# Does Academic Research Destroy Stock Return Predictability?*

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**ABSTRACT**

We study the out-of-sample and post-publication return-predictability of 97 variables that academic studies show to predict cross-sectional stock returns. Portfolio returns are 26% lower out-of-sample and 58% lower post-publication. The out-of-sample decline is an upper bound estimate of data mining effects. We estimate a 32% (58% - 26%) lower return from publication-informed trading. Post-publication declines are greater for predictors with higher in-sample returns, and returns are higher for portfolios concentrated in stocks with high idiosyncratic risk and low liquidity. Predictor portfolios exhibit post-publication increases in correlations with other published-predictor portfolios. Our findings suggest investors learn about mispricing from academic publications.

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

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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 97 predictors 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 predictor's returns over three distinct periods: (i) the original study's sample; (ii) after the original sample but before publication; and (iii) post-publication. Previous studies attribute cross-sectional return predictability to statistical biases, rational pricing, and mispricing. By comparing return-predictability between these three periods, we can better differentiate between these explanations.

*Statistical Bias.* If return-predictability in published studies is solely 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. Fama (1991) addresses this issue 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." 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.

*Rational Expectations versus Mispricing.* Differences between in-sample and post-publication returns are determined by both statistical biases and the extent to which investors learn from the publication. Cochrane (1999) explains that if predictability reflects risk it is likely to persist: "Even if the opportunity is widely publicized, investors will not change their portfolio decisions, and the relatively high average return will remain." Cochrane's logic follows Muth's (1961) rational expectations hypothesis, and thus 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 entirely reflects rational expectations, then publication will not convey information that causes a rational agent to behave differently. Thus, once the impact of statistical bias is removed, pre- and post-publication return-predictability should equate.

If return-predictability reflects mispricing and publication causes sophisticated investors to learn about and trade against the mispricing, then we expect the returns associated with a predictor to disappear or at least decay after the paper is published.[4] Decay, as opposed to disappearance, will occur if impediments prevent arbitrage from fully eliminating mispricing. Examples of such impediments include systematic noise trader risk (Delong, Shleifer, Summers, and Waldman (1990)) and idiosyncratic risk and transaction costs (Pontiff (1996, 2006)). These effects can be worsened by the principal-agent relations that exist between investors and investment professionals, Shleifer and Vishny (1997)).[5]

*Findings.* We conduct our analysis with 97 different characteristics from 80 different studies, using long-short portfolio strategies that buy and sell extreme quintiles that are based on each predictor. The average predictor's long-short return declines by 26% out-of-sample. This 26% estimate is an upper bound on the effect of statistical biases, since some traders are likely to learn about the predictor before publication, and their trading will cause the return decay to be greater than the pure decay from statistical bias.

The average predictor's long-short return shrinks 58% post-publication. Combining this finding with an estimated statistical bias of 26% implies a lower bound on the publication effect of about 32%. We can reject the hypothesis that return-predictability disappears entirely, and we can also reject the hypothesis that post-publication return-predictability does not change. This post-publication decline is robust to a general time trend, to time indicators used by other authors, and to time fixed effects.

The decay in portfolio returns is larger for predictor portfolios with higher in-sample returns and higher in-sample t-statistics. We also find evidence that decay is larger for predictors that can be constructed with only price and trading data, and therefore likely to represent violations of weak form market efficiency. Post-publication returns are lower for predictors that are less costly to arbitrage; i.e., predictor portfolios concentrated in liquid stocks and low idiosyncratic risk stocks. Our findings are consistent with mispricing accounting for some or all of the original return predictability, and investors learning about this mispricing.

We further investigate the effects of publication by studying traits that reflect trading activity. We find that stocks within the predictor portfolios have post-publication increases in trading volume, and that the difference in short interest between stocks in the short and long sides of each portfolio increases after publication. These findings are consistent with the idea that academic research draws attention to predictors.[6]

Publication has an effect on correlations between predictor portfolio returns. Yet-to-be-published predictor portfolios returns are correlated, and after a predictor is featured in a publication its portfolio return correlation with other yet-to-be-published predictor portfolios decreases, while its correlation with other already-published predictor portfolio returns increases. One interpretation of this finding is that some portion of predictor portfolio returns is the result of mispricing and mispricing has a common source; this is why in-sample predictor portfolios returns are correlated. This interpretation is consistent with the irrational comovement models proposed in Lee, Shleifer, and Thaler (1991) and Barberis and Shleifer (2003). Publication could then cause more arbitrageurs to trade on the predictor, which causes predictor portfolios to become more correlated with already-published predictor portfolios that are also pursued by arbitrageurs, and less correlated with yet-to-be-published predictor portfolios.

Our findings are related to contemporaneous research that investigates how the magnitude of sophisticated capital affects anomaly returns (Hanson and Sundareram, 2014, Kokkonen and Suominen 2014, and Akbas, Armstrong, Sorescu, and Subrahmanyam, 2014). Unlike these papers, we do not consider proxies for variation in sophisticated capital levels. Rather, our results suggest that academic publications transmit information to sophisticated investors.

## I. 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 peer-reviewed finance, accounting, and economics journals, where the null of no return 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 97 cross-sectional relations from 80 different studies. The predictors and the associated studies are detailed in the paper's Internet Appendix. We include all variables that relate to cross-sectional returns, including those with strong theoretical motivation such as Fama and MacBeth's 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 in the *Journal of Financial Economics*. Haugen and Baker (1996) investigate more than four predictors, but some of their predictors were documented by other authors earlier and are therefore associated with other publications in our study.

Our goal is not to perfectly replicate the findings in each paper. This is impossible since CRSP data changes over time and papers often omit details about precise calculations. Moreover, in some cases 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 with the help of the paper's authors 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, but does cover S&P ratings, so we use S&P rating downgrades instead. Returns are equally weighted unless the primary study presents value-weighted portfolio results (e.g., Ang, Hodrick, Xing, and Zhang, 2006).

For some characteristics such as momentum, higher characteristic values are associated with higher returns, and for other characteristics such as size, higher characteristic values are associated with lower returns. We form long-short portfolios based on the extreme 20$^{th}$ percentiles of the characteristic. The long-side is the side with the higher returns as documented by the original publication. For three characteristics, our long-short in-sample average return has the opposite sign as the original paper, and the average return is statistically insignificant from zero. Our results are robust to the inclusion or removal of these portfolios.

16 of our 97 predictors are indicator variables. For these cases, if the original paper demonstrated higher returns for firms assigned with the indicator, these firms are included in the long-side portfolio and an equal-weighted portfolio of all other stocks is used as the short side. If the original paper demonstrates lower returns for indicated firms, then non-indicated firms form the long-side portfolio, and the portfolio of indicated firms forms the short side.

The average correlation across predictor portfolios is 0.033. This finding is in-line with Green, Hand, and Zhang (2013) who report an average correlation of 0.09 among 60 quantitative portfolios. There are of course both higher and negative correlations among the predictors in our sample. As we explain in more detail below, we explicitly control for such cross-correlations when computing the standard errors for our test statistics.

