1. Effect of Strategy Combinations for Equity Market Neutral Strategies

2. Primer on Fama-Macbeth 2-stage estimation

EFFECTS OF STRATEGY COMBINATIONS

There are 3 gains from combining market neutral equity strategies:

- Lower trading costs due to internal trade crossing
- Higher returns due to internal position netting
- Diversification

INTERNAL TRADE CROSSING

Consider market neutral strategies s_1 and s_2, two dates *t* and *t-1*, trading a universe with 3 securities, A, B and C

Desired position for s_1 on *t-1* is (\$1,\$2, \$-3), and for s_2, is (\$2, \$1, \$-3)

Desired position for s_1 on t is (\$2, \$1, \$-3) and for s_2 is (\$1, \$2, \$-3)

Therefore we have \$6 of AUM in s_1 and \$6 in s_2 for total portfolio AUM of \$12

INTERNAL TRADE CROSSING

If s_1 and s_2 were traded individually:

- Total date t turnover for s_1 would be \$2. We buy \$1 of A and sell \$1 of B
- Total date t turnover for s_2 would also be \$2. We sell \$1 of A and buy \$1 of B

However, since we are holding both s_1 and s_2 in the same portfolio:

- s_1 and s_2 can 'trade' with each other internally
- Specially, s_1 can 'buy' \$1 of asset A that s_2 wants to sell, vice versa for asset B

Total turnover for entire portfolio of \$12 is zero

Overall, internal trade crossing saves on bid-ask spreads, commissions, and reduces market impact

INTERNAL POSITION NETTING

Consider two strategies s_1 and s_2, one trading date t, trading a universe with 3 securities, A, B and C. Both s_1 and s_2 perform 10% a year in backtest

Target position for s_1 on date t is (\$1.5, \$1.5, \$-3) for total gross market value of \$6 and total net market value of \$0

Target position for s_2 on date t is (\$-3, \$1.5, \$1.5) for total gross market value of \$6 and total net market value of \$0

Total desired gross market value is \$12 (i.e. your clients provide \$12 of AUM to manage)

INTERNAL POSITION NETTING

Adding s_1 and s_2, we find that aggregate target position vector for date *t* is ($-1.5, $3, $-1.5)

Although we added two strategies with combined target gross market value of $12 on date *t*, the result only has gross market value of $6.

We need to 'gross up' aggregate target position vector for date t by 2x, to get ($-3, $6, $-3), in order to obtain gross market value of $12 and fully deploy all the AUM our client has provided

INTERNAL POSITION NETTING

Recall that s_1 and s_2 both perform 10% a year in backtest

Expected returns when investing $6 in GMV on *s1* is $0.60 for 1 year, same for s_2

If we trade both strategies individually, our expected returns will be $1.2 a year on AUM of $12

However, by combining both strategies and taking advantage of internal position netting, our expected returns is now $2.4 a year on AUM of $12

Expected returns are double in this example due to internal position netting!

DIVERSIFICATION

Recall our two market neutral strategies s_1 and s_2, which produce returns of u_1 and u_2, and have volatility (standard deviation) of returns = σ_1 and σ_2. Formally:

- $s_1 \sim N(u_1, \sigma_1)$
- $s_2 \sim N(u_2, \sigma_2)$
- Note: Normality of returns is not critical assumption in derivation. We put it here for ease of exposition

For simplicity, assume both strategies are uncorrelated, but have similar volatilities and returns. Formally:

- $\text{Covariance}(s_1, s_2) = 0$
- $\sigma_1 = \sigma_2 = \sigma$
- $u_1 = u_2 = u$

In this setup, Sharpe ratio of $s_1 = u_1/\sigma_1$, Sharpe ratio of $s_2 = u_2/\sigma_2$. Both strategies have similar Sharpe ratios $= u/\sigma$, even though they are uncorrelated

DIVERSIFICATION

Consider a portfolio A which is 50% invested in s_1, and 50% invested in s_2

Expected returns of A is $(u1 + u2)/2 = u$

Volatility of A

- $= \sqrt{\text{Variance}(0.5 \times s_1 + 0.5 \times s_2)}$
- $= \sqrt{(0.5^2 \times \text{Var}(s_1) + 0.5^2 \times \text{Var}(s_2) + 2 \times 0.5 \times 0.5 \times \text{Covariance}(s_1, s_2))}$
- $= \sqrt{(0.5^2 \times \text{Var}(s_1) + 0.5^2 \times \text{Var}(s_2))}$
- $= 0.5 \times \sqrt{(Var(s_1) + Var(s_2))}$
- $= \sigma/\sqrt{2}$

DIVERSIFICATION

Sharpe ratio of portfolio A:

