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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 shown 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 that investors learn about mispricing from academic publications.

FINANCE RESEARCH HAS UNCOVERED many cross-sectional relations between predetermined variables and future stock returns. Beyond their historical insights, these relations are relevant to the extent that they provide insights into the future. Whether the typical relation continues outside 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

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[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

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note whether a specific cross-sectional relation continues out-of-sample, no study compares in-sample returns, post-sample returns, and post-publication returns for 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, whereas 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 for 97 characteristics shown to predict cross-sectional stock returns in peer-reviewed finance, accounting, and economics journals. Our goal is to better understand what happens to return predictability outside a study's sample period. We compare each predictor's returns over three distinct periods: (i) the original study's sample period, (ii) the period after the original sample but before publication, and (iii) the post-publication period. Previous studies attribute cross-sectional return predictability to statistical biases, rational pricing, and mispricing. By comparing the return predictability of the three periods, we can better differentiate between these explanations.

A. Statistical Bias

If return predictability in published studies results solely from statistical biases, then predictability should disappear out of sample. We use the term "statistical biases" to describe a broad array of biases inherent to research. Fama (1991, p. 1585) addresses this issue when he notes that "With many 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 driven by such biases, we should observe a decline in return predictability out-of-sample.

B. Rational Expectations Versus Mispricing

Differences between in-sample and post-publication returns can be determined by both statistical biases and the extent to which investors learn from

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, Pontiff, and Watanabe (2009). For an analysis of calendar effects, see Sullivan, Timmermann, and White (2001).

[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 their second subperiod, whereas Chordia, Subrahmanyan, and Tong show that none of their characteristics are statistically significant in their second subperiod. Green, Hand, and Zhang (2013) identify 300 published and unpublished characteristics but they do not estimate characteristic decay parameters as a function of publication or sample-end dates.

the publication. Cochrane (1999, p. 71) 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 nonrisk models such as Amihud and Mendelson's (1986) transaction-based model and Brennan's (1970) tax-based model. If return predictability reflects only rational expectations, then publication will not convey information that induces a rational agent to behave differently. Thus, once the impact of statistical bias is removed, pre- and post-publication return predictability should be equal.

If return predictability reflects mispricing and publication leads sophisticated investors to learn about and trade against the mispricing, then we expect the returns associated with a predictor should disappear or at least decay after the paper is published.[3] Decay, as opposed to disappearance, will occur if frictions prevent arbitrage from fully eliminating mispricing. Examples of such frictions include systematic noise trader risk (Delong et al. (1990)) and idiosyncratic risk and transaction costs (Pontiff (1996, 2006)). These effects can be magnified by principal-agent problems between investors and investment professionals (Shleifer and Vishny (1997)).[4]

C. Findings

We conduct our analysis using 97 different predictors from 79 different academic studies. We use long-short portfolio strategies that simultaneously 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 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 that the decay is larger for predictors that can be constructed with only price and trading data and therefore are likely to represent violations of weak-form market efficiency.

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

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

Post-publication returns are lower for predictors that are less costly to arbitrage, that is predictor portfolios more 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 observe 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.[5]

Publication also affects the 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 already-published predictor portfolio returns increases. One interpretation of this finding is that some portion of predictor portfolio returns results from 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, causing 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), Akbas et al. (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.

The paper is organized as follows. In Section I we describe our research method. In Section II we describe our anomaly sample and discuss some summary statistics. Section III presents the main empirical findings. We conclude in Section IV.

I. Research Method

We begin by identifying studies that find cross-sectional relations between observable variables and future stock returns. We do not study time-series predictability. We limit ourselves to studies in peer-reviewed finance, accounting, and economics journals in which the null of no return predictability is rejected

[5] 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 estimate the difference between in- and out-of-sample short interest.

at the 5% level. We also require that the predicting variable be constructed with publicly available data. The studies were mostly identified with search engines such as Econlit by searching for articles in finance and accounting journals using words such as "cross-section." Some studies were identified in reference lists in books or other papers. We also contacted other finance professors and inquired about predictive variables we may have missed.

Most studies that we identify demonstrate cross-sectional predictability with either Fama-MacBeth (1973) slope coefficients or long-short portfolio returns. Some of the studies demonstrate a univariate relation between the given variable and subsequent returns, whereas 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 of these studies to be useful to investors, we include them in our analyses.

