. The spread portfolio returns are regressed on an 80-factor model comprising the excess return on the market portfolio and factor mimicking portfolios for size, book-to-market, investment, profitability, momentum, short-term reversal, and long-term reversal constructed for the different universes (World, World excl. United States, Developed, Developed excl. United States, Emerging, Americas, Europe, United States, Japan). The figure shows the alphas of time series regressions of portfolio returns on the factors. The sample period is 4/1993–9/2016. All variables are defined in Appendix A.

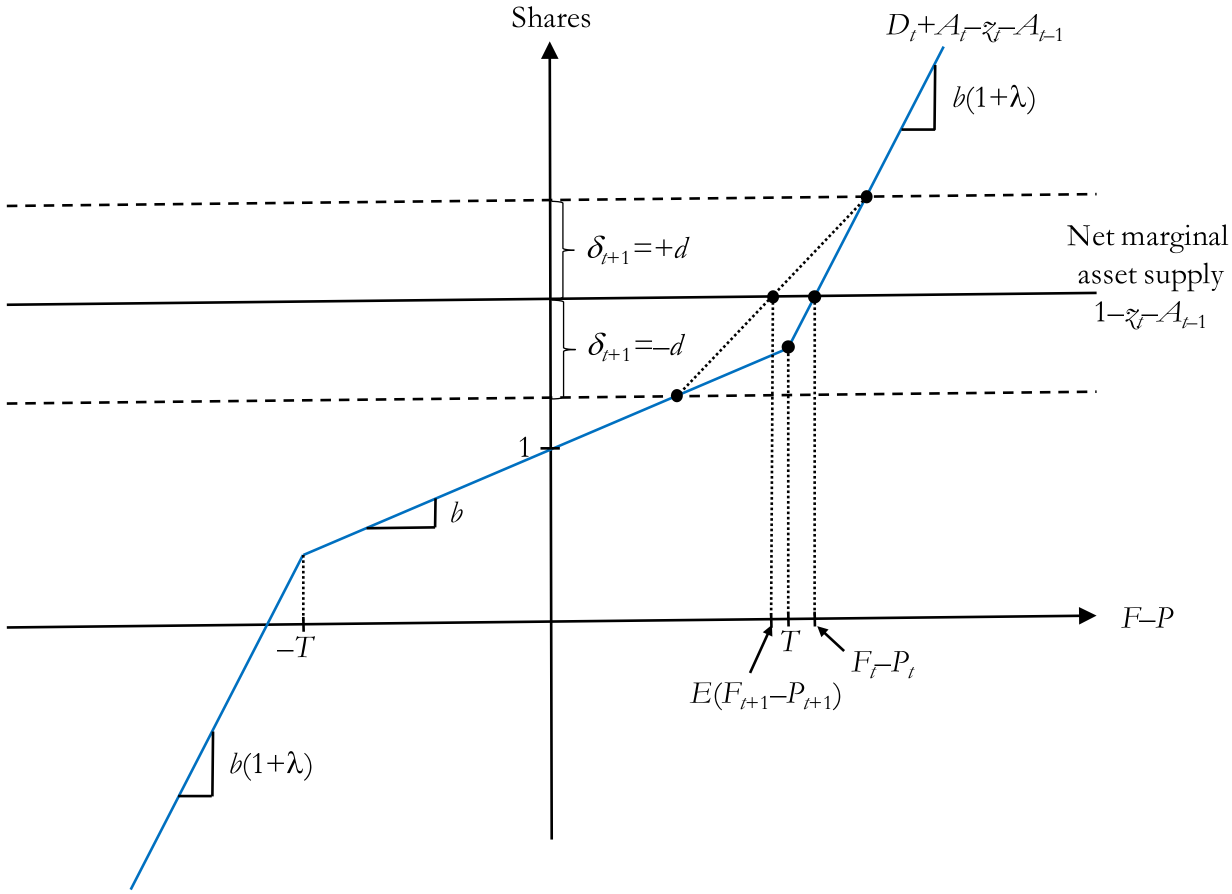

Fig. 2. Mispricing and transactions costs. The figure shows an illustration of the relation between mispricing and transactions costs. The vertical axis shows the number of shares demanded/supplied, and the horizontal axis shows mispricing as the difference between the Fair Value F and the Price P of one share. D_t is the number of shares demanded by domestic investors at date t, $F_t–P_t$ is difference between a share's fair value F_t and its market price P_t at date t, b is the sensitivity of demand to mispricing, and z_t is noise trading demand from errors in estimation, liquidity needs, or sentiment at date t. A_t is number of shares demanded by international arbitrageurs at date t, T are transaction costs and other frictions, and λ is the relative elasticity of arbitrageurs vs. domestic demand with respect to mispricing. $+d$ and $–d$ are realizations of random changes of noise trader demand. The model is described in detail in Appendix B.

Table 1
Summary statistics.
The table reports averages of characteristics of the sample firms. In particular, it reports the time series average of the mean characteristics across all firms, the average cross-sectional correlation of the characteristic with the mispricing signal, as well as the average of the mean characteristics across quintiles of firms sorted by the mispricing signal from Q1 (most overpriced) to Q5 (most underpriced). Statistics are shown separately for firms from all countries (World), from all countries excluding the United States (World excl. U.S.) and from the United States. The sample period is April 1993 to September 2016. All variables are defined in Appendix A.

			Signal quintiles				
Characteristics	All	Correlation	Q1 (overvalued)	Q2	Q3	Q4	Q5 (undervalued)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
World							
Mispricing signal	1.97	1.00	-6.06	-0.43	0.54	1.91	13.91
Market capitalization ($ millions)	2,823.7	-0.02	4,216.4	5,429.1	3,108.0	1061.4	299.7
Book/market	0.71	0.12	0.51	0.52	0.61	0.77	1.13
Beta	0.928	-0.04	0.977	0.972	0.959	0.919	0.815
Accruals	0.136	-0.01	0.145	0.151	0.141	0.132	0.112
Gross profitability	0.332	0.00	0.323	0.338	0.336	0.335	0.329
Return from prior month t (%)	1.767	-0.01	2.679	2.223	1.709	1.312	0.942
Return from month t−1 to t−11 (%)	21.90	-0.03	36.05	28.06	20.57	15.31	10.19
Return from month t–12 to t–59 (%)	103.32	-0.02	129.57	116.57	108.88	89.10	73.55
World (excl. U.S.)							
Mispricing signal	1.97	1.00	-5.93	-0.55	0.57	2.06	13.70
Market capitalization ($ millions)	2,150.0	-0.03	2,613.2	4,354.6	2,660.1	873.9	233.0
Book/market	0.80	0.10	0.60	0.60	0.71	0.87	1.22
Beta	0.831	-0.06	0.887	0.883	0.857	0.795	0.731
Accruals	0.125	-0.02	0.139	0.136	0.128	0.120	0.100
Gross profitability	0.296	0.00	0.295	0.307	0.300	0.295	0.285
Return from prior month t (%)	1.611	-0.01	2.355	1.914	1.572	1.296	0.927
Return from month t−1 to t−11 (%)	20.13	-0.02	32.58	23.64	18.90	15.63	10.15
Return from month t–12 to t–59 (%)	98.51	-0.02	131.28	113.03	104.29	80.75	63.94
United States							
Mispricing signal	2.25	1.00	-5.33	-0.13	0.50	1.60	14.63
Market capitalization ($ millions)	4,072.8	-0.04	7,427.5	7,635.7	3,634.1	1291.2	376.1
Book/market	0.56	0.19	0.37	0.38	0.47	0.59	0.97
Beta	1.099	-0.05	1.131	1.126	1.146	1.148	0.947
Accruals	0.153	-0.02	0.156	0.172	0.161	0.150	0.129
Gross profitability	0.388	0.01	0.366	0.386	0.393	0.397	0.397
Return from prior month t (%)	1.921	-0.02	3.036	2.518	1.810	1.282	1.038
Return from month t−1 to t−11 (%)	23.53	-0.05	39.41	32.54	21.87	14.42	11.15
Return from month t–12 to t–59 (%)	105.78	-0.03	124.02	117.19	108.21	95.88	85.71

Table 2
Portfolio sorts.

The table reports averages and selected test statistics of portfolio returns by region. Panel A also reports the total and average number of sample firms. In particular, the table reports the time series average of the mean return across all firms, the average cross-sectional correlation between returns and the mispricing signal, as well as the average return across quintiles of firms sorted by the mispricing signal from Q1 (most overpriced) to Q5 (most underpriced). The table also shows the time series average of the quintile spread (the difference between the return for the most undervalued firms (5th quintile) and the most overvalued firms (1st quintile)) as well as the associated *t*-statistic of a test against zero. Moreover, the table reports the fraction of time series observations of the quintile spread that is greater than zero and the *p*-value of a binomial test against 50%. Panel A reports results for equal-weighted portfolios, while Panel B shows results for value-weighted portfolios. The sample period is April 1993 to September 2016. All variables are defined in Appendix A.

