...and nothing else matters? On the dimensionality and predictability of international stock returns

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This Version: May 2017

Abstract

We use the information contained in 161 cross-sectional trade signals to explore the multidimensionality and predictability of individual stock returns in five international markets (North America, Europe, Pacific, Japan, and Emerging Markets). All markets are highly dimensional, but the most important return predictors differ across regions. Exploiting these characteristics, a single globally diversified high-dimensioned long/short return forecast strategy realizes a monthly value-weighted four-factor alpha of 1.9% and an annualized Sharpe ratio of 3.4. Collectively, these results add to our understanding of market integration, data mining, and the degree of informational efficiency of global stock markets.

Keywords: Anomalies, international stock markets, multidimensionality, market efficiency, return predictability

JEL Classification Codes: G11, G12, G14

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We thank Jeremiah Green, Bruce Jacobs, Julian Thimme, seminar participants at the Colloquium on Financial Markets in Cologne (2017), and at the Centre for European Economic Research (ZEW) in Mannheim (2017) for valuable comments. Furthermore, we are grateful to Dennis Rommel for valuable research assistance.

1 Introduction

The massive increase in the number of apparent stock return predictors over time has received considerable attention in the asset pricing literature recently. Given the evidence, the appeal of low-dimensioned factor models like Sharpe's (1964) CAPM, Fama's and French's (1993) three-factor model, or Carhart's (1997) four-factor model, which have been the workhorses in empirical asset pricing for five decades, seemingly disappears. However, which of these factors really "matter"? In order to provide additional answers to this question, we compute 161 cross-sectional trade signals[1], and estimate the dimensionality and out-of-sample predictability of stock returns in 44 countries across five regions (North America, Europe, Pacific, Japan, and Emerging Markets).

Non-U.S. stock markets are economically very important yet under-researched.[2] They thus offer an ideal out-of-sample setting to enhance our understanding of how many and which variables provide independent information about stock returns when considered jointly. In this regard, we extent previous work on the cross-section of U.S. stock returns which traces back to Jacobs and Levy (1988) who test 25 return predictors and find 9 of them having a t-statistic greater than 3.

More recently, Green et al. (2017) reexamine this "Multidimensionality Challenge" (Cochrane, 2011, p. 1060) by simultaneously testing 94 different predictors.[3] While they show that 27 of the 94 predictors have a t-statistic above 3 in multivariate regressions, they also note that this dimensionality is to a large extent due to microcap stocks which tend to be over-represented in traditional (OLS) regressions. Outside of microcaps, they find that 12 characteristics are reliably independent determinants of stock returns. This evidence suggests that return predictability is substantially weaker among larger stocks and hence, more difficult to be exploited by institutional investors. In a similar vein, Hou et al. (2017) show that 286 out of a total of 447 previously established anomaly variables are statistically insignificant at a 5% level once they control for the impact of microcap stocks. Green et al. (2017) also document a substantial decrease in return

[1] In the following we use the terms trade signals, anomaly variables, (return) predictors, and return predictive signals interchangeably.

[2] According to the World Bank, the United States represent about 24% of the world's GDP in 2015 and about 40% of the total worldwide market capitalization at the end of 2015. Yet, only 16% of all empirical studies published in the top four Finance journals examine non-US countries (Karolyi, 2016).

[3] Further selcected published work in this area includes Fama and French (2008); Haugen and Baker (1996); Stambaugh et al. (2012); Lewellen (2015); Jacobs and Levy (2014); Fama and French (2015).

predictability post-2003 for U.S. non-microcap stocks.

Our global findings are in many aspects similar to the U.S. evidence, but there are also remarkable differences which extent our knowledge on the multidimensionality challenge. Consistent with prior results for the U.S., we find that expected stock returns are highly dimensional in all regions during our sample period from 1989 to 2015. For North America, 42 of the 161 implemented anomaly variables exhibit absolute t-statistics above a critical threshold of 3 in multivariate regressions (see Harvey et al., 2016). For Europe, 33 trade signals can predict one-month ahead stock returns with a t-statistic above 3. For the Pacific region, Japan, and Emerging Markets, the corresponding numbers are 24, 33, and 19 highly significant predictors. Also in line with the US evidence, there are substantially fewer predictors surpassing a critical t-statistic of 3 in value-weighted regressions which alleviate the impact of microcap stocks (18, 15, 11, 12, and 13 significant predictors respectively). Nonetheless, the multidimensionality of stock returns is apparently a global phenomenon.

Our international perspective yields a number of further insights. While a few variables such as the same calendar month anomaly (see Heston and Sadka, 2008), lagged price momentum (see Novy-Marx, 2012), the book-to-market equity ratio (see Rosenberg et al., 1985), the analyst forecast revision ratio (see Achour et al., 1998), or three-day abnormal earnings announcement returns (see Chan et al., 1996) show up as consistent significant predictors around the globe, the significance of many other variables varies substantially across regions. Moreover, with the exception of the book-to-market ratio, the anomaly variables commonly used in established or new asset pricing models (see Fama and French, 1993, 2015; Hou et al., 2015, 2016) like size, asset growth or profitability rarely show up among the most significant predictors in any region. In line with the findings of Green et al. (2017), we also observe a significant drop in the degree of multidimensionality for the North American value-weighted stock sample after 2002. Yet, this drop has not occurred anywhere else. In fact, for regions such as Emerging Markets or Pacific, the level of predictability is stronger in the later part of the sample period.

In sum, many signals which have been primarily or exclusively studied for US stocks appear to be priced in international markets. To assess their economic significance, it is important to stress that many of these predictors also work predominantly among smaller stocks. Nonetheless, our international results suggest that data mining does not sufficiently explain why there are so many significant return predictors proposed in the literature on the U.S. market. The results also contribute to recent claims (Goyal, 2012; Subrahmanyam, 2010) to consolidate our knowledge on the large number of individual anomalies discovered during the last 50 years.

Next, we switch from an in-sample view to an out-of-sample perspective. Following Green et al. (2017) and Lewellen (2015), we examine historical relations between returns and predictor variables in multivariate regressions on a rolling-window basis for each international market.[4] We map the regression coefficients to the stocks' current values for the predictor variables to obtain a composite estimate of the stocks' expected returns. Stock-level regressions show that this composite multidimensional return forecast is a highly significant predictor of actual future returns. At the portfolio level, we document that decile-based long/short strategies based on the multidimensional forecast yield robust monthly returns in the range of roughly 4% for equal-weighted portfolios and 2% for value-weighted portfolios. Additionally, the performance substantially exceeds those of lower-dimensioned strategies, and it is not explained by competing asset pricing models.

In sum, stock returns around the world are highly dimensional, and a lot of the cross-sectional variation in expected global returns is predictable. These insights add to the growing literature on stock return predictability in international markets (e.g., Griffin et al., 2010; Hou et al., 2011; Fama and French, 2012, 2016; Jacobs, 2016; Jacobs and Müller, 2016).

One possibility for our findings is that expected stock returns emanate form a large set of different systematic factors for which investors require a rational compensation. In line with the argument in MacKinlay (1995), this risk-based explanation would suggest that the deviation in expected returns is also accompanied by increased variance due to return comovement. However, while delivering higher returns, the multidimensional strategies are typically substantially less volatile than lower-dimensioned approaches. Moreover, a further puzzling insight which our study reveals is a surprisingly low correlation of the multidimensional strategies across regions. Consequently, international diversification benefits are substantial leading to an annualized Sharpe

[4]For the U.S. stock market, a couple of recent working papers have started to examine whether alternatives to the traditional multivariate Fama and MacBeth (1973) regression approach may lead to improved return forecasts (see e.g., Feng et al., 2017; Freyberger et al., 2017; Green and Liechty, 2017; Messmer and Audrino, 2017). We leave tests of these approaches for international stocks as an interesting avenue for future research.

ratio of 3.4 for the value-weighted global strategy. The four-factor alpha is similarly impressive and amounts to 1.86% per month with a t-statistic of 12.67 for the value-weighted strategy. In addition, we do not find that multidimensional strategies suffer from crash risk.

As an alternative explanation, we explore the possibility of mispricing coupled with limits to arbitrage. To this end, we relate the return series of long/short equity hedge funds, which are thought to exploit mispricings, with the returns series of our multidimensional strategies. We find that hedge fund returns are significantly positively correlated with the North American strategy only. This finding suggests that hedge funds are for some reason not exploiting mispricings in international markets, which is consistent with Jacobs and Müller (2016).

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 provides an overview of the return predictors. Section 4 presents the empirical findings. Section 5 contains a discussion of the limitations of our analysis. Section 6 concludes.

2 Data

We gather data from three Thomson Reuters databases: Stock returns (measured in US-Dollar) and further stock-related measures are from Datastream, accounting data (annual and interim) are from Worldscope, and analyst data including earnings forecasts and recommendations are from I/B/E/S. Our sample is restricted to equities and the sample period ranges from January 1989 to December 2015. However, data for interim accounting and earnings measures is generally not available before 1992. Our sample period begin is the same as in the international study of Fama and French (2012) and avoids the existence of too many missing data values.

We follow previous work (see e.g., Ince and Porter, 2006; Griffin et al., 2010; Hou et al., 2011; Jacobs and Müller, 2016) in cleaning the Datastream data. The major screens are as follows. We require stocks to have a non-missing Datastream and Worldscope identifier as well as to have return data over the most recent six months, market capitalization data, and data on the book value of equity. Further, we use the generic filter rules proposed in Griffin et al. (2010) to exclude non-common equity, and we use the methodology of Ince and Porter (2006) to include delisted stocks in our analysis only up to the point of their actual delisting. This procedure ensures our sample to be free from survivorship bias. Finally, to limit the impact of outliers and presumably wrong data, we winsorize returns at the 0.1% and 99.9% level.

We include stocks from 44 countries in our analysis, which we divide into five regions for analysis purposes. Basically, we use the countries constituting the MSCI North America, Europe, Pacific and Emerging Markets Indices as of December 2015. However, due to its economic importance, we treat Japan as a separate region as in Fama and French (2012). For each country except the US, we include all exchange-listed companies in our sample. For the US, we require stocks to be listed at one of the three major exchanges NYSE, NASDAQ, or AMEX to ensure better comparability with existing research.

Following these sample definitions, our final sample consists of approximately 5.9 million firm-month observations. Table 1 provides sample summary statistics on a country level. Non-US stock markets comprise approximately 76% of the overall sample of firms, and constitute on average roughly 60% of the total stock market capitalization. This suggests that the US stock market, while being economically the most important, is far from having a dominant role in our sample.

Insert Table 1 here

Figure 1 illustrates a strong increase in total firm observations per year, primarily driven by the development of the Emerging Markets and the Pacific region. For Europe and North America, we observe a decline in the average number of stocks in recent years, particularly since 2008 (see also Doidge et al., 2016).

Insert Figure 1 here

Fama and French (2008) note that anomalous return predictability results can be heavily influenced by microcap stocks, which they define as stocks that are smaller than the 20th percentile of market equity for New York Stock Exchange (NYSE) stocks. They show that microcaps represent only 3% of the total market capitalization of the U.S. stock market, but account for about 60% of the number of stocks. For the international markets in our study, Table 2 shows the percentage number and relative market weight of stocks for portfolios sorted by NYSE size deciles. The results suggest that the fraction of stocks which are counted as microcaps by the definition of Fama and French (2008) is at least as large in international markets as it is for the U.S. For instance, for Europe, 66.6% of all stocks are microcaps which account for about 3.3% of the total market capitalization.

Insert Table 2 here

3 Selection of Return Predictors and Data Preparation

We screen the existing literature focusing on collections of published anomalies over the past decades to identify return predictors which are computable in our international dataset (see Green et al., 2016; Hou et al., 2015; Harvey et al., 2016; Jacobs, 2015; Jacobs and Müller, 2016; McLean and Pontiff, 2016). Some trade signals such as short interest (Dechow et al., 2001) or the corporate governance index (Gompers et al., 2003) cannot be used because we are not aware of a source for international firms. Moreover, unlike some prior work, we do not consider combinations of trade signals (e.g. momentum and idiosyncratic volatility), but leave the study of such interaction effects in a multidimensional context to future work. Our approach yields a total of 161 distinct variables, for which Table 3 provides an overview along with the acronyms, the reference papers, as well as the percentage of missing data points in relation to the total number of firm-months in the sample.

Insert Table 3 here

For the construction of the trade signals, we follow the methodologies used in the reference papers as closely as possible. In some cases there is no exact match for Compustat data in Worldscope. In such circumstances, we compute the trade signal using those Worldscope variables which in our view reflect the intent of the original study as closely as possible. In line with recent suggestions in the literature (Lewellen, 2015), we update variables monthly, whenever possible. For instance, in order to construct the book-market equity ratio, we use monthly updated data on a stock's market capitalization. We assume that annual accounting data is available six months after fiscal year end, and that interim accounting data is available in the month following the earnings announcement.

To account for possible data errors and outliers, we trim all trade signals at the 1% and 99% level and set values below or above these thresholds to missing. To limit the influence of data errors and outliers further, we sort all continuous trade signals in deciles at the country-month level, i.e. we cross-sectionally assign values from 1 to 10. Our country-based sorts intent to control for different accounting standards across countries, particularly in the earlier part of the sample period. For binary indicator variables, stocks receive a value of 10 if the binary condition is fulfilled, and 1 otherwise. For instance, sin stocks (Hong and Kacperczyk, 2009), receive a value of 10 if they belong to a particular sin industry, and 1 if they do not belong to a sin industry or if the industry classification is missing.

As Table 3 reveals, and despite our reliance on well-maintained databases and the selected sample period, there are still substantial amounts of missing data. In order to retain these observations for the regression analysis, we finally reset all missing variable values to the cross-sectional mean country decile value, which is typically close to 5.5. In rare cases, country observations for one particular trade signal are entirely missing, and we use the cross-sectional mean regional decile. Because interim accounting data is not available prior to 1992 for the international dataset (i.e. for the first three years of our total 26 years sample period), we set all return predictors that are based on this data to 5.5 before 1992. We are aware of the potential estimation errors that may arise as a result of our procedure and discuss them in Section 5.

4 Empirical Results

4.1 Multidimensionality of Stock Returns

We follow the procedure of Green et al. (2017) and explore the degree of multidimensionality via Fama and MacBeth (1973) regressions of stock returns on the full set of 161 trade signals. We report our results in Table 4 separately for every international stock market (Panel A: North America, Panel B: Europe, Panel C: Japan, Panel D: Pacific, Panel E: Emerging Markets). Moreover, we separate each panel further by presenting the results for traditional ordinary least squares (OLS) regressions in the left part of the table, as well as the results for value-weighted least squares

(VWLS) regressions in the right part.

OLS regressions equally weight each observation and thereby better document how widespread a return phenomenon is. However, this approach has recently been criticized because the results may be largely driven by microcap stocks which are not tradeable for many investors (e.g., Green et al., 2017; Hou et al., 2017). VWLS regressions weight each stock by its market value in a particular month, and may hence provide a better assessment of the economic importance of a return predictor. To balance the pros and cons of both approaches, we continue to report equal-weighted and value-weighted return results with equal emphasis in the remainder text unless otherwise noted. However, to evaluate the economic importance of a result, value-weighted returns are arguably preferable.

Insert Table 4 here

Given the long list of return predictors, Table 4 rather provides a summary of the extent of multidimensionality. That is, we report individual regression coefficients as well as t-statistics only for the 15 most significant predictors in each specification, and shift the complete results to the Appendix. For the presentation of the results, we scale all predictor variables such that the resulting coefficients can be interpreted as annualized decile 10 minus decile 1 long/short returns that are orthogonal to all other trade signals.

The results in Panel A for the North American stock market show that many of the included variables are also statistically significant. In the OLS regressions, 42 (70) predictors have an associated absolute t-statistic larger than 3 (2). In the VWLS regressions, 18 (36) predictors have an associated absolute t-statistic larger than 3 (2).

One concern with regard to these findings is that our long list of trade signals may lead to a substantial degree of multicollinearity among the independent variables, which may cause an overestimation of the true extent of multidimensionality. To address this concern, we calculate variance inflation factors (VIF) for all independent variables. Typically accepted values for a VIF are up to 10 (see e.g., Gujarati and Porter, 2009), and Green et al. (2017) use a VIF cut-off of 7 to eliminate some of the variables from their regression model. While we do not exclude variables from the model, we report statistical significance separately also only for those variables that have a VIF below 7.[5] For the OLS regressions and the North American sample, Panel A shows that 38 of the 42 variables with an absolute t-statistic larger than 3 have a VIF below 7. For the VWLS regression 17 of the 18 predictors with a t-value exceeding 3 have a VIF below 7. Additionally, we report results also for a much more conservative threshold of a VIF below 2. For this case, we still observe that 23 (9) of all predictors have an absolute t-statistic exceeding 3 for the North American stock market in the OLS (VWLS) model.

This apparently high dimensionality is also present in other markets as the remaining Panels in Table 4 show. In Europe, there are 33 (15) highly statistically significant predictors with an absolute t-statistic above 3 in the OLS (VWLS) regressions. Corresponding numbers for the OLS model are 33 for Japan, 24 for Pacific, and 19 for Emerging Markets. In the VWLS model, Japan has 11, the Pacific regions has 12, and Emerging Markets have 13 highly significant predictors.

Taking VIFs into account does not alter the picture materially. For instance, Emerging Markets continue to have 13 (8) predictors with a t-statistic exceeding 3 and a VIF below 7 (below 2) for the VWLS model. Moreover, it is not clear that a t-statistic of 3 is required to acknowledge statistical significance for the international dataset. While Harvey et al. (2016) suggest to use this hurdle rate for newly discovered anomalies, their critique traces mainly back to the extensive amount of data mining that has occurred for the CRSP/Compustat US stock sample. Instead, we study anomalies that have already been discovered, and which have been primarily or exclusively tested for US stocks.

Accepting a lower t-value as an alternative threshold to determine statistical significance, the impression of multidimensionality is reinforced for the international stock sample. For instance, Panel B shows that for the European stock sample, 65 (35) predictors have an absolute t-value above 2 in the OLS (VWLS) regression. For Japan, Pacific, and Emerging Markets, there are 54, 41, and 34 trade signals with a t-statistic above 2 for the OLS regressions. For the VWLS regression model the corresponding numbers for Japan, Pacific, and Emerging Markets are 28, 23, and 27, respectively.

We next turn to the question which variables "matter" the most. Interestingly, only a few

[5]Green et al. (2017) note that they obtain similar results if they do not exclude variables on the basis of the VIF criterion.

variables show up quite consistently among the 15 most significant predictors in every region and also irrespective of whether the OLS or the VWLS regression model is considered. These predictors are the same calendar month variable (*ret_scm*), the one-month reversal effect (*rev_1m*), the analyst forecast earnings revision ratio (*eer*), lagged price momentum (*mom_7_12*), three-day abnormal earnings announcement returns (*ear3d*), and the book-to-market equity ratio (*bm_mo*).[6]

For many other variables, the observed significance fluctuates substantially. Some variables such as share volume divided by market capitalization (*vol_mcap*) are statistically significant predictors in every region, but only with regard to the OLS regressions. Other variables, such as the traditional six months price momentum (*mom_2_6*) are highly statistically significant in both the OLS and VWLS regressions, but only for some regions (Europe and Pacific), and not for others. Interestingely, the evidence also shows that with the exception of the book-to-market equity ratio, many variables which have received considerable attention in theoretical and empirical asset pricing work such as the size effect, profitability, or investment (see Fama and French, 1993, 2015; Hou et al., 2015, 2016) are typically not among the most significant or most consistent signals.

4.2 Multidimensionality of Stock Returns: Pre- and Post 2003 Experience

Green et al. (2017) find that particularly in value-weighted regressions, the number of highly statistically significant predictors of US stock returns has fallen considerably since the end of 2002. To extent this test to an international level, we split the sample period such that the second part runs from January 2003 onwards. Results are reported in Table 5. Because Green et al. (2017) do not find the same sharp drop in multidimensionality for small stocks, and to limit the size of the table, we restrict the sub-sample analysis to VWLS regressions.

Insert Table 5 here

Panel A of Table 5 shows that our results for North America are in line with those shown by Green et al. (2017) for their US stock sample. While 17 predictors with a VIF below 7 have an

[6]The consistency and significance of the same calendar month variable supports the notion of Subrahmanyam (2010) who argues that this anomaly should receive more attention in future research. Keloharju et al. (2016) have addressed this task and provide additional valuable insights regarding the effect.

absolute t-statistic exceeding 3 in the pre-2003 period, only 3 predictors continue to do so post-2003. For other statistical thresholds, a similar decline is visible.

We continue to examine potential changes in the level of predictability before and after 2003 for the remaining four regions (Europe in Panel B, Japan in Panel C, Pacific in Panel D, and Emerging Markets in Panel E). For Europe, the number of significant predictors has declined as well for all reported levels of significance. However, the drop appears to be far less substantial. For instance, Europe has 13 (8) predictors with a VIF below 7 that exceed a t-statistic of 3 in the pre-2003 (post-2003) period. For Japan and the Pacific region, there is no clear pattern. While the number of predictors that are significant with a t-statistic above 3 has increased over time in both regions, the total number of trade signals with a t-statistic above 2 or alternatively above 1.65 remains about the same. Emerging Markets are different from the remaining regions in that it shows an increasing trend in the number of significant signals. For instance, 6 variables with a VIF below 7 have an absolute t-statistic above 3 in the pre-2003 period, but 14 variables achieve this level of significance afterwards.[7]

Overall, we do not detect any further evidence of a comparably strong decline in the extent of multidimensionality as in North America. We return to this issue later in Section 4.5 when we inspect how the out-of-sample strategy returns have changed over time.

4.3 Predictability of Stock Returns

After having documented the high dimensionality in stock returns as well as the profound cross-regional and time-series variations, we switch from an in-sample view to an out-of-sample perspective. That is, we investigate to what extent we can use past relations between returns and trade signals to forecast actual returns. To run the analysis, we follow Green et al. (2017) and Lewellen (2015), and multiply the Fama and MacBeth (1973) regression coefficients obtained from the past 120 months with the firm's current (i.e. beginning-of-month) characteristics. This yields a multidimensional return forecast for the next month. Because we use only information that was

[7] The increase in multidimensionality for Emerging Markets may be explained by a number of reasons that are not mutually exclusive. For instance, we might be able to confirm statistical significance more often due to the increase in the number of stocks over time. Another possibility is that the data to construct the trade signals might be of higher quality for developing countries in the more recent period.

available to investors at each point in time to derive at the forecast, our test is out-of-sample. To create a time-series of predictions for every stock, we update the regression coefficients monthly using a rolling-window approach. Moreover, to have a sufficient amount of sample months, we start the out-of-sample tests in January 1995. Therefore, prior to January 1999, we use less than 120 months to "train" our dataset.

4.3.1 Stock-level Regressions

Our first out-of-sample test involves stock-level regressions. Specifically, we regress realized stock returns on predicted returns from our multidimensional model. Ideally, we would like to have a predictor which provides an unbiased forecast of the actual returns (i.e., a regression coefficient close to one) with a high forecast accuracy (i.e., a high t-statistic for the coefficient). To assess the quality of our multidimensional forecast along those lines, we also construct alternative composite return forecasts that use fewer characteristics. Specifically, we construct alternative forecasts on the basis of the four characteristics of the Carhart (1997) model, the five characteristics of the Fama and French (2015) model, the 15 variables employed by Lewellen (2015), and the 11 variables examined by Stambaugh et al. (2012). Our results for Fama and MacBeth (1973) regressions are shown in Table 6.

Insert Table 6 here

In line with our previous approach, we report results separately for each region. Panel A shows results for North America, Panel B for Europe, Panel C for Japan, Panel D for the Pacific region, and Panel E for Emerging Markets. The univariate regression results for our multidimensional forecast can be taken from the first column. For North America, the slope is 0.9439 with a t-statistic of 15.52. This indicates that the model is highly capable of predicting a stock's return out-of-sample, but slightly overestimates the true variation in realized returns: For every 1% increase in the predicted return, the actual return will only increase by about 0.9439%.

The remaining coefficient estimates in column (1) are 0.9658 for Europe, 0.7862 for Japan, 0.8540 for the Pacific region, and 0.6993 for Emerging Markets. While this shows that the prediction bias is largest for Emerging Markets, the explanatory power of the multidimensional forecast is pronounced in every region with t-statistics ranging from a low of 15.24 (Pacific) to a high of 17.96 (Europe).