$= \upsilon \,/\, (\sigma/\sqrt{2})$

$= (\upsilon \,/\, \sigma) \times \sqrt{2}$

$=$ Sharpe ratio of $s_1 \times \sqrt{2}$, or

$=$ Sharpe ratio of $s_2 \times \sqrt{2}$

Even though both component strategies had the same Sharpe ratio of υ/σ, a portfolio which is equal weighted both has a Sharpe ratio higher by factor of $\sqrt{2}$

DIVERSIFICATION

Overall, Sharpe ratio of combination will scale with sqrt of # strategies

What is the critical assumption?

$$\mathbf{Covariance}(s_1, s_2) = 0$$

i.e. we want PNL correlation of both strategies to be 0, or (realistically) as low as possible

FAMA-MACBETH REGRESSION

This is a two step process to determine factor risk premium

FAMA-MACBETH REGRESSION

In the first stage, we run a separate regression for each asset, or portfolio of assets.

The ‘dependent variable’ for each regression is historical time series returns on the asset, while the independent variable(s) would be historical time series values of each factor for that asset

EXAMPLE DATASET DIMENSIONS

Suppose we have 500 assets (stocks), and we put one stock in each portfolio. We can also group the stocks

There is quarterly data available for the stock returns and for each factor over exactly 10 years

Say there are two factors we are interested in (market cap and profitability)

Therefore, for each of the 3 variables (stock returns, market cap and profitability), we have a 500 columns by 40 rows dataset.

FIRST STEP REGRESSION DETAILS

In this example, we run 500 regressions, one for each asset.

For each asset *i*, we run following regression:

$$\boldsymbol{R}_{i,t} = \alpha_i + \beta_1 * \boldsymbol{MarketCap}_{i,t} + \beta_2 * \boldsymbol{Profitability}_{i,t}$$

FIRST STEP REGRESSION DETAILS

In the previous slide, dependent variable vector for each regression is 40 rows by 1 column (vector of quarterly returns for the stock in question)

The independent variable panel for each regression is 40 rows by 3 columns.

- First column is all '1's, which allows for estimation of constant term
- Second column will be values of market cap factor over last 10 years (40 quarters)
- Third column will be values of profitability factor over last 10 years (40 quarters)

From these 500 regressions, we obtain a 500 rows by 3 columns panel:

- Each regression gives us 3 numbers: a constant term, a coefficient estimate on market cap and another coefficient estimate on profitability
- From all 500 regressions, we get the 500 rows by 3 columns panel
- The 500 coefficient estimates on market cap (for example) give the factor exposure of each of the 500 assets to the market cap factor

SECOND STEP REGRESSION DETAILS

In the second step, we run 40 regressions, one for each month.

For each month-regression, the dependent variable is a 500 rows by 1 column vector, which are the returns for each of the 500 stocks for that month

SECOND STEP REGRESSION DETAILS

For each month-regression, the independent variables are a 500 rows by 3 columns vector.

- First column is a column of 1s, which allows for estimation of the constant term
- Second column would be estimated coefficients for each of the 500 stocks on the market cap factor
- Third column would be estimated coefficients for each of the 500 stocks on the profitability factor

From this step, we obtain a 40 rows by 3 columns panel:

- For each month-regression, we obtain 3 coefficients: a constant term, the risk premium associated with market cap, and the risk premium associated with profitability

From the 40 rows by 3 columns panel, we can obtain 2 numbers:

- By averaging the estimated risk premium on market cap across all 40 numbers, we get an average risk premium on market cap
- Same for profitability

