Global Market Inefficiencies

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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, but relatively less so in countries with quantifiable market frictions, particularly trading costs, that deter arbitrageurs.

Keywords: International finance, valuation, asset pricing, market efficiency, fundamental analysis, Point-in-Time, Theil-Sen, transaction costs, principal components, 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.[3] Moreover, if the restrictions generate residuals that correlate with the pricing kernel, risk adjustments are needed to assess efficiency. To this end, we estimate fair values by restricting replicating portfolio weights to be best-fit functions of the most commonly reported accounting items (Bartram and Grinblatt, 2018). Thus, two firms with the same accounting data have identical fair values. Imposed across all assets in a country on a given date, the restriction identifies a unique projection matrix of replicating portfolios. This procedure is isomorphic to hedonic pricing – given by a date's unique linear function of a firm's most recently reported accounting items that best fits existing market prices in a given country that month.[4]

In this paper, we study global equity market efficiency using monthly fair values assigned by replicating portfolios for more than 25,000 firms from 36 countries in the 1993-2016 sample period. We then assess whether the percentage deviations of firms' estimated fair values from their market prices – a mispricing signal – predict their future risk-adjusted returns. The annual accounting information required to construct the fair

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[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."

[3] The same monograph, perhaps recognizing the difficulties of practical implementation, eschews this approach. On p. 64, Ross (2005) uses upper bounds on aggregate hedge fund alphas to measure efficiency. He estimates the inefficiency of the 50 trillion USD global financial market that existed in 1996 at less than 0.1% per dollar invested. The less than 0.1% estimate is the almost 800 billion USD investment by hedge funds and other sophisticated institutions times an alpha of 4% per year for each dollar placed under sophisticated management divided by 50 trillion USD.

[4] See Bartram and Grinblat (2018, Appendix A) for proof of the equivalence.

value estimates are publicly reported by the time we formulate trades from the mispricing signals; the data source reports the day of disclosure for each accounting item, including revisions. To our knowledge, this is the first study to use international accounting data that was readily available to investors.

Economically and statistically significant differences in the risk-adjusted returns of the most under- and overpriced within-country stock quintiles are widespread. However, these differences are greater in emerging markets, in the Asia Pacific region (including its developed countries), and in countries with higher trading costs. 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. 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 equally and value-weighted portfolios.

We are 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), and traditional factor models using both a 44-factor model for international stocks developed from the international factors in Fama and French (2016), and our own 80-factor model for international stocks. We also show that our strategy is relatively orthogonal to known anomalies, and because of our agnostic approach to misvaluation, is neither data-snooped nor reliant on any exploratory analysis that makes use of returns.

To assess robustness, the paper's fair value estimates also employ another estimation technique (Theil-Sen), implemented in another context by Ohlson and Kim (2015), that is more robust to outliers. Moreover, we consider two other alternative approaches to measure fair values. One alternative estimates fair value by omitting the regression constant and thus does not require the market portfolio to be fairly valued. The other alternative, 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. These alternatives generally lead to similar and sometimes larger global profits from mispricing.

Risk-adjusted profits from mispricing exceed country-specific institutional investor transactions costs from fees, commissions and market impact. Moreover, 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 estimated profitability would be zero. Thus, global equity markets are inefficient, but are relatively less efficient in countries with quantifiable market frictions, particularly trading costs, that deter arbitrageurs.

We model these findings as an equilibrium outcome of simple linear reduced-form demand functions. In equilibrium, noise trading and stale arbitrageur demand induce deviations of prices from fair value, with friction-related bands that surround fair value constraining the deviations. The greater are the frictions, the wider the bands. Rational arbitrageurs trade in order to capture alpha up to the point where transaction costs and other frictions or opportunity costs make their trades unattractive. Consequently, arbitrageurs help prices converge to fair value, particularly when prices lie near the bands surrounding a stock's fair value. It is this convergence that leads to observable risk-adjusted returns and larger returns when frictions are greater.

Separate from Ross's theoretical insight or those found in our model, the use of profits from trading strategies is a long-established procedure for assessing efficiency. One of the most prominent papers on the relative efficiency of global markets, Griffin, Kelly, and Nardari (2010), judges efficiency from the return spreads of long-short strategies based on the short-term past return (week and month) reversal, momentum, and earnings surprise anomalies. These anomalies were chosen because the return spreads from strategies based on them are claimed to be orthogonal to the pricing kernel, mitigating concerns about risk adjustment. Griffin, Kelly, and Nardari (2010) conclude that emerging markets have similar or smaller return spreads from these anomalies and thus, are *not* less efficient than developed countries' markets.

Our paper adds to the literature on the determinants of cross-sectional expected returns. A large body of research relates return premia to firm characteristics (or factors derived from them), including earnings surprises (Ball and Brown, 1968), size (Banz 1981), book-to-market (Fama and French, 1992), momentum

(Jegadeesh and Titman, 1993), accruals (Sloan, 1996), cash flow-to-price (Hou, Karolyi and Kho, 2011), profitability (Novy-Marx, 2013), etc. In fact, Harvey, Liu and Zhu (2016) and Green, Hand and Zhang (2013) document more than 300 return predictors that academics and practitioners have identified. However, the field has yet to resolve whether the returns earned from these predictors are compensation for risk or evidence of inefficiency. Moreover, McLean and Pontiff (2016) as well as Chordia, Subrahmanyam, and Tong (2014) show that the predictive power of signals has decreased after their publication and with the passage of time. The signal we use generates consistently profitable trading profits within quintiles of firms stratified by 22 other prominent alpha-generating anomalies and thus does not proxy for something "already discovered." Moreover, our signal is not reverse engineered from returns as returns play no role in its construction.

While most of the existing anomaly studies tend to focus on the U.S. equity market, several studies analyze drivers of international stock return premia. 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 the impact of cultural differences as well as differences in financial market development and institutional quality on cross-country differences in momentum profits. Titman, Wei, and Xie (2013) look at asset growth's effect on return premia across countries, finding larger effects from this attribute in countries with 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 both proxies for investment frictions and limits-to-arbitrage.

As noted above, our paper's emerging vs. developed markets results contrast with those from Griffin, Kelly and Nardari (2010), but also from Jacobs (2016), who finds that profits from 11 anomalies are not more prevalent in emerging markets. The trading signal we use, the percentage deviation of an asset's estimated fair value from its price, is a more direct and natural choice for assessing efficiency. In addition, we control for past returns, earnings surprises and yields, accruals, and other sources of return premia, including country fixed effects, and generate more plausible findings: The mispricing signal's greater profits in emerging markets and in markets with high trading costs are more consistent with conventional wisdom about the relative efficiency of equity markets that differ by development and market frictions.

Finally, our signal may be less subject to methodological flaws, like data snooping, that (for U.S. discovered anomalies) can exaggerate an anomaly's true effect in the United States compared to dissimilar countries. This criticism extends to fair values obtained from traditional asset pricing models, which estimate stationary structural parameters. These models may also facilitate the identification of replicating portfolio weights, and offer an alternative route to studying mispricing and market efficiency. However, discretion in parameters and cash flow forecast models makes their implementation complex, somewhat arbitrary, and thus subject to data snooping bias. 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 earnings forecasts).

2 Measurement of Mispricing and Market Frictions

2.1 Mispricing Signal

The size of risk-adjusted returns (alpha) from trading strategies employing public information is a commonly used metric of inefficiency. In a semi-strong form efficient market, for example, investors cannot earn alpha by trading on public information (Fama 1970). Moreover, 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 may 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 may exhibit higher alphas if there is limited supply of investable "smart money" that is mobile across countries.

In this spirit, we analyze the profitability of Bartram and Grinblatt's (2018) mispricing signal across the world's equity markets. The signal first estimates the fair market capitalization of each stock as the market price of a replicating portfolio with identical accounting data, constructed from stocks within the same country.

When restricting the 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.

To minimize concern about data snooping, we closely mimic Bartram and Grinblatt's (2018) procedure with three innocuous exceptions: First, we employ annual data from Thomson Reuters' Worldscope Point-in-Time (PIT) database for international accounting data to maximize coverage and ensure comparability across countries, while their study of U.S. stocks used the quarterly U.S.-only Compustat Point-in-Time database. Second, we use 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 CRSP.

As noted earlier, fair values and residuals are equivalently obtained with hedonic linear least squares prediction of firms' 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 value and residuals are known to market participants at the time of portfolio formation because the study exclusively uses the Worldscope PIT database. This database details when the reported value (in local currency) for a specific accounting item 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.

We also estimate a second fair value for each firm with an alternative to least squares ("OLS") that is more robust to outliers. This alternative is inspired by the by the Theil (1950) and Sen (1968) ("TS" henceforth) median coefficient, which is estimated across a large number of perfectly fit slopes from subsets of the sample.

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

Given the high and sometimes perfect correlations between the regressors, the coefficients and thus their median are not uniquely identified in our setting. The latter issue is addressed by adapting the TS methodology to each firm's median fair value. [6]

2.2 Transaction Costs and Other Frictions

To investigate the impact of transactions costs, we use data from Elkins McSherry LLC on commissions, fees, 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. To convert transaction costs to alpha reductions, we multiply total trading costs per dollar invested by twice a portfolio's turnover and reduce alpha accordingly. Turnover for an underpriced portfolio or overpriced portfolio is separately calculated: each is the average of USD-equivalent purchases and sales per USD-equivalent invested in the portfolio. 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 as a share of 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

[6] The TS fair value is given by simulation. Each simulation draw for a country identifies 100 random firms in a month and fits the 21 accounting variables to the market capitalizations of the firms in that month. For each month, we repeat the draw of 100 firms 10,000 times before identifying the median predicted market capitalizations for each firm as the TS fair value estimate. If the country has fewer than 100 firms that month, TS estimation is identical to OLS estimation.

Rating (from PRS Group), the logged geographical size of the country in Square KM (from CIA Factbook), 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).

3 Sample and Data Sources

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. OTC Bulletin Board and 'Pink Sheet' stocks, ADRs, secondary listings, and stocks with beginning-of-month share prices below 5 USD,[7] 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. The portfolio formation sample period commences in March 1993, the first month when all of the regions we study and most of the countries within them have the required data for at least 30 firms.[8]

For international comparisons requiring common units, we employ U.S. Dollar equivalents. Monthly USD-translated stock returns and both local currency and USD market capitalization are from Datastream.[9] 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 winsorized at the top and bottom 0.1% of the final sample.[10] 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.

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[7] Hou, Xue, and Zhang (2017) find that 64% of 447 anomalies discovered in the literature 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 10 mio. market capitalization filter.

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

[9] Since we are studying the performance of country-neutral long/short portfolios, results using local currency returns would be identical to those reported in the paper.

[10] While Datastream lacks codes for delisting due to poor performance, unlike CRSP, 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.

The Elkins McSherry LLC 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. Figure 1 Panel A's pie chart shows the number of firms from each country; Panel B groups these countries into five regions – based on geography and, within each region, by stage of development ("Developed" vs. "Emerging"). Panel A shows the largest numbers of firms coming 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%). Figure 2 depicts the sample size's evolution over time: starting with about 3,700 firms in 1993, and increasing 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 United States 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 U.S.

4 Empirical Results

4.1 Univariate Analysis of Market Efficiency

4.1.1 *Summary Statistics*

At the end of each month, we sort every global stock meeting the sample's criteria into intra-country mispricing quintiles. The sorted trading signal is the percentage deviation of a firm's fair value estimate from its market capitalization – the former being the prediction from that month's intra-country OLS regression of market capitalization on 21 firm-level accounting variables, 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.).[11] 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 a global sort of 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 includes 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, which, in turn, are comparable to the U.S.-only pattern portrayed in Bartram and Grinblatt (2018).

All three groupings indicate that the undervalued firms (Q5) tend to have higher book-to-market ratios, and lower betas, accruals, market capitalizations, and past returns. Consisting of low-accrual small-value stocks, beaten up over the past month and 5 years, we expect Q5 to have higher subsequent returns. However, their lower returns over the prior year and lower betas 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 correlations between the characteristics and mispricing. The crudeness justifies the aggregations into quintiles. Had the Bartram and Grinblatt (2018) technique been focused more on accurate fair value estimation, other procedures would have been used, including additional prediction variables both current and historical, pruning of unneeded prediction variables, models of cash flow growth with analyst forecasts, and Bayesian shrinkage of fair value estimates.

[11] 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.

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 risk-adjusted return spreads as better metrics of true convergence and efficiency. Our use of quintiles from the signal takes advantage of the quintile sorts' ability to cast a wide net. For example, quintile 5's firms all have signals with a relatively greater tendency to capture truly undervalued firms and a relative smaller tendency to capture truly overvalued firms, compared to quintile 1.

4.1.2 Return Spreads

With this motivation in mind, Table 2 reports time-series averages of USD-translated returns for equal- (Panel A) and value-weighted (Panel B) portfolios of stocks by geographic and developmental regions, stratified by quintiles for the intra-country mispricing signal. 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. Table 2 focuses on OLS estimates of fair value, but also provides return spreads and test statistics for TS estimates of mispricing (on its right).

The first row of the table's two panels 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. The spread is positive in 62% of the months studied. The subsequent row shows that the World's high return spread is largely driven by quintiles from non-U.S. countries, which exhibit a significant 60 bp per month spread compared to an insignificant 26 bp in the U.S. The smallest spreads are in Europe (8 bp); the largest are in emerging markets (123 bp).

Panel A's equally-weighted return spreads illustrate that developed countries besides the United States have lower return spreads than emerging markets countries. For example, the quintile spreads are 42, 47, and

123 bp per month for stocks in developed, developed excluding the United States, and emerging markets, respectively. Spreads are also larger in the Asia Pacific region (109 bp), which has a large number of firms from emerging markets (like Korea and China). However, developed Japan also shows a large return spread (96 bp). The right portion of Table 2 reports monthly return spreads with TS fair value estimates. Except for Europe (33 bp) and Japan (55 bp), Panel A's TS-fair value return spreads and their OLS counterparts are of similar magnitude.

Panel B's value-weighted portfolios show modestly smaller OLS (and highly similar TS) return spreads, but a similar monotonic or nearly monotonic pattern as their equal-weighted counterpart in Panel A, particularly for the groupings with larger numbers of firms. In Panel B's top two rows, the average monthly Q5-Q1 OLS return spread is 31 bp for the full sample, with a significant average monthly OLS spread of 49 bp for stocks outside the United States, and an insignificant 23 bp in the United States. The performance of value-weighted portfolio strategies is similarly strong and significant for Asia Pacific, Emerging Markets, and Japan. In these three regions, the value-weighted OLS return spreads are 103, 124, and 84 bp, respectively.[12]

In sum, Table 2 documents significant return spreads from signals derived from a large set of accounting variables. Trading profits exist for many of the equally- 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 in order to better assess the incremental performance of the mispricing signal.

4.2 Multivariate Analysis of Market Efficiency

4.2.1 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 and control variables known at the end of month t. It reports time series averages of the coefficients across all months along with Fama and

[12] Using CRSP and Compustat for signal inputs with the same accounting items, sample firms and time period, strategy payoffs are 2.3% higher per year with quarterly compared to annual accounting data. Thus, lower frequency accounting data explains Table 2's lower performance, compared to Bartram and Grinblatt (2018).

MacBeth (1973) test statistics. Panel A studies the 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). The cross-sectional regression measures the mispricing signal's efficacy from the coefficient b_t in

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

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.

The regressions use quintile dummies (Q2, Q3, Q4, and Q5, with Q1 omitted) for all of the non-fixed-effect regressors instead of the 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.[13]

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 100 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 the mispricing signal, both here and throughout the paper, are based on intra-country sorts, as they are based on the intra-country mispricing signal. The quintiles for all controls are also based on intra-country sorts, except, following research precedent, size quintiles both here and throughout the paper are based on NYSE breakpoints. To allow a fair comparison, all variables are constructed using the

[13] 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 adjustment or when forcing industry fixed effects coefficients to be one negligibly differ from those reported in Table 3.

latest market valuations and point-in-time accounting data available to investors at the time (Asness and Frazzini, 2013).

