Technological links and predictable returns

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1. Introduction

Background

- Tversky and Kahneman (1974) and Daniel et al. (1998) , among others, suggest that investors may overweigh their own prior beliefs and underweight observable public signals.
- Market pricing dynamics when a subset of investors have limited attention (Merton, 1987; Hong and Stein, 1999; Hirshleifer and Teoh, 2003 ; and Peng and Xiong, 2006).
- Innovative efficiency (Hirshleifer et al., 2013), and innovative originality (Hirshleifer et al., 2018), all have predictive power for its future stock returns.

1. Introduction

Research idea

Many of the largest firms in the world, such as Amazon, Google, Intel, and Samsung, may have minimal overlap in product space, yet are closely aligned in terms of technological expertise.

These technological affinities transcend industry boundaries which can be key drivers of the economic fortune of today's businesses.

Firms do not conduct their technological research in isolation; in contrast, they frequently interact with each other, leading to an innovation process characterized by common shocks and knowledge spillovers (Jaffe et al., 1993).

These common shocks and spillover effects can in turn impact firms'stock returns.

we examine the implications of technological affinity for market price discovery and firms'stock returns.

1. Introduction

Related researches

- Bekkerman and Khimich (2017 ; hereafter BK) also examines the pricing implications of firms' technological link. The motivating research question and main results of the two studies are similar.

Difference

- Technological affinity Measures: Textual analysis to patent documents(BK's); Pairwise distance using patent technology class distribution(this article).
- Data range: BK o examine stock returns from 1997 onward; while this article has a much longer period (from 1963 onward).

Similarity

- Firms' technological links contain valuable information that market prices only fully incorporate over time.

1. Introduction

Research question

- Can firms' technological link predict the future return?
- If the answer is yes, what's the underlying mechanism?

Motivation

- There was no study on the predictive effect of innovations by tech-peer firms.
- This research may find a new way to arbitrage.