	Firms				Signal quintiles					Q5-Q1 (undervalued - overvalued)			
	Total	Average	Return	Correlation	Q1 (overvalued)	Q2	Q3	Q4	Q5 (undervalued)	Fraction > 0	[*p*-value]	Average	[*t*-statistic]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Panel A: Equal-weighted portfolios													
World	25,731	7,040	0.85	0.008	0.63	0.70	0.81	0.95	1.16	62.1	[0.00]	0.53	[4.44]
World (excl. U.S.)	16,619	4,425	0.77	0.010	0.57	0.60	0.69	0.85	1.17	64.2	[0.00]	0.60	[5.95]
Developed	20,285	6,213	0.83	0.007	0.65	0.71	0.82	0.92	1.07	57.4	[0.01]	0.42	[3.34]
Developed (excl. U.S.)	11,173	3,598	0.74	0.010	0.57	0.60	0.68	0.79	1.04	57.8	[0.01]	0.47	[4.18]
Emerging	5,446	827	1.17	0.015	0.81	0.79	0.97	1.27	2.04	68.4	[0.00]	1.23	[6.30]
Americas	10,540	2,972	0.99	0.004	0.82	0.89	0.99	1.10	1.14	52.8	[0.34]	0.32	[1.87]
Europe	6,581	2,011	0.93	0.003	0.92	0.89	0.91	0.94	1.00	50.0	[1.00]	0.08	[0.80]
Asia Pacific	8,370	2,011	0.59	0.025	0.19	0.29	0.45	0.74	1.28	67.4	[0.00]	1.09	[6.54]
United States	9,112	2,615	0.97	0.000	0.82	0.88	1.00	1.09	1.08	50.0	[1.00]	0.26	[1.46]
Japan	4,249	1,451	0.52	0.023	0.19	0.23	0.40	0.62	1.15	64.2	[0.00]	0.96	[4.89]
Panel B: Value-weighted portfolios													
World			0.73	0.008	0.65	0.77	0.78	0.85	0.96	54.3	[0.15]	0.31	[1.40]
World (excl. U.S.)			0.60	0.008	0.46	0.68	0.65	0.73	0.95	57.8	[0.01]	0.49	[2.21]
Developed			0.74	0.008	0.68	0.78	0.81	0.90	0.91	52.1	[0.47]	0.23	[1.08]
Developed (excl. U.S.)			0.62	0.010	0.50	0.70	0.69	0.78	0.91	55.3	[0.07]	0.40	[1.86]
Emerging			0.77	0.009	0.33	0.63	0.90	1.00	1.57	61.7	[0.00]	1.24	[3.76]
Americas			0.86	0.007	0.82	0.83	0.95	1.12	1.03	52.1	[0.47]	0.20	[0.93]
Europe			0.82	0.005	0.79	0.82	0.77	0.91	1.10	57.4	[0.01]	0.31	[1.66]
Asia Pacific			0.35	0.024	0.05	0.42	0.53	0.69	1.07	60.3	[0.00]	1.03	[3.38]
United States			0.86	0.007	0.80	0.82	0.99	1.15	1.03	52.8	[0.34]	0.23	[0.97]
Japan			0.33	0.024	0.13	0.44	0.52	0.67	0.96	61.3	[0.00]	0.84	[3.44]

Table 3
Fama-MacBeth regressions.
The table shows results from Fama MacBeth (1973) regressions. Across different specifications, the return in the next month is regressed on the mispricing signal, control variables as well as country and industry fixed effects. Regressions use firm characteristics as controls, i.e. market beta, book-to-market, market capitalization, short-term reversal, momentum, long-term reversal, accruals, earnings momentum (SUE), gross profitability and earnings yield, employing quintile dummies for the characteristics as regressors. Each month's quintiles are determined from sorts of firms with non-missing values for all characteristics. Signal quintiles are based on country breakpoints. Size quintiles are based on NYSE breakpoints. All other quintiles are based on country breakpoints. The regressions include dummy variables for quintiles 2, 3, 4 and 5 of each characteristic, but the table only displays the coefficients of the quintile dummy with the largest amount of the characteristic (Q5) for brevity. Panel A shows results for regressions with firm characteristics controls based on the global sample. Panel B reports only the coefficient on the 5th quintile dummy variable of the mispricing signal for the same specifications as in Panel A by region. All regressions use dummy variables based on 38 Fama French industry classifications as well as country dummy variables. The table shows the average regression coefficients, associated *t*-statistics, as well as the average number of observations and adjusted r-squared. The sample period is April 1993 to September 2016. All variables are defined in Appendix A.

	Specification 1		Specification 2	
	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]
Panel A: Global sample				
Mispricing Signal (Q5)	0.43	[6.55]	0.29	[4.47]
Beta (Q5)	-0.01	[-0.05]	0.03	[0.18]
Market capitalization (Q5)	0.06	[0.47]	0.06	[0.47]
Book/market (Q5)	0.29	[3.23]	0.39	[4.90]
Short-term reversal (Q5)	-1.06	[-8.54]	-1.09	[-8.81]
Momentum (Q5)	0.62	[3.96]	0.65	[4.30]
Long-term reversal (Q5)	-0.19	[-2.19]	-0.23	[-2.73]
Accruals Q5			-0.27	[-5.35]
SUE (Q5)			-0.08	[-1.37]
Gross profitability (Q5)			0.51	[8.11]
Earnings yield (Q5)			0.37	[4.33]
Intercept	0.86	[1.96]	0.59	[1.31]
Number of observations	3,445		3,445	
Adj. R-Squared	0.15		0.15	
Country controls	Yes		Yes	
Industry controls	Yes		Yes	

(continued)

Table 3
Fama-MacBeth regressions (continued).

	Specification 1		Specification 2	
	Coefficient	[t-statistic]	Coefficient	[t-statistic]
Panel B: Results by region				
World	0.43	[6.55]	0.29	[4.47]
World (excl. U.S.)	0.49	[6.45]	0.35	[4.58]
Developed	0.37	[5.09]	0.22	[3.14]
Developed (excl. U.S.)	0.41	[4.96]	0.26	[3.13]
Emerging	0.83	[3.02]	0.63	[2.21]
Americas	0.27	[2.36]	0.12	[1.02]
Europe	0.08	[1.01]	-0.03	[-0.35]
Asia Pacific	0.82	[6.57]	0.60	[4.53]
United States	0.24	[1.84]	0.10	[0.77]
Japan	0.78	[5.51]	0.54	[3.78]

Table 4
Emerging vs. developed markets.
The table shows results from Fama MacBeth (1973) regressions. Across different specifications, the return in the next month is regressed on the mispricing signal, market beta, book-to-market, market capitalization, short-term reversal, momentum, long-term reversal, accruals, earnings momentum (SUE), gross profitability and earnings yield. The table employs quintile dummies for the characteristics as regressors. Each month's quintiles are determined from sorts of firms with non-missing values for all characteristics. Signal quintiles are based on country breakpoints. Size quintiles are based on NYSE breakpoints. All other quintiles are based on country breakpoints. The regressions include dummy variables for quintiles 2, 3, 4 and 5 of each characteristic. The panel shows results for the global sample and the same specifications as in Table 3 Panel A, but adds fixed effects for regions and degree of development as well as their interaction with the mispricing signal quintile dummies. All regressions use dummy variables based on 38 Fama French industry classifications. For brevity, the panel only reports the coefficient on the 5th quintile dummy variable of the mispricing signal (Q5) as well as its interactions with the region and development fixed effects. The panel shows the average regression coefficients, associated *t*-statistics, as well as the average number of observations and adjusted r-squared. The sample period is April 1993 to September 2016. All variables are defined in Appendix A.