Our search process identifies 79 different studies. Based on these studies, we examine 97 cross-sectional relations. The various predictors and their associated studies are detailed in the paper's Internet Appendix.[6] We include all variables that relate to cross-sectional returns, including those with strong theoretical motivation such as Fama and MacBeth's (1973) market beta and Amihud's (2002) liquidity measure.

Our goal is not to perfectly replicate the findings in each paper. This is impossible since CRSP data change over time and papers often omit details about precise calculations. Moreover, in some cases we are unable to exactly reconstruct a given predictor. In such cases, we calculate a characteristic that captures the intent of the study. As an example, 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 similar variable that we expect to contain much of the same information. As another example, 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.

For some characteristics such as momentum, higher characteristic values are associated with higher returns, while for other characteristics such as size, higher characteristic values are associated with lower returns. We form long-short portfolios based on the extreme 20$^{\text{th}}$ percentiles of the characteristic. The long side is the side with the higher returns as documented by the original publication.

Sixteen of our predictors are indicator variables. For these cases, if the original paper demonstrates higher returns for firms assigned with the indicator, then these firms are included in the long-side portfolio, and an equal-weighted

[6] The Internet Appendix is available in the online version of the article on the *Journal of Finance* website.

portfolio of all other stocks is used to form the short-side portfolio. If the original paper demonstrates lower returns for indicated firms, then non-indicated firms form the long-side portfolio and the indicated firms form the short-side portfolio.

Three predictors are variables with three discrete values (long, short, and neutral). For example, Barth and Hutton (2004) develop a strategy of buying low accrual stocks with increases in analysts' earnings forecasts, and selling low accrual stocks with decreases in earnings forecasts. In cases like this, our long-short portfolio follows the original paper. We provide detailed descriptions of all 97 predictors in the paper's Internet Appendix.

The average correlation across the returns of the 97 predictor portfolios is 0.033. This finding is consistent 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 below, we explicitly control for such cross-correlations when computing the standard errors of our test statistics.

In an earlier version of the paper we also 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 (1973) 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.

II. Important Dates and Summary Statistics

We segment periods based on both the end-of-sample date and the publication date. We do so because these are easily identifiable 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, in contrast, 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. However, some market participants may not read the paper until years after publication. Post-publication decay in return predictability may therefore be a slow process. We are unaware of theories on how long the decay should take or on the functional form of the decay. Despite the simplicity of our approach, the publication date generates robust estimates of return decay.

Table I provides summary statistics for the predictor portfolios that we study. For the 97 portfolios, the average monthly in-sample return is 0.582%. The average out-of-sample, pre-publication return is 0.402%, whereas the average post-publication return is 0.264%. Returns are equal-weighted unless the primary study presents value-weighted portfolio results as its primary finding, and the only study in our sample that does this is Ang et al. (2006).

The average length of time between the end-of-the sample and publication dates is 56 months. In comparison, the average original in-sample span is 323

Table I
Summary Statistics

This table reports summary statistics for the predictor portfolios studied in this paper. The returns are equal-weighted by predictor portfolio, that is, we first estimate the statistic for each predictor portfolio, and then take an equal-weighted average across the portfolios. 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
Standard deviation of mean out-of-sample portfolio return	0.651
Mean observations out-of-sample	56
Mean portfolio return post-publication	0.264
Standard deviation of mean post-publication portfolio return	0.516
Mean observations post-publication	156

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. We consider two variations. A previous version of this paper considers publication dates based on arrival time stamps at Boston metropolitan libraries. This variation produced nearly identical results. Another version considers the publication date to be the earlier of the actual publication date and the first time the paper appears on the SSRN. The average number of months between the end-of-sample and SSRN dates is 44 months, and we again obtain the same results.

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 predictors produce t-statistics that are greater than 1.50. With respect to the 12 predictors that do not reach this significance level, in some cases the original paper reports event study abnormal returns that do not survive in our portfolio sorts. In other cases, we do not have the same data used by the original authors. Portfolio formation also contributes to differences in statistical significance. We focus on long-short quintile returns, while some of the original papers that demonstrate predictability use Fama-MacBeth (1973) slope coefficients or buy-and-hold returns.