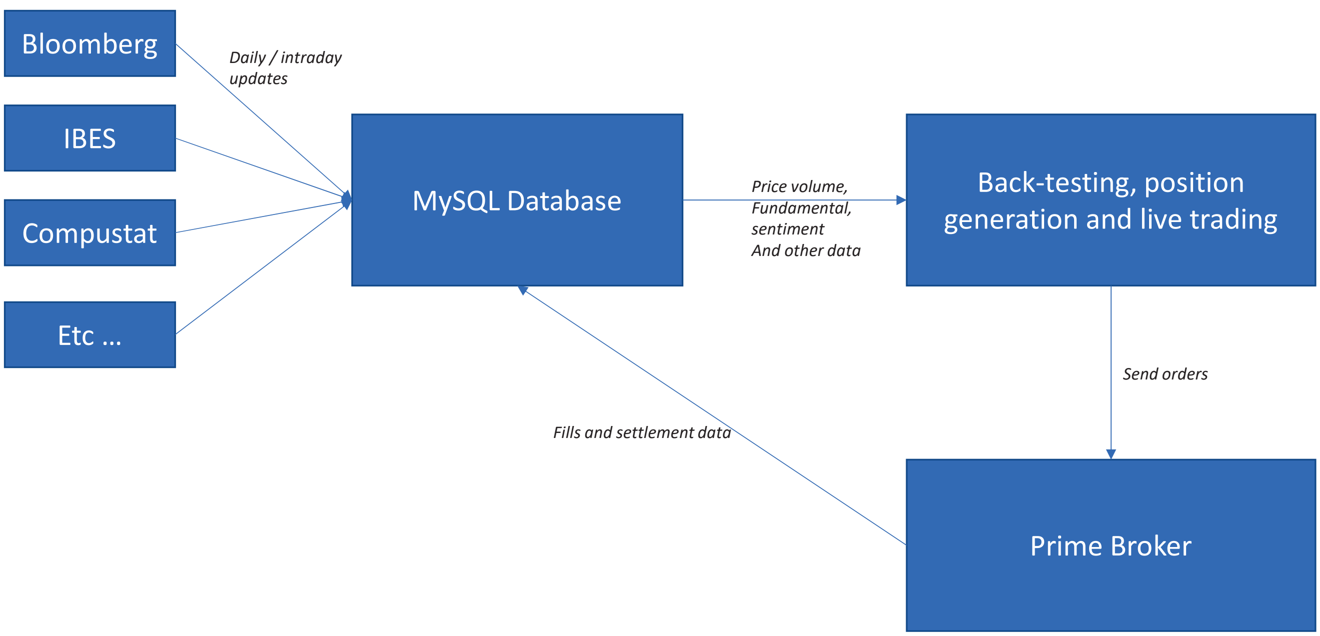
SUMMARY OF 2 STEP PROCESS

From the first step, estimated coefficients are conceptually factor loadings. These describe how much each stock is 'exposed' to the factor

From the second step, we obtain factor risk premiums. These describe the returns compensation for holding the stock in question

Practical implementation of market neutral strategies

Systems Architecture



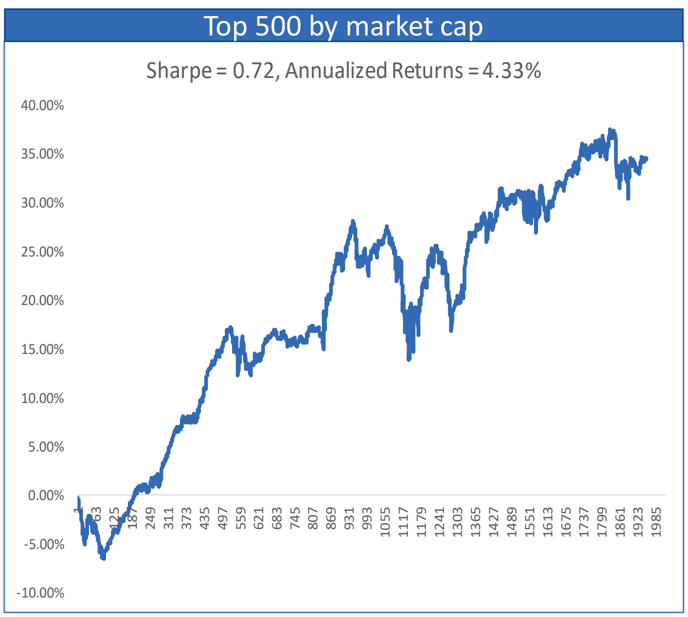
Database maintenance

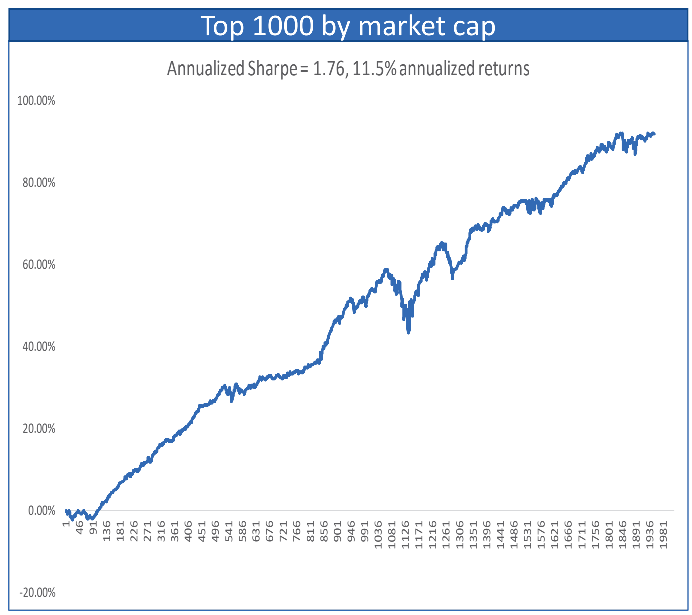
- Normalizing data frequency
- Merging unique keys (tickers, cusips, isins, Bloomberg tickers, Thomson Reuters IDs, etc)
- Handling delisting and lookahead bias
- Price adjustment with dividends and stock splits

Universe selection

- Trade off between trading costs and pre-cost performance
- Market cap: min (and also max?)
- Average daily trading volume
- How often do we rebalance the trading universe?

