Active Technological Similarity and Mutual Fund Performance

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Outline

- Introduction
- Research design
- Empirical result
- Robust Test
- Conclusion

Motivation

- Technological innovation is critical for every corporations.
- Recent work demonstrates that markets are slow to incorporate information regarding technological innovation because such information tends to be non-financial and difficult to process
- Therefore, We hypothesize that a mutual fund manager's **superior understanding of technological innovation** is a key source of informational advantage that leads to **superior performance**

Literatures-Tech innovation

1. Gu (2005) shows that changes in corporate technological innovation positively correlate with future earnings
2. However, markets are slow to incorporate technological innovative efficiency (Gu, 2005 and Hirshleifer et al., 2013)
3. Further consistent with the gradual incorporation of technological innovation information, a portfolio of technologically similar firms predicts the focal firm’s stock return(Lee et al., 2019 and Bekkerman et al., 2020)

Literatures- Fund Managerial

1. Managers gain an information advantage via personal and professional relationships
    1. information supplied by college alumni (Cohen et al., 2008)
    2. Affiliated banks (Massa and Rehman 2008)
    3. Pension business relationships (Duan et al., 2018)
    4. Geographically nearby firms (Coval & Moskowitz 1999, 2001)

Literatures- Fund Managerial

2. There is relatively little evidence regarding other skills a mutual fund manager may use to garner positive alpha.
    1. Trades in “experience” industry (Cici, Gehde-Trapp, Goricke, and Kempf (2018))
    2. Understand the lead-lag relations between suppliers and customers garner superior performance (Huang and Kale (2013))
    3. Fund managers hold more concentrated/active portfolios (Kacperczyk et al., 2005), Cremers and Petajisto (2009), and Amihud and Goyenko (2013))

Contribution

1. We add to fund managers skills work by providing a heretofore unidentified source of fund alpha—fund managers using their superior knowledge regarding technological innovation.
2. Different from the concentration/activeness literature treating the underlying source as a latent variable, we hypothesize a specific source for managers' ability to outperform.
3. Our study also contributes to the literature investigating how asset prices respond to corporate technological innovation

Active Technological Similarity

- We define firm i’s position in technology space as the distribution of the firm’s patenting activities across the 642 patent technology classes measured over the previous year:

$$T_{m,i} = (T_{m,i,1}, T_{m,i,2}, \ldots, T_{m,i,k}, \ldots, T_{m,i,642})'$$

- $T_{m,i,k}$, is the share of firm i’s patents in patent class k over the previous year (i.e., q-3 to q, inclusive)

$$T_{m,i,k} = \frac{n_{i,k}}{\sum_{k=1}^{642} n_{i,k}}$$

Active Technological Similarity

- We analogously calculate $T_{m,-i,\omega}$, the distribution of patents of the remaining stocks (firm i excluded) held by mutual fund m (at the end of quarter q):

$$T_{m,-i,\omega} = (T_{m,-i,1}, T_{m,-i,2}, \ldots, T_{m,-i,k}, \ldots, T_{m,-i,642})'$$

- $T_{m,-i,k}$ computes the value-weighted fraction of patents held in patent class k by the rest of the mutual fund's holdings

$$T_{m,-i,k} = \frac{\sum_{j \in m; j \neq i} \omega_{m,j} n_{j,k}}{\sum_{k=1}^{642} \sum_{j \in m; j \neq i} \omega_{m,j} n_{j,k}}$$

Active Technological Similarity

- We compute the technological similarity between each stock held by the fund and the rest of the fund's portfolio as the cosine similarity between the technology weight vectors

$$\left\langle T_{m,i} \cdot T_{m,-i,\omega} \right\rangle = \frac{T_{m,i} T_{m,-i,\omega}{}'}{\left(T_{m,i} T_{m,i}{}'\right)^{1/2} \left(T_{m,-i,\omega} T_{m,-i,\omega}{}'\right)^{1/2}}$$

- Technological similarity (TS) of fund m's portfolio is simply the weighted (by the fund's portfolio weights) average of above equation

$$TS_m = \sum_i \omega_{m,i} \left\langle T_{m,i} \cdot T_{m,-i,\omega} \right\rangle$$