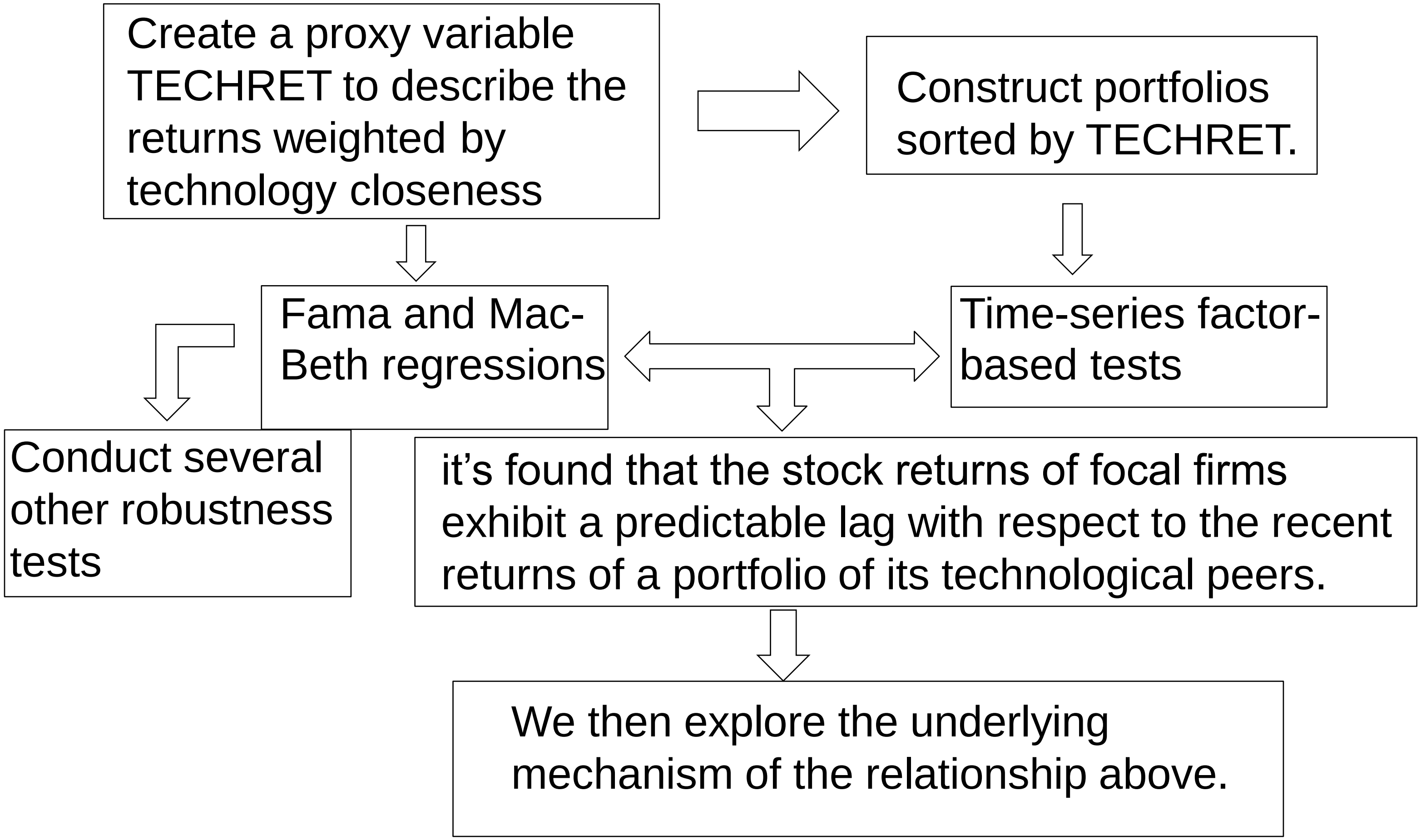
1. Introduction

Conclusion

- Firms’ technological links contain valuable information that market prices only fully incorporate over time.
- The predictive ability of tech-links is more pronounced when focal firms: (a) have a stronger and more specific technology focus, (b) receive lower investor attention, and (c) are more difficult to arbitrage.
- Evidence that stock prices slowly reflect value-related technology-related information shows the potential for misallocation of resources, especially in technology-intensive companies.
- Our results using limited attention proxies suggest that the problem may be mitigated, in part, by elevating the visibility of the technological mappings across firms.

1. Introduction

Framework



2. Research design: Data

- The main data set used in this study pairs Google patent data with firm identifiers from the CRSP database.
  - ➢ Construct technology-linkage variables.

- Our main sample consists of firms in the intersection of the Google patent data, CRSP, and Compustat.
  - ➢ Focus the analysis on common stocks exclude financial firms
  - ➢ Impose at least a six-month gap between fiscal-year end month and the portfolio formation date.