Analyst revisions strategy over different universes





Both backtests use exactly same code otherwise

Realistic simulation assumptions

- Roundlotting: some brokers will cross spread mandatorily if order is not round lot (unless LIMIT order)

- Maximum % of stock owned: do we want to exceed 5%?

- Position liquidity: max % of ADV owned

- Short locates: are all positions that we want to short ‘doable’?

Realistic simulation assumptions

- Execution quality:
  - Assume execution at VWAP or MOC
  - What is spread cost paid?
  - What is market impact?

- Is commissions in mils (‘cents per share’) or bps?

Common functions: Industry Neutrality

- Industry neutral, versus just ‘market neutral’

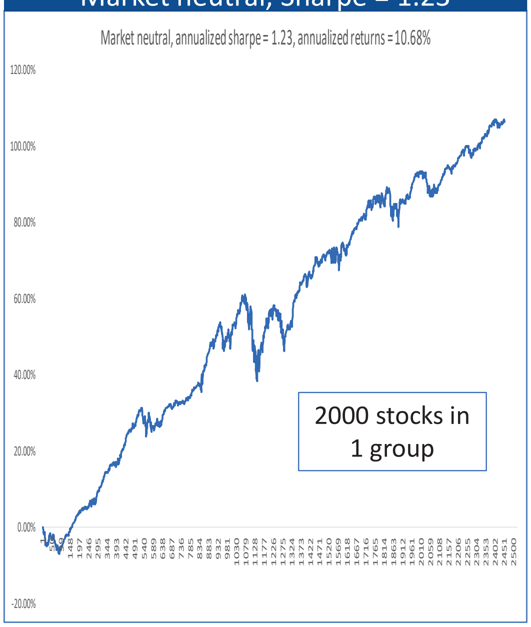
- Pseudocode for market neutral:
  - Generate weights for stocks based on alpha factor. Call this weight vector **W**
  - Compute mean of all weights. Call this scalar = $\mathbf{w}_{\mathbf{bar}}$
  - Final weight for each stock in market neutral portfolio = **W** – $\mathbf{w}_{\mathbf{bar}}$

- Pseudocode for industry neutral:
  - Generate weights for stocks based on alpha factor. Call this weight vector **W**
  - For each unique industry, compute mean of all weights in that group. Let industry i’s mean = $\mathbf{w}_{\mathbf{\_bar\_i}}$
  - Final weight for each stock in market neutral portfolio = **W** – $\mathbf{w}_{\mathbf{\_bar\_i}}$ if stock is in industry *i*

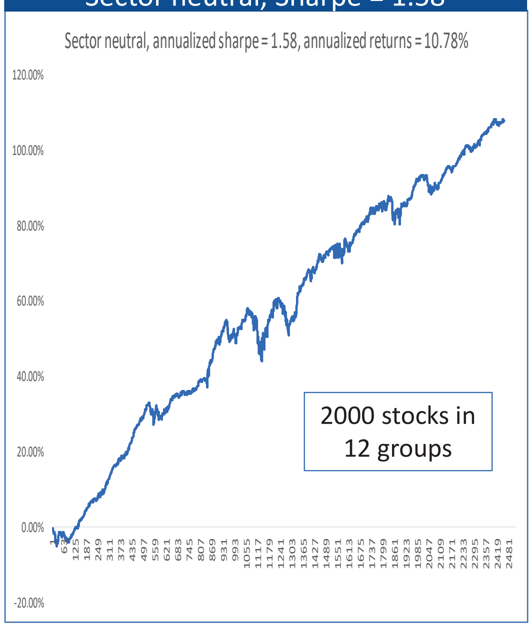
- What do we mean by ‘industry’?

Analyst revisions strategy with different neutrality

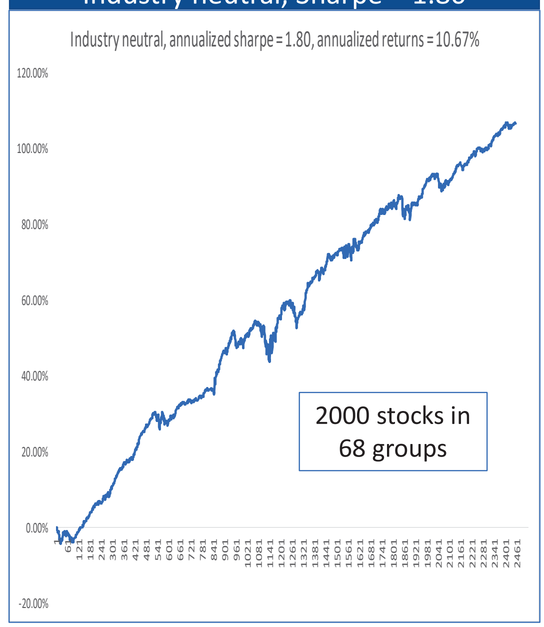
Market neutral, Sharpe = 1.23



Sector neutral, Sharpe = 1.58



Industry neutral, Sharpe = 1.80



All 3 backtests use exactly same code otherwise

Common functions: Weigh by Rank

- Consider two market neutral alpha formats:

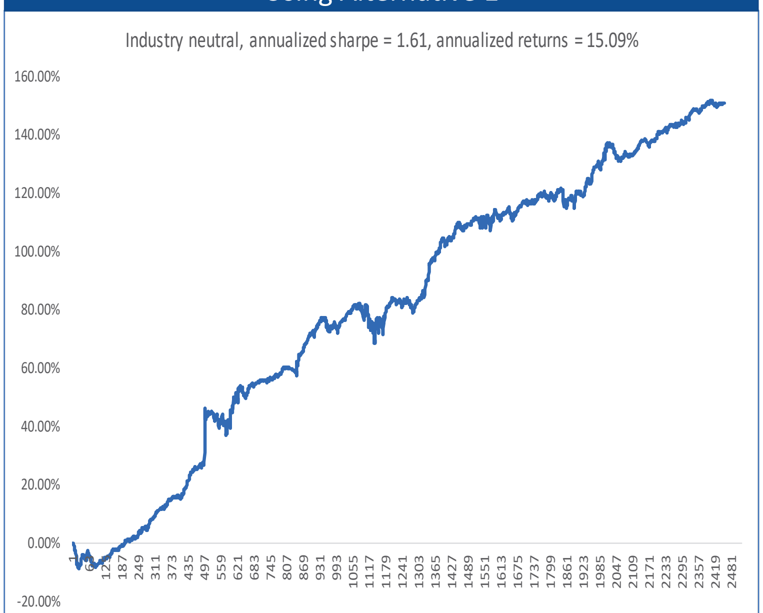
- Alternative 1:
  - Sort by alpha factor (e.g. one year return)
  - Give each stock a weight = alpha factor. Stocks with more extreme values of one year return will have weights at extreme ends of distribution
  - Make weight vector market/ industry neutral

- Alternative 2:
  - Sort by alpha factor (e.g. one year return)
  - Give each stock a weight = ***CROSS_SECTIONAL_RANK***(alpha factor) on that day . Stocks with more extreme values of one year return will still have weights at extreme ends of distribution
  - Make weight vector market/ industry neutral

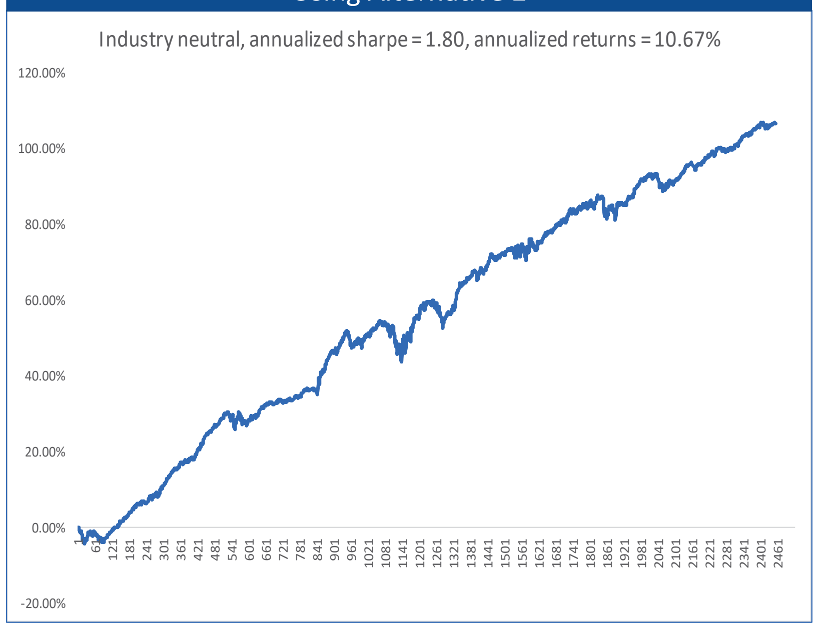
- Trick question: which is better and why?