Overall, the tests reveal that our high-dimensioned model with the full set of trade signals is able to make valuable return predictions. But how does it perform in comparison to the lower-dimensioned models? The inspection of columns (2) to (5) in Table 6 shows that all alternative predictors have regression coefficients in the range of one. The t-statistics range between a low of 2.53 (Fama and French (2015) model for Europe) and a high of 13.41 (Lewellen (2015) model for Emerging Markets). This suggests that the alternative models generally also do a good job of capturing the variation in returns when considered in isolation.

To run a horse race between the different forecasts, we next conduct multivariate regressions including all forecasts and report our findings in column (6) of each Panel. Except for the Stambaugh et al. (2012) composite return forecast for Europe, the lower-dimensioned models lose their statistical significance entirely in the multivariate model. In contrast, the multidimensional forecast remains a highly statistically and economically significant predictor of one-month ahead realized returns. The evidence implies that despite potential model overfitting concerns, high-dimensioned composite measures predict returns more accurately than lower dimensioned alternative models, and are generally able to capture their explanatory power.

In column (7) of Table 6, we report the results of VWLS regressions of realized returns on our multidimensional predictor. In comparison to column (1), i.e. the OLS regressions, we see a substantial drop in the regression coefficients and the t-statistics. This drop is observable for every market. For instance, for North America the model indicates that for every 1% increase in the predicted return, the actual return will only increase by about 0.5806% with a t-statistic of 6.80. Hence, for larger stocks the model overestimates the true variation in realized returns more severely. However, as judged by the t-statistics, the strong out-of-sample predictability persists in the VWLS regression for every market.

4.3.2 Portfolio Returns

Our second out-of-sample test relies on long/short portfolios that are formed on the basis of the multidimensional forecast as well as its lower-dimensioned alternatives. We sort stocks into deciles for every predictor and every market, and compute the equal-weighted and value-weighted returns of a strategy that is long in decile 10 and short in decile 1. The rebalancing frequency is monthly. Table 7 summarizes the return and risk properties of these portfolios.

Insert Table 7 here

Portfolios that are constructed from the multidimensional forecast turn out to be highly profitable across the globe. The return of the equal-weighted portfolio amounts to 5.21% per month for North America, 4.05% for Europe, 3.49% for Japan, 5.24% for Pacific, and 3.49% for Emerging Markets. The value-weighted returns are about half the size, ranging from 1.82% per month (Japan) to 2.31% per month (North America). The associated t-staticstics and the Sharpe ratios are sizeable.

From Table 7, one can see that in terms of returns the multidimensional strategy outperforms other strategies based on lower-dimensioned forecasts comfortably in all international markets. However, a comparison in terms of risk is more interesting in order to receive a first indication to what extent this outperformance might be driven by higher systematic risk. To this end, Table 7 reports the monthly return volatility, skewness, kurtosis, and the minimum monthly return of the strategies.

Although the portfolio approach diversifies away much of the idiosyncratic stock risk, we would expect that under the risk-based explanation stocks in the long and short part of the portfolios should have similar exposures to systematic risk factors and hence tend to comove together. This would suggest that unless different systematic risk factors could be hedged against each other within the same market, the higher returns of the multidimensional strategy should be accompanied by a higher volatility in comparison to the lower-dimensioned strategies.

Table 7 shows that rather the opposite is true: For North America, Europe, and Japan, the multidimensional strategy portfolios have a volatility that is substantially smaller than that of their lower-dimensioned alternatives. For instance, the monthly volatility of the North American multidimensional strategy is 3.91% for equal-weighted returns and 4.67% for value-weighted returns. Instead, a portfolio build upon the Fama and French (2015) model yields a monthly volatility of 5.79% for equal-weighted returns and 6.33% for value-weighted returns. For the Pacific region and Emerging Markets, we also observe a lower volatility of the multidimensional strategy for value-weighted returns. For equal-weighted returns, there is no clear picture for the latter two regions.

From the inspection of the minimum return, the skewness, and the kurtosis, one can also see that crash risk, which has been proposed as a potential explanation of high unconditional returns for the momentum effect (see e.g., Daniel and Moskowitz, 2016; Grundy and Martin, 2001), unlikely serves as an explanation for the high returns accruing to the multidimensional strategy. The minimum returns are typically much closer to zero for the multidimensional strategy than for the other strategies. And while the kurtosis is large for the Japanese equal-weighted portfolio (30.53), the positive skewness (3.56) indicates that the fat tails lie primarily in the right part of the return distribution.

4.3.3 Robustness Tests

We next test to what extent plausible variations in our out-of-sample predictability analysis may affect our conclusions. Specifically, we consider eight different robustness tests for which we report the results in Table 8. Panel A in this table shows the regression coefficients and associated t-statistics that are obtained from regressing realized returns on predicted returns for the robustness tests. Panel B and C report the corresponding long/short equal-weighted and value-weighted strategy returns and t-statistics.

Insert Table 8 here

Robustness test 1 constructs the forecast from a pooled panel regression with up to 120 past months instead of a Fama and MacBeth (1973) regression. The main difference between the two approaches is that in a pooled panel model each observation is equally weighted, whereas in a Fama and MacBeth (1973) regression every month is equally-weighted. As shown in column (1), Panel

A, pooled estimates lead to lower regression coefficients. However, the reported strategy returns in Panels B and C are similar to the baseline results. For the second robustness test, reported in column (2) of Table 8, we rely on an in-sample estimation period of 60 months. The regression coefficients in Panel A are again lower than those reported in the baseline test. The strategy returns in Panels B and C are not substantially different.

Despite a relatively good fit between predicted and realized returns in our baseline test, our approach is vulnerable to potential in-sample estimation errors and model overfitting. To address this concern in a simple way, we shrink the estimated coefficients in a further robustness test using the p-values. Specifically, the shrinkage coefficient is obtained by multiplying the coefficient with (1-(p-value[%]/100)), where the p-value refers to a test that the absolute value of the in-sample coefficient equals zero. Therefore, coefficients with low statistical significance are shrunken to a value of zero, whereas coefficients with very high statistical significance remain largely unchanged. Column (3) shows that the regression slopes are typically closer to one with the shrinkage procedure. The returns of the long/short portfolio returns do not change materially.

In robustness test (4), we test a rolling six-months estimate of the multidimensional forecast to predict returns. We observe that the six-months estimates produce a lower fit between predicted and realized returns in Panel A of Table 8. The reduced forecasting power is also evident from the portfolio returns in Panel B and C which are consistently lower than the baseline results. Regarding the fact that many highly significant predictors in Table 4 are short-term oriented, these findings are in line with expectations. However, for practical purposes it is interesting to notice that while a six-months rolling strategy reduces the portfolio turnover likely by about 80% (5/6), the impact on the abnormal returns is far less.

Finally, we examine four additional tests. In robustness test 5, we use returns in local currency as opposed to returns in US-Dollar. Robustness test 6 skips the first trading day of the month, and robustness test 7 excludes financial firms (SIC codes between 6000 and 6999). Robustness test 8 includes only the largest 20% of all firms in a given region, i.e. excludes 80% of the sample. The results of robustness tests 5, 6, and 7 are similar to the baseline results. Focusing on the largest 20% leads to slope coefficients that are in the range of 0.50 in Panel A and also to lower portfolio returns. This finding is in line with the value-weighted regressions and portfolio results, and demonstrates that the multidimensional forecast is less successful when we focus on larger firms.

4.4 Explanatory Power of Asset Pricing Models and Global Diversification

We proceed with an examination to what extent the abnormal long/short returns of the multidimensional strategies are explained by common asset pricing factor models. To this end, we investigate the following models: the CAPM, the Fama and French (1993) three-factor model (denoted as $FF3$), the Carhart (1997) four-factor model ($C4$), the Carhart (1997) four factor model augmented with the short-term reversal factor ($C4 + STREV$), the Fama and French (2015) five-factor model ($FF5$), the Hou et al. (2015) q-factor model (HXZ) and an "all-factors" model, containing all unique factors of these models, which are 10 in total.

We construct the factors separately for each region following the methodologies described on Kenneth French's website[8] and in Hou et al. (2015) as closely as possible. To calculate the market factor we use the corresponding regional MSCI index as the market factor, and the risk-free rate from Kenneth French's website. For the remaining factors, we chose a size-decile based breakpoint of 8 to sort stocks into small caps and large caps. In line with the procedure of Griffin (2002), we construct the factors separately for every country, and compute the regional factors as market weighted averages of the country-specific components.[9]

Table 9 reports our main findings from the asset pricing model regressions. The results are again presented separately for every region, and for equal-weighted and value-weighted multidimensional strategy returns. Because the factors of the models are commonly thought of as capturing systematic risk, we are primarily interested in the reduction of the monthly alpha of the strategies as well as the overall explanatory power of the models as measured by the R^2's. To keep the table size manageable, we therefore do not report individual factor exposures.

Insert Table 9 here

For equal-weighted multidimensional portfolios, the considered asset pricing models largely fail

[8] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[9] Our constructions lead to factor returns for North America that are highly correlated with the "original" US-factors (above 0.9 for all factors), and achieve similar average returns.

to explain a substantial part of the abnormal returns. The reduction in the alpha is largest in Europe when we focus on the "all-factors" model with a decrease from a 4.05% raw return per month to a 3.29% alpha or -20.71%.[10] The R^2's show a wide range, but no model is able to explain more than 63.20% of the equal-weighted strategy returns.

Turning to the value-weighted returns, the asset pricing models do a slightly better job in capturing the abnormal strategy returns. For North America, the $C4 + STREV$-model leads to the highest reduction in the alpha, which is about 15%. For Europe, Japan, Pacific, and Emerging Markets, the alpha is at most reduced by about 45%, 33%, 27%, and 15%, respectively. The relatively large reduction which we observe for Europe comes mainly from the inclusion of the momentum factor. For Japan, the reduction is to a large extent explained by the short-term reversal factor. Nonetheless, the t-statistics associated with the monthly alphas are always larger than 5, suggesting a high remaining degree of statistical significance. The R^2's range between 0% and 46%.

Overall, the results document that the strategies are truly "multidimensional" in a sense that they are not well explained by a long-list of standard asset pricing factors. In a more general context, our findings suggest that the tested asset pricing models are not well-specified to describe the returns of composite anomaly strategies when assessed at a global perspective. This is consistent with our previous result that the most significant predictors are typically not included in many standard asset pricing models. Moreover, if one interprets the factors as risk factors, systematic risk does not seem to explain the performance of the multidimensional strategies.

To elaborate further on the question to what extent risk explains the abnormal returns, we next focus on the potential benefits of international diversification. Therefore, we study the correlations of the value-weighted and equal-weighted strategies between the different international markets, and investigate the performance and risk properties of a globally diversified multidimensional strategy. If the alphas of the strategies represent a compensation for underlying global risk factors, we would expect that the return series are highly correlated and that diversification benefits are marginal. Our results are shown in Table 10.

[10]We compute the percentage change as $(4.05 - 3.29)/(0.5 \cdot (4.05 + 3.29))$.

Insert Table 10 here

Panel A in Table 10 displays the cross-regional correlations for equal-weighted long/short portfolios. As can be seen, the correlations range between -0.18 and 0.29. Averaged across all correlation pairs, the mean correlation is 0.08. The correlations for the value-weighted returns are reported in Panel B. They are comparably low, with an average value of 0.07 across all pairs. This suggests that there are substantial diversification benefits.

In Panel C, we report performance statistics for the globally diversified multidimensional strategy. We calculate the equal-weighted global strategy return as the average across equal-weighted regional strategy returns, and the value-weighted global strategy return as the average across value-weighted regional strategy returns. The equal-weighted global strategy achieves a monthly raw return of 4.30% with a t-statistic of 36.32. The Carhart (1997) four-factor alpha is similar (4.13%; t-statistic of 32.91). The strategy has positive returns in nearly 99% of the sample months, and realizes an annualized Sharpe ratio of 7.93. The value-weighted global strategy has a monthly raw return (four-factor alpha) of 2.03% (1.86%) with a t-statistic of 15.74 (12.67). The annualized Sharpe ratio is 3.43.

The increase in the annualized Sharpe ratios follows from the reduced volatility of the global strategies. As shown in Panel D of Table 10, the monthly volatility of the global strategy is 1.88% for equal-weighted returns and 2.05% for value-weighted returns. Compared to the average monthly volatility across the five regions, this amounts to a sizeable risk reduction of more than 50%. The benefits of the international diversification are also visible from the reduction of the kurtosis compared to the average kurtosis and from the minimum monthly return over the entire sample period, which is -2.88% for the equal-weighted portfolio, and -3.98% for the value-weighted portfolio.

Overall, there are large diversification benefits for the multidimensional strategies which indicates that global risk factors are unlikely to explain the alphas. However, if financial markets are highly segmented, part of the alphas may still be attributable to regional systematic risk factors. Crash risk, as evidenced by the minimum returns, does not seem to provide a good explanation of the large strategy returns either.

4.5 Time Trends

Table 5 shows a decline of significant predictors for the North American stock sample in in-sample regressions. In this section, we test to what extent this decline is also present for the out-of-sample strategy. Specifically, we regress the time series of the strategy returns on a time variable which equals the number of months passed since the start of the out-of-sample period in January 1995, divided by 12. Defined this way, we can interpret the regression coefficient for the time variable as the average decrease in the monthly portfolio returns for every year of our sample period. We report our findings in Panel A of Table 11.

Insert Table 11 here

The second row in Panel A of Table 11 shows that there is a statistically significant negative regression coefficient for the time variable (denoted as *time_id*) with regard to the value-weighted North American strategy (coefficient: -0.0016; t-statistic: -3.32). The estimated regression results are economically substantial: They suggest that the monthly returns of the value-weighted multidimensional strategy have decreased from 4.03% per month at the start of the sample period, to only about 0.70% per month at the end of our sample. We also find a statistically significant decrease in profitability for the equal-weighted North American strategy. However, for the equal-weighted returns, the economical as well as the statistical significance is weaker (coefficient: -0.0009; t-statistic: -2.57).

Turning to the multidimensional strategies for the other regions, we are not able to detect a similar pattern over time. One half of the remaining regression coefficients for *time_id* is negative, and one half is positive. Moreover, while the remaining negative regression coefficients are never statistically significant, some of the positive coefficients are also statistically significant. For instance, the regression estimates suggest that the equal-weighted Pacific strategy has increased by 0.24% for every year since 1995 with a t-statistic of 5.00.

These results do not only line up with those from the multidimensionality tests in Section 4.2, but are also consistent with the findings of Jacobs and Müller (2016). They show that among a large set of international stock markets, only the US market shows a significant post-publication decline in long/short anomaly returns. However, unlike Jacobs and Müller (2016), we investigate composite anomaly strategies and we do not specifically focus on publication dates.

In addition to the time trend in returns, we are also interested in a potential time trend in correlations. The previous section highlights substantial diversification benefits as a result of a low correlation between the regional multidimensional strategies. Both risk-based explanations of our findings as well as arbitrage considerations suggest that the correlations should have increased if financial markets had become more integrated over time. To test for a time trend in correlations, we proceed as follows: For every region we compute the average equal-weighted and value-weighted portfolio returns across all other international markets. We then compute rolling 24-months correlations between the return for every region and the return of the corresponding international strategy. For instance, for the equal-weighted North American strategy, we compute the average return across the equal-weighted strategies for Europe, Japan, Pacific, and Emerging Markets, and consider them as the "international" counterpart. Our approach yields a time-series of monthly return correlations which we regress on $time\_id$. We report our findings in Panel B of Table 11. To account for the overlapping nature of our tests, we rely on West and Newey (1987) adjusted t-statistics with a lag of 23 months.

Overall, Panel B does not show clear evidence of a trend in correlations over time. Again, we find that one half of the coefficients is positive, and one half is negative. Most of the t-statistics are below 2 in absolute terms. The evidence suggests that the surprisingly large diversification benefits for the multidimensional strategies have not become lower over time. This finding differs from the results for passive international diversification strategies based on market indexes (see e.g., Driessen and Laeven, 2007). It also suggests that the evidence of increased correlation trends for individual anomalies as reported in Asness et al. (2013) may not necessarily be transferable to composite strategies or the broad universe of trade signals.

4.6 Hedge Funds and Multidimensional Strategies

Finally, we turn to the question of whether sophisticated market participants trade on the apparent mispricing. To this end, we relate the return series of long/short equity hedge funds to the return series of the multidimensional strategies. Hedge funds are commonly thought of as classical arbitrage traders that aim to exploit deviations from market efficiency. Hence, we would expect a positive correlation between the return series.

Following Menzly and Ozbas (2010) we use the Credit Suisse Long/Short Equity Hedge Fund Index to measure the returns of long/short equity hedge funds. This is a value-weighted index which starts in January 1994 and is often used for benchmark purposes. The results of our regressions, which relate the excess monthly returns of the hedge fund index to the returns of the multidimensional strategies for the different regions, are shown in Table 12.

Insert Table 12 here

In the regression displayed in column (1) of Table 12, the value-weighted multidimensional strategy return for North America is the only explanatory variable. The results suggest that hedge funds exploit the return predictability in the North American stock sample. The regression coefficient of 0.2307 is highly statistically significant (t-value: 5.23), and the R^2 is 16.1%.

Columns (2) to (5) of Table 12 provide results of the same univariate tests for the other regional multidimensional strategies. We do not find further evidence of positive and statistically significant regression coefficients. Moreover, the reported R^2's in these columns are low, ranging between 0.1% and 2.4%. The evidence is not consistent with the idea that hedge funds seek to benefit from international return predictability, at least not at a large scale. As shown in column (6), our conclusion remains, if we include the long/short return series for all five markets simultaneously as independent variables.

Next, we also add the four North American factors of the Carhart (1997) model $MKTRF$, SMB, HML, and UMD, and the North American one-month reversal factor $STREV$ as explanatory variables to the regression. With the inclusion of these standard factors, we account for known facts about the trading behavior of hedge funds. For instance, it is well-understood that despite implicit market neutrality, most hedge funds load positively on the market factor, and that many institutional investors follow momentum strategies (see Menzly and Ozbas, 2010; Grinblatt and Keloharju, 2000; Grinblatt et al., 1995). Our results are shown in column (7) of Table 12.

The significant positive influence of the North American strategy return remains, even though it is substantially reduced (coefficient 0.0745; t-statistic 3.33). In contrast, the point estimates and t-statistics for the other regional strategy returns are close to zero.[11]

Overall, our evidence is consistent with the idea that hedge funds are more actively engaged in arbitrage trading in North American stocks, and probably in particular in US stocks, than in international stocks. This may explain why we observe only with regard to North America a lower multidimensionality in returns after 2002, and also a decreasing time trend for the multidimensional strategy. The findings of Cao et al. (2016), who report that the average US-stock ownership of hedge funds has dramatically increased since the early 2000's, are also in line with this interpretation.

5 Limitions and Discussion of our Results

Our work has limitations with regard to both, the in-sample multidimensionality regressions as well as the out-of-sample predictability tests, which may affect our conclusions. One obvious concern is that any assessment of significance in the multivariate regressions rests on the total list of tested variables. Adding new predictors, some existing predictors may lose their significance, while other variables may become more significant. Moreover, because we replace missing variable values in the regressions, our multidimensionality tests also suffer from estimation errors. While the replacement procedure is technically imperative, it is possible that multidimensionality would be lower if we knew the true values for all trade signals. A more conservative interpretation of our findings is therefore that under the given constrains of data availability, surprisingly many variables are helpful in describing the cross-section of stock returns.

We also acknowledge that our impression of a high dimensionality in returns is subjective. It stems primarily from the observation that many variables that are not included in popular asset pricing models, are statistically significant drivers of stock returns. Alternatively, one can hold the

[11] For the sake of brevity and because the hedge fund index return itself is value-weighted, we do not report the results of regressing the hedge fund returns on the equal-weighted strategy returns. However, our insights are qualitatively comparable: In regressions as shown in columns (6) or (7) of Table 12, the North American equal-weighted strategy return is the only multidimensional strategy return that is statistically significantly positively related to the hedge fund index return. The explanatory power as measured by the R^2 is 10.2% in an univariate regression.

view that the majority of the tested variables are not or only marginally related to stock returns in multivariate regressions, or that they are less relevant for economically important (i.e. large) stocks. This interpretation is in line with the assessment of Harvey et al. (2016) who argue that many of the factor discoveries in the anomaly literature are likely false discoveries. Collectively however, our international tests suggest that 1) the anomaly literature has been able to substantially expand our knowledge on stock return predictability, and that 2) even new asset pricing models largely fail to explain this composite predictability.

Limitations of our out-of-sample predictability tests are as follows. First, one can argue that our tests are not strictly out-of-sample because we treat all variables as available at the begin of our out-of-sample period in 1995, even though some predictors were published later. Second, given the amount of missing data values as well as the problem of regression overfitting in general, our tests may also underscore the true extent of predictability. This appears to be particularly true for large cap stocks for which the fit between forecasted returns and realized returns is weaker. We leave it to future work whether and how the regression predictions might be improved.[12]

6 Conclusion

We find strong evidence that stock returns are highly dimensional across all international stock market regions (North America, Europe, Pacific, Japan, Emerging Markets). Estimates of expected stock returns, derived from using a stock's current return predictive signals and historical regression slopes, line up quite well with realized returns in those markets. This out-of-sample return predictability holds even for the largest sample firms, even though it is reduced by about 50%.

Our results provide a challenge for low-dimensioned asset pricing models because we find that many significant in-sample predictors are not included as factors in these models, and because a substantial fraction of the abnormal returns of multidimensional out-of-sample trading strategies

[12] A further limitation is that we have not tested to what extent our results are affected by transaction costs. Real-trade transaction cost data appears to be difficult to obtain, in particular for many international markets. However, two facts suggest that the out-of-sample return predictability is too large to be explained by transaction costs. First, as shown in Section 4.3.3 strategies based on rolling six-months forecasts, which largely reduce portfolio turnover, also generate substantial monthly long/short returns. Second, using proprietary real-life trading data, Frazzini et al. (2012) report average total implementation costs of approximately 15 basis points per trade for international long/short strategies.

remains unexplained by these models. Moreover, we also show that the risks of multidimensional strategies can be reduced substantially through global diversification. Applying this opportunity, we obtain hedge portfolio returns that are remarkably large without being excessively risky. Our study thus demonstrates how much investors would have benefited from anomalies research in finance at a global scale.

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Figure 1: Average number of stocks per year and region

This figure illustrates the regional composition of the universe of stocks during the sample period from January 1989 to December 2015. Delisted stocks are dropped after the respective delisting date. We require U.S. stocks to be listed at one of the three major exchanges NYSE, AMEX or NASDAQ, and we exclude stocks without a valid Worldscope identifier.