In an earlier version of the paper we also calculated 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. We obtain similar findings using both methods, so for the sake of brevity we only report quintile returns.

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 demarcation for estimating statistical bias. The publication date, however, provides only a proxy for when market participants learn about a predictor. As we mention above, we assume that more investors know about a predictor after the publication date as compared to before the publication date. Some market participants may not read the paper until 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.

## II. Creating the Data and In-Sample Replicability

Summary statistics for the characteristics that we study are provided in Table I. For the 97 portfolios, the average monthly in-sample return is 0.582 percent; the average out-of-sample, pre-publication return is 0.402 percent; the average post-publication return is 0.264 percent.

[Insert Table I Here]

The average length of time between the end of the sample and the date of publication is 56 months. For comparison, the average original in-sample span is 323 months, and the average post-publication span is 156 months. Our sample ends in 2013.

The publication date is determined by the year and month on the cover of the journal. Two variations were considered. A previous version of this paper considered publication dates based on arrival time stamps at Boston metropolitan libraries, but this distinction produced nearly identical results. Another version considered 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, and, again, we get the same findings using this method.

Although we include all 97 predictors in our tests, 12 of our predictors produce portfolio returns with in-sample t-statistics that are less than 1.50. Thus, a total of 85 (97 – 12) or 88% of the predictor's produce t-statistics that are greater than 1.50. With respect to the 12 predictors that did not reach this significance level, in some cases, the original paper demonstrates abnormal returns from an event study and the effect did not survive in monthly cross-sectional regressions. In other cases, we do not have the exact same data used by the original authors. Lastly, portfolio formation also contributes to differences in statistical significance. We focus on long-short quintile returns, while some the original papers that demonstrate predictability use Fama-MacBeth slope coefficients or buy and hold returns.

## III. Main Results

*A. Characteristic Dynamics Relative to End of Sample and Publication Dates*

In this Section of the paper we formally study the returns of each predictor relative to its sample-end and publication dates. Our baseline regression model is described in Equation (1):

$$R_{it} = \alpha_{i,} + \beta_1\, Post\ Sample\ Dummy_{i,t} \ +\ \beta_2\, Post\ Publication\ Dummy_{i,t} \ +\ e_{it} \quad (1)$$

In Equation 1 the dependent variable is the monthly return for predictor *i* in month *t*. the post-sample dummy is equal to one if month *t* is after the end of the original sample but still pre-publication and zero otherwise, while the post-publication dummy is equal to 1 if the month is post-publication and zero otherwise. The variable $\alpha_i$ is a predictor fixed effect.

As we mention previously, correlations across predictor portfolios are low, averaging only 0.033. However there is variation in the correlations, with some portfolios being highly correlated, and others uncorrelated. We therefore compute our standard errors with via Feasible Generalized Least Squares method, under the assumption of contemporaneous cross correlation between returns. Clustering on time (as we did in previous drafts) produces similar results, with slightly smaller standard errors in most cases.

The post-sample coefficient estimates the impact of statistical biases on predictor in sample performance. This is an upper bound estimate, as it could be the case that sophisticated traders are aware of the working paper before publication. The post-publication coefficient estimates both the impact of statistical biases and the impact of publication. If statistical biases are the source of in-sample predictability, then the coefficients for both the post-sample and the post-publication dummy should be -0.582, which is the negative of the average in-sample mean return (reported in Table I). Such a finding would be consistent with Fama's (1991) conjecture that much of the return-predictability in academic studies is the outcome of data-mining.

If predictors' returns are entirely the result of mispricing and arbitrage resulting from publication corrects all mispricing, then the post-publication coefficient will be equal to -0.582 and the post-sample dummy 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 of the coefficients should equal zero.

*B. Predictor Return Dynamics Relative to End-of-Sample and Publication Dates*

Table II presents regression estimates of how predictability changes out-of-sample and post-publication. Column 1 reports the results for our main specification, which is an estimate of Equation 1 within our sample of the 97 predictors. The post-sample coefficient in this regression is -0.150 percent, and it is statistically significant. Thus, our best estimate of the post-sample decline is 15.0 basis points. The post-publication coefficient is -0.337, and it is also statistically significant. This shows that, on average, predictor portfolios are 33.7 basis points lower post-publication compared to before publication. Table I shows that the average predictor has an in-sample mean return of 58.2 basis points per month. Hence, post-sample and post-publication returns decline relative to the in-sample mean by 26% and 58% respectively.

[Insert Table II Here]

The regression in the second column includes only 85 predictors; it excludes the 12 predictors that generated t-statistics with values that are less than 1.5. The exclusion of these does not change the basic inference reported in column 1. The post-sample and post-publication coefficients are -0.180 and -0.387 respectively in column 2, similar to the results in column 1. The average in-sample return for the 85 predictors is 0.652 (not in tables), so the post-publication decay in percentage terms is similar if these other 12 predictors are included. The average return in-sample is larger because we are excluding the 12 predictors that do not have less significant in-sample predictability.

At the bottom of Table II, we report tests of whether the post-publication and out-of-sample but pre-publication coefficients are equal. In both of the regressions described above, the coefficients are significantly different at the 5% level. 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.

The bottom of Table II also reports tests of whether the returns of the predictor portfolios disappear entirely post-publication. This test is generated from a linear restriction that equates the post-publication coefficient to the average of the sums of the fixed effects and the intercept.[7] This test, along with the t-test on the post-publication coefficient, allow us to easily reject both nulls, i.e., we reject the null that post-publication, anomaly returns decay entirely, and we reject the null that they do not decay.

The regression in the third column includes the predictor fixed effects along with interactions between the in-sample mean return of each predictor and the out-of-sample and post-publication dummy variables. The interactions test whether predictors portfolio returns with higher in-sample means decline more post-publication. We do not include the in-sample mean in the regression by itself because it does not vary over time and we include predictor fixed-effects.

In column 3 the coefficient for post-sample is 0.157, while the coefficient for the post-sample interaction with the in-sample mean is -0.532. As we mention above, the average in-sample monthly return of the 97 portfolios is 0.582 percent (see Table I), so the overall post-sample effect is 0.157 + (-0.532 x 0.582) = -0.153, similar to the post-sample coefficient in column 1. The standard deviation of the in-sample means is of 0.395 (see Table I). Hence, a portfolio with an in-sample mean return that is one standard deviation more than average, has a -0.532 x 0.395 = -0.210 basis point decline in post-sample monthly return. This could reflect the fact that predictors with larger in-sample returns are likely to have a higher degree of statistical bias. Alternatively, it could reflect the fact that arbitrageurs or more likely to learn about and trade on predictors with higher returns before publication. This relation is also displayed in Figure 1.A, which plots the average in-sample mean for each predictor against its post-publication decline, and shows that predictors with larger in-sample returns have greater post-publication declines.

