Does Academic Research Destroy Stock Return Predictability?*

R. David McLean
University of Alberta and MIT Sloan School of Management
Phone: 774-270-2300
Email: rdmclean@ualberta.ca

Jeffrey Pontiff
Boston College
Phone: 617-552-6786
Email: pontiff@bc.edu

May 16, 2013

Abstract

We study the out-of-sample and post-publication return-predictability of 82 characteristics that are identified in published academic studies. The average out-of-sample decay due to statistical bias is about 10%, but not statistically different from zero. The average post-publication decay, which we attribute to both statistical bias and price pressure from aware investors, is about 35%, and statistically different from both 0% and 100%. Our findings point to mispricing as the source of predictability. Post-publication, stocks in characteristic portfolios experience higher volume, variance, and short interest, and higher correlations with portfolios that are based on published characteristics. Consistent with costly (limited) arbitrage, post-publication return declines are greater for characteristic portfolios that consist of stocks with low idiosyncratic risk.

Keywords: Return predictability, limits of arbitrage, publication impact, market efficiency, comovement, statistical bias.

JEL Code: G00, G14, L3, C1

* We are grateful to the Q Group and the Dauphine-Amundi Chair in Asset Management for financial support. We thank participants at the Financial Research Association's 2011 early ideas session, seminar participants at Babson College, Bocconi University, Brandeis University, Boston College, CKGSB, HBS, Georgia State University, HEC Montreal, MIT, Northeastern University, University of Toronto, University of Maryland, City University of Hong Kong International Conference, Finance Down Under Conference 2012, University of Georgia, University of Washington Summer Conference, European Finance Association (Copenhagen), 1st Luxembourg Asset Management Conference, and Turan Bali, Shane Corwin, Mark Bradshaw, Alex Edmans, Lian Fen, Bruce Grundy, Pierluigi Balduzzi, David Chapman, Wayne Ferson, Francesco Franzoni, Xiaohui Gao, Thomas Gilbert, Clifford Holderness, Darren Kisgen, Owen Lamont, Jay Ritter, Robin Greenwood, Paul Schultz, Bruno Skolnik, Jeremy Stein, Matti Suominen, Allan Timmermann, Michela Verado, Artie Woodgate, and Jianfeng Yu for helpful conversations.

Finance research has uncovered many cross-sectional relations between predetermined variables and future stock returns. Beyond historical curiosity, these relations are relevant to the extent they provide insight into the future. Whether or not the typical relation continues outside of a study's original sample is an open question, the answer to which can shed light on why cross-sectional return predictability is observed in the first place.[1] Although several papers note whether a specific cross-sectional relation continues, no study compares in-sample returns, post-sample returns, and post-publication returns among a large sample of predictors. Moreover, previous studies produce contradictory messages. As examples, Jegadeesh and Titman (2001) show that the relative returns to high-momentum stocks increased after the publication of their 1993 paper, while Schwert (2003) argues that since the publication of the value and size effects, index funds based on these variables fail to generate alpha.[2]

In this paper, we synthesize information from 82 characteristics that have been shown to explain cross-sectional stock returns in peer-reviewed finance, accounting, and economics journals. Our goal is to better understand what happens to return-predictability outside of a study's sample period. We compare each characteristic's return-predictability over three distinct periods: (i) the original study's sample; (ii) after the original sample but before publication; and (iii) post publication. Previous studies contend that return-predictability is either the outcome of a rational asset pricing model, statistical biases, or mispricing. By comparing return-

[1] We focus on cross-sectional variables. For an analysis of the performance of time-series variables, see LeBaron (2000) and Goyal and Welch (2008). For an analysis of calendar effects, see Sullivan, Timmermann, and White (2011).

[2] Lewellen (2011) uses 15 variables to produce a singular rolling cross-sectional return proxy and shows that it predicts, with decay, next period's cross section of returns. Haugen and Baker (1996) and Chordia, Subrahmanyan, and Tong (2011) compare characteristics in two separate subperiods. Haugen and Baker show that each of their characteristics produces statistically significant returns in the second-subperiod, whereas Chordia, Subrahmanyan, and Tong show that none of their characteristics is statistically significant in their second-subperiod. Green, Hand, Zhang (2012) identify 300 published and unpublished characteristics but they do not estimate characteristic decay parameters as a function of publication or sample-end dates.

predictability across these three distinct periods, we are able to give insight into what best explains the typical characteristic's return-predictability.

Pre-publication, out-of-sample predictability. If return-predictability in published studies is the result of statistical biases, then predictability should disappear out of sample. We use the term "statistical biases" to describe a broad array of biases that are inherent to research.

At least three statistical biases could affect observed stock return-predictability. First, Leamer (1978) shows the impact of "specification search" biases, which occur if the choice of model is influenced by the model's result. Lo and MacKinlay (1990) examine a specific type of specification search bias found in finance, which they refer to as the "data snooping bias." A second type of bias is sample selection bias, studied in Heckman (1979), where the sample construction is influenced by the result of the test. [3] A third type of bias arises when researchers conduct multiple tests of the same hypothesis. This bias goes back to Bonferroni (1935) and is applied to finance by Fama (1991) when he notes that, "With clever researchers on both sides of the efficiency fence, rummaging for forecasting variables, we are sure to find instances of 'reliable' return predictability that are in fact spurious." Harvey, Liu, and Zhu (2013) argue that this bias has worsened over time; as researchers mine an increasing number of characteristics, an increasing number of studies will be published that falsely reject the null. To the extent that the results of the studies in our sample are caused by such biases, we should observe a decline in return-predictability out-of-sample.

Post-publication predictability. We assume that more market participants know about a predictor after a paper documenting the predictor has been published, as compared to before the paper's publication date. However, we do not assume that the publication date is a precise

[3] Along these lines, a strategy's spuriously high returns can attract academic attention to the strategy, making the publication date endogenous. We thank Allan Timmermann for pointing out this possibility.

transition date. Papers are often presented at conferences and distributed before publication, causing information to be released before the publication date. On the other hand, market participants may be slow to respond to academic studies, so information may begin to work its way into prices long after the publication date. Most of our tests examine whether return-predictability is different after the publication date as compared to before the publication date. [4]

The literature makes conflicting predictions about post-publication predictability. Cochrane (1999) explains that if predictability reflects risk, then it is likely to persist regardless of how many people know about it: "Even if the opportunity is widely publicized, investors will not change their portfolio decisions, and the relatively high average return will remain." Cochrane's argument follows Muth's (1961) rational expectations hypothesis, and thus the logic can be broadened to non-risk models such as Amihud and Mendelson's (1986) transaction-based model and Brennan's (1970) tax-based model. If return-predictability reflects rational expectations, then pre- and post-publication (and out-of-sample but pre-publication) return-predictability should be similar.[5]

Alternatively, if return-predictability is the result of mispricing and if publication draws the attention of sophisticated investors who trade against the mispricing, then we might expect the effects to disappear after the paper is published or at least continue at a reduced level if costs prevent arbitrage from fully eliminating mispricing (see Delong, Shleifer, Summers, and Waldman (1990), Pontiff (1996, 2006), and Shleifer and Vishny (1997)) [6]. We can differentiate

[4] To our knowledge, the first empirical examination of the effects of academic research on capital markets is Mittoo and Thompson's (1990) study of the size effect. They use a regime switching model to illustrate a post-1983 difference in returns to size portfolios.

[5] This logic can be extended to irrational return predictability as well. Industry research may lead academic research, such that the information in academic publications is redundant to market participants.

[6] For evidence of limited arbitrage in short sellers and mutual funds, see Duan, Hu, and McLean (2009 and 2010).

this effect from that of statistical biases by finding a greater decline post-publication as compared to any decline out of-sample but pre-publication.

Findings. We conduct our analysis using 82 different characteristics from 68 different studies. We are able to replicate 72 of the characteristics in-sample; for 10 of the characteristics we could not find statistically significant return predictability in the original sample. For the 72 characteristics that we could replicate, the post-sample but pre-publication period is useful for estimating statistical bias. We find that on average, return-predictability declines by 10% during this period, implying that a 5% alpha reflects a bias-free alpha of 4.5%. This finding is statistically insignificant—we cannot reject the hypothesis that there are no statistical biases. Our 10% estimate is probably too high, since some traders could learn about the predictor before publication and their actions will cause some decay that is captured in the 10%. We are able to reject hypotheses that involve large levels of statistical bias. For basic specifications, we can reject with 95% confidence that post-sample decay is greater than 32%.

We estimate that the average characteristic's return decays by 35% post-publication. Thus, an in-sample alpha of 5% is expected to decay to 3.25% post-publication. Combining this finding with an estimated statistical bias of 10% implies a lower bound on the publication effect of about 25%. We can reject the hypothesis that post-publication return-predictability does not change and we can also reject the hypothesis that return-predictability disappears entirely. We use the Social Science Research Network (SSRN) posting date as a substitute for publication date and our results do not change. Our estimation shows both a lower average predictability after publication and a linear decay in predictability during the post-publication months. The post-publication decline is robust to controls for time trends in characteristic returns, time indicators used by other authors, and characteristic returns simply being lower during the later years in our sample.

We further investigate the effects of publication by studying traits that reflect trading activity. We find that stocks within characteristic portfolios have post-publication increases in variance, turnover, and dollar volume. The difference in the relative amount of short interest between stocks in the short and long sides of each characteristic portfolio also increases after publication. These findings are consistent with the idea that academic research draws attention to characteristics.[7]

Across characteristics, the post-publication decline is greatest for characteristics that are less costly to arbitrage; i.e., characteristics that require more trading in stocks with high market values, high liquidity, low idiosyncratic risk, and that pay dividends. Hence, our findings are consistent with mispricing being the source of characteristic return-predictability, as post-publication returns decline the most for portfolios that are the least costly to arbitrage. Surprisingly, a proxy for systematic risk, which should identify predictability that is the result of rational asset pricing, is associated with larger (albeit insignificant) declines in predictability.