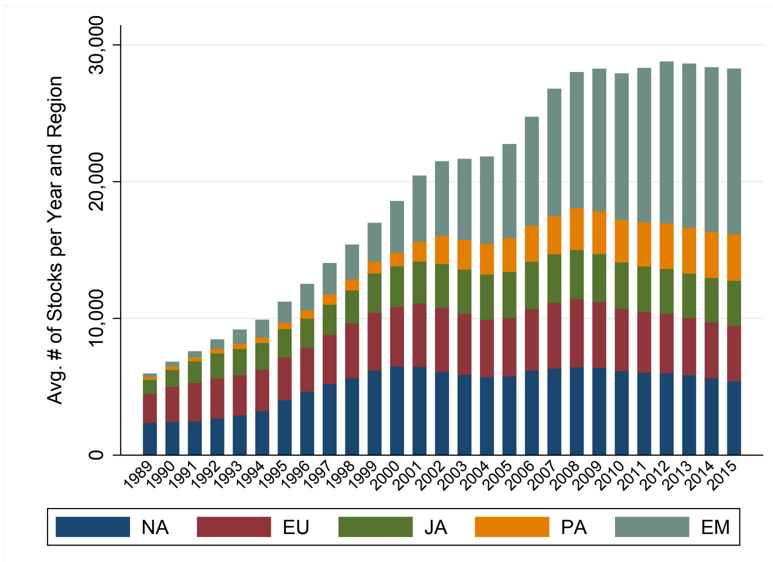

Table 1: Summary Statistics

Panel A of this table shows summary statistics for the 44 countries included in the sample. Columns 3 and 4 provide the start date and end date for each country. The sample period ranges from 1/1989 to 12/2015, but for some emerging market countries coverage in Datastream starts later. Column 5 shows the average number of firms per month. Column 7 shows the average monthly total market value of equity of the firms included in the sample in billions of U.S. dollars. Columns 6 and 8 report the corresponding percentages in relation to the entire sample. Panel B of this table provides analogous summary statistics with firms sampled at regional level.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Region	Country	Start	End	Avg. # firms	Avg. % of firms	Avg. MV	% of MV
			Panel A: Summary statistics at country level				
North America	Canada	1/1989	12/2015	1082	4.86	730.70	2.41
	USA	1/1989	12/2015	4061	24.05	10568.35	39.66
Europe	Austria	1/1989	12/2015	68	0.41	57.43	0.20
	Belgium	1/1989	12/2015	98	0.60	165.48	0.58
	Denmark	1/1989	12/2015	149	0.92	110.44	0.35
	Finland	1/1989	12/2015	92	0.48	129.24	0.42
	France	1/1989	12/2015	564	3.24	1131.30	3.96
	Germany	1/1989	12/2015	587	3.26	940.13	3.58
	Ireland	1/1989	12/2015	43	0.28	51.41	0.17
	Italy	1/1989	12/2015	204	1.24	385.78	1.41
	Netherland	1/1989	12/2015	116	0.77	402.56	1.52
	Norway	1/1989	12/2015	141	0.76	128.35	0.38
	Portugal	1/1989	12/2015	50	0.31	37.35	0.14
	Spain	1/1989	12/2015	117	0.71	413.38	1.43
	Sweden	1/1989	12/2015	243	1.21	264.74	0.86
	Switzerland	1/1989	12/2015	190	1.13	696.30	2.23
	United Kingdom	1/1989	12/2015	1256	7.84	1893.54	7.30
Japan	Japan	1/1989	12/2015	2757	15.44	3229.48	16.71
Pacific	Australia	1/1989	12/2015	807	3.56	532.87	1.70
	Hong Kong	1/1989	12/2015	557	2.44	727.90	2.11
	New Zealand	1/1989	12/2015	67	0.33	22.83	0.09
	Singapore	1/1989	12/2015	350	1.58	206.84	0.68
Emerging Markets	Czech Republic	6/1996	12/2015	30	0.14	28.54	0.08
	Brazil	1/1995	12/2015	88	0.36	267.14	0.65
	Chile	2/1990	12/2015	120	0.58	97.41	0.31
	China	8/1991	12/2015	1008	3.93	1458.73	3.38
	Colombia	8/1992	12/2015	35	0.16	59.47	0.15
	Egypt	12/1997	12/2015	67	0.25	37.29	0.09
	Greece	1/1989	12/2015	165	0.82	58.94	0.20
	Hungary	6/1993	12/2015	27	0.12	17.21	0.05
	India	8/1990	12/2015	957	3.83	510.66	1.30
	Indonesia	1/1989	12/2015	202	0.92	116.98	0.32
	Korea	1/1989	12/2015	814	3.47	441.11	1.29
	Malaysia	1/1989	12/2015	509	2.36	176.94	0.64
	Mexico	1/1989	12/2015	85	0.43	163.74	0.47
	Peru	6/1992	12/2015	76	0.32	32.66	0.10
	Philippines	6/1989	12/2015	114	0.53	54.88	0.16
	Poland	6/1992	12/2015	183	0.71	73.87	0.19
	Qatar	7/2004	12/2015	32	0.12	91.46	0.21
	Russia	6/1997	12/2015	159	0.58	433.27	1.06
	South Africa	1/1989	12/2015	217	1.16	213.97	0.80
	Taiwan	1/1989	12/2015	742	2.98	382.21	1.14

Table 1 continued

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Region	Country	Start	End	Avg. # firms	Avg. % of firms	Avg. MV	% of MV
Panel B: Summary statistics at regional level							
North America		1/1989	12/2015	5144	28.91	11299.05	42.07
Europe		1/1989	12/2015	3920	23.15	6807.40	24.54
Japan		1/1989	12/2015	2757	15.44	3229.48	16.71
Pacific		1/1989	12/2015	1781	7.91	1490.43	4.58
Emerging Markets		1/1989	12/2015	5757	24.59	4465.10	12.10

Table 2: Fraction of stocks and market capitalization by NYSE size deciles

This table shows in Panel A the fraction of stocks in % by NYSE size deciles for each region. Panel B shows for each size decile portfolio the market weight in % of the total market capitalization in a region. All numbers are monthly averages over the sample period from 1/1989 to 12/2015. NYSE size decile breakpoints are obtained from Kenneth French.

Region	Decile 1	2	3	4	5	6	7	8	9	Decile 10
Panel A: Percentage of stocks per NYSE size decile										
North America	47.2%	12.6%	8.6%	6.7%	5.5%	4.5%	4.1%	3.8%	3.5%	3.4%
Europe	54.7%	11.9%	7.5%	5.7%	4.6%	3.6%	3.3%	3.1%	2.9%	2.7%
Japan	48.2%	12.3%	8.1%	6.7%	6.4%	5.5%	4.8%	4.5%	3.7%	3.0%
Pacific	58.1%	11.7%	7.7%	5.8%	4.7%	3.3%	2.5%	2.3%	2.4%	1.5%
Emerging Markets	52.8%	13.3%	9.7%	7.2%	5.2%	3.7%	3.1%	2.7%	1.7%	0.6%
Panel B: Percentage of total market capitalization per NYSE size decile										
North America	1.2%	1.4%	1.7%	2.1%	2.6%	3.4%	4.7%	7.3%	13.5%	62.2%
Europe	1.6%	1.7%	2.0%	2.4%	3.1%	3.7%	5.2%	8.2%	14.9%	57.1%
Japan	3.3%	2.8%	2.8%	3.4%	4.1%	5.1%	6.7%	10.5%	17.6%	43.9%
Pacific	3.6%	2.9%	3.1%	3.7%	4.6%	4.9%	6.1%	9.7%	17.5%	43.9%
Emerging Markets	4.9%	5.1%	6.0%	6.6%	7.0%	7.8%	9.9%	14.2%	17.4%	21.1%

Table 3: Return predictor overview

This table provides an overview of the return predictors. We list the acronym, description, reference paper, and the percentage of missing values for each predictor. In the multivariate regressions, we replace these missing values with the cross-sectional mean country decile value (typically close to 5.5). Return predictors are sorted alphabetically by their acronyms, which are used in the following tables if we refer to individual predictors. To construct the variables, we use Thomson Reuters Datastream, Worldscope, and I/B/E/S. The sample period ranges from 1/1989 to 12/2015.

#	Acronym	Description	Reference Paper	Missings [%]
1	a_turn	Asset turnover	Soliman (2008)	10.68
2	acc_dp	Accruals as defined in Richardson et al. (2005)	Richardson et al. (2005)	14.44
3	acc_pi	Accruals as defined in Piotroski(2000)	Piotroski (2000)	3.37
4	acc_slo	Accruals as defined in Sloan (1996)	Sloan (1996)	23.54
5	accq	Accrual quality	Francis et al. (2005)	41.91
6	aci	Abnormal corporate investment	Titman et al. (2004)	17.03
7	admcap_mo	Advertisement expense to market	Chan et al. (2001)	43.68
8	ag	Asset growth	Cooper et al. (2008)	7.02
9	age	Firm age	Barry and Brown (1984)	0.97
10	amihud	Amihud's measure (illiquidity)	Amihud (2002)	15.58
11	an_value	Analyst value	Frankel and Lee (1998)	59.22
12	avg_turn_12m	Average monthly turnover previous 12 months	Lewellen (2015)	0.97
13	avol3d	Abnormal volume around earnings announcement	Choi and Jung-Wook (2001)	35.86
14	b1f_mktrf_1m	CAPM market beta using daily returns from the previous month	Ang et al. (2006)	18.28
15	b1f_mktrf_60m	CAPM beta (low frequency, 60 months)	Baker et al. (2011)	9.67
16	b1f_res_1m	Residual volatility using daily returns from the previous month	Ang et al. (2006)	18.16
17	b1f_res_60m	Residual volatility (low frequency, 60 months)	Baker et al. (2011)	9.43
18	bm_mo	Book-to-market	Rosenberg et al. (1985)	0.00
19	cash	Cash holdings	Palazzo (2012)	8.97
20	cashdebt	Cash flow to debt	Ou and Penman (1989)	22.42
21	cashpr_mo	Cash productivity	Chandrashekar and Rao (2009)	9.81
22	ccdi2_mo	Dividend initiation; monthly from Datastream	Michaely et al. (1995)	0.00
23	ccdi_an	Dividend initiation; annually from Worldscope	Michaely et al. (1995)	0.12
24	ccdo2_mo	Dividend omission; monthly from Datastream	Michaely et al. (1995)	19.40
25	ccdo_an	Dividend omission; annually from Worldscope	Michaely et al. (1995)	0.00
26	ccdr2_mo	Dividend resumption; monthly from Datastream	Boehme and Sorescu (2002)	19.40
27	ccdr_an	Dividend resumption; annually from Worldscope	Boehme and Sorescu (2002)	0.12
28	cdind	Convertible debt indicator	Valta (2016)	0.00
29	cegth3	Capital expenditure	Anderson and Garcia-Feijoo (2006)	29.13
30	cf_mcap_mo	Cash flow / market capitalization	Lakonishok et al. (1994)	8.71
31	cf_var_mo	Cash flow variance	Haugen and Baker (1996)	41.44
32	cfp_ia_mo	Industry-adjusted cash flow to price ratio	Asness et al. (2000)	10.33
33	change_recom	Change in recommendation	Jegadeesh et al. (2004)	94.47
34	chatoia	Industry-adjusted change in asset turnover	Soliman (2008)	17.42
35	chempia	Industry-adjusted change in employees	Asness et al. (2000)	28.34
36	chgn_at	Change in asset turnover	Soliman (2008)	17.35
37	chgn_pm	Change in profit margin	Soliman (2008)	14.32
38	chnanalyst	Change in number of analysts	Scherbina (2007)	11.17

Table 3 continued

#	Acronym	Description	Reference Paper	Missings [%]
39	chng_dy_mo	Change in dividend yield	Jacobs (2015)	6.67
40	chng_dyds	Change in Datastream expected dividend yield	Jacobs (2015)	1.91
41	chpmia	Industry-adjusted change in profit margin	Soliman (2008)	14.40
42	com_eq	Composite equity issuance	Daniel and Titman (2006)	26.27
43	corwin0	Bid-ask spread	Amihud and Mendelson (1986)	25.52
44	coskew	Coskewness	Harvey and Siddique (2000)	9.87
45	cto	Capital turnover	Haugen and Baker (1996)	6.75
46	currat	Current ratio	Ou and Penman (1989)	12.73
47	dXFIN1	Net external financing 1	Richardson and Sloan (2003)	12.26
48	dXFIN2	Net external financing 2	Bradshaw et al. (2006)	19.01
49	d_seo_3yr	Dummy for public seasoned equity offering	Loughran and Ritter (1995)	0.00
50	depr	Depreciation-to-gross-PPE	Holthausen and Larcker (1992)	17.75
51	diss	Debt issuance	Spiess and Affleck-Graves (1999)	2.62
52	dolvol	Dollar trading volume	Chordia et al. (2001)	8.77
53	down_f	Down forecast	Barber et al. (2001)	8.85
54	dpfs	Dummy for unfunded pension liability	Franzoni and Marn (2006)	0.00
55	dprc_mo	Debt/Price constructed monthly as in Lewellen (2015)	Litzenberger and Ramaswamy (1982)	5.03
56	dur	Equity duration	Dechow et al. (2004)	12.10
57	dy_mo	Dividend yield constructed monthly as in Lewellen (2015)	Litzenberger and Ramaswamy (1982)	5.09
58	dyds	Dividend yield estimate from Datastream	Litzenberger and Ramaswamy (1982)	0.84
59	e_cons	Earnings consistency	Alwathainani (2009)	55.83
60	ear3d	Earnings announcement return	Chan et al. (1996)	31.11
61	ebp	Enterprise component of book/price	Penman and Richardson (2007)	11.70
62	eer	Earnings forecast revision ratio	Czaja et al. (2013)	55.11
63	efp	Analysts earnings forecasts-to-price	Elgers et al. (2001)	52.55
64	egr	Change in common shareholder equity	Richardson et al. (2005)	7.93
65	em	Enterprise multiple	Loughran and Wellman (2011)	13.33
66	eps_disp	Dispersion in forecasted EPS	Diether et al. (2002)	63.10
67	eps_price	Current EPS scaled by price	Chan et al. (1996)	32.86
68	eqea	Earnings announcement premium	Lamont and Frazzini (2007)	0.00
69	exp_div	Dividend month	Hartzmark and Solomon (2013)	0.00
70	failure	Failure probability	Campbell et al. (2008)	31.22
71	fscore	F-Score	Piotroski (2000)	28.47
72	gp	Gross profitability (Gross profits-to-assets)	Novy-Marx (2013)	14.89
73	gr_lt_noa	Growth in net operating assets	Fairfield et al. (2003)	23.53
74	gscore	G-Score	Mohanram (2005)	15.13
75	herf	Herfindahl index	Hou and Robinson (2006)	1.10
76	hire	Employee growth rate	Belo et al. (2014)	27.94
77	ia	Capital investment	Titman et al. (2004)	16.78
78	ig	Investment growth	Xing (2008)	17.52
79	iltr_5y_vw	Value-weighted industry long-term return (5 years)	Bondt and Thaler (1985) and Moskowitz and Grinblatt (1999)	4.50
80	imom_2_6_vw	6-month industry momentum	Moskowitz and Grinblatt (1999)	2.19
81	imom_7_12_vw	Lagged value-weighted industry momentum	Novy-Marx (2012) and Moskowitz and Grinblatt (1999)	2.41

Table 3 continued

#	Acronym	Description	Reference Paper	Missings [%]
82	ipo_rd	IPO no R&D	Guo et al. (2006)	0.00
83	iret_scm_vw	Value-weighted industry return same calendar month	Keloharju et al. (2016)	2.26
84	irev_13_18_vw	Value-weighted industry return month (t-13) to (t-18)	Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999)	2.67
85	irev_1m_vw	Value-weighted industry return previous month	Jegadeesh (1990) and Moskowitz and Grinblatt (1999)	2.32
86	ivc	Inventory changes	Thomas and Zhang (2002)	16.42
87	ivg	Inventory growth	Belo and Lin (2012)	28.74
88	lbp	Leverage component of Book/Price	Penman and Richardson (2007)	11.64
89	lgr	Change in long-term debt	Richardson et al. (2005)	29.64
90	ltg	Long-term growth forecast of analysts	Porta (1996)	65.81
91	ltr_5y	Long-term reversal	Bondt and Thaler (1985)	26.17
92	margin	Profit margin	Soliman (2008)	17.42
93	margin_sal_chng	Percentage change in gross margin - percentage change in sales	Abarbanell and Bushee (1998)	29.63
94	market_lev_mo	Market leverage	Bhandari (1988)	1.11
95	max_ret_daily	Maximum daily return in prior month	Bali et al. (2011)	0.45
96	meanrec	Average value of analyst recommendation	Jegadeesh et al. (2004)	56.93
97	min_ret_daily	Minimum daily return during previous month	Bali et al. (2011)	0.47
98	mom_2_6	6-month momentum	Jegadeesh (1990)	0.00
99	mom_7_12	Lagged momentum	Novy-Marx (2012)	3.41
100	nanalyst	Number of analysts covering stock	Elgers et al. (2001)	9.51
101	nc_oac	Noncurrent operating asset changes	Soliman (2008)	18.18
102	nincr	Percentage positive earnings quarters	Barth et al. (1999)	69.89
103	nincr_up	Number of consecutive quarters with earnings increases	Barth et al. (1999)	69.85
104	nit_mcap_mo	Earnings-to-price	Basu (1977)	0.93
105	noa_lev	Level of net operating assets	Hirshleifer et al. (2004)	13.79
106	nop_mo	Net payout yield	Boudoukh et al. (2007)	18.85
107	ns	Net stock issues	Pontiff and Woodgate (2008)	3.27
108	ns_ti	Sales-to-inventories	Ou and Penman (1989)	23.70
109	nwc_chng	Net working capital changes	Soliman (2008)	41.69
110	op_ff	Operating profitability	Fama and French (2006)	15.09
111	op_lev	Operating Leverage	Novy-Marx (2011)	35.88
112	org_cap	Organizational Capital	Eisfeldt and Papanikolaou (2013)	17.88
113	oscore	Distress risk Ohlson	Ohlson (1980)	18.95
114	P52_wh	52-week high	George and Hwang (2004)	0.30
115	pchcapx_ia	Percentage change in CAPEX-percentage change in industry CAPEX	Abarbanell and Bushee (1998)	17.90
116	pchcurrat	Percentage change in current ratio	Ou and Penman (1989)	18.13
117	pchdepr	Percentage change in Depreciation-to-gross-PPE	Holthausen and Larcker (1992)	22.83
118	pchquick	Percentage change in quick ratio	Ou and Penman (1989)	29.50
119	pchsale_pchrect	Percentage change in sales - percentage change in accounts receivable	Abarbanell and Bushee (1998)	18.28
120	pchsaleinv	Percentage change in sales-to-inventory	Ou and Penman (1989)	28.97

Table 3 continued

#	Acronym	Description	Reference Paper	Missings [%]
121	pfdelay	Price delay	Hou and Moskowitz (2005)	14.54
122	pm	Profit margin	Soliman (2008)	7.88
123	poa	Percent operating accruals	Hafzalla et al. (2011)	19.50
124	pta	Percent total accruals	Hafzalla et al. (2011)	19.78
125	quick	Quick ratio	Ou and Penman (1989)	24.35
126	rd_inc	Unexpected R&D increases	Eberhart et al. (2004)	0.00
127	rdmcap_mo	R&D to market cap	Guo et al. (2006)	65.75
128	re_1	Revisions in analysts' earnings forecasts (1 month holding period)	Chan et al. (1996)	53.65
129	re_6	6-months rolling revisions in analysts' earnings forecasts	Chan et al. (1996)	50.49
130	realestate	Real estate holdings	Tuzel (2010)	54.41
131	retComp	Customer-supplier (lead-lag)	Menzly and Ozbas (2010)	26.41
132	ret_scm	Seasonality momentum	Heston and Sadka (2008)	3.57
133	rev_13_18	Stock-reversal month (t-13) to (t-18)	Jegadeesh and Titman (1993)	6.08
134	rev_1m	Short-term reversal	Lehmann (1990)	1.45
135	rna	Return on net operating assets	Soliman (2008)	15.69
136	roaq	Profitability	Balakrishnan et al. (2010)	35.02
137	roavol	Earnings volality	Francis et al. (2004)	59.72
138	roic	Return on invested capital	Brown and Rowe (2007)	9.45
139	rsup1	Revenue surprise scaled by market value	Jegadeesh and Livnat (2006)	41.37
140	rsup2	Revenue surprise scaled by standard deviation	Jegadeesh and Livnat (2006)	79.77
141	sal_sga_chng	Percentage change in sales - percentage change in SG&A	Abarbanell and Bushee (1998)	36.82
142	salecash	Sales-to-cash	Ou and Penman (1989)	9.36
143	salerec	Sales-to-receivables	Ou and Penman (1989)	9.86
144	sesm_retew	Style-based earnings surprise measure; constructed from returns	Mueller (2016)	2.01
145	sg	Sales growth	Lakonishok et al. (1994)	9.97
146	share_vol	Turnover	Datar et al. (1998)	0.95
147	shum	Distress risk Shumway	Shumway (2001)	3.32
148	sin	Sin stock	Hong and Kacperczyk (2009)	0.00
149	size	Size	Banz (1981)	0.00
150	sprc_mo	Sales-to-price	Lewellen (2015)	0.67
151	std_dolvol	Volume variance	Chordia et al. (2001)	0.52
152	stdevrec	Standard deviation of analyst recommendations	Jegadeesh et al. (2004)	57.29
153	sue	Earnings surprise scaled by standard deviation	Rendleman et al. (1982)	79.45
154	suemv	Earnings surprise scaled by market value	Livnat and Mendenhall (2006)	38.38
155	tang	Debt capacity-to-firm tangibility	Hahn and Lee (2009)	11.53
156	tax1	Taxable income to book income if book income is positive	Lev and Nissim (2004)	28.29
157	tax2	Taxable income to book income if book income is negative	Lev and Nissim (2004)	76.30
158	vol_mcap	Volume / Mcap	Haugen and Baker (1996)	0.89
159	vol_trend	Volume trend	Haugen and Baker (1996)	29.07
160	zero	Zero-trading days	Liu (2006)	0.00
161	zscore	Z-score (less financial distress)	Dichev (1998)	25.70

Table 4: In-sample multivariate regression results

This table provides the results of Fama and MacBeth (1973) regressions of stock returns on the full set of 161 trade signals. We study five international stock markets (Panel A: North America, Panel B: Europe, Panel C: Japan, Panel D: Pacific, Panel E: Emerging Markets). The dependent variable is the monthly stock return minus the average stock return across all stocks in the particular region, all measured in US-Dollars. Standard OLS regression results are reported in the left part of the table, and value-weighted least squares (VWLS) results are reported in the right part of the table. Variance inflation factors (VIF) are reported to assess the degree of multicollinearity. t-statistics are adjusted using the procedure of West and Newey (1987) with a lag of four months. We report summary regression statistics as well as the coefficients for the 15 most significant trade signals with a $VIF < 7$. For the regressions, we scale all trade signals such that the resulting coefficients can be interpreted as annualized decile 10 minus decile 1 long/short returns that are orthogonal to all other trade signals. The regression results for all characteristics are displayed in the Appendix. The sample period ranges from 1/1989 to 12/2015.