Analyst revisions strategy with different ranking schemes

Using Alternative 1



Using Alternative 2



Both backtests use exactly same code otherwise

Common functions: Maximum Position Weight

- Constrain portfolio to put maximum of x% gross market value on any single position

- Two advantages:
  - Limits liquidity and idiosyncratic risk in trading
  - Lessens overfitting due to deriving large portion of PNL from single position

Common functions: Decays

- Spreads turnover over multiple days
  - Reduces trading costs and market impact
  - May potentially reduce performance

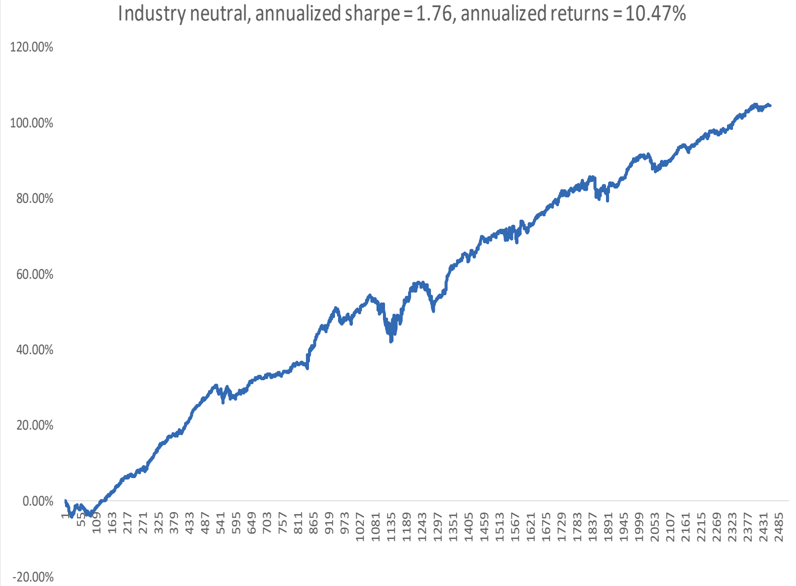
- Pseudocode [linear window]:
  - ➢ *Alpha[i,t] = (alpha_raw[i,t] + (1/2)*alpha_raw[i,t-1] + (1/3)*alpha_raw[i,t-2] + … + (1/n)*alpha_raw[i,i-n+1])/(1+1/2+1/3+…+1/n)*

- Pseudocode [exponential decay]:
  - ➢ *Alpha[i,t] = (alpha_raw[i,t] + decay_factor*alpha[i,t-1])/(1+decay_factor)*

Analyst revisions strategy with different decays

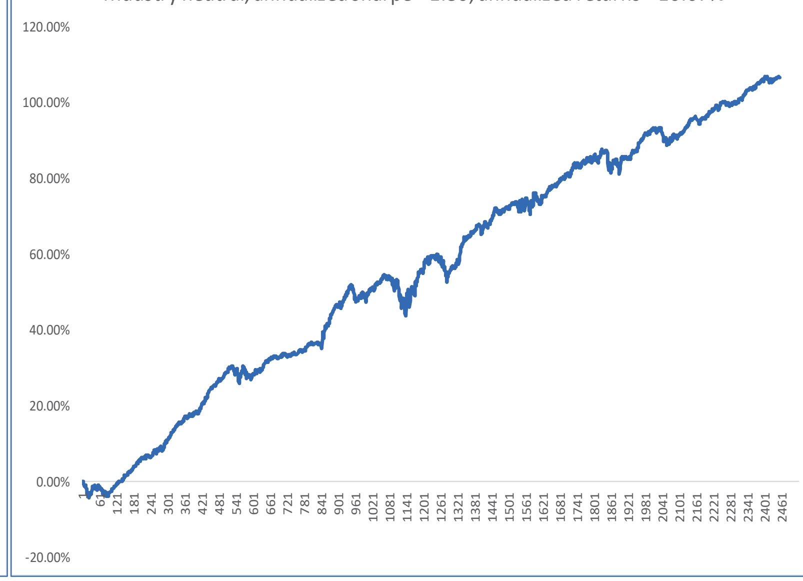
Decay = 2, estimated market impact 6.1 bps per trade, 13% daily turnover

Industry neutral, annualized sharpe = 1.76, annualized returns = 10.47%



Decay = 1, estimated market impact 6.8 bps per trade, 19% daily turnover

Industry neutral, annualized sharpe = 1.80, annualized returns = 10.67%



Alpha decay: Does Academic Research Destroy Stock Return Predictability?

MCLEAN, R. D. and PONTIFF, J. (2016), Does Academic Research Destroy Stock Return Predictability?. The Journal of Finance, 71: 5-32.

- Finance research has uncovered many cross-sectional relationships between price-volume, corporate finance, macro-economic variables and future stock returns

- This paper compares 82 characteristics that have been shown to explain cross-sectional stock returns in finance, accounting and economics journals; for each strategy, the authors compare:
  - In-sample returns
  - Out of sample, pre-publication returns
  - Out of sample, post-publication returns

Goal is to understand what happens to return-predictability outside of a study's sample period

Sample period studied	Reason
Pre-publication, out of sample predictability	Some papers contend return-predictability is outcome of statistical bias / data mining. If this is true, return predictability should disappear out of sample
Post publication, out of sample predictability	More market participants know about a predictor after a paper has been published A relevant question is whether predictors decay after publication If predictability reflects risk, Cochrane (99) explains it is likely to persist without decay no matter how many people know about it On the other hand, if return-predictability is result of mispricing (e.g. due to behavioural reasons), sophisticated investors may trade against it and effects could disappear or continue at reduced levels after publication