III. Empirical Analyses and Results

A. Portfolio Returns Relative to End-of-Sample and Publication Dates

In this section 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):

$$R_{it} = \alpha_i + \beta_1 \, Post\ Sample\ Dummy_{i,t} + \beta_2 \, Post\ Publication\ Dummy_{i,t} \; + \; e_{it}. \tag{1}$$

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, whereas the post-publication dummy is equal to one if the month is post-publication and zero otherwise. The variable α_i captures predictor fixed effects.

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 being uncorrelated. We therefore compute our standard errors using feasible generalized least squares (FGLS) under the assumption of contemporaneous cross-correlation between returns. Clustering on time (as in previous drafts) produces similar results, with slightly smaller standard errors in most cases.

The post-sample coefficient, β_1, 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, β_2, 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 on both the post-sample and post-publication dummies 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. In contrast, if predictors' returns are entirely the result of mispricing and arbitrage resulting from publication corrects all mispricing, then the post-publication coefficient should be equal to -0.582 and the post-sample dummy should be close to zero. In the remaining 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 estimates equation (1) on our full sample of 97 predictors. The post-sample coefficient in this regression is -0.150%, and statistically

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 one if the month is after the sample period used in the original study and zero otherwise. *Post-Publication (P)* is equal to one 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-statistics are the in-sample t-statistic of each predictor portfolio. Standard errors (in parentheses) 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, respectively. 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 × Mean			−0.532***	
			(0.221)	
P × Mean			−0.548***	
			(0.178)	
S × t-statistic				−0.061***
				(0.023)
P × 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 : S = P	0.024	0.021		
Null: P = −1 × (mean)	0.000	0.000		
Null: S = −1 × (mean)	0.000	0.000		

significant. Thus, our best estimate of the post-sample decline is 15.0 bps. The post-publication coefficient is −0.337, and it is also statistically significant. These results show that, on average, predictor portfolios are 33.7 bps lower post-publication compared to before publication. Table I shows that the average predictor has an in-sample mean return of 58.2 bps per month. Hence, post-sample and post-publication returns decline relative to the in-sample mean by 26% and 58%, respectively.

The regression in the second column includes only 85 predictors. It excludes the 12 predictors that generate t-statistics with values less than 1.5. Exclusion of these predictors 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, so the post-publication decay in percentage terms is similar if these other 12 predictors are included. The average in-sample return is larger when we exclude the 12 predictors because we are excluding the 12 predictors that lack significant in-sample predictability.

At the bottom of Table II, we report tests of whether the post-publication coefficient and out-of-sample but pre-publication coefficient 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, that should be fully reflected in the out-of-sample but pre-publication coefficient.

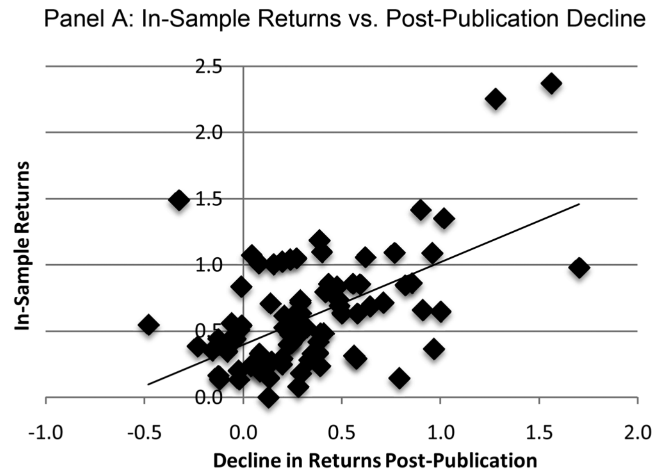
The bottom of Table II also reports tests of whether predictor portfolio returns disappear entirely post-publication. This test is generated from a linear restriction that equates the post-publication coefficient to the average sum of the fixed effects and the intercept.[7] This test, along with the t-test on the post-publication coefficient, allows us to easily reject both nulls, that is, we reject the null that anomaly returns decay entirely post-publication, 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 predictor 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 on the post-sample dummy is 0.157, whereas the coefficient on the interaction between the post-sample dummy and the in-sample mean is −0.532. As we mention above, the average in-sample monthly return for the 97 portfolios is 0.582% (see Table I), so the overall post-sample effect is $0.157 + (-0.532 \times 0.582) = -0.153$, similar to the post-sample coefficient in column (1). The standard deviation of the in-sample mean return is 0.395 (see Table I). Hence, a portfolio with an in-sample mean return that is one standard deviation more than average has a $-0.532 \times 0.395 = -0.210$ bp decline in post-sample monthly return. This could reflect predictors with larger in-sample returns having a larger degree of statistical bias. Alternatively, it could reflect arbitrageurs being more likely to learn about and trade on predictors with higher returns before publication. Similarly, the the post-publication dummy is −0.002, and the interaction between the post-sample dummy and in-sample mean is −0.548. This relation is also displayed in Figure 1 (Panel 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.