Panel A: North America

A.1.: OLS regression results				A.2.: VWLS regression results			
# Predictors:	161			# Predictors:	161		
# Stock-months:	1552408			# Stock-months:	1552408		
Avg. R-squared:	0.12			Avg. R-squared:	0.30		
Mean VIF:	2.72			Mean VIF:	2.87		
Median VIF:	2.12			Median VIF:	2.24		
Assessment of significance:				Assessment of significance:			
	All	VIF<7	VIF<2		All	VIF<7	VIF<2
# $\|t$-stats$\|$ >3.0	42	38	23	# $\|t$-stats$\|$ >3.0	18	17	9
# $\|t$-stats$\|$ > 2.0	70	66	36	# $\|t$-stats$\|$ >2.0	36	35	14
# $\|t$-stats$\|$ >1.65	79	74	38	# $\|t$-stats$\|$ >1.65	51	50	23
The 15 most significant predictors with VIF<7:				The 15 most significant predictors with VIF<7:			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
rev_1m	-22.87	-13.46	2.00	ret_scm	7.98	8.07	1.16
vol_mcap	39.62	11.57	4.31	rev_1m	-14.96	-7.47	2.84
ear3d	9.01	10.42	1.08	min_ret_daily	9.37	5.80	3.00
std_dolvol	-24.69	-9.16	6.63	share_vol	-16.59	-5.38	2.64
avg_turn_12m	15.91	8.99	3.11	vol_mcap	12.55	5.23	3.57
ret_scm	6.87	8.74	1.11	eqea	3.08	4.60	1.08
suemv	8.27	7.91	1.52	mom_7_12	7.59	4.52	1.83
irev_1m_vw	10.19	7.82	1.37	chng_dyds	4.28	4.49	3.24
bm_mo	15.06	7.11	4.82	age	-6.57	-4.27	1.73
chnanalyst	2.85	5.53	1.15	eer	4.29	3.79	1.72
eqea	3.50	5.46	1.07	change_recom	4.74	3.61	1.12
eer	6.71	5.27	1.60	amihud	-8.60	-3.55	2.26
mom_7_12	6.28	5.24	1.63	herf	5.24	3.48	1.82
amihud	-10.92	-4.78	6.29	oscore	6.50	3.43	4.63
avol3d	2.78	4.70	1.13	exp_div	-1.64	-3.41	1.17

Table 4 continued

Panel B: Europe							
B.1.: OLS regression results				B.2.: VWLS regression results			
# Predictors:	161			# Predictors:	161		
# Stock-months:	1161963			# Stock-months:	1161963		
Avg. R-squared:	0.11			Avg. R-squared:	0.34		
Mean VIF:	2.34			Mean VIF:	2.54		
Median VIF:	1.88			Median VIF:	1.93		
Assessment of significance:				Assessment of significance:			
	All	VIF<7	VIF<2		All	VIF<7	VIF<2
# |t-stats| >3.0	33	33	19	# |t-stats| >3.0	15	15	7
# |t-stats| >2.0	65	65	33	# |t-stats| >2.0	35	35	18
# |t-stats| >1.65	78	78	42	# |t-stats| >1.65	50	50	26
The 15 most significant predictors with VIF<7:				The 15 most significant predictors with VIF<7:			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
ret_scm	7.67	11.98	1.14	mom_7_12	9.97	7.25	1.65
ear3d	7.86	11.93	1.09	efp	11.47	6.86	2.97
vol_mcap	22.60	11.10	4.78	ret_scm	6.26	6.69	1.15
std_dolvol	-16.79	-10.82	5.59	rev_1m	-11.35	-6.26	3.52
b1f_res_1m	-9.86	-10.03	2.15	eqea	5.04	6.06	1.03
efp	11.79	9.17	2.35	ear3d	4.25	4.94	1.08
share_vol	-12.05	-8.88	4.59	eer	3.92	4.51	1.32
mom_2_6	11.09	8.79	2.22	bm_mo	7.92	3.94	3.76
mom_7_12	8.87	8.20	1.63	b1f_res_1m	-5.49	-3.65	2.56
eqea	5.98	7.77	1.03	irev_1m_vw	4.42	3.57	1.44
bm_mo	11.61	7.22	3.74	std_dolvol	-7.65	-3.53	3.14
eer	5.99	6.87	1.23	cdind	-3.29	-3.33	1.12
irev_1m_vw	4.86	6.01	1.21	mom_2_6	5.77	3.18	2.34
rev_1m	-9.52	-5.87	2.54	amihud	-7.00	-3.17	4.49
imom_2_6_vw	4.31	5.84	1.05	nop_mo	3.93	3.16	2.56

Table 4 continued

Panel C: Japan

C.1.: OLS regression results				C.2.: VWLS regression results			
# Predictors:	161			# Predictors:	161		
# Stock-months:	877504			# Stock-months:	877504		
Avg. R-squared:	0.21			Avg. R-squared:	0.44		
Mean VIF:	3.36			Mean VIF:	3.43		
Median VIF:	2.19			Median VIF:	2.21		
Assessment of significance:				Assessment of significance:			
	All	VIF<7	VIF<2		All	VIF<7	VIF<2
# |t-stats| >3.0	33	30	17	# |t-stats| >3.0	11	11	5
# |t-stats| >2.0	54	47	26	# |t-stats| >2.0	28	27	13
# |t-stats| >1.65	66	59	33	# |t-stats| >1.65	47	43	24
The 15 most significant predictors with VIF<7:				The 15 most significant predictors with VIF<7:			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
ret_scm	6.80	10.63	1.16	ret_scm	7.57	7.04	1.26
vol_mcap	26.99	9.47	5.08	vol_mcap	17.54	5.43	6.73
ear3d	5.17	6.86	1.07	rev_1m	-12.00	-5.09	4.85
rev_1m	-16.88	-6.58	3.33	bm_mo	11.20	4.80	4.29
roaq	11.30	6.35	3.05	ltg	4.61	4.52	1.25
bm_mo	11.39	6.23	4.43	ear3d	4.12	3.95	1.10
b1f_res_1m	-7.02	-5.96	3.37	std_dolvol	-10.68	-3.90	5.47
rdmcap_mo	5.57	5.60	1.24	eer	4.12	3.83	1.38
eer	5.72	5.59	1.21	share_vol	-9.50	-3.74	5.19
rev_13_18	-4.69	-5.48	1.22	chng_dyds	6.19	3.47	3.74
exp_div	6.18	5.48	1.02	rev_13_18	-3.51	-3.06	1.41
avol3d	3.75	5.47	1.08	aci	-6.99	-2.94	4.68
suemv	7.10	5.45	1.47	ltr_5y	-4.64	-2.79	1.86
ltg	5.19	5.25	1.13	rdmcap_mo	3.66	2.61	1.64
share_vol	-11.41	-4.88	4.37	salerec	3.40	2.50	2.13

Table 4 continued

Panel D: Pacific							
D.1.: OLS regression results				D.2.: VWLS regression results			
# Predictors:	161			# Predictors:	161		
# Stock-months:	542558			# Stock-months:	542558		
Avg. R-squared:	0.27			Avg. R-squared:	0.54		
Mean VIF:	2.56			Mean VIF:	2.85		
Median VIF:	1.95			Median VIF:	2.06		
Assessment of significance:				Assessment of significance:			
	All	VIF<7	VIF<2		All	VIF<7	VIF<2
# |t-stats| >3.0	24	23	11	# |t-stats| >3.0	12	12	7
# |t-stats| >2.0	41	40	21	# |t-stats| >2.0	23	21	11
# |t-stats| >1.65	49	48	26	# |t-stats| >1.65	31	29	14
The 15 most significant predictors with VIF<7:				The 15 most significant predictors with VIF<7:			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
vol_mcap	38.16	12.77	3.55	ret_scm	8.56	5.29	1.15
share_vol	-28.36	-9.07	5.61	share_vol	-16.30	-4.55	5.21
max_ret_daily	-17.25	-6.75	2.59	ear3d	6.73	4.41	1.12
eer	12.52	6.23	1.24	avg_turn_12m	12.14	4.25	3.62
std_dolvol	-20.12	-5.85	4.02	amihud	-15.87	-4.18	6.26
corwin0	-10.25	-5.80	1.44	eer	6.81	3.85	1.39
ear3d	7.45	5.61	1.07	mom_2_6	11.13	3.82	2.39
min_ret_daily	-13.42	-5.06	2.46	std_dolvol	-12.45	-3.70	4.10
avg_turn_12m	15.13	4.73	2.18	zero	11.50	3.66	1.86
ret_scm	6.70	4.62	1.10	suemv	7.02	3.49	1.58
mom_2_6	12.51	4.49	2.14	mom_7_12	8.46	3.43	1.69
meanrec	-6.55	-4.13	1.25	d_seo_3yr	-3.67	-3.27	1.31
sesm_retew	9.36	4.11	1.08	meanrec	-5.33	-2.88	1.52
rev_1m	-12.94	-3.98	2.01	bm_mo	9.09	2.76	5.65
zero	9.86	3.97	2.43	sesm_retew	6.20	2.49	1.14

Table 4 continued

Panel E: Emerging Markets

E.1.: OLS regression results				E.2.: VWLS regression results			
# Predictors:	161			# Predictors:	161		
# Stock-months:	1772128			# Stock-months:	1772128		
Avg. R-squared:	0.20			Avg. R-squared:	0.39		
Mean VIF:	2.61			Mean VIF:	2.75		
Median VIF:	1.81			Median VIF:	2.04		
Assessment of significance:				Assessment of significance:			
	All	VIF<7	VIF<2		All	VIF<7	VIF<2
# |t-stats| >3.0	19	19	10	# |t-stats| >3.0	13	13	8
# |t-stats| >2.0	34	33	13	# |t-stats| >2.0	27	26	15
# |t-stats| >1.65	49	47	21	# |t-stats| >1.65	37	36	18
The 15 most significant predictors with VIF<7:				The 15 most significant predictors with VIF<7:			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
avg_turn_12m	10.32	6.88	2.63	ltg	5.85	3.95	1.26
share_vol	-15.51	-6.16	3.50	bm_mo	10.58	3.92	5.23
b1f_res_1m	-11.67	-6.00	2.79	efp	14.27	3.84	6.29
vol_mcap	17.17	5.54	3.24	retComp	8.83	3.74	1.40
ret_scm	6.30	5.06	1.12	mom_7_12	7.08	3.55	1.55
bm_mo	13.60	4.72	4.75	cdind	-6.58	-3.54	1.09
ltg	6.12	4.60	1.10	dyds	6.14	3.32	2.11
imom_2_6_vw	6.44	4.35	1.06	corwin0	-6.17	-3.20	1.33
meanrec	-4.06	-4.10	1.15	eer	6.79	3.17	1.29
corwin0	-7.28	-3.95	1.29	ret_scm	4.26	3.13	1.13
std_dolvol	-10.35	-3.67	3.51	pm	-6.76	-3.13	4.27
retComp	7.09	3.52	1.24	rev_1m	-8.29	-3.05	2.76
ear3d	5.02	3.48	1.06	irev_1m_vw	7.33	3.03	1.45
rev_1m	-9.02	-3.41	2.19	avg_turn_12m	6.69	2.83	3.17
mom_7_12	6.01	3.32	1.58	chng_dyds	4.13	2.56	2.16

Table 5: Multidimensionality Tests: Pre- and Post 2003

This table provides the number of statistically significant trade signals from Fama and MacBeth (1973) regressions of stock returns on the full set of 161 trade signals. We study five international stock markets (Panel A: North America, Panel B: Europe, Panel C: Japan, Panel D: Pacific, Panel E: Emerging Markets). The dependent variable is the monthly stock return minus the average stock return across all stocks in the particular region, all measured in US-Dollars. The sample period is split into two periods. The first part, for which results are reported in the left part of the table, is from 1/1989 to 12/2002. The second part, for which results are reported in the right part of the table, is from 1/2003 to 12/2015. To conserve space, the table reports results only for value-weighted least squares (VWLS) regressions. Variance inflation factors (VIF) are computed to assess the degree of multicollinearity. t-statistics are adjusted using the procedure of West and Newey (1987) with a lag of four months.

Panel A: VWLS regression results for North America							
A.1.: Pre 2003				A.2.: Post 2003			
	All	VIF<7	VIF<2		All	VIF<7	VIF<2
# $\lvert t\text{-stats}\rvert > 3.0$	17	17	9	# $\lvert t\text{-stats}\rvert > 3.0$	4	3	1
# $\lvert t\text{-stats}\rvert > 2.0$	38	38	14	# $\lvert t\text{-stats}\rvert > 2.0$	22	20	9
# $\lvert t\text{-stats}\rvert > 1.65$	62	62	24	# $\lvert t\text{-stats}\rvert > 1.65$	39	35	17
Panel B: VWLS regression results for Europe							
B.1.: Pre 2003				B.2.: Post 2003			
	All	VIF<7	VIF<2		All	VIF<7	VIF<2
# $\lvert t\text{-stats}\rvert > 3.0$	13	13	5	# $\lvert t\text{-stats}\rvert > 3.0$	8	8	5
# $\lvert t\text{-stats}\rvert > 2.0$	35	35	17	# $\lvert t\text{-stats}\rvert > 2.0$	22	22	12
# $\lvert t\text{-stats}\rvert > 1.65$	42	41	20	# $\lvert t\text{-stats}\rvert > 1.65$	32	32	16
Panel C: VWLS regression results for Japan							
C.1.: Pre 2003				C.2.: Post 2003			
	All	VIF<7	VIF<2		All	VIF<7	VIF<2
# $\lvert t\text{-stats}\rvert > 3.0$	6	5	3	# $\lvert t\text{-stats}\rvert > 3.0$	9	9	6
# $\lvert t\text{-stats}\rvert > 2.0$	28	21	13	# $\lvert t\text{-stats}\rvert > 2.0$	25	25	13
# $\lvert t\text{-stats}\rvert > 1.65$	44	36	20	# $\lvert t\text{-stats}\rvert > 1.65$	32	31	15
Panel D: VWLS regression results for Pacific							
D.1.: Pre 2003				D.2.: Post 2003			
	All	VIF<7	VIF<2		All	VIF<7	VIF<2
# $\lvert t\text{-stats}\rvert > 3.0$	5	5	4	# $\lvert t\text{-stats}\rvert > 3.0$	10	10	4
# $\lvert t\text{-stats}\rvert > 2.0$	17	17	10	# $\lvert t\text{-stats}\rvert > 2.0$	22	20	11
# $\lvert t\text{-stats}\rvert > 1.65$	29	29	17	# $\lvert t\text{-stats}\rvert > 1.65$	33	30	15
Panel E: VWLS regression results for Emerging Markets							
E.1.: Pre 2003				E.2.: Post 2003			
	All	VIF<7	VIF<2		All	VIF<7	VIF<2
# $\lvert t\text{-stats}\rvert > 3.0$	6	6	3	# $\lvert t\text{-stats}\rvert > 3.0$	16	14	9
# $\lvert t\text{-stats}\rvert > 2.0$	16	16	10	# $\lvert t\text{-stats}\rvert > 2.0$	30	26	12
# $\lvert t\text{-stats}\rvert > 1.65$	29	29	17	# $\lvert t\text{-stats}\rvert > 1.65$	38	34	16

Table 6: Out-of-sample return regressions

This table summarizes the out-of-sample forecast abilities (Fama and MacBeth (1973) regression coefficients and West and Newey (1987) *t*-statistics with four lags) of different composite return forecasts for realized stock returns. We examine five different forecast models for five international stock markets (Panel A: North America, Panel B: Europe, Panel C: Japan, Panel D: Pacific, Panel E: Emerging Markets). *E(RET) Multidimensional* is our model with the full set of 161 trade signals. *E(RET) C1997* uses the four characteristics of the Carhart (1997) model. *E(RET) FF2015* uses the five characteristics of the Fama and French (2015) model. *E(RET) L2015* uses the set of 15 variables employed by Lewellen (2015). *E(RET) SYY2012* relies on the 11 variables examined by Stambaugh et al. (2012). All return forecasts are derived from multiplying a firm's current characteristics with the corresponding regression coefficients from past Fama and MacBeth (1973) regressions of up to 120 months (estimated separately for every forecast model). The dependent variable is the monthly stock return minus the average monthly stock return across all stocks in the particular region, all measured in US-Dollars. Standard OLS regression results are reported in columns (1) to (6), and value-weighted least squares (VWLS) results (only for *E(RET) Multidimensional*) are reported in column (7). *t*-statistics are in parentheses. The sample period ranges from 1/1989 to 12/2015, and the out-of-sample regressions run from 1/1995 onwards.

Panel A: Predictive return regressions for North America

Forecast model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
E(RET) Multidimensional	0.9439					0.9498	0.5806
	(15.52)					(18.17)	(6.80)
E(RET) C1997		0.8754				0.1508	
		(4.98)				(0.73)	
E(RET) FF2015			0.8726			0.1428	
			(3.41)			(0.54)	
E(RET) L2015				0.7966		-0.1872	
				(5.86)		(-1.40)	
E(RET) SYY2012					0.9406	0.1051	
					(5.48)	(0.64)	
Regression model	OLS	OLS	OLS	OLS	OLS	OLS	VWLS
Observations	1,363,479	1,363,479	1,363,479	1,363,479	1,363,479	1,363,479	1,363,479
R-squared	0.009	0.006	0.006	0.005	0.004	0.024	0.011
Number of groups	252	252	252	252	252	252	252

Panel B: Predictive return regressions for Europe

Forecast Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
E(RET) Multidimensional	0.9658					0.8832	0.6091
	(17.96)					(21.57)	(10.13)
E(RET) C1997		1.0666				0.1358	
		(6.25)				(0.66)	
E(RET) FF2015			0.9030			-0.1274	
			(2.53)			(-0.37)	
E(RET) L2015				1.0366		-0.1589	
				(9.22)		(-0.95)	
E(RET) SYY2012					1.1209	0.3431	
					(8.53)	(2.89)	
Regression model	OLS	OLS	OLS	OLS	OLS	OLS	VWLS
Observations	979,058	979,058	979,058	979,058	979,058	979,058	979,058
R-squared	0.010	0.009	0.003	0.007	0.009	0.021	0.012
Number of groups	252	252	252	252	252	252	252

Table 6 continued

Panel C: Predictive return regressions for Japan							
Forecast model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
E(RET) Multidimensional	0.7862					0.7643	0.4479
	(16.09)					(15.19)	(8.39)
E(RET) C1997		0.8064				0.0957	
		(4.47)				(0.26)	
E(RET) FF2015			0.8444			0.2259	
			(4.85)			(0.60)	
E(RET) L2015				0.8518		0.0402	
				(5.59)		(0.22)	
E(RET) SYY2012					0.5999	0.1669	
					(2.76)	(0.91)	
Regression model	OLS	OLS	OLS	OLS	OLS	OLS	VWLS
Observations	764,302	764,302	764,302	764,302	764,302	764,302	764,302
R-squared	0.011	0.013	0.012	0.011	0.012	0.041	0.013
Number of groups	252	252	252	252	252	252	252

Panel D: Predictive return regressions for Pacific							
Forecast model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
E(RET) Multidimensional	0.8540					0.7874	0.4129
	(15.24)					(15.51)	(7.29)
E(RET) C1997		1.0811				0.1503	
		(7.07)				(0.79)	
E(RET) FF2015			1.1105			-0.0166	
			(5.43)			(-0.07)	
E(RET) L2015				0.9917		0.1585	
				(10.01)		(1.45)	
E(RET) SYY2012					0.9426	0.0387	
					(7.09)	(0.31)	
Regression model	OLS	OLS	OLS	OLS	OLS	OLS	VWLS
Observations	520,645	520,645	520,645	520,645	520,645	520,645	520,645
R-squared	0.010	0.008	0.006	0.007	0.005	0.023	0.013
Number of groups	252	252	252	252	252	252	252

Panel E: Predictive return regressions for Emerging Markets							
Forecast model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
E(RET) Multidimensional	0.6933					0.6106	0.4778
	(17.07)					(12.79)	(7.98)
E(RET) C1997		0.9647				0.1027	
		(9.38)				(0.70)	
E(RET) FF2015			0.9601			0.1300	
			(8.82)			(0.78)	
E(RET) L2015				0.9008		0.1877	
				(13.41)		(1.46)	
E(RET) SYY2012					0.8226	0.1310	
					(7.78)	(1.04)	
Regression model	OLS	OLS	OLS	OLS	OLS	OLS	VWLS
Observations	1,728,553	1,728,553	1,728,553	1,728,553	1,728,553	1,728,553	1,728,553
R-squared	0.006	0.003	0.003	0.003	0.002	0.012	0.008
Number of groups	252	252	252	252	252	252	252

Table 7: Out-of-sample long/short portfolio results

This table summarizes the out-of-sample long/short hedge portfolio returns on the basis of different composite return forecasts. We examine five different forecast models for five international stock markets (Panel A: North America, Panel B: Europe, Panel C: Japan, Panel D: Pacific, Panel E: Emerging Markets). *E(RET) Multidimensional* is our model with the full set of 161 trade signals. *E(RET) C1997* uses the four characteristics of the Carhart (1997) model. *E(RET) FF2015* uses the five characteristics of the Fama and French (2015) model. *E(RET) L2015* uses the set of 15 variables employed by Lewellen (2015). *E(RET) SYY* relies on the 11 variables examined by Stambaugh et al. (2012). All return forecasts are derived from multiplying a firm's current characteristics with the corresponding regression coefficients from past Fama and MacBeth (1973) regressions of up to 120 months (estimated separately for every forecast model). The hedge portfolios go long in the stock decile with the highest expected return forecast and short in the stock decile of stocks with the lowest expected return forecast. We calculate equal-weighted (*ew*) and value-weighted (*vw*) portfolio returns (measured in US-Dollars), and rebalance monthly. Reported are the monthly raw long-short return and the associated t-value, the percentage of months in which the strategy returns were above zero, the annualized Sharpe ratio, the monthly volatility, the minimum return, the skewness, and the kurtosis of the strategy returns. The sample period ranges from 1/1989 to 12/2015, and the out-of-sample portfolio tests run from 1/1995 onwards.

Panel A: Hedge portfolio results for North America

Forecast model	Weights	ret [%]	t-stat(ret)	%>0	Sharpe	Vola[%]	Min	Skew	Kurt
E(RET) Multidimensional	ew	5.21	21.19	95.63	4.62	3.91	-4.08	1.76	9.64
E(RET) Multidimensional	vw	2.31	7.85	76.98	1.71	4.67	-13.25	1.27	9.52
E(RET) C1997	ew	1.45	4.70	67.46	1.03	4.89	-20.14	0.63	10.09
E(RET) C1997	vw	0.88	2.35	60.71	0.51	5.93	-27.50	0.56	11.89
E(RET) FF2015	ew	1.44	3.95	57.14	0.86	5.79	-20.37	1.65	12.71
E(RET) FF2015	vw	0.58	1.46	52.78	0.32	6.33	-18.86	1.28	11.23
E(RET) L2015	ew	1.99	6.74	72.62	1.47	4.69	-19.16	1.86	18.19
E(RET) L2015	vw	0.52	1.41	55.16	0.31	5.81	-20.98	1.43	15.34
E(RET) SYY2012	ew	1.66	5.50	70.63	1.20	4.78	-17.91	0.95	13.15
E(RET) SYY2012	vw	0.94	2.70	61.11	0.59	5.53	-21.34	0.24	8.14

Panel B: Hedge portfolio results for Europe

Forecast model	Weights	ret [%]	t-stat(ret)	%>0	Sharpe	Vola[%]	Min	Skew	Kurt
E(RET) Multidimensional	ew	4.05	24.27	97.22	5.30	2.65	-4.59	0.65	5.96
E(RET) Multidimensional	vw	2.00	9.42	78.17	2.06	3.37	-10.20	-0.21	5.24
E(RET) C1997	ew	1.79	7.04	78.57	1.54	4.03	-17.60	0.26	8.63
E(RET) C1997	vw	1.12	3.67	65.87	0.80	4.84	-16.28	-0.04	6.01
E(RET) FF2015	ew	0.95	5.31	64.68	1.16	2.85	-12.91	-0.11	7.19
E(RET) FF2015	vw	0.74	3.15	58.73	0.69	3.74	-15.88	-0.21	6.23
E(RET) L2015	ew	2.37	10.39	86.11	2.27	3.63	-12.82	0.16	7.88
E(RET) L2015	vw	1.21	4.06	66.27	0.89	4.73	-19.39	0.21	8.54
E(RET) SYY2012	ew	2.48	9.88	82.54	2.16	3.99	-16.69	-0.50	7.39
E(RET) SYY2012	vw	1.77	4.86	70.24	1.06	5.78	-25.81	-0.57	7.65

Table 7 continued

Panel C: Hedge portfolio results for Japan									
Forecast model	Weights	ret [%]	t-stat(ret)	%>0	Sharpe	Vola[%]	Min	Skew	Kurt
E(RET) Multidimensional	ew	3.49	17.77	93.25	3.88	3.12	-1.53	3.56	30.53
E(RET) Multidimensional	vw	1.82	7.11	70.24	1.55	4.05	-9.52	1.01	8.33
E(RET) C1997	ew	1.15	3.52	62.70	0.77	5.20	-17.15	1.63	18.41
E(RET) C1997	vw	0.63	1.59	53.17	0.35	6.29	-22.94	0.85	11.13
E(RET) FF2015	ew	1.34	4.69	63.49	1.02	4.55	-14.20	1.28	11.69
E(RET) FF2015	vw	0.94	2.36	54.76	0.52	6.31	-18.22	0.82	7.32
E(RET) L2015	ew	1.37	4.89	67.06	1.07	4.45	-14.72	0.44	8.42
E(RET) L2015	vw	0.65	1.68	55.16	0.37	6.15	-20.23	0.19	4.82
E(RET) SYY2012	ew	0.72	2.54	63.10	0.55	4.48	-16.79	0.66	13.14
E(RET) SYY2012	vw	-0.26	-0.77	50.79	-0.17	5.30	-18.81	-0.15	5.28

Panel D: Hedge portfolio results for Pacific									
Forecast model	Weights	ret [%]	t-stat(ret)	%>0	Sharpe	Vola[%]	Min	Skew	Kurt
E(RET) Multidimensional	ew	5.24	17.40	92.06	3.80	4.78	-19.60	-0.33	8.17
E(RET) Multidimensional	vw	2.12	8.03	73.02	1.75	4.20	-9.76	0.71	5.89
E(RET) C1997	ew	2.90	8.63	75.40	1.88	5.33	-22.73	-0.16	6.90
E(RET) C1997	vw	1.65	4.29	63.89	0.94	6.12	-23.17	0.12	5.23
E(RET) FF2015	ew	2.45	7.85	69.44	1.71	4.95	-22.29	0.28	7.49
E(RET) FF2015	vw	0.87	2.35	52.38	0.51	5.86	-19.28	1.07	6.97
E(RET) L2015	ew	3.37	11.14	84.92	2.43	4.80	-24.87	-1.04	9.65
E(RET) L2015	vw	1.97	5.49	69.05	1.20	5.71	-24.61	-0.30	6.49
E(RET) SYY2012	ew	2.19	8.19	76.98	1.79	4.24	-17.33	-0.36	7.82
E(RET) SYY2012	vw	1.40	4.15	65.87	0.90	5.37	-20.29	-0.65	6.14

Panel E: Hedge portfolio results for Emerging Markets									
Forecast model	Weights	ret [%]	t-stat(ret)	%>0	Sharpe	Vola[%]	Min	Skew	Kurt
E(RET) Multidimensional	ew	3.49	18.57	93.65	4.05	2.98	-13.72	-1.34	11.02
E(RET) Multidimensional	vw	1.92	7.98	71.43	1.74	3.82	-9.37	0.37	5.16
E(RET) C1997	ew	1.90	9.48	80.16	2.07	3.17	-11.76	-0.58	6.84
E(RET) C1997	vw	0.93	2.75	56.75	0.60	5.34	-25.71	-0.25	5.33
E(RET) FF2015	ew	2.02	13.96	80.16	3.05	2.30	-3.42	0.80	5.30
E(RET) FF2015	vw	1.08	3.33	56.75	0.73	5.17	-17.54	0.37	4.07
E(RET) L2015	ew	2.42	15.34	89.68	3.35	2.51	-7.85	0.91	8.20
E(RET) L2015	vw	1.71	5.72	65.48	1.25	4.75	-22.26	-0.02	6.27
E(RET) SYY2012	ew	1.46	8.58	75.40	1.87	2.69	-12.55	-0.92	7.93
E(RET) SYY2012	vw	0.98	4.30	65.87	0.94	3.61	-9.51	0.02	5.10

Table 8: Robustness tests for the multidimensional strategy

This table summarizes the results of robustness tests for the multidimensional return forecast. Robustness test 1 constructs the forecast from a pooled panel regression with up to 120 past months instead of a Fama and MacBeth (1973) regression. Robustness test 2 uses a training period of 60 months instead of 120 months. To account for estimation error, robustness test 3 shrinks the regression coefficients for the individual trade signals when computing the multidimensional forecast. The shrinkage coefficient is obtained by multiplying the coefficient with (1-(p-value[%]/100)), where the p-value refers to a test that the absolute value of the coefficient equals zero. Robustness test 4 uses a rolling 6-month estimate of the forecast. Robustness test 5 uses returns in local currency as opposed to returns in US-Dollar. Robustness test 6 skips the first trading day of the month. Robustness test 7 excludes financial firms (SIC codes between 6000 and 6999). Finally, robustness test 8 includes only the largest 20% of all firms in a given region. Panel A reports the results of Fama and MacBeth (1973) OLS regressions of realized stock returns on the multidimensional return forecast (coefficients and associated t-statistics). Panel B reports monthly returns and the associated t-statistics of long/short hedge portfolios with equal-weighted components. Panel C reports monthly returns and the associated t-statistics of long/short hedge portfolios with value-weighted components. In each panel, we report the results separately for North America (NA), Europe (EU), Japan (JA), Pacific (PA), and Emerging Markets (EM). t-statistics are in parentheses. The sample period ranges from 1/1989 to 12/2015, and the out-of-sample portfolio tests run from 1/1995 onwards.

