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Active Technological Similarity and Mutual Fund Performance

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Abstract

We examine whether superior understanding of technological innovation is a source of mutual fund managers' ability to garner positive abnormal returns. Consistent with our hypothesis, the inter-quintile annual net Carhart alpha spread for mutual funds sorted on changes in the technological similarity (TS) of their portfolio holdings is 282 basis points. Moreover, because changes in TS are largely orthogonal to other predictors of mutual fund success (e.g., industry concentration, active share, fund R^2, and lag fund alpha), changes in TS can be combined with other measures to help identify the best performing funds.

I. Introduction

Recent work demonstrates that markets are slow to incorporate information regarding technological innovation, because such information tends to be nonfinancial and difficult to process (e.g., Cohen, Diether, and Malloy (2013); Hirshleifer, Hsu, and Li (2013), (2018); Lee, Sun, Wang, and Zhang (2019)). 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. Specifically, we measure exposure to technological innovation by the value-weighted overlap in the distribution of patents held by each of the firms in the fund's portfolio. We hypothesize that an increase in the "technological" similarity of a manager's portfolio holdings will be associated with future positive abnormal returns for the fund through 2 nonmutually exclusive mechanisms. First, an informed manager may increase her portfolio exposure

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to a technological innovation when the associated technological space is undervalued. Second, even if the technological space is fairly valued on average, a better-informed manager may be able to identify undervalued firms within that space, and increase her portfolio concentration by overweighting those securities.

Consistent with our hypothesis, mutual funds that increase the technological similarity (TS) of their portfolio (that we denote active technological similarity (ATS)) average higher subsequent returns. For example, mutual funds in the top ATS quintile subsequently outperform funds in the bottom ATS quintile by 282 basis points annually (net Carhart alphas). For our sample period, the economic magnitude of the effect is larger than that of other documented factors that predict variation in mutual fund performance such as industry concentration (Kacperczyk, Sialm, and Zhang (2005)), active share (Cremers and Petajisto (2009)), fund R^2 (Amihud and Goyenko (2013)), and lag fund performance (e.g., Brown and Goetzmann (1995), Gruber (1996)). Moreover, our results are robust. For example, the results continue to hold when controlling for standard asset pricing variables, when controlling for fund characteristics, and when we split our sample into 2 periods.

Because ATS is largely orthogonal to fund concentration/activeness measures and lag performance, combining ATS with these measures yields results much stronger than either measure independently. For example, a portfolio of high-industry concentration funds averages an annual net Carhart alpha of 0.65% and a portfolio of high-ATS funds averages an annual net Carhart alpha of 0.88%. A portfolio limited to high-industry concentration/high-ATS funds, however, yields an annual net Carhart alpha of 4.1%.[1]

Given mutual funds typically have limited (or 0) short exposures, we further hypothesize that the relation between ATS and subsequent returns will primarily arise from trades that increase the TS of the fund's holdings. For instance, if a manager's informational advantage suggests that a technology is currently undervalued, the manager will increase her exposure to the technology. As the technology becomes fairly valued, the manager will reduce her exposure to that (previously overweighted) technology (i.e., move to a better-diversified portfolio). As a result, an increase in TS will be associated with future positive abnormal returns, while a decrease in TS will not be associated with future abnormal returns (i.e., abnormal returns near 0).

To examine this hypothesis, we next investigate fund ATS-increasing vs. fund ATS-decreasing transactions. Specifically, we partition every trade made by a mutual fund into ATS-increasing trades (i.e., trades that increase the TS of a fund's portfolio) and ATS-decreasing trades. Consistent with both our hypothesis and previous work that suggests managers' ability to garner positive abnormal returns primarily arises from their purchases (e.g., Chan and Lakonishok (1993), Puckett and Yan (2011)), the ability of high-ATS funds to outperform low-ATS funds primarily arises from the trades that increase the fund's ATS.

Our work adds to the literature examining the source of mutual fund managers' ability to earn abnormal returns. Most of this work investigates the hypothesis that

[1]In contrast to their relation with ATS, the 3 concentration/activeness measures (industry concentration, active share, and fund R^2) are strongly correlated.

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managers gain an information advantage via personal and professional relationships (i.e., "better-connected" managers). For example, mutual fund managers appear to use information supplied by college alumni (Cohen, Frazzini, and Malloy (2008)), affiliated banks (Massa and Rehman (2008)), pension business relationships (Duan, Hotchkiss, and Jiao (2018)), and geographically nearby firms (Coval and Moskowitz (1999), (2001)). In contrast to the better-connected source of information literature, there is relatively little evidence regarding other advantages or skills a mutual fund manager may use to garner positive alpha. Notable exceptions include evidence that managers with nonfinance work experience earn abnormal returns for trades in their "experience" industry (Cici, Gehde-Trapp, Goricke, and Kempf (2018)) and managers that understand the lead–lag relations between suppliers and customers garner superior performance (Huang and Kale (2013)).[2] We add to this work by providing evidence of a heretofore unidentified source of fund alpha – fund managers using their superior knowledge regarding technological innovation.

Our work is also related to the literature that suggests that better-informed fund managers hold more concentrated/active portfolios (e.g., Kacperczyk et al. (2005), Cremers and Petajisto (2009), Amihud and Goyenko (2013)). Broadly, this literature differs from the literature discussed in the previous paragraph in that, rather than attempting to identify how (i.e., specific sources of manager information or skill) some managers outperform, the concentration/activeness literature treats the underlying source as a latent variable and recognizes that, regardless of the source, a better-informed/highly skilled manager will tend to hold a more concentrated and active portfolio. Thus, our work (as well as the literature discussed previously) differs fundamentally from the concentration/activeness literature as we hypothesize a specific source for managers' ability to outperform – the markets' slow incorporation of information related to technological innovations. Moreover, we demonstrate that because ATS is largely orthogonal to these well-known predictors of fund performance, ATS can be combined with other metrics to generate substantially better predictors of fund success.