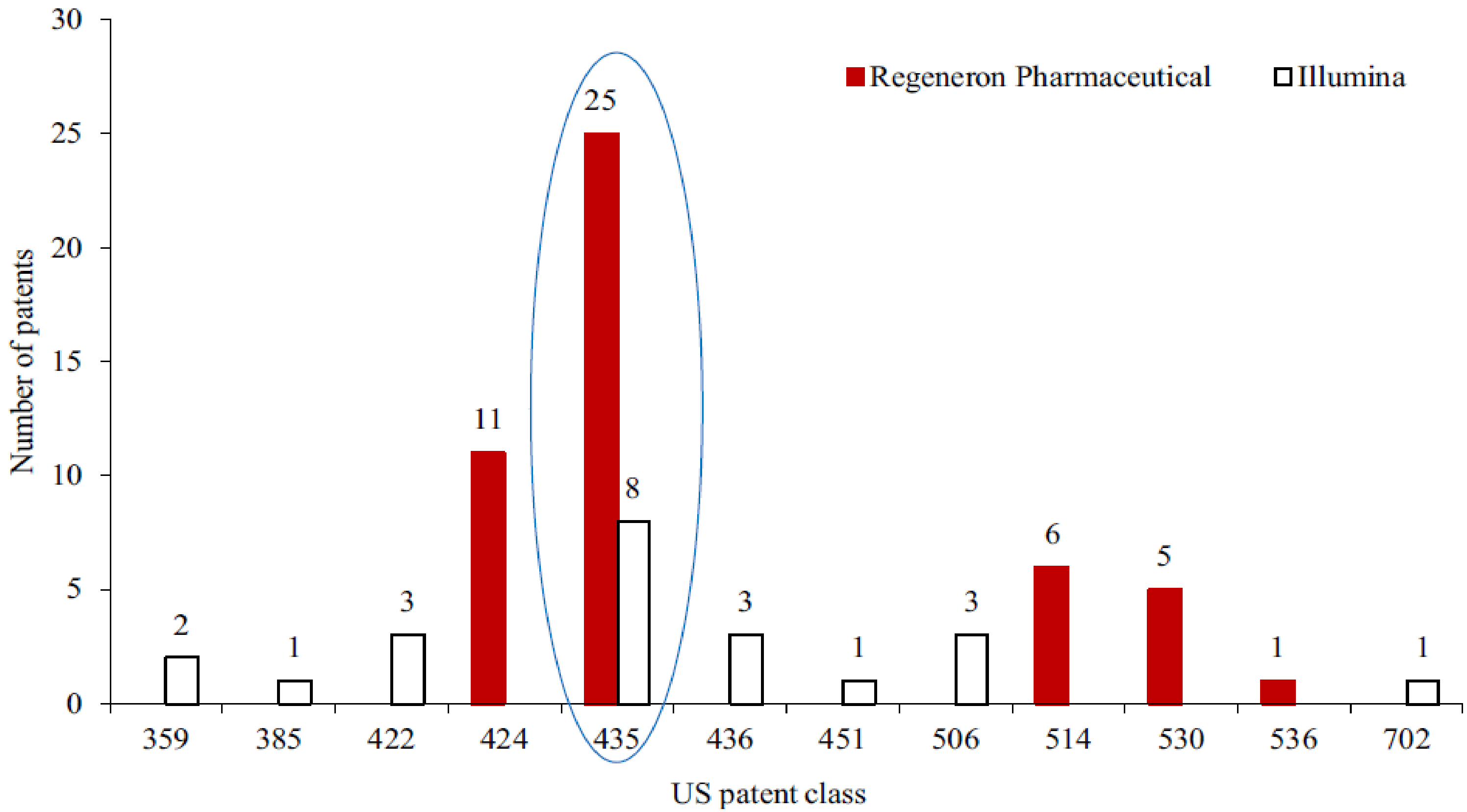
2. Research design: Variable

$$TECH_{ijt} = \frac{(T_{it}T'_{jt})}{(T_{it}T'_{it})^{1/2}(T_{jt}T'_{jt})^{1/2}} \Rightarrow TECHRET_{it} = \frac{\sum_{j \neq i} TECH_{ijt} \cdot RET_{jt}}{\sum_{j \neq i} TECH_{ijt}}$$

- $TECH_{ijt}$: pairwise measure of technological closeness.
- T_{it} : a vector of firm i 's proportional share of patents across 427 USPTO technology classes over the rolling past five years as of time t.

- $TECHRET_{it}$: the average monthly return of technology-linked firms in the technology space, weighted by pairwise technology closeness.
- RET_{jt}: the raw return of firm j at month t.

2. Research design: Variable



- Because of the overlap, the two companies are deemed to be close tech-peers (TECH = 0.71).
- While it is natural for firms in the same industry to share similar technologies, close technological affinity can often cut across industrial boundaries.