Robustness Test	(1) Pooled estimates	(2) Test period 60 months	(3) Shrink	(4) Rolling 6 months	(5) Local returns	(6) First day skipped	(7) Excluding financials	(8) Largest 20% of firms
Panel A: Firm-level regression slopes: $ret = alpha + beta \cdot E(RET)Multidimensional + \varepsilon$.								
Region	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
North America	0.7785	0.7581	0.9645	0.7926	0.9397	0.8489	0.9708	0.4721
	(14.32)	(14.04)	(16.44)	(10.28)	(15.45)	(14.73)	(15.39)	(8.43)
Europe	0.8424	0.7865	1.0103	0.8412	0.9713	0.9224	0.9885	0.6477
	(15.44)	(14.70)	(18.13)	(12.16)	(18.12)	(17.10)	(18.10)	(10.33)
Japan	0.7048	0.6153	0.8203	0.6130	0.7861	0.6887	0.8099	0.4025
	(18.90)	(17.52)	(16.69)	(9.13)	(16.20)	(15.36)	(16.39)	(7.78)
Pacific	0.8459	0.6754	0.9139	0.7554	0.8454	0.7959	0.8611	0.4255
	(23.81)	(14.25)	(14.27)	(11.06)	(15.57)	(14.80)	(15.31)	(8.21)
Emerging Markets	0.7407	0.6203	0.7352	0.6397	0.6955	0.6784	0.7018	0.4682
	(18.94)	(11.90)	(18.09)	(13.58)	(18.02)	(16.97)	(17.62)	(9.82)

Table 8 continued

Robustness Test	(1) Pooled estimates	(2) Test period 60 months	(3) Shrink	(4) Rolling 6 months	(5) Local returns	(6) First day skipped	(7) Excluding financials	(8) Largest 20% of firms
Panel B: Hedge portfolio results; equal-weighted returns								
Region	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
North America	5.37	5.43	5.22	3.29	5.19	4.69	5.35	2.46
	(17.34)	(16.11)	(22.02)	(12.97)	(21.24)	(18.74)	(21.20)	(9.31)
Europe	4.13	3.93	4.09	2.95	4.07	3.86	4.15	2.55
	(19.10)	(16.53)	(24.37)	(15.59)	(24.53)	(22.85)	(24.16)	(11.20)
Japan	3.66	3.43	3.56	1.86	3.49	3.05	3.61	1.55
	(18.46)	(17.64)	(18.49)	(9.71)	(17.87)	(15.34)	(18.03)	(6.92)
Pacific	5.50	5.18	5.33	3.84	5.18	4.81	5.27	2.38
	(16.97)	(16.30)	(16.94)	(13.17)	(17.58)	(16.57)	(17.33)	(9.35)
Emerging Markets	3.59	3.39	3.51	2.68	3.48	3.42	3.54	2.19
	(14.62)	(12.40)	(19.54)	(14.88)	(19.91)	(17.86)	(18.28)	(8.54)
Panel C: Hedge portfolio results; value-weighted returns								
Region	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
North America	2.33	2.12	1.96	1.25	2.27	2.16	2.40	2.09
	(6.45)	(5.51)	(6.79)	(3.90)	(7.82)	(7.32)	(7.69)	(6.75)
Europe	2.24	2.53	2.36	1.87	2.02	1.85	2.06	1.75
	(8.58)	(8.60)	(10.77)	(7.90)	(9.48)	(8.83)	(9.56)	(7.98)
Japan	2.03	1.74	2.00	0.79	1.81	1.65	1.93	1.44
	(8.92)	(6.82)	(7.64)	(2.51)	(7.15)	(6.17)	(7.81)	(5.68)
Pacific	1.86	1.51	2.20	1.36	2.03	1.98	2.23	1.60
	(6.54)	(4.04)	(7.04)	(4.46)	(8.01)	(7.56)	(8.78)	(5.30)
Emerging Markets	1.85	2.20	2.26	1.68	1.91	1.90	2.00	1.79
	(5.85)	(7.24)	(8.90)	(6.75)	(8.26)	(7.45)	(7.80)	(6.72)

Table 9: Alphas and R^2's of competing asset pricing models

This table reports results from various asset pricing models to explain the out-of-sample long/short hedge portfolio returns on the basis of the multidimensional composite return forecast. We examine the results separately for five international stock markets (Panel A: North America, Panel B: Europe, Panel C: Japan, Panel D: Pacific, Panel E: Emerging Markets). Results for the equal-weighted (value-weighted) returns of the multidimensional strategy are reported in the left (right) part of the table. We investigate the following asset pricing models: the CAPM, the Fama and French (1993) three-factor model ($FF3$), the Carhart (1997) four-factor model ($C4$), the Carhart (1997) four factor model augmented with the short-term reversal factor ($C4 + STREV$), the Fama and French (1993) five-factor model ($FF5$), the Hou et al. (2015) q-factor model (HXZ) and an "all-factor" model, containing all unique factors of these models. To calculate the market factor we use the corresponding regional MSCI index as the market factor, and the risk-free rate from Kenneth French's website. For Japan we use the MSCI Japan. Remaining factors are constructed separately for each country using the methodologies of Fama and French (1993), Fama and French (2015), and Hou et al. (2015), and then averaged across all countries within a region using the methodology of Griffin (2002). $\Delta\alpha$ is the percentage change of the model alpha in comparison to the raw long-short return of the strategy as shown in Table 7. The sample period ranges from 1/1995 to 12/2015.

Panel A: North America								
Factor Model	A.1: Equal-Weighted Strategy				A.2: Value-Weighted Strategy			
	α [%]	t-stat(α)	$\Delta\alpha$ [%]	R^2 [%]	α [%]	t-stat(α)	$\Delta\alpha$ [%]	R^2 [%]
CAPM	5.21	20.44	0.00	0.00	2.25	7.53	-2.63	0.70
FF3	5.30	22.25	1.71	15.20	2.37	8.36	2.56	13.80
C4	5.23	19.79	0.38	16.10	2.02	7.94	-13.39	30.50
C4+STREV	5.20	20.48	-0.19	16.70	1.98	7.69	-15.38	31.70
FF5	5.41	22.11	3.77	20.30	2.55	7.69	9.88	17.40
HXZ	5.43	18.60	4.14	14.00	2.22	7.19	-3.97	17.50
All factors	5.30	20.72	1.71	24.80	2.09	7.65	-10.00	41.20

Panel B: Europe								
Factor Model	B.1: Equal-Weighted Strategy				B.2: Value-Weighted Strategy			
	α [%]	t-stat(α)	$\Delta\alpha$ [%]	R^2 [%]	α [%]	t-stat(α)	$\Delta\alpha$ [%]	R^2 [%]
CAPM	4.12	25.03	1.71	7.60	2.06	9.83	2.96	3.10
FF3	4.04	26.26	-0.25	13.90	2.05	9.97	2.47	9.30
C4	3.38	29.22	-18.03	60.00	1.51	7.28	-27.92	28.50
C4+STREV	3.38	29.12	-18.03	60.40	1.49	7.43	-29.23	33.60
FF5	3.69	23.88	-9.30	31.60	1.77	7.43	-12.20	16.00
HXZ	3.49	23.48	-14.85	36.60	1.32	6.46	-40.96	29.10
All factors	3.29	26.16	-20.71	63.20	1.26	6.19	-45.40	39.50

Table 9 continued

Factor Model	Panel C: Japan C.1: Equal-Weighted Strategy				C.2: Value-Weighted Strategy			
	α [%]	t-stat(α)	$\Delta\alpha$ [%]	R^2 [%]	α [%]	t-stat(α)	$\Delta\alpha$ [%]	R^2 [%]
CAPM	3.49	17.77	0.00	0.70	1.82	7.10	0.00	0.20
FF3	3.49	18.42	0.00	15.60	1.85	7.02	1.63	4.60
C4	3.50	19.22	0.29	23.80	1.86	7.31	2.17	11.10
C4+STREV	3.24	21.72	-7.43	42.10	1.42	6.71	-24.69	42.50
FF5	3.52	17.53	0.86	17.20	1.85	6.71	1.63	4.60
HXZ	3.61	15.63	3.38	14.40	1.81	6.18	-0.55	2.60
All factors	3.29	21.60	-5.90	43.10	1.30	6.02	-33.33	46.00

Factor Model	Panel D: Pacific D.1: Equal-Weighted Strategy				D.2: Value-Weighted Strategy			
	α [%]	t-stat(α)	$\Delta\alpha$ [%]	R^2 [%]	α [%]	t-stat(α)	$\Delta\alpha$ [%]	R^2 [%]
CAPM	5.21	17.34	-0.57	0.40	2.13	7.97	0.47	0.10
FF3	5.20	19.29	-0.77	17.40	2.11	7.56	-0.47	0.50
C4	4.87	15.16	-7.32	20.90	1.71	5.95	-21.41	7.20
C4+STREV	4.80	14.23	-8.76	22.90	1.71	5.93	-21.41	7.20
FF5	4.99	14.80	-4.89	19.60	1.97	5.93	-7.33	1.70
HXZ	5.34	17.78	1.89	16.50	2.06	6.64	-2.87	0.40
All factors	4.82	12.87	-8.35	27.10	1.61	5.29	-27.35	8.90

Factor Model	Panel E: Emerging Markets E.1: Equal-Weighted Strategy				E.2: Value-Weighted Strategy			
	α [%]	t-stat(α)	$\Delta\alpha$ [%]	R^2 [%]	α [%]	t-stat(α)	$\Delta\alpha$ [%]	R^2 [%]
CAPM	3.50	19.09	0.29	0.30	1.91	7.96	-0.52	0.00
FF3	3.37	16.94	-3.50	8.40	2.01	7.76	4.58	1.40
C4	3.14	13.20	-10.56	15.20	1.66	6.18	-14.53	11.20
C4+STREV	3.14	13.46	-10.56	16.70	1.66	6.14	-14.53	11.30
FF5	3.31	13.07	-5.29	8.60	1.96	6.14	2.06	4.80
HXZ	3.22	13.00	-8.05	12.60	1.72	5.74	-10.99	2.80
All factors	3.05	10.81	-13.46	24.60	1.72	5.27	-10.99	16.00

Table 10: Diversification Benefits

This table shows results of exploring potential diversification benefits for the multidimensional strategy. Panel A reports correlations between equal-weighted long/short hedge portfolio returns across international stock markets (North America, Europe, Japan, Pacific, and Emerging Markets). Panel B reports correlations between value-weighted long/short hedge portfolio returns across international stock markets. Panel C reports performance statistics of a globally diversified equal-weighted (*ew*) and value-weighted (*vw*) multidimensional strategy. The equal-weighted global strategy return is calculated as the average across equal-weighted regional strategy returns. The value-weighted global strategy return is calculated as the average across value-weighted regional strategy returns. Reported are the monthly raw long-short return and the associated t-value, the monthly Carhart (1997) four factor alpha and the associated t-value, the percentage of months in which the strategy returns were above zero, and the annualized Sharpe ratio of the strategy. To calculate the four factor alpha for the global strategy, we average all regional factors. Panel D reports risk properties of the global strategy. Reported are the monthly return volatility, the reduction in the volatility compared to the average volatility across the five regional multidimensional strategies, the kurtosis, the reduction in the kurtosis compared to the average kurtosis across the five regional multidimensional strategies, the skewness, and the minimum monthly return. The sample period ranges from 1/1995 to 12/2015.

Panel A: Correlations of equal-weighted portfolio returns for international stock markets						
Region	(1)	(2)	(3)	(4)	(5)	(6)
(1) North America	1.00					
(2) Europe	0.18	1.00				
(3) Japan	0.18	0.02	1.00			
(4) Pacific	0.25	0.03	0.08	1.00		
(5) Emerging Markets	-0.12	0.09	-0.18	0.29	1.00	
(6) Global	0.61	0.41	0.40	0.74	0.38	1.00
Panel B: Correlations of value-weighted portfolio returns for international stock markets						
Region	(1)	(2)	(3)	(4)	(5)	(6)
(1) North America	1.00					
(2) Europe	0.11	1.00				
(3) Japan	0.03	0.02	1.00			
(4) Pacific	0.04	0.08	0.06	1.00		
(5) Emerging Markets	0.06	0.11	-0.03	0.26	1.00	
(6) Global	0.54	0.46	0.43	0.57	0.53	1.00
Panel C: Performance of the globally diversified multidimensional strategy						
Weights	ret [%]	t-stat(ret)	alp4f [%]	t-stat(alp4f)	%>0	Sharpe
ew	4.30	36.32	4.13	32.91	98.81	7.93
vw	2.03	15.74	1.86	12.67	86.11	3.43
Panel D: Risk of the globally diversified multidimensional strategy						
Weights	Vola[%]	Δ(Vola) [%]	Kurt	Δ(Kurt) [%]	Skew	Min [%]
ew	1.88	-59.99	9.24	-34.33	0.72	-2.88
vw	2.05	-64.88	3.99	-52.50	0.52	-3.98

Table 11: Time trends in returns and correlations

This table reports the results of the time trend analysis. Panel A shows the results for a trend in long/short portfolio returns. For every region (North America, Europe, Japan, Pacific, and Emerging Markets) we regress equal-weighted (*ew*) and value-weighted (*vw*) returns of the multidimensional strategy on a time variable (*time_id*). The time variable is equal to the number of months passed since January 1995 divided by 12. Panel B shows the results for a trend in correlations between long/short portfolio returns. For every region we compute the average equal-weighted and value-weighted portfolio returns across all other international markets. We then compute rolling 24-months correlations between the return for every region and the return of the corresponding international strategy. This yields a time-series of monthly return correlations which we regress on *time_id*. To account for the overlapping nature of our tests, we report West and Newey (1987) adjusted t-statistics with a lag of 23 months in Panel B. The sample period ranges from 1/1989 to 12/2015, and the out-of-sample portfolio tests run from 1/1995 onwards.

Panel A: Time trend in portfolio returns							
Region	Weights	Const	t-stat(const)	beta(*time_id*)	t-stat(beta)	N	R^2
North America	ew	0.0620	(11.52)	-0.0009	(-2.57)	252	0.021
North America	vw	0.0403	(6.06)	-0.0016	(-3.32)	252	0.045
Europe	ew	0.0374	(11.63)	0.0003	(1.33)	252	0.005
Europe	vw	0.0207	(5.40)	-0.0001	(-0.18)	252	0.000
Japan	ew	0.0404	(7.74)	-0.0005	(-1.46)	252	0.010
Japan	vw	0.0228	(3.91)	-0.0004	(-1.04)	252	0.004
Pacific	ew	0.0274	(4.08)	0.0024	(5.00)	252	0.090
Pacific	vw	0.0223	(3.42)	-0.0001	(-0.21)	252	0.000
Emerging Markets	ew	0.0245	(5.46)	0.0010	(3.11)	252	0.040
Emerging Markets	vw	0.0105	(2.01)	0.0008	(1.91)	252	0.017
Panel B: Time trend in correlations							
Region	Weights	Const	t-stat(const)	beta(*time_id*	t-stat(beta)	N	R^2
North America	ew	0.3024	(4.28)	-0.0051	(-0.84)	228	0.028
North America	vw	0.0961	(0.76)	0.0044	(0.53)	228	0.013
Europe	ew	0.0710	(0.43)	0.0030	(0.25)	228	0.004
Europe	vw	0.1390	(0.93)	-0.0022	(-0.24)	228	0.002
Japan	ew	-0.0668	(-0.98)	0.0189	(3.23)	228	0.273
Japan	vw	0.2434	(1.98)	-0.0186	(-2.05)	228	0.140
Pacific	ew	0.3292	(2.56)	-0.0015	(-0.15)	228	0.002
Pacific	vw	0.2953	(6.53)	-0.0100	(-2.09)	228	0.103
Emerging Markets	ew	-0.0074	(-0.07)	0.0112	(1.47)	228	0.098
Emerging Markets	vw	0.2273	(2.60)	0.0029	(0.45)	228	0.009

Table 12: Hedge fund returns and multidimensional strategies

The regressions reported in this table investigate the relation between hedge fund returns and long/short hedge returns derived from the multidimensional return predictor for five international markets (North America, Europe, Japan, Pacific, and Emerging Markets). For instance, $Multidimensional\ NA$ is the value-weighted monthly return of the strategy which goes long in the North American stock decile with the highest expected return forecast and short in the North American stock decile with the lowest expected return forecast. The dependent variable is the monthly excess return of the Credit Suisse Long/Short Equity Hedge Fund Index. The independent variables are the four North American factors of the Carhart (1997) model $MKTRF$, SMB, HML, and UMD, the North American one-month reversal factor $STREV$, and the value-weighted long/short hedge returns of the multidimensional strategies. t-statistics are reported in parentheses. The sample period ranges from 1/1995 to 12/2015.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Multidimensional NA	0.2307					0.2410	0.0745
	(5.23)					(6.13)	(3.33)
Multidimensional EU		-0.1236				-0.1671	-0.0257
		(-2.29)				(-4.36)	(-0.90)
Multidimensional JA			0.0256			0.0168	-0.0097
			(0.53)			(0.43)	(-0.45)
Multidimensional PA				0.0188		0.0128	-0.0006
				(0.31)		(0.25)	(-0.02)
Multidimensional EM					0.0468	0.0411	0.0146
					(0.88)	(0.97)	(0.57)
MKTRF							0.4619
							(17.53)
SMB							0.2771
							(9.69)
HML							-0.0444
							(-1.35)
UMD							0.0976
							(5.60)
STREV							-0.0835
							(-3.20)
Alpha [%]	0.09	0.87	0.57	0.59	0.53	0.26	0.17
	(0.53)	(4.08)	(2.68)	(2.78)	(2.68)	(1.09)	(1.33)
N	252	252	252	252	252	252	252
R-squared	0.161	0.024	0.002	0.001	0.004	0.206	0.777

Supplemental Appendix for ...and nothing else matters? On the dimensionality and predictability of international stock returns

This Version: March 2017

This appendix shows full results for all trade signals of the Fama and MacBeth (1973) regressions reported in Table 3 of the paper.

Table A1: In-sample return regressions: Full results for North America

This table provides the results of Fama and MacBeth (1973) regressions of stock returns on the full set of 161 trade signals for North America. We study five international stock markets (North America, Europe, Japan, Pacific, and Emerging Markets). The dependent variable is the monthly stock return minus the average stock return across all stocks in the particular region, all measured in US-Dollars. Standard OLS regression results are reported in the left part of the table, and value-weighted least squares (VWLS) results are reported in the right part of the table. Variance inflation factors (VIF) are reported to assess the degree of multicollinearity. For each characteristic, the VIF is calculated as $1/(1\text{-}R2)$ with the $R2$ being obtained from regressing each characteristic on all the other characteristics in a pooled regression. t-statistics are adjusted using the procedure of West and Newey (1987) with a lag of four months. For the regressions, we scale all trade signals such that the resulting coefficients can be interpreted as annualized decile 10 minus decile 1 long/short returns that are orthogonal to all other trade signals. Whereas we report only the 15 most significant variables in the paper, we show full results here. The sample period ranges from 1/1989 to 12/2015.