All four regressions in Panel A of Table 3 (the World sample) show a significant coefficient on the quintile 5 mispricing dummy. Quintile 5 stocks earn 24 to 43 bp per month more than quintile 1 stocks, controlling for prominent sources of return premia. (Except for earnings surprises (SUE), the control variables show the expected signs and are often significant.) The *t*-statistics of the mispricing quintile 5 coefficients range from 3.44 to 6.55. As for magnitude, the mispricing signal seems to influence returns to about the same degree as book-to-market and is slightly weaker than momentum. For example, the most underpriced quintile's coefficients are modestly larger than the quintile 5 coefficients for book-to-market in two of Panel A's regressions and modestly weaker in the other two.[14]

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 (with OLS) 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.) The OLS results are particularly strong in Emerging Markets (83 and 63 bp), Asia Pacific (82 and 60 bp), and Japan (78 and 54 bp). The TS results are broadly similar except for Europe and Japan. For Europe, they show greater performance from the mispricing signal (33 and 18 bp, both significant) than the OLS results; for Japan, they show weaker performance (49 and 15 bp with the latter being insignificant) than their OLS counterparts.

4.2.2 Cross-Sectional Regressions with IPCA Factor Model Expected Returns

To control for risk, we also employ Instrumented Principal Component Analysis (IPCA), developed by Kelly, Pruitt, and Su (2018).[15] IPCA allows for latent factors and time-varying factor betas by introducing observable characteristics as instruments for the unobservable dynamic factor betas. This new approach to modelling risk

[14] To further control for size, we also run Fama-MacBeth regressions using market capitalization as weights (WLS). In these regressions, the most underpriced stocks still outperform the most overpriced stocks by 18-32 bp (*t*-statistics between 1.68 and 2.92).

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

accounts for many cross-sectional anomalies as factor risk exposure. For example, Kelly, Pruitt, and Su (2018) show that a 5-factor IPCA model explains the cross-section of U.S. stock returns significantly more accurately than the Fama and French (1993, 2015) 3- and 5-factor models, or even a 6-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 an international sample of 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 obtains the mapping by regressing returns on the product of the factors obtained from the first set of projections and characteristics. After an initial guess for gamma and factor premia, 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 10 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 5-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 premia to vary over time, but also factor betas as a function of changes in firm characteristics. Thus, with the 12-instrument model, time-varying risk premia associated with our mispricing signal's ability to proxy for a risk factor are fully controlled for in the analysis below.

Table 3 Panel C 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 5-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.

With OLS- or TS-estimated mispricing signals, the unconstrained regressions' high *t*-statistics in Table 3 Panel C indicate that the IPCA-predicted returns are important for explaining the cross section of returns. What is telling, however, is that both signals yield highly significant spreads between the IPCA-controlled return of the most under- and overpriced quintiles of global stocks. For example, the unconstrained regression indicates a highly significant spread of 41 bp between the two extreme quintiles of the OLS signal. Moreover, the quintile spreads with the OLS and TS signals are larger than the coefficients from Specification 2 of Table 3 Panel A, which uses quintile dummies for the 10 characteristics as controls. Table 3 Panel C's unconstrained regressions also illustrate 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 Panel C, however, the monotonicity with the unconstrained regressions supports claims that we are identifying pricing inefficiencies because we are controlling for the factor risk associated with mispricing. The constrained regressions in Table 3 Panel C also exhibit a significant and monotonic or nearly monotonic effect from mispricing – separate from the effect of the mispricing signal on factor betas. The coefficients on the OLS mispricing quintiles are smaller than those in the unconstrained regression, but only marginally smaller for the TS mispricing quintiles. The constrained regression is equivalent to a stepwise regression because it necessarily has a coefficient of one in the first-step regression by construction.

Table 3 Panel D reports the coefficient on the quintile 5 mispricing dummy by region for Panel C's specifications, thus mirroring Table 3 Panel B. The quintile spreads remain large and significant for all of Panel D's rows except for Europe and the United States. The unconstrained results are particularly strong in Emerging Markets (85 and 100 bp), Asia Pacific (90 and 76 bp), and Japan (67 and 53 bp). Europe's unconstrained TS results show significant performance from the TS mispricing signal (31 bp) compared to the OLS results, as was the case in Table 3 Panel A. Otherwise, the conclusions about relative efficiency across regions are broadly similar across Panel D's four columns.

In sum, the lessons from Table 3 Panel A and B are unchanged by altering the controls to expected returns from the 5-factor IPCA model, even though we additionally control for the factor risk premia implicit in the mispricing signal. This was a tall 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.

4.2.3 Time-Series Regressions

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, HML, or the profitability factor, 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.

Denote $r_{q,t+1}$ to be the USD industry-adjusted month $t+1$ return (which subtracts the return of an equally-weighted global industry portfolio) on quintile portfolio q based on its end of month t mispricing signal.[16] 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.

[16] Following the literature, we subtract the return of an *equally 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.

For the five quintile portfolios, sorted by their intra-country mispricing signal, Table 4 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- (Panel A) or value-weight (Panel B) the industry-adjusted returns of the group's stocks. Table 4 also reports the spread in alphas between the most under- and over-priced quintiles.

The 80-factor alphas in the middle third of Table 4'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 10 (sub-)samples/regions listed in Table 4's rows. All 80 factors are used in each of the 10 regions' regressions to be consistent with a literature that suggests regional and global factors improve risk adjustment [17] and for fair comparisons across regions. Thus, Europe's factor regression includes the 8 global factors and the 8 European versions of the factors, but also the 8 factors tied to the Americas, United States, Asia Pacific, Developed Markets, Developed Markets ex. U.S., etc. [18] The 80-factor specification thus nest the Fama-French (1993) 3-factor, Carhart (1997) 4-factor, and Fama-French (2015) 5-factor models within it.

The bottom third of Table 4 reports the alphas of the industry-adjusted quintile portfolio returns benchmarked against all 44 of the U.S. and international factors available in the French data library as of August 2017. [19] This 44-factor specification nests the Fama-French (1993) 3-factor, Carhart (1997) 4-factor, and Fama-French (2015) 5-factor models, as well as the Fama and French (2016) international factor model. The 44-factors exclusively employ returns from developed countries and primarily reflect larger firms. Only about 50

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

[18] Following Fama and French (1993, 2016), 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 10 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.

[19] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html for details on factor construction.

per cent of the Asia Pacific (and no Emerging Markets) firms are from developed countries. For this reason, 44-factor inferences about these two regions should be viewed with caution and skepticism.

The top third of Table 4'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 industry-adjusted monthly return spread for the world is 55 bp (56 bp with TS quintiles), but is 53 bp in Table 2. With Panel B's value weighting, the spread for the world is 35 bp (49 bp with TS quintiles) but 31 bp (44 bp with TS quintiles) in Table 2. As with Table 2, applying the trading signal to Emerging Markets and Asia Pacific 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) may not be extremely profitable. The relatively weaker return spreads in the United States dilute the performance of the developed markets at large and the Americas (particularly when value weighting). Europe's four industry-adjusted return spreads also are not as strong as the Asia Pacific spread; however, among the four, only Europe's OLS industry-adjusted return spread in Panel A (equal weighting) is small and insignificant.

Controlling for factor exposures has little effect on these conclusions.[20] 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.

[20] In Berk (1995), firms with lower market capitalizations (like our underpriced firms) tend to have higher discount rates, holding constant the future cash flows that are to be discounted. Tautologically, if the book value of equity or the linear combination of accounting items we use to generate fair value are future cash flow proxies, a value premium or a premium for our underpriced firm has to be the outcome of a higher discount rate. The higher discount rate, in turn, is equivalent to a higher average return. Berk (1995) represents a challenge to discoverers of alpha generating investment strategies to demonstrate that sentiment rather than an omitted risk factor lies behind the variation in discount rates. If our mispricing "works" because it proxies for an omitted risk factor, 80- and 44-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.

For Europe, the 80-factor adjustment seems to improve OLS signal performance to significance with Panel A's equal weighting, while Panel B's 44-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 three OLS global spreads in Panel A are 59 bp for both the 80- and 44-factor benchmarks, with the industry-adjusted return marginally lower. The comparable TS-quintile spreads range from 52 to 56 bp. In Panel B, the OLS spreads range from 29 to 41 bp, while the TS-quintile spreads range from 36 to 56 bp. The similarities of the spreads across the top, middle, and bottom thirds of Table 4's two panels, as well as the similarity to the spreads in Table 2, suggest that factor risk exposure is an unlikely driver of the success of the trading strategy.

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, OLS World quintile 1, which would be shorted, earns significant alphas of -27 and -23 bp with its two factor benchmarks, while quintile 5 earns a significant 32 and 36 bp, respectively. By contrast, short positions are the primary drivers of significant alpha spreads for most other alpha-generating anomalies. While short sales restrictions could explain why those anomalies persist, the same barrier does not exist for investment in the Q5 portfolios. Table 4 contains exceptions, however: The most glaring is that overpriced Emerging Markets stocks (Q1) appear to have positive (but insignificant) alpha in Panels A and B with the 44-factor benchmark, but negative alphas with every other metric. We suspect that this is a benchmarking issue tied to the absence of any emerging markets stock in the 44-factor benchmark.

To analyze the effect of stale information, Figure 3 shows risk-adjusted returns (alphas) for major regions when delaying the entire 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 performance of stale signals in emerging markets and developed markets outside the United States decays more slowly, approaching zero 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.

Overall, Table 4 indicates that the payoffs to equal- and value-weighted strategies remain significant in various regions of the word after adjusting for a broad set 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.

4.2.4 Geography vs. Economic Development as the Driver of Alpha

The alpha generating strategies discussed 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 emerging markets' returns (Harvey, 1995), information leakage prior to their release to the public (Bhattacharya, Daouk, Jorgenson and Kehr, 2000) and excess returns to trading strategies based on simple combinations of fundamental characteristics (Rouwenhorst, 1999; Van der Hart, Slagter and Van Dijk, 2003). However, more recent papers focused on specific alpha-generating strategies, discussed earlier, reached an opposite conclusion: namely, that strategies are not more profitable and sometimes are less profitable in emerging markets. Moreover, economic development is correlated with geographic region and both are related to the efficacy of the mispricing signal. This correlation makes it particularly difficult to assess whether emerging markets are less efficient than developed markets, *ceteris paribus*.

To assess if geographic region or economic development influences the efficiency of the mispricing signal, Table 5 Panel A reports the average cross-sectional regression coefficients of the two specifications and two estimation procedures from Table 3 Panel A, but includes geographic (with Americas the omitted dummy), and economic development (with Developed the omitted dummy) fixed effects and interaction terms with the five mispricing quintile dummies. Country fixed effects, used in the four regressions in the table's top half of the table, are replaced by geographic and economics region fixed effects in the table's bottom half. For parsimony, we report only the coefficients on the interactions terms; coefficients on the unreported controls are similar to Table 3 Panel A.

All eight regressions in Table 5 Panel A indicate that the state of economic development influence alpha. The significant coefficients on the Q5 interactions with emerging markets are significant in all eight regressions; their magnitudes imply that the mispricing strategy produces 61-74 bp more alpha per month in emerging markets, controlling for geographic region. By contrast, Asia Pacific, the region with the largest alpha, experiences 26-50 bp additional alpha compared to the Americas (the omitted region) controlling for the state of economic development. The marginal contribution from Asia to the strategy's efficacy (compared to the Americas) tends to be significant in the OLS regressions, but insignificant or marginally significant at the 10% level in the regressions with TS signals.

As a robustness check using the alternative time series methodology of Table 4, Table 5 Panel B splits each of the three geographic regions (Americas, Asia Pacific, and Europe; with Africa/Middle East excluded due to lack of firms and time series observations) into Emerging and Developed sub-regions. It reports the 80-factor alphas for OLS equal-weighted quintile portfolios 1 and 5 (left half of Table 5) as well as the OLS and TS extreme quintile spreads (right half) for each of the six sub-regions along with test statistics.[21] The "Difference" rows report differences between Emerging and Developed Markets for each of the three geographic regions, as well as the average of the three regions. All t-statistics for the 80-factor alphas are based on the monthly time series of excess returns or return differences of the relevant portfolio studied. Since the t-statistics require all time series to be of the same length for comparison purposes and aggregation, the sample length here starts later than the sample studied in Tables 4 and in Panel A of Table 5. Here, trading on the mispricing strategy starts in August 2002 due to the lack of earlier data on Emerging Americas.

Both the OLS and TS alpha spreads of Panel B portray the same picture: Emerging Markets have higher alpha spreads than Developed Markets, controlling for region. The OLS and TS alpha spread differences between Emerging and Developed markets, averaged across the three regions, are 39 bp (t = 1.95) and 52 bp (t = 2.66), respectively. Note that Europe's emerging markets tend to have negative but insignificant alphas (largely due to the poor performance of the strategy in Russia), while its developed markets exhibit positive

[21] We omit the 44-factor model for addressing the issue of whether Emerging Markets *per se* have higher alphas because the 44-factor model has no Emerging Markets firms influencing its returns. Results using models restricted to only the global and regional factors are economically and statistically stronger.

insignificant alphas. However, Europe's relatively small and opposite-signed difference between its two market types is far outweighed by the superior performance of the strategy within the emerging Americas and Asia Pacific regions. For the Americas, the larger alpha spread comes from the large alpha difference between the Q5 stock portfolios comprising its emerging (Brazil and Chile) and developed markets (United States and Canada). For the Asia Pacific region, the superior spread performance comes from the more negative alpha of its Q1 emerging markets portfolio compared to Asia's developed markets (Japan and Australia).

4.2.5 Buy-and-Hold Portfolios

The mispricing signal is based on annual accounting data. However, trades take place every month as new market valuations become known and (for some firms) new accounting data is released to the public. Performance from the mispricing signal does not account for the transactions costs that would be incurred by this monthly turnover. Sophisticated traders tend to reduce turnover when strategies are implemented for optimal 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 twelve 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 6, which reports industry-adjusted (top third), 80- (middle third), and 44- factor (bottom third) alphas along with test statistics, shows that the reduced turnover strategy is less profitable, as expected. However, except for Asia Pacific and Japan, a comparison with Table 4 Panel A indicates an average reduction in 80-factor OLS 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 4 is large in Japan, with the more sizable Asia Pacific reduction largely due to Japan. However, except for Japan with TS fair values, alpha spreads remain significant from the buy-and-hold strategy if they were previously significant with Table 4's monthly rebalancing strategy.

The relatively greater alpha loss with the buy and hold strategy in Japan – and the possible need to incur the transaction costs of a higher turnover strategy – may deter arbitrageurs. This fact could explain why the profits from the mispricing signal in Tables 3 and 4 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. We investigate the issue of trading frictions more broadly below.

4.3 Turnover and Transactions Costs

4.3.1 Transaction Costs and Other Country Attributes

Neoclassical finance contends that competition among arbitrageurs eliminates profitable trading opportunities based on public information. However, arbitrageurs face frictions, particularly trading costs, that may 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 – data obtained from Elkins McSherry LLC – with our strategy's country-specific turnover in each month, as described in Section 2. Table 7 reports the effect of these trading costs in the Q1 (most overpriced) and Q5 (most underpriced) portfolios. The top half of Table 7 focuses on the effect of transaction costs on the monthly rebalancing strategy studied in Table 4; the bottom half on the impact for Table 6's buy-and-hold strategy.