2. Research design: Variable

Panel A: Descriptive statistics

	Mean	Sd	Min	Q1	Med	Q3	Max
Sample description (cross-section)							
of Firms	956	293	189	908	961	1187	1363
% Value of CRSP	52.56	5.94	37.72	48.50	50.72	58.03	65.93
Average # of tech-peers per focal firm	280	214	1	117	227	394	1251
Key variables							
TECH	0.11	0.16	0.00	0.01	0.04	0.12	1.00
RET	0.01	0.14	−1.00	−0.06	0.01	0.07	4.23
TECHRET	0.01	0.07	−0.34	−0.03	0.01	0.05	0.84
INDRET	0.01	0.06	−0.33	−0.02	0.01	0.04	0.30

Panel B: Pearson (Spearman) correlations above (below) the diagonal

		1	2	3	4	5	6	7	8	9	10
$TECHRET_{t-1}$	1		**0.203**	**0.123**	**0.031**	**0.010**	0.009	0.005	**−0.009**	−0.001	**0.028**
$INDRET_{t-1}$	2	**0.209**		**0.143**	**0.014**	0.011	0.003	0.010	0.001	−0.005	**0.028**
RET_{t-1}	3	**0.127**	**0.144**		0.007	**0.028**	**0.024**	**0.012**	**−0.021**	−0.002	**−0.046**
MOM	4	**0.035**	**0.013**	0.011		**0.089**	**0.049**	**0.048**	**−0.048**	−0.008	**0.027**
SIZE	5	**0.017**	0.008	**0.060**	**0.144**		**−0.349**	−0.002	**0.069**	**−0.019**	**−0.025**
BM	6	**0.012**	0.003	**0.016**	**0.044**	**−0.337**		**−0.259**	**−0.268**	**−0.187**	**0.025**
GP	7	0.003	0.011	**0.018**	**0.052**	**−0.041**	**−0.304**		**0.030**	**−0.108**	**0.012**
AG	8	**−0.009**	0.004	**−0.013**	**−0.049**	**0.146**	**−0.350**	**0.121**		**0.081**	**−0.020**
RD	9	0.000	−0.009	−0.009	**−0.031**	**−0.034**	**−0.231**	**0.114**	**0.058**		−0.003
RET_t	10	**0.029**	**0.028**	**−0.050**	**0.037**	**0.016**	**0.016**	**0.019**	**−0.011**	**−0.010**	

- *INDERT: industry return*
- *MOM: medium-term momentum*

2. Research design: Method

Construct portfolios

- 1. Sort all firms into deciles at the beginning of each month, based on $TECHRET_{t-1}$.
- 2. Rebalance the decile portfolios to maintain either equal or value weights.
- 3. Holds the top 10% of firms as ranked by $TECHRET_{t-1}$ and sells short the bottom 10% (L/S)
- 4. Compute these returns by subtracting either the risk-free yield (excess returns) or by using a variety of factor models (CAPM alpha, or three-to-six factor alphas).

3. Empirical result: Time-series factor-based tests

Panel A: Portfolio returns						
Decile	Excess returns (%)	CAPM alpha (%)	3-Factor alpha (%)	4-Factor alpha (%)	5-Factor alpha (%)	6-Factor alpha (%)
1	0.42	−0.16	−0.33	−0.13	−0.27	−0.12
(Low)	(1.46)	(−1.04)	(−2.66)	(−1.09)	(−2.17)	(−0.99)
10	1.59	1.05	0.93	0.95	1.10	1.09
(High)	(5.38)	(5.37)	(6.41)	(6.36)	(8.11)	(7.97)
L/S	**1.17**	**1.22**	**1.26**	**1.08**	**1.37**	**1.21**
(Equal-weights)	(5.47)	(5.70)	(5.88)	(4.98)	(6.49)	(5.76)
L/S	**0.69**	**0.74**	**0.80**	**0.65**	**0.86**	**0.73**
(Value-weights)	(3.19)	(3.40)	(3.62)	(2.91)	(3.81)	(3.24)

L/S: the alpha of a zero-cost portfolio that holds the top 10% stocks ranked by TECHRET and sells short the bottom 10%.

These results show that high (low) tech-momentum stocks earn high (low) subsequent returns, after controlling for common risk factors.