	Regressions with country fixed effects				Regressions with geographic region and development controls			
	Specification 1		Specification 2		Specification 1		Specification 2	
	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]
Mispricing signal (Q5)	0.29	[2.68]	0.13	[1.22]	0.25	[2.27]	0.08	[0.78]
*Mispricing signal (Q5) * Emerging*	0.61	[2.17]	0.65	[2.35]	0.62	[2.20]	0.66	[2.38]
*Mispricing signal (Q5) * Asia Pacific*	0.48	[2.52]	0.47	[2.52]	0.50	[2.65]	0.50	[2.68]
*Mispricing signal (Q5) * Europe*	-0.30	[-2.24]	-0.23	[-1.75]	-0.26	[-1.96]	-0.19	[-1.45]
*Mispricing signal (Q5) * Africa*	-0.32	[-0.74]	-0.30	[-0.69]	-0.34	[-0.79]	-0.32	[-0.74]
Number of observations	3,445		3,445		3,445		3,445	
Adj. R-Squared	0.15		0.16		0.12		0.12	
Firm characteristic controls	Yes		Yes		Yes		Yes	
Country controls	Yes		Yes		No		No	
Development control	No		No		Yes		Yes	
Geographic region controls	No		No		Yes		Yes	
Industry controls	Yes		Yes		Yes		Yes	

Table 5
Country determinants of trading profits.
The table shows results from firm-level Fama-MacBeth (1973) regressions. The stock return in the next month is regressed on the mispricing signal, firm characteristic controls (i.e. market beta, book-to-market, market capitalization, short-term reversal, momentum, long-term reversal, accruals, earnings momentum (SUE), gross profitability and earnings yield) and country characteristics interacted with the mispricing signal. The table employs quintile dummies for the characteristics as regressors. Each month's quintiles are determined from sorts of firms with non-missing values for all characteristics. Signal quintiles are based on country breakpoints. Size quintiles are based on NYSE breakpoints. All other quintiles are based on country breakpoints. The regressions include dummy variables for quintiles 2, 3, 4 and 5 of each characteristic. The quintile dummies for the mispricing signal are also interacted with various country characteristics. For brevity, the panel only displays the coefficients of 5th quintile of the mispricing signal as well as the interactions of that quintile dummy with the country characteristics. All regressions use dummy variables based on 38 Fama French industry classifications as well as country dummy variables. The panel shows the average regression coefficients, associated *t*-statistics, as well as the average number of observations and adjusted r-squared. The sample period is April 1993 to September 2016. All variables are defined in Appendix A.

	Specification 1		Specification 2	
	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]
Mispricing signal (Q5)	0.04	[0.29]	1.45	[0.54]
Trading Costs				
*Mispricing signal (Q5) * Transactions costs*	0.75	[2.13]	1.43	[1.87]
Regulatory				
*Mispricing signal (Q5) * Short sales dummy*			0.00	[0.00]
*Mispricing signal (Q5) * Common law*			-0.94	[-2.21]
Economic & financial development				
*Mispricing signal (Q5) * Deposit banks' assets/GDP*			-0.01	[-1.19]
*Mispricing signal (Q5) * Private credit by deposit money banks/GDP*			0.01	[0.81]
*Mispricing signal (Q5) * Stock market turnover ratio*			0.00	[0.14]
*Mispricing signal (Q5) * Country risk (inverse index)*			0.01	[0.38]
*Mispricing signal (Q5) * Geographical size (log)*			0.05	[0.61]
Informational environment				
*Mispricing signal (Q5) * Analyst coverage*			-0.01	[-0.73]
Characteristics of equity market				
*Mispricing signal (Q5) * Market volatility*			-8.11	[-2.53]
*Mispricing signal (Q5) * Correlation with world market*			-1.76	[-1.29]
*Mispricing signal (Q5) * Number of listed companies (log)*			0.15	[1.09]
Intercept	0.49	[1.10]	-0.23	[-0.24]
Number of observations	3,440		3,440	
Adj. R-Squared	0.15		0.16	
Firm characteristic controls	Yes		Yes	
Country controls	Yes		Yes	
Industry controls	Yes		Yes	

Table 6
Time-series factor model regressions.

The table shows results from factor model time series regressions. Stocks are sorted each month by country into quintiles based on the mispricing signal and combined into equal-weighted or value-weighted portfolios by region. Portfolio returns are in excess of the industry portfolios based on 38 Fama French industry classifications. Regressions are performed separately for each of the portfolios. Additionally, a spread portfolio is formed as the difference between the returns of the portfolios Q5 (most undervalued stocks) and Q1 (most overvalued stocks). Portfolio returns are regressed alternatively on an intercept (Industry-adjusted Returns), on an 80-factor model comprising the excess return on the market portfolio and factor mimicking portfolios for size, book-to-market, investment, profitability, momentum, short-term reversal, and long-term reversal constructed for the different universes (World, World excl. United States, Developed, Developed excl. United States, Emerging, Americas, Europe, United States, Japan), and a 50-factor model (that includes all available factors from the Ken French data library, namely the return on the market portfolio minus the risk-free rate (Mkt_RF), small minus big (SMB), high minus low (HML), conservative minus aggressive (CMA), robust minus weak (RMW), short-term reversal (ST_Rev), momentum (Mom), long-term reversal (LT_Rev) for the United States, and Mkt_RF, SMB, HML, CMA, RMW and winners minus losers (WML) for Global, Global ex US, Europe, Japan, Asia Pacific ex Japan, North America, and Emerging Markets). The table reports the regression coefficients of the regression intercept and associated *t*-statistics of time series regressions of portfolio excess returns on the factors. Results in Panel A are for equal-weighted portfolios, while results in Panel B are for value-weighted portfolios. The sample period is April 1993 to September 2016. All variables are defined in Appendix A.

(continued)

Table 6
Time-series factor model regressions (continued).

	Q5-Q1		Q1 (overvalued)		Q2		Q3		Q4		Q5 (undervalued)	
	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]
Panel A: Equal-weighted portfolios												
Industry-adjusted returns												
World	0.55	[5.51]	-0.22	[-4.28]	-0.14	[-2.41]	-0.04	[-1.05]	0.12	[2.70]	0.33	[5.27]
World (excl. U.S.)	0.61	[6.89]	-0.29	[-3.40]	-0.24	[-3.26]	-0.14	[-1.82]	0.03	[0.36]	0.33	[3.15]
Developed	0.45	[4.20]	-0.21	[-3.41]	-0.13	[-1.92]	-0.03	[-0.71]	0.09	[1.57]	0.24	[3.30]
Developed (excl. U.S.)	0.49	[4.91]	-0.28	[-2.84]	-0.24	[-2.67]	-0.15	[-1.62]	-0.03	[-0.26]	0.21	[1.71]
Emerging	1.16	[5.95]	-0.06	[-0.18]	-0.07	[-0.21]	0.10	[0.31]	0.43	[1.29]	1.10	[3.00]
Americas	0.35	[2.41]	-0.05	[-0.37]	0.03	[0.20]	0.12	[0.93]	0.25	[1.76]	0.30	[2.23]
Europe	0.09	[1.01]	0.07	[0.52]	0.05	[0.39]	0.08	[0.63]	0.12	[0.95]	0.16	[1.19]
Asia Pacific	1.10	[7.11]	-0.67	[-2.88]	-0.55	[-2.56]	-0.37	[-1.71]	-0.10	[-0.47]	0.43	[1.75]
United States	0.29	[1.89]	-0.05	[-0.37]	0.02	[0.11]	0.13	[0.87]	0.25	[1.56]	0.24	[1.65]
Japan	0.97	[5.32]	-0.66	[-2.45]	-0.60	[-2.44]	-0.41	[-1.67]	-0.22	[-0.85]	0.31	[1.14]
Factor model alphas (80 factors)												
World	0.59	[5.99]	-0.27	[-4.50]	-0.09	[-2.10]	0.01	[0.29]	0.10	[2.49]	0.32	[5.32]
World (excl. U.S.)	0.73	[6.96]	-0.22	[-3.60]	-0.15	[-3.82]	-0.02	[-0.44]	0.14	[3.40]	0.51	[7.11]
Developed	0.48	[4.65]	-0.25	[-4.06]	-0.07	[-1.45]	0.03	[0.73]	0.08	[1.84]	0.23	[3.44]
Developed (excl. U.S.)	0.63	[5.38]	-0.19	[-2.80]	-0.10	[-2.19]	0.04	[0.87]	0.16	[3.19]	0.44	[5.30]
Emerging	0.97	[3.82]	-0.46	[-2.34]	-0.60	[-3.28]	-0.53	[-2.96]	-0.22	[-1.15]	0.51	[2.00]
Americas	0.27	[1.99]	-0.31	[-3.19]	-0.08	[-1.02]	-0.05	[-0.74]	-0.05	[-0.62]	-0.05	[-0.47]
Europe	0.23	[2.29]	-0.04	[-0.52]	-0.05	[-0.82]	0.03	[0.62]	0.04	[0.63]	0.20	[2.00]
Asia Pacific	1.15	[6.21]	-0.53	[-3.91]	-0.33	[-4.06]	-0.15	[-1.95]	0.14	[1.46]	0.63	[4.76]
United States	0.18	[1.27]	-0.33	[-3.11]	-0.10	[-1.18]	-0.06	[-0.88]	-0.07	[-0.81]	-0.14	[-1.41]
Japan	1.07	[4.78]	-0.37	[-2.34]	-0.22	[-2.27]	0.01	[0.13]	0.28	[2.69]	0.70	[4.29]
Factor model alphas (Fama French data library, 50 factors)												
World	0.70	[6.73]	-0.32	[-4.93]	-0.17	[-3.37]	-0.03	[-0.82]	0.07	[1.73]	0.38	[5.89]
World (excl. U.S.)	0.80	[7.42]	-0.24	[-3.54]	-0.14	[-2.75]	-0.01	[-0.20]	0.12	[2.23]	0.56	[7.31]
Developed	0.65	[5.87]	-0.32	[-4.24]	-0.14	[-2.28]	0.00	[-0.10]	0.08	[1.47]	0.33	[4.30]
Developed (excl. U.S.)	0.76	[6.34]	-0.24	[-3.03]	-0.08	[-1.20]	0.05	[0.84]	0.16	[2.40]	0.52	[5.77]
Emerging	0.92	[3.45]	-0.16	[-0.42]	-0.52	[-1.44]	-0.30	[-0.80]	-0.02	[-0.05]	0.75	[1.75]
Americas	0.46	[3.09]	-0.38	[-3.41]	-0.25	[-2.72]	-0.11	[-1.38]	-0.07	[-0.79]	0.08	[0.73]
Europe	0.25	[2.35]	-0.11	[-1.42]	-0.05	[-0.65]	0.02	[0.33]	0.00	[-0.00]	0.14	[1.35]
Asia Pacific	1.29	[6.63]	-0.46	[-3.00]	-0.27	[-2.36]	-0.10	[-0.77]	0.19	[1.43]	0.84	[5.05]
United States	0.41	[2.55]	-0.39	[-3.23]	-0.27	[-2.83]	-0.12	[-1.37]	-0.07	[-0.73]	0.02	[0.17]
Japan	1.30	[5.56]	-0.41	[-2.54]	-0.13	[-1.22]	0.02	[0.21]	0.30	[2.55]	0.88	[5.13]