According to Table 7's first row, turnover for the world strategy is 39% 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 7'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 4% 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 40% of the alpha spread, reducing the pre-transaction cost 80-factor alpha spread from 59 to 33 bp per month. The largest trading costs are in emerging markets, with a 79 bp per month reduction in the alpha spread, in part because the emerging markets only strategy has the highest turnover, at 52% per month.

However, dividing the 79 bp by 52% 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 7's top half are positive except for Europe; all of the regions that were significantly positive before transaction costs remain so after transaction costs, except for Emerging Markets. Moreover, investors can mitigate these costs by reducing turnover, as the annually rebalanced buy and hold strategy does in the lower half of Table 7. The associated reduction in turnover leads to trading costs that are about 1/5 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 – resuscitating Emerging Markets as significantly profitable. In Japan, the cost of signal delay outweighs the trading cost reduction, cutting its net-of-transaction cost alpha by almost 30 bp per month, and explaining the lower buy-and-hold alpha after transaction costs in the Asia Pacific region.

If profits to trading strategies based on mispricing estimates are a measure of market efficiency, then profits should vary across countries as a function of transaction costs, short sales restrictions, and perhaps other country characteristics that might influence limits to arbitrage – thereby impeding the process that makes a country's stock prices reflect fair value. We have already seen that the mispricing signal leads to a more profitable strategy in the Emerging Markets and Asia Pacific regions than in other parts of the world. The former two represent the geographic and economic regions with the highest transaction costs, and compared to the rest of the world, almost all of the countries that prohibit short sales (which have the highest alpha spreads) come from emerging Asia.

To assess the degree to which differences in transaction costs and other country attributes influence the profitability of our strategy before transaction costs, Table 8 Panel A 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 (employed in Table 7's calculation). The other "kitchen sink" specification also employs country characteristics derived from the union of regressors used in Griffin, Kelly and Nardari (2010) to study market efficiency across countries. Appendix A contains a detailed description of the regressors. For parsimony, we report only the coefficients on the interaction terms.

The transaction costs interaction terms in Panel A, whether with OLS and or TS mispricing estimation, indicate that transaction costs positively influence alpha. In all three regressions, however, there is no significant coefficient on the mispricing signal. In the first specification, which employs transaction cost as the only country interaction, this yields an interesting insight: the mispricing signal is not significantly profitable in a hypothetical country lacking trading costs. For a country like Korea, which has about 0.5% per dollar of traded as its cost, the 0.75 OLS coefficient in the leftmost regression predicts a Q5-Q1 alpha spread of 0.375 bp per month (or about 5% per year).

Panel A'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 pair's interaction coefficients with transaction costs are about twice as large as those without the kitchen sink controls. 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 pair of "kitchen sink" regressions also indicate that common law and market volatility inversely relate to the alpha spread.

We checked these results for robustness with the larger number of firms available from Table 4's time series methodology. Table 8 Panel B reports averages of the monthly coefficients (along with Fama and MacBeth (1973) *t*-statistics) from cross-sectional regressions of each country's Q5 minus Q1 80-factor (pre-transaction-cost) alpha spread for that month against the country characteristics used in Panel A. The monthly alpha is the country's intercept plus residual from a country-specific time series regression that mimics Table 4 Panel A's 80-factor equally weighted regression. Thus, in contrast to Panel A, which gives every global firm equal weight, each country gets the same weight in Panel B's regression. All specifications also include a within-country market portfolio return regressor because the 80-factor model uses 10 broader market indices, but not country indices, as a factor control. (By contrast, Table 8 Panel A uses country fixed effects.)

In each of Panel B's specifications, transaction costs are again positively and significantly related to the pre-transaction cost 80-factor alpha spreads. This finding supports Panel A's conclusion that transaction costs *per se* play a role in the degree of inefficiency exhibited by a country's stock market. Indeed, the insignificant intercept in Panel B's specification (1) suggests (like Panel A) that in the absence of transaction costs, a country's alpha spread should be zero. The coefficient on the correlation of the country index with the world index is significant in Table 8 Panel B (unlike Panel A), suggesting that the degree to which the country is integrated into world markets matters for trading profits. To the extent that country risk can be hedged with offsetting positions in other countries, arbitrageurs find investment in the country's stocks attractive, reducing mispricing. The protection of arbitrageur profits with an advanced law system would similarly explain the negative sign on the common law country dummy, but in contrast to Panel A, it is not significant in Panel B and far smaller in magnitude.

While three other variables are also significant, one of which is and two others that are not significant in Panel A, the high degree of collinearity makes it difficult to tell a coherent story about their significance. First, high intra-country market volatility (significant in both Panel A and B) weakens the country's alpha spreads. One could argue that high market volatility deters arbitrageurs and should generate a positive coefficient. However, holding the number of stocks in a country and the correlation of the country index portfolio with the market fixed, a country's stock market volatility is largely tied to the average covariance between pairs of its stocks. Countries with high covariance between the pairs, and thus high market volatility, are more attractive to arbitrageurs because long-short strategies are less risky with high average covariance. The greater competition lowers alphas.

Second, the number of listed companies is significantly positively related to alpha in both specifications. Here, there are two opposing arguments about the coefficient's sign as well. The log of the number of firms (significant only in Panel B) tends to increase the variance-lowering effect of diversification, attracting arbitrageurs, implying a negative coefficient. However, countries with a large number of firms are also more likely to have Q1 and Q5 quintiles within which a few of the quintile's firms exhibit high degrees of mispricing, implying a positive coefficient on the number of firms.

As an alternative to speculation about the theoretically correct signs for each of the significant regressors in Panels A and B of Table 8, Panel C reports *F*-statistics that assess whether groups of variables can jointly explain differences in the monthly alphas across countries. In all regressions, it appears that transaction costs (where the *F*-statistic merely squares the *t*-statistic), as well as the five regressors tied to equity market characteristics, are jointly consistently significant.

4.3.2 A Model of Mispricing and Transactions Costs

The results above 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

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

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

$$A_t = \iota_t b\lambda\left(\left|F_t - P_t\right| - T\right) + A_{t-1}\text{, where} \tag{4}$$

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.

Equation (4) 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 (Equations (3) and (4)) and setting it equal to the aggregate supply of one share, equilibrium prices solve $D_t + A_t = 1$ or

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

Equivalently,

$$P_t = F_t - \frac{\iota_t T\lambda}{1+\lambda} + \frac{z_t + A_{t-1}}{b\left(1+\lambda\left|\iota_t\right|\right)}. \tag{5}$$

Equation (5) 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 equation (5) to

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

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 Figure 4 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

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

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. Figure 4 illustrates the case where $\kappa = 1$ and the two realizations of δ_{t+1} generate future prices that attract additional capital in "$+d$ state" and no additional capital in the "$-d$ state." On the right of Figure 4's vertical axis, shares are underpriced and to 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 Equation (5) as λ approaches infinity, implying

$$P_t = F_t - \iota_t T .$$

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.[22]

5 Robustness Tests and Additional Analyses

5.1 Is the Mispricing Signal a Proxy for Other Known Anomalies?

Table 1's analysis noted that underpriced firms are "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 9 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.

[22] Note that the degree of convexity experienced by the pair of noise trading innovations, starting from the rightmost kink or nearby, does not vary with T. This is an artifact of the binomial distribution's bounded outcomes for noise trading. For continuous and unbounded density functions of noise trading, the innovations could generate future equilibria to the left of the leftmost kink. Allowing future noise trading realizations to cause equilibria that cross over the concave kink on the left reduces (but generally does not eliminate) the effect of Jensen's inequality on expected returns. In this case, larger T widens the gap between kinks, reduces this likelihood of crossing the left kink, and increases expected returns for trades of the same sign as $F - P$. A sufficient distributional condition is that date t noise trading innovations be unbounded, symmetric, continuous, and have a density that is declining in the absolute value of the innovation's realization.

The procedure is as follows: Each month, we sort stocks into quintiles based on one of 22 return-predictive characteristics. Within each quintile, stocks are then sorted into mispricing quintiles. Table 9's alpha spreads are from a long-short trading strategy in the extreme mispricing quintiles produced for each of the 22 subgroups. If any of the 22 characteristics is masquerading as our mispricing variable, the lack of mispricing signal variation in within each of 110 subgroups should greatly reduce the alpha spreads from the mispricing signal and their significance.

The top half of Table 9 shows alpha spreads within subgroups for the 80-factor model and OLS fair value equal-weighted mispricing quintiles; its bottom-half has spreads from the 44-factor model. Both panels exhibit statistically and economically significant alpha spreads in almost all the subgroups. There are a few scattered exceptions to significance. For example, the mispricing strategy has an insignificant 44-factor alpha for the top two market capitalization quintiles of stocks. Because the size-based quintiles are from NYSE break-points, these tend to be the very largest and most liquid firms in a country. We are not surprised by the low alpha spreads in these two quintiles. Size is not a powerful alpha anomaly, however, and it would be hard to argue that the mispricing signal generates significant alpha spreads because it is really a size anomaly in disguise. The approximately 26 bp alpha spread for the highest one-month past return stocks is marginally insignificant as well. 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.

5.2 Alternative Approaches to Parsimonious Fair Value Estimation

Up to now, estimated fair value has been the predicted market capitalizations of firms from cross-sectional regressions of market capitalization on accounting variables. To assess whether related approaches to parsimonious fair value estimation generate profits from mispricing, Table 10 studies two alternative mispricing signals. Panel A's signal uses the same fair value regression but omits the constant from the regression; Panel B studies a signal where the regressors are analyst earnings forecasts.

When fair-value regressions have a constant – as is the case so far – the regression residuals sum to zero, thus implying that the market portfolio is fairly valued. By contrast, forcing the regression intercept to be zero makes the fair value regression homogeneous of degree one, leading to the plausible conclusion that firms with zeros for all 21 accounting items (including total book assets) have zero fair value. To study this alternative signal, Table 10 Panel A reports extreme quintile return spreads and industry-adjusted extreme return spreads (top half), as well as alpha spreads from the two factor models (bottom half). The spreads are the return differences of equally weighted portfolios of firms sorted into the two extreme mispricing quintiles using OLS and TS fair value regressions that lack an intercept. All of the alpha spreads, including those for Europe and the Americas, are now significant. By contrast, the strongest performers from fair value estimation with an intercept – Asia Pacific, Japan, and Emerging Markets – are modestly weaker (but still have highly significant alpha spreads) when fair value is estimated without an intercept. On balance, the alternative fair valuation without an intercept generates less cross-region variation in the mispricing strategy's performance.

Table 10 Panel B, employing a layout that mirrors Panel A, estimates fair value by cross-sectionally regressing within-country market capitalizations on IBES FY1 and FY2 consensus earnings forecasts each month.[23] According to Liu and Thomas (2000) and Johannesson and Ohlson (2016, 2017), consensus earnings forecasts for the next two fiscal years as regression predictors better account for market values and returns than more sophisticated models. Mispricing quintiles again derive from the percentage deviation of fitted to actual market capitalization. Contrasting Panel B with Table 4, we see that the strongest performers from this IBES-based fair value estimation (with an intercept) – Asia Pacific and Emerging Markets – are about the same or modestly stronger than those derived from the 21-regressor accounting signal. At the same time, the IBES-signal alpha spreads in developed markets are modestly weaker and consistently insignificant compared to the 21-regressor accounting signal. However, when the same tables are compared for firms that have data on both types of signals, the alpha spreads are also about same as those deriving from the accounting variables alone.[24]

We also replicate Table 5's results on geography vs. state of development as a driver of alpha spreads for both Fama-MacBeth and time-series regressions with Table 10's two alternative signals. (The formal table

[23] We calculate total earnings forecasts by multiplying IBES's per share forecast with the number of outstanding shares (from IBES, or if unavailable, from Worldscope). Note that IBES earnings forecast data that was publicly available at the time may differ from the forecast researchers now analyze (see Call, Hewitt, Watkins and Yohn (2016)).

[24] For the same firms, combining the 21 accounting and 2 IBES variables neither enhances nor diminish alpha spreads.

is omitted for brevity.) Using identical sample periods (as IBES forecast data have less or no coverage in the more distant past), emerging markets experience significantly higher alpha spreads than developed markets with Table 10 Panel B's IBES signal, controlling for geography and other factors. However, with Panel A's no-constant signal using the 21 accounting variables, a country's economic development is not a significant predictor of alpha spreads.

This last finding does not alter our conclusion that emerging markets are more lucrative "hunting grounds" for alpha. Any strategy that generates abnormally high risk-adjusted returns proves market inefficiency. The fact that some alternative alpha-seeking strategy works less effectively in some countries does not prove the perceived relative efficiency of the country's financial markets; it merely says that the alternative mispricing signal is a weaker sorter of mispriced firms than its alternative.

Finally, we investigate the R-squared fit of fair value regressions with alternatively 21 accounting regressors and 2 IBES regressors by weighting each country's fair value regression R-squared by the number of firms in the country using only firms that have both pairs of signals. Each month's R-squared comparison differs; however, summary statistics indicate that the fair value estimates from the IBES FY1 and FY2 regressors fit to actual market capitalizations generate similar weighted average R-squared: 89% is the time series average and median R-squared for the IBES regressors vs. 92% average and median for the 21-accounting regressors. (Moreover, the increase in average and median R-squared from adding the two IBES regressors (96% vs. 92%) is small.)

6 Conclusion

Using international point-in-time accounting data, we 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. We also borrow a popular approach from the literature: using earnings forecasts in lieu of accounting items, and obtain similar alpha spreads.

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 to 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 may 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 may or may not 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, but not in Japan.

One of our more interesting findings here is that, in a hypothetical country with zero trading costs, the mispricing signal does not lead to a positive 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 lost alpha foregone 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 in Table 4. 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" in Table 4. 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.

It would also be useful to understand whether our methodology could be used to forecast the returns of a country's stock market as a whole. Studying inter-country mispricing is a tall order, as accounting standards differ across the world and currency translations may add a great deal of noise to the outcome, complicating inferences. We skirted these issues by forming long-short portfolios within each country to analyze intra-country mispricing. We did, however, run our fair value regression globally each month, using dollar equivalents for all variables and taking value-weighted and equal-weighted residuals within each country as a proxy for its stock market's overall level of misvaluation. These residuals were unable to significantly predict the corresponding equal- and value-weighted returns of the country portfolios. Whether this lack of predictability is due to the noise introduced by currency movements and differing accounting standards, or due to the efficient prices of each country's stock index portfolio is impossible to ascertain at this point.

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 may 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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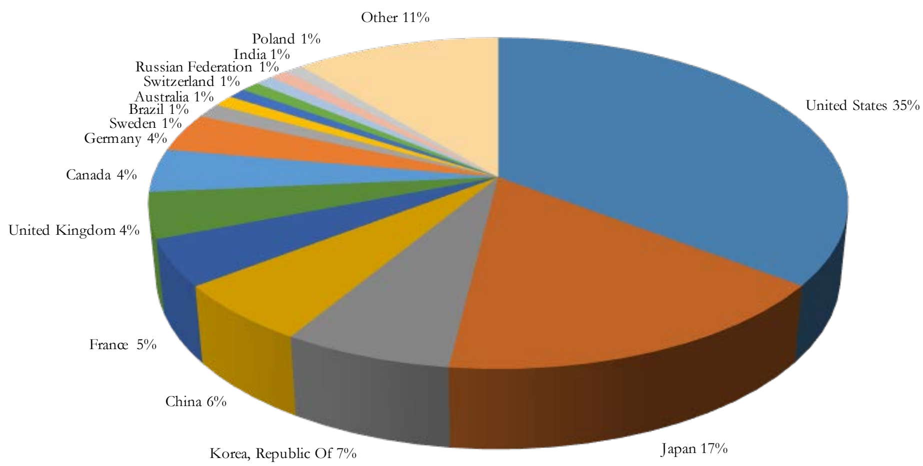
Figure 1: Sample Countries and Regions

The figure shows the distribution of the sample firms across countries (Panel A) and regions (Panel B). Panel B also distinguishes between firms of a region in emerging (shaded-colored) and developed (solid-colored) markets.