Our final investigation is whether publication is associated with changes in covariance between characteristics. We find that yet-to-be-published characteristic portfolios are correlated. However, after a characteristic is published its correlation with other yet-to-be-published characteristic portfolios decreases, while its correlation with other already-published characteristic portfolios increases. One interpretation of this finding is that characteristics are the result of mispricing and mispricing has a common source; this is why in-sample characteristic portfolios are correlated. This interpretation is consistent with the irrational comovement models

[7] Drake, Rees and Swanson (2011) demonstrate that short interest is more pronounced in the low-return segment of several characteristic sorted portfolios. Their study does not account for the difference between in- and out-of-sample short interest.

proposed in Lee, Shleifer, and Thaler (1991) and Barberis and Shleifer (2003). Publication then causes more arbitrageurs to trade on the characteristic, which causes characteristic portfolios to become more correlated with already-published characteristic portfolios that are also pursued by arbitrageurs, and less correlated with yet-to-be-published characteristic portfolios.

1. Research Method

We identify studies that find cross-sectional relations between variables that are known in a given month and stock returns in the following month(s). We do not study time series predictability. We limit ourselves to studies in academic peer-reviewed finance, accounting, and economics journals, where the null of no cross-sectional predictability is rejected at the 5% level, and to studies that can be constructed with publicly available data. Most often, these studies are identified with search engines such as Econlit by searching for articles in finance and accounting journals with words such as "cross-section." Some studies are located from reference lists in books or other papers. Lastly, in the process of writing this paper, we contacted other finance professors and inquired about cross-sectional relations that we may have missed.

Most studies that we identify either demonstrate cross-sectional predictability with Fama-MacBeth (1973) slope coefficients or with long-short portfolio returns. Some of the studies that we identify demonstrate a univariate relation between the characteristic and subsequent returns, while other studies include additional control variables. Some studies that we identify are not truly cross-sectional, but instead present event-study evidence that seems to imply a cross-sectional relation. Since we expect the results from these studies to provide useful information to investors, we also include them in our analyses.

We use 82 cross-sectional relations from 68 different studies. We include all variables that relate to cross-sectional returns, including those with strong theoretical motivation such as Fama and MacBeth's landmark 1973 study of market beta in the *Journal of Political Economy* and Amihud's 2002 study of a liquidity measure in the *Journal of Financial Markets*. The study with the most number of original cross-sectional relations that we utilize (4) is Haugen and Baker's 1996 study of cross-section stock returns in the *Journal of Financial Economics*. Haugen and Baker (1996) investigate more than four cross-sectional relations, but some of these relations were documented by other authors earlier and are therefore associated with other publications in our study. The first study in our sample is Blume and Husic's 1972 *Journal of Finance* study of how price level relates to future stock returns. The most recent study is Bali, Cakici, and Whitelaw's 2011 *Journal of Financial Economics* study that shows that the maximum daily return that a security experiences in the preceding month predicts the next period's monthly return.

We are unable to exactly construct all of the characteristics. In such cases, we calculate a characteristic that captures the intent of the study. As examples, Franzoni and Marin (2006) show that a pension funding variable predicts future stock returns. This variable is no longer covered by Compustat, so we use available data from Compustat to construct a variable that we expect to contain much of the same information. Dichev and Piotroski (2001) show that firms that are downgraded by Moody's experience negative future abnormal returns. Compustat does not cover Moody's ratings. It does cover S&P ratings, so we use S&P rating downgrades instead. Characteristics that use accounting data are winsorized, such that values that are below the 1^{st} percentile are assigned the value of the 1^{st} percentile, and values that are above the 99th percentile are assigned the value of the 99^{th} percentile.

We estimate each characteristic's return-predictability using two different methods. First, we calculate monthly Fama-MacBeth (1973) slope coefficient estimates using a continuous measure of the characteristic (e.g. firm size or past returns). As Fama (1976) shows, Fama-MacBeth slope coefficients are returns from long-short portfolios with unit net exposure to the characteristic. Second, we calculate the return of a portfolio that each month invests in stocks in the top 20th percentile of the characteristic (the strategy's long-side) minus the return of a portfolio that invests in stocks in the bottom 20th percentile of the characteristic. We report our basic findings using both methods.

We segment periods based on the end of the sample and the publication date because they are clear, agreeable dates that may be associated with changes in predictability. The end of the original sample provides a clear point to estimation statistical bias. The publication date however, is not a clear point for examining the impact of market participants learning about a predictor (assuming the predictor is the result of mispricing). As we mention above, we assume that more investors know about a predictor during the sample period after the publication date as compared to the sample period before the publication date. Some market participants will read a working paper version before publication, while some will read the paper years after publication. Hence, post-publication decay in return-predictability may be a slow process and we are unaware of theories of how long the decay should take and the functional form of the decay. Despite the simplicity of our approach, the publication date generates robust estimates of return decay.

2. Creating the Data and In-Sample Replicability

Summary statistics for the characteristics that we study are provided in Table 1. We define the publication date as the date based on the journal's year and issue. For this date convention, the average length of time between the end of the sample and publication is 55 months. For comparison, the average original in-sample span is 323 months, and the average out-of-sample span is 139 months. We also consider the publication date to be the earlier of the actual publication date and the first time that paper appeared on the SSRN. The average number of months between the end of the sample and SSRN date is 44 months. The generous number of cross-sectional characteristics yields a total number of 3,971 out-of-sample but pre-publication observations, and 9,984 post-publication observations.

As we mention previously, for all characteristics, we calculate monthly Fama-MacBeth slope coefficients using continuous measures of the characteristic (e.g., size or past returns). Fifteen of our 82 characteristics involve binary variables, such as dividend initiation (Michaely, Thaler, and Womack, 1995). For all characteristics that do not involve a binary characteristic, we also calculate the long-short portfolio monthly return using extreme quintiles. Returns are equally weighted unless the primary study presents value-weighted portfolio results (e.g., Ang, Hodrick, Xing, and Zhang, 2006;Bali and Cakici, 2008).

Our goal is not to perfectly replicate a paper. This is impossible since CRSP data changes over time and papers often omit details about precise calculations. Ten of our average in-sample Fama-MacBeth slope coefficients produce t-statistics that are between -1.50 and 1.50.[8] We do not include these characteristics in the paper's main tests. Thus, a total of 72 (82 – 10) characteristics are used in the paper's primary tests.

[8] If a characteristic is not associated with a t-statistic outside of the -1.50 to 1.50 range, both co-authors independently wrote code to estimate the effect.

Admittedly, the decision to use a t-statistic cut-off of 1.50 is arbitrary. The decision was motivated by a desire to utilize as many characteristics as possible, while still measuring the same essential characteristic as the original paper. Given that some papers feature characteristics with t-statistics that are close to 2.0 and that we are not perfectly replicating the original authors' methodology, a cut-off of 1.50 seemed reasonable to us. That stated, only two of the 72 characteristics that we include in the paper's analyses have t-statistics that are less than 1.80.

2.1. Preliminary Findings

Table 2 reports characteristic-level summary statistics regarding the out-of-sample and post publication return-predictability of the 72 predictors that we were able to replicate. To be included in these tests, we require that a characteristic portfolio have at least 36 monthly observations during the measurement period (e.g., post-publication). This yields 60 predictors that we can study out-of-sample, and 66 predictors that are can study post-publication. We relax this restriction in our pooled regression tests, which weight each characteristic-month observation equally, rather than each characteristic.

To estimate the statistics in Table 2, we first calculate the in-sample mean for each characteristic portfolio, as described in the previous section. We then scale the monthly out-of-sample and post-publication portfolios by the in-sample means. We use the scaled values to generate statistics that reflect the average out-of-sample and post-publication return of each portfolio relative to its in-sample mean. We generate individual statistics for each characteristic portfolio and then take a simple average across all of the characteristics. We do this for the continuous (Fama-MacBeth slope) version of each characteristic portfolio (Panel A), the quintiles version (Panel B), and either the continuous or quintile version depending on which specification has the highest in-sample t-statistic (Panel C). We refer to the specifications that select the specification based on the in-sample t-statistics as "strongest."

For example, Panel A shows that if we use the continuous estimation of each characteristic portfolio then the average characteristic's return is 78% of its in-sample mean during the out-of-sample, but pre-publication period. However, this effect is not statistically significant (*t*-statistic = -1.40). Once published, the average characteristic's return is only 51% of its in-sample mean, and this decline is highly significant (*t*-statistic = -4.91). The results are similar throughout the 3 panels, which contain the continuous, extreme quintiles, and strongest form versions of the characteristics. The strongest form includes whichever method (continuous or extreme quintiles) yields the largest *t*-statistic.

Because these results are summarized at the characteristic level, the statistics give more weight to observations from characteristics that have shorter sample periods. As an example, the size effect (Banz, 1981) has monthly observations that go back to 1926, while the distress effect (Dichev, 1998), which uses credit ratings data, begins in 1981. Hence, if we equal-weight each characteristic, as we do in Table 2, then one observation from the distress characteristic gets a much larger weight than does one observation from the size characteristic. Also, the statistics in Table 2 do not consider correlations across the characteristic portfolios. In the subsequent section, we estimate random effect regressions that are robust to these issues, and those tests also find an insignificant decline out-of-sample and a significant decline post-publication.