(continued)

Table 6
Time-series factor model regressions (continued).

	Q5-Q1		Q1 (overvalued)		Q2		Q3		Q4		Q5 (undervalued)	
	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]
Panel B: Value-weighted portfolios												
Industry-adjusted returns												
World	0.35	[1.78]	-0.22	[-1.71]	-0.08	[-0.66]	-0.13	[-1.24]	-0.03	[-0.32]	0.13	[1.00]
World (excl. U.S.)	0.51	[2.62]	-0.40	[-3.15]	-0.19	[-1.60]	-0.22	[-1.77]	-0.11	[-0.89]	0.10	[0.66]
Developed	0.28	[1.47]	-0.19	[-1.51]	-0.07	[-0.57]	-0.11	[-0.93]	0.00	[0.03]	0.09	[0.71]
Developed (excl. U.S.)	0.44	[2.33]	-0.37	[-2.78]	-0.18	[-1.41]	-0.19	[-1.51]	-0.08	[-0.65]	0.07	[0.47]
Emerging	1.14	[3.52]	-0.50	[-1.46]	-0.17	[-0.44]	0.07	[0.24]	0.25	[0.75]	0.64	[1.66]
Americas	0.23	[1.13]	0.00	[-0.00]	0.00	[-0.02]	0.00	[0.03]	0.22	[1.40]	0.23	[1.33]
Europe	0.35	[2.33]	-0.08	[-0.52]	-0.07	[-0.46]	-0.10	[-0.65]	0.10	[0.61]	0.27	[1.72]
Asia Pacific	1.05	[3.71]	-0.84	[-3.41]	-0.39	[-1.65]	-0.34	[-1.59]	-0.21	[-0.91]	0.21	[0.72]
United States	0.25	[1.13]	-0.02	[-0.09]	-0.02	[-0.09]	0.04	[0.29]	0.24	[1.44]	0.23	[1.24]
Japan	0.87	[3.90]	-0.76	[-2.97]	-0.39	[-1.56]	-0.31	[-1.34]	-0.21	[-0.91]	0.11	[0.41]
Factor model alphas (80 factors)												
World	0.29	[1.67]	-0.24	[-2.18]	0.02	[0.24]	-0.10	[-1.29]	0.00	[-0.03]	0.05	[0.46]
World (excl. U.S.)	0.44	[2.35]	-0.22	[-1.95]	0.00	[0.03]	-0.10	[-1.25]	0.12	[1.10]	0.23	[1.81]
Developed	0.14	[0.82]	-0.22	[-2.08]	0.01	[0.19]	-0.09	[-1.18]	-0.03	[-0.29]	-0.09	[-0.77]
Developed (excl. U.S.)	0.29	[1.56]	-0.19	[-1.72]	0.00	[0.02]	-0.08	[-0.95]	0.06	[0.63]	0.10	[0.80]
Emerging	0.98	[2.55]	-0.48	[-1.73]	-0.21	[-0.71]	-0.19	[-0.86]	0.30	[1.13]	0.50	[1.77]
Americas	0.01	[0.07]	-0.16	[-1.45]	0.01	[0.13]	-0.11	[-1.11]	0.01	[0.06]	-0.15	[-1.15]
Europe	0.32	[1.98]	-0.17	[-1.57]	-0.05	[-0.73]	-0.13	[-1.40]	0.16	[1.29]	0.15	[1.20]
Asia Pacific	1.29	[4.73]	-0.59	[-3.69]	-0.07	[-0.55]	0.09	[0.70]	0.26	[1.79]	0.71	[3.85]
United States	0.02	[0.11]	-0.19	[-1.57]	0.01	[0.12]	-0.12	[-1.10]	0.01	[0.07]	-0.16	[-1.16]
Japan	0.93	[3.90]	-0.40	[-2.76]	0.00	[0.01]	0.16	[1.30]	0.24	[1.91]	0.52	[3.59]
Factor model alphas (Fama French data library, 50 factors)												
World	0.60	[3.21]	-0.30	[-2.63]	-0.05	[-0.50]	-0.10	[-1.13]	0.06	[0.62]	0.30	[2.26]
World (excl. U.S.)	0.52	[2.27]	-0.17	[-1.40]	-0.09	[-0.95]	-0.08	[-0.85]	0.10	[0.76]	0.35	[2.16]
Developed	0.51	[2.90]	-0.29	[-2.51]	-0.03	[-0.35]	-0.05	[-0.53]	0.13	[1.28]	0.22	[1.86]
Developed (excl. U.S.)	0.40	[1.84]	-0.15	[-1.18]	-0.06	[-0.61]	-0.01	[-0.15]	0.18	[1.40]	0.25	[1.77]
Emerging	1.15	[2.57]	-0.36	[-0.86]	-0.64	[-1.34]	-0.43	[-1.18]	-0.21	[-0.54]	0.79	[1.69]
Americas	0.42	[2.21]	-0.28	[-2.14]	0.01	[0.08]	-0.11	[-1.01]	0.07	[0.52]	0.14	[1.01]
Europe	0.25	[1.39]	-0.09	[-0.74]	-0.08	[-0.79]	-0.10	[-0.91]	0.09	[0.66]	0.16	[1.16]
Asia Pacific	1.34	[3.81]	-0.40	[-2.10]	-0.15	[-0.84]	-0.02	[-0.14]	0.30	[1.32]	0.94	[3.26]
United States	0.45	[2.18]	-0.30	[-2.14]	0.02	[0.17]	-0.09	[-0.72]	0.09	[0.69]	0.14	[0.96]
Japan	1.13	[4.21]	-0.42	[-2.42]	0.01	[0.09]	0.27	[1.86]	0.41	[2.54]	0.71	[4.22]

Table 7
Mispricing strategies within quintiles of other anomalies.
The table shows intercepts and *t*-statistics from time series regressions of monthly industry-adjusted portfolio returns of a mispricing-based spread portfolio on alternatively 80 (Panel A) and 50 factors (Panel B). Stocks are first sorted each month into quintiles, designated by column heading, based on the row's firm characteristic. Within each of the former quintiles, stocks are further sorted into quintiles based on the mispricing signal and combined into equal-weighted portfolios. Portfolio returns are in excess of the industry portfolios based on 38 Fama French industry classifications. The industry-adjusted return difference of the most underpriced and overpriced stocks within each cell are then regressed on an 80-factor model comprising the excess return on the market portfolio and factor mimicking portfolios for size, book-to-market, investment, profitability, momentum, short-term reversal, and long-term reversal constructed for the different universes (World, World excl. United States, Developed, Developed excl. United States, Emerging, Americas, Europe, United States, Japan), and a 50-factor model (that includes all available factors from the Ken French data library, namely Mkt_RF, SMB, HML, CMA, RMW, ST_Rev, Mom, LT_Rev for the United States, and Mkt_RF, SMB, HML, CMA, RMW and WML for Global, Global ex US, Europe, Japan, Asia Pacific ex Japan, North America, and Emerging Markets). The sample period is April 1993 to September 2016. All variables are defined in Appendix A.

(continued)

Table 7
Mispricing strategies within quintiles of other anomalies (continued).