3. Empirical result

Panel B: Risk factor loadings

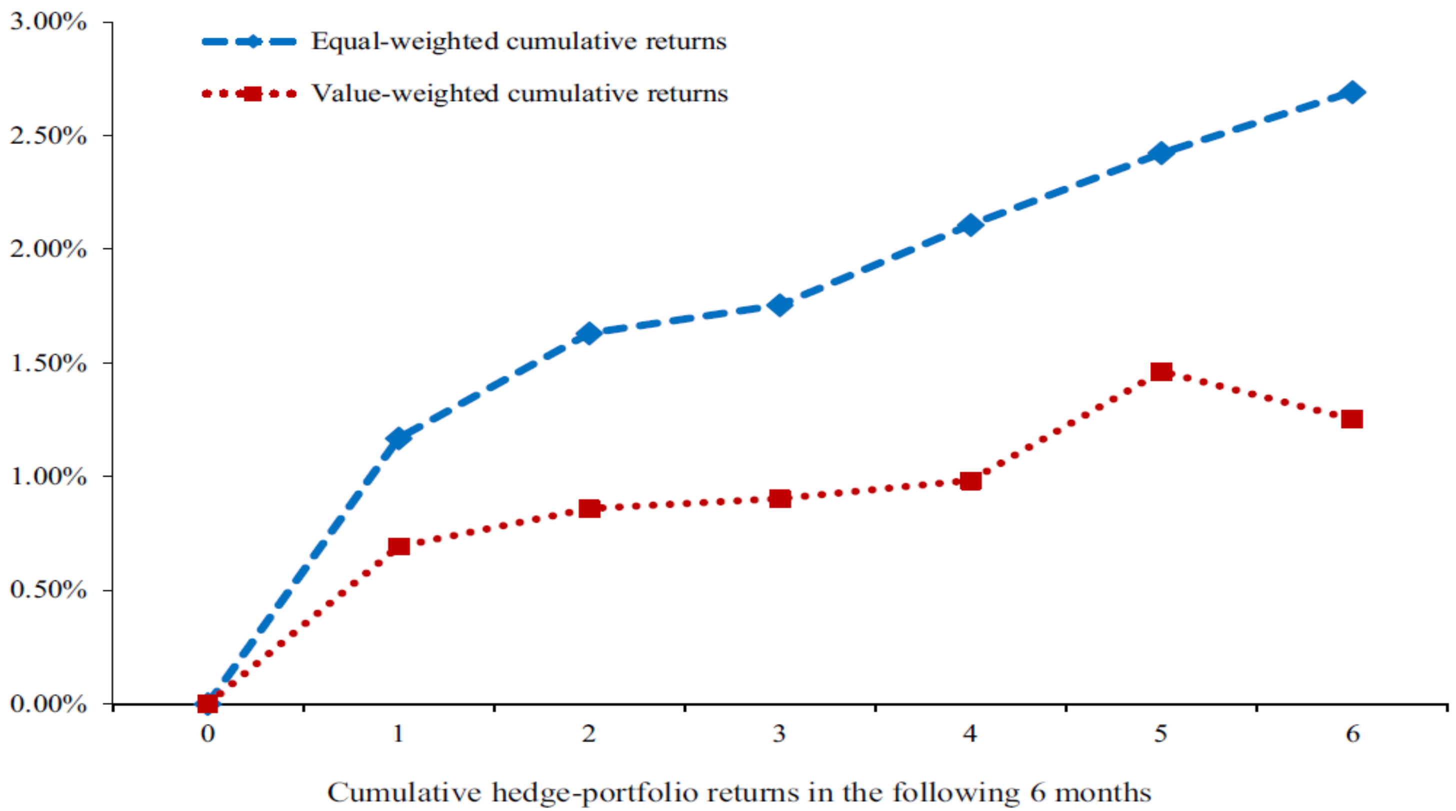
	Alpha	MKT	SMB	HML	MOM
1	−0.13	1.11	0.83	−0.08	−0.21
(Low)	(−1.09)	(40.08)	(21.52)	(−1.80)	(−7.84)
10	0.95	0.95	1.07	−0.21	−0.02
(High)	(6.36)	(27.59)	(22.34)	(−3.91)	(−0.45)
L/S	**1.08**	**−0.16**	**0.24**	−0.13	**0.20**
(Equal-weights)	(4.98)	(−3.14)	(3.51)	(−1.70)	(4.03)
L/S	**0.65**	**−0.10**	0.01	−0.08	**0.16**
(Value-weights)	(2.91)	(−2.00)	(0.16)	(−1.05)	(3.17)