Panel A: Countries



Panel B: Regions

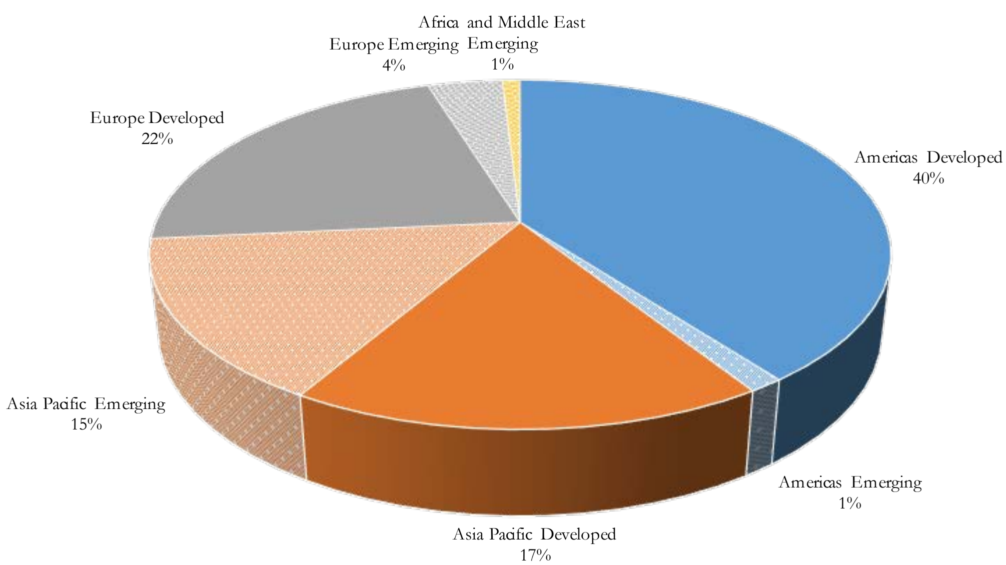


Figure 2: Sample Size over Time

The figure shows the sample size by region over time.

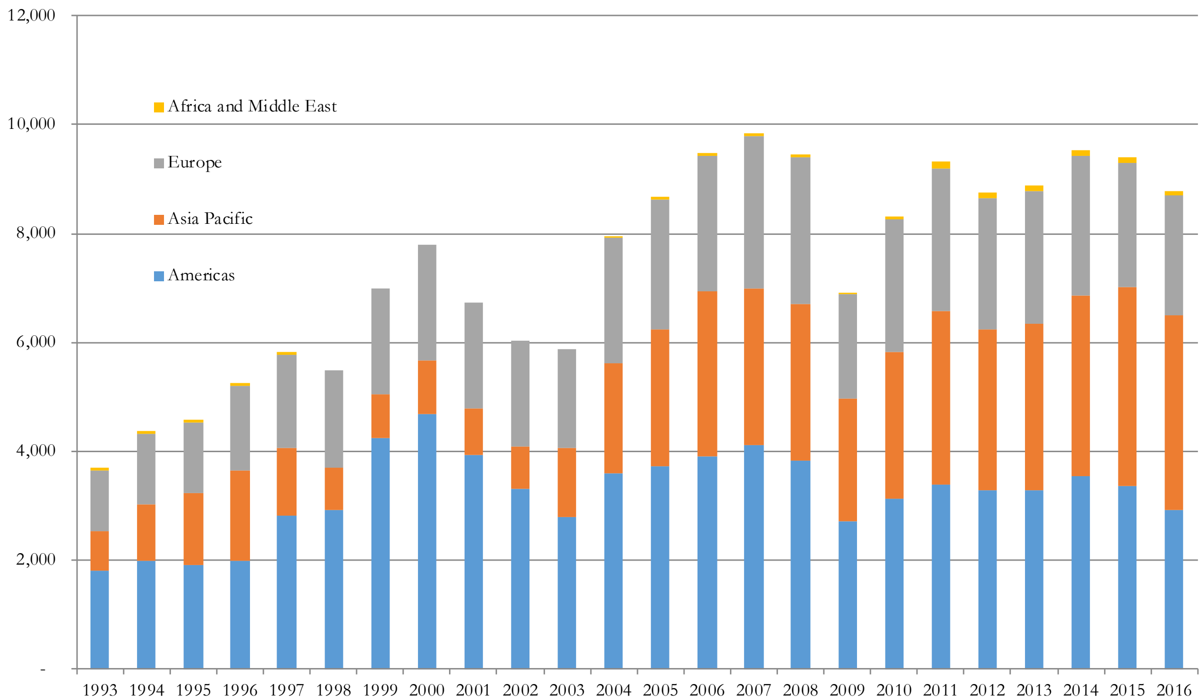


Figure 3: Lagged Signals

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 equally-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. All variables are defined in Appendix A.

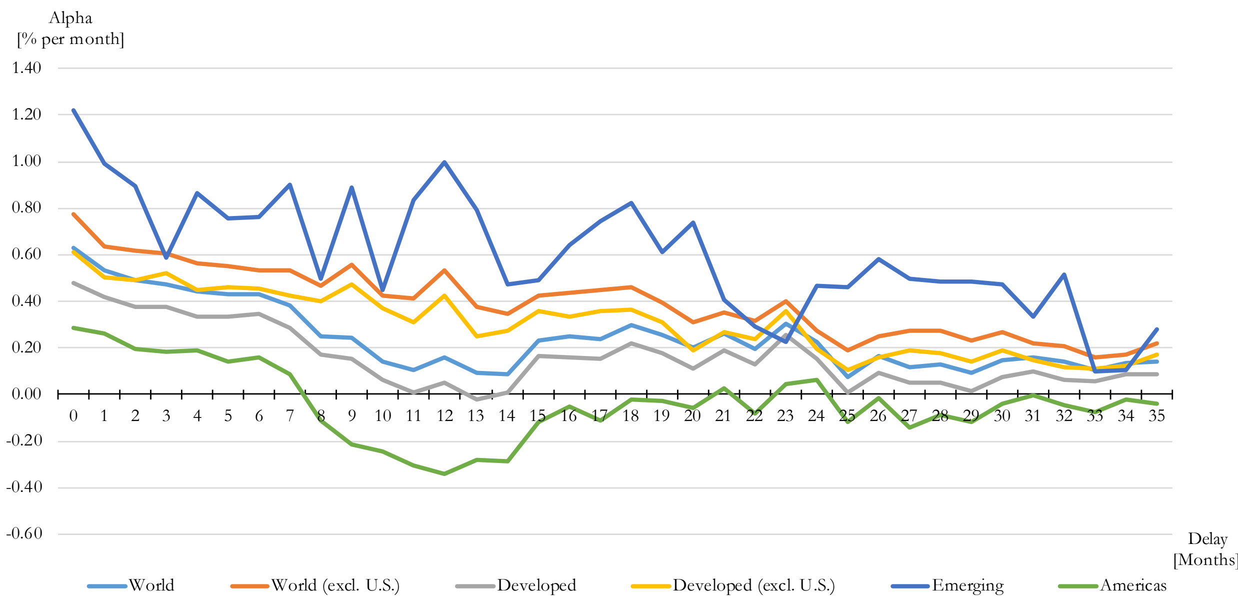


Figure 4: Mispricing and Transactions Costs

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 Section 4.3.2.

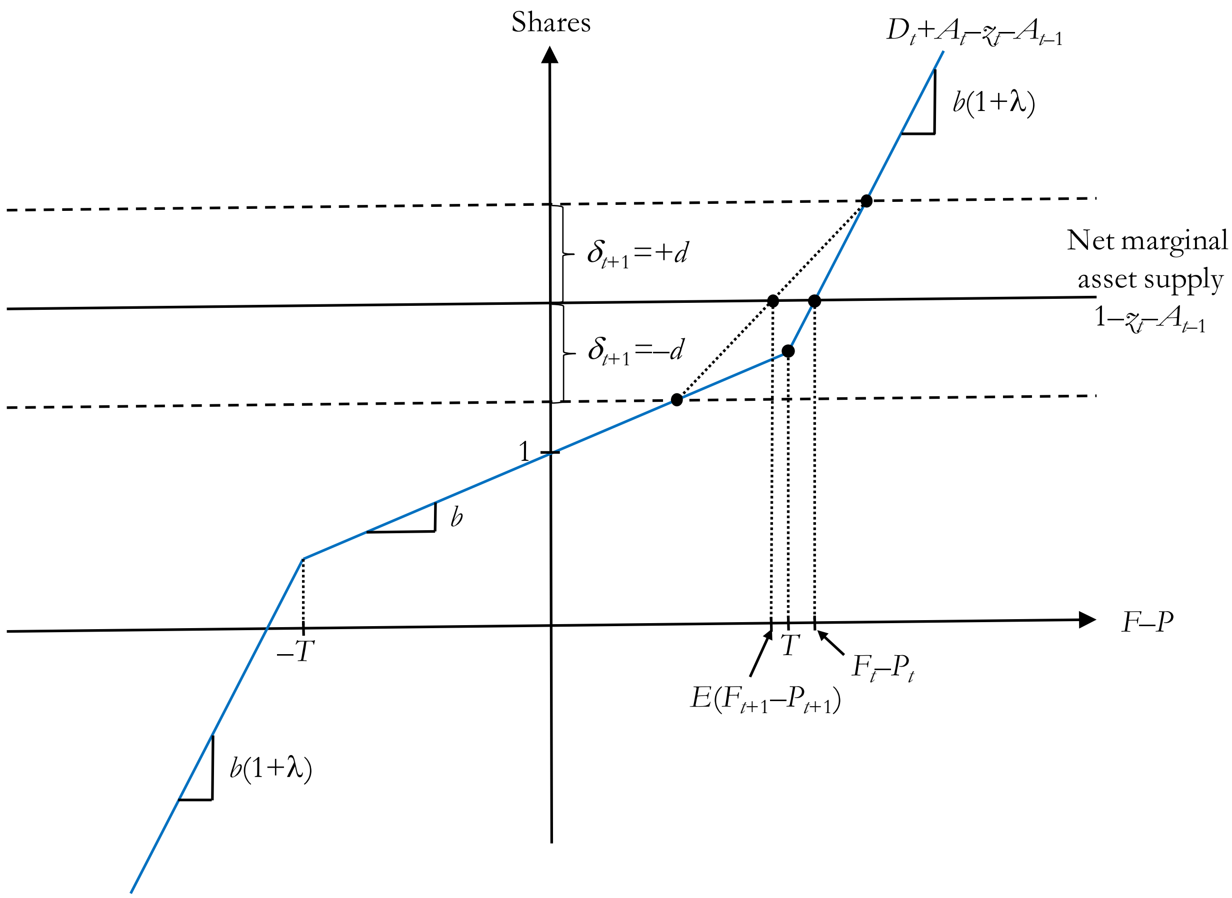


Table 1: Summary Statistics

The table reports averages of characteristics of the sample firms. In particular, the table 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). The table is based on signals from OLS regressions as described in the text. 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. All variables are defined in Appendix A.

			Signal Quintiles				
	All	Correlation	Q1 (Overvalued)	Q2	Q3	Q4	Q5 (Undervalued)
World							
Mispricing	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
Prior Month Return 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	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
Prior Month Return 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	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
Prior Month Return 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 0. 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%. Columns under the OLS heading report results for signals from OLS regressions, while columns under the TS heading show results for signals from Theil-Sen regressions as described in the text. Panel A reports results for equal weighted portfolios, while Panel B shows results for value weighted portfolios. All variables are defined in Appendix A.

				OLS										TS	
	Firms				Signal Quintiles					Q5-Q1 (Undervalued - Overvalued)				Q5-Q1	
	Total	Average	Return	Correlation	Q1 (Overvalued)	Q2	Q3	Q4	Q5 (Undervalued)	Fraction > 0	*p*-value	Average	*t*-stat	Average	*t*-stat
Panel A: Equally-weighted Portfolios															
World	25,731	7,040	0.8526	0.0082	0.6334	0.7013	0.8123	0.9495	1.1640	62.1	[0.00]	0.5307	[4.44]	0.5294	[3.88]
World (excl. U.S.)	16,619	4,425	0.7750	0.0104	0.5693	0.5991	0.6881	0.8498	1.1693	64.2	[0.00]	0.5999	[5.95]	0.5915	[5.26]
Developed	20,285	6,213	0.8322	0.0068	0.6469	0.7095	0.8151	0.9168	1.0698	57.4	[0.01]	0.4229	[3.34]	0.4073	[2.82]
Developed (excl. U.S.)	11,173	3,598	0.7352	0.0103	0.5710	0.5990	0.6788	0.7904	1.0367	57.8	[0.01]	0.4657	[4.18]	0.4200	[3.34]
Emerging	5,446	827	1.1748	0.0146	0.8086	0.7883	0.9692	1.2740	2.0418	68.4	[0.00]	1.2332	[6.30]	1.3047	[6.70]
Americas	10,540	2,972	0.9888	0.0039	0.8243	0.8882	0.9935	1.0960	1.1399	52.8	[0.34]	0.3157	[1.87]	0.3570	[1.86]
Europe	6,581	2,011	0.9303	0.0035	0.9155	0.8930	0.9109	0.9360	0.9955	50.0	[1.00]	0.0800	[0.80]	0.3272	[3.36]
Asia Pacific	8,370	2,011	0.5882	0.0255	0.1866	0.2872	0.4490	0.7365	1.2801	67.4	[0.00]	1.0935	[6.54]	0.8509	[4.49]
United States	9,112	2,615	0.9737	-0.0004	0.8179	0.8793	0.9974	1.0933	1.0784	50.0	[1.00]	0.2606	[1.46]	0.3210	[1.62]
Japan	4,249	1,451	0.5181	0.0230	0.1910	0.2314	0.3999	0.6199	1.1474	64.2	[0.00]	0.9563	[4.89]	0.5526	[2.44]
Panel B: Value-weighted Portfolios															
World			0.7278	0.0082	0.6531	0.7713	0.7807	0.8545	0.9586	54.3	[0.15]	0.3055	[1.40]	0.4365	[1.88]
World (excl. U.S.)			0.6044	0.0085	0.4643	0.6822	0.6549	0.7315	0.9527	57.8	[0.01]	0.4883	[2.21]	0.5402	[2.67]
Developed			0.7435	0.0079	0.6781	0.7800	0.8144	0.9047	0.9106	52.1	[0.47]	0.2325	[1.08]	0.3614	[1.53]
Developed (excl. U.S.)			0.6208	0.0099	0.5023	0.6963	0.6891	0.7764	0.9068	55.3	[0.07]	0.4044	[1.86]	0.3977	[1.89]
Emerging			0.7742	0.0092	0.3324	0.6350	0.8982	0.9952	1.5696	61.7	[0.00]	1.2372	[3.76]	1.1237	[3.71]
Americas			0.8586	0.0072	0.8242	0.8276	0.9483	1.1152	1.0284	52.1	[0.47]	0.2041	[0.93]	0.3243	[1.15]
Europe			0.8175	0.0053	0.7883	0.8243	0.7659	0.9110	1.0990	57.4	[0.01]	0.3107	[1.66]	0.3827	[2.18]
Asia Pacific			0.3525	0.0240	0.0485	0.4220	0.5310	0.6850	1.0736	60.3	[0.00]	1.0251	[3.38]	1.0436	[3.67]
United States			0.8621	0.0069	0.8039	0.8169	0.9855	1.1475	1.0294	52.8	[0.34]	0.2255	[0.97]	0.3378	[1.16]
Japan			0.3327	0.0240	0.1254	0.4421	0.5195	0.6741	0.9649	61.3	[0.00]	0.8395	[3.44]	0.8580	[2.95]

Table 3: Fama-MacBeth Regressions

The table shows results from Fama MacBeth (1973) regressions. Across different specifications, the return in the next period is regressed on the mispricing signal, control variables as well as country and industry fixed effects. Columns under the OLS heading report results for signals from OLS regressions, while columns under the TS heading show results for signals from Theil-Sen regressions as described in the text. Regressions in Panels A and B 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. Regressions in Panels C and D use model expected returns from an Instrumented Principal Components Analysis (IPCA) as controls. 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 1). Panel C reports the coefficients on mispricing quintile dummies 2-5, the IPCA model expected return (for unconstrained models) and the regression intercept. Panel D reports only the coefficient on the 5th quintile dummy variable of the mispricing signal for the same specifications as in Panel C 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. *, **, and *** indicate statistical significance at the 10% (5%, 1%) significance level. All variables are defined in Appendix A.