3. Main Results

3.1. Characteristic Dynamics Relative to End of Sample and Publication Dates

We now more formally study the return-predictability of each characteristic relative to its original sample period and publication date. Our regression methodology utilizes random effects, which control for cross-portfolio correlations. In the discussion that follows, PR_{it} denotes the portfolio return associated with characteristic *i* in month *t*; this is either the Fama-MacBeth slope coefficient from a regression of monthly returns on characteristic *i* in month *t* or the return from the extreme quintiles portfolio.

We first compute the average portfolio return for each characteristic *i* using the same sample period as in the original study. This average will be expressed as $\overline{PR_{\iota}}$. The next step is to normalize each monthly portfolio return by scaling the observation by $\overline{PR_{\iota}}$. This normalized portfolio return will be denoted as $\widetilde{PR}_{it}$. In order to document changes in return predictability from in-sample to out-of-sample and from in-sample to post-publication, we estimate the following equation:

$$\widetilde{PR}_{it} = H_{int} + H_{post-sample}\, D_{it}^{post-sample} + H_{post-pub} D_{it}^{post-pub} + e_{it} \tag{1}$$

In this equation, $D_{it}^{post-sample}$ is a dummy variable that is equal to one if month *t* is after the end of the original sample but still pre-publication and zero otherwise, while $D_{it}^{post-pub}$ is equal to 1 if the month is post-publication and zero otherwise. e_{it} is the residual from the estimation and the *H* coefficients are mean estimates of the respective period's return as a fraction of the characteristic's in-sample mean return.

For the basic specification in equation (1), the intercept, H_{int}, will be very close to unity. This occurs since the average normalized portfolio return that is neither post-sample nor post-publication is unity by construction—the normalized return is the actual in-sample return divided by the in-sample average. This accomplishes the objective of allowing us to interpret the slopes on the dummy variables as percentage decays of in-sample returns. A benefit of using returns that are normalized by the in-sample mean as opposed to using the in-sample mean as an independent variable, is that this enables us to use a longer time-series to estimate the appropriate variance-covariance matrix. As we mention above, the portfolio returns from the same month are likely to be correlated and, because of this, we estimate equation (1) with random-effects by characteristic portfolios. In addition, we also cluster our standard errors on time. In unreported results, we cluster on anomaly, which produces larger t-statistics.

The coefficient, $H_{post-sample}$, estimates the total impact of statistical biases on characteristic performance (under the assumption that sophisticated traders are unaware of the working paper before publication). $H_{post-pub}$ estimates both the impact of statistical biases and the impact of publication. If statistical biases are the cause of in-sample predictability, then both $H_{post-sample}$ and $H_{post-pub}$ should be equal to -1. Such a finding would be consistent with Fama's (1991) conjecture that return-predictability in academic studies is the outcome of data-mining. If characteristics are the result of mispricing and arbitrage resulting from publication corrects all mispricing, then $H_{post-pub}$will be equal to -1 and $H_{post-sample}$ will be close to zero. In the other extreme, if there are no statistical biases and academic papers have no influence on investors' actions, then both $H_{post-sample}$ and $H_{post-pub}$ should equal zero.

3.2. Characteristic Dynamics Relative to End of Sample and Publication Dates

Table 3 presents regression estimates of how predictability varies through the life cycle of a publication. In order to provide perspective, the first column departs from the methodology used in the rest of this Table (and Table 4) by presenting results from estimation on raw, long-short extreme quintile returns that are not scaled by the in-sample mean. Column 1 shows that the average characteristic has a monthly in-sample long-short return of 42.8 basis points, which decays by 5.2 basis points post-sample, and by 17.3 basis points after the publication date (the 5.2 basis points are also reflected in the 17.3 basis points).

The second column labeled "Continuous," uses Fama-MacBeth coefficients (again, scaled by in-sample means) generated from regressions that use continuous measures of the characteristic (e.g., size or past returns) as the dependent variable. The results suggest that between the end of the sample and the publication date, the magnitude of the long-short returns fall, on average, by about 20%, and this effect is statistically significant (p-value =0.090). Using the regression standard error, we can reject the hypothesis that the decay during this period is greater than 43.5% at the 95% confidence level. Post-publication, the total decline is 42% and statistically significant from both 0 and -100%. Thus, cross-sectional predictability continues post-publication at a significant, albeit muted level.

In the third column, the dependent variable is the extreme quintiles return scaled by the in-sample mean. The post-publication coefficient is -0.347 and statistically significant, reflecting an average decline of 34.7 basis points in the months post-publication. The out-of-sample coefficient is -0.015 which is statistically indistinguishable from zero.

The fourth column uses either the Fama-MacBeth coefficients from regressions that use continuous variables or long-short extreme quintile portfolios, depending on which method produces the highest in-sample statistical significance. In this regression, the out-of-sample decay is 9.7%, but not statistically significant. The post-publication decline is estimated to be 37%, which is similar to the slopes (42% and 35%) estimated in the regressions that use the continuous and quintiles estimates respectively. If the original cross-sectional relations were purely noise, then selecting a weighting method based on in-sample significance would produce the largest decay in post-sample returns, however this is not the case.

The fifth column considers an alternative publication date that is based on either the actual publication date or the first SSRN posting date, whichever is earliest. In this regression, the post-publication coefficient estimates a decay of 34%, showing that small changes to publication dates do not have a material effect on the findings. This finding makes sense, since the post-publication coefficient is essentially a test of the difference between the in-sample and post-publication values of the normalized portfolio returns. We have a total of 9,984 post-publication portfolio-month returns, which increases to 10,797 if we instead use the SSRN posting date as the publication date. Hence, this change in definition increases the post-publication sample by only 7.5%, which is not a large difference.

We include the portfolio's last month's return and the sum of the portfolio's last 6 months' and 12 months' returns in the final three regressions. Recent work by Moskowitz, Ooi, and Pedersen (2010) and Asness, Moskowitz and Pedersen (2009) finds broad momentum across asset classes and correlation of momentum returns across classes. The pervasiveness of the results in these papers suggests that momentum, or perhaps shorter-term persistence, might exist among our larger sample of characteristics. All three of these lagged return coefficients are positive and significant, which is broadly consistent with the findings of Moskowitz, et al. The publication coefficient remains significant in each of these regressions, suggesting a post-publication decline of about 30% once past returns are considered.

At the bottom of Table 3, we report tests of whether the coefficient for post-publication is greater than the coefficient for out-of-sample but pre-publication. In all but the last regressions the difference is statistically significant. Hence, the decline in return-predictability that is observed post-publication exceeds the decline in return-predictability that is observed out-of-sample, but pre-publication. This difference tells us that there is an effect associated with publication that cannot be explained by statistical biases, which should be fully reflected in the out-of-sample but pre-publication coefficients.

3.3. Publication Effect or Time Trend?

It could be the case that the dissemination of academic research has no effect on return-predictability, and that our end-of-sample and publication coefficients reflect a time trend or a trend that proxies for lower costs of corrective trading. For example, anomalies might reflect mispricing and declining trading costs have made arbitrage less costly, which is why we observe the drop post-publication. Goldstein, Irvine, Kandel, and Wiener (2009) present evidence that brokerage commissions dropped dramatically from 1977 to 2004, while Anand, Irvine, Puckett and Venkataraman (2012) show that, over the last decade, execution costs have fallen. Chordia, Subrahmanyam, and Tong (2011) show that in the 1993 to 1999 time period, ten characteristics that were previously associated with cross-sectional returns failed to achieve statistical significance. They attribute this result to lower transaction costs and more trading activity from informed traders. Hence, it could be the case that characteristics are diminishing because the costs of trading on these characteristics have declined over time.

The regressions in Table 4 use the returns for the method (continuous vs. quintiles) that produces the most statistically significant in-sample returns. This follows the Table 3 specifications that are labeled “Strongest.” We construct a time variable that is equal to 1/100 in January 1926 and increases by 1/100 during each consecutive month in our sample. In the regression, where months after 1926 (time) is used as the only right hand side variable ,time produces a negative slope coefficient that is significant at the 1% level. In Column 2, we add in the post-publication and post-sample indicators and the slope on time is now insignificant, while the out-of-sample and post-publication indicators are similar to those reported in Table 3. Hence, modeling anomaly returns with a discrete publication effect appears to dominate a linear time effect.

Columns 3 and 4 use a post-1993 indicator variable to proxy for the discrete bifurcation of the data that Chordia, et al. coefficient is -12.2% in Column 3, which is consistent with Chordia, et al., however the p-value is 0.255, exceeding the typical bound of significance. When the post-sample and post-publication indicators are included in Column 4, the post-1993 indicator becomes insignificant, while the post-publication variable is negative and significant.

Columns 5 and 6 use spreads as a time-series variable. Spreads are estimated from daily high and low prices using the method of Corwin and Schultz (2012). The average is calculated using all the stocks that are traded in the CRSP universe during the month. The average spread coefficient is positive and insignificant in specifications where it is used alone as an independent variable (Column 5) or with the discrete indications (Column 6). The broad message from these specifications is that simple functions of time are unable to explain post-publication declines in anomaly returns.

Column 7 of Table 4 considers whether or not there is a trend within each sub-period: (i) in-sample, (ii) out-of-sample, but post publication, and (iii) post-publication. A variable that is equal to the number of months since the beginning of the sub-period is used. If the month is not within the sub-period, this variable is assigned a value of zero. This regression includes the indicators for post-sample and post-publication too.

Some readers have posited that quantitative investors are likely to select stocks based on characteristics that have yet to be identified by academic research. If this is the case, we expect that characteristic return predictability will decrease during the original sample period. In Column 7, the in-sample trend is positive but insignificant, showing that characteristic predictability tends to *increase* during in-sample periods. This fails to support the idea that quantitative investor trading reduces predictability before publication.