$$R_i = a_i + b_i R_M + s_i E(SMB) + h_i E(HMI) + \varepsilon_i$$

MOM: medium-term price momentum

- The L/S hedge portfolio has a negative loading on the market return (MKT), and positive loadings on SMB and MOM .
- In other words, this strategy will do especially well in down markets, and when small firms and momentum firms do well.
- But even after controlling for these exposures, the strategy produces significant monthly alphas.

3. Empirical result: Cumulative returns



At the beginning of every calendar month, all firms are ranked in ascending order on the basis of the return of a portfolio of its tech-peers at the end of the previous month.

3. Empirical result: Fama and Mac-Beth regressions

Dep. variable $\times 100$	(1) RET_t	(2) RET_t	(3) RET_t	(4) RET_t - $INDRET_t$
$TECHRET_{t-1}$	0.629***	0.583***	0.735***	0.654***
	(4.10)	(5.92)	(6.54)	(6.06)
$INDRET_{t-1}$			0.552***	0.046
			(5.20)	(0.39)
SIZE		−0.834***	−0.793***	−0.805***
		(−3.38)	(−3.19)	(−3.41)
BM		0.619***	0.584***	0.525***
		(3.95)	(3.53)	(3.32)
GP		0.557***	0.442***	0.410***
		(4.26)	(3.46)	(3.19)
AG		−0.453***	−0.430***	−0.466***
		(−5.38)	(−4.84)	(−5.53)
RD		0.443*	0.374	0.401*
		(1.67)	(1.50)	(1.91)
RET_{t-1}		−2.291***	−2.164***	−2.181***
		(−12.79)	(−12.51)	(−12.49)
MOM		0.376*	0.428**	0.408**
		(1.83)	(1.99)	(2.10)
INTERCEPT	0.984**	1.571**	1.556***	1.012***
	(1.98)	(2.45)	(3.81)	(3.48)
Industry fixed effect	Yes	Yes	No	No
N	540,895	540,895	540,895	540,895
Average R^2	0.091	0.142	0.076	0.065

Consistent with the time-series factor-based tests, $TECHRET_{t-1}$ remains a strong predictor of next month's focal firm return in all three specifications.

3. Empirical result: Regression results

Panel A: Fama-MacBeth regression

	(1)	(2)	(3)	(4)
Dep. variable $\times 100$	RET_t Full sample	RET_t Add supply-chain	RET_t Add conglomerate	RET_t Add turnover
$TECHRET_{t\text{-}1}$	0.583***	0.550***	0.439***	0.551***
	(5.92)	(5.70)	(3.42)	(5.77)
$INDRET_{t\text{-}1}$		0.576***	0.195	
		(6.26)	(1.63)	
$CUSTRET_{t\text{-}1}$		0.255***		
		(2.69)		
$SUPPRET_{t\text{-}1}$		0.073		
		(0.79)		
$PCRET_{t\text{-}1}$			0.351***	
			(2.88)	
TURNOVER				−0.194
				(−1.12)

INDRET: lagged industry returns.
CUSTRET & SUPPRET : lagged returns from a portfolio of the focal firm's customers and suppliers.
PCRET : a portfolio of pseudo-conglomerate returns.

The coefficient on $TECHRET_{t-1}$ remains significant after controlling for all other variables above.