[Insert Figure 1 Here]

The final regression in Table II interacts the post-sample and post-publication dummies with the predictor's in-sample t-statistic. The average in-sample t-statistic is 3.55 and the standard deviation of the t-statistics is 2.39 (not reported in tables). Hence, the regression estimates an incremental decline for a characteristic portfolio with a t-statistic that is one standard deviation higher than average of -0.146 post-sample and -0.151 post-publication. This relation is plotted in Figure 1.B. The results here are consistent with the idea that arbitrageurs devote more capital to characteristic portfolios with that are associated with higher in-sample return. In an untabulated specification we condition decay on in-sample Sharpe ratios, and estimate very similar results.

Previous versions of the paper considered whether or not decay is related to the cumulative number of academic citations generated by the publication that introduced the portfolio returns associated with the predictor. Once we control for publication date, this measure has little incremental value in explaining decay.

*C. A Closer Look at Predictor Return Dynamics around the Sample-End and Publication Dates*

Figure 2 further considers changes in predictability by examining finer post-sample and post-publication partitions. The figure plots the coefficients from a regression of predictor returns on 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 variable for each of the first five years post-publication, and a dummy variable for all of the months that are at least five years after publication. Some caution is needed in interpreting this figure. Although the estimates in this figure are interesting, statistical power is lower from partitioning the results, and theory does not guide us regarding the appropriate partitions.

[Insert Figure 2 Here]

The publication process often takes years. This gives unscrupulous researchers the opportunity to choose where to end their samples with the purpose of reporting stronger results. Figure 2 shows that the coefficient for the last 12 months of the sample period is positive, which means that the last 12 months of the sample has higher returns than the other in-sample months, which could be consistent with researchers choosing to end samples opportunistically. However, the coefficient for the first 12 months post-sample is virtually zero, showing that the first 12 months post-sample has on average the same returns as compared to the average returns in-sample; if authors where selectively choosing their sample periods, then this coefficient should be negative.

Figure 2 shows that after the first 12 months out-of-sample, returns are lower as compared to in-sample, and stay that way throughout the life of the predictor. After the first year post-sample and during the remaining months out-of-sample but before publication, returns are lower by more than 20 basis points. Returns remain at this level throughout the first two years post-publication, and then begin to decay further. In the third year we estimate a decay of 40.8 basis points; in the fourth year decay is 43.3 basis points; and in the fifth year decay is 20.5 basis points. After the fifth year predictors' returns are on average 33.9 basis points lower as compared to in-sample.

Some readers suggest that we examine post-publication returns as a function of the persistence of the predictor (how often the portfolio turns over). Initially, decay may be muted if new capital flows into portfolios that are determined by a persistent predictor. For example, new flows into high book-to-market stocks might cause a temporary increase in the returns of book-to-market portfolios. This would not occur in portfolios that are formed on less persistent predictors, such as last month's stock return. In an earlier version of the paper, this possibility was considered. We found some evidence that portfolio returns to more persistent predictors decayed less following publication, however the effect was not statistically significant.

*D. Controlling for Time Trends and Persistence*

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 (see Goldstein, Irvine, Kandel, and Wiener (2009) and Anand, Irvine, Puckett, and Venkataraman (2012)), which is why we observe the drop post-publication. Consistent with this idea, Chordia, Subrahmanyam, and Tong (2013) show that the returns of the different predictors decline after 1993, which they attribute to more hedge funds and lower trading costs. Hence, it could be the case that characteristic returns are diminishing because the costs of trading on these characteristics have declined over time.

[Insert Table III Here]

We study these possibilities in Table III. 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 column 1 we estimate a regression of monthly portfolio returns on the time variable and predictor fixed effects. The time variable produces a negative slope coefficient that is significant at the 1% level, which is consistent with the idea that portfolio returns have declined over time.

In column 2 we estimate the effect of a dummy variable that is equal to 1 if the year is after 1993 and zero otherwise. We use this specification because, as we mention above, Chordia, Subrahmanyam, and Tong (2013) show that 12 predictors have lower returns post-1993. Consistent with Chordia et al. the post-1993 coefficient is negative and significant in our sample.

In column 3, we relate decay to a time trend, the post-1993 indicator, and the post-sample and post-publication indicator variables. The time trend variable is now negative and significant, however the post-1993 dummy variable is now *positive* and statistically significant. The post-publication coefficient is -0.362, and statistically significant, similar to the estimate reported in our main specification in Table II. Thus, consideration of a time trend and a 1993 break has little impact on post-publication return decay.

An alternative way to control for time effects is to include time fixed effects. Time fixed effects demean each monthly anomaly return by the average anomaly return in the same month. Hence, including time fixed effects allows for parameter estimation that is free from all forms of time-series decay.

We report an estimation that that includes time fixed effects in column 4. This regression estimates coefficients that are very close to the Table II coefficients. Characteristic returns decline of 17.9 basis points out-of-sample, and 31.0 basis points post-publication; both coefficients are significant at the 5% level. Based on the average in-sample return of 58.2 basis points, this specification implies a sizeable 53% drop in post-publication predictability, and this is after all of the time effects have been removed.

In the final two regressions in Table III we test whether predictor returns are persistent, and whether controlling for persistence changes the publication effect. Recent work by Moskowitz, Ooi, and Pedersen (2013) and Asness, Moskowitz and Pedersen (2013) finds broad momentum across asset classes and correlation of momentum returns across classes, while Grundy and Martin (2001) fail to find significant momentum in the Fama-French factors. We include the predictor's last month's return and the sum of its last 12 months' returns in regressions 5 and 6 respectively. Both of the lagged return coefficients are positive and significant, which is broadly consistent with the findings of Moskowitz, Ooi, and Pedersen. The post-publication coefficient remains significant in each of these regressions, suggesting a post-publication decline of about 25 to 30 basis points once persistence is controlled for.

### *E. Do Returns and Post-Publication Decay Vary Across Predictor Types?*

In this section, we group predictors into four broad categories and examine variation in pre-publication returns, post-publication returns, and the post-publication return decay. We designate the predictor categories as: i) Event; (ii) Market; (iii) Valuation; and (iv) Fundamentals.

Event predictors are based on events within the firm, external events that affect the firm, and changes in firm-performance. Examples of event predictors include share issues, changes in financial analyst recommendations, and unexpected increases in R&D spending. Market predictors are predictors that can be constructed using only financial data, such as volume, prices, returns, and shares outstanding. Momentum, long-term reversal, and market value of equity are included in our sample of market predictors.

Valuation predictors are ratios, where one of the numbers reflects a market value and the other reflects fundamentals. Examples of valuation predictors include sales-to-price and book-to-market. Finally, fundamental predictors are constructed with financial statement data and analyst expectations of financial statement data. Debt, taxes, and accruals (all scaled by total assets) are examples of fundamental predictors.