Panel A: Regressions with Firm Characteristics for Global Sample

	OLS						TS					
	(1)			(2)			(1)			(2)		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Mispricing Signal Q5	0.4297	[6.55]	***	0.2903	[4.47]	***	0.4160	[5.98]	***	0.2377	[3.44]	***
Beta Q5	-0.0081	[-0.05]		0.0288	[0.18]		-0.0065	[-0.04]		0.0244	[0.15]	
Market Capitalization Q5	0.0571	[0.47]		0.0567	[0.47]		0.0476	[0.39]		0.0425	[0.35]	
Book/Market Q5	0.2880	[3.23]	***	0.3862	[4.90]	***	0.2782	[3.09]	***	0.4054	[5.06]	***
Short-term Reversal Q5	-1.0627	[-8.54]	***	-1.0902	[-8.81]	***	-1.0594	[-8.51]	***	-1.0888	[-8.79]	***
Momentum Q5	0.6246	[3.96]	***	0.6467	[4.30]	***	0.6257	[3.96]	***	0.6442	[4.28]	***
Long-term Reversal Q5	-0.1890	[-2.19]	**	-0.2309	[-2.73]	***	-0.2061	[-2.42]	**	-0.2370	[-2.81]	***
Accruals Q5				-0.2715	[-5.35]	***				-0.2739	[-5.40]	***
SUE Q5				-0.0796	[-1.37]					-0.0795	[-1.38]	
Gross Profitability Q5				0.5149	[8.11]	***				0.5164	[8.14]	***
Earnings Yield Q5				0.3745	[4.33]	***				0.3730	[4.29]	***
Intercept	0.8583	[1.96]	*	0.5860	[1.31]		0.8783	[2.01]	**	0.6056	[1.35]	
Observations	3,445			3,445			3,445			3,445		
Adj. RSquare	0.15			0.15			0.15			0.15		
Country Controls	Yes			Yes			Yes			Yes		
Industry Controls	Yes			Yes			Yes			Yes		

(continued)

Table 3: Fama-MacBeth Regressions (continued)

Panel B: Regressions with Firm Characteristics by Region

	OLS						TS					
	(1)			(2)			(1)			(2)		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
World	0.4297	[6.55]	***	0.2903	[4.47]	***	0.4160	[5.98]	***	0.2377	[3.44]	***
World (excl. U.S.)	0.4876	[6.45]	***	0.3505	[4.58]	***	0.4940	[6.74]	***	0.3071	[4.14]	***
Developed	0.3664	[5.09]	***	0.2231	[3.14]	***	0.3418	[4.59]	***	0.1579	[2.13]	**
Developed (excl. U.S.)	0.4129	[4.96]	***	0.2648	[3.13]	***	0.4054	[5.09]	***	0.2052	[2.54]	**
Emerging	0.8282	[3.02]	***	0.6296	[2.21]	**	0.7969	[3.04]	***	0.5880	[2.06]	**
Americas	0.2660	[2.36]	**	0.1157	[1.02]		0.1957	[1.66]	*	0.0441	[0.38]	
Europe	0.0821	[1.01]		-0.0281	[-0.35]		0.3317	[4.09]	***	0.1805	[2.22]	**
Asia Pacific	0.8188	[6.57]	***	0.5970	[4.53]	***	0.6517	[5.41]	***	0.3803	[2.79]	***
United States	0.2408	[1.84]	*	0.1025	[0.77]		0.1791	[1.38]		0.0303	[0.23]	
Japan	0.7786	[5.51]	***	0.5419	[3.78]	***	0.4892	[3.79]	***	0.1532	[1.12]	

Panel C: Regressions with IPCA Expected Returns for Global Sample

	OLS						TS					
	Unconstrained			Contrained			Unconstrained			Contrained		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Mispricing Signal Q5	0.4080	[4.95]	***	0.2057	[2.22]	**	0.5097	[5.85]	***	0.5062	[5.10]	***
Mispricing Signal Q4	0.2536	[3.67]	***	0.1143	[1.31]		0.2748	[3.85]	***	0.3864	[4.38]	***
Mispricing Signal Q3	0.1138	[1.92]	*	0.1266	[1.71]	*	0.1737	[2.55]	**	0.2376	[2.56]	**
Mispricing Signal Q2	0.0390	[0.81]		-0.0213	[-0.29]		0.1084	[1.73]	*	0.1452	[1.78]	*
IPCA Model Expected Return	0.2214	[10.36]	***				0.2204	[10.57]	***			
Intercept	0.7683	[2.03]	**	0.8556	[1.19]		0.6484	[1.75]	*	0.4745	[0.94]	
Observations	3,445			3,445			3,445			3,445		
Adj. RSquare	0.13			0.05			0.13			0.04		
Country Controls	Yes			Yes			Yes			Yes		
Industry Controls	Yes			Yes			Yes			Yes		

Panel D: Regressions with IPCA Expected Returns by Region

	OLS						TS					
	Unconstrained			Contrained			Unconstrained			Contrained		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
World	0.4080	[4.95]	***	0.2057	[2.22]	**	0.5097	[5.85]	***	0.5062	[5.10]	***
World (excl. U.S.)	0.4835	[5.48]	***	0.2536	[2.61]	***	0.5281	[6.09]	***	0.6800	[6.60]	***
Developed	0.3441	[4.13]	***	0.1123	[1.10]		0.3637	[3.98]	***	0.4101	[4.32]	***
Developed (excl. U.S.)	0.4089	[4.33]	***	0.4755	[4.35]	***	0.4129	[4.45]	***	0.4458	[4.15]	***
Emerging	0.8541	[3.67]	***	0.5090	[2.10]	**	0.9977	[4.35]	***	0.7923	[3.24]	***
Americas	0.2123	[2.05]	**	0.0120	[0.09]		0.2806	[2.47]	**	0.3355	[2.55]	**
Europe	0.0915	[1.10]		0.1453	[1.12]		0.3135	[3.89]	***	0.1838	[1.38]	
Asia Pacific	0.8971	[7.95]	***	0.4238	[3.00]	***	0.7575	[6.26]	***	0.4485	[3.53]	***
United States	0.1691	[1.53]		-0.0328	[-0.25]		0.2758	[2.41]	**	0.1510	[1.08]	
Japan	0.6676	[5.26]	***	0.2929	[2.14]	**	0.5288	[4.54]	***	0.4348	[2.98]	***

Table 4: 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 equally-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 44-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, and North America). 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. Columns under the OLS heading report results for signals from OLS regressions, while columns under the TS heading show results for signals from Theil-Sen regressions as described in the text. Results in Panel A are for equally-weighted portfolios, while results in Panel B are for value-weighted portfolios. *, **, and *** indicate statistical significance at the 10% (5%, 1%) significance level. All variables are defined in Appendix A.

(continued)

Table 4: Time-Series Factor Model Regressions (continued)

Panel A: Equal-weighted Portfolios

	OLS																		TS		
	Q1 (Overvalued)			Q2			Q3			Q4			Q5 (Undervalued)			Q5-Q1			Q5-Q1		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Industry-Adjusted Returns																					
World	-0.2246	[-4.28]	***	-0.1443	[-2.41]	**	-0.0364	[-1.05]		0.1175	[2.70]	***	0.3258	[5.27]	***	0.5504	[5.51]	***	0.5553	[4.96]	***
World (excl. U.S.)	-0.2851	[-3.40]	***	-0.2395	[-3.26]	***	-0.1413	[-1.82]	*	0.0294	[0.36]		0.3264	[3.15]	***	0.6115	[6.89]	***	0.6048	[6.42]	***
Developed	-0.2101	[-3.41]	***	-0.1344	[-1.92]	*	-0.0328	[-0.71]		0.0871	[1.57]		0.2380	[3.30]	***	0.4481	[4.20]	***	0.4392	[3.67]	***
Developed (excl. U.S.)	-0.2827	[-2.84]	***	-0.2362	[-2.67]	***	-0.1485	[-1.62]		-0.0259	[-0.26]		0.2050	[1.71]	*	0.4877	[4.91]	***	0.4433	[4.12]	***
Emerging	-0.0594	[-0.18]		-0.0663	[-0.21]		0.0979	[0.31]		0.4327	[1.29]		1.0957	[3.00]	***	1.1552	[5.95]	***	1.2413	[6.46]	***
Americas	-0.0495	[-0.37]		0.0302	[0.20]		0.1234	[0.93]		0.2536	[1.76]	*	0.3010	[2.23]	**	0.3505	[2.41]	**	0.4045	[2.44]	**
Europe	0.0681	[0.52]		0.0488	[0.39]		0.0807	[0.63]		0.1229	[0.95]		0.1610	[1.19]		0.0929	[1.01]		0.3307	[3.82]	***
Asia Pacific	-0.6693	[-2.88]	***	-0.5509	[-2.56]	**	-0.3745	[-1.71]	*	-0.1045	[-0.47]		0.4296	[1.75]	*	1.0989	[7.11]	***	0.8683	[5.17]	***
United States	-0.0533	[-0.37]		0.0171	[0.11]		0.1255	[0.87]		0.2472	[1.56]		0.2414	[1.65]	*	0.2947	[1.89]	*	0.3669	[2.12]	**
Japan	-0.6576	[-2.45]	**	-0.6046	[-2.44]	**	-0.4149	[-1.67]	*	-0.2153	[-0.85]		0.3132	[1.14]		0.9708	[5.32]	***	0.5791	[2.81]	***
Factor Model Alphas (80 Factors)																					
World	-0.2688	[-4.50]	***	-0.0945	[-2.10]	**	0.0108	[0.29]		0.0954	[2.49]	**	0.3191	[5.32]	***	0.5879	[5.99]	***	0.5617	[6.94]	***
World (excl. U.S.)	-0.2201	[-3.60]	***	-0.1538	[-3.82]	***	-0.0179	[-0.44]		0.1435	[3.40]	***	0.5137	[7.11]	***	0.7339	[6.96]	***	0.6150	[5.94]	***
Developed	-0.2545	[-4.06]	***	-0.0692	[-1.45]		0.0307	[0.73]		0.0824	[1.84]	*	0.2277	[3.44]	***	0.4822	[4.65]	***	0.4614	[5.27]	***
Developed (excl. U.S.)	-0.1880	[-2.80]	***	-0.1000	[-2.19]	**	0.0404	[0.87]		0.1600	[3.19]	***	0.4422	[5.30]	***	0.6302	[5.38]	***	0.4917	[4.10]	***
Emerging	-0.4568	[-2.34]	**	-0.5965	[-3.28]	***	-0.5315	[-2.96]	***	-0.2159	[-1.15]		0.5103	[2.00]	**	0.9671	[3.82]	***	0.9052	[3.60]	***
Americas	-0.3147	[-3.19]	***	-0.0831	[-1.02]		-0.0499	[-0.74]		-0.0497	[-0.62]		-0.0455	[-0.47]		0.2692	[1.99]	**	0.4112	[3.75]	***
Europe	-0.0371	[-0.52]		-0.0507	[-0.82]		0.0344	[0.62]		0.0441	[0.63]		0.1968	[2.00]	**	0.2339	[2.29]	**	0.4971	[5.25]	***
Asia Pacific	-0.5251	[-3.91]	***	-0.3320	[-4.06]	***	-0.1543	[-1.95]	*	0.1351	[1.46]		0.6275	[4.76]	***	1.1526	[6.21]	***	0.6182	[3.34]	***
United States	-0.3291	[-3.11]	***	-0.1004	[-1.18]		-0.0640	[-0.88]		-0.0721	[-0.81]		-0.1446	[-1.41]		0.1845	[1.27]		0.3672	[3.17]	***
Japan	-0.3690	[-2.34]	**	-0.2183	[-2.27]	**	0.0116	[0.13]		0.2762	[2.69]	***	0.6966	[4.29]	***	1.0656	[4.78]	***	0.3825	[1.63]	
Factor Model Alphas (Fama French Data Library, 44 Factors)																					
World	-0.2341	[-3.78]	***	-0.1399	[-2.88]	***	-0.0491	[-1.29]		0.0706	[1.99]	**	0.3588	[6.00]	***	0.5929	[6.10]	***	0.5204	[6.45]	***
World (excl. U.S.)	-0.2066	[-3.21]	***	-0.1264	[-2.71]	***	-0.0398	[-0.82]		0.1273	[2.63]	***	0.5286	[7.55]	***	0.7352	[7.43]	***	0.6519	[6.88]	***
Developed	-0.2584	[-3.60]	***	-0.1306	[-2.12]	**	-0.0512	[-1.03]		0.0400	[0.79]		0.2781	[3.83]	***	0.5365	[5.18]	***	0.4434	[5.15]	***
Developed (excl. U.S.)	-0.2545	[-3.39]	***	-0.1006	[-1.68]	*	-0.0279	[-0.48]		0.1011	[1.62]		0.4422	[5.10]	***	0.6966	[6.28]	***	0.5634	[5.14]	***
Emerging	0.2612	[0.68]		-0.2475	[-0.69]		-0.0302	[-0.08]		0.3731	[0.94]		1.0257	[2.34]	**	0.7645	[2.99]	***	0.9057	[3.57]	***
Americas	-0.2474	[-2.37]	**	-0.1883	[-2.13]	**	-0.1076	[-1.42]		-0.0803	[-0.96]		0.0746	[0.71]		0.3220	[2.32]	**	0.2974	[2.49]	**
Europe	-0.0771	[-1.01]		-0.0511	[-0.72]		-0.0259	[-0.40]		0.0287	[0.38]		0.1645	[1.72]	*	0.2416	[2.43]	**	0.4603	[5.16]	***
Asia Pacific	-0.3461	[-2.42]	**	-0.1842	[-1.72]	*	-0.0553	[-0.48]		0.2231	[1.79]	*	0.8252	[5.47]	***	1.1714	[6.47]	***	0.7578	[4.39]	***
United States	-0.2458	[-2.15]	**	-0.2002	[-2.17]	**	-0.1197	[-1.47]		-0.0896	[-0.97]		0.0042	[0.04]		0.2500	[1.66]	*	0.2438	[1.96]	*
Japan	-0.3447	[-2.29]	**	-0.0912	[-0.95]		0.0126	[0.12]		0.2523	[2.28]	**	0.7998	[4.93]	***	1.1444	[5.25]	***	0.5436	[2.48]	**

(continued)

Table 4: Time-Series Factor Model Regressions (continued)
Panel B: Value-weighted Portfolios