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
rev_1m	-22.87	-13.46	2.00	ret_scm	7.98	8.07	1.16
vol_mcap	39.62	11.57	4.31	rev_1m	-14.96	-7.47	2.84
ear3d	9.01	10.42	1.08	min_ret_daily	9.37	5.80	3.00
std_dolvol	-24.69	-9.16	6.63	share_vol	-16.59	-5.38	2.64
avg_turn_12m	15.91	8.99	3.11	vol_mcap	12.55	5.23	3.57
ret_scm	6.87	8.74	1.11	eqea	3.08	4.60	1.08
suemv	8.27	7.91	1.52	mom_7_12	7.59	4.52	1.83
irev_1m_vw	10.19	7.82	1.37	chng_dyds	4.28	4.49	3.24
bm_mo	15.06	7.11	4.82	age	-6.57	-4.27	1.73
chnanalyst	2.85	5.53	1.15	eer	4.29	3.79	1.72
eqea	3.50	5.46	1.07	change_recom	4.74	3.61	1.12
eer	6.71	5.27	1.60	amihud	-8.60	-3.55	2.26
mom_7_12	6.28	5.24	1.63	herf	5.24	3.48	1.82
amihud	-10.92	-4.78	6.29	oscore	6.50	3.43	4.63
avol3d	2.78	4.70	1.13	exp_div	-1.64	-3.41	1.17
max_ret_daily	-11.15	-4.55	3.44	re_6	-3.20	-3.16	1.40
failure	-8.76	-4.55	3.15	eps_price	-4.36	-3.16	2.24
herf	5.62	4.52	1.66	egr	-2.78	-2.94	2.49
gscore	3.83	4.49	1.46	roaq	5.84	2.88	3.46
age	-6.52	-4.46	1.65	size	-11.65	-2.85	3.63
imom_2_6_vw	6.28	4.44	1.08	noa_lev	-5.62	-2.84	5.92
cf_var_mo	-5.73	-4.30	1.84	aci	4.57	2.75	3.84
dy_mo	-4.89	-4.14	5.63	an_value	-6.18	-2.66	6.57
ebp	-7.28	-4.12	2.45	std_dolvol	-5.46	-2.62	2.47
rev_13_18	-4.22	-3.94	1.24	ear3d	1.77	2.52	1.12
change_recom	8.35	3.94	1.12	ltg	2.88	2.46	1.57
lbp	-4.75	-3.92	2.00	gr_lt_noa	4.89	2.43	5.32
org_cap	4.97	3.83	2.52	iret_scm_vw	3.87	2.41	1.11
mom_2_6	5.92	3.76	2.25	avol3d	2.53	2.39	1.16
sesm_retew	6.18	3.71	1.08	tax2	-4.57	-2.30	1.08
rsup1	4.44	3.70	1.34	roic	-5.58	-2.28	5.01
eps_price	5.06	3.68	2.55	mom_2_6	5.24	2.25	2.64
dXFIN2	-4.15	-3.57	3.07	lbp	-4.17	-2.24	4.19
iret_scm_vw	4.49	3.41	1.06	nc_oac	-2.78	-2.07	3.75
dyds	4.02	3.34	5.59	pchquick	3.07	2.00	3.43
cdind	-2.60	-3.18	1.12	retComp	2.80	1.99	1.37
oscore	4.75	3.14	3.80	bm_mo	3.51	1.97	5.01
tax2	-4.95	-3.12	1.10	cdind	-1.57	-1.94	1.15

Table A1 continued

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
nanalyst	-4.26	-3.00	3.07	ns	-1.93	-1.94	1.48
d_seo_3yr	-2.21	-2.98	1.18	cf_mcap_mo	4.17	1.92	5.35
margin	3.82	2.89	2.44	pfdelay	-5.13	-1.80	1.20
chgn_pm	2.34	2.86	1.76	pchdepr	2.06	1.80	1.84
nit_mcap_mo	-5.37	-2.85	5.80	pchcapx_ia	-4.82	-1.79	4.27
pchcurrat	-2.87	-2.81	2.50	irev_1m_vw	2.68	1.78	1.47
shum	-5.83	-2.81	5.68	imom_7_12_vw	2.80	1.77	1.17
rdmcap_mo	3.20	2.79	1.33	zscore	2.76	1.74	3.57
corwin0	-3.31	-2.74	1.88	b1f_res_1m	-3.47	-1.73	4.21
ns_ti	2.98	2.71	1.42	rd_inc	6.20	1.70	1.11
ag	-3.57	-2.68	3.76	stdevrec	-1.35	-1.69	1.12
tang	3.45	2.64	2.41	rna	3.34	1.66	4.95
dpfs	2.24	2.45	1.14	avg_turn_12m	3.15	1.65	3.05
re_6	2.07	2.45	1.30	chpmia	1.83	1.65	1.08
chng_dy_mo	-2.86	-2.43	3.19	failure	-3.61	-1.60	4.36
P52_wh	-6.91	-2.42	3.53	chnanalyst	0.81	1.59	1.03
chng_dyds	2.57	2.41	3.24	em	2.14	1.57	1.96
exp_div	-0.96	-2.40	1.30	chng_dy_mo	-1.61	-1.54	3.21
pchquick	2.79	2.35	2.32	vol_trend	-2.10	-1.53	1.98
roic	-4.39	-2.34	4.70	margin_sal_chng	1.79	1.53	2.09
imom_7_12_vw	3.23	2.31	1.07	imom_2_6_vw	2.38	1.52	1.18
ccdo2_mo	-1.50	-2.23	1.08	realestate	2.54	1.52	1.08
quick	-3.40	-2.22	2.41	depr	1.97	1.51	2.32
dprc_mo	-2.87	-2.11	3.67	nwc_chng	-2.26	-1.49	2.18
retComp	3.16	2.10	1.36	org_cap	2.12	1.49	1.75
b1f_res_1m	-3.99	-2.03	4.37	ccdo2_mo	1.45	1.47	1.06
em	2.02	2.00	1.57	pchcurrat	-1.99	-1.43	3.69
pchsale_pchrect	1.58	2.00	1.27	acc_dp	2.72	1.42	3.67
meanrec	-1.73	-1.98	1.20	nincr	8.09	1.40	2.21
acc_pi	-2.50	-1.98	2.13	cegth3	-2.48	-1.37	4.90
ia	-2.40	-1.91	3.00	chgn_at	1.49	1.35	1.97
currat	3.02	1.89	3.31	com_eq	1.78	1.30	1.83
poa	-1.77	-1.88	1.89	b1f_mktrf_60m	-1.94	-1.29	1.49
nop_mo	1.66	1.88	2.61	ccdi2_mo	-2.08	-1.29	1.21
cashdebt	2.13	1.72	2.26	salerec	1.58	1.28	1.56
noa_lev	-2.71	-1.69	4.91	shum	-2.98	-1.28	4.75
rd_inc	4.00	1.61	1.18	dXFIN2	-1.90	-1.27	3.33
chpmia	1.36	1.59	1.15	ccdr2_mo	-1.47	-1.27	1.04
ccdo_an	-1.99	-1.57	1.03	dolvol	3.49	1.26	2.84
tax1	1.16	1.51	1.14	pchsaleinv	1.95	1.22	3.22
realestate	1.58	1.50	1.07	d_seo_3yr	-0.87	-1.22	1.15
chatoia	1.56	1.49	1.48	rev_13_18	-1.42	-1.21	1.33
roaq	2.40	1.49	3.31	ipo_rd	1.18	1.20	1.32
op_ff	2.11	1.39	3.20	cashdebt	1.83	1.20	2.56
acc_slo	1.59	1.31	2.67	eps_disp	1.38	1.20	1.89
ccdi_an	-0.95	-1.30	1.06	e_cons	1.22	1.18	1.17
gp	1.84	1.30	3.63	suemv	1.30	1.16	1.71
iltr_5y_vw	-1.98	-1.29	1.28	iltr_5y_vw	-2.20	-1.16	1.38
roavol	1.42	1.23	1.49	nincr_up	-6.38	-1.15	3.35
ccdi2_mo	-1.25	-1.20	1.13	chempia	1.95	1.14	1.80
sal_sga_chng	0.91	1.17	1.51	poa	-1.09	-1.12	2.11
com_eq	-1.17	-1.17	1.56	margin	2.07	1.08	3.59
dXFIN1	1.65	1.16	3.36	ebp	-2.32	-1.07	4.23
nincr	5.33	1.11	1.93	rdmcap_mo	1.29	1.04	1.41
pfdelay	-2.76	-1.08	1.28	zero	-3.12	-1.02	1.54

Table A1 continued

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
stdevrec	-0.55	-1.06	1.13	pm	-1.70	-1.02	4.36
salecash	-2.25	-1.05	5.94	ia	1.48	1.01	3.26
pta	1.01	1.03	1.69	gscore	0.98	0.97	1.46
cfp_ia_mo	1.78	0.98	2.59	meanrec	0.97	0.95	1.36
coskew	0.78	0.97	1.03	roavol	1.29	0.94	1.72
re_1	1.54	0.90	1.83	tang	1.44	0.94	2.94
ns	-0.90	-0.90	1.36	sin	1.95	0.91	1.08
chempia	-0.99	-0.89	2.12	acc_slo	1.48	0.90	2.96
ltg	0.80	0.83	1.27	sesm_retew	2.16	0.90	1.14
hire	0.99	0.82	2.61	quick	1.61	0.88	3.87
fscore	-0.83	-0.81	2.27	P52_wh	-2.47	-0.86	3.71
dur	-1.10	-0.78	2.97	chgn_pm	0.93	0.86	1.72
op_lev	-1.20	-0.73	2.91	lgr	-0.91	-0.84	2.24
nincr_up	-3.26	-0.70	2.93	re_1	-0.86	-0.83	1.97
accq	-0.56	-0.69	1.32	rsup2	-2.38	-0.77	1.53
b1f_mktrf_60m	-0.68	-0.67	1.40	admcap_mo	1.09	0.76	2.44
nwc_chng	-0.65	-0.60	2.32	cf_var_mo	-1.01	-0.76	2.05
cf_mcap_mo	1.19	0.58	4.56	nop_mo	0.91	0.76	2.33
pchsaleinv	-0.74	-0.58	2.61	acc_pi	-0.91	-0.74	2.74
depr	0.73	0.57	1.81	diss	0.41	0.74	2.30
b1f_mktrf_1m	0.78	0.56	1.23	cashpr_mo	0.92	0.73	3.22
rna	0.81	0.53	3.99	b1f_mktrf_1m	1.10	0.71	1.56
margin_sal_chng	-0.53	-0.53	1.84	ivc	1.00	0.69	3.41
aci	0.59	0.52	2.79	sue	-2.64	-0.65	2.62
e_cons	0.43	0.51	1.09	a_turn	-1.21	-0.63	6.21
pm	-0.64	-0.48	3.63	currat	-1.15	-0.60	5.11
a_turn	-0.71	-0.47	4.56	irev_13_18_vw	-0.92	-0.59	1.27
egr	0.43	0.47	2.68	sg	-0.91	-0.56	4.66
pchcapx_ia	-0.99	-0.46	6.46	down_f	-0.33	-0.55	1.72
rsup2	-0.86	-0.45	1.34	ns_ti	-0.69	-0.52	1.59
zscore	-0.76	-0.45	2.52	cfp_ia_mo	0.89	0.52	2.01
cashpr_mo	0.58	0.44	2.74	ccdo_an	-0.94	-0.46	1.03
ivc	-0.82	-0.41	3.09	dur	0.75	0.45	4.23
sprc_mo	-0.94	-0.41	6.90	dprc_mo	0.76	0.44	5.31
sg	0.56	0.39	3.48	chatoia	0.51	0.43	1.34
sin	0.77	0.37	1.05	rsup1	-0.49	-0.43	1.43
cegth3	-0.43	-0.34	3.08	b1f_res_60m	0.67	0.39	2.69
b1f_res_60m	0.49	0.32	2.88	max_ret_daily	0.72	0.36	3.33
ccdr_an	-0.29	-0.32	1.09	ag	0.54	0.35	4.41
sue	-0.56	-0.32	2.18	pta	-0.31	-0.28	1.72
cash	0.70	0.32	5.46	dpfs	0.32	0.27	1.31
ltr_5y	-0.38	-0.32	1.92	ccdr_an	-0.44	-0.27	1.07
pchdepr	0.27	0.32	1.60	op_ff	-0.45	-0.26	3.08
ivg	0.61	0.30	4.54	coskew	-0.16	-0.20	1.05
cto	0.45	0.26	6.33	dyds	0.29	0.19	6.88
min_ret_daily	0.34	0.24	3.24	corwin0	-0.29	-0.18	1.83
salerec	-0.25	-0.22	1.70	pchsale_pchrect	0.15	0.17	1.29
down_f	-0.18	-0.19	1.68	nit_mcap_mo	-0.24	-0.12	6.55
eps_disp	0.17	0.17	1.43	ig	-0.32	-0.12	5.48
diss	0.09	0.17	2.09	op_lev	-0.20	-0.10	4.35
chgn_at	-0.17	-0.15	2.03	gp	-0.20	-0.09	4.88
nc_oac	-0.17	-0.14	2.92	ccdi_an	-0.07	-0.08	1.04
zero	0.34	0.13	1.98	ltr_5y	0.10	0.06	2.08
gr_lt_noa	-0.16	-0.10	3.97	sal_sga_chng	-0.06	-0.06	1.36
vol_trend	0.10	0.09	1.80	nanalyst	0.09	0.06	1.61

Table A1 continued

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
ccdr2_mo	-0.08	-0.08	1.02	accq	0.05	0.06	1.42
acc_dp	-0.08	-0.07	2.92	dXFIN1	-0.07	-0.05	4.72
irev_13_18_vw	0.08	0.06	1.16	tax1	-0.04	-0.05	1.22
lgr	-0.04	-0.05	1.70	ivg	0.05	0.02	5.79
admcap_mo	-0.06	-0.05	2.33	hire	0.02	0.02	2.66
ipo_rd	-0.05	-0.05	1.39	fscore	0.01	0.01	2.29
share_vol	-39.88	-10.68	7.13	efp	24.61	9.47	7.01
efp	27.89	10.12	10.18	market_lev_mo	4.16	1.47	12.28
an_value	-16.62	-7.17	9.94	dy_mo	-2.05	-1.24	7.20
market_lev_mo	12.15	5.43	7.06	cash	1.17	0.47	10.02
dolvol	-4.66	-1.96	10.13	sprc_mo	0.73	0.23	8.54
ig	-0.43	-0.19	7.22	salecash	-0.47	-0.22	8.12
size	-0.06	-0.02	10.38	cto	0.09	0.04	8.33

Table A2: In-sample return regressions: Full results for Europe

This table provides the results of Fama and MacBeth (1973) regressions of stock returns on the full set of 161 trade signals for Europe. We study five international stock markets (North America, Europe, Japan, Pacific, and Emerging Markets). The dependent variable is the monthly stock return minus the average stock return across all stocks in the particular region, all measured in US-Dollars. Standard OLS regression results are reported in the left part of the table, and value-weighted least squares (VWLS) results are reported in the right part of the table. Variance inflation factors (VIF) are reported to assess the degree of multicollinearity. For each characteristic, the VIF is calculated as 1/(1-$R2$) with the $R2$ being obtained from regressing each characteristic on all the other characteristics in a pooled regression. t-statistics are adjusted using the procedure of West and Newey (1987) with a lag of four months. For the regressions, we scale all trade signals such that the resulting coefficients can be interpreted as annualized decile 10 minus decile 1 long/short returns that are orthogonal to all other trade signals. Whereas we report only the 15 most significant variables in the paper, we show full results here. The sample period ranges from 1/1989 to 12/2015.

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
ret_scm	7.67	11.98	1.14	mom_7_12	9.97	7.25	1.65
ear3d	7.86	11.93	1.09	efp	11.47	6.86	2.97
vol_mcap	22.60	11.10	4.78	ret_scm	6.26	6.69	1.15
std_dolvol	-16.79	-10.82	5.59	rev_1m	-11.35	-6.26	3.52
b1f_res_1m	-9.86	-10.03	2.15	eqea	5.04	6.06	1.03
efp	11.79	9.17	2.35	ear3d	4.25	4.94	1.08
share_vol	-12.05	-8.88	4.59	eer	3.92	4.51	1.32
mom_2_6	11.09	8.79	2.22	bm_mo	7.92	3.94	3.76
mom_7_12	8.87	8.20	1.63	b1f_res_1m	-5.49	-3.65	2.56
eqea	5.98	7.77	1.03	irev_1m_vw	4.42	3.57	1.44
bm_mo	11.61	7.22	3.74	std_dolvol	-7.65	-3.53	3.14
eer	5.99	6.87	1.23	cdind	-3.29	-3.33	1.12
irev_1m_vw	4.86	6.01	1.21	mom_2_6	5.77	3.18	2.34
rev_1m	-9.52	-5.87	2.54	amihud	-7.00	-3.17	4.49
imom_2_6_vw	4.31	5.84	1.05	nop_mo	3.93	3.16	2.56
avg_turn_12m	6.68	5.32	3.97	chng_dyds	3.26	2.87	2.86
ns_ti	4.61	5.27	1.67	ltg	2.83	2.80	1.32
cf_var_mo	-3.80	-4.61	1.63	min_ret_daily	3.58	2.79	2.18
roaq	6.13	4.53	2.45	dyds	4.11	2.76	2.39
suemv	4.06	4.47	1.36	iret_scm_vw	2.82	2.66	1.08
sesm_retew	5.58	4.25	1.19	meanrec	-3.10	-2.66	1.34
ltg	2.79	4.12	1.14	dy_mo	-4.11	-2.63	3.62
corwin0	-3.22	-4.08	1.24	tax1	2.44	2.60	1.27
min_ret_daily	-3.77	-4.05	2.25	avol3d	2.34	2.46	1.10
an_value	-4.36	-3.74	2.05	ns_ti	3.25	2.28	2.16
noa_lev	-4.76	-3.62	4.73	com_eq	-2.33	-2.26	1.47
re_6	2.21	3.48	1.24	max_ret_daily	3.38	2.25	2.34
change_recom	6.29	3.42	1.09	change_recom	3.22	2.24	1.08
dprc_mo	-3.87	-3.28	3.66	depr	2.73	2.24	1.79
imom_7_12_vw	3.07	3.27	1.05	chatoia	2.24	2.22	1.35
avol3d	2.96	3.17	1.06	op_lev	-2.93	-2.20	2.00
tax1	1.67	3.15	1.20	gscore	-2.02	-2.19	1.44
rev_13_18	-2.56	-3.02	1.22	pm	3.61	2.17	3.51
cdind	-2.79	-2.98	1.07	avg_turn_12m	3.06	2.05	4.47
market_lev_mo	4.65	2.97	5.03	share_vol	-3.28	-2.05	3.46
nop_mo	3.11	2.95	2.75	imom_7_12_vw	2.37	1.99	1.15
currat	3.45	2.91	4.02	cf_mcap_mo	-3.49	-1.96	4.45
ccdi_an	-1.73	-2.89	1.04	chgn_at	2.50	1.96	1.93
b1f_mktrf_1m	-2.88	-2.86	1.18	pfdelay	-4.65	-1.89	1.30
b1f_res_60m	2.90	2.80	2.05	age	-2.40	-1.87	1.61

Table A2 continued

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
dy_mo	-2.66	-2.75	4.20	margin	2.87	1.86	4.12
nwc_chng	2.56	2.69	2.25	herf	-1.52	-1.85	1.26
poa	-5.09	-2.67	1.64	an_value	-3.04	-1.81	2.49
depr	2.63	2.66	1.59	acc_dp	2.41	1.80	3.51
diss	-1.55	-2.62	2.20	iltr_5y_vw	2.27	1.79	1.31
shum	-3.88	-2.61	5.60	diss	-1.18	-1.78	2.41
rdmcap_mo	3.33	2.56	1.13	roic	2.68	1.74	3.68
meanrec	-2.06	-2.55	1.19	dXFIN1	-2.28	-1.71	3.71
retComp	2.78	2.51	1.20	sal_sga_chng	2.14	1.69	1.17
ivc	-2.83	-2.51	3.66	zero	2.95	1.67	1.74
acc_slo	-2.34	-2.50	2.74	vol_mcap	3.11	1.62	5.38
aci	2.45	2.47	3.08	tax2	-7.30	-1.60	1.06
quick	-2.81	-2.46	3.41	aci	2.23	1.55	3.84
sal_sga_chng	1.71	2.40	1.20	retComp	2.52	1.53	1.37
dyds	2.15	2.39	2.85	rev_13_18	-1.74	-1.52	1.28
amihud	-3.02	-2.38	3.32	lgr	1.98	1.52	2.49
salerec	2.22	2.33	1.59	dXFIN2	-4.11	-1.50	2.28
pm	2.48	2.29	3.48	rna	-2.63	-1.49	4.33
tang	1.90	2.27	1.95	ipo_rd	-1.80	-1.43	1.43
cto	-3.37	-2.26	4.43	margin_sal_chng	1.53	1.33	1.70
rsup1	1.99	2.25	1.19	ns	-1.25	-1.32	1.36
eps_price	2.18	2.24	2.15	b1f_mktrf_60m	-1.99	-1.32	1.51
b1f_mktrf_60m	-2.10	-2.19	1.44	sg	-2.29	-1.29	3.79
cashdebt	1.93	2.13	2.66	op_ff	1.56	1.29	2.28
ipo_rd	-2.18	-2.11	1.52	pchsaleinv	2.15	1.28	3.65
dur	-2.28	-2.00	2.96	em	-1.56	-1.24	1.85
herf	1.56	1.99	1.22	down_f	-1.24	-1.23	1.60
nincr	5.96	1.93	1.68	poa	-3.96	-1.21	1.78
ns	1.33	1.91	1.32	ccdi_an	-1.00	-1.19	1.02
rsup2	1.61	1.89	1.16	ccdr2_mo	-1.91	-1.12	1.03
ltr_5y	-1.67	-1.87	1.64	imom_2_6_vw	1.20	1.10	1.16
re_1	1.97	1.85	1.70	failure	1.72	1.10	2.43
stdevrec	1.02	1.83	1.27	nincr_up	-7.01	-1.09	2.61
ccdo2_mo	-1.27	-1.82	1.07	admcap_mo	1.44	1.08	1.63
oscore	2.56	1.81	3.68	nincr	5.86	1.07	1.87
lgr	1.70	1.78	2.05	roaq	1.59	1.05	2.46
chng_dy_mo	-1.46	-1.74	2.49	dpfs	3.79	1.03	1.37
realestate	1.39	1.67	1.05	sesm_retew	1.59	1.01	1.18
iltr_5y_vw	1.76	1.64	1.17	cashdebt	1.60	0.99	3.12
ccdo_an	-1.55	-1.61	1.13	nit_mcap_mo	1.80	0.99	5.28
op_ff	1.44	1.61	2.36	ia	-1.20	-0.99	3.02
down_f	-1.44	-1.61	1.86	pchcapx_ia	-2.41	-0.99	4.47
acc_pi	-1.16	-1.59	1.72	a_turn	1.82	0.98	6.13
ccdr2_mo	-1.68	-1.56	1.03	vol_trend	1.14	0.97	1.53
chng_dyds	1.53	1.55	2.54	irev_13_18_vw	-1.30	-0.95	1.25
cash	2.04	1.53	5.19	nwc_chng	-1.48	-0.95	1.94
a_turn	1.97	1.53	4.62	rsup2	1.35	0.94	1.23
nanalyst	-1.84	-1.52	2.79	chnanalyst	-0.63	-0.93	1.05
cf_mcap_mo	-2.00	-1.51	4.12	egr	0.92	0.92	2.07
gp	2.06	1.51	4.00	fscore	-1.11	-0.92	2.12
pchsale_pchrect	-1.09	-1.48	1.39	ccdr_an	1.13	0.89	1.06
margin_sal_chng	1.11	1.48	1.54	rsup1	1.11	0.89	1.20
cfp_ia_mo	1.76	1.42	2.67	cfp_ia_mo	-1.68	-0.86	1.98
irev_13_18_vw	1.17	1.38	1.14	re_1	1.14	0.84	1.83
nit_mcap_mo	1.81	1.35	5.28	accq	0.77	0.83	1.35
egr	1.13	1.32	2.38	dprc_mo	-1.42	-0.81	4.59

Table A2 continued

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
cegth3	-1.31	-1.31	3.10	salerec	-0.94	-0.81	1.68
nincr_up	-4.55	-1.29	2.39	noa_lev	-1.64	-0.81	6.86
d_seo_3yr	-1.37	-1.25	1.28	zscore	-1.29	-0.81	3.27
pchcapx_ia	-2.18	-1.25	6.46	stdevrec	0.73	0.80	1.35
chgn_at	0.96	1.25	1.97	ccdo_an	-1.20	-0.79	1.18
zscore	-1.42	-1.22	2.48	ccdo2_mo	0.86	0.78	1.04
nc_oac	-1.12	-1.21	2.65	size	2.02	0.77	2.98
max_ret_daily	1.47	1.21	2.36	chgn_pm	-0.73	-0.76	1.51
age	-1.44	-1.20	1.72	org_cap	0.66	0.73	1.33
coskew	0.71	1.19	1.01	quick	-1.17	-0.72	5.25
roic	-1.08	-1.14	3.50	d_seo_3yr	0.55	0.69	1.25
fscore	-0.84	-1.09	2.08	cf_var_mo	-0.73	-0.69	1.63
dXFIN2	-2.33	-1.08	2.17	ccdi2_mo	1.02	0.68	1.24
com_eq	-0.79	-1.08	1.42	chng_dy_mo	0.76	0.67	2.87
chatoia	0.75	1.07	1.45	tang	0.73	0.67	2.25
chpmia	-0.80	-1.07	1.13	chempia	0.63	0.63	1.60
ccdi2_mo	0.97	1.07	1.19	dolvol	-1.47	-0.60	4.59
admcap_mo	1.18	1.01	1.55	ivg	1.12	0.59	5.98
gr_lt_noa	1.20	1.01	3.70	P52_wh	-1.68	-0.59	3.15
tax2	-2.01	-1.00	1.03	ivc	-1.00	-0.58	3.93
em	0.78	0.94	1.43	eps_disp	-0.75	-0.57	1.54
salecash	1.34	0.94	5.33	sue	-0.94	-0.55	2.05
acc_dp	-0.96	-0.93	2.98	cashpr_mo	-0.62	-0.54	2.47
exp_div	-0.72	-0.93	1.05	ltr_5y	-0.62	-0.46	1.75
rd_inc	4.26	0.91	1.08	pta	-1.16	-0.46	1.60
cashpr_mo	-0.82	-0.91	1.87	rd_inc	-2.64	-0.45	1.03
sue	-1.38	-0.89	1.75	exp_div	0.46	0.44	1.02
op_lev	-1.03	-0.87	1.88	chpmia	0.37	0.43	1.07
pta	1.84	0.85	1.69	coskew	-0.38	-0.43	1.04
ivg	1.19	0.84	5.08	gr_lt_noa	-0.77	-0.41	6.16
zero	1.19	0.83	2.43	cto	0.77	0.40	5.89
dXFIN1	-0.92	-0.83	2.93	oscore	0.78	0.40	3.49
iret_scm_vw	0.63	0.81	1.03	roavol	-0.63	-0.40	1.34
P52_wh	-2.03	-0.77	3.14	realestate	0.77	0.38	1.11
vol_trend	-0.66	-0.77	1.39	salecash	0.74	0.38	6.54
eps_disp	-0.66	-0.70	1.25	corwin0	-0.40	-0.37	1.24
accq	-0.52	-0.69	1.23	hire	-0.38	-0.36	2.16
chnanalyst	0.39	0.65	1.15	currat	0.64	0.35	5.84
chgn_pm	0.49	0.63	1.62	dur	-0.52	-0.34	3.43
chempia	-0.43	-0.55	1.72	b1f_res_60m	0.45	0.34	1.93
rna	-0.59	-0.51	4.19	shum	0.63	0.32	3.39
dpfs	1.75	0.48	1.21	sprc_mo	-0.65	-0.29	6.22
roavol	0.68	0.43	1.21	nanalyst	-0.37	-0.27	1.70
margin	-0.45	-0.42	2.94	ig	-0.65	-0.26	5.31
e_cons	0.29	0.41	1.07	gp	-0.44	-0.24	4.68
lbp	0.36	0.39	1.95	lbp	-0.34	-0.23	3.11
sprc_mo	-0.75	-0.39	6.23	rdmcap_mo	0.34	0.22	1.32
ccdr_an	0.31	0.39	1.08	pchdepr	-0.21	-0.22	1.56
failure	-0.42	-0.37	2.18	cegth3	-0.30	-0.22	4.25
sin	-0.36	-0.35	1.08	pchsale_pchrect	0.22	0.20	1.38
pchdepr	-0.26	-0.31	1.44	nc_oac	0.25	0.19	3.45
org_cap	0.25	0.23	1.41	eps_price	-0.21	-0.17	1.85
pchcurrat	-0.26	-0.22	3.59	suemv	-0.32	-0.14	1.46
size	-0.33	-0.18	6.75	pchquick	-0.24	-0.14	6.06
pfdelay	0.34	0.15	1.16	sin	0.16	0.12	1.12

Table A2 continued

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
ag	0.14	0.11	3.40	ebp	0.17	0.11	3.67
gscore	0.07	0.10	1.45	re_6	0.08	0.08	1.37
sg	-0.10	-0.09	3.25	ag	0.11	0.07	3.60
ebp	0.09	0.08	2.51	acc_slo	0.10	0.07	2.65
ia	-0.07	-0.07	3.01	acc_pi	-0.07	-0.06	2.44
pchquick	-0.08	-0.06	3.46	b1f_mktrf_1m	0.09	0.06	1.61
pchsaleinv	0.07	0.06	2.97	pchcurrat	-0.08	-0.04	6.08
dolvol	-0.08	-0.05	4.07	e_cons	0.03	0.04	1.14
hire	-0.01	-0.01	2.23	market_lev_mo	2.21	0.98	7.83
ig	-0.39	-0.21	7.08	cash	-0.35	-0.18	7.08

Table A3: In-sample return regressions: Full results for Japan

This table provides the results of Fama and MacBeth (1973) regressions of stock returns on the full set of 161 trade signals for Japan. We study five international stock markets (North America, Europe, Japan, Pacific, and Emerging Markets). The dependent variable is the monthly stock return minus the average stock return across all stocks in the particular region, all measured in US-Dollars. Standard OLS regression results are reported in the left part of the table, and value-weighted least squares (VWLS) results are reported in the right part of the table. Variance inflation factors (VIF) are reported to assess the degree of multicollinearity. For each characteristic, the VIF is calculated as 1/(1-$R2$) with the $R2$ being obtained from regressing each characteristic on all the other characteristics in a pooled regression. t-statistics are adjusted using the procedure of West and Newey (1987) with a lag of four months. For the regressions, we scale all trade signals such that the resulting coefficients can be interpreted as annualized decile 10 minus decile 1 long/short returns that are orthogonal to all other trade signals. Whereas we report only the 15 most significant variables in the paper, we show full results here. The sample period ranges from 1/1989 to 12/2015.