Summary of predictors used in study

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

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

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

Limited to academic peer-reviewed finance, accounting and economics journals, where the null of no cross-sectional predictability is rejected at the 5% level

Also limited to studies that can be constructed with publicly available data

Earliest study is Blume and Husic's 1972 Journal of Finance study of how price level relates to future stock returns

Most recent study is Bali, Cakici and Whitelaw's 2011 Journal of Financial Economics study on how maximum daily return in the preceding month is a predictor

Methodology

- Each predictor's return-predictability is computed using two different methods:
  - Monthly Fama-MacBeta (1973) slope coefficient estimates using a continuous measure of the characteristic (e.g. firm size or past returns)
  - Return on portfolio that each month invests in stocks in the top 20^{th} percentile of the characteristic minus the return of a portfolio that invests in stocks in the bottom 20^{th} percentile
  - Average insample period is 323 months and average out of sample period is 139 months. Average number of months between end of insample and publication date is 44 months

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

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

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

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

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

Panel A shows that, using the continuous estimation of each predictor portfolio, average return is 78% of its in-sample mean during out of sample but pre-publication period (not statistically significant)

Once published, average predictor's return is only 51% of its in-sample mean, and the decline is highly significant (t-statistic = -4.91)

Comparing sample means may overweigh predictors with shorter data periods

- Some predictors (e.g. the size effect, Banz 1981) have data that go back to 1926

- Others effects (e.g. the distress effect (Dichev, 1998) which uses credit ratings data only begins in 1981

- By taking the simple average across each characteristic (as in Table 2), each observation from the distress characteristic gets a larger weight than an observation from the size characteristic. The authors subsequently use random effect regressions to address this

Regression methodology

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

where $\widetilde{PR}_{it}$ is monthly portfolio return for each characteristic normalized by average portfolio return for that characteristic i using the same in sample period as the original study

Table 3: (Continued)

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

Publication Effect or Time Trend?

- It is possible that results simply reflect a time trend or a trend that proxies for lower costs of trading
- For example, anomalies may appear because of mispricing due to limits to arbitrage
- However, as trading costs decrease, arbitraging away the anomalies become easier. This could be driving the observed decay post publication
- Goldstein, Irvine, Kandel and Wiener (2009) show evidence that brokerage commissions dropped dramatically from 1977 to 2004
- Anand, Irvine, Puckett and Venkataraman (2012) show that execution costs fell over the last decade
- We need to distinguish between following two possibilities:
  - Anomaly decay is due to publication of results
  - Anomaly decay is due to lower trading costs over time

Table 4: (Continued)

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

- The time variable increases by 1/100 for each sample month.
- In column 1 where only time alone is used, it produces a negative slope coefficient that is significant at the 1% level
- However, in column 2 where post-publication and post-sample indicators are added, the slope on time is now insignificant, while out of sample and post-publication indicators are similar to those previously reported. Hence, modelling anomaly returns with publication effects appear to dominate a linear time effect

Table 4: (Continued)

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

- Columns 3 and 4 use a post 1993 indicator variable, and find results that are qualitatively similar to columns 1 and 2
- Columns 5 and 6 use trading spreads as a time series variable. Spreads are estimated from daily high and low prices using the method of Corwin and Schultz (2012).
- Average spread is positive and statistically insignificant when used alone as independent variable (column 5), or with publication variables (column 6).
- Simple functions of trading costs are therefore unable to explain post-publication declines in anomaly returns

Table 4: (Continued)

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

- Column 7 considers whether there is a time trend within each of the 3 sub-periods (i) in-sample, (ii) out of sample but post publication and (iii) post-publication
- In column 7, the only significant coefficient is for the post publication period, where predictability falls by around 9.5% every 100 months
- This suggests that some market participants continue to learn about strategies slowly after the publication date

Table 4: (Continued)

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

- Columns 9 and 10 examine whether academic citations proxy for alpha decay.
- For each year post-publication, the number of social science citations and the cumulative number of citations are used as explanatory variables
- Both variables are negative, albeit not statistically significant

Table 5 in the paper further considers changes in predictability by examining finer post-sample and post-publication partitions

- Some additional questions:
  - Do the authors of academic papers engage in data mining?
  - Does the flow of new capital into portfolios have an effect on alpha decay?
  - Do the larger presence of institutional traders later in the sample cause predictors to decay faster?