From Column 7, the post-sample, pre-publication trend is negative, large, and insignificant. If the post-sample slope is solely affected by statistical bias, then we would expect the post-sample dummy to capture an immediate change in the level of expected returns. The negative (albeit insignificant) post-sample but pre-publication slope lends support to the notion that sophisticated traders start trading on characteristics before publication. This biases our slope on our out-of-sample dummy in Table 3 to be too negative, as the inclusion of the out-of-sample trend variable results in the out-of-sample dummy coefficient switching signs from negative to positive.

The post-publication trend is negative and significant. For each 100 months, predictability falls by about 9.5%. This slope "competes" with the post-publication slope, which falls to -26.1% (versus 36.9% in Table 3), but it is still statistically significant. This result tells us that some of the post-publication decline in predictability that we measure in Table 3 captures decay that occurs in the months and years after publication. This suggests that some market participants continue to learn about strategies slowly after the publication date.

Column 8 replaces the random monthly effects estimation with monthly fixed effects estimation. This specification estimates a slightly higher post-sample slope of -18.9% and a post-publication slope that is slightly lower, -32.2%.

Columns 9 and 10 examine whether academic citations proxy for information. For each year post-publication, we use the number of Social Science Citation Index cites for the publication and the cumulative number of citations since publication as right-hand side variables. The citation variables are both negative, but insignificant.

3.3. A Closer Look at Characteristic Dynamics

Table 5 further considers changes in predictability by examining finer post-sample and post-publication partitions. The first column provides results for the entire sample, and in particular whether authors or journals engage in blatant data mining and whether the Table 4 specification is well-specified. The second column considers whether the flow of new capital into portfolios that are formed by more persistent characteristics causes temporarily lower decay. The third column considers whether the larger presence of institutional traders later in the sample causes more recently discovered characteristic predictability to decay more quickly. Some caution is needed in interpreting these tables. These specifications consider decay partitioned into finer periods, but at the cost of larger standard errors.

The regression contains dummy variables that signify the last 12 months of the original sample, the first 12 months out-of sample, and the other out-of-sample months. In addition, the publication dummy is split up into six different variables; one dummy for each of the first five years post-publication, and one dummy for all of the months that are at least five years after publication.

The publication process often takes years. This gives researchers the opportunity to choose where to end their samples with the purpose of reporting stronger results. In the first column of results in Table 5, the coefficient for the last 12 months of the sample period is negative and insignificant, while the coefficient for the first 12 months out-of-sample is positive and insignificant. The slopes on these coefficients are the opposite signs of what we would expect if authors were opportunistically selecting sample end dates.

The out-of-sample but pre-publication coefficient and the coefficients for the first 2 years post-publication are all negative and similar in magnitude (-0.178 to -0.292), while the coefficients for post-publication years 3, 4, and 5 demonstrate the biggest decay in predictability. For this time period, predictability declines to about half of what it is in-sample. The coefficient for all months after the fifth year is -0.307. Hence, characteristics appear to make large declines during years 3-5, and then partially recover thereafter, albeit at a level that is 30% lower than in-sample.

The second column reports results for characteristics that are more persistent. We measure persistence as average monthly portfolio turnover within the extreme quintiles. We define more persistent characteristics as those with portfolio turnover that is below the sample median. For more persistent characteristics, we might expect higher returns right after publication. This is because if new capital flows to a strategy that is persistent, the characteristic stocks will be subject to contemporaneous buying and selling pressures that exacerbate cross-sectional predictability in the short run. Consistent with this idea, we find that more persistent strategies have an increase in portfolio returns following publication—portfolio returns increase by 21.2% versus a decay of 16.3% for the entire sample (reported in Column 1). These findings flip-flop for the second year post publication. Again, some caution is needed since the standard errors tend to be large. Also, market participants may learn about strategies before, right around, and long after publication dates, so testing for an effect right around the publication date may not reflect how information from studies flows into prices.

The third column reports results for characteristics that were published on or after 1999, the median publication year in our sample. We expect that after 1999 more institutional money was devoted to quantitative strategies. The third column fails to find evidence that market reactions to more recent publications are more efficient in the short run. Looking at the first 5 post-publication coefficients, the more recent specification contains less decay for 4 coefficients. In fact, for the first two years post publication, anomaly predictability *increases* instead of decays. In the long-run, the decay eventually becomes more pronounced for the more recent sample. For the longest results (P>60), the post-publication decay is -56.6% compared to -36.6% for the entire sample.

3.4. Publication and Trading in Characteristic Portfolios

If academic publication provides market participants with information that they trade on, then this trading activity is likely to affect not only prices, but also other indicators of trading activity. To test for such effects, we perform monthly ranks based on turnover, dollar value of trading volume, and stock return variance. Turnover is measured as shares traded scaled by shares outstanding, while dollar volume is measured as shares traded multiplied by price. Variance is calculated from monthly stock returns over the preceding thirty-six months. We focus on cross-sectional rankings because these trading activity measures are likely to have market-wide time-trends (e.g, turnover is, on average, higher now as compared to 1930). For each characteristic portfolio, we compute the average ranking among the stocks that enter either the long or the short side of the characteristic portfolio each month. We scale each portfolio-month ranking by the portfolio's average in-sample average ranking and test whether the ranking changes out-of-sample and post-publication.

We also test whether relative shorting increases after a paper is published. With short interest, we do not compute rankings, but instead measure short interest as shares shorted scaled by shares outstanding. Each month, we subtract the average short interest of the long side of each characteristic portfolio from the average short interest of the short side of each characteristic portfolio. The long and short sides are the extreme quintiles based on monthly sorts of each characteristics.

We report the results from these tests in Tables 6. Similar to Table 3, Table 6 estimates a regression akin to Eq. (1); only the dependent variable is either the normalized rank of the trading characteristic or the difference between extreme quintiles in short interest, rather than the normalized return. We cluster our standard errors on characteristic, rather than time, as the traits tend to be persistent. Clustering on time in these regressions produces larger t-statistics.

The results show that variance and dollar volume are significantly higher during the period that is post sample but pre-publication, while turnover is not. Hence, there appears to be an increase in trading among characteristic stocks even before a paper is published, suggesting that information from papers may get to some investors before the paper is published. The effects are greatest with dollar volume; the average dollar volume rank of a firm in a characteristic portfolio is 2.5% higher out-of-sample but pre-publication as compared to in-sample.

The slopes for variance, turnover, and dollar volume are all significantly higher post-publication. Moreover, each of the post-publication coefficients is greater than the out-of-sample coefficient, although the differences are not statistically significant. The coefficients suggest that post-publication, the average rank within the characteristic portfolios increases by 1.2%, 2.5%, and 3.1% for variance, turnover, and dollar volume respectively.

The final column reports the results from the short interest regression. Recall that the short interest variable is the short interest on the short side minus the short interest on the long side. This variable is not scaled by its in-sample mean, so the intercept reflects any difference in shorting before the paper was published. The coefficients in this regression are reported in percent. If investors recognize that characteristic stocks are mispriced, then there should be more shorting on the short side than on the long side. The intercept is 0.109 (p-value =0.045), so the average difference in short interest between the short and long side of the characteristic portfolios is 0.109% before publication. The mean and median levels of short interest in our sample (1976-2011) are 3.45% and 0.77% respectively, so this difference is economically meaningful. This result suggests that some practitioners knew that stocks in the characteristic portfolios were mispriced and traded accordingly. This could be because practitioners were trading on the characteristic or it could reflect practitioners trading on other strategies, which happen to be correlated with the characteristics. As an example, short sellers might evaluate firms individually with fundamental analyses. The resulting positions might be stocks with low book-to-market ratios, high accruals, high stock returns over the last few years, etc., even though short sellers were not directly choosing stocks on these traits.

Post-sample, relative shorting increases by 0.372, although the effect is not statistically significant. Post-publication, relative shorting increases by 0.935% relative to in-sample, and this effect is statistically significant. Economically, the effect represents an increase in relative shorting of nine-fold post-publication relative to in-sample (the intercept is 0.109%, which reflects the in-sample mean). So although some practitioners may have known about these strategies before publication, the results here suggest that publication made the effects more widely known.

3.5. Which Characteristics Decline the Most?

In this section, we ask which characteristics decline the most post publication. Some of the results in the previous tables are consistent with the idea that publication attracts arbitrageurs, which results in smaller characteristic returns post-publication. As we explain in the Introduction, Pontiff (1996, 2006) and Shleifer and Vishny (1997) point out that costs associated with arbitrage can prevent arbitrageurs from fully eliminating mispricing. By this logic, characteristic portfolios that consist more of stocks that are costlier to arbitrage (e.g., smaller stocks, less liquid stocks, stocks with more idiosyncratic risk) should decline less post-publication. If anomalous returns are the outcome of rational asset pricing, we would not expect the post-publication decline to be related to arbitrage costs. Keep in mind that our returns are scaled by the in-sample mean, so a decline implies that the returns shrink towards zero; characteristics that produce negative returns have an increase in returns, while characteristics that produce positive returns experience a decrease in returns.

Previous papers in the limited arbitrage literature relate arbitrage costs to differences in returns across stocks within a characteristic portfolio (see Pontiff, 2006; Duan, Hu, and McLean, 2010; and McLean, 2010). In contrast, we estimate differences across characteristic portfolios. Another difference between our test and the previous literature is that previous studies assume rational expectations of the informed traders throughout the entire sample. In this framework, the informed trader had knowledge of the characteristic before (and after) the publication date. Our current test assumes that publication provides information to some sophisticated traders which, in turn, causes decay in return-predictability post-publication. This test is a better test of costly arbitrage, since some rational models predict a relation between predictability and idiosyncratic risk (for example, Vayanos and Wooley, 2012).