Our study also contributes to the literature investigating how asset prices respond to corporate technological innovation. Gu (2005) shows that changes in corporate technological innovation (as measured by changes in patent citations) positively correlate with future earnings, and that both markets and analysts fail to incorporate this information in a timely manner. Hirshleifer et al. (2013) find that markets are slow to incorporate technological innovative efficiency (measured as patents per research and development dollar or patent citations per research and development dollar) and attribute the effect to investors' inability to quickly incorporate uncertain and hard-to-process information.[3] Two recent studies (Lee et al. (2019), Bekkerman, Fich, and Khimich (2020)) find that, further consistent with the

[2]These categories are not mutually exclusive. It is possible, e.g., that a fund manager may do a better job timing her "experience" industry, because she has a better understanding of the industry or because she has personal contacts within the industry who provide her nonpublic information.

[3]The authors also note that q-theory could, theoretically, explain a positive relation between technological innovation efficiency and subsequent returns, that is, such investments may be risky and investors require a higher return. Consistent with the mispricing explanation, however, the authors find the effect is strongest in stocks with low investor attention and hard-to-value stocks.

gradual incorporation of technological innovation information, a portfolio of technologically similar firms predicts the focal firm's stock return. Our study suggests that this previously documented slow incorporation of technological innovation information is economically meaningful and serves as a key informational advantage for mutual fund managers with technological innovation expertise.

II. Active Technological Similarity, Data, and Summary Statistics

A. Active Technological Similarity

We use the method developed by Jaffe (1986) to measure the similarity of patent class distributions which, following the literature (e.g., Qiu, Wang, and Zhou (2018), Lee et al. (2019)), we denote "technological" similarity. Specifically, a firm's patents are distributed across 642 Cooperative Patent Classification (CPC) technology classes as assigned by the United States Patent and Trademark Office (USPTO).[4] TS is measured as the cosine similarity across technology classes. Jaffe (1986), Bloom, Schankerman, and Van Reenen (2013), and Lee et al. (2019) use this measure to capture TS between firm pairs. Qiu et al. (2018) use the measure to capture a firm's TS with the economy (i.e., the similarity of a firm's patent distribution with the patent distribution across all public firms). We follow this intuition and measure the TS of the stocks held in a mutual fund's portfolio.

Specifically, at the end of each quarter q, we define a vector of portfolio weights as $\omega_m = (\ldots,\omega_{m,i},\ldots)'$, where $\omega_{m,i}$ is firm i's weight in mutual fund m's portfolio. Following previous work, 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:

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

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

$$(2) \qquad T_{m,i,k} = \frac{n_{i,k}}{\sum_{k=1}^{642} n_{i,k}},$$

where $n_{i,k}$ is the number of patents firm i holds in CPC class k (we omit the end of quarter q subscript for brevity). Note that the m subscript indicates that firm i is held by fund m – firm i's patent distribution is, of course, the same for all funds holding the security (i.e., $T_{m,i,k} = T_{i,k}$).

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

[4]The USPTO moved from the United States Patent Classification system to the CPC system at the end of 2013. USPTO retroactively provided CPC patent classes to pre-2014 patents. Thus, we assess a firm's patents using the 642 CPC patent classes (also known as patent groups). Additional details are available at https://www.uspto.gov/patents-application-process/patent-search/classification-standards-and-development.

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

Note that ω subscript is included to recognize that the patent distribution of the remaining stocks in the portfolio is a function of fund m's weights in each of those securities. Specifically, the kth element of $T_{m,i,\omega}$ for fund m is:

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

where $n_{j,k}$ is the number of firm j's patents in CPC class k and $\omega_{m,j}$ is fund m's portfolio weight in firm j at the end of quarter q. In short, $T_{m,i,k}$ computes the value-weighted fraction of patents held in patent class k by the rest of the mutual fund's holdings (i.e., excluding firm i).

Given a mutual fund's portfolio, the patent distribution for each holding (equation (1)), and the patent distribution for the rest of the fund's portfolio (equation (3)), we compute the TS between each stock held by the fund and the rest of the fund's portfolio as the cosine similarity between the technology weight vectors:

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

$\langle T_{m,i} \cdot T_{m,-i,\omega} \rangle$ is bound by (inclusive) 0 and 1. A value close to 1 means that firm i held by fund m is technologically similar to the mass center of fund m's remaining holdings. Analogously, a value of 0 means that firm i has no technological overlap with any of fund m's remaining holdings.

Given the technological overlap of each stock held by fund m with the remaining stocks held by the same fund (i.e., $\langle T_{m,i} \cdot T_{m,-i,\omega} \rangle$), the TS of fund m's portfolio is simply the weighted (by the fund's portfolio weights) average of equation (5):

(6) $$\mathrm{TS}_m = \sum_i \omega_{m,i} \langle T_{m,i} \cdot T_{m,-i,\omega} \rangle.$$

Because each element is bound between 0 and 1 and the weights sum to 1, TS_m is also bound by 0 and 1.[5] The portfolio weight ($\omega_{m,i}$) reflects the relative importance of each stock in a fund's portfolio. In short, TS_m is the weighted average TS between individual firm i held by fund m and the rest of the stocks held by fund m at the end of quarter q. A close-to-unity value indicates that firms held in a fund's portfolio exhibit similar technological innovations.

Our hypothesis focuses on changes in exposure to a technology space, rather than exposure levels, for several reasons. First