The final regression in Table II interacts the post-sample and post-publication dummies with a predictor's in-sample t-statistic. The average

[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 in-sample return. We then test whether this value minus the coefficient on either publication or post-sample is equal to zero.



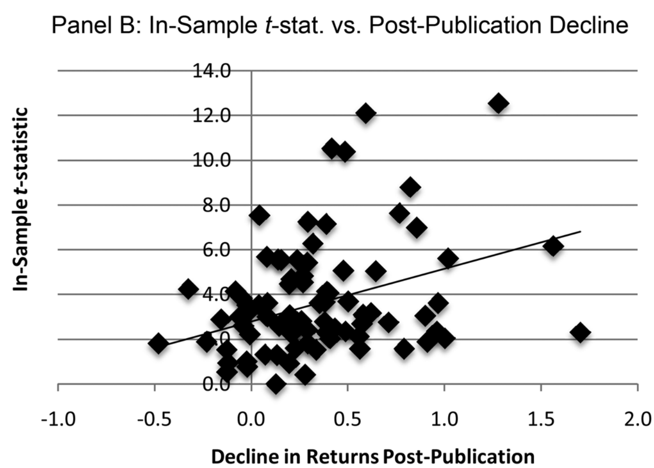


Figure 1. The relation between in-sample returns and post-publication decline in returns. Panel A plots the relation between in-sample returns and post-publication declines in returns. For each predictor, we estimate the mean return to a long-short portfolio that contemporaneously buys and sells the extreme quintiles during the sample period of the original study. We then estimate the mean return for the period after the paper is published through 2013. To be included in the figure, a predictor's in-sample return has to generate a t-statistic greater than 1.5; 85 of the 97 predictors that we examine meet this criterion. The predictor also has to have at least three years of post-publication return data. This excludes 10 of the 85 predictors, resulting in a sample of 75 predictors. Panel B repeats this exercise, but it plots in-sample t-statistic against post-publication declines. The returns are reported in percent, e.g., 1.5 is a monthly return of 1.5%.

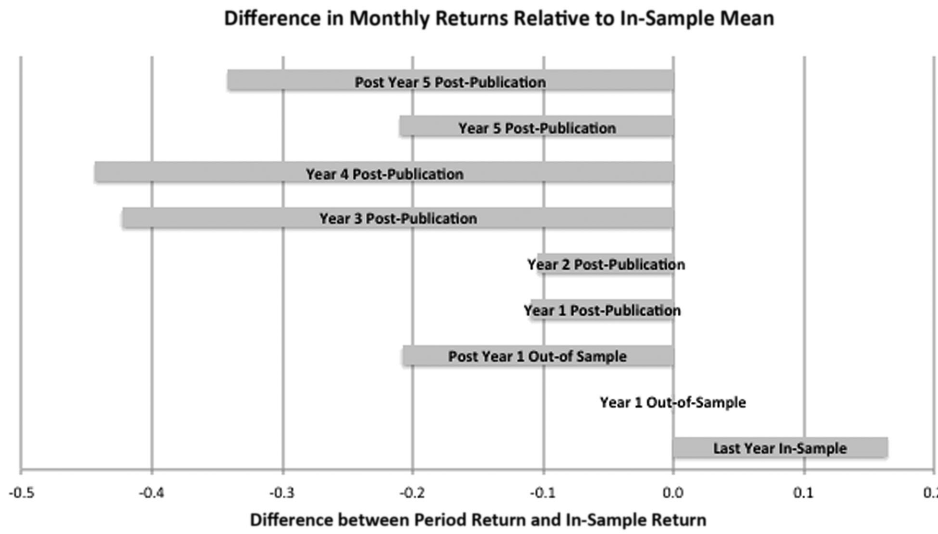


Figure 2. Predictor return dynamics around the sample-end and publication dates. This figure explores changes in predictability by examining finer post-sample and post-publication partitions. The figure plots the coefficients from a regression containing dummy variables that signify the last 12 months 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 into six different variables, namely, 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 returns are reported in percent, e.g., 1.5 is a monthly return of 1.5%.