To create the costly arbitrage variables, we perform monthly ranks of all of the stocks in CRSP based on three transaction cost measures: size, dollar volume, and bid-ask spreads, and two holding costs measures: idiosyncratic risk and a dividend-payer dummy. Idiosyncratic risk is a holding cost since idiosyncratic risk is incurred every period the position is open (Pontiff, 1996 and 2006). We compute monthly idiosyncratic risk by regressing daily returns on the twelve value-weighted industry portfolios from Ken French's website. For each day, we square that day's residuals and, to correct for autocorrelation, add two times the product of that day's and the previous day's residual. The monthly measure is created by adding up the daily data from a given month.

Pontiff (1996 and 2006) explains that dividends mitigate holding costs since they decrease the effective duration of the position. The intuition is that dividends reduce the future amount of capital devoted to the arbitrage, thus reducing the cumulative holding costs.[9] We use a dummy variable equal to unity if a firm paid a dividend and zero otherwise. Firm size is measured as the market value of equity. Average monthly spreads are estimated from daily high and low prices using the method of Corwin and Schultz (2012). Stocks with high dollar volume and low spreads are more liquid, and should therefore be less costly to arbitrage, as should larger stocks.

For each characteristic-month, we compute the average ranking for each trait among the stocks that are in either the long or the short side of the characteristic portfolio. We create a characteristic-month average for each trait, and then take an average of the monthly averages to

[9] This result assumes that the level of the mispricing is unaffected by the dividend payout. The result also holds for the case where the level of mispricing is influenced by mispricing, but the relative mispricing is not. For proof, see the appendix in Pontiff (2006).

come up with a single in-sample-characteristic average. We measure the traits in-sample, as it could be the case that trading caused by publication has an effect on the variables.

We also consider other variables that we expect to be related to decay in predictability—Sharpe ratio, t-statistic, and R^2. The Sharpe ratio is a popular measure of portfolio performance and we expect it to proxy for the attractiveness of the strategy to a professional trader. We measure the Sharpe ratio by scaling each strategy's in-sample mean monthly return by its in-sample monthly return standard deviation. The t-statistic is simply the t-statistic that we compute for the in-sample portfolio return. We expect this variable to communicate the confidence of an investor with respect to the predictability associated with the characteristic. R^2 is a measure of the systematic risk associated with characteristic. R^2 is estimated in the regressions described in Section 1 in which we regress monthly stock returns on each trait (e.g., size, trading volume). The R^2 for each characteristic is the average R^2 from the in-sample, monthly regressions. We expect that characteristics that are associated with greater R^2 are more likely to display predictability that is the outcome of an asset pricing model, and thus, less likely to decay.

In Table 7, the dependent variable is the normalized characteristic return, limited to post-publication months. The results show that there are significantly larger post-publication declines for characteristic portfolios with lower arbitrage costs. Characteristic portfolios that on average consist of larger stocks, stocks with smaller bid ask spreads, and stocks with high dollar volume decline more. Characteristic portfolios that on average consist of stocks with lower idiosyncratic volatility and stocks that pay dividends also decline more post-publication. Sharpe ratios, t-statistics, and systematic risk do not exhibit a significant relation to the decay in a characteristic's stock return-predictability.

3.6. Which Arbitrage Costs Matter Most?

In the previous section, the results show that consistent with costly arbitrage, size, spreads, dollar volume, idiosyncratic risk, and dividends, all have statistically significant effects on a characteristic's post-publication decay. In this section, we try to determine which of these variables has the greatest effect.

In Table 8, the first regression includes only dividends and idiosyncratic risk and the two holding cost variables. We see that idiosyncratic risk makes the effect of dividends insignificant, while the idiosyncratic risk coefficient is positive and significant, as it was in the previous table. In the next three regressions, we add in each of the transaction cost variables, and find that each of these is insignificant in the presence of idiosyncratic risk and dividends. Throughout all of the regressions in Table 8, idiosyncratic risk is the only factor that has a significant effect on the post-publication decline. This result is consistent with Pontiff (2006), who reviews a literature that relates arbitrage costs to alpha across stocks within characteristic portfolios. This literature finds that characteristic return-predictability is stronger in stocks with high idiosyncratic risk, even more so than stocks with high transaction costs.

3.7. The Effects of Publication on Correlations Access Characteristic Portfolios

In this section, we study the effects that publication has on correlations across characteristic portfolios.

Simple correlations between characteristic-based portfolios are lower than we expected. The mean pairwise correlation in our study is 0.050 and the median is 0.047. These levels of correlation imply even lower covariance than Green, et al. (2012), who show that R^2 between characteristic returns ranges from 6% to 20%. Our results, and those in Green, et al., suggest that multi-characteristic investing is likely to enjoy substantial diversification benefits.

If characteristics reflect mispricing and if mispricing has common causes (e.g., investor sentiment), then we might expect in-sample characteristic portfolios to be correlated with other in-sample characteristic portfolios. This effect is shown in Lee, Shleifer, and Thaler (1991) Barberis and Shleifer (2003), Barberis, Shleifer and Wurgler (2005). If publication causes arbitrageurs to trade in a characteristic, then it could cause a characteristic portfolio to become more highly correlated with other published characteristics and less correlated with unpublished characteristics.

In Table 9, each characteristic portfolio's return is regressed on an equal-weighted portfolio of all of the other characteristics that are pre-publication and post-publication. We include a dummy variable that indicates whether the characteristic is post-publication, and interactions between this dummy variable and the pre-publication and post-publication characteristic portfolios returns. As before, the monthly characteristic returns are scaled by their in-sample mean.

The results show that while a characteristic is pre-publication, its returns are significantly related to the returns of other pre-publication characteristic portfolios. The slope coefficient is 0.634 and its p-value is 0.00. In contrast, the slope coefficient or beta of a pre-publication portfolio with portfolios that are post-publication is 0.025. These findings are consistent with Lee, Shleifer, and Thaler (1991) and Barberis and Shleifer (2003).

The interactions show that once a characteristic is published, its returns are less correlated with the returns of other pre-publication characteristic portfolios and more correlated with the returns of other post-publication characteristic portfolios. The slope on the interaction of the post-publication dummy with the return of the portfolio consisting of in-sample characteristics is

-0.555 (p-value = 0.00). Hence, once a characteristic is published, the correlation of its returns with the returns of other yet-to-be-published characteristic returns virtually disappears, as the overall coefficient reduces to 0.634 – 0.555 = 0.079. The slope on the interaction of the post-publication dummy and the returns of the other post-publication characteristics is 0.399 (p-value = 0.00), so there is a significant correlation between the portfolio returns of a published characteristic and other published characteristics.

4. Conclusions

This paper studies 82 characteristics that have been shown to explain cross-sectional stock returns in peer reviewed finance, accounting, and economics journals. We compare each characteristic's return predictability over three distinct periods: (i) within the original study's sample period; (ii) outside of the original sample period but before publication; and (iii) post publication.

We use the period during which a characteristic is outside of its original sample but still pre-publication to estimate an upper bound on the effect of statistical biases. We estimate the effect of statistical bias to be about 10%. This is an upper bound, because some investors could learn about a predictor while the study is still a working paper. The average characteristic's return decays by about 35% post-publication. We attribute this post-publication effect both to statistical biases and to arbitrageurs who observe the finding. Combining this finding with an estimated statistical bias of 10% implies a publication effect of about 25%.

Several of our findings support the contention that cross-sectional predictability is the result of mispricing. First, variance, turnover, dollar volume, and short interest all increase significantly in characteristic portfolios post-publication. This is consistent with the idea that academic research draws attention to characteristic strategies, which results in more trading in characteristic-portfolio stocks. Second, characteristic portfolios that consist more of stocks that are costly to arbitrage decline less post-publication. This is consistent with the idea that arbitrage costs limit arbitrage and protect mispricing. Finally, we find that before a characteristic is featured in an academic publication, the returns of the corresponding characteristic portfolio are highly correlated with the returns of other portfolios of yet-to-be-published characteristic stocks. This is consistent with behavioral finance models of comovement. After publication, a characteristic portfolio's correlation with yet-to-be-published characteristic portfolios returns decreases and its correlation with already-published characteristic portfolios returns increases.

References

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, "The cross-section of volatility and expected returns," *Journal of Finance* 61, 259-299.

Amihud, Yakov, 2002, "Illiquidity and stock returns: Cross-section and time-series effects," *Journal of Financial Markets* 5, 31-56.

Amihud, Yakov, and Haim Mendelson, 1986, "Asset pricing and the bid–ask spread," *Journal of Financial Economics* 17, 223–249.

Anand, Amber, Paul Irvine, Andy Puckett, and Kumar Venkataraman, forthcoming, "Performance of Institutional Trading Desks: An Analysis of Persistence in Trading Costs," *Review of Financial Studies*.

Asness, Clifford S., Tobias J. Moskowitz, and Lasse H. Pedersen, 2009, "Value and momentum everywhere," Working paper, New York University.

Barberis, Nicholas, and Andrei Shleifer, 2003, "Style investing," *Journal of Financial Economics* 68, 161-199.

Barberis, Nicholas, Andrei Shleifer, and Jeffrey Wurgler, 2005, "Comovement," *Journal of Financial Economics* 75, 283-317.

Bali, Turan G., and Nusret Cakici, 2008, "Idiosyncratic Volatility and the Cross Section of Expected Returns," *Journal of Financial and Quantitative Analysis* 43, 29-58.

Bali, Turan G., Nusret Cakici, and F. Robert Whitelaw, 2011, "Maxing out: Stocks as lotteries and the cross-section of expected returns," *Journal of Financial Economics* 99, 427-446.

Banz, Rolf W., 1981, "The relationship between return and market value of common stocks," *Journal of Financial Economics* 9, 3-18.