3. Empirical result: Tests under draconian control

Panel B: Abnormal returns after excluding all tech-peers from the same industry as the focal firm

	Equal-weighted		Value-weighted	
	Excess returns (%)	6-Factor alpha (%)	Excess returns (%)	6-Factor alpha (%)
Exclude peers from same Fama-French 48 industry grouping	**0.78**	**0.84**	**0.40**	**0.43**
	(4.69)	(4.96)	(1.99)	(2.05)
Exclude peers from same 3-digit SIC industry grouping	**0.88**	**0.96**	**0.52**	**0.63**
	(5.30)	(5.66)	(2.68)	(3.06)

- To be absolutely certain we have not rediscovered the industry momentum effect, we recompute our TECHRET measure using only tech-peers from a different industry.

- We continue to find six-factor alphas that are both economically and statistically significant even when we exclude all tech-peers that belong to the same three-digit SIC industry as the focal firm.

3. Empirical result: Correction for bias of correlated alphas

Decile	Excess returns (%)	CAPM alpha (%)	3-Factor alpha (%)	4-Factor alpha (%)	5-Factor alpha (%)	6-Factor alpha (%)
L/S	**0.98**	**0.99**	**1.09**	**0.86**	**1.25**	**1.05**
(Equal weights)	(5.16)	(5.19)	(5.84)	(4.62)	(6.94)	(5.97)
L/S	**0.67**	**0.68**	**0.80**	**0.59**	**0.93**	**0.74**
(Value weights)	(3.26)	(3.32)	(3.88)	(2.84)	(4.46)	(3.60)

The misspecification(alpha) inherent in the underlying asset pricing model will induces bias, because economically linked firms are more likely to have correlated alphas.

⇨

Use the tech-peers' idiosyncratic return, rather than their raw re- turn, when constructing $TECHRET_{t-1}$

- After removing correlated alphas, we still find that returns of tech-peers predict focal firm returns.
- The results indicate that the information being extracted from the returns of the tech-peer portfolio is largely orthogonal to the peer firms' common exposure to factor returns.

3. Empirical result: Other robustness tests

1. Technology-linked return predictability across time

- We divide our full sample period into 1963–1979, 1980–1989,1990–1999, and 2000–2012.
- The coefficients of $TECHRET_{t-1}$ are all positive and statistically significant after controlling for various return determinants.

2. Persistence of technology closeness

- While predictability decreases with the number of lagged years, even three-year-old technology closeness measures work quite well.
- One implication is that investors do not need extremely timely information on patents to implement this strategy. Even relatively ‘stale’ technology mappings have some predictive power for focal firm returns.

4. Underlying mechanisms analysis

Results from the analyses thus far suggest that the technology momentum may be driven by slow dissemination of technology-related fundamental news.

We further explore the cross-sectional sensitivity of our main results to various firm characteristics associated with:

- the nature of its technological innovations
- the extent to which investors might be attentive to such innovations
- the costs that investors face if they attempt to arbitrage the mispricing.

4. Underlying mechanism: Technology-related channels

We evaluate the sensitivity from two dimensions:

- Technology-intensity—— the size of its R&D spending or the number of patents, both scaled by sales.
- Technology-specificity ——by calculating its applicability across different industries.

Dep. variable $\times 100$	(1) RET_t	(2) RET_t	(3) RET_t	(4) RET_t
$TECHRET_{t-1}$	0.355*** (3.80)	0.348*** (3.72)	0.496*** (4.98)	0.445*** (4.97)
$TECHRET_{t-1} \times$ *R&D > median*	0.448*** (3.10)			
$TECHRET_{t-1} \times$ *Patent > median*		0.470*** (3.35)		
$TECHRET_{t-1} \times$ *Specificity_FF48 > median*			0.187* (1.76)	
$TECHRET_{t-1} \times$ *Specificity_SIC3 > median*				0.236** (2.36)
Controls (SIZE, BM, GP, AG, RD, RET_{t-1}*, MOM, and interaction dummies)*	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
N	540,895	540,895	540,895	540,895
Average R^2	0.145	0.146	0.145	0.146

4. Underlying mechanism: Investors' limited attention

If technology momentum is related to limited attention, we should observe a stronger effect for firms that receive less investor attention.