As we mention previously, the average correlation among the predictor portfolio returns is 0.033, while the median is 0.018. The correlation is not higher within the groups. Valuation predictor portfolios' returns have the highest within-group correlation, averaging 0.058, while market predictor portfolios have the lowest, averaging 0.021. The reason for this is that there can be both very high and very low return correlations within each group. As an example, the highest correlation in our sample is 0.933, which is between the returns of the price and size portfolios. The lowest correlation is -0.895, which is between the returns of the price and 52-week high portfolios. Similarly, the momentum and price portfolios' returns have a correlation of -0.715. All of these predictors are market predictors. As in the previous tables we estimate our standard errors via a FGLS method that accounts for contemporaneous cross-correlations.

We formally test for differences between the four predictor portfolio groups in the regressions reported in Table IV. Using all data, monthly returns are regressed on a dummy variable representing one of the four-predictor types, a post-publication dummy, and an interaction between the post-publication and predictor type variables.

$$R_{i,t} = \alpha_{i,} + \beta_1\, Post\ Publication\ Dummy_i + \beta_2\, Predictor\ Type\ Dummy_i\ +$$
$$\beta_3\, Post\ Publication\ Dummy_i\ x\ Predictor\ Type\ Dummy_i + \ e_{it}\ \ (2)$$

The coefficient for the *Predictor Type Dummy* ($\beta_2$) in Table IV estimates whether the in-sample average returns of a group are different than those of the other groups. The results show that compared to the other categories of predictors, market-based predictors have the highest pre-publication returns, while fundamental predictors have the lowest pre-publication returns.

[Insert Table IV Here]

The coefficient for the interaction ($\beta_3$) tests whether post-publication declines vary across the predictor groups. The decline for the market-based predictor portfolio returns is largest, although it is not significantly different from the declines of the other predictors. Valuation predictor returns have the lowest (and significant) declines post-publication.

We can estimate differences in post-publication expected returns by adding the type coefficient to the interaction coefficient ($\beta_2$ + $\beta_3$). These sums and the associated p-values are reported in the bottom two rows of Table IV. Despite the high pre-publication returns of market based predictors, post-publication market-based predictor returns are not significantly higher than the non-market based predictors. This is consistent with the results in Table II, which show that predictors with higher in-sample returns have larger declines in returns post-publication. The bottom two rows also show that post-publication returns are significantly lower for fundamental predictors, so the pre-publication differences in returns are persistent post-publication.

### *F. Costly Arbitrage*

The results in the previous tables are consistent with the idea that publication attracts arbitrageurs, which results in lower 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, predictor portfolios consisting 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 predictor returns are the outcome of rational asset pricing, then the post-publication decline should not be related to arbitrage costs.[8]

Previous papers in the costly arbitrage literature relate arbitrage costs to differences in returns across stocks within a predictor portfolio (see Pontiff, 2006; Duan, Hu, and McLean, 2010; and McLean, 2010). In contrast, we estimate the relation between arbitrage costs and expected returns across (instead of within) portfolios. Another difference between our tests and the previous literature is that previous studies assume that the informed trader had knowledge of the predictor before (and after) the publication date. Our tests consider the possibility that publication informs arbitrageurs, which, in turn, affects the decay in return-predictability post-publication.

Our costly arbitrage variables include three transaction cost variables: size, bid-ask spreads, and dollar volume, and two holding cost variables: idiosyncratic risk and a dividendpayer dummy. We also create a costly arbitrage index, which is the first principal component of the five costly arbitrage variables.

Large stocks, stocks with high dollar volume, and stocks with low spreads are more liquid, and should therefore be less costly to arbitrage. Hence, we expect long-short returns to be lower in predictor portfolios concentrated in such stocks. 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). Dollar volume is the number of shares traded during the past month multiplied by the month-end stock price.

Idiosyncratic risk limits the amount that an investor will invest in a mispriced stock (Treynor and Black, 1973, and Pontiff, 1996 and 2006), so we expect returns to be higher in predictor portfolios concentrated in high idiosyncratic risk stocks. We compute monthly idiosyncratic risk by regressing daily returns on the twelve value-weighted industry portfolios from Ken French's website. We estimate a regression for each stock using the last 24 months of daily data. 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 idiosyncratic risk measure is created by adding up the daily sum of residual products from a given month. If the industry factor model regression contains less than 30 observations, the stock is not assigned an idiosyncratic risk measure for that 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 one if a firm paid a dividend and zero otherwise. We expect returns to be lower in predictor portfolios concentrated in stocks that pay dividends.

The costly arbitrage index is based on the first principal component of the five costly arbitrage variables. A higher value if the index is associated with lower arbitrage costs, and therefore lower expected portfolio returns. The index has positive correlations with the size, dividends, and dollar volume variables, and negative correlations with the spreads and idiosyncratic risk variables.

Our procedure to estimate the arbitrage cost of each predictor portfolio is a follows. First, for each month, we compute the average cross-sectional ranking for a trait (e.g. size or idiosyncratic risk) among all of the stocks CRSP. Each stock-month observation is therefore assigned a ranking value between 0 and 1. Next, each month, we estimate the average rank for the stocks that are in either the long or the short sides of each predictor portfolio. This creates a time-series of monthly rank-averages for each trait. We then take the average of each time-series to estimate a single costly arbitrage variable for each predictor. We only use in-sample months to create the costly arbitrage variables, as it could be the case that trading caused by publication has an effect on the costly arbitrage variables.

We report the results from these tests in Table V. The dependent variable in the regressions reported in Table V is a predictor's monthly return. We estimate the following regression equation:

$$R_{i,t} = \alpha_{i,} + \beta_1 \, Post\ Publication\ Dummy_{i,t} + \beta_2 \, Arbitrage\ Cost_i \ +$$

$$\beta_3 \, Post\ Publication\ Dummy_{i,t} \ x \ Arbitrage\ Cost_i + \ e_{it} \ (3)$$

Table V largely supports the notion that some sophisticated traders exert price pressure pre-publication, but the price pressure is tempered by arbitrage costs. If some sophisticated traders implement predictor strategies pre-publication, then we expect portfolios with higher arbitrage costs to have higher post-publication returns. This effect is ascertained from the slopes on the non-interacted arbitrage cost variables ($\beta_2$). Five of the costly arbitrage variables (including the index) have slopes with the expected sign, and all five are statistically significant. The dollar volume variable produces a slope in the opposite direction—predictor portfolios concentrated in stocks with high dollar volume of trading tend to have higher in-sample returns, although this effect is not statistically significant.

[Insert Table V Here]

Post-publication knowledge of a predictor should be widespread, and we therefore expect portfolios that are easier to arbitrage to have lower post-publication returns. The sum of the costly arbitrage coefficient ($\beta_2$) plus the coefficient for the interaction between the post-publication dummy and the arbitrage cost variable ($\beta_3$) should therefore reflect higher expected returns for predictors that are more costly to arbitrage. The sum of these coefficients and the associated p-values are presented in the last two rows of Table VI. All six six of these sums have the correct expected sign, and five of the six are statistically significant.