	OLS												TS	
	Q1 (Overvalued)		Q2		Q3		Q4		Q5 (Undervalued)		Q5-Q1		Q5-Q1	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Industry-Adjusted Returns														
World	-0.2150	[-1.71] *	-0.0772	[-0.66]	-0.1348	[-1.24]	-0.0348	[-0.32]	0.1303	[1.00]	0.3453	[1.78] *	0.4931	[2.68] ***
World (excl. U.S.)	-0.4004	[-3.15] ***	-0.1933	[-1.60]	-0.2174	[-1.77] *	-0.1114	[-0.89]	0.1046	[0.66]	0.5051	[2.62] ***	0.5834	[3.59] ***
Developed	-0.1924	[-1.51]	-0.0686	[-0.57]	-0.1057	[-0.93]	0.0031	[0.03]	0.0892	[0.71]	0.2816	[1.47]	0.4269	[2.27] **
Developed (excl. U.S.)	-0.3658	[-2.78] ***	-0.1791	[-1.41]	-0.1924	[-1.51]	-0.0825	[-0.65]	0.0713	[0.47]	0.4371	[2.33] **	0.4513	[2.66] ***
Emerging	-0.5030	[-1.46]	-0.1685	[-0.44]	0.0746	[0.24]	0.2463	[0.75]	0.6370	[1.66] *	1.1400	[3.52] ***	1.0570	[3.55] ***
Americas	-0.0001	[-0.00]	-0.0027	[-0.02]	0.0036	[0.03]	0.2181	[1.40]	0.2340	[1.33]	0.2341	[1.13]	0.3841	[1.58]
Europe	-0.0813	[-0.52]	-0.0681	[-0.46]	-0.1011	[-0.65]	0.0954	[0.61]	0.2656	[1.72] *	0.3469	[2.33] **	0.4246	[2.99] ***
Asia Pacific	-0.8402	[-3.41] ***	-0.3863	[-1.65] *	-0.3430	[-1.59]	-0.2109	[-0.91]	0.2053	[0.72]	1.0455	[3.71] ***	1.0909	[4.45] ***
United States	-0.0151	[-0.09]	-0.0153	[-0.09]	0.0436	[0.29]	0.2405	[1.44]	0.2336	[1.24]	0.2487	[1.13]	0.3848	[1.51]
Japan	-0.7644	[-2.97] ***	-0.3855	[-1.56]	-0.3128	[-1.34]	-0.2146	[-0.91]	0.1077	[0.41]	0.8721	[3.90] ***	0.9076	[3.55] ***
Factor Model Alphas (80 Factors)														
World	-0.2373	[-2.18] **	0.0177	[0.24]	-0.1023	[-1.29]	-0.0031	[-0.03]	0.0536	[0.46]	0.2909	[1.67] *	0.5620	[4.76] ***
World (excl. U.S.)	-0.2154	[-1.95] *	0.0019	[0.03]	-0.1030	[-1.25]	0.1168	[1.10]	0.2284	[1.81] *	0.4438	[2.35] **	0.5688	[4.44] ***
Developed	-0.2242	[-2.08] **	0.0141	[0.19]	-0.0946	[-1.18]	-0.0282	[-0.29]	-0.0856	[-0.77]	0.1386	[0.82]	0.4652	[4.16] ***
Developed (excl. U.S.)	-0.1916	[-1.72] *	0.0015	[0.02]	-0.0768	[-0.95]	0.0638	[0.63]	0.0990	[0.80]	0.2906	[1.56]	0.4573	[3.77] ***
Emerging	-0.4826	[-1.73] *	-0.2072	[-0.71]	-0.1924	[-0.86]	0.2972	[1.13]	0.4982	[1.77] *	0.9808	[2.55] **	0.7615	[2.09] **
Americas	-0.1618	[-1.45]	0.0149	[0.13]	-0.1089	[-1.11]	0.0070	[0.06]	-0.1481	[-1.15]	0.0137	[0.07]	0.2478	[1.63]
Europe	-0.1736	[-1.57]	-0.0512	[-0.73]	-0.1330	[-1.40]	0.1581	[1.29]	0.1503	[1.20]	0.3239	[1.98] **	0.4204	[2.82] ***
Asia Pacific	-0.5885	[-3.69] ***	-0.0656	[-0.55]	0.0851	[0.70]	0.2591	[1.79] *	0.7056	[3.85] ***	1.2941	[4.73] ***	0.7814	[4.02] ***
United States	-0.1861	[-1.57]	0.0137	[0.12]	-0.1173	[-1.10]	0.0086	[0.07]	-0.1636	[-1.16]	0.0226	[0.11]	0.2252	[1.39]
Japan	-0.4048	[-2.76] ***	0.0006	[0.01]	0.1622	[1.30]	0.2384	[1.91] *	0.5215	[3.59] ***	0.9262	[3.90] ***	0.6206	[3.05] ***
Factor Model Alphas (Fama French Data Library, 44 Factors)														
World	-0.1855	[-1.71] *	-0.0409	[-0.47]	-0.0971	[-1.20]	0.0275	[0.28]	0.2199	[1.77] *	0.4054	[2.31] **	0.3553	[2.78] ***
World (excl. U.S.)	-0.1328	[-1.19]	-0.0986	[-1.09]	-0.0869	[-1.01]	0.1312	[1.09]	0.3168	[2.09] **	0.4496	[2.15] **	0.5324	[4.05] ***
Developed	-0.1793	[-1.64]	-0.0279	[-0.31]	-0.0608	[-0.70]	0.0624	[0.62]	0.1332	[1.19]	0.3126	[1.90] *	0.2709	[2.21] **
Developed (excl. U.S.)	-0.1227	[-1.06]	-0.0668	[-0.71]	-0.0398	[-0.43]	0.1649	[1.37]	0.2152	[1.59]	0.3380	[1.71] *	0.4252	[3.38] ***
Emerging	0.1121	[0.26]	-0.6064	[-1.31]	-0.2095	[-0.56]	0.2442	[0.61]	0.9963	[2.17] **	0.8842	[2.13] **	0.8178	[2.14] **
Americas	-0.1621	[-1.31]	0.0186	[0.16]	-0.1148	[-1.11]	-0.0184	[-0.16]	0.0240	[0.19]	0.1861	[1.04]	0.0609	[0.38]
Europe	-0.0298	[-0.26]	-0.0978	[-1.03]	-0.1737	[-1.64]	0.0604	[0.45]	0.0803	[0.62]	0.1101	[0.66]	0.2248	[1.55]
Asia Pacific	-0.3314	[-1.85] *	0.0069	[0.04]	0.0403	[0.24]	0.2978	[1.39]	0.7536	[2.81] ***	1.0850	[3.29] ***	0.8018	[3.75] ***
United States	-0.1809	[-1.37]	0.0403	[0.33]	-0.0868	[-0.78]	-0.0103	[-0.08]	0.0127	[0.09]	0.1937	[1.00]	0.0164	[0.10]
Japan	-0.3665	[-2.28] **	0.1464	[1.06]	0.2559	[1.91] *	0.3321	[2.21] **	0.5567	[3.51] ***	0.9232	[3.68] ***	0.7334	[3.51] ***

Table 5: Emerging vs. Developed Markets

Panel A shows results from Fama MacBeth (1973) regressions. Across different specifications, the return in the next period 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. Columns under the OLS heading report results for signals from OLS regressions, while columns under the TS heading show results for signals from Theil-Sen regressions as described in the text. 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, but the table only displays the coefficients of the quintile dummy with the largest amount of the characteristic (Q5) for brevity. 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. The panel only reports the coefficient on the 5th quintile dummy variable of the mispricing signal 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. Panel B 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 equally-weighted portfolios stratified by region (Americas, Europe, Asia Pacific) and degree of development (Emerging, Developed). Portfolio returns are in excess of the industry portfolios based on 38 Fama French industry classifications. Regressions are performed separately for each of the quintile portfolios in each of the strata. 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 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 panel reports time-series averages and associated *t*-statistics of monthly alphas (calculated as the sum of the intercept and the residuals) from the time-series regressions for the respective portfolio. Differences between Emerging Markets and Developed Markets are based on differences in the monthly alphas. The average across regions is based on averaging monthly alphas requiring non-missing alphas in a month for all three regions. 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. Columns under the OLS heading report results for signals from OLS regressions, while columns under the TS heading show results for signals from Theil-Sen regressions as described in the text. *, **, and *** indicate statistical significance at the 10% (5%, 1%) significance level. All variables are defined in Appendix A.

(continued)

Table 5: Emerging vs. Developed Markets (continued)

Panel A: Fama MacBeth Regressions

	OLS						TS					
	(1)			(2)			(1)			(2)		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Regressions with Country Fixed Effects												
Mispricing Signal Q5	0.2873	[2.68]	***	0.1255	[1.22]		0.2778	[2.54]	**	0.1007	[0.97]	
Mispricing Signal Q5 * Emerging	0.6115	[2.17]	**	0.6499	[2.35]	**	0.7138	[2.58]	**	0.7301	[2.70]	***
Mispricing Signal Q5 * Asia Pacific	0.4770	[2.52]	**	0.4714	[2.52]	**	0.2935	[1.63]		0.2593	[1.44]	
Mispricing Signal Q5 * Europe	-0.2982	[-2.24]	**	-0.2309	[-1.75]	*	-0.0668	[-0.52]		-0.0388	[-0.31]	
Mispricing Signal Q5 * Africa	-0.3188	[-0.74]		-0.2981	[-0.69]		-0.5096	[-1.21]		-0.4492	[-1.07]	
Observations	3,445			3,445			3,445			3,445		
Adj. RSquare	0.15			0.16			0.15			0.16		
Characteristic Controls	Yes			Yes			Yes			Yes		
Country Controls	Yes			Yes			Yes			Yes		
Development Control	No			No			No			No		
Geographic Region Controls	No			No			No			No		
Industry Controls	Yes			Yes			Yes			Yes		
Regressions with Geographic Region and Development Controls												
Mispricing Signal Q5	0.2457	[2.27]	**	0.0813	[0.78]		0.2440	[2.21]	**	0.0650	[0.62]	
Mispricing Signal Q5 * Emerging	0.6227	[2.20]	**	0.6622	[2.38]	**	0.7213	[2.59]	**	0.7405	[2.72]	***
Mispricing Signal Q5 * Asia Pacific	0.5022	[2.65]	***	0.5033	[2.68]	***	0.3222	[1.79]	*	0.2922	[1.63]	
Mispricing Signal Q5 * Europe	-0.2648	[-1.96]	*	-0.1950	[-1.45]		-0.0399	[-0.31]		-0.0104	[-0.08]	
Mispricing Signal Q5 * Africa	-0.3448	[-0.79]		-0.3233	[-0.74]		-0.5325	[-1.26]		-0.4702	[-1.11]	
Observations	3,445			3,445			3,445			3,445		
Adj. RSquare	0.12			0.12			0.12			0.12		
Characteristic Controls	Yes			Yes			Yes			Yes		
Country Controls	No			No			No			No		
Development Control	Yes			Yes			Yes			Yes		
Geographic Region Controls	Yes			Yes			Yes			Yes		
Industry Controls	Yes			Yes			Yes			Yes		

(continued)

Table 5: Emerging vs. Developed Markets (continued)

Panel B: Factor Model Regressions

		OLS									TS		
		Q1			Q5			Q5-Q1			Q5-Q1		
		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Average	Emerging	-0.3164	[-2.51]	**	0.5398	[2.85]	***	0.8562	[4.73]	***	0.8739	[4.95]	***
	Developed	-0.2486	[-5.05]	***	0.2240	[3.95]	***	0.4726	[5.68]	***	0.3545	[4.45]	***
	Difference	-0.0677	[-0.51]		0.3159	[1.63]		0.3836	[1.95]	*	0.5194	[2.66]	***
Americas	Emerging	-0.3477	[-1.46]		1.0486	[2.55]	**	1.3963	[3.38]	***	1.4428	[3.39]	***
	Developed	-0.3151	[-4.63]	***	-0.2085	[-2.70]	***	0.1065	[1.02]		0.2843	[3.49]	***
	Difference	-0.0327	[-0.13]		1.2571	[3.07]	***	1.2898	[3.00]	***	1.1585	[2.67]	***
Asia Pacific	Emerging	-1.1315	[-5.26]	***	0.3887	[1.53]		1.5202	[6.10]	***	1.4490	[5.75]	***
	Developed	-0.3689	[-2.87]	***	0.7266	[5.45]	***	1.0956	[5.97]	***	0.2369	[1.15]	
	Difference	-0.7625	[-3.16]	***	-0.3379	[-1.12]		0.4246	[1.36]		1.2121	[3.79]	***
Europe	Emerging	0.5301	[1.97]	*	0.1822	[0.58]		-0.3479	[-1.18]		-0.2699	[-0.91]	
	Developed	-0.0619	[-1.14]		0.1538	[1.82]	*	0.2158	[2.45]	**	0.5425	[6.73]	***
	Difference	0.5921	[2.12]	**	0.0284	[0.09]		-0.5637	[-1.83]	*	-0.8124	[-2.58]	**

Table 6: 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 equally-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 44-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, and North America). 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. Columns under the OLS heading report results for signals from OLS regressions, while columns under the TS heading show results for signals from Theil-Sen regressions as described in the text. *, **, and *** indicate statistical significance at the 10% (5%, 1%) significance level. All variables are defined in Appendix A.

(continued)

Table 6: Overlapping Buy and Hold Investment Strategies (continued)