Barberis, Nicholas, Andrei Shleifer, and Jeffrey Wurgler, 2005, "Comovement," *Journal of Financial Economics* 75, 283-317.

Blume, Marshal E. and Frank, Husic, 1973, "Price, beta, and exchange listing," *Journal of Finance* 28, 283-299.

Bonferroni, C. E. "Il calcolo delle assicurazioni su gruppi di teste." In Studi in Onore del Professore Salvatore Ortu Carboni. Rome: Italy, pp. 13-60, 1935.

Boyer, Brian, 2011, "Style-related Comovement: Fundamentals or Labels?," *Journal of Finance* 66, 307-332.

Brennan, Michael J., 1970, "Taxes, market valuation, and corporate financial policy," *National Tax Journal* 23, 417–427.

Chordia, Tarun, Avanidhar Subrahmanyam, and Qing Tong, 2011, "Trends in the cross-section of expected stock returns," Working paper, Emory University.

Cochrane, John H., 1999, "Portfolio Advice for a Multifactor World," *Economic Perspectives* Federal Reserve Bank of Chicago 23, 59-78.

Corwin, Shane A., and Paul Schultz, 2012, "A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices," *Journal of Finance* 67, 719-759.

Drake, Michael S., Lynn Rees, and Edward P. Swanson, 2011, "Should investors follow the prophets or the Bears? Evidence on the use of public information by analysts and short sellers," *Accounting Review* 82, 101-130.

Duan, Ying, Gang Hu, and R. David McLean, 2009, "When is Stock-Picking Likely to be Successful? Evidence from Mutual Funds," *Financial Analysts Journal* 65, 55-65.

Duan, Ying, Gang Hu, and R. David McLean, 2009, "Costly Arbitrage and Idiosyncratic Risk: Evidence from Short Sellers," Journal *of Financial Intermediation* 19, 564-579.

De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990, "Noise trader risk in financial markets," *Journal of Political Economy* 98, 703–738.

Dichev, Ilia D., 1998, "Is the Risk of Bankruptcy a Systematic Risk?," *The Journal of Finance* 53, 1131-1148.

Dichev, Ilia D., and Joseph D. Piotroski, 2001, "The long-run stock returns following bond ratings changes," *Journal of Finance* 56, 173-203.

Fama, Eugene F., 1976, *Foundations of Finance*, Basic Books, New York (New York).

Fama, Eugene F., 1991, "Efficient capital markets: II," *Journal of Finance* 46, 1575-1617.

Fama, Eugene F., and French, Kenneth R., 1992, "The cross-section of expected stock returns," *Journal of Finance* 47, 427-465.

Fama, Eugene F., and James D. MacBeth, 1973, "Risk, return, and equilibrium: Empirical tests," *Journal of Political Economy* 81, 607-636.

Franzoni, Francesco and Jose M. Marin, 2006, "Pension Plan Funding and Stock Market Efficiency," *Journal of Finance* 61, 921-956.

Greenwood, Robin. 2008, "Excess Comovement of Stock Returns: Evidence from Cross-sectional Variation in Nikkei 225 Weights," *Review of Financial Studies* 21, 1153-1186.

Goldstein, Michael, Paul Irvine, Eugene Kandel, and Zvi Weiner, 2009, “Brokerage commissions and Institutional trading patterns,” *Review of Financial Studies* 22, 5175-5212

Hanson, Samuel G., and Adi Sunderam, 2011, “The growth and limits of arbitrage: Evidence from short interest,” Working paper, Harvard Business School.

Harvey, Campbell R., Yan Liu, and Heqing Zhu, 2013, “… and the cross-section of expected returns,” unpublished working paper, Duke University

Haugen, Robert A, and Nardin L. Baker, 1996, “Commonality in the determinants of expected stock returns,” *Journal of Financial Economics* 41, 401-439.

Heckman, James, 1979, "Sample selection bias as a specification error," *Econometrica* 47, 153–161.

Hedges, Larry V., 1992, “Modeling publication selection effects in meta-analysis,” *Statistical Science* 7, 246-255.

Hwang, Byoung-Hyoun and Baixiao Liu, 2012, “Which anomalies are more popular? And Why?, Purdue working paper.

Goyal, Amit, and Ivo Welch, 2008, “A comprehensive look at the empirical performance of equity premium prediction,” *Review of Financial Studies* 21, 1455-1508.

Green, Jeremiah, John R. M. Hand, and X. Frank Zhang, 2012, “The Supraview of Return Predictive Signals,” Working paper, Pennsylvania State University.

Grundy, Bruce D. and Spencer J. Martin, J. Spencer, 2001, "Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing," *Review of Financial Studies* 14, 29-78.

Jegadeesh, Narasimhan and Sheridan Titman, 1993, “Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency,” *Journal of Finance* 48, 65-91.

Jegadeesh, Narasimhan, and Sheridan Titman, 2001, “Profitability of momentum strategies: An evaluation of alternative explanations,” *Journal of Finance* 56, 699-720.

Jegadeesh, Narasimhan and Sheridan Titman, 2011, “Momentum,” Working paper, Emory University.

LeBaron, Blake, 2000, “The Stability of Moving Average Technical Trading Rules on the Dow Jones Index,” *Derivatives Use, Trading and Regula*tion 5, 324-338.

Leamer, Edward E., 1978, *Specification Searches: Ad Hoc Inference with Nonexperimental Data*, New York: John Wiley & Sons.

Lee, Charles, Andrei Shleifer, and Richard Thaler, 1991, Investor sentiment and the closed-end fund puzzle, *Journal of Finance* 46, 75-109.

Lewellen, Johnathan, 2011, "The cross-section of expected returns," Working paper, Tuck School of Business, Dartmouth College.

Lo, Andrew, and Craig MacKinlay, 1990, "Data-snooping biases in tests of financial asset pricing models," *Review of Financial Studies* 3, 431-467.

McLean, R. David, 2010, "Idiosyncratic risk, long-term reversal, and momentum," *Journal of Financial and Quantitative Analysis*, 45, 883-906.

Michaely, Roni, Richard Thaler, and Kent L. Womack, 1995, "Price reactions to dividend initiations and omissions: Overreaction or drift?," *Journal of Finance* 50, 573-608.

Milian, Jonathan A., 2013, "Overreacting to a History of Underreaction?," working paper, Florida International University

Mittoo, Usha, and Rex Thompson, 1990, "Do capital markets learn from financial economists?," working paper, Southern Methodist University

Moskowitz, Tobias, Yao Hua Ooi, and Lasse H. Pedersen, 2010, "Time series momentum," Working paper, New York University.

Muth, John F., 1961, "Rational Expectations and the Theory of Price Movements," *Econometrica* 29, 315–335.

Naranjo, Andy, M. Nimalendran, and Mike Ryngaert, 1998, "Stock returns, dividend yields and taxes," *Journal of Finance* 53, 2029-2057.

Pontiff, Jeffrey, 1996, "Costly arbitrage: Evidence from closed-end funds," *Quarterly Journal of Economics* 111, 1135-1151.

Pontiff, Jeffrey, 2006, "Costly arbitrage and the myth of idiosyncratic risk," *Journal of Accounting and Economics* 42, 35-52.

Ritter, Jay R., 1991, "The long-run performance of initial public offerings," *Journal of Finance* 46, 3-27.

Schwert, G. William, 2003, "Anomalies and market efficiency," Handbook of the Economics of Finance, edited by G.M. Constantinides, M. Harris and R. Stulz, Elsevier Science B.V.

Sharpe, William F., 1964, "Capital asset prices: A theory of market equilibrium under conditions of risk," *Journal of Finance* 19, 425-442

Shleifer, Andrei, and Robert W. Vishny, 1992, "Liquidation Values and Debt Capacity: A Market Equilibrium Approach," *Journal of Finance* 47, 1343-1366

Sloan, Richard G., 1996, "Do stock prices fully reflect information in accruals and cash flows about future earnings?," *Accounting Review* 71, 289-315

Stein, Jeremy C, 2009, "Presidential address: Sophisticated investors and market efficiency," *Journal of Finance* 64, 1517-1548.

Sullivan, Ryan, Allan Timmermann, and Halbert White, 2001, Dangers of data mining: The cse of calendar effects in stock returns, *Journal of Econometrics* 105, 249-286.

Treynor, Jack, and Fischer Black, 1973, How to Use Security Analysis to Improve Portfolio Selection," *Journal of Business* 46, 66-86.

Vayanos, Dimitri and Paul Woolley, forthcoming, "An institutional theory of momentum and reversal," *Review of Financial Studies*

Wahal, Sunil, and M. Deniz Yavuz, 2009, "Style Investing, Comovement and Return Predictability," Working Paper, Arizona State University.

Table 1. Summarizing the characteristics in and out-of-sample.

This table reports summary statistics for the 82 different return-predicting characteristics studied in this paper. The second column reports the number of characteristics that fit the criteria described in the first column, and that number as a percentage of the total number of characteristics in parentheses. Each continuous characteristic is estimated twice; once using a continuous variable and once using a portfolio variable that is equal to 1 if the stock is in the buy quintile, -1 if the stock is in the sell quintile, and zero otherwise.