For brevity, we do not report a specification that includes, simultaneously, all five of the primary costly arbitrage variables and all five of the interactions. Caution is needed in interpreting such results due to high correlation between right-hand-side variables. Regarding in-sample returns, idiosyncratic risk is the only costly arbitrage variable that commands a statistically significant slope with the expected sign. Post-publication, returns are lower for predictor portfolios that contain stocks with more idiosyncratic risk. The post-publication effects for spreads and size have the correct expected signs, but are insignificant. Idiosyncratic risk's post-publication p-value is 0.000. This finding is consistent with Pontiff's (2006) review of the literature that leads him to conclude, "idiosyncratic risk is the single largest cost faced by arbitrageurs."

*G. Post-Publication Trading Activity in Predictor Portfolios*

If academic publication provides market participants with information, then informed trading activity should affect not only prices, but also other indicators of trading. We therefore test whether trading volume, dollar trading volume, variance, and short interest increase in predictor portfolios during the months after publication. To perform these tests we estimate the regression describe in Equation 1, but replace monthly stock returns with a monthly measure of one of the traits.

Trading volume is measured as shares traded, while dollar volume is measured as shares traded multiplied by price. Variance is the monthly stock return squared. We compute the average value of each variable among the stocks that enter either the long or the short side of the predictor portfolio each month, and test whether the means change post-publication. We take the log of each variable and use these as the dependent variables in our regressions. Short interest is measured as shares shorted scaled by shares outstanding. We measure the difference in short interest between the short and long side of each portfolio each month, and use the difference as the dependent variable in our regressions. If publication draws short sellers to predictors, then this relative shorting measure should increase post-publication.

Previous studies show that all of these variables increase over time during our sample period, so we include time fixed effects in all but the short interest specification, which measures the difference between the long and short sides in each cross-section.

We report the results from these tests in Table VI. The results show that trading volume and dollar volume are significantly higher during the period that is post-sample but pre-publication. Hence, there appears to be an increase in trading among predictor portfolio stocks even before a paper is published, suggesting that information from papers may get to some investors before the paper is published. Variance is significantly lower during this period.

[Insert Table VI Here]

The post-publication coefficients show that trading volume and dollar volume are significantly higher in predictor portfolios after publication. The dependent variables are logs, so the coefficients show that post-publication trading volume and dollar volume increase by 18.7% and 9.7% respectively. Variance on the other hand declines by 6.5% post-publication. Lower volatility could reflect less noise trading (Shiller (1981) and Pontiff (1997)).

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. The coefficients in this regression are reported in percent. If investors recognize that predictor portfolio stocks are mispriced, then there should be more shorting on the short side than on the long side. The average difference in short interest between the short and long side of the characteristic portfolios in-sample is 0.143%. The mean and median levels of short interest in our sample (1976-2012) are 3.45% and 0.77% respectively, so this difference is economically meaningful. This result suggests that some practitioners knew prior to publication that stocks in the predictor portfolios were mispriced and traded accordingly. This could be because practitioners were trading on the predictor, or it could reflect practitioners trading on other strategies, which happen to be correlated with the predictor. 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 based on these traits.

Post-sample, relative shorting increases by 0.166%, and post-publication, relative shorting increases by 0.315%. Economically, the post-publication effect represents an increase in relative shorting of three-fold post-publication relative to in-sample. So although some practitioners may have known about these strategies before publication, the results here suggest that publication made the effects more widely known. These short interest results are consistent with Hanson and Sunderam (2014), who use short interest as a proxy for sophisticated investors, and find that increases in short interest are associated with lower future returns in value and momentum stocks.

*H. The Effects of Publication on Correlations Among Characteristic Portfolios*

In this section, we study the effects that publication has on correlations among characteristic portfolios. If predictor returns reflect mispricing and if mispricing has common causes (e.g., investor sentiment), then we might expect in-sample predictor portfolios to be correlated with other in-sample predictor portfolios. This effect is suggested in Lee, Shleifer, and Thaler (1991), Barberis and Shleifer (2003), and Barberis, Shleifer and Wurgler (2005). If publication causes arbitrageurs to trade on a predictor, then publication could also cause a predictor portfolio to become more highly correlated with other published predictors and less correlated with unpublished characteristics because of fund flows or other factors common to arbitrage portfolios.

In Table VII, predictor portfolio returns are regressed on the returns of an equal-weighted portfolio of all other predictors that are pre-publication, and a second equal-weighted portfolio of all of the other predictors that are post-publication. We include a dummy variable that indicates whether the predictor is post-publication, and interactions between this dummy variable and the pre-publication and post-publication predictor portfolios returns.

[Insert Table VII Here]

The results show that before-publication predictor returns are significantly related to the returns of other pre-publication predictor portfolios. The coefficient or beta for the pre-publication predictor portfolio is 0.748 and it is statistically significant. In contrast, the beta for a pre-publication portfolio with portfolios that are post-publication is -0.008 and insignificant. These findings are consistent with Lee, Shleifer, and Thaler (1991) and Barberis and Shleifer (2003).

The interactions show that once a predictor is published, its returns are less correlated with the returns of other pre-publication predictor portfolios and more correlated with the returns of other post-publication predictor portfolios. The coefficient for the interaction between the post-publication dummy and the return of the portfolio consisting of in-sample predictors is -0.653 and highly significant. Hence, once a predictor is published, the beta of its returns with the returns of other yet-to-be-published predictors' returns virtually disappears, as the overall coefficient reduces to 0.748 – 0.674 = 0.074. The coefficient for the interaction of the post-publication dummy with the returns of the other post-publication predictors is 0.652 and significant at the 1% level, suggesting that there is a significant relation between the portfolio returns of published predictors and other published predictors.

## IV. Conclusions

This paper studies 97 characteristics that have been shown to explain cross-sectional stock returns in peer reviewed finance, accounting, and economics journals. Forming portfolios based on the extreme quintiles for each predictor, we compare each predictor'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 predictor 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 26%. This is an upper bound, because some investors could learn about a predictor while the study is still a working paper. The average predictor's return declines by 58% post-publication. We attribute this post-publication effect both to statistical biases and to the price impact of sophisticated traders. Combining this finding with an estimated statistical bias of 26% implies a publication effect of 32%.

Our estimate of post-publication decay in predictor returns is statistically significant relative to two null hypotheses--we can reject the null of no post-publication decay and we can also reject the null that post-publication returns decay entirely.