	OLS																		TS		
	Q1 (Overvalued)			Q2			Q3			Q4			Q5 (Undervalued)			Q5-Q1			Q5-Q1		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Industry-Adjusted Returns																					
World	-0.1582	[-4.15]	***	-0.1070	[-2.57]	**	-0.0483	[-1.38]		0.0680	[1.44]		0.2581	[4.10]	***	0.4163	[4.92]	***	0.4348	[4.08]	***
World (excl. U.S.)	-0.2678	[-3.36]	***	-0.1825	[-2.58]	**	-0.1523	[-2.07]	**	-0.0228	[-0.27]		0.2246	[2.18]	**	0.4924	[5.90]	***	0.4548	[4.99]	***
Developed	-0.1464	[-3.05]	***	-0.1041	[-1.99]	**	-0.0486	[-1.05]		0.0493	[0.84]		0.2013	[2.65]	***	0.3477	[3.85]	***	0.3544	[3.12]	***
Developed (excl. U.S.)	-0.2718	[-2.91]	***	-0.1944	[-2.33]	**	-0.1685	[-1.91]	*	-0.0598	[-0.59]		0.1485	[1.22]		0.4203	[4.61]	***	0.3442	[3.33]	***
Emerging	-0.0095	[-0.03]		0.0621	[0.19]		0.1121	[0.35]		0.2511	[0.80]		0.6986	[2.09]	**	0.7081	[4.39]	***	0.7737	[4.36]	***
Americas	0.0584	[0.49]		0.0570	[0.43]		0.1328	[1.03]		0.2243	[1.54]		0.2766	[2.11]	**	0.2182	[1.81]	*	0.3560	[2.25]	**
Europe	0.0324	[0.25]		0.0522	[0.41]		0.0282	[0.22]		0.0872	[0.66]		0.1324	[0.97]		0.1001	[1.12]		0.2901	[3.42]	***
Asia Pacific	-0.6039	[-2.66]	***	-0.4399	[-2.08]	**	-0.3637	[-1.78]	*	-0.1920	[-0.92]		0.2195	[0.96]		0.8234	[6.38]	***	0.5815	[3.81]	***
United States	0.0679	[0.53]		0.0580	[0.40]		0.1337	[0.95]		0.2053	[1.28]		0.2279	[1.62]		0.1599	[1.24]		0.3179	[1.92]	*
Japan	-0.6150	[-2.37]	**	-0.5040	[-2.11]	**	-0.4258	[-1.80]	*	-0.2807	[-1.15]		0.1533	[0.58]		0.7683	[5.17]	***	0.3709	[1.96]	*
Factor Model Alphas (80 Factors)																					
World	-0.1684	[-3.82]	***	-0.0559	[-1.53]		-0.0422	[-1.15]		0.0198	[0.53]		0.2474	[4.50]	***	0.4158	[5.18]	***	0.4189	[5.41]	***
World (excl. U.S.)	-0.1249	[-2.25]	**	-0.0798	[-2.29]	**	-0.0436	[-1.19]		0.0951	[2.42]	**	0.3874	[5.76]	***	0.5123	[5.50]	***	0.4534	[4.54]	***
Developed	-0.1434	[-3.07]	***	-0.0327	[-0.80]		-0.0294	[-0.73]		0.0100	[0.23]		0.1832	[2.96]	***	0.3266	[3.86]	***	0.3309	[3.89]	***
Developed (excl. U.S.)	-0.0724	[-1.18]		-0.0320	[-0.83]		-0.0061	[-0.15]		0.1134	[2.52]	**	0.3410	[4.40]	***	0.4134	[4.08]	***	0.3380	[2.91]	***
Emerging	-0.5930	[-3.23]	***	-0.5397	[-2.92]	***	-0.3859	[-2.34]	**	-0.2759	[-1.60]		0.2740	[1.25]		0.8670	[4.47]	***	0.9060	[4.42]	***
Americas	-0.2258	[-3.06]	***	-0.0583	[-0.86]		-0.0891	[-1.32]		-0.1287	[-1.62]		-0.0340	[-0.37]		0.1918	[1.70]	*	0.3342	[3.27]	***
Europe	-0.0066	[-0.10]		-0.0196	[-0.37]		-0.0516	[-0.97]		0.0549	[0.79]		0.2104	[2.24]	**	0.2170	[2.41]	**	0.4244	[4.71]	***
Asia Pacific	-0.3776	[-2.97]	***	-0.2189	[-3.10]	***	-0.1206	[-1.77]	*	0.0039	[0.05]		0.3669	[2.94]	***	0.7445	[4.52]	***	0.3603	[2.01]	**
United States	-0.2195	[-2.78]	***	-0.0601	[-0.84]		-0.0978	[-1.35]		-0.1716	[-1.96]	*	-0.1116	[-1.14]		0.1079	[0.89]		0.2843	[2.63]	***
Japan	-0.1686	[-1.14]		-0.0767	[-1.06]		0.0216	[0.29]		0.1027	[1.24]		0.4311	[2.84]	***	0.5997	[3.17]	***	0.1098	[0.49]	
Factor Model Alphas (Fama French Data Library, 44 Factors)																					
World	-0.1737	[-3.69]	***	-0.1131	[-3.14]	***	-0.1084	[-3.32]	***	0.0094	[0.25]		0.2692	[4.87]	***	0.4429	[5.56]	***	0.4054	[5.32]	***
World (excl. U.S.)	-0.1353	[-2.31]	**	-0.0706	[-1.78]	*	-0.0608	[-1.48]		0.1079	[2.37]	**	0.4058	[5.97]	***	0.5411	[6.08]	***	0.4529	[4.97]	***
Developed	-0.1961	[-3.33]	***	-0.1195	[-2.47]	**	-0.1187	[-2.64]	***	-0.0102	[-0.20]		0.2166	[3.10]	***	0.4127	[4.81]	***	0.3508	[4.18]	***
Developed (excl. U.S.)	-0.1718	[-2.36]	**	-0.0729	[-1.34]		-0.0653	[-1.18]		0.1026	[1.74]	*	0.3590	[4.17]	***	0.5308	[5.40]	***	0.3818	[3.54]	***
Emerging	0.1569	[0.39]		-0.0637	[-0.16]		0.0063	[0.02]		0.1185	[0.31]		0.6188	[1.50]		0.4619	[2.20]	**	0.6003	[2.65]	***
Americas	-0.2137	[-2.55]	**	-0.1741	[-2.44]	**	-0.1912	[-2.83]	***	-0.1698	[-2.16]	**	-0.0014	[-0.01]		0.2123	[1.86]	*	0.2857	[2.79]	***
Europe	-0.0962	[-1.37]		-0.1024	[-1.63]		-0.1246	[-1.93]	*	0.0158	[0.21]		0.1302	[1.41]		0.2264	[2.64]	***	0.3821	[4.56]	***
Asia Pacific	-0.2089	[-1.54]		-0.0235	[-0.22]		0.0276	[0.28]		0.1759	[1.73]	*	0.6126	[4.38]	***	0.8215	[5.23]	***	0.4735	[2.76]	***
United States	-0.2160	[-2.37]	**	-0.1812	[-2.39]	**	-0.2037	[-2.78]	***	-0.2046	[-2.36]	**	-0.0561	[-0.53]		0.1600	[1.30]		0.2627	[2.41]	**
Japan	-0.1970	[-1.42]		0.0199	[0.22]		0.0418	[0.47]		0.1965	[2.08]	**	0.6219	[4.01]	***	0.8188	[4.51]	***	0.2807	[1.29]	

Table 7: 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 4 (for monthly rebalancing) and Table 6 (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. All variables are defined in Appendix A.

	Q1				Q5				Q5-Q1			
	Alpha	One-Way Turnover	Transactions Costs	Net Performance	Alpha	One-Way Turnover	Transactions Costs	Net Performance	Alpha	One-Way Turnover	Transactions Costs	Net Performance
Monthly Rebalancing												
World	-0.2688	20%	0.1357	-0.1331	0.3191	19%	0.1250	0.1941	0.5879	39%	0.2607	0.3272
World ex U.S.	-0.2201	23%	0.1677	-0.0524	0.5137	20%	0.1516	0.3621	0.7339	43%	0.3193	0.4146
Developed	-0.2545	20%	0.1180	-0.1365	0.2277	18%	0.1075	0.1202	0.4822	38%	0.2255	0.2567
Developed ex U.S.	-0.1880	22%	0.1420	-0.0460	0.4422	20%	0.1254	0.3168	0.6302	42%	0.2673	0.3629
Emerging	-0.4568	27%	0.4006	-0.0562	0.5103	25%	0.3888	0.1215	0.9671	52%	0.7895	0.1776
Americas	-0.3147	17%	0.0935	-0.2212	-0.0455	16%	0.0890	-0.1345	0.2692	33%	0.1825	0.0867
Europe	-0.0371	24%	0.1767	0.1396	0.1968	20%	0.1458	0.0510	0.2339	43%	0.3225	-0.0886
Asia Pacific	-0.5251	22%	0.1627	-0.3624	0.6275	22%	0.1657	0.4618	1.1526	44%	0.3284	0.8242
United States	-0.3291	17%	0.0872	-0.2419	-0.1446	16%	0.0845	-0.2291	0.1845	33%	0.1717	0.0128
Japan	-0.3690	21%	0.1107	-0.2583	0.6966	21%	0.1148	0.5818	1.0656	43%	0.2255	0.8401
Buy-and-Hold												
World	-0.1684	4%	0.0284	-0.1400	0.2474	4%	0.0270	0.2204	0.4158	8%	0.0554	0.3604
World ex U.S.	-0.1249	5%	0.0336	-0.0913	0.3874	4%	0.0313	0.3561	0.5123	9%	0.0649	0.4474
Developed	-0.1434	4%	0.0254	-0.1180	0.1832	4%	0.0238	0.1594	0.3266	8%	0.0492	0.2774
Developed ex U.S.	-0.0724	4%	0.0290	-0.0434	0.3410	4%	0.0263	0.3147	0.4134	9%	0.0553	0.3581
Emerging	-0.5930	5%	0.0747	-0.5183	0.2740	5%	0.0758	0.1982	0.8670	10%	0.1505	0.7165
Americas	-0.2258	4%	0.0221	-0.2037	-0.0340	4%	0.0215	-0.0555	0.1918	8%	0.0436	0.1482
Europe	-0.0066	5%	0.0350	0.0284	0.2104	4%	0.0302	0.1802	0.2170	9%	0.0652	0.1518
Asia Pacific	-0.3776	5%	0.0337	-0.3439	0.3669	5%	0.0346	0.3323	0.7445	9%	0.0684	0.6761
United States	-0.2195	4%	0.0208	-0.1987	-0.1116	4%	0.0205	-0.1321	0.1079	8%	0.0413	0.0666
Japan	-0.1686	4%	0.0242	-0.1444	0.4311	5%	0.0248	0.4063	0.5997	9%	0.0490	0.5507

Table 8: Country Determinants of Trading Profits

The table shows results from firm-level (Panel A) and country-level (Panel B) Fama-MacBeth (1973) regressions of monthly mispricing strategy performance on country characteristics. In Panel A, the stock return in the next period 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. Columns under the OLS heading report results for signals from OLS regressions, while columns under the TS heading show results for signals from Theil-Sen regressions as described in the text. The panel 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. In Panel B, stocks are sorted each month by country into quintiles based on the mispricing signal and combined into equally weighted quintile portfolios by country. A spread portfolio is formed by country as the difference between the returns of the portfolios Q5 (most undervalued stocks) and Q1 (most overvalued stocks), with adjustment for industry portfolio returns based on 38 Fama French industry classifications. Spread portfolio returns for each country 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 resulting monthly alphas for each country (calculated as the sum of the intercept and the residuals) are regressed on various country characteristics by month and subsequently averaged across months. The Panel reports Fama-MacBeth coefficients and associated *t*-statistics in column, as well as the average number of observations and average R-Squared. Panel C reports *F*-statistics and associated *p*-values of *F*-Tests that test whether the averages of the time-series of cross-sectional coefficients of specification (2) in Panel A and Panel B are jointly zero for the variables in a particular group. *, **, and *** indicate statistical significance at the 10% (5%, 1%) significance level. All variables are defined in Appendix A.

(continued)

Table 8: Country Determinants of Trading Profits (continued)

Panel A: Fama MacBeth Regressions with Firm and Country Characteristics

	OLS						TS		
	(1)			(2)			(2)		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Mispricing Signal Q5	0.0376	[0.29]		1.4506	[0.54]		2.5423	[0.98]	
Trading Costs									
Mispricing Signal Q5 * Transactions Costs	0.7512	[2.13]	**	1.4271	[1.87]	*	1.4562	[2.03]	**
Regulatory									
Mispricing Signal Q5 * Short Sales Dummy				0.0001	[0.00]		-0.1526	[-0.19]	
Mispricing Signal Q5 * Common Law				-0.9359	[-2.21]	**	-1.3780	[-3.34]	***
Economic & Financial Development									
Mispricing Signal Q5 * Deposit Banks' Assets/GDP				-0.0105	[-1.19]		-0.0192	[-2.19]	**
Mispricing Signal Q5 * Private Credit by Deposit Money Banks/GDP				0.0073	[0.81]		0.0142	[1.60]	
Mispricing Signal Q5 * Stock Market Turnover Ratio				0.0004	[0.14]		-0.0018	[-0.59]	
Mispricing Signal Q5 * Country Risk (inverse index)				0.0082	[0.38]		-0.0053	[-0.24]	
Mispricing Signal Q5 * Geographical Size (log)				0.0536	[0.61]		0.0544	[0.59]	
Informational Environment									
Mispricing Signal Q5 * Analyst Coverage				-0.0079	[-0.73]		-0.0084	[-0.75]	
Characteristics of Equity Market									
Mispricing Signal Q5 * Market Volatility				-8.1052	[-2.53]	**	-8.6890	[-2.70]	***
Mispricing Signal Q5 * Correlation with World Market				-1.7625	[-1.29]		-1.0576	[-0.82]	
Mispricing Signal Q5 * Number of Listed Companies (Log)				0.1539	[1.09]		0.2212	[1.56]	
Intercept	0.4879	[1.10]		-0.2265	[-0.24]		-0.6476	[-0.70]	
Observations	3,440			3,440			3,440		
Adj. Rsquare	0.15			0.16			0.16		
Firm Characteristic Controls	Yes			Yes			Yes		
Country Controls	Yes			Yes			Yes		
Industry Controls	Yes			Yes			Yes		

(continued)

Table 8: Country Determinants of Trading Profits (continued)

Panel B: Fama-MacBeth Regressions of Factor Model Alphas

	OLS						TS		
	(1)			(2)			(2)		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Trading Costs									
Transactions Costs	0.5675	[1.90]	*	1.4761	[2.84]	***	1.1798	[2.23]	**
Regulatory									
Short Sales Dummy				0.9398	[1.15]		0.7704	[0.92]	
Common Law				-0.2669	[-0.91]		-0.4901	[-1.74]	*
Economic & Financial Development									
Deposit Banks' Assets/GDP				0.0101	[1.41]		-0.0003	[-0.04]	
Private Credit by Deposit Money Banks/GDP				-0.0056	[-0.81]		0.0026	[0.39]	
Stock Market Turnover Ratio				0.0000	[0.00]		0.0002	[0.10]	
Country Risk (inverse index)				0.0029	[0.18]		-0.0022	[-0.13]	
Geographical Size (log)				-0.0195	[-0.31]		-0.0283	[-0.44]	
Informational Environment									
Analyst Coverage				0.0148	[1.66]	*	0.0110	[1.22]	
Characteristics of Equity Market									
Market Volatility				-5.6187	[-2.08]	**	-5.4231	[-2.05]	**
Correlation with World Market				-3.5399	[-3.06]	***	-2.4503	[-2.12]	**
Number of Listed Companies (Log)				0.2981	[2.62]	***	0.3459	[3.00]	***
Market Index Return	1.0864	[0.53]		-0.4421	[-0.12]		-0.0995	[-0.03]	
Intercept	-0.0400	[-0.27]		-1.1664	[-0.61]		-0.8688	[-0.46]	
Adj. Rsquare	0.03			0.04			0.0557		
Observations	22.7			22.7			22.7		

Panel C: F-Tests

	Table 8 Panel A						Table 8 Panel B					
	OLS			TS			OLS			TS		
	F-Value	*p*-value		F-Value	*p*-value		F-Value	*p*-value		F-Value	*p*-value	
Trading Costs	3.51	0.062	*	4.12	0.043	**	8.05	0.005	***	4.98	0.026	**
Regulatory	2.44	0.089	*	5.64	0.004	***	0.92	0.399		1.70	0.184	
Economic & Financial Development	0.84	0.523		2.32	0.044	**	1.22	0.300		0.32	0.902	
Informational Environment	0.53	0.468		0.56	0.453		2.77	0.097	*	1.50	0.222	
Characteristics of Equity Market	3.44	0.017	**	4.09	0.007	***	4.65	0.001	***	4.05	0.003	***

Table 9: 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 and 44 factors. 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 equally-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 44-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, and North America). *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively. All variables are defined in Appendix A.