in-sample t-statistic is 3.55 and the standard deviation of the t-statistics is 2.39. Hence, the regression estimates an incremental decline for a characteristic portfolio with a t-statistic that is one standard deviation higher than the average of -0.146 post-sample and -0.151 post-publication. The post-publication effect is plotted in Figure 1 (Panel B). The results here are consistent with the idea that arbitrageurs devote more capital to characteristic portfolios that are associated with higher in-sample returns. In an untabulated specification we condition decay on in-sample Sharpe ratios and estimate very similar results.

Previous versions of the paper consider whether decay is related to the cumulative number of academic citations to the publication that introduces the portfolio returns associated with the predictor. After controlling for the publication date, this measure has little incremental value in explaining decay.

C. A Closer Look at Predictor Return Dynamics around the End-of-Sample 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 for the last 12 months of the original sample, the first 12 months out-of sample, and the remaining out-of-sample months. In addition, the publication dummy is split into six variables, namely, a 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.

The publication process often takes years. This gives unscrupulous researchers an opportunity to choose their sample-ends so as to report stronger results. Figure 2 shows that the coefficient on the dummy for the last 12 months of the original sample is positive, which means that the last 12 months of the sample have higher returns than the other in-sample months, which could be consistent with researchers ending their samples opportunistically. However, the coefficient on the dummy for the first 12 months post-sample is virtually zero, which indicates that the first 12 months post-sample have on average the same returns as the in-sample months. If authors were 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. After the first 12 months post-sample and during the remaining out-of-sample months but before publication, returns are more than 20 basis points lower. Returns remain at this level the first two years post-publication, and then decay further: In the third year we estimate a decay of 40.8 bps; in the fourth year decay is 43.3 bps; and in the fifth year decay is 20.5 bps. After the fifth year post-publication predictors returns are on average 33.9 bps lower as compared to in-sample.

One might suggest that we examine post-publication returns as a function of the predictor's persistence (i.e., how often the portfolio turns over). Initial 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, whereas portfolios based on less persistent predictors, such as last month's stock return, would not generate such an effect. We consider this possibility in an earlier version of the paper. We find some evidence that portfolio returns to more persistent predictors decay less following publication, but the effect is 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' returns may drop post-publication if anomalies reflect mispricing and declining trading costs have made arbitrage less costly (see Goldstein et al. (2009) and Anand et al. (2012)). Consistent with this idea, Chordia, Subrahmanyam, and Tong (2013) show that the returns of the 12 anomalies decline after 1993, which they attribute to an increase in hedge funds and lower trading costs.

To examine the possibility that our results reflect a time effect and not a publication effect, we construct a time variable that is equal to 1/100 in January 1926 and increases by 1/100 each month in our sample. Tale III presents the results. 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 one 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 after 1993. The post-1993 coefficient is negative but insignificant 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 still 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, adding 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. Column (4) of Table III reports an estimation that includes time fixed effects. The estimated coefficients are very close to those in Table II. In particular, predictor returns are 17.9 bps lower out-of-sample and 31.0 bps lower post-publication, both significant at the 5% level. Based on the average in-sample return of 58.2 bps, this specification implies a sizeable 53% drop in post-publication predictability after all 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, whereas Grundy and Martin (2001) fail to find significant momentum in the Fama-French factors. We include the predictor's prior-month's return and the sum of its returns over the last 12 months' returns in columns (5) and (6), respectively. Both of the lagged return coefficients are positive and significant, which is broadly consistent with Moskowitz, Ooi, and Pedersen (2013). The post-publication coefficient remains significant in each of these regressions, suggesting a post-publication decline of about 25 to 30 bps 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 variations in pre-publication returns, post-publication returns, and the

Table III

Time Trends 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 one if the month is after the sample period used in the original study and zero otherwise. *Post-Publication (P)* is equal to one if the month is after the official publication date and zero otherwise. *Time* is the number of months divided by 100 post-January 1926. *Post-1993* is equal to one if the year is greater than 1993 and zero otherwise. *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 (in parentheses) 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, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Time	−0.069***		−0.069***			
	(0.011)		(0.026)			
Post-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-Publication			−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

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 from financial statement data and analysts' 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, whereas 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, whereas market predictor portfolios

Table IV

Predictor Returns across Different Predictor Types

This table tests whether predictor returns and changes in returns post-publication vary across 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 differs from the other three types. The bottom two rows test whether post-publication returns for each predictor type are different than those of the other three types. Standard errors (in parentheses) 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, respectively.