Define a size-based dummy variable.

Dep. variable ×100	(1) RET_t	(2) RET_t	(3) RET_t	(4) RET_t	(5) RET_t	(6) RET_t
$TECHRET_{t-1}$	0.839***	0.829***	0.897***	0.838***	0.293***	0.544***
	(5.58)	(5.07)	(4.75)	(4.41)	(3.33)	(3.41)
$TECHRET_{t-1}$ × Size > median	−0.592***					
	(−3.05)					
$TECHRET_{t-1}$ × Analyst > median		−0.434**				
		(−2.50)				
$TECHRET_{t-1}$ × InstitOwn > median			−0.519***			
			(−2.72)			
$TECHRET_{t-1}$ × News > median				−0.804***		
				(−3.00)		
$TECHRET_{t-1}$ × IdioVol > median					0.509***	
					(3.35)	
$TECHRET_{t-1}$ × Bad news						0.933**
						(2.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	540,895	462,323	412,786	165,300	540,895	540,895
Average R^2	0.146	0.119	0.119	0.108	0.147	0.145

4. Underlying mechanisms: Cost of arbitrage

We also expect to see a stronger return effect for stocks with more binding arbitrage costs, as investors are less able (or willing) to fully update these firms' prices.

Dep. variable $\times 100$	(1) RET_t	(2) RET_t	(3) RET_t	(4) RET_t	(5) RET_t	(6) RET_t
$TECHRET_{t-1}$	0.839***	0.829***	0.897***	0.838***	0.293***	0.544***
	(5.58)	(5.07)	(4.75)	(4.41)	(3.33)	(3.41)
$TECHRET_{t-1}$ ×	−0.592***					
Size > median	(−3.05)					
$TECHRET_{t-1}$ ×		−0.434**				
Analyst > median		(−2.50)				
$TECHRET_{t-1}$ ×			−0.519***			
InstitOwn > median			(−2.72)			
$TECHRET_{t-1}$ ×				−0.804***		
News > median				(−3.00)		
$TECHRET_{t-1}$ ×					0.509***	
IdioVol > median					(3.35)	
$TECHRET_{t-1}$ ×						0.933**
Bad news						(2.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	540,895	462,323	412,786	165,300	540,895	540,895
Average R^2	0.146	0.119	0.119	0.108	0.147	0.145

Both of these findings lend support to our prediction that the technology momentum effect is stronger for difficult-to-arbitrage stocks.

5. Risk explanations

We've found that technology momentum can't be explained by well-known risk factors, such as the Fama-French five-factors and the momentum factor.

Nevertheless, it is still possible that other unobserved risks could drive our results. We conduct several tests in this section to examine this possibility:

- Returns around earnings announcements
- Displacement risk
- Investment-specific technological change
- Evidence from non-return-based metrics(SUE)

6. Conclusion

1. The technology-linked firms' returns can predict focal firm returns, and the technology momentum effect is still robust after controlling for a variety of predictive variables.
2. The return predictability is driven by slow adjustment to fundamental news, rather than a compensation for bearing more risk.
3. The return predictability is much stronger for focal firms with high technology-intensity and high technology-specificity.
4. Evidence that stock prices slowly reflect value-related technology-related information shows the potential for misallocation of resources, especially in technology-intensive companies.

7. Inspiration

- From a firm's perspective, educating investors on its technological capabilities, perhaps through greater media coverage, may likewise yield improvements in pricing efficiency.

- From an investor's perspective, greater attention to technology-linkages could lead to better investment decisions.

- In today's technology-driven world, it seems especially important for researchers to better understand the mechanism through which such technological attributes impact information processing costs, and thus market prices.