Several of our findings support the idea some or all of the original cross-sectional predictability is the result of mispricing. First, the returns of predictor portfolios with larger in-sample means decline more post-publication, and strategies concentrated in stocks that are more costly to arbitrage have higher expected returns post-publication. Arbitrageurs should pursue trading strategies with the highest after-cost returns, so these results are consistent with the idea that publication attracts sophisticated investors. Second, we find that turnover, dollar volume, and especially short interest increase significantly in predictor portfolios post-publication. This is also consistent with the idea that academic research draws trading attention to the predictors. Finally, we find that before a predictor is featured in an academic publication, its returns are correlated with the returns of other yet-to-be-published predictors, but its returns are not correlated with those of published predictors. This is consistent with behavioral finance models of comovement. After publication, a predictor's correlation with yet-to-be-published predictors is close to zero, and its correlation with already-published predictors becomes significant.

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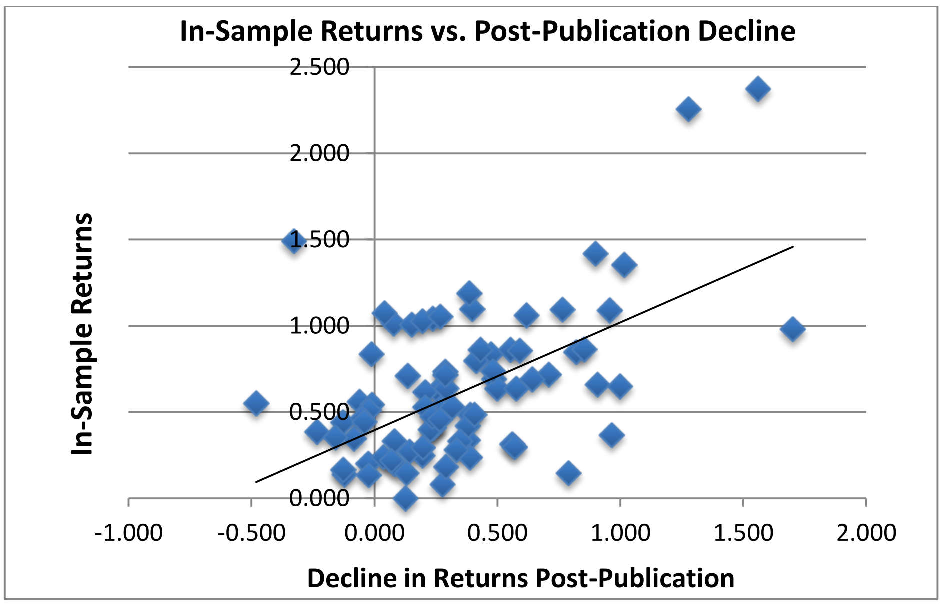
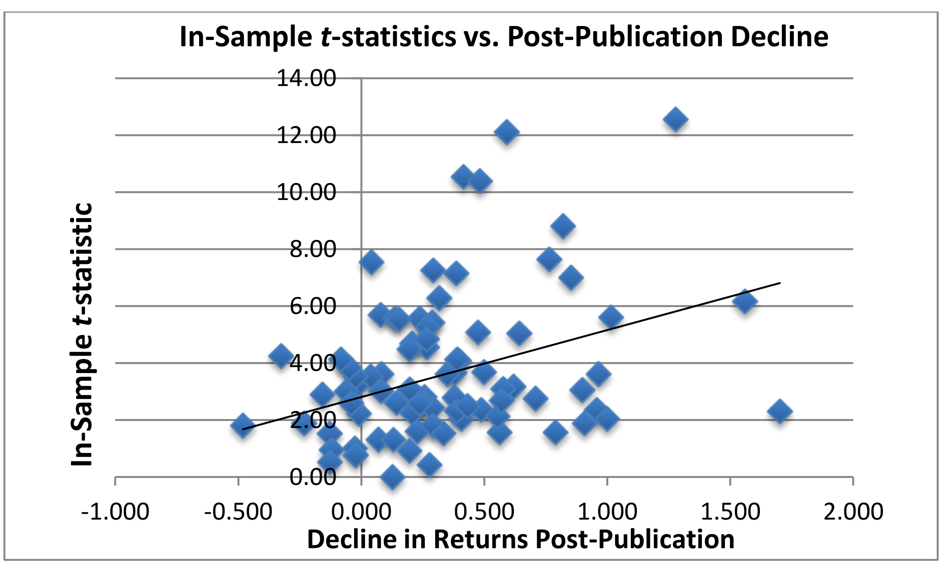
## Figure 1: The relation between in-sample returns and post-publication decline in returns

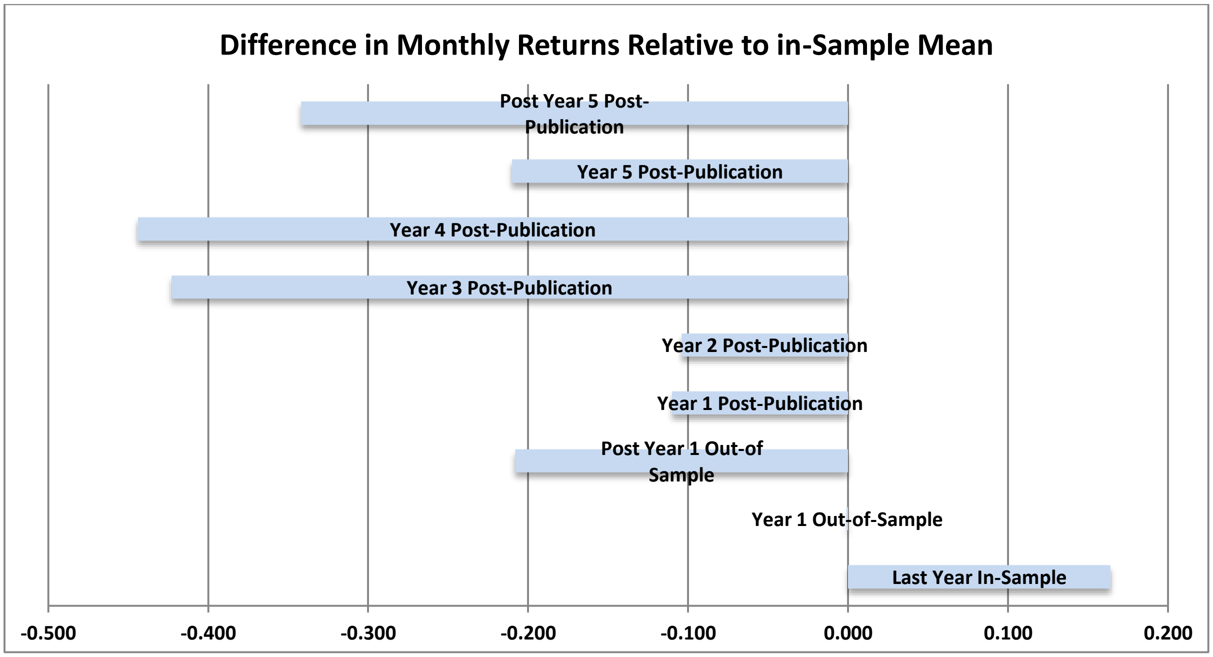
Figure 1.A plots the relation between in-sample returns and the post-publication decline in returns. For each predictor, we estimate the mean return to a long-short portfolio that contemporaneously buys and sells the extreme quintiles of each predictor characteristic during the sample period of the original study. We then estimate the mean returns for the period after the paper is published through 2012. To be included in the figure, a predictor's in-sample returns had to generate a t-statistic greater than 1.5. 80 of the 95 predictors that we examine met this criterion. The predictor also had to have at least three years of post-publication return data. This excluded 10 of the 80 predictors, resulting in a sample of 70 predictors. Figure 1.B repeats this exercise, only it plots the in-sample t-statistic against the post publication decline



## Figure 2: Predictor Return Dynamics around the Sample-End and Publication Dates

Figure 2 explores changes in predictability by examining finer post-sample and post-publication partitions. The figure plots the coefficients from a regression containing 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.