Variable	(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 × Market	−0.244			
	(0.169)			
Event		−0.098**		
		(0.046)		
P × Event		0.105		
		(0.091)		
Valuation			−0.056	
			(0.063)	
P × Valuation			0.186	
			(0.131)	
Fundamental				−0.201***
				(0.045)
P × 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 × Type)	0.060	0.007	0.121	−0.176
p-value	0.210	0.922	0.256	0.012

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 FGLS, which accounts for contemporaneous cross-correlations.

We formally test for differences between the four predictor portfolio groups 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 the interaction between the post-publication and the predictor type dummy:

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

The coefficient on the *Predictor Type Dummy*, β_2, estimates whether the in-sample average returns of a group are different from 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.

The coefficient on the interaction, β_3, tests whether post-publication declines vary across predictor groups. The decline for the market-based predictor portfolio returns is largest, although it is not significantly different from the declines for the other predictors. Valuation predictor returns have the smallest declines post-publication.

Differences in post-publication expected returns are given by the sum of the type coefficient and the interaction coefficients $\beta_2 + \beta_3$. The sums and their 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 those of the non-market-based predictors. This result is consistent with the results in Table II, which shows 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 this pre-publication difference in returns is persistent post-publication.

F. Costly Arbitrage

The results above 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) suggest that costs associated with arbitrage can prevent arbitrageurs from fully eliminating mispricing. By this logic, predictor portfolios concentrated in 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

[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.

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 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 dividend-payer 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 therefore 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, 2006)), and thus returns should be higher in predictor portfolios concentrated in high idiosyncratic risk stocks. We compute monthly idiosyncratic risk by regressing daily returns on the 12 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 residuals. The monthly idiosyncratic risk measure is created by cumulating the daily sum of residual products for a given month. If the industry factor model regression contains less than 30 observations, the stock is not assigned an idiosyncratic risk measure in that month.

Pontiff (1996, 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 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 for 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 of 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.

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

We estimate the arbitrage cost of each predictor portfolio as 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 in CRSP. Each stock-month observation is therefore assigned a ranking between zero and one. Next, for each month, we estimate the average rank of 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 affects the costly arbitrage variables. We then estimate the following regression,

$$R_{i,t} = \alpha_{i,} + \beta_1 \, \textit{Post Publication Dummy}_{i,t} + \beta_2 \, \textit{Arbitrage Cost}_i + \beta_3 \, \textit{Post Publication Dummy}_{i,t} \times \textit{Arbitrage Cost}_i + e_{it}, \quad (3)$$

where the dependent variable is a predictor's monthly return. We report the results in Table V. The results largely support 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 portfolios with higher arbitrage costs should have higher pre-publication returns. This effect is given by the slopes on the non-interacted arbitrage cost variables, β_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.

Post-publication knowledge of a predictor should be widespread, and we thus expect portfolios that are easier to arbitrage to have lower post-publication returns. The sum of the costly arbitrage coefficient, β_2, plus the coefficient on the interaction between the post-publication dummy and the arbitrage cost variable, β_3, should therefore reflect higher expected returns for predictors that are more costly to arbitrage. The sum of these coefficients and their associated p-values are presented in the last two rows of Table V. All 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 simultaneously includes all five of the primary costly arbitrage variables and all five of the interactions. Caution is needed in interpreting such results due to high correlations between the 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 expected signs but are insignificant. Idiosyncratic risk's post-publication p-value is 0.000. These findings are consistent with Pontiff's (2006, p. 35) review of the literature that

Table V

Costly Arbitrage and the Persistence of Predictor Returns

These regressions test 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 spreads), assigning each stock a value between zero and one 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 the 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 the average monthly bid-ast Spreads 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 one 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 (in parentheses) 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, respectively. The bottom two rows test whether the sum of the costly arbitrage variable (*CA*) plus the interaction between the publication dummy and the costly arbitrage variable ($P \times CA$) is statistically different from zero.