Total number of return-predicting characteristics:	82
Mean year of publication of return-predicting characteristic	1999.3
Median year of publication of return-predicting characteristic	2001.0
Characteristics from Finance journals	61 (74%)
Characteristics from Accounting journals	19 (24%)
Characteristics from Economics journals	2 (2%)
Characteristics that are binary (e.g., credit rating downgrade):	15 (18%)
Characteristics that are continuous (e.g., size):	67 (82%)
Characteristics that we could replicate in-sample:	72 (88%)
Replicated, continuous characteristics that are stronger as a continuous variable	36 (50%)
Replicated, continuous characteristics that are stronger as a quintile portfolio variable	36 (50%)

Table 2. Summary of the out-of-sample and post-publication return predictability of the characteristics

This table reports summary statistics for the out-of-sample and post-publication return predictability of the 82 replicated return-predicting characteristics used in this paper. To be included in these tests the characteristic had to both be replicated in-sample and have at least 36 observations in the out-of-sample or post-publication measurement period. Each continuous characteristic is estimated twice; first using a continuous variable and then using a portfolio variable that is equal to 1 if the stock is in the long quintile, -1 if the stock is in the sell quintile, and zero otherwise. We estimate the in-sample mean portfolio return for each characteristic and then scale each monthly portfolio return by the in-sample mean. We then take averages of the scaled coefficients during the out-of-sample and post-publication periods for each characteristic, average the averages across characteristics, and report these statistics in the table below. A value of 1 means the average characteristic-portfolio is the same during the in-sample and out-of-sample period. A value of less than 1 (greater than 1) means the return-predictability declined (increased) out-of-sample. The t-statistic tests whether the reported value is equal to 1.

Panel A: Continuous	Out of Sample but Pre-Publication	Post Publication
Average Scaled Coefficient	0.78	0.51
Standard Deviation	1.22	0.81
t-statistic	-1.40	-4.91
Percentage <1	63%	82%
Anomalies Included	60	66

Panel B: Quintile	Out of Sample but Pre-Publication	Post Publication
Average Scaled Coefficient	0.90	0.47
Standard Deviation	1.29	1.20
t-statistic	-0.58	-3.62
Percentage <1	57%	68%
Anomalies Included	60	66

Panel C: Strongest	Out of Sample but Pre-Publication	Post Publication
Average Scaled Coefficient	0.77	0.51
Standard Deviation	1.16	0.97
t-statistic	-1.56	-4.02
Percentage <1	65%	78%
Anomalies Included	60	66

Table 3. Regression of long-short characteristic based returns on time indicator variables.

This regression models the return-predictability of each characteristic over time, relative to its original sample period and publication date. Each monthly coefficient is scaled by the characteristic's mean coefficient during the study's original sample period. This scaled variable is the dependent variable, and it is regressed on dummy variables that signal whether the month is out of sample but pre-publication and post-publication. *Post Sample* equals 1 if the month is after the end of the sample, but pre-publication. *Post Publication* is equal to 1 if the month is after the official publication date. *Post SSRN* is equal to 1 if the month is either after the official publication date or if the month is after the first month that the study is available on SSRN. All indicator variables are equal to 0 if they are not equal to 1. We also include lagged values measured over the last 1 month, and the sum of returns over the last 6 and 12 months. The regression labeled *Continuous* uses Fama-MacBeth slopes that are generated using continuous variables. The regression labeled *Quintile*s uses Fama-MacBeth slopes from long-short quintile portfolios. The regression labeled *Strongest* uses either *Continuous* or *Quintiles* returns, depending on which method produces stronger in-sample statistical significance. P-values are in brackets for the hypothesis that the coefficient equals 0. In the three bottom rows, we report p-values from Chi-Squared tests of the hypotheses that the post-sample and post-publication coefficients are equal and that each of the coefficients is equal to -1. The regressions include random effects. Standard errors are clustered on time.

Table 3: (Continued)

	Quintiles (Raw Returns)	Continuous	Quintiles	Strongest	Strongest	Strongest	Strongest	Strongest
Post Sample	-0.052	-0.202	-0.015	-0.097	-0.102	-0.105	-0.104	-0.105
	(0.041)	(0.119)	(0.124)	(0.112)	(0.119)	(0.111)	(0.113)	(0.114)
	[0.203]	[0.090]	[0.902]	[0.386]	[0.389]	[0.345]	[0.359]	[0.345]
Post Publication	-0.173	-0.422	-0.347	-0.369		-0.343	-0.324	-0.280
	(0.053)	(0.095)	(0.112)	(0.093)		(0.094)	(0.099)	(0.094)
	[0.001]	[0.000]	[0.002]	[0.000]		[0.000]	[0.001]	[0.000]
Post SSRN					-0.343			
					(0.079)			
					[0.000]			
1-Month Return						0.134		
						(0.027)		
						[0.000]		
6-Month Return							0.030	
							(0.009)	
							[0.001]	
12-Month Return								0.024
								(0.006)
								[0.000]
Constant	0.428	0.986	1.040	0.982	0.961	0.851	0.805	0.805
	(0.066)	(0.071)	(0.084)	(0.070)	(0.062)	(0.068)	(0.077)	(0.077)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
R^2	0.000	0.000	0.000	0.000	0.000	0.020	0.020	0.011
Obs.	37,676	37,676	37,676	37,676	37,676	37,676	37,676	37,676
PP-PS=0	0.098	0.073	0.010	0.020	0.050	0.050	0.070	0.150
PS=-1	NA	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PP=-1	NA	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 4: Time Trend vs. Publication Effect

This regression models the return-predictability of each characteristic over time and relative to the characteristic's original sample period and publication date. We use either continuous variables or quintile portfolios based on the variables to generate the coefficient, depending on which method has stronger in-sample statistical significance. Each monthly coefficient is scaled by the characteristic's mean coefficient during the study's original sample period. This scaled variable is the dependent variable, and it is regressed on dummy variables that signal whether the month is out of sample but pre-publication and post-publication. *Post Sample* equals 1 if the month is after the end of the sample, but pre-publication. *Post Publication* is equal to 1 if the month is after the official date publication date. *Time* is the number of months (in hundreds) post-Jan. 1926. *Time Post-Publication* is the number of months (in hundreds) post-publication. The time coefficients and standard errors are reported in percent. *Post-1993* is equal to1 if the year is greater than 1993 and 0 otherwise. All indicator variables are equal to 0 if they are not equal to 1. *I-Time* is the number of months (in hundreds) after the beginning of the original sample. If the observation falls outside the original sample, I-Time is set to 0. *S-Time* is the number of months (in hundreds) after the end of the original sample, but before publication. If the observation falls outside this range, S-Time is set to 0. *P-Time* is the number of months (in hundreds) after the publication date. If the observation is before the publication date, P-Time is set to 0. *Average Spread* is the average estimated bid-ask spread as a percentage of the share price of all CRSP stocks. *Citations* is the number of Social Science Citation Index in the current year, and *Sum Cites* is the accumulation of Citations starting at the publication date through the current year. Fama-MacBeth slopes from either continuous variables or long-short extreme quintiles are used based on which return has stronger in-sample statistical significance. P-values are in brackets for the hypothesis that the coefficient equals 0. In the three bottom rows, we report p-values from Chi-Squared tests of the hypotheses that the post-sample and post-publication coefficients are equal and that each of the coefficients is equal to -1. The regressions include random effects. Standard errors are clustered on time.

Table 4: (Continued)

	1	2	3	4	5	6	7	8	9	10
S		-0.029		-0.069		-0.152	0.040	-0.189	-0.154	-0.155
		0.119		0.128		0.117	0.197	0.122	0.114	0.114
		0.806		0.588		0.194	0.841	0.121	0.178	0.175
P		-0.365		-0.425		-0.441	-0.261	-0.322	-0.363	-0.372
		0.094		0.098		0.094	0.105	0.103	0.101	0.105
		0.000		0.000		0.000	0.013	0.002	0.000	0.000
Time	-0.058	0.003								
	0.019	0.000								
	0.002	0.900								
Post 1993			-0.122	0.099						
			0.107	0.122						
			0.255	0.419						
Average					22.915	45.307				
Spread					32.366	32.108				
					0.479	0.158				
I-Time							0.014			
							0.019			
							0.447			
S-Time							-0.392			
							0.419			
							0.349			
P-Time							-0.095			
							0.048			
							0.046			
Citations									-0.003	
									0.003	
									0.373	
Sum Cites										-0.000
										0.000
										0.462
Constant	1.037	0.952	0.924	0.951	0.737	0.740	0.956	0.972	0.982	0.982
	0.087	0.151	0.072	0.074	0.176	0.172	0.048	0.036	0.696	0.696
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.000
N	37,680	37,680	37,680	37,680	37,680	37,680	37,680	37,680	37,680	37,680
Month FE?	No	No	No	No	No	No	No	Yes	No	No

Table 5: A closer look at the effects of post-sample and post-publication

This regression models the return-predictability of each characteristic relative to its original sample period and publication date. Either continuous variables or quintile portfolios are used to generate the monthly portfolio-coefficient, depending on which method has stronger in-sample statistical significance. Each monthly coefficient is scaled by the characteristic's mean coefficient during the study's original sample period. This scaled variable is the dependent variable, and it is regressed on dummy variables that signal the position of the month in time relative to the study's original sample period and the study's publication date. *Last 12* is equal to 1 if the month is during the last year of the original sample period. *First 12* is equal to 1 during the first 12 months subsequent to the end of the original sample period. *Post First 12* equals 1 if the month is after the end of the sample and after the first 12 months subsequent to the end of the original sample period, but pre-publication. *P1-12* is equal to 1 during the first 12 months after the official date publication date. *P13-24* is equal to 1 during months 13-24 after the publication date. *P25-36* is equal to 1 during months 25-36 after the publication date. *P37-48* is equal to 1 during months 37-48 after the publication date. *P49-60* is equal to 1 during months 49-60 after the publication date. *P>60* is equal to 1 during all months after 60 months after the publication date. All indicator variables are equal to 0 if they are not equal to 1. The regressions include random effects. The first row is the coefficient estimate. The second row is the time clustered standard error. The third row is the p-value. The first regression includes all observations. The second regression presents results for characteristics that form portfolios with the least turnover. The third regression presents results for characteristics that were published during or after 1999.