	Q1		Q2		Q3		Q4		Q5	
	Coefficient	[t-statistic]	Coefficient	[t-statistic]	Coefficient	[t-statistic]	Coefficient	[t-statistic]	Coefficient	[t-statistic]
Panel A: 80-factor model alphas										
Beta	0.59	[4.58]	0.51	[4.51]	0.45	[4.41]	0.36	[2.84]	0.59	[3.16]
Book/market	0.36	[2.12]	0.23	[1.87]	0.34	[2.68]	0.58	[5.05]	0.66	[4.99]
Market capitalization	0.69	[6.11]	0.48	[4.48]	0.36	[3.08]	0.22	[1.63]	0.27	[2.58]
Short-term reversal	0.89	[5.67]	0.42	[3.47]	0.52	[4.41]	0.48	[3.95]	0.33	[1.95]
Momentum	0.63	[3.73]	0.43	[3.88]	0.65	[5.99]	0.59	[5.12]	0.85	[5.41]
Long-term reversal	0.74	[4.66]	0.67	[5.44]	0.58	[5.31]	0.35	[3.08]	0.46	[3.13]
Accruals	0.90	[6.23]	0.73	[6.25]	0.40	[3.84]	0.66	[5.25]	0.32	[2.05]
SUE	0.47	[2.80]	0.56	[3.91]	0.42	[3.06]	0.41	[3.17]	0.72	[4.25]
Gross profitability	0.59	[4.13]	0.69	[5.95]	0.65	[4.94]	0.61	[4.80]	0.30	[1.91]
ROA	0.76	[4.38]	0.70	[5.58]	0.63	[5.54]	0.61	[5.38]	0.34	[2.33]
Scaled NOA	0.59	[3.34]	0.70	[5.48]	0.69	[6.13]	0.47	[4.48]	0.45	[3.42]
Share issuance	0.46	[3.50]	0.69	[5.32]	0.67	[4.56]	0.14	[0.94]	0.49	[2.67]
Composite equity issuance	0.58	[3.63]	0.70	[6.33]	0.50	[4.41]	0.32	[2.88]	0.26	[1.89]
Asset growth	0.60	[4.21]	0.64	[5.38]	0.80	[7.02]	0.50	[3.97]	0.30	[1.95]
Capital investment	0.68	[4.79]	0.51	[4.21]	0.59	[4.64]	0.72	[5.76]	0.33	[2.66]
Investment ratio	0.84	[6.58]	0.70	[5.58]	0.48	[3.57]	0.49	[3.76]	0.37	[2.76]
External financing	0.53	[5.07]	0.48	[4.51]	0.96	[6.66]	0.53	[3.50]	0.33	[2.19]
Z-score	0.39	[2.79]	0.41	[3.75]	0.47	[3.99]	0.86	[6.30]	0.71	[4.51]
Leverage	0.72	[3.55]	0.44	[3.19]	0.51	[4.60]	0.58	[5.20]	0.64	[4.81]
Earnings/price	0.61	[3.47]	0.57	[3.75]	0.25	[2.08]	0.42	[4.15]	0.61	[5.05]
Dividends/price	0.37	[2.24]	0.77	[5.27]	0.66	[5.69]	0.57	[5.49]	0.35	[3.52]
Cash flow/price	0.73	[3.59]	0.28	[2.02]	0.41	[3.61]	0.39	[3.84]	0.58	[4.45]

(continued)

Table 7
Mispricing strategies within quintiles of other anomalies (continued).

	Q1		Q2		Q3		Q4		Q5	
	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]
Panel B: 50-factor model alphas (Fama French data library)										
Beta	0.69	[5.10]	0.51	[4.09]	0.50	[4.18]	0.46	[3.37]	0.63	[3.05]
Book/market	0.40	[2.14]	0.37	[2.80]	0.41	[3.15]	0.56	[4.39]	0.65	[4.54]
Market capitalization	0.78	[6.72]	0.62	[4.76]	0.34	[2.82]	0.31	[2.08]	0.25	[2.04]
Short-term reversal	1.09	[6.71]	0.59	[4.64]	0.65	[5.02]	0.53	[4.14]	0.45	[2.42]
Momentum	0.71	[4.01]	0.52	[4.15]	0.74	[6.16]	0.68	[5.50]	0.77	[4.45]
Long-term reversal	0.87	[5.20]	0.70	[5.27]	0.70	[6.05]	0.38	[3.03]	0.49	[2.89]
Accruals	0.99	[6.51]	0.76	[5.85]	0.50	[4.40]	0.78	[6.25]	0.48	[2.78]
SUE	0.67	[3.71]	0.73	[4.92]	0.50	[3.48]	0.60	[4.11]	0.87	[5.00]
Gross profitability	0.66	[4.46]	0.83	[6.80]	0.65	[4.64]	0.89	[6.15]	0.46	[2.75]
ROA	0.76	[4.09]	0.83	[6.37]	0.62	[5.41]	0.69	[5.42]	0.52	[3.19]
Scaled NOA	0.81	[4.32]	0.72	[5.43]	0.76	[6.42]	0.44	[3.74]	0.52	[3.86]
Share issuance	0.68	[5.01]	0.73	[5.22]	1.00	[6.55]	0.54	[3.39]	0.49	[2.48]
Composite equity issuance	0.66	[3.86]	0.75	[6.15]	0.64	[5.20]	0.55	[4.50]	0.42	[2.80]
Asset growth	0.73	[4.79]	0.74	[5.95]	0.79	[6.42]	0.62	[4.33]	0.41	[2.47]
Capital investment	0.60	[4.06]	0.68	[4.83]	0.64	[4.59]	0.97	[7.16]	0.49	[3.48]
Investment ratio	0.81	[5.84]	0.79	[5.66]	0.59	[4.26]	0.59	[4.36]	0.51	[3.63]
External financing	0.61	[5.24]	0.61	[5.31]	1.07	[7.13]	0.83	[4.90]	0.28	[1.72]
Z-score	0.45	[3.05]	0.44	[3.79]	0.56	[4.23]	0.87	[5.87]	0.95	[5.68]
Leverage	0.81	[3.65]	0.63	[4.33]	0.69	[5.47]	0.64	[5.48]	0.63	[4.59]
Earnings/price	0.70	[3.75]	0.74	[4.74]	0.43	[3.45]	0.55	[4.96]	0.65	[5.00]
Dividends/price	0.55	[3.17]	0.76	[4.80]	0.61	[4.92]	0.71	[6.01]	0.45	[4.09]
Cash flow/price	0.84	[3.88]	0.47	[3.23]	0.41	[3.25]	0.56	[5.18]	0.65	[4.70]

Table 8
Fama-MacBeth regressions with IPCA expected returns.
The table shows results from Fama MacBeth (1973) regressions. Across different specifications, the return in the next month is regressed on the mispricing signal, model expected returns from an Instrumented Principal Components Analysis (IPCA) as well as country and industry fixed effects. Each month signal quintiles are determined based on country breakpoints. The IPCA is estimated for each region with five factors and twelve instruments. The twelve instruments are the mispricing signal, market beta, book-to-market, market capitalization, short-term reversal, momentum, long-term reversal, accruals, earnings momentum (SUE), gross profitability, earnings yield, and a constant. The unconstrained Fama MacBeth regression includes the IPCA model expected return as an independent variable, while the constrained regression subtracts it from the dependent variable (so that its coefficient is constrained to one). Panel A reports the coefficients on mispricing quintile dummies 2–5, the IPCA model expected return (for unconstrained models) and the regression intercept for the global sample. Panel B reports only the coefficient on the 5th quintile dummy variable of the mispricing signal for the same specifications as in Panel A by region. All regressions use dummy variables based on 38 Fama French industry classifications as well as country dummy variables. The table shows the average regression coefficients, associated *t*-statistics, as well as the average number of observations and adjusted r-squared. The sample period is April 1993 to September 2016. All variables are defined in Appendix A.

	Unconstrained model		Contrained model	
	Coefficient	[*t*-statistic]	Coefficient	[*t*-statistic]
Panel A: Global sample				
Mispricing signal (Q5)	0.41	[4.95]	0.21	[2.22]
Mispricing signal (Q4)	0.25	[3.67]	0.11	[1.31]
Mispricing signal (Q3)	0.11	[1.92]	0.13	[1.71]
Mispricing signal (Q2)	0.04	[0.81]	-0.02	[-0.29]
IPCA model expected return	0.22	[10.36]		
Intercept	0.77	[2.03]	0.86	[1.19]
Number of observations	3,445		3,445	
Adj. R-Squared	0.13		0.05	
Country controls	Yes		Yes	
Industry controls	Yes		Yes	
Panel B: Results by region				
World	0.41	[4.95]	0.21	[2.22]
World (excl. U.S.)	0.48	[5.48]	0.25	[2.61]
Developed	0.34	[4.13]	0.11	[1.10]
Developed (excl. U.S.)	0.41	[4.33]	0.48	[4.35]
Emerging	0.85	[3.67]	0.51	[2.10]
Americas	0.21	[2.05]	0.01	[0.09]
Europe	0.09	[1.10]	0.15	[1.12]
Asia Pacific	0.90	[7.95]	0.42	[3.00]
United States	0.17	[1.53]	-0.03	[-0.25]
Japan	0.67	[5.26]	0.29	[2.14]

Table 9
Overlapping buy-and-hold investment strategies.