Active Technological Similarity

- Specifically, we define active technological similarity (ATS) as the difference between a fund's TS at the end of quarter q and what its TS would have been had the manager not traded over quarter q

$$ATS_m = TS_m - PASSIVE\_TS_m = \sum_i \left(\omega_{m,i} \left\langle T_{m,i} \cdot T_{m,-i,\omega} \right\rangle - \boxed{\tilde{\omega}_{m,i}} \left\langle T_{m,i} \cdot T_{m,-i,\tilde{\omega}} \right\rangle \right)$$

- We begin by computing a fund's end of quarter portfolio weights had the manager made no trades in quarter q as

$$\tilde{\omega}_{m,i,q} = \frac{\omega_{m,i,q-1}(1+RET_{i,q})}{\sum_i \omega_{m,i,q-1}(1+RET_{i,q})}$$

Data

- We use the updated the CRSP-matched Google patent data from Kogan et al. (2017) to measure technological similarity.
  - This dataset covers 1.94 million patents with application filing dates between 1926 and 2017
  - we use the patent application date (rather than grant date) to capture the time the technological innovation begins impacting real production

Data

- Monthly fund returns and characteristics(CRSP survivor-bias-free mutual fund database) mutual fund holdings(Thomson-Reuters mutual fund holdings database)
  - We employ the “follow the money” approach of Elton, Gruber, and Blake (1996) and Gruber (1996) to address merged funds.
  - We eliminate balanced, bond, money market, international, and index funds (Huang et al. 2011).
  - We also drop funds with a total market value of reported holdings under 80% or over 120% of the total net assets
  - We remove the first two years of return data to eliminate incubation bias and exclude funds with TNA less than $15 m

Data

  - For funds with multiple share classes, we compute value-weighted fund characteristics, based on the oldest share class.
  - We also require funds to have at least 20 monthly returns over the previous two years.
  - Fund TNA is winsorized at 99% level. Fund flow, expense ratio, and ATS are winsorized at the 1% and 99%.

- Our final sample includes 2,895 distinct funds with an average of 641 funds per quarter for a total of 87,804 fund-quarter ATS observations over 1983:Q4-2017:Q4.

Empirical Analysis

A. ATS and Fund Characteristics

$$\text{logit}(\text{Top } ATS_{m,q} \text{ quintile}) = \alpha_{style} + \beta_1 \log(TNA_{m,q}) + \beta_2 \log(AGE_{m,q}) + \beta_3 EXP\_RATIO_{m,q} + \beta_4 TURNOVER_{m,q} + \varepsilon_{m,q}$$

	1	2	3	4	5
log(TNA)	-0.041***	-0.040***	-0.014	-0.038***	-0.014
	(-3.09)	(-2.97)	(-0.81)	(-2.83)	(-0.85)
log(AGE)	-0.006	0.044*	0.021	-0.003	0.021
	(-0.18)	(1.70)	(0.53)	(-0.11)	(0.54)
EXP_RATIO	0.128***	0.146***	0.092	0.089**	0.085
	(2.93)	(3.99)	(1.56)	(2.04)	(1.46)
TURNOVER	0.263***	0.260***	0.404***	0.256***	0.402***
	(8.98)	(8.70)	(12.80)	(8.64)	(12.71)
INDUSTRY_CONCENTRATION		2.520***			0.732
		(5.52)			(1.21)
ACTIVE_SHARE			1.819***		1.701***
			(8.96)		(7.73)
FUND_R^2				-1.434***	-0.299
				(-4.67)	(-0.72)
Fund Style Indicators	Y	Y	Y	Y	Y
No. Quarters	137	137	126	137	126
Observations	86,832	86,355	53,320	86,832	53,279