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
ret_scm	6.80	10.63	1.16	ret_scm	7.57	7.04	1.26
vol_mcap	26.99	9.47	5.08	vol_mcap	17.54	5.43	6.73
ear3d	5.17	6.86	1.07	rev_1m	-12.00	-5.09	4.85
rev_1m	-16.88	-6.58	3.33	bm_mo	11.20	4.80	4.29
roaq	11.30	6.35	3.05	ltg	4.61	4.52	1.25
bm_mo	11.39	6.23	4.43	ear3d	4.12	3.95	1.10
b1f_res_1m	-7.02	-5.96	3.37	std_dolvol	-10.68	-3.90	5.47
rdmcap_mo	5.57	5.60	1.24	eer	4.12	3.83	1.38
eer	5.72	5.59	1.21	share_vol	-9.50	-3.74	5.19
rev_13_18	-4.69	-5.48	1.22	chng_dyds	6.19	3.47	3.74
exp_div	6.18	5.48	1.02	rev_13_18	-3.51	-3.06	1.41
avol3d	3.75	5.47	1.08	aci	-6.99	-2.94	4.68
suemv	7.10	5.45	1.47	ltr_5y	-4.64	-2.79	1.86
ltg	5.19	5.25	1.13	rdmcap_mo	3.66	2.61	1.64
share_vol	-11.41	-4.88	4.37	salerec	3.40	2.50	2.13
std_dolvol	-9.03	-4.40	5.38	exp_div	4.13	2.47	1.03
nanalyst	5.22	4.24	3.16	chpmia	-2.29	-2.38	1.08
lbp	-4.36	-4.17	2.29	vol_trend	3.78	2.33	1.71
rsup1	7.10	4.16	1.22	eqea	3.92	2.32	1.10
change_recom	8.65	4.16	1.34	ccdi_an	-2.55	-2.32	1.01
eqea	3.80	4.11	1.07	suemv	4.19	2.30	1.56
admcap_mo	5.31	4.03	3.17	cf_var_mo	-3.07	-2.23	2.15
ebp	-5.10	-3.78	3.20	P52_wh	-6.11	-2.17	3.27
irev_1m_vw	4.29	3.67	1.22	lbp	-2.85	-2.13	3.85
sesm_retew	5.55	3.60	1.13	chng_dy_mo	3.84	2.09	3.84
max_ret_daily	-3.84	-3.44	2.84	acc_dp	-3.57	-2.05	3.61
eps_price	-3.81	-3.18	2.65	ivc	-4.10	-2.01	5.59
ns	3.05	3.08	1.31	avol3d	2.29	1.99	1.11
ltr_5y	-3.87	-3.07	1.62	roaq	5.04	1.97	2.69
retComp	3.03	3.01	1.20	ccdo_an	5.19	1.96	1.13
imom_2_6_vw	2.86	2.72	1.05	e_cons	2.21	1.95	1.21
op_ff	3.15	2.71	2.89	nwc_chng	3.54	1.93	2.51
salerec	2.79	2.68	1.88	sin	4.45	1.89	1.08
cf_var_mo	-3.16	-2.63	1.95	com_eq	-1.99	-1.87	1.23
e_cons	1.90	2.60	1.13	nanalyst	1.97	1.84	2.58
nc_oac	-2.37	-2.60	3.02	depr	2.56	1.83	2.21
ivc	-3.25	-2.59	5.56	chgn_pm	-1.95	-1.77	1.76
P52_wh	-7.59	-2.55	2.98	pfdelay	-5.55	-1.75	1.29
chpmia	-1.84	-2.54	1.07	chempia	2.58	1.75	2.32
chng_dyds	3.35	2.43	3.31	meanrec	-1.85	-1.73	1.29

Table A3 continued

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
down_f	-2.11	-2.42	2.16	retComp	2.56	1.72	1.30
ccdi2_mo	-3.83	-2.38	1.24	rsup2	6.67	1.71	1.22
ns_ti	2.33	2.30	2.17	ccdr2_mo	-3.71	-1.67	1.08
chnanalyst	1.31	2.22	1.26	b1f_res_1m	-3.57	-1.62	3.55
herf	1.75	2.20	1.18	nc_oac	2.18	1.61	3.17
meanrec	-1.94	-2.12	1.18	corwin0	-2.04	-1.46	1.20
ia	1.84	2.03	3.47	gscore	1.47	1.41	1.52
corwin0	-2.24	-1.96	1.31	ag	2.09	1.39	3.61
iltr_5y_vw	-2.10	-1.91	1.14	hire	-2.10	-1.37	2.67
chng_dy_mo	2.15	1.83	3.29	max_ret_daily	-2.16	-1.36	2.90
acc_slo	-2.00	-1.78	3.56	sg	-2.46	-1.35	4.64
org_cap	2.10	1.73	1.69	change_recom	3.28	1.34	1.56
nit_mcap_mo	2.53	1.72	6.29	re_6	1.57	1.32	1.41
ccdr2_mo	-2.74	-1.69	1.07	acc_slo	-2.60	-1.32	3.37
pchsale_pchrect	-1.10	-1.69	1.40	imom_2_6_vw	1.94	1.29	1.26
ccdo_an	2.31	1.68	1.17	ccdi2_mo	-3.19	-1.24	1.42
gp	-2.37	-1.68	5.93	cashpr_mo	-2.10	-1.23	4.47
dprc_mo	-2.21	-1.66	5.96	cfp_ia_mo	1.77	1.22	2.43
com_eq	-1.27	-1.65	1.24	ns	1.47	1.19	1.32
age	-3.98	-1.60	2.32	gp	-2.69	-1.16	6.54
hire	-1.74	-1.58	2.96	pchsaleinv	2.62	1.14	5.36
cdind	-1.00	-1.54	1.27	margin	2.71	1.12	6.08
zscore	2.47	1.52	5.06	ccdo2_mo	1.63	1.08	1.09
nincr	3.41	1.48	1.49	margin_sal_chng	-1.37	-1.08	2.10
d_seo_3yr	0.77	1.48	1.30	irev_1m_vw	1.65	1.07	1.45
ipo_rd	2.22	1.47	1.44	age	-2.87	-1.07	2.10
dyds	2.01	1.47	3.41	sesm_retew	1.89	1.06	1.18
imom_7_12_vw	1.40	1.46	1.05	ig	2.83	1.04	4.79
b1f_mktrf_1m	1.21	1.44	1.34	cegth3	2.40	1.04	4.65
re_1	-1.88	-1.41	1.57	dyds	2.07	1.03	3.50
oscore	2.04	1.39	5.00	pchsale_pchrect	-0.92	-1.03	1.33
zero	1.85	1.39	2.01	ebp	-1.79	-1.02	4.79
b1f_res_60m	-1.50	-1.38	2.22	lgr	-1.08	-1.02	2.46
ccdi_an	-0.92	-1.35	1.02	dprc_mo	-2.01	-1.00	6.25
accq	0.75	1.30	1.24	roavol	3.42	0.99	1.34
cashdebt	-1.51	-1.28	3.51	org_cap	1.51	0.97	1.78
irev_13_18_vw	1.36	1.26	1.09	d_seo_3yr	0.62	0.93	1.29
min_ret_daily	-1.10	-1.22	2.36	imom_7_12_vw	1.37	0.90	1.26
poa	-2.20	-1.22	1.87	rsup1	3.03	0.88	1.23
pfdelay	-3.29	-1.20	1.32	ccdr_an	1.69	0.84	1.09
margin	1.59	1.18	5.61	b1f_mktrf_60m	-1.52	-0.83	1.71
ccdr_an	1.33	1.06	1.09	irev_13_18_vw	-1.23	-0.83	1.30
re_6	1.19	1.05	1.21	min_ret_daily	1.06	0.82	2.35
cfp_ia_mo	1.04	1.04	2.17	ipo_rd	1.81	0.81	1.31
b1f_mktrf_60m	1.37	1.04	1.59	roic	2.01	0.79	6.21
aci	-1.74	-1.03	4.86	sue	-4.56	-0.78	1.76
ccdo2_mo	0.93	1.02	1.15	accq	0.65	0.78	1.25
dy_mo	-1.38	-1.00	4.47	down_f	-0.61	-0.76	1.70
roavol	1.89	0.97	1.30	eps_price	-1.31	-0.71	2.10
depr	1.03	0.88	1.95	avg_turn_12m	-1.69	-0.69	5.35
eps_disp	-0.90	-0.88	1.17	chnanalyst	0.47	0.66	1.14
failure	-2.10	-0.88	5.26	chgn_at	-0.96	-0.66	2.15
pchdepr	-0.65	-0.87	1.30	op_lev	1.89	0.61	6.96
tax1	0.48	0.84	1.32	ns_ti	-0.70	-0.58	2.30
avg_turn_12m	-1.55	-0.81	4.23	zscore	-1.28	-0.58	6.29
pchsaleinv	1.07	0.79	5.51	pchdepr	-0.52	-0.57	1.39

Table A3 continued

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
tang	-0.77	-0.78	2.58	nincr	2.57	0.57	1.56
em	-0.90	-0.78	1.53	pm	1.09	0.56	5.30
dXFIN1	-0.73	-0.71	3.58	tang	0.73	0.49	2.95
sue	1.82	0.69	1.63	rd_inc	3.53	0.48	1.02
coskew	0.41	0.67	1.01	diss	-0.29	-0.47	2.61
sin	1.09	0.66	1.03	nit_mcap_mo	0.98	0.47	5.51
mom_7_12	0.86	0.65	1.73	b1f_res_60m	-0.90	-0.47	2.09
egr	-0.66	-0.63	2.99	nop_mo	0.85	0.47	2.29
nwc_chng	0.52	0.59	2.92	dXFIN1	-0.79	-0.46	3.62
sg	0.80	0.57	4.66	oscore	0.84	0.43	4.07
stdevrec	0.45	0.57	1.13	op_ff	0.67	0.41	3.28
chatoia	-0.39	-0.56	1.37	gr_lt_noa	-1.05	-0.40	5.48
vol_trend	0.60	0.56	1.42	ia	-0.51	-0.38	3.48
noa_lev	-0.89	-0.55	6.16	pchcapx_ia	0.98	0.37	3.76
nop_mo	-0.78	-0.54	2.19	dXFIN2	0.74	0.37	2.34
acc_pi	-0.54	-0.53	2.12	dpfs	1.10	0.37	1.63
dpfs	1.25	0.50	1.33	nincr_up	-1.96	-0.34	2.18
chempia	0.55	0.50	2.60	tax2	-1.01	-0.33	1.10
chgn_pm	-0.36	-0.49	1.88	pta	-0.54	-0.33	1.43
sal_sga_chng	0.35	0.49	1.51	cf_mcap_mo	-0.62	-0.31	4.41
roic	-0.65	-0.46	5.40	tax1	0.29	0.31	1.38
nincr_up	-1.09	-0.45	2.05	iltr_5y_vw	-0.50	-0.29	1.31
diss	0.20	0.43	2.42	dy_mo	0.57	0.27	4.91
cashpr_mo	-0.64	-0.42	4.96	mom_2_6	0.62	0.27	2.76
cf_mcap_mo	-0.57	-0.41	4.13	coskew	-0.21	-0.25	1.06
rsup2	0.64	0.40	1.15	zero	-0.36	-0.25	1.34
mom_2_6	-0.55	-0.37	2.26	egr	-0.29	-0.24	2.51
acc_dp	0.40	0.36	3.90	iret_scm_vw	-0.32	-0.23	1.15
op_lev	0.75	0.31	6.86	eps_disp	0.25	0.22	1.43
dur	0.38	0.31	3.78	re_1	-0.31	-0.21	1.71
pta	0.41	0.29	1.58	shum	-0.57	-0.20	4.90
ag	0.31	0.28	3.78	rna	0.43	0.19	6.47
margin_sal_chng	-0.21	-0.25	2.09	admcap_mo	0.32	0.17	3.97
gr_lt_noa	-0.34	-0.23	5.33	dur	-0.28	-0.16	4.09
dXFIN2	-0.42	-0.22	2.41	herf	0.18	0.15	1.33
cegth3	0.37	0.21	4.16	poa	0.30	0.15	1.91
tax2	-0.33	-0.17	1.07	mom_7_12	0.22	0.14	1.94
pm	0.20	0.14	5.80	stdevrec	-0.09	-0.10	1.29
lgr	-0.13	-0.14	2.33	em	0.15	0.10	1.92
rna	-0.21	-0.14	6.76	sal_sga_chng	-0.11	-0.10	1.48
rd_inc	-0.69	-0.12	1.02	cashdebt	-0.16	-0.09	3.90
chgn_at	-0.08	-0.11	2.22	chatoia	0.06	0.06	1.32
fscore	-0.06	-0.07	2.07	noa_lev	0.12	0.05	6.93
iret_scm_vw	0.05	0.05	1.03	b1f_mktrf_1m	0.06	0.04	1.77
gscore	-0.01	-0.02	1.54	realestate	0.07	0.04	1.08
realestate	-0.02	-0.01	1.04	fscore	0.04	0.03	2.09
efp	20.88	3.68	17.30	cdind	0.02	0.03	1.40
market_lev_mo	6.53	3.02	10.25	acc_pi	0.04	0.02	2.89
dolvol	-8.08	-3.01	9.25	size	-0.01	0.00	4.37
an_value	-13.98	-2.67	17.38	ivg	5.64	2.16	8.58
cto	-6.15	-2.55	10.78	efp	9.86	1.87	14.40
shum	-5.71	-2.35	8.05	cash	5.42	1.83	9.61
amihud	4.80	2.31	7.29	pchcurrat	3.99	1.73	9.55
ivg	2.27	1.52	8.87	failure	4.52	1.60	7.29
sprc_mo	3.00	1.45	8.68	pchquick	-3.22	-1.50	9.82

Table A3 continued

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
size	-3.67	-1.36	8.45	a_turn	-3.59	-1.41	8.12
cash	2.33	1.17	10.09	amihud	-4.45	-1.37	9.03
salecash	2.00	1.04	9.54	sprc_mo	3.57	1.36	8.14
pchquick	-1.11	-0.72	7.63	salecash	2.62	1.05	8.32
currat	1.74	0.70	11.75	dolvol	-2.87	-0.90	8.06
a_turn	-1.30	-0.66	7.35	cto	-2.84	-0.88	12.19
pchcurrat	0.99	0.65	7.58	an_value	-3.02	-0.61	14.58
pchcapx_ia	-0.95	-0.50	7.30	quick	1.52	0.57	13.61
ig	0.90	0.46	8.10	currat	-1.46	-0.53	13.42
quick	0.20	0.09	11.07	market_lev_mo	-0.43	-0.14	12.87

Table A4: In-sample return regressions: Full results for Pacific

This table provides the results of Fama and MacBeth (1973) regressions of stock returns on the full set of 161 trade signals for Pacific. We study five international stock markets (North America, Europe, Japan, Pacific, and Emerging Markets). The dependent variable is the monthly stock return minus the average stock return across all stocks in the particular region, all measured in US-Dollars. Standard OLS regression results are reported in the left part of the table, and value-weighted least squares (VWLS) results are reported in the right part of the table. Variance inflation factors (VIF) are reported to assess the degree of multicollinearity. For each characteristic, the VIF is calculated as 1/(1-$R2$) with the $R2$ being obtained from regressing each characteristic on all the other characteristics in a pooled regression. t-statistics are adjusted using the procedure of West and Newey (1987) with a lag of four months. For the regressions, we scale all trade signals such that the resulting coefficients can be interpreted as annualized decile 10 minus decile 1 long/short returns that are orthogonal to all other trade signals. Whereas we report only the 15 most significant variables in the paper, we show full results here. The sample period ranges from 1/1989 to 12/2015.

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
vol_mcap	38.16	12.77	3.55	ret_scm	8.56	5.29	1.15
share_vol	-28.36	-9.07	5.61	share_vol	-16.30	-4.55	5.21
max_ret_daily	-17.25	-6.75	2.59	ear3d	6.73	4.41	1.12
eer	12.52	6.23	1.24	avg_turn_12m	12.14	4.25	3.62
std_dolvol	-20.12	-5.85	4.02	amihud	-15.87	-4.18	6.26
corwin0	-10.25	-5.80	1.44	eer	6.81	3.85	1.39
ear3d	7.45	5.61	1.07	mom_2_6	11.13	3.82	2.39
min_ret_daily	-13.42	-5.06	2.46	std_dolvol	-12.45	-3.70	4.10
avg_turn_12m	15.13	4.73	2.18	zero	11.50	3.66	1.86
ret_scm	6.70	4.62	1.10	suemv	7.02	3.49	1.58
mom_2_6	12.51	4.49	2.14	mom_7_12	8.46	3.43	1.69
meanrec	-6.55	-4.13	1.25	d_seo_3yr	-3.67	-3.27	1.31
sesm_retew	9.36	4.11	1.08	meanrec	-5.33	-2.88	1.52
rev_1m	-12.94	-3.98	2.01	bm_mo	9.09	2.76	5.65
zero	9.86	3.97	2.43	sesm_retew	6.20	2.49	1.14
suemv	8.06	3.85	1.41	aci	-5.64	-2.48	3.68
bm_mo	12.28	3.61	5.40	chgn_pm	-5.14	-2.45	1.43
market_lev_mo	12.05	3.54	6.50	vol_mcap	7.44	2.27	4.31
exp_div	-5.46	-3.33	1.09	irev_1m_vw	4.21	2.24	1.29
avol3d	3.93	3.17	1.11	dy_mo	-5.71	-2.22	4.21
re_6	5.14	3.13	1.22	nc_oac	-6.33	-2.12	3.37
d_seo_3yr	-3.84	-3.05	1.29	rev_13_18	-3.64	-1.92	1.34
roaq	8.07	3.04	3.02	max_ret_daily	-4.49	-1.89	2.91
dolvol	-11.90	-2.95	5.80	acc_slo	-5.04	-1.82	2.53
rev_13_18	-5.56	-2.91	1.22	lbp	-3.90	-1.79	2.50
b1f_res_1m	-7.63	-2.85	2.52	sue	-4.22	-1.77	2.31
imom_2_6_vw	3.99	2.74	1.07	exp_div	-3.30	-1.73	1.05
shum	-10.08	-2.73	5.20	gscore	3.14	1.71	1.62
lbp	-4.38	-2.64	1.41	cash	5.99	1.70	6.67
tang	4.76	2.59	2.22	vol_trend	3.72	1.65	1.87
eps_disp	-4.07	-2.50	1.18	re_6	3.11	1.62	1.40
imom_7_12_vw	4.05	2.45	1.06	ag	4.24	1.60	3.98
cto	-7.38	-2.42	6.02	admcap_mo	3.46	1.53	1.91
quick	-6.80	-2.40	2.62	rev_1m	-5.11	-1.48	3.01
lgr	6.03	2.38	1.49	size	-6.75	-1.45	4.29
nc_oac	-6.58	-2.35	2.78	b1f_res_1m	-4.32	-1.45	3.16
mom_7_12	5.10	2.32	1.59	accq	3.70	1.44	1.37
chgn_pm	-4.36	-2.16	1.47	min_ret_daily	3.72	1.38	2.43
salerec	3.45	2.11	1.70	acc_dp	4.70	1.37	3.35
stdevrec	2.49	2.03	1.25	pchcapx_ia	5.97	1.35	6.89