## Table I: Summary Statistics

This table reports summary statistics for the predictors studied in this paper. The returns are equal-weighted by predictor portfolio, i.e., we first estimate the statistic for each predictor portfolio, and then take an equal-weighted average across predictors portfolio. The reported standard deviations are the standard deviations of the predictors' mean returns. Our sample period ends in 2013.

| | |
|---|---|
| Number of Predictor Portfolios | 97 |
| Predictors Portfolios with t-statistic>1.5 | 85 (88%) |
| Mean Publication Year | 2000 |
| Median Publication Year | 2001 |
| Predictors from Finance journals | 68 (70%) |
| Predictors from Accounting journals | 27 (28%) |
| Predictors from Economics journals | 2 (2%) |
| Mean Portfolio Return In-Sample | 0.582 |
| Standard Deviation of Mean In-Sample Portfolio Return | 0.395 |
| Mean Observations In-Sample | 323 |
| Mean Portfolio Return Out-of Sample | 0.402 |
| Std. Dev. of Mean Out-of-Sample Portfolio Return | 0.651 |
| Mean Observations Out-of-Sample | 56 |
| Mean Portfolio Return Post-Publication | 0.264 |
| Std. Dev. of Mean Post-Publication Portfolio Return | 0.516 |
| Mean Observations Post-Publication | 156 |

## Table II: Regression of predictor portfolio returns on post-sample and post-publication indicators

The regressions test for changes in returns relative to the predictor's sample-end and publication dates. The dependent variable is the monthly return to a long-short portfolio that is based on the extreme quintiles of each predictor. Post-Sample (S) is equal to 1 if the month is after the sample period used in the original study and zero otherwise. Post-Publication (P) is equal to 1 if the month is after the official publication date and zero otherwise. Mean is the in-sample mean return of the predictor portfolio during the original sample period. t-statistic is the in-sample t-statistic of each predictor portfolio. Standard errors are computed under the assumption of contemporaneous cross-sectional correlation between panel portfolio residuals. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. The bottom three rows report p-values from tests of whether post-sample and post-publication changes in returns are statistically different from one another and whether any declines are 100% of the in-sample mean (the effects disappears entirely).

| Variables | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post-Sample (S) | -0.150*** | -0.180** | 0.157 | 0.067 |
| | (0.077) | (0.085) | (0.103) | (0.112) |
| Post-Publication (P) | -0.337*** | -0.387*** | -0.002 | -0.120 |
| | (0.090) | (0.097) | (0.078) | (0.114) |
| S x Mean | | | -0.532*** | |
| | | | (0.221) | |
| P x Mean | | | -0.548*** | |
| | | | (0.178) | |
| S x t-statistic | | | | -0.061*** |
| | | | | (0.023) |
| P x t-statistic | | | | -0.063*** |
| | | | | (0.018) |
| Predictor FE? | Yes | Yes | Yes | Yes |
| Observations | 51,851 | 45,465 | 51,851 | 51,944 |
| Predictors (N) | 97 | 85 | 97 | 97 |
| Null Hypothesis: S=P | 0.024 | 0.021 | NA | NA |
| Null: P = -1*(Mean) | 0.000 | 0.000 | | |
| Null: S=-1*(Mean) | 0.000 | 0.000 | | |

## Table III: Time Trend and Persistence in Predictor Returns

The regressions reported in this table test for time trends and persistence in predictor returns. Post-Sample (S) is equal to 1 if the month is after the sample period used in the original study and zero otherwise. Post-Publication (P) is equal to 1 if the month is after the official publication date and zero otherwise. Time is the number of months divided by 100 post-Jan. 1926. 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. 1-Month Return and 12-Month Return are the predictor's return from the last month and the cumulative return over the last 12 months. Standard errors are computed under the assumption of contemporaneous cross-sectional correlation between panel portfolio residuals. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

**Table III: (Continued)**

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Time | -0.069*** | | -0.069*** | | | |
| | (0.011) | | (0.026) | | | |
| 1993 | | -0.120 | 0.303*** | | | |
| | | (0.074) | (0.118) | | | |
| Post-sample | | | -0.190** | -0.179** | -0.132* | -0.128 |
| | | | (0.081) | (0.080) | (0.076) | (0.078) |
| Post Pub. | | | -0.362*** | -0.310** | -0.295*** | -0.258*** |
| | | | (0.124) | (0.122) | (0.089) | (0.093) |
| 1-Month Return | | | | | 0.114*** | |
| | | | | | (0.015) | |
| 12-Month Return | | | | | | 0.020*** |
| | | | | | | (0.004) |
| Observations | 51,851 | 51,851 | 51,851 | 51,851 | 51,754 | 50,687 |
| Char. FE? | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE? | No | No | No | Yes | No | No |

## Table IV: Predictor returns across different predictor types

This table tests whether predictor returns and changes in returns post-publication vary across different types of predictors. To conduct this exercise we split our predictors into four groups: (i) Event; (ii) Market; (iii) Valuation; and (iv) Fundamentals. We regress monthly predictor returns on dummy variables that signify each predictor group. Each column reports how each predictor type is different from the other three types. The bottom two rows test whether post-publication expected returns for each predictor type is different the other three types. Standard errors are computed under the assumption of contemporaneous cross-sectional correlation between panel portfolio residuals. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

**Table IV: (Continued)**

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post-Publication (P) | -0.208*** | -0.316*** | -0.310*** | -0.301*** |
| | (0.059) | (0.097) | (0.080) | (0.089) |
| Market | 0.304*** | | | |
| | (0.079) | | | |
| P x Market | -0.244 | | | |
| | (0.169) | | | |
| Event | | -0.098** | | |
| | | (0.046) | | |
| P x Event | | 0.105 | | |
| | | (0.091) | | |
| Valuation | | | -0.056 | |
| | | | (0.063) | |
| P x Valuation | | | 0.186* | |
| | | | (0.131) | |
| Fundamental | | | | -0.201*** |
| | | | | (0.045) |
| P x Fundamental | | | | 0.025 |
| | | | | (0.089) |
| Constant | 0.482*** | 0.606*** | 0.585*** | 0.630*** |
| | (0.036) | (0.052) | (0.000) | (0.053) |
| Observations | 51,851 | 51,851 | 51,851 | 51,851 |
| Predictors | 97 | 97 | 97 | 97 |
| Type + (P x Type) | 0.060 | 0.007 | 0.121 | -0.176 |
| p-value | 0.210 | 0.922 | 0.256 | 0.012 |