Empirical Analysis

B. Portfolio Sorts

Panel A: ATS Quintiles

Quintile	Net Return	Gross Carhart Alpha	Net Carhart Alpha: All	Net Carhart Alpha: Early period (1984-2000)	Net Carhart Alpha: Late period (2001-2018)
5 (High)	1.032***	0.187***	0.073*	0.066	0.075*
	(4.26)	(4.56)	(1.74)	(1.02)	(1.84)
4	0.947***	0.090**	-0.026	0.053	-0.110***
	(3.97)	(2.13)	(-0.61)	(0.70)	(-3.02)
3	0.921***	0.059	-0.051	-0.038	-0.074**
	(3.99)	(1.42)	(-1.19)	(-0.47)	(-2.07)
2	0.908***	0.039	-0.070*	-0.032	-0.118***
	(3.91)	(1.08)	(-1.87)	(-0.46)	(-3.34)
1 (Low)	0.797***	-0.053	-0.162***	-0.143*	-0.171***
	(3.38)	(-1.34)	(-4.03)	(-1.93)	(-4.51)
Difference:	0.236***	0.240***	0.235***	0.210***	0.246***
High-Low	(7.71)	(7.86)	(7.72)	(3.99)	(8.15)

Empirical Analysis

B. Portfolio Sorts

Difference: High-Low	0.236*** (7.71)	0.240*** (7.86)	0.235*** (7.72)	0.210*** (3.99)	0.246*** (8.15)

Panel B: Net Carhart Alpha for Concentration Metrics and Lag Alpha

Quintile	Industry Concentration (1984-2018)	Active Share (1984-2015)	Fund R^2 (1984-2018)	Lag Alphas (1984-2018)
5 (High)	0.054	0.039	-0.119***	0.036
	(0.89)	(0.59)	(-3.81)	(0.74)
1 (Low)	-0.100***	-0.078**	0.091	-0.115**
	(-4.19)	(-2.46)	(1.60)	(-2.35)
Difference: High-Low	0.154***	0.117**	-0.210***	0.151***
	(2.94)	(2.04)	(-3.62)	(2.73)

Empirical Analysis

C. Multivariate Analysis

Dependent variable is fund m's net monthly Carhart alpha (in percentage)

	1	2	3	4	5
ATS (%)	0.028***	0.030***	0.029***	0.014***	0.043***
	(5.14)	(4.25)	(4.36)	(3.03)	(3.60)
log(TNA)		-0.038**	-0.037**	-0.035***	-0.038
		(-2.47)	(-2.48)	(-3.07)	(-1.41)
log(AGE)		0.005	0.009	0.007	0.011
		(0.27)	(0.50)	(0.36)	(0.37)
TURNOVER		0.009	0.006	0.045*	-0.032
		(0.39)	(0.29)	(1.90)	(-0.88)
EXP_RATIO		-0.023	-0.028	-0.023	-0.032
		(-0.84)	(-0.98)	(-0.77)	(-0.67)
σ(FUND_RETURN)		0.100	0.082	0.008	0.155
		(0.97)	(0.92)	(0.26)	(0.89)
LAG_FUND_ALPHA		0.301***	0.290***	0.324***	0.257***
		(6.88)	(7.38)	(5.57)	(4.81)
FLOW		-0.316	-0.299	0.211*	-0.802
		(-0.76)	(-0.74)	(1.76)	(-1.02)
log(FAMILY_SIZE)		0.001	-0.000	0.009**	-0.009*
		(0.29)	(-0.02)	(2.53)	(-1.92)
Fund Style Indicators	N	N	Y	Y	Y
No. Months	411	411	411	204	207
Average R^2	0.005	0.097	0.119	0.121	0.116

Empirical Analysis

D. ATS, Fund Activeness, and Lag Fund Alpha

- Previous work reveals that fund performance is related to both lag fund alpha and measures of fund portfolio concentration/activeness.
- ATS, however, is fundamentally different from measures of portfolio concentration/activeness as ATS is a trade-based measure, the concentration/activeness metrics are levels-based measures.
- Thus, it is likely that ATS can be combined with other measures to increase the ability to identify managers with superior skill

$$ATS_m = TS_m - PASSIVE\_TS_m = \sum_i \left(\omega_{m,i} \left\langle T_{m,i} \cdot T_{m,-i,\omega} \right\rangle - \boxed{\tilde{\omega}_{m,i}} \left\langle T_{m,i} \cdot T_{m,-i,\tilde{\omega}} \right\rangle \right)$$