Panel A: 80-Factor Model Alphas

	Q1			Q2			Q3			Q4			Q5		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Beta	0.5872	[4.58]	***	0.5080	[4.51]	***	0.4538	[4.41]	***	0.3558	[2.84]	***	0.5872	[3.16]	***
Book/Market	0.3585	[2.12]	**	0.2295	[1.87]	*	0.3419	[2.68]	***	0.5809	[5.05]	***	0.6614	[4.99]	***
Market Capitalization	0.6929	[6.11]	***	0.4835	[4.48]	***	0.3584	[3.08]	***	0.2170	[1.63]		0.2704	[2.58]	**
Short-term Reversal	0.8854	[5.67]	***	0.4185	[3.47]	***	0.5229	[4.41]	***	0.4751	[3.95]	***	0.3279	[1.95]	*
Momentum	0.6264	[3.73]	***	0.4278	[3.88]	***	0.6489	[5.99]	***	0.5941	[5.12]	***	0.8473	[5.41]	***
Long-term Reversal	0.7371	[4.66]	***	0.6717	[5.44]	***	0.5799	[5.31]	***	0.3539	[3.08]	***	0.4551	[3.13]	***
Accruals	0.8965	[6.23]	***	0.7336	[6.25]	***	0.4022	[3.84]	***	0.6575	[5.25]	***	0.3164	[2.05]	**
SUE	0.4651	[2.80]	***	0.5626	[3.91]	***	0.4228	[3.06]	***	0.4083	[3.17]	***	0.7193	[4.25]	***
Gross Profitability	0.5876	[4.13]	***	0.6893	[5.95]	***	0.6484	[4.94]	***	0.6123	[4.80]	***	0.3029	[1.91]	*
ROA	0.7642	[4.38]	***	0.6952	[5.58]	***	0.6324	[5.54]	***	0.6108	[5.38]	***	0.3446	[2.33]	**
Scaled NOA	0.5911	[3.34]	***	0.6972	[5.48]	***	0.6883	[6.13]	***	0.4677	[4.48]	***	0.4474	[3.42]	***
Share Issuance	0.4642	[3.50]	***	0.6896	[5.32]	***	0.6671	[4.56]	***	0.1370	[0.94]		0.4868	[2.67]	***
Composite Equity Issuance	0.5804	[3.63]	***	0.6967	[6.33]	***	0.5017	[4.41]	***	0.3168	[2.88]	***	0.2584	[1.89]	*
Asset Growth	0.5987	[4.21]	***	0.6425	[5.38]	***	0.7996	[7.02]	***	0.5003	[3.97]	***	0.2973	[1.95]	*
Capital Investment	0.6781	[4.79]	***	0.5108	[4.21]	***	0.5937	[4.64]	***	0.7187	[5.76]	***	0.3291	[2.66]	***
Investment Ratio	0.8433	[6.58]	***	0.7025	[5.58]	***	0.4779	[3.57]	***	0.4873	[3.76]	***	0.3738	[2.76]	***
External Financing	0.5308	[5.07]	***	0.4780	[4.51]	***	0.9649	[6.66]	***	0.5281	[3.50]	***	0.3305	[2.19]	**
Z-Score	0.3863	[2.79]	***	0.4086	[3.75]	***	0.4681	[3.99]	***	0.8567	[6.30]	***	0.7135	[4.51]	***
Leverage	0.7157	[3.55]	***	0.4352	[3.19]	***	0.5059	[4.60]	***	0.5798	[5.20]	***	0.6439	[4.81]	***
Earnings/Price	0.6148	[3.47]	***	0.5680	[3.75]	***	0.2493	[2.08]	**	0.4233	[4.15]	***	0.6078	[5.05]	***
Dividends/Price	0.3672	[2.24]	**	0.7664	[5.27]	***	0.6563	[5.69]	***	0.5681	[5.49]	***	0.3537	[3.52]	***
Cash Flow/Price	0.7327	[3.59]	***	0.2774	[2.02]	**	0.4116	[3.61]	***	0.3890	[3.84]	***	0.5802	[4.45]	***

(continued)

Table 9: Mispricing Strategies within Quintiles of Other Anomalies (continued)

Panel B: 44-Factor Model Alphas (Fama French Data Library)

	Q1			Q2			Q3			Q4			Q5		
	Coef	t-stat		Coef	t-stat		Coef	t-stat		Coef	t-stat		Coef	t-stat	
Beta	0.6217	[4.94]	***	0.4643	[4.07]	***	0.4119	[3.73]	***	0.3485	[2.74]	***	0.5342	[2.80]	***
Book/Market	0.3026	[1.73]	*	0.2365	[1.89]	*	0.3114	[2.59]	**	0.5355	[4.52]	***	0.6215	[4.71]	***
Market Capitalization	0.7363	[6.92]	***	0.5222	[4.34]	***	0.2817	[2.53]	**	0.1358	[0.97]		0.1640	[1.44]	
Short-term Reversal	1.0144	[6.77]	***	0.4879	[4.14]	***	0.5950	[4.97]	***	0.3887	[3.29]	***	0.2643	[1.54]	
Momentum	0.7073	[4.39]	***	0.4585	[3.96]	***	0.6950	[6.34]	***	0.5704	[4.92]	***	0.6108	[3.82]	***
Long-term Reversal	0.7021	[4.51]	***	0.6344	[5.25]	***	0.5721	[5.29]	***	0.2844	[2.41]	**	0.3701	[2.38]	**
Accruals	0.8776	[6.29]	***	0.6137	[5.07]	***	0.4495	[4.31]	***	0.6752	[5.74]	***	0.3733	[2.36]	**
SUE	0.6603	[3.99]	***	0.6143	[4.43]	***	0.3843	[2.87]	***	0.5321	[3.97]	***	0.7634	[4.79]	***
Gross Profitability	0.6232	[4.57]	***	0.7427	[6.55]	***	0.5352	[4.15]	***	0.7686	[5.73]	***	0.3016	[1.95]	*
ROA	0.7184	[4.19]	***	0.7877	[6.56]	***	0.5341	[4.99]	***	0.6011	[5.16]	***	0.3657	[2.40]	**
Scaled NOA	0.7118	[4.10]	***	0.6464	[5.25]	***	0.6396	[5.76]	***	0.3385	[3.09]	***	0.4283	[3.41]	***
Share Issuance	0.5248	[4.07]	***	0.6956	[5.39]	***	0.8171	[5.74]	***	0.3305	[2.20]	**	0.4624	[2.59]	**
Composite Equity Issuance	0.5119	[3.26]	***	0.6007	[5.10]	***	0.5190	[4.56]	***	0.4880	[4.37]	***	0.3020	[2.17]	**
Asset Growth	0.7472	[5.33]	***	0.6297	[5.49]	***	0.7167	[6.23]	***	0.4905	[3.72]	***	0.3139	[2.07]	**
Capital Investment	0.5266	[3.89]	***	0.5215	[4.00]	***	0.4583	[3.49]	***	0.8546	[6.73]	***	0.4817	[3.72]	***
Investment Ratio	0.7467	[5.87]	***	0.7068	[5.58]	***	0.5730	[4.37]	***	0.5259	[4.18]	***	0.3768	[2.86]	***
External Financing	0.4942	[4.58]	***	0.5318	[5.06]	***	0.9256	[6.61]	***	0.7761	[5.05]	***	0.1742	[1.18]	
Z-Score	0.4457	[3.24]	***	0.3892	[3.57]	***	0.4369	[3.51]	***	0.7782	[5.67]	***	0.7649	[4.88]	***
Leverage	0.5854	[2.87]	***	0.5229	[3.89]	***	0.6156	[5.33]	***	0.5511	[5.06]	***	0.5956	[4.71]	***
Earnings/Price	0.6666	[3.85]	***	0.5766	[3.94]	***	0.3336	[2.90]	***	0.4802	[4.66]	***	0.6012	[5.01]	***
Dividends/Price	0.4746	[2.99]	***	0.6184	[4.22]	***	0.5465	[4.81]	***	0.5880	[5.31]	***	0.3763	[3.69]	***
Cash Flow/Price	0.7338	[3.61]	***	0.3108	[2.31]	**	0.3779	[3.28]	***	0.4881	[4.88]	***	0.5166	[4.02]	***

Table 10: Alternative Signals

The table shows results from factor model time-series regressions with alternative signals. Stocks are sorted each month by country into quintiles based on the mispricing signal and combined into equally-weighted portfolios by region. In Panel A, signals are from regressions of the 21 accounting variables on market capitalization without intercept. In Panel B, signals are from regressions of analysts' consensus forecasts of aggregate earnings for the next two fiscal years (FY1 and FY2) on market capitalization (with intercept). A spread portfolio is formed as the difference between the returns of the portfolios Q5 (most undervalued stocks) and Q1 (most overvalued stocks), with and without adjustment for industry portfolio returns based on 38 Fama French industry classifications. Spread portfolio returns with and without industry adjustment are regressed on an intercept (reported under the headings Returns and Industry-Adjusted Returns). Moreover, spread portfolio returns with industry adjustment 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), and a 44-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, and North America). The table reports the regression coefficients of the regression intercept and associated *t*-statistics of the time-series regressions. Columns under the OLS heading report results for signals from OLS regressions, while columns under the TS heading show results for signals from Theil-Sen regressions as described in the text. *, **, and *** indicate statistical significance at the 10% (5%, 1%) significance level. All variables are defined in Appendix A.

Panel A: Signals without Intercept

	Returns						Industry-Adjusted Returns					
	OLS			TS			OLS			TS		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
World	0.6897	[5.03]	***	0.6650	[4.64]	***	0.7142	[6.66]	***	0.7064	[6.24]	***
World (excl. U.S.)	0.6411	[6.67]	***	0.6964	[6.34]	***	0.6521	[8.24]	***	0.7071	[8.11]	***
Developed	0.6627	[4.60]	***	0.6173	[4.08]	***	0.6929	[6.10]	***	0.6650	[5.51]	***
Developed (excl. U.S.)	0.5956	[5.70]	***	0.6267	[5.18]	***	0.6141	[7.01]	***	0.6438	[6.56]	***
Emerging	0.8862	[4.62]	***	1.0313	[5.45]	***	0.8475	[4.45]	***	0.9961	[5.30]	***
Americas	0.6805	[3.34]	***	0.5555	[2.71]	***	0.7382	[4.42]	***	0.6437	[3.75]	***
Europe	0.4429	[5.45]	***	0.5488	[5.62]	***	0.4528	[6.30]	***	0.5500	[6.60]	***
Asia Pacific	0.8487	[5.02]	***	0.8883	[5.01]	***	0.8479	[5.65]	***	0.9014	[5.88]	***
United States	0.6686	[3.10]	***	0.5492	[2.59]	**	0.7217	[4.03]	***	0.6354	[3.51]	***
Japan	0.7770	[3.94]	***	0.7578	[3.64]	***	0.7763	[4.34]	***	0.7711	[4.14]	***

	80-Factor Model Alphas						44-Factor Model Alphas					
	OLS			TS			OLS			TS		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
World	0.5942	[8.76]	***	0.6390	[9.07]	***	0.5768	[8.14]	***	0.5665	[7.74]	***
World (excl. U.S.)	0.5475	[6.42]	***	0.6149	[6.69]	***	0.5846	[6.96]	***	0.6111	[6.97]	***
Developed	0.5980	[8.06]	***	0.6189	[8.06]	***	0.5919	[7.65]	***	0.5583	[6.98]	***
Developed (excl. U.S.)	0.5493	[5.70]	***	0.5873	[5.52]	***	0.6068	[6.49]	***	0.6011	[6.01]	***
Emerging	0.4464	[1.84]	*	0.5968	[2.46]	**	0.5490	[2.27]	**	0.7199	[2.99]	***
Americas	0.6574	[6.20]	***	0.6569	[6.78]	***	0.5650	[5.03]	***	0.4967	[4.59]	***
Europe	0.4517	[5.37]	***	0.5669	[6.25]	***	0.4141	[5.08]	***	0.4769	[5.38]	***
Asia Pacific	0.6071	[3.92]	***	0.6009	[3.71]	***	0.7185	[4.76]	***	0.7157	[4.69]	***
United States	0.6600	[5.65]	***	0.6563	[6.21]	***	0.5553	[4.62]	***	0.4898	[4.27]	***
Japan	0.5780	[3.06]	***	0.5068	[2.50]	**	0.7151	[3.97]	***	0.6450	[3.39]	***

(continued)

Table 10: Alternative Signals (continued)

Panel B: Signals with Earnings Forecasts

	Returns						Industry-Adjusted Returns					
	OLS			TS			OLS			TS		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
World	0.5160	[2.92]	***	0.5389	[2.90]	***	0.5495	[4.02]	***	0.5742	[3.98]	***
World (excl. U.S.)	0.6276	[4.67]	***	0.5859	[4.19]	***	0.6297	[5.52]	***	0.5903	[5.10]	***
Developed	0.4475	[2.47]	**	0.4734	[2.49]	**	0.4761	[3.37]	***	0.5036	[3.38]	***
Developed (excl. U.S.)	0.5145	[3.71]	***	0.4682	[3.27]	***	0.5026	[4.21]	***	0.4582	[3.83]	***
Emerging	1.4588	[4.75]	***	1.4350	[4.69]	***	1.6084	[5.39]	***	1.5906	[5.35]	***
Americas	0.3957	[1.71]	*	0.4824	[2.00]	**	0.4560	[2.46]	**	0.5439	[2.80]	***
Europe	0.2254	[1.68]	*	0.2289	[1.71]	*	0.1941	[1.64]		0.2019	[1.72]	*
Asia Pacific	1.1099	[5.25]	***	1.0165	[4.41]	***	1.1220	[5.78]	***	1.0287	[4.97]	***
United States	0.3879	[1.61]		0.4772	[1.90]	*	0.4403	[2.26]	**	0.5322	[2.60]	***
Japan	0.9677	[4.08]	***	0.8424	[3.28]	***	0.9689	[4.40]	***	0.8419	[3.63]	***

	80-Factor Model Alphas						44-Factor Model Alphas					
	OLS			TS			OLS			TS		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
World	0.2493	[2.09]	**	0.1918	[1.75]	*	0.1160	[0.92]		0.1213	[1.02]	
World (excl. U.S.)	0.5005	[3.98]	***	0.4082	[3.48]	***	0.4210	[3.64]	***	0.3787	[3.54]	***
Developed	0.1588	[1.26]		0.0961	[0.84]		0.0486	[0.37]		0.0543	[0.44]	
Developed (excl. U.S.)	0.3690	[2.72]	***	0.2600	[2.08]	**	0.3266	[2.67]	***	0.2738	[2.45]	**
Emerging	1.2186	[3.24]	***	1.2434	[3.32]	***	1.1679	[3.04]	***	1.1963	[3.13]	***
Americas	0.0117	[0.07]		0.0028	[0.02]		-0.1113	[-0.62]		-0.0527	[-0.31]	
Europe	0.0409	[0.29]		0.0569	[0.40]		0.1300	[0.96]		0.1538	[1.12]	
Asia Pacific	1.0721	[4.96]	***	0.8295	[4.14]	***	0.8034	[4.03]	***	0.6919	[3.85]	***
United States	-0.0149	[-0.08]		-0.0233	[-0.14]		-0.1665	[-0.86]		-0.1026	[-0.57]	
Japan	0.9285	[3.56]	***	0.6004	[2.50]	**	0.6829	[2.97]	***	0.5187	[2.54]	**

Appendix A: Variable Definitions

The table shows the definitions of the main variables used in the paper.

Variable	Definition
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	Pretax 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	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., 2001, p. 22)
Gross Profitability	(Revenue - Cost of Goods Sold)/Total Assets (Novy-Marx 2013)
ROA	Return on Assets
EarningsYield	Earnings/Price
Market Capitalization	Stock Market Capitalization (in U.S. Dollars)
Book/Market	(Book Equity + Deferred Taxes)/Market Capitalization
Mispricing Percentage	-1 * Residual/ Market Capitalization
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)

(continued)

Appendix A: Variable Definitions (continued)

Variable	Definition
Other Firm-level Variables	
Z-Score	Z-Score (Ferguson and Shockley, 2003)
Leverage	Leverage (Ferguson and Shockley, 2003)
Earnings/Price	Earnings/Price (Penman, Richardson, Riggoni, and Tuna 2014)
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)
Factor Model Variables	
Mkt_RF	Monthly market index return net of risk-free rate
SMB	Monthly Small Minus Big (SMB) size portfolio return
HML	Monthly High Minus Low (HML) book/market portfolio return
CMA	Monthly Conservative Minus Aggressive (CMA) investment portfolio return
RMW	Monthly Robust Minus Weak (RMW) profitability portfolio return
Mom (WML)	Monthly Winner Minus Losers (WML) momentum portfolio return
ST_Rev	Monthly Short-term Reversal (ST_Rev) portfolio return
LT_Rev	Monthly Long-term Reversal (LT_Rev) 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 KM (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)