Table 5: (Continued)

	All	More Persistent	More Recent
Last 12	-0.078	-0.320	0.178
	0.215	0.267	0.314
	0.718	0.230	0.571
First 12	0.306	0.412	1.182
	0.217	0.307	0.337
	0.158	0.181	0.000
Post-First 12	-0.305	-0.296	-0.627
	0.121	0.157	0.136
	0.012	0.060	0.000
P1-12	-0.163	0.212	0.572
	0.218	0.350	0.206
	0.455	0.545	0.006
P13-24	0.006	-0.169	0.356
	0.226	0.380	0.358
	0.978	0.658	0.320
P25-36	-0.517	-1.029	-0.161
	0.225	0.400	0.360
	0.021	0.010	0.654
P37-48	-0.617	-0.581	-0.770
	0.237	0.347	0.262
	0.009	0.094	0.003
P49-60	-0.435	-0.604	-0.352
	0.221	0.363	0.259
	0.049	0.096	0.174
P>60	-0.366	-0.215	-0.566
	0.095	0.208	0.206
	0.000	0.300	0.006
Constant	0.963	0.941	1.026
	0.063	0.096	0.069
	0.000	0.000	0.000
R^2	0.001	0.002	0.003
N	37,680	17,082	21,619

Table 6:

Regression of relative trading differences for portfolio stocks

This regression models the dynamics of the traits of stocks in each characteristic portfolio, relative to the characteristic's original sample period and publication date. For each stock during each month in every long-short (highest and lowest quintiles) characteristic portfolio, we compute its percentile ranking relative to all stocks based on monthly variance (return squared), monthly share turnover (shares traded scaled by shares outstanding), and monthly dollar value of volume (shares traded multiplied by price). We then generate a monthly stock-average for each characteristic. Each monthly average is scaled by the mean of the monthly averages during the characteristic's original sample period. For short interest (shares shorted scaled by shares outstanding), we take the average short interest in the short quintile for each characteristic, and subtract from it the average short interest in the long quintile. The short interest findings are reported in percent. *Post Sample* is equal to 1 if the month is after the end of the sample, but pre-publication. *Post Publication* is equal to 1 if the month is after the official date of the journal that published the study. The regressions include random effects. Standard errors are clustered on time and reported in parentheses. P-values are in brackets for the hypothesis that the coefficient equals 0. The bottom row reports p-values from a test of whether the post-sample slope coefficient is equal to the post-publication slope coefficient.

	Variance	**Turnover**	**Dollar Volume**	**Short Interest**
Post Sample	0.006	0.010	0.025	0.372
	(0.004)	(0.015)	(0.014)	(0.270)
	[0.085]	[0.507]	[0.061]	[0.169]
Post Publication	0.012	0.025	0.031	0.935
	(0.004)	(0.013)	(0.012)	(0.450)
	[0.001]	[0.049]	[0.013]	[0.038]
Constant	0.999	1.003	0.999	0.109
	(0.001)	(0.0.003)	(0.004)	(0.054)
	[0.000]	[0.000]	[0.000]	[0.045]
R^2	0.010	0.009	0.007	0.009
Obs.	38,694	38,694	38,620	26,758
PP=PS	0.130	0.395	0.645	0.091

Table 7: Portfolio characteristics and the persistence return predictability

This regression tests whether different stock-traits are associated with a characteristics' change in return-predictability post-publication. The sample is limited to post-publication months. The dependent variable is the monthly long-short return of a characteristic scaled by its monthly in-sample mean. We use either continuous variables or quintile portfolios based on the variables to generate the characteristic's monthly return, depending on which method has stronger in-sample statistical significance. The independent variables reflect various traits of the stocks in each characteristic portfolio. Each characteristic portfolio contains stocks in the highest and lowest quintiles, based on a contemporaneous ranking of the characteristic (e.g., momentum or accruals). To measure the traits of the stocks within the portfolio, we do the following: we first rank all of the stocks in CRSP on the trait (e.g., size or turnover), assigning each stock a value between 0 and 1 based on its size rank; we then take the average rank of all of the stocks in the characteristic portfolio for that month; tfinally, for each characteristic, we take an average of its portfolio's monthly trait averages, using all of the months that are in-sample. Hence, in the size regression reported in the first column, the independent variable is the average market value rank of the stocks in the characteristic portfolio during the in-sample period for the characteristic. Average monthly spreads are estimated from daily high and low prices using the method of Corwin and Schultz (2012). Dollar volume is shares traded multiplied by stock price. Idiosyncratic risk is daily stock return variance, which is orthogonal to the market and industry portfolios. Dividends is a dummy equal to 1 if the firm paid a dividend during the last year and zero otherwise. Sharpe is the in-sample ratio of returns to standard deviation of returns. T-statistic is the in-sample t-statistic. R^2 is the average in-sample R^2 from a regression of monthly stock returns on the characteristic. The regressions include random effects. Standard errors are clustered on time, and are reported in parentheses. P-values are in brackets for the hypothesis that the coefficient equals 0.

	Size	**Spreads**	**Dollar Volume**	**Idio. Risk**	**Dividends**	**Sharpe**	**T-Stat.**	**R^2**
Coefficient	-1.490	0.999	-1.671	4.054	-1.381	0.129	0.002	-3.906
	(0.598)	(0.592)	(0.642)	(0.855)	(0.352)	(0.125)	(0.013)	(4.524)
	[0.013]	[0.092]	[0.009]	[0.000]	[0.000]	[0.301]	[0.900]	[0.388]
Constant	1.442	0.176	1.380	-1.420	1.439	0.560	0.589	0.648
	(0.339)	(0.262)	(0.296)	(0.430)	(0.233)	(0.101)	(0.117)	(0.098)
	[0.000]	[0.502]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
R^2	0.000	0.000	0.001	0.000	0.001	0.000	0.000	0.000
Obs.	9,823	9,823	9,823	9,823	9,823	9,823	9,823	9,823

Table 8: Portfolio Characteristics and Post-Publication Return Decay:

Holding Costs vs. Transaction Costs

This regression tests whether different stock-traits are associated with a characteristic's change in return-predictability post-publication. The sample is limited to post-publication months. The dependent variable is the monthly long-short return of a characteristic scaled by its monthly in-sample mean. We use either continuous variables or quintile portfolios based on the variables to generate the characteristic's monthly return, depending on which method has stronger in-sample statistical significance. The independent variables reflect various traits of the stocks in each characteristic portfolio. Each characteristic portfolio contains stocks in the highest and lowest quintiles, based on a contemporaneous ranking of the characteristic (e.g., momentum or accruals). To measure the traits of the stocks within the portfolio, we do the following: we first rank all of the stocks in CRSP on the trait (e.g., size or turnover), assigning each stock a value between 0 and 1 based on its size rank; we then take the average rank of all of the stocks in the characteristic portfolio for that month; finally, for each characteristic, we take an average of its portfolio's monthly trait averages, using all of the months that are in-sample. Size is the average market value rank of the stocks in the characteristic portfolio during the in-sample period for the characteristic. Average monthly spreads are estimated from daily high and low prices using the method of Corwin and Schultz (2012). Dollar volume is shares traded multiplied by stock price. Idiosyncratic risk is daily stock return variance, which is orthogonal to the market and industry portfolios. Dividends is a dummy equal to 1 if the firm paid a dividend during the last year and zero otherwise. The regressions include random effects. Standard errors are clustered on time, and are reported in parentheses. P-values are in brackets for the hypothesis that the coefficient equals 0.

Idio Risk	3.900	3.957	4.810	3.164
	(1.630)	(1.810)	(1.576)	(1.747)
	[0.017]	[0.029]	[0.002]	[0.070]
Size		0.047		
		(1.086)		
		[0.965]		
Spreads			-1.086	
			(1.238)	
			[0.380]	
Dollar Vol.				-0.138
				(0.667)
				[0.836]
Dividends	-0.083	-0.086	-1.285	-0.520
	(0.663)	(0.694)	(0.898)	(1.383)
	[0.901]	[0.901]	[0.152]	[0.707]
Intercept	-1.294	-1.347	-0.281	-0.804
	(1.183)	(1.443)	(0.724)	(0.793)
	[0.274]	[0.351]	[0.697]	[0.311]
R^2	0.002	0.002	0.002	0.002
N	9,823	9,823	9,823	9,823

Table 9: Regressions of strategy returns on return indices of other strategies

This regression models the return-predictability of each characteristic, relative to its original sample period and publication date, and relative to the returns of other characteristics. The dependent variable is the monthly long-short return of a characteristic, scaled by its monthly in-sample mean. The regression uses either *Continuous* or *Quintile* returns, depending on which method produces stronger in-sample statistical significance. *Post Publication* is equal to 1 if the month is after the official date of the journal that published the study. *Other In* is an equal weighted return of all other long-short returns for which the current month implies that the characteristic is in the original study's sample period. *Other Post* is an equal weighted return of all other long-short returns for which the current month implies that the characteristic is after the study's publication date. All indicator variables are equal to 0 if they are not equal to 1. The regressions include random effects. Standard errors are clustered on time and are reported in parentheses. P-values are in brackets for the hypothesis that the coefficient equals 0.

	Coeff.	**SE**	**P>z**
Other-In	0.634	0.03	0.000
Other-Post	0.025	0.02	0.136
*Post Pub * Other In*	-0.555	0.05	0.000
*Post Pub * Other Post*	0.399	0.06	0.000
Post Pub	-0.071	0.06	0.260
Constant	0.351	0.04	0.000
Within R^2	0.024		
Between R^2	0.126		
Overall R^2	0.024		
Obs.	30,534		