Empirical Analysis

D. ATS, Fund Activeness, and Lag Fund Alpha

a) Correlation

	ATS	INDUSTRY_ CONCENTRATION	ACTIVE_ SHARE	FUND_R^2	LAG_FUND _ALPHA
ATS	1	0.009	0.066	-0.023	0.006
		(0.28)	(0.01)	(0.01)	(0.44)
INDUSTRY_	-0.022	1	0.453	-0.405	0.071
CONCENTRATION	(0.01)		(0.01)	(0.01)	(0.01)
ACTIVE_SHARE	0.042	0.372	1	-0.489	0.101
	(0.01)	(0.01)		(0.01)	(0.01)
FUND_R^2	0.011	-0.373	-0.400	1	-0.063
	(0.09)	(0.01)	(0.01)		(0.01)
LAG_FUND	-0.005	0.051	0.089	-0.060	1
_ALPHA	(0.49)	(0.01)	(0.01)	(0.01)	

Empirical Analysis

D. ATS, Fund Activeness, and Lag Fund Alpha

b) Double sort - Lag Fund Alpha

	ATS Quintile					ATS Dif:
Quintile	5 (High)	4	3	2	1 (Low)	High-Low
Panel A: Lag Alpha and ATS						
5 (High)	0.212***	0.029	0.075	0.040	-0.104*	0.317***
	(3.25)	(0.50)	(1.35)	(0.70)	(-1.73)	(4.78)
4	0.094*	-0.015	-0.026	-0.082*	-0.134***	0.229***
	(1.75)	(-0.30)	(-0.58)	(-1.89)	(-2.98)	(4.07)
3	0.059	-0.068	-0.042	-0.085**	-0.222***	0.281***
	(1.07)	(-1.55)	(-0.88)	(-2.03)	(-4.91)	(5.38)
2	0.002	-0.088*	-0.123**	-0.102**	-0.097**	0.099*
	(0.03)	(-1.84)	(-2.35)	(-2.30)	(-2.03)	(1.77)
1 (Low)	0.025	-0.090	-0.191***	-0.127**	-0.232***	0.257***
	(0.41)	(-1.46)	(-3.21)	(-2.19)	(-4.52)	(4.49)
Difference:	0.187***	0.118	0.266***	0.167**	0.128*	
High-Low	(2.59)	(1.64)	(3.76)	(2.31)	(1.95)	

Empirical Analysis

D. ATS, Fund Activeness, and Lag Fund Alpha

b) Double sort - Fund Activeness

Quintile	ATS Quintile 5 (High)	4	3	2	1 (Low)	ATS Dif: High-Low
Panel B: Industry Concentration and ATS						
5 (High)	0.342***	0.087	0.062	0.122	-0.251***	0.593***
	(4.21)	(1.11)	(0.92)	(1.60)	(-3.96)	(9.37)
4	0.033	0.018	-0.087	-0.076	-0.132**	0.167**
	(0.55)	(0.30)	(-1.50)	(-1.45)	(-2.42)	(2.53)
3	0.050	-0.041	-0.033	-0.069	-0.189***	0.239***
	(1.05)	(-0.94)	(-0.65)	(-1.33)	(-4.00)	(4.77)
2	0.002	-0.081*	-0.074*	-0.085**	-0.143***	0.145***
	(0.04)	(-1.91)	(-1.85)	(-2.20)	(-3.61)	(3.31)
1 (Low)	-0.057*	-0.102***	-0.068**	-0.141***	-0.061*	0.004
	(-1.78)	(-3.36)	(-2.01)	(-5.47)	(-1.74)	(0.11)
Difference:	0.384***	0.189**	0.131**	0.264***	-0.190***	
High-Low	(4.69)	(2.57)	(2.03)	(3.48)	(-2.96)	