**Table V: Costly arbitrage and the persistence of predictor returns**

This regression tests whether arbitrage costs are associated with declines in predictability post-publication. The dependent variable is a predictor portfolio's monthly long-short return. The independent variables reflect various traits of the stocks in each predictor portfolio. To measure the strength of the traits of the stocks within a portfolio, 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 rank. We then take the average rank of all of the stocks in the portfolio for that month. Finally, we take an average of predictor'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 predictor's portfolio during the in-sample period for the predictor. 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. Index is the first principal component of the other five measures. Standard errors are computed under the assumption of contemporaneous cross-sectional correlation between panel portfolio residuals. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. The bottom two rows test whether the sum of the costly arbitrage variable (CA) plus the interaction between the costly arbitrage variable and publication (P x CA) is statistically different than zero.

**Table V: (Continued)**

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Post-Pub. (P) | -0.190 | -0.139 | 0.215 | -0.242 | -0.321** | -0.264*** |
| | (0.274) | (0.235) | (0.230) | (0.273) | (0.211) | (0.001) |
| P x Size | -0.138 | | | | | |
| | (0.459) | | | | | |
| Size | -1.064** | | | | | |
| | (0.236) | | | | | |
| P x Spreads | | -0.301 | | | | |
| | | (0.603) | | | | |
| Spreads | | 1.228** | | | | |
| | | (0.252) | | | | |
| P x Dol.Vol. | | | -1.059** | | | |
| | | | (0.500) | | | |
| Dol. Vol. | | | 0.215 | | | |
| | | | (0.308) | | | |
| P x Idio. Risk | | | | -0.047 | | |
| | | | | (0.554) | | |
| Idio. Risk | | | | 2.064*** | | |
| | | | | (0.330) | | |
| P x Div. | | | | | -0.321 | |
| | | | | | (0.211) | |
| Div. | | | | | -0.526*** | |
| | | | | | (0.145) | |
| P x Index | | | | | | -0.009 |
| | | | | | | (0.019) |
| Index | | | | | | -0.056*** |
| | | | | | | (0.011) |
| Constant | 1.145*** | 0.146* | 0.476*** | -0.469*** | 0.855*** | 0.565*** |
| | (0.130) | (0.174) | (0.144) | (0.171) | (0.097) | (0.000) |
| Observations | 51,851 | 51,851 | 51,851 | 51,851 | 51,851 | 51,851 |
| CA + (P x CA) | -1.202 | 0.927 | -0.844 | 2.017 | -0.847 | -0.065 |
| p-value | 0.003 | 0.096 | 0.000 | 0.000 | 0.144 | 0.000 |

## Table VI: Trading activity dynamics in predictor portfolio stocks

This regression models the dynamics of the traits of stocks in predictor portfolios, relative to the predictor's original sample period and publication date. We perform monthly ranks based on turnover, dollar value of trading volume, and stock return variance. Trading Volume is measured as shares traded, while dollar volume is measured as shares traded multiplied by price. Variance is the monthly stock return squared. For each predictor portfolio, we compute the average of each variable among the stocks that enter either the long or the short side of the characteristic portfolio each month, and test whether it increases out-of-sample and post-publication. 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-Sample (S) is equal to 1 if the month is after the sample period used in the original study and zero otherwise. Post-Publication (P) is equal to 1 if the month is after the official publication date and zero otherwise. Standard errors are computed under the assumption of contemporaneous cross-sectional correlation between panel portfolio residuals. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

| Variables | Variance | Trading Volume | Dollar Volume | Short - Long Short Interest |
|---|---|---|---|---|
| Post-Sample (S) | -0.054*** | 0.092*** | 0.066*** | 0.166*** |
| | (0.007) | (0.001) | (0.007) | (0.014) |
| Post-Pub.(P) | -0.065*** | 0.187*** | 0.097*** | 0.315*** |
| | (0.008 | (0.013) | (0.007) | (0.013) |
| Observations | 52,632 | 52,632 | 52,632 | 41,026 |
| Time FE? | Yes | Yes | Yes | No |
| Predictor FE? | Yes | Yes | Yes | Yes |
| Null: S=P | 0.156 | 0.000 | 0.000 | 0.000 |

**Table VII: Regressions of predictor returns on return indices of other predictors**

This regression models the returns of each predictor relative to the returns of other predictors. The dependent variable is a predictor's monthly long-short return. Post-Publication (P) is equal to 1 if the month is after the official publication date and zero otherwise. In-Sample Index Return is the equal-weighted return of all other unpublished predictor portfolios. Post-Publication Index Return is an equal-weighted return of all other published predictor portfolios. Standard errors are computed under the assumption of contemporaneous cross-sectional correlation between panel portfolio residuals. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

| Variables | Coefficients |
|---|---|
| In-Sample Index Returns | 0.748*** |
| | (0.000) |
| Post-Publication Index Return | -0.008 |
| | (0.243) |
| P x In-Sample Index Returns | -0.674*** |
| | (0.033) |
| P x Post-Publication Index Return | 0.652*** |
| | (0.045) |
| Publication (P) | -0.880* |
| | (0.042) |
| Constant | 0.144*** |
| | (0.267) |
| Observations | 42,975 |
| Predictors | 97 |

[1] Similar to Mittoo and Thompson's (1990) study of the size effect, we use a broad set of predictors to focus on out-of-sample, cross-sectional predictability. For an analysis of the performance of out-of-sample time-series predictability, see LeBaron (2000) and Goyal and Welch (2008). For an analysis of cross-sectional predictability using international data, see Fama and French (1998), Rouwenhorst (1998), and McLean, Watanabe, and Pontiff (2009). For an analysis of calendar effects, see Sullivan, Timmermann, and White (2011).

[2] Lewellen (2014) 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 (2013) 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.

[4]We do not distinguish between mispricing and "risk-reward deals" since both are inconsistent with rational expectations. Liu, Lu, Sun, and Yan (2014) develop a model of risk-reward deals and learning that is a framework for our findings.

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

[6] 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.

[7] The expected return of a predictor in-sample is the sum of the regression intercept and the predictor's fixed effect. We take the average of these sums, which is equal to the average predictor's return in sample. We then test whether this value minus the coefficient for either publication or post-sample is equal to zero.

[8] Our exercise recognizes that if returns reflect mispricing, then, in equilibrium, portfolios that incur higher costs will deliver higher returns. This approach deviates from an earlier literature, such as Lesmond, Schill, and Zhou (2004) and Korajczyk and Sadka (2004), who question whether costs eliminate the excess return of a particular portfolio.

[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).