Table 5: (Continued)

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

The first 2 rows involve dummy variables that signify the last 12 months of the original sample and the first 12 months out of sample

Publication process often takes years. This gives researchers opportunity engage in data mining by choosing where to end their samples with the purpose of reporting stronger results

We find that coefficient for the last 12 months of sample period is negative and insignificant, while that for the first 12 months out of sample is positive and insignificant. These are opposite of what we would expect if authors were opportunistically selecting sample end dates

Table 5: (Continued)

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

- There appears to be the largest decline in profitability during years 3 to 5; returns partially recover thereafter, albeit to a level that is 30% lower than in-sample

- Second column reports results for predictors that are more persistent (i.e. have average monthly portfolio turnover below sample median).

- For more persistent characteristics, portfolio returns increase by 21.2% post publication, versus a decay of 16.3% for the entire sample. These findings reverse for the second year post publication

Table 5: (Continued)

	All	More Persistent	More Recent
Last 12	-0.078	-0.320	0.178
	0.215	0.267	0.314
	0.718	0.230	0.571
First 12	0.306	0.412	1.182
	0.217	0.307	0.337
	0.158	0.181	0.000
Post-First 12	-0.305	-0.296	-0.627
	0.121	0.157	0.136
	0.012	0.060	0.000
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P37-48	-0.617	-0.581	-0.770
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	0.009	0.094	0.003
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	0.049	0.096	0.174
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	0.095	0.208	0.206
	0.000	0.300	0.006
Constant	0.963	0.941	1.026
	0.063	0.096	0.069
	0.000	0.000	0.000
R^2	0.001	0.002	0.003
N	37,680	17,082	21,619

The third column reports results for characteristics that were published on or after the median sample publication year of 1999

More institutional money is expected to be devoted to quantitative strategies after 1999

The third column fails to find evidence that market reactions to more recent publications are more efficient in the short run after publication

Effects on other market activity

- If academic publication provides market participants with information that they trade on, this is likely to affect not only prices, but also turnover, dollar trading volume, stock return variance and short interest

- Short interest is the quantity of shares that investors have shorted but not yet covered or closed out, normalized by the total number of outstanding shares

Table 6:

Regression of relative trading differences for portfolio stocks

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

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

Results from Table 6 show that variance and dollar volume are significantly higher during the period that is post sample but pre-publication

There appears to be an increase in trading among characteristic stocks even before a paper is published, suggesting that information from papers may get to some investors before paper is published.

Average dollar volume rank of firm in a characteristic portfolio is 2.5% higher out of sample but pre-publication compared to in-sample

Table 6:

Regression of relative trading differences for portfolio stocks

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

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

Regression slopes for variance, turnover and dollar volume are all significantly higher post-publication

Coefficients suggest that post-publication, the average rank within the characteristic portfolios increases by 1.2%, 2.5%, and 3.1% for variance, turnover and dollar volume respectively

Table 6:

Regression of relative trading differences for portfolio stocks

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

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

Final column reports results from the short interest regression

The short interest variable is short interest on the short side minus short interest on the long side, and is unscaled

In sample average difference in short interest between short and long side of the portfolios is 0.109%

Post-sample, relatively shorting increases to 0.372%, and further increases to 0.935% post publication relative to in-sample. The latter effect is statistically significant

There is therefore a 9-fold increase in relative shorting post-publication relative to in-sample

If alpha decay is due to arbitrageurs, predictors which are costlier to arbitrage should decline less

- Costs associated with arbitrage can prevent arbitrageurs from fully eliminating mispricing

- Characteristic portfolios consisting more of stocks that are costlier to arbitrage (e.g. smaller stocks, less liquid stocks) should decay less

- Additionally, if anomalous returns are outcome of rational asset pricing models (e.g. due to risk), then there should not be any post-publication decline related to arbitrage costs

Table 7: Portfolio characteristics and the persistence return predictability

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

Stocks are ranked on 3 measures of transactions cost: size, dollar volume and bid-ask spreads

Dependent variable for Table 7 is normalized predictor return, limited to post-publication months

There are significantly larger post-publication declines for portfolios with lower arbitrage costs

Predictors that trade portfolios that consist of larger stocks, stocks with smaller bid-ask spreads and stocks with high dollar volume decline more

Table 7: Portfolio characteristics and the persistence return predictability

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

Stocks are also ranked on 2 measures of holding costs, which is idiosyncratic risk and dividends

Idiosyncratic risk is a holding cost since it is incurred every period the position is open. Additionally, dividends reduce the future amount of capital devoted to the arbitrage, thus reducing cumulative holding costs

Predictors that trade portfolios which consist of stocks with lower idiosyncratic volatility and higher dividends (i.e. lower holding costs) also decline more post-publication

Table 7: Portfolio characteristics and the persistence return predictability

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

Predictors that are more attractive to professional traders may also experience greater decay

Sharpe ratio is computed by dividing each strategy's mean in sample monthly return by its standard deviation; t-statistic is computed over in-sample portfolio return, and the R-squared represents portion of returns explained by asset pricing model (and thus less likely to decay)

These 3 variables as a whole do not exhibit a significant relationship with alpha decay