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)	(0.078)
P × Size	−0.138					
	(0.459)					
Size	−1.064**					
	(0.236)					
P × Spreads		−0.301				
		(0.603)				
Spreads		1.228**				
		(0.252)				
P × Dol.Vol.			−1.059*			
			(0.500)			
Dol. Vol.			0.215			
			(0.308)			
P × Idio. Risk				−0.047		
				(0.554)		
Idio. Risk				2.064***		
				(0.330)		
P × Div.					−0.321	
					(0.211)	
Div.					−0.526***	
					(0.145)	
P × 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 × 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

leads him to conclude that "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 after publication. To do so, we re-estimate the regression described in equation (1), but replace monthly stock returns with a monthly measure of one of the traits.

Trading volume is measured as shares traded, whereas 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 use the logs of these variables 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 sides 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 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, while variance is significantly lower. Hence, there appears to be an increase in trading among predictor portfolio stocks even before a paper is published, suggesting that the information content of papers may get to some investors before the paper is published.

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, in contrast, declines by 6.5% post-publication. Lower volatility could reflect less noise trading (Shiller (1981) and Pontiff (1997)).

The final column reports 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 (the dependent variable is multiplied by 100). 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 sides of the characteristic portfolios in-sample is 0.143% (not in tables). The mean and median levels of short interest in our sample (1976 to 2013) are 3.45% and 0.77%, respectively, so this

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 the 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, whereas *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 long quintile for each characteristic, and subtract from it the average short interest in the short quintile. The short interest findings are reported in percent (the dependent variable is multiplied by 100). *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 one if the month is after the sample period used in the original study and zero otherwise. *Post-Publication (P)* is equal to one if the month is after the official publication date and zero otherwise. Standard errors (in parentheses) 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, respectively.

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-Publication (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

difference is economically meaningful. This result suggests that some practitioners know prior to publication that stocks in the predictor portfolios are mispriced and trade accordingly. This could be because practitioners are trading on the predictor, or it could reflect practitioners trading on other strategies that happen to be correlated with the predictor. As an example, if short sellers evaluate firms individually with fundamental analysis, their resulting positions may be stocks with low book-to-market, high accruals, high stock returns over the last few years, etc., even though short sellers are not 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 a three-fold increase in shorting post-publication relative to in-sample. So, although some practitioners may know about these strategies before publication, the results here suggest that publication makes 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.

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 one 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 (in parentheses) 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, respectively.

Variables	Coefficients
In-Sample Index Returns	0.748***
	(0.027)
Post-Publication Index Return	−0.008
	(0.004)
P × In-Sample Index Returns	−0.674***
	(0.033)
P × Post-Publication Index Return	0.652***
	(0.045)
Publication (P)	−0.081
	(0.042)
Constant	0.144***
	(0.019)
Observations	42,975
Predictors	97

H. The Effects of Publication on Correlations among Characteristic Portfolios

In this section, we study the effects that publication has on correlations between characteristic portfolios. If predictor returns reflect mispricing and if mispricing has a common source (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 predictors because of fund flows or other factors common to arbitrage portfolios.

In Table VII, we regress predictor portfolio returns on the returns of an equal-weighted index of all other predictor portfolios that are pre-publication, and a second equal-weighted index of all of the other predictor portfolios 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 indices.

The results show that pre-publication predictor returns are significantly related to the returns of other pre-publication predictor portfolios. The coefficient (or beta) on the pre-publication predictor portfolio is 0.748 and statistically significant. In contrast, the β for a pre-publication portfolio on other post-publication portfolios is -0.008 and insignificant. Hence, the returns of unpublished predictors are correlated with the returns of other unpublished predictors, but not with the returns of published predictors.

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 an interaction between the post-publication dummy and the return of the portfolio consisting of in-sample predictors is -0.653 and highly significant. These results show that, 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 decreases to $0.748 - 0.674 = 0.074$. The coefficient on the interaction between the post-publication dummy and 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. Conclusion

This paper studies 97 characteristics shown to explain cross-sectional stock returns in peer-reviewed finance, accounting, and economics journals. Using portfolios based on the extreme quintiles for each predictor, we compare each predictor's return predictability over three distinct periods: (i) the original study's sample period, (ii) the period outside the original sample period but before publication, and (iii) the post-publication period.

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 both the null of no post-publication decay and to the null that post-publication returns decay entirely.

Several of our findings support the idea that 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 result 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 finding 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 positive significant.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.