Table A4 continued

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
gscore	3.39	1.96	1.45	acc_pi	-3.17	-1.33	2.67
nanalyst	-4.85	-1.95	3.15	gp	4.58	1.33	5.30
irev_1m_vw	3.39	1.87	1.15	dyds	3.02	1.32	3.32
failure	-4.23	-1.87	1.19	noa_lev	-4.60	-1.32	6.54
dy_mo	-4.61	-1.86	5.25	re_1	3.53	1.31	2.23
chatoia	2.71	1.74	1.47	nop_mo	2.49	1.27	2.90
ccdi_an	-2.60	-1.73	1.10	ltg	2.09	1.27	1.34
cf_mcap_mo	-6.21	-1.66	6.82	cegth3	2.99	1.27	4.10
zscore	3.96	1.63	2.65	salerec	2.27	1.25	1.83
sue	-5.40	-1.62	1.84	op_ff	-4.30	-1.23	4.39
iret_scm_vw	2.56	1.53	1.02	sal_sga_chng	1.61	1.22	1.17
ivc	-4.74	-1.51	2.75	lgr	3.06	1.20	1.97
chng_dy_mo	-3.30	-1.49	2.51	iret_scm_vw	2.09	1.16	1.06
cegth3	3.27	1.45	2.65	iltr_5y_vw	-2.50	-1.16	1.44
b1f_mktrf_60m	2.82	1.40	1.37	egr	2.84	1.15	2.53
dyds	2.96	1.39	3.90	nanalyst	-2.94	-1.12	2.33
cdind	-2.32	-1.34	1.12	salecash	4.09	1.11	6.41
amihud	-3.95	-1.34	3.25	chgn_at	2.10	1.11	1.99
cashpr_mo	3.79	1.33	3.67	chempia	3.16	1.10	1.43
P52_wh	-5.71	-1.30	3.09	em	2.64	1.09	2.06
noa_lev	-4.43	-1.22	4.83	eps_price	-2.60	-1.07	2.53
oscore	3.28	1.22	3.39	tax1	1.67	1.06	1.28
ag	2.77	1.22	3.75	chatoia	1.68	1.01	1.37
coskew	-1.55	-1.21	1.06	chnanalyst	1.35	0.99	1.07
re_1	3.61	1.20	1.98	roavol	2.78	0.98	1.47
ltr_5y	-2.39	-1.20	1.73	nincr	3.65	0.97	2.12
ns_ti	2.26	1.19	1.34	eqea	1.71	0.96	1.04
roavol	3.26	1.18	1.24	rsup2	-1.38	-0.94	1.29
pchdepr	-2.34	-1.17	1.38	b1f_mktrf_60m	2.27	0.93	1.50
aci	-2.81	-1.16	2.48	b1f_res_60m	-2.72	-0.92	2.25
pchsale_pchrect	-2.00	-1.14	1.35	dXFIN2	-2.21	-0.92	3.53
acc_pi	-2.01	-1.14	1.81	ccdo2_mo	1.24	0.91	1.06
cf_var_mo	-2.82	-1.14	1.64	depr	2.24	0.90	1.93
ltg	1.69	1.12	1.12	ccdi2_mo	-2.20	-0.88	1.37
ipo_rd	-2.08	-1.12	1.62	pta	1.52	0.88	1.82
chng_dyds	-2.12	-1.07	2.53	retComp	1.83	0.86	1.17
nop_mo	2.56	1.03	3.23	chpmia	1.51	0.86	1.09
pta	1.72	1.03	1.98	down_f	1.58	0.86	1.96
rsup2	2.10	1.02	1.17	avol3d	1.26	0.83	1.18
acc_slo	-2.47	-1.02	2.45	stdevrec	-1.26	-0.81	1.45
fscore	1.91	1.00	2.32	pchdepr	-1.73	-0.79	1.56
margin	2.82	1.00	2.62	ia	1.80	0.72	2.69
change_recom	7.65	0.96	1.04	rd_inc	5.04	0.71	1.02
eqea	1.79	0.95	1.02	hire	-2.01	-0.70	1.67
sin	-1.82	-0.91	1.14	cashpr_mo	1.98	0.69	3.89
op_lev	-1.51	-0.91	1.95	realestate	1.48	0.67	1.10
cashdebt	2.12	0.90	2.33	currat	-2.31	-0.66	5.20
rsup1	1.89	0.82	1.23	ipo_rd	-1.26	-0.66	1.66
acc_dp	2.27	0.81	2.98	coskew	-1.01	-0.65	1.10
hire	-1.89	-0.81	1.66	b1f_mktrf_1m	-1.34	-0.65	1.52
nwc_chng	-1.80	-0.78	2.01	a_turn	2.47	0.65	6.42
chnanalyst	1.09	0.76	1.25	op_lev	-1.35	-0.65	2.38
e_cons	-1.66	-0.76	1.07	margin	-2.13	-0.64	3.16
ebp	-1.78	-0.76	2.18	sg	-2.03	-0.63	3.74
down_f	1.69	0.74	2.50	dur	2.17	0.63	3.33
com_eq	-1.17	-0.71	1.87	cdind	-1.09	-0.62	1.14

Table A4 continued

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
ccdi2_mo	1.52	0.71	1.27	irev_13_18_vw	-1.23	-0.62	1.32
age	-1.92	-0.68	1.77	nit_mcap_mo	2.58	0.61	6.51
ns	1.05	0.67	1.36	ccdr2_mo	1.01	0.60	1.05
chgn_at	1.19	0.67	2.06	nincr_up	-2.07	-0.59	3.00
dur	1.96	0.67	2.57	oscore	1.55	0.58	3.02
currat	1.81	0.66	3.33	chng_dyds	1.20	0.57	2.61
chempia	1.63	0.65	1.54	pm	-1.96	-0.57	3.09
iltr_5y_vw	-1.14	-0.65	1.19	dXFIN1	-1.58	-0.56	4.53
dXFIN2	-1.60	-0.64	3.13	ccdr_an	1.15	0.55	1.17
realestate	-1.42	-0.60	1.03	ivc	-1.69	-0.53	2.92
b1f_mktrf_1m	-1.03	-0.58	1.12	sin	1.16	0.53	1.31
org_cap	-0.85	-0.57	1.45	change_recom	1.66	0.51	1.07
op_ff	-1.96	-0.56	3.70	ltr_5y	-1.04	-0.50	1.90
dprc_mo	-1.52	-0.55	3.69	imom_7_12_vw	0.89	0.48	1.21
ccdo_an	-1.49	-0.51	1.13	age	-1.26	-0.46	1.98
gr_lt_noa	1.83	0.50	3.50	org_cap	-0.82	-0.45	1.48
diss	-0.70	-0.49	1.99	chng_dy_mo	1.00	0.45	2.60
sal_sga_chng	0.55	0.49	1.26	pchquick	1.52	0.45	4.49
nincr_up	2.85	0.49	2.39	ebp	-1.28	-0.45	3.34
ivg	1.89	0.49	3.64	ns	0.62	0.44	1.48
egr	-1.01	-0.42	3.04	nwc_chng	1.12	0.43	1.74
retComp	1.03	0.40	1.15	cf_var_mo	0.99	0.43	1.98
pchcurrat	-1.54	-0.40	2.53	roic	-1.48	-0.38	5.18
vol_trend	0.79	0.37	1.57	pfdelay	-1.24	-0.37	1.27
salecash	-1.20	-0.37	6.50	cashdebt	0.94	0.37	2.67
ccdo2_mo	0.49	0.36	1.09	tang	0.82	0.35	2.68
pchquick	1.35	0.35	2.33	roaq	0.87	0.29	2.88
ccdr_an	-0.52	-0.35	1.17	com_eq	-0.51	-0.28	1.96
sg	-1.04	-0.35	2.85	pchsale_pchrect	-0.50	-0.27	1.36
b1f_res_60m	0.75	0.34	2.42	dpfs	1.26	0.27	1.30
rd_inc	2.51	0.34	1.07	fscore	0.64	0.27	2.26
ccdr2_mo	-0.41	-0.33	1.04	margin_sal_chng	-0.53	-0.26	1.69
chpmia	0.47	0.32	1.10	rsup1	-0.58	-0.26	1.35
tax2	-1.48	-0.31	1.12	rna	-0.96	-0.25	4.73
pm	0.84	0.29	3.13	ccdo_an	0.84	0.25	1.19
admcap_mo	0.59	0.24	1.76	ns_ti	-0.55	-0.24	1.63
nincr	-1.09	-0.24	1.66	cfp_ia_mo	0.52	0.24	2.19
rna	0.66	0.23	4.43	failure	-0.64	-0.24	1.77
accq	0.61	0.22	1.20	zscore	-0.64	-0.23	3.05
dpfs	-0.87	-0.19	1.08	quick	-0.63	-0.22	4.72
cfp_ia_mo	0.34	0.18	2.33	ivg	0.91	0.21	5.11
roic	-0.58	-0.17	4.35	shum	0.73	0.21	3.12
a_turn	0.60	0.17	6.01	corwin0	-0.40	-0.20	1.55
tax1	0.26	0.17	1.15	rdmcap_mo	-0.77	-0.19	1.14
margin_sal_chng	0.30	0.17	1.48	herf	-0.31	-0.19	1.28
pchsaleinv	0.41	0.17	2.46	e_cons	0.36	0.18	1.15
pfdelay	0.48	0.15	1.15	tax2	0.98	0.18	1.32
herf	0.19	0.13	1.23	diss	-0.29	-0.17	2.25
em	0.27	0.13	1.55	pchcurrat	0.64	0.17	4.79
depr	-0.25	-0.12	1.59	eps_disp	0.29	0.15	1.40
irev_13_18_vw	0.21	0.11	1.16	P52_wh	-0.50	-0.13	3.29
cash	0.32	0.10	5.11	imom_2_6_vw	0.16	0.09	1.23
poa	0.19	0.09	1.92	dprc_mo	-0.28	-0.09	4.78
rdmcap_mo	0.34	0.07	1.11	ccdi_an	-0.15	-0.09	1.06
gp	-0.11	-0.03	4.33	cf_mcap_mo	-0.19	-0.04	6.34

Table A4 continued

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
dXFIN1	0.07	0.03	3.32	pchsaleinv	0.14	0.04	3.66
eps_price	0.04	0.02	2.50	poa	0.03	0.01	2.06
ia	0.01	0.01	2.49	gr_lt_noa	0.00	0.00	5.13
size	-14.24	-3.51	7.07	cto	-8.82	-2.37	7.97
sprc_mo	6.87	1.51	8.57	dolvol	-9.01	-2.11	7.70
ig	-1.42	-0.40	8.01	ig	-5.98	-1.36	7.57
efp	2.13	0.39	11.74	efp	3.60	0.64	13.43
an_value	1.25	0.25	11.67	an_value	1.04	0.19	13.10
pchcapx_ia	0.55	0.16	7.86	sprc_mo	0.36	0.08	8.41
nit_mcap_mo	0.38	0.11	7.96	market_lev_mo	0.14	0.04	9.11

Table A5: In-sample return regressions: Full results for Emerging Markets

This table provides the results of Fama and MacBeth (1973) regressions of stock returns on the full set of 161 trade signals for Emerging Markets. We study five international stock markets (North America, Europe, Japan, Pacific, and Emerging Markets). The dependent variable is the monthly stock return minus the average stock return across all stocks in the particular region, all measured in US-Dollars. Standard OLS regression results are reported in the left part of the table, and value-weighted least squares (VWLS) results are reported in the right part of the table. Variance inflation factors (VIF) are reported to assess the degree of multicollinearity. For each characteristic, the VIF is calculated as 1/(1-$R2$) with the $R2$ being obtained from regressing each characteristic on all the other characteristics in a pooled regression. t-statistics are adjusted using the procedure of West and Newey (1987) with a lag of four months. For the regressions, we scale all trade signals such that the resulting coefficients can be interpreted as annualized decile 10 minus decile 1 long/short returns that are orthogonal to all other trade signals. Whereas we report only the 15 most significant variables in the paper, we show full results here. The sample period ranges from 1/1989 to 12/2015.

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
avg_turn_12m	10.32	6.88	2.63	ltg	5.85	3.95	1.26
share_vol	-15.51	-6.16	3.50	bm_mo	10.58	3.92	5.23
b1f_res_1m	-11.67	-6.00	2.79	efp	14.27	3.84	6.29
vol_mcap	17.17	5.54	3.24	retComp	8.83	3.74	1.40
ret_scm	6.30	5.06	1.12	mom_7_12	7.08	3.55	1.55
bm_mo	13.60	4.72	4.75	cdind	-6.58	-3.54	1.09
ltg	6.12	4.60	1.10	dyds	6.14	3.32	2.11
imom_2_6_vw	6.44	4.35	1.06	corwin0	-6.17	-3.20	1.33
meanrec	-4.06	-4.10	1.15	eer	6.79	3.17	1.29
corwin0	-7.28	-3.95	1.29	ret_scm	4.26	3.13	1.13
std_dolvol	-10.35	-3.67	3.51	pm	-6.76	-3.13	4.27
retComp	7.09	3.52	1.24	rev_1m	-8.29	-3.05	2.76
ear3d	5.02	3.48	1.06	irev_1m_vw	7.33	3.03	1.45
rev_1m	-9.02	-3.41	2.19	avg_turn_12m	6.69	2.83	3.17
mom_7_12	6.01	3.32	1.58	chng_dyds	4.13	2.56	2.16
rev_13_18	-4.85	-3.28	1.19	lbp	-7.43	-2.45	2.95
salecash	-8.24	-3.19	6.89	roaq	6.75	2.44	2.96
cdind	-6.36	-3.08	1.06	b1f_mktrf_1m	5.17	2.39	1.44
efp	13.21	3.05	4.76	rev_13_18	-3.78	-2.18	1.22
dyds	4.67	2.78	2.39	diss	-2.99	-2.17	2.09
irev_1m_vw	4.84	2.77	1.26	ns	-2.98	-2.13	1.33
cashpr_mo	5.05	2.73	3.03	iret_scm_vw	4.20	2.06	1.03
pm	-4.85	-2.70	4.33	chgn_at	3.99	2.05	2.25
roaq	9.06	2.54	3.29	suemv	4.71	2.03	1.66
mom_2_6	6.03	2.40	2.08	ccdi2_mo	-4.40	-2.02	1.31
min_ret_daily	-4.23	-2.38	2.12	imom_2_6_vw	4.11	2.01	1.13
iltr_5y_vw	4.43	2.33	1.14	egr	4.69	1.93	2.37
eps_price	5.33	2.30	2.64	std_dolvol	-6.18	-1.92	2.93
chgn_at	4.13	2.11	2.49	lgr	4.15	1.89	1.77
eer	7.73	2.06	1.17	nop_mo	4.01	1.89	3.30
size	-5.98	-2.04	5.36	max_ret_daily	-4.16	-1.89	2.36
nwc_chng	-4.05	-2.04	3.04	dXFIN2	4.53	1.82	3.18
down_f	-4.51	-2.02	2.07	aci	-5.49	-1.81	3.95
lgr	4.12	2.00	1.61	change_recom	6.92	1.78	1.08
dprc_mo	3.77	2.00	4.98	dprc_mo	3.95	1.78	5.83
ccdi2_mo	-3.91	-1.95	1.26	rsup1	-7.50	-1.73	1.35
ccdi_an	-2.58	-1.92	1.07	down_f	-3.25	-1.62	1.68
chnanalyst	2.95	1.87	1.35	rsup2	-3.74	-1.54	1.34
noa_lev	-3.73	-1.85	5.12	eqea	-2.50	-1.52	1.03
cashdebt	3.17	1.84	3.01	share_vol	-4.79	-1.50	3.23

Table A5 continued

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
b1f_mktrf_1m	3.15	1.81	1.20	mom_2_6	4.08	1.49	2.10
ccdr2_mo	-4.24	-1.78	1.04	margin	3.39	1.49	4.70
rdmcap_mo	8.59	1.75	1.08	cashpr_mo	3.10	1.48	3.96
nc_oac	3.36	1.74	3.23	op_lev	-6.33	-1.45	3.60
egr	3.60	1.71	2.66	b1f_mktrf_60m	-3.00	-1.43	1.42
tax1	-2.68	-1.67	1.16	depr	3.19	1.41	1.68
pchsaleinv	3.58	1.65	3.70	rd_inc	-8.12	-1.39	1.02
sin	3.23	1.62	1.06	iltr_5y_vw	2.33	1.39	1.24
diss	-2.57	-1.57	1.97	zscore	-3.66	-1.38	3.02
iret_scm_vw	2.75	1.57	1.02	gp	4.67	1.38	6.08
change_recom	9.25	1.54	1.03	cashdebt	3.22	1.38	3.19
com_eq	-3.04	-1.52	1.36	chng_dy_mo	-3.60	-1.37	2.08
rsup1	4.62	1.49	1.23	ccdo2_mo	2.03	1.36	1.05
realestate	1.37	1.49	1.08	ivg	-4.51	-1.35	6.29
nit_mcap_mo	-4.88	-1.48	5.65	pta	3.19	1.33	1.55
ccdr_an	2.22	1.44	1.10	nincr	-4.57	-1.31	2.10
lbp	-2.35	-1.41	2.15	rdmcap_mo	4.92	1.27	1.17
salerec	2.00	1.38	1.65	chpmia	2.96	1.24	1.05
vol_trend	-2.01	-1.38	1.44	b1f_res_1m	-2.54	-1.15	2.69
re_6	1.84	1.37	1.17	vol_mcap	4.20	1.15	3.73
hire	-3.82	-1.36	1.71	herf	1.54	1.14	1.10
depr	2.46	1.36	1.56	sin	2.42	1.11	1.15
ns_ti	2.38	1.33	1.69	ltr_5y	3.46	1.10	1.65
suemv	4.72	1.33	1.51	accq	2.40	1.10	1.18
dolvol	-3.74	-1.32	4.93	meanrec	-1.40	-1.09	1.30
cfp_ia_mo	2.10	1.32	1.90	ipo_rd	2.60	0.99	1.49
stdevrec	1.78	1.30	1.17	ear3d	2.90	0.96	1.06
pfdelay	3.05	1.27	1.07	b1f_res_60m	2.05	0.96	1.82
quick	-3.11	-1.26	5.23	gr_lt_noa	3.38	0.94	5.59
gp	3.69	1.24	5.88	roavol	-3.24	-0.90	1.30
chempia	2.94	1.21	1.58	ag	-2.50	-0.89	3.88
an_value	-5.90	-1.20	4.64	nwc_chng	-2.56	-0.86	2.22
op_lev	-5.52	-1.17	3.15	salerec	1.59	0.85	1.73
acc_pi	-1.78	-1.16	1.81	dy_mo	1.86	0.82	3.87
ns	-1.48	-1.15	1.30	chempia	-1.91	-0.79	1.43
aci	-3.04	-1.14	3.65	cegth3	-2.50	-0.78	4.02
cegth3	-3.24	-1.14	3.31	zero	1.88	0.78	1.48
rsup2	-2.69	-1.14	1.23	ccdr_an	-1.21	-0.78	1.07
zero	2.55	1.12	1.41	pchdepr	1.67	0.75	1.51
b1f_mktrf_60m	-2.31	-1.10	1.34	pchsaleinv	-2.05	-0.75	4.19
sg	-3.11	-1.10	4.00	ebp	-2.73	-0.74	3.48
margin	2.20	1.07	4.11	hire	1.91	0.74	1.60
fscore	2.11	1.06	2.21	vol_trend	-1.46	-0.73	1.58
accq	2.47	1.06	1.15	dpfs	4.04	0.72	1.22
em	1.76	0.98	1.37	an_value	-2.75	-0.70	6.07
chpmia	1.26	0.95	1.08	eps_price	2.12	0.70	2.25
pchsale_pchrect	-1.50	-0.93	1.44	nit_mcap_mo	-2.32	-0.67	6.17
ccdo_an	-2.67	-0.91	1.09	ns_ti	-1.42	-0.66	1.99
dXFIN2	1.51	0.89	3.03	acc_dp	1.74	0.66	3.79
re_1	-3.46	-0.87	1.54	pchquick	1.83	0.66	5.97
herf	0.81	0.83	1.07	re_6	1.24	0.65	1.31
sesm_retew	1.53	0.83	1.10	nanalyst	1.32	0.63	2.04
cf_var_mo	-1.95	-0.82	1.54	cf_mcap_mo	-1.76	-0.61	5.90
sal_sga_chng	-1.49	-0.80	1.31	e_cons	-1.42	-0.61	1.12
chng_dyds	1.39	0.79	2.08	fscore	-1.19	-0.60	2.06
avol3d	1.10	0.79	1.07	quick	-1.69	-0.60	6.71

Table A5 continued

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
chatoia	-1.05	-0.77	1.49	ccdi_an	1.18	0.59	1.04
ia	-1.60	-0.75	3.22	realestate	-0.83	-0.58	1.14
zscore	1.56	0.73	2.59	currat	-1.89	-0.56	6.66
nop_mo	1.81	0.67	3.47	sue	-1.09	-0.55	2.24
acc_dp	1.34	0.60	4.15	cf_var_mo	-1.38	-0.54	1.81
irev_13_18_vw	-1.04	-0.60	1.14	sesm_retew	-1.69	-0.53	1.12
margin_sal_chng	-1.00	-0.58	1.70	chgn_pm	-1.47	-0.53	1.57
imom_7_12_vw	0.87	0.57	1.06	tang	0.96	0.53	2.16
pchcurrat	1.36	0.55	4.65	pchcurrat	-1.48	-0.52	6.02
dXFIN1	-1.00	-0.54	3.82	admcap_mo	1.80	0.51	2.21
d_seo_3yr	-0.95	-0.54	1.23	pfdelay	1.15	0.50	1.19
ipo_rd	1.56	0.52	1.40	poa	2.08	0.49	1.84
gscore	-0.66	-0.51	1.60	cfp_ia_mo	1.14	0.47	1.65
dur	1.18	0.50	2.77	re_1	-1.60	-0.46	1.72
acc_slo	1.29	0.49	4.06	irev_13_18_vw	-1.05	-0.45	1.22
pchdepr	-0.89	-0.49	1.40	op_ff	-1.04	-0.44	3.98
cto	-1.36	-0.48	5.94	age	-1.03	-0.42	1.62
chng_dy_mo	-1.22	-0.48	2.00	stdevrec	-0.50	-0.40	1.43
ccdo2_mo	-0.66	-0.47	1.06	d_seo_3yr	0.58	0.40	1.34
cf_mcap_mo	-1.26	-0.46	4.93	acc_slo	1.27	0.39	3.48
coskew	0.61	0.46	1.04	chnanalyst	0.61	0.38	1.14
dy_mo	1.18	0.46	4.41	nc_oac	-0.89	-0.37	3.57
nanalyst	1.02	0.46	2.61	noa_lev	1.03	0.36	6.11
nincr_up	1.95	0.44	2.36	gscore	-0.64	-0.35	1.54
ebp	-1.19	-0.40	2.53	em	-0.80	-0.33	1.94
sue	0.73	0.38	1.80	ccdr2_mo	-0.85	-0.33	1.04
oscore	-0.93	-0.37	3.83	ia	-0.74	-0.30	3.17
dpfs	2.23	0.36	1.10	org_cap	0.60	0.29	1.57
org_cap	-0.96	-0.35	1.52	imom_7_12_vw	0.42	0.28	1.12
rna	0.67	0.34	5.94	roic	-0.77	-0.27	4.78
a_turn	-1.00	-0.34	6.58	chatoia	0.52	0.26	1.45
exp_div	-0.52	-0.33	1.04	P52_wh	-0.71	-0.25	2.63
nincr	-1.13	-0.28	1.72	shum	0.81	0.25	3.06
amihud	0.85	0.28	4.05	amihud	0.94	0.24	4.69
ltr_5y	0.87	0.26	1.60	ccdo_an	0.69	0.24	1.11
tax2	-1.53	-0.26	1.03	avol3d	0.50	0.22	1.09
roic	0.58	0.24	5.03	exp_div	-0.34	-0.22	1.03
ivc	-0.63	-0.24	4.19	dolvol	0.54	0.20	4.76
chgn_pm	-0.53	-0.23	1.68	sg	-0.51	-0.18	3.98
ivg	0.61	0.23	5.92	com_eq	-0.37	-0.17	1.36
b1f_res_60m	0.34	0.21	1.75	nincr_up	0.52	0.15	2.96
pchquick	-0.50	-0.21	4.58	dur	-0.33	-0.15	3.13
tang	-0.33	-0.20	1.89	size	-0.61	-0.14	3.25
eqea	-0.32	-0.18	1.02	pchsale_pchrect	-0.26	-0.14	1.31
shum	-0.52	-0.17	5.31	a_turn	-0.41	-0.13	6.71
max_ret_daily	-0.32	-0.17	2.46	dXFIN1	0.24	0.10	3.97
age	0.46	0.16	1.61	eps_disp	0.21	0.09	1.32
poa	-0.19	-0.16	1.91	sal_sga_chng	-0.17	-0.08	1.25
ag	0.27	0.13	4.09	failure	-0.22	-0.08	2.23
e_cons	-0.19	-0.10	1.06	ivc	0.23	0.07	4.05
failure	-0.22	-0.10	1.70	tax2	-0.49	-0.07	1.05
rd_inc	-0.32	-0.07	1.02	oscore	-0.21	-0.07	2.96
eps_disp	0.15	0.07	1.12	acc_pi	0.12	0.06	2.39
roavol	0.22	0.07	1.14	coskew	0.07	0.05	1.07
currat	-0.13	-0.05	5.56	min_ret_daily	0.05	0.03	2.05

Table A5 continued

A.1.: OLS regression results				A.2.: VWLS regression results			
Acronym	FM coef.	t-stat	VIF	Acronym	FM coef.	t-stat	VIF
P52_wh	-0.15	-0.05	2.61	margin_sal_chng	0.05	0.03	1.80
op_ff	0.10	0.04	3.66	tax1	-0.03	-0.02	1.23
gr_lt_noa	-0.10	-0.03	4.11	rna	0.04	0.01	5.00
admcap_mo	0.10	0.03	1.95	salecash	-5.97	-2.11	8.14
pta	0.00	0.00	1.64	sprc_mo	4.25	1.30	7.63
market_lev_mo	8.10	2.86	8.04	pchcapx_ia	4.54	1.08	7.72
pchcapx_ia	5.68	1.74	9.07	cash	-1.60	-0.59	8.01
sprc_mo	4.28	1.59	7.09	cto	-1.44	-0.40	7.11
cash	-2.75	-1.10	7.00	ig	0.91	0.22	8.52
ig	-1.87	-0.64	9.43	market_lev_mo	0.33	0.11	10.02

References

West, K. D., and W. K. Newey, 1987, "A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix," *Econometrica*, 55, 703–708.