The table shows results from factor model time series regressions for buy-and-hold returns by region. Stocks are sorted each month by country into quintiles based on the mispricing signal and combined into equal-weighted. Portfolio returns are in excess of the industry portfolios based on 38 Fama French industry classifications. Following Jegadeesh and Titman (1993, 2001) each portfolio is held for 12 months. The strategy return is the simple average of the returns to the twelve overlapping portfolios at each point in time. Regressions are performed separately for each of the quintile portfolios, where the portfolio of the most overvalued stocks is Q1, while the most undervalued stocks are in portfolio Q5. Additionally, a spread portfolio is formed as the difference between the returns of the portfolios Q5 and Q1. Portfolio returns are regressed alternatively on an intercept (Industry-adjusted Return), on an 80-factor model comprising the excess return on the market portfolio and factor mimicking portfolios for size, book-to-market, investment, profitability, momentum, short-term reversal, and long-term reversal constructed for the different universes (World, World excl. United States, Developed, Developed excl. United States, Emerging, Americas, Europe, United States, Japan), and a 50-factor model (that includes all available factors from the Ken French data library, namely Mkt_RF, SMB, HML, CMA, RMW, ST_Rev, Mom, LT_Rev for the United States, and Mkt_RF, SMB, HML, CMA, RMW and WML for Global, Global ex US, Europe, Japan, Asia Pacific ex Japan, North America, and Emerging Markets). The table reports the regression coefficients of the regression intercept and associated *t*-statistics of time series regressions of portfolio excess returns on the factors. The sample period is April 1993 to September 2016. All variables are defined in Appendix A.

(continued)

Table 9
Overlapping buy-and-hold investment strategies (continued).

	Q5-Q1		Q1 (overvalued)		Q2		Q3		Q4		Q5 (undervalued)	
	Coefficient	[t-statistic]	Coefficient	[t-statistic]	Coefficient	[t-statistic]	Coefficient	[t-statistic]	Coefficient	[t-statistic]	Coefficient	[t-statistic]
Industry-adjusted returns												
World	0.42	[4.92]	-0.16	[-4.15]	-0.11	[-2.57]	-0.05	[-1.38]	0.07	[1.44]	0.26	[4.10]
World (excl. U.S.)	0.49	[5.90]	-0.27	[-3.36]	-0.18	[-2.58]	-0.15	[-2.07]	-0.02	[-0.27]	0.22	[2.18]
Developed	0.35	[3.85]	-0.15	[-3.05]	-0.10	[-1.99]	-0.05	[-1.05]	0.05	[0.84]	0.20	[2.65]
Developed (excl. U.S.)	0.42	[4.61]	-0.27	[-2.91]	-0.19	[-2.33]	-0.17	[-1.91]	-0.06	[-0.59]	0.15	[1.22]
Emerging	0.71	[4.39]	-0.01	[-0.03]	0.06	[0.19]	0.11	[0.35]	0.25	[0.80]	0.70	[2.09]
Americas	0.22	[1.81]	0.06	[0.49]	0.06	[0.43]	0.13	[1.03]	0.22	[1.54]	0.28	[2.11]
Europe	0.10	[1.12]	0.03	[0.25]	0.05	[0.41]	0.03	[0.22]	0.09	[0.66]	0.13	[0.97]
Asia Pacific	0.82	[6.38]	-0.60	[-2.66]	-0.44	[-2.08]	-0.36	[-1.78]	-0.19	[-0.92]	0.22	[0.96]
United States	0.16	[1.24]	0.07	[0.53]	0.06	[0.40]	0.13	[0.95]	0.21	[1.28]	0.23	[1.62]
Japan	0.77	[5.17]	-0.62	[-2.37]	-0.50	[-2.11]	-0.43	[-1.80]	-0.28	[-1.15]	0.15	[0.58]
Factor model alphas (80 factors)												
World	0.42	[5.18]	-0.17	[-3.82]	-0.06	[-1.53]	-0.04	[-1.15]	0.02	[0.53]	0.25	[4.50]
World (excl. U.S.)	0.51	[5.50]	-0.12	[-2.25]	-0.08	[-2.29]	-0.04	[-1.19]	0.10	[2.42]	0.39	[5.76]
Developed	0.33	[3.86]	-0.14	[-3.07]	-0.03	[-0.80]	-0.03	[-0.73]	0.01	[0.23]	0.18	[2.96]
Developed (excl. U.S.)	0.41	[4.08]	-0.07	[-1.18]	-0.03	[-0.83]	-0.01	[-0.15]	0.11	[2.52]	0.34	[4.40]
Emerging	0.87	[4.47]	-0.59	[-3.23]	-0.54	[-2.92]	-0.39	[-2.34]	-0.28	[-1.60]	0.27	[1.25]
Americas	0.19	[1.70]	-0.23	[-3.06]	-0.06	[-0.86]	-0.09	[-1.32]	-0.13	[-1.62]	-0.03	[-0.37]
Europe	0.22	[2.41]	-0.01	[-0.10]	-0.02	[-0.37]	-0.05	[-0.97]	0.05	[0.79]	0.21	[2.24]
Asia Pacific	0.74	[4.52]	-0.38	[-2.97]	-0.22	[-3.10]	-0.12	[-1.77]	0.00	[0.05]	0.37	[2.94]
United States	0.11	[0.89]	-0.22	[-2.78]	-0.06	[-0.84]	-0.10	[-1.35]	-0.17	[-1.96]	-0.11	[-1.14]
Japan	0.60	[3.17]	-0.17	[-1.14]	-0.08	[-1.06]	0.02	[0.29]	0.10	[1.24]	0.43	[2.84]
Factor model alphas (Fama French data library, 50 factors)												
World	0.47	[5.46]	-0.22	[-4.50]	-0.13	[-3.34]	-0.08	[-2.34]	0.02	[0.51]	0.25	[4.19]
World (excl. U.S.)	0.54	[5.60]	-0.14	[-2.28]	-0.09	[-2.02]	-0.05	[-1.09]	0.10	[2.02]	0.40	[5.43]
Developed	0.44	[4.73]	-0.21	[-3.51]	-0.11	[-2.28]	-0.06	[-1.38]	0.04	[0.79]	0.23	[3.09]
Developed (excl. U.S.)	0.52	[4.89]	-0.12	[-1.62]	-0.05	[-0.86]	-0.01	[-0.13]	0.15	[2.54]	0.40	[4.50]
Emerging	0.57	[2.53]	-0.18	[-0.48]	-0.27	[-0.72]	-0.23	[-0.61]	-0.22	[-0.61]	0.39	[0.99]
Americas	0.27	[2.20]	-0.30	[-3.43]	-0.18	[-2.50]	-0.14	[-1.99]	-0.13	[-1.53]	-0.03	[-0.26]
Europe	0.22	[2.35]	-0.09	[-1.23]	-0.11	[-1.64]	-0.09	[-1.35]	0.02	[0.19]	0.13	[1.28]
Asia Pacific	0.88	[5.21]	-0.30	[-2.13]	-0.11	[-0.97]	-0.02	[-0.17]	0.15	[1.35]	0.57	[3.78]
United States	0.24	[1.79]	-0.31	[-3.26]	-0.19	[-2.41]	-0.14	[-1.85]	-0.14	[-1.53]	-0.07	[-0.62]
Japan	0.87	[4.48]	-0.24	[-1.61]	-0.03	[-0.34]	0.05	[0.51]	0.23	[2.34]	0.64	[3.84]

Table 10
Turnover and transactions costs.
The table shows monthly one-way turnover, transactions costs as well as gross and net performance of the mispricing investment strategy. Results are reported separately for strategies with monthly rebalancing and buy-and-hold strategies that rebalance annually. The first column of each panel reproduces the 80-factor alphas from Table 6 (for monthly rebalancing) and Table 9 (buy-and-hold) separately for the returns of the portfolios of the most overvalued stocks (Q1), the most undervalued stocks (Q5) and the spread portfolio (Q5–Q1) for each of the regions. The second column reports one-way turnover (in percent per month). The third column reports the monthly transactions costs based on two-way turnover associated with the respective portfolio using the total transactions cost estimate from Elkins/McSherry. The last column of each panel reports the transactions cost adjusted (net) performance as the difference between the alpha and the transactions costs. The sample period is April 1993 to September 2016. All variables are defined in Appendix A.