Empirical Analysis

D. ATS, Fund Activeness, and Lag Fund Alpha

c) Panel regression

	1	2	3	4	5
ATS (%)	0.029***	0.028***	0.019***	0.029***	0.020***
	(4.36)	(4.28)	(4.87)	(4.44)	(4.98)
LAG_FUND_ALPHA	0.290***	0.290***	0.292***	0.283***	0.298***
	(7.38)	(7.62)	(6.26)	(7.17)	(6.62)
INDUSTRY_		0.013***			0.003
CONCENTRATION (×100)		(5.06)			(1.01)
ACTIVE_SHARE (×100)			0.412***		0.172
			(4.00)		(1.52)
FUND_R^2 (×100)				-1.190***	-1.091***
				(-6.33)	(-3.65)
Fund Style Indicators	Y	Y	Y	Y	Y
Fund Characteristics	Y	Y	Y	Y	Y
No. Months	411	411	381	411	381
Avg. No. Funds	641	622	415	641	403
Average R^2	0.119	0.129	0.139	0.127	0.159

Empirical Analysis

E. ATS-increasing and ATS-decreasing Trades

- A given trade either increases the fund's ATS:

$$\omega_{m,i}\left\langle T_{m,i}\cdot T_{m,-i,\omega}\right\rangle-\tilde{\omega}_{m,i}\left\langle T_{m,i}\cdot T_{m,-i,\tilde{\omega}}\right\rangle>0$$

- Or decreases the fund's ATS:

$$\omega_{m,i}\left\langle T_{m,i}\cdot T_{m,-i,\omega}\right\rangle-\tilde{\omega}_{m,i}\left\langle T_{m,i}\cdot T_{m,-i,\tilde{\omega}}\right\rangle<0$$

- Thus, we partition the trades of funds in each ATS quintile into ATS-increasing trades and ATS-decreasing trades in quarter q.

Empirical Analysis

E. ATS-increasing and ATS-decreasing Trades

	ATS Quintile					Difference:
	5 (High)	4	3	2	1 (Low)	High-Low
Panel A: Market-Adjusted Returns						
ATS-increasing trades	0.637***	0.330***	0.094	0.096	0.054	0.583***
	(5.34)	(3.10)	(1.00)	(1.11)	(0.60)	(7.84)
ATS-decreasing trades	0.171**	0.119	0.091	0.116	0.053	0.118*
	(1.98)	(1.37)	(1.05)	(1.39)	(0.45)	(1.72)
Difference: Inc. – Dec.	0.465***	0.211***	0.003	-0.020	0.001	0.464***
	(7.58)	(4.23)	(0.08)	(-0.41)	(0.02)	(4.59)
Panel B: DGTW-Adjusted Returns						
ATS-increasing trades	0.597***	0.281***	0.075	0.076	0.086	0.511***
	(8.06)	(4.71)	(1.41)	(1.40)	(1.36)	(9.06)
ATS-decreasing trades	0.101*	0.064	0.050	0.074	0.054	0.047
	(1.72)	(1.24)	(1.00)	(1.34)	(0.71)	(1.01)
Difference: Inc. – Dec.	0.496***	0.217***	0.025	0.002	0.033	0.463***
	(10.10)	(5.18)	(0.62)	(0.05)	(0.71)	(6.36)

Robustness

A. ATS Based on Patent Grant Dates
B. Active Technological Similarity (ATS) and Long-Term Returns (over quarters q+1, q+2, q+3, and q+4)
C. Alternative Measures(FFC, FF3, DGTW)
D. Industry Active Technological Similarity (ATS) and Future Industry Performance
E. Technological Similarity (TS) and Future Performance
F. ATS and Changes in Fund Activeness/Concentration

Conclusion

- We propose a ATS measure that captures the fund managers' superior understanding of the role of technological innovation.
- Funds that increase the technological similarity of their holdings earn larger subsequent returns.
- Superior knowledge regarding technological innovation is a previously unidentified and important source of some managers' ability to outperform.
- ATS is largely orthogonal to other predictors of fund performance, it can be combined with lag fund alpha, industry concentration, active share, or fund R2 to better identify skilled managers.