	Q1					Q5					Q5-Q1				
	Alpha	One-way turnover	Transactions costs	Net performance	[*t*-statistic]	Alpha	One-way turnover	Transactions costs	Net performance	[*t*-statistic]	Alpha	One-way turnover	Transactions costs	Net performance	[*t*-statistic]
Monthly rebalancing															
World	-0.27	14%	0.10	-0.17	[-2.95]	0.32	13%	0.09	0.23	[3.91]	0.59	29%	0.19	0.40	[4.11]
World ex U.S.	-0.22	15%	0.11	-0.11	[-1.83]	0.51	14%	0.10	0.41	[5.70]	0.73	30%	0.22	0.51	[4.86]
Developed	-0.25	14%	0.08	-0.17	[-2.79]	0.23	13%	0.07	0.15	[2.35]	0.48	28%	0.16	0.32	[3.14]
Developed ex U.S.	-0.19	14%	0.09	-0.10	[-1.46]	0.44	13%	0.08	0.36	[4.30]	0.63	29%	0.19	0.45	[3.83]
Emerging	-0.46	18%	0.25	-0.20	[-1.00]	0.51	17%	0.25	0.26	[0.97]	0.97	36%	0.53	0.44	[1.63]
Americas	-0.31	14%	0.07	-0.24	[-2.49]	-0.05	12%	0.07	-0.11	[-1.12]	0.27	26%	0.14	0.13	[1.01]
Europe	-0.04	16%	0.12	0.08	[1.10]	0.20	14%	0.10	0.09	[0.98]	0.23	32%	0.23	0.00	[0.04]
Asia Pacific	-0.53	14%	0.10	-0.42	[-3.14]	0.63	14%	0.11	0.52	[3.92]	1.15	29%	0.22	0.94	[5.02]
United States	-0.33	13%	0.07	-0.26	[-2.51]	-0.14	12%	0.06	-0.21	[-2.00]	0.18	26%	0.13	0.05	[0.41]
Japan	-0.37	13%	0.07	-0.30	[-1.90]	0.70	14%	0.07	0.62	[3.83]	1.07	28%	0.15	0.92	[4.12]
Buy-and-hold															
World	-0.17	3%	0.02	-0.15	[-3.42]	0.25	3%	0.02	0.23	[4.20]	0.42	6%	0.04	0.38	[4.72]
World ex U.S.	-0.12	3%	0.02	-0.10	[-1.89]	0.39	3%	0.02	0.37	[5.47]	0.51	6%	0.05	0.47	[5.04]
Developed	-0.14	3%	0.02	-0.13	[-2.74]	0.18	3%	0.02	0.17	[2.73]	0.33	6%	0.03	0.29	[3.48]
Developed ex U.S.	-0.07	3%	0.02	-0.05	[-0.90]	0.34	3%	0.02	0.32	[4.19]	0.41	6%	0.04	0.37	[3.73]
Emerging	-0.59	3%	0.05	-0.55	[-3.00]	0.27	3%	0.05	0.23	[1.06]	0.87	7%	0.10	0.77	[3.99]
Americas	-0.23	3%	0.01	-0.21	[-2.87]	-0.03	3%	0.01	-0.05	[-0.51]	0.19	6%	0.03	0.16	[1.44]
Europe	-0.01	3%	0.02	0.02	[0.21]	0.21	3%	0.02	0.19	[2.04]	0.22	6%	0.05	0.17	[1.94]
Asia Pacific	-0.38	3%	0.02	-0.36	[-2.82]	0.37	3%	0.02	0.35	[2.78]	0.74	6%	0.05	0.70	[4.26]
United States	-0.22	3%	0.01	-0.21	[-2.62]	-0.11	3%	0.01	-0.12	[-1.27]	0.11	5%	0.03	0.08	[0.67]
Japan	-0.17	3%	0.02	-0.15	[-1.05]	0.43	3%	0.02	0.42	[2.75]	0.60	6%	0.03	0.57	[3.01]

Appendix A. Variable definitions

This Appendix contains the variable name and the description (or construction) of the main variables used in the paper.

Signal variables

TotalAssets: total assets
NetIncomeAvailableToCommo: net income available to common
NetIncomeBeforeExtraItems: net income before extra items/preferred dividends
PreferredDividendRequirem: preferred dividend requirements
NetIncomeBeforePreferredD: net income before preferred dividends
NetSalesOrRevenues: net sales or revenues
ExtraItemsGainLossSaleOfA: extra items & gain/loss sale of assets
PPENet: property, plant and equipment - net
LongTermDebt: long term debt
CommonEquity: common equity
PreferredStock: preferred stock
OtherIncomeExpenseNet: other income/expense - net
TotalLiabilities: total liabilities
PretaxIncome: pre-tax income
IncomeTaxes: income taxes
OtherAssetsTotal: other assets - total
OtherLiabilities: other liabilities
CashShortTermInvestments: cash & short term investments
OtherCurrentAssets: other current assets
OtherCurrentLiabilities: other current liabilities
CashDividendsPaidTotal: cash dividends paid – total

Other firm-level variables

Accruals: [NOA(t)-NOA(t-1)]/NOA(t-1), where NOA(*t*) = operating assets (*t*) – operating liabilities (*t*). Operating assets is calculated as total assets less cash and short-term investments. Operating liabilities is calculated as total assets less total debt less book value of total common and preferred equity less minority interest (Richardson et al., 2005).
Gross profitability: (revenue - cost of goods sold)/total assets (Novy-Marx 2013).
ROA: return on Assets
Earnings yield: earnings/price
Market capitalization: stock market capitalization (in U.S. Dollars)
Book/market: (book equity + deferred taxes)/market capitalization
Mispricing signal: –1 * residual/market capitalization (Bartram and Grinblatt 2018)
Beta: monthly market beta with regards to the world market estimated over prior 36 months
Short-term reversal: return in prior month
Momentum: return in prior year excluding prior month
Long-term reversal: return in prior five years excluding prior year
SUE: quarterly earnings surprise based on a rolling seasonal random walk model (Livnat and Mendenhall, 2006, p. 185).
Scaled NOA: scaled NOA (Hirshleifer, Hou, Teoh, and Zhang, 2004)
Share issuance: share issuance (Fama and French, 2008)
Composite equity issuance: composite equity issuance (Daniel and Titman, 2006)
Asset growth: asset growth (Cooper, Gulen and Schill, 2008)
Capital investment: abnormal capital investment (Titman, Wei, and Xie, 2004)
Investment ratio: investment ratio (Lyandres, Sun, and Zhang, 2008)
External financing: external financing (Bradshaw, Richardson, and Sloan, 2006)
Z-score: z-score (Ferguson and Shockley, 2003)
Leverage: leverage (Ferguson and Shockley, 2003)
Earnings/price: earnings/price (Penman, Richardson, Riggoni, and Tuna 2018)
Dividends/price: dividends/price (Fama and French, 1992)
Cash flow/price: cash flow/price (Hou, Karolyi, and Kho, 2011)
IPCA model expected return: expected return from a conditional instrumented principal components analysis (IPCA) model with five factors and twelve instruments (Kelly et al., 2018)

(continued)

Appendix A. Variable definitions (continued)

Factor model variables

Mkt_RF: monthly market index return net of risk-free rate
SMB: monthly small minus big size portfolio return
HML: monthly high minus low book/market portfolio return
CMA: monthly conservative minus aggressive investment portfolio return
RMW: monthly robust minus weak profitability portfolio return
Mom (WML): monthly momentum or winners minus losers portfolio return
ST_Rev: monthly short-term reversal portfolio return
LT_Rev: monthly long-term reversal portfolio return

Country-level variables

Short sales dummy: short sales is a dummy variable that equals one if short sales are allowed (from Jain, Jain, McInish and McKenzie, 2013)

Common law: legal origin UK (from LaPorta, López-de-Silanes and Shleifer, 2008)

Deposit banks' assets/GDP: total assets held by deposit money banks as a share of GDP. Assets include claims on domestic real nonfinancial sector which includes central, state and local governments, nonfinancial public enterprises and private sector. Deposit money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits (from World Bank financial development database)

Private credit by deposit money banks/GDP: the financial resources provided to the private sector by domestic money banks as a share of GDP. Domestic money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits (from World Bank financial development database)

Stock market turnover ratio: total value of shares traded during the period divided by the average market capitalization for the period (from World Bank financial development database)

Country risk: composite country risk rating (from PRS Group)

Geographical size (log): geographical size of country in square kilometers (from CIA Factbook)

Analyst coverage: sum of ranks by the average percentage of firms covered in each country and the average number of estimates (setting missing values to zero) (from IBES)

Transactions costs: estimate of total transactions (from Elkins/McSherry LLC)

Market volatility: annualized standard deviation of weekly market index returns in the prior 52 weeks

Correlation with world market: correlation between weekly returns of market index with world market index in the prior 52 weeks

Market index return: return on the local value-weighted market index

Number of listed companies (log): number of publically listed companies (from World Bank financial development database)

Appendix B. A Theoretical Model of Profits from Fair Value – The Role of Jensen's Inequality

The results portray a world in which rational arbitrageurs trade in a country's stock market as long as transaction costs and other frictions or opportunity costs do not deter their trades. These arbitrageurs help tie price movements to bands surrounding a stock's fair value, where countries with greater frictions have wider bands. These bands can be derived from a simple reduced-form model. Consider aggregate domestic demand for a stock in a given country with one share in supply. A plausible and tractable form for downward sloping demand in price is represented by the linear function

$$D_t = 1 + b\left(F_t - P_t\right) + z_t \text{, where} \tag{3}$$

D_t = number of shares demanded by domestic investors at date *t,*

$F_t - P_t$ = difference between a share's fair value F_t and its market price P_t at date *t,*

b = sensitivity of demand to mispricing, and

z_t = noise trading demand from errors in estimation, liquidity needs, or sentiment at date *t.*

If these domestic investors were the only market participants, aggregate demand in the absence of noise trading is consistent with these investors holding one share only when $F_t = P_t$. However, equilibrium prices are not at fair value when the demand of noise traders is non-zero. To clear noise trading demand as well as the mispricing sensitive demand component, the price must satisfy

$$P_t = F_t + \frac{z_t}{b}. \tag{4}$$

Thus, the share price is above fair value when noise trading demand is positive and below fair value when noise trading demand is negative. Moreover, the equation above implies that prices follow a martingale whenever both F and z follow a martingale. Unless noise trading mean-reverts to zero, prices have no mechanism for the co-integration of prices with fair values.

We now introduce international arbitrageurs. These investors face frictions and costs not born by others and are assumed to have a demand function of

$$A_t = \iota_t b\lambda\left(\left|F_t - P_t\right| - T\right) + A_{t-1} \text{, where} \tag{5}$$

A_t = number of shares demanded by international arbitrageurs at date t,

T = transaction costs and other frictions > 0,

ι_t = indicator variable equaling 1 if $F_t - P_t - T > 0$, -1 if $P_t - F_t - T > 0$, and 0 otherwise,

λ = relative elasticity of arbitrageurs vs. domestic demand with respect to mispricing.

Eq. (5) indicates that the flow of new arbitrageur trades changes arbitrageur demand according to the first term on its right side, $\iota_t b\lambda(|F_t - P_t| - T)$. If fair value's deviation from price is positive and exceeds T, $\iota_t = 1$ and arbitrageurs add to their existing stock position (or reduce a short position). In contrast, they short stock (or sell owned stock) in aggregate when the share price exceeds fair value by more than T. When T exceeds mispricing's magnitude, arbitrageur shareholdings do not change, remaining at the prior period's level, A_{t-1}. This last case reflects the prohibitive cost of unwinding the prior arbitrage position. Unlike domestic investors, international arbitrageurs do not have a constant in their demand function because they are long-short investors who do not benefit from the risk sharing that comes from buying and holding a country's stock. As active management intermediaries investing the assets of clients who already maintain passive risk sharing positions on their own, arbitrageurs deploy the excess capital of these clients solely to capture alpha.

While the model's reduced-form linear demand functions are not derived from the first principles of preferences, they are familiar from the exponential utility normal payoff framework. Consistent with the approach taken in Grinblatt and Han (2005), reduced-form linear demand functions are extremely tractable and useful for obtaining closed form equilibrium prices. Aggregating demand from both types of investors (Eq. (3) and (5)) and setting it equal to the aggregate supply of one share, equilibrium prices solve $D_t + A_t = 1$ or

$$1+ b\left(F_t - P_t\right) + z_t + \iota_t b\lambda\left(\left|F_t - P_t\right| - T\right) + A_{t-1} = 1. \tag{6}$$

Equivalently,

$$P_t = F_t - \frac{\iota_t T\lambda}{1+\lambda} + \frac{z_t + A_{t-1}}{b\left(1+\lambda\left|\iota_t\right|\right)}. \tag{7}$$

Eq. (7) is the sum of three terms with the middle term and possibly the λ in the third term representing the degree to which prices are pushed closer to fair value by arbitrageurs' date t flow of funds. If the stock price is below fair value less transaction costs due to the existence of a past net short position by arbitrageurs and noise traders (the third term), ι_t and the middle term are positive. In this case, larger frictions T imply lower prices that are further away from fair value because higher transaction costs deter the flow of funds from arbitrageurs that would otherwise narrow the gap between fair value and price. A parallel argument applies when the price is above fair value. However, if transaction costs exceed the magnitude of mispricing, $\iota_t = 0$, reducing Eq. (7) to

$$P_t = F_t + \frac{z_t + A_{t-1}}{b}. \tag{8}$$

In this region, the local dynamics of risk-adjusted prices depend on the dynamics of noise trading. If noise trading demand follows a random walk, since risk-adjusted fair values also follow a martingale process, risk-adjusted market prices will appear to locally follow a random walk. When the magnitude of mispricing approaches or exceeds transaction costs, so that next period's mispricing has a nonnegligible probability of crossing the transaction cost boundary, mispricing will tend to revert to zero and appear autoregressive until it is sufficiently inside the transactions cost boundary. If noise trading is autoregressive, which seems more plausible, mispricing will be more autoregressive due to the existence of international arbitrageurs.

As Fig. 2 illustrates, the additional convergence of prices to fair value can stem even from random walk arbitrageur demand as a consequence of Jensen's inequality. Consider the case where noise trading follows the process

$$z_t = kz_{t-1} + \delta_t, \tag{9}$$

where δ_t is an i.i.d. binomial random variable that equals $+d$ or $-d$ with equal probability, and κ is a nonnegative autoregression parameter that cannot exceed 1. Fig. 2 illustrates the case where $\kappa = 1$ and the two realizations of δ_{t+1} generate future prices that attract additional capital in the "$+d$ state" and no additional capital in the "$-d$ state." On the right of Fig. 2's vertical axis shares are underpriced, and on the left they are overpriced. What we term "Net marginal asset supply," which determines mispricing at the intersection of supply and demand, is given by $1 - z_t - A_{t-1}$, as the figure's solid horizontal line.

The positive slope of the twice-kinked demand curve is given by the sensitivity of domestic demand with respect to mispricing, b, which represents demand when mispricing is between $+T$ and $-T$. There is higher demand sensitivity, $b(1 + \lambda)$, from both domestic demand and international arbitrageurs, generating locally convex demand at the kink associated with underpricing (above T) and locally concave demand at the overpricing kink (below $-T$) due to lower domestic demand in the "–d state." Because of these kinks, a relatively modest symmetric change in the noise trading realization $z_{t+1} - z_t$, is going to shift the date t horizontal net supply curve to one of the two dashed lines near the rightmost kink in the figure. By Jensen's inequality, the expected change in $F - P$ is negative, but would be positive if we performed the same exercise at the leftmost kink. Thus, if F follows a random walk, expected price changes are positive when stocks are underpriced and negative when overpriced. This is true even if noise trading follows a random walk as seen by the equal distance of the two dotted horizontal lines of future supply from the solid line representing current supply of the asset. If $\kappa < 1$, underpricing would shrink even more between t and $t+1$ as both dotted lines would be lower in the figure.

A sufficiently high value of λ implies that arbitrage capital drives prices arbitrarily close to fair value plus or minus T. To see this, take the limit of Eq. (7) as λ approaches infinity, implying

$$P_t = F_t - \iota_t T \, . \tag{10}$$

In this case of perfectly elastic arbitrageur demand, as transactions costs T approach zero, prices converge to fair value.

The reduced-form model is consistent with our empirical findings. Stocks whose prices deviate from fair value by a small amount, such as those in mispricing quintiles 2–4, exhibit insignificant convergence to fair value. Only stocks with extreme mispricing, due to noise trading, such as stocks in the extreme mispricing quintiles, show significant risk-adjusted alphas. The model suggests that such alphas are the result of convergence of prices to fair value due to the flow of funds by arbitrageurs. We can also see that for a given level of mispricing, stocks with small transaction costs are less likely to experience the same degree of convergence as stocks with large transaction costs. Moreover, we are more likely to find a large degree of mispricing associated with stocks with large transaction costs. Large transaction costs have wider regions between the transaction cost boundaries where Jensen's inequality plays a minimal role if any. This allows mispricing of stocks in some countries to become sufficiently large, and be picked up in quintile mispricing sorts like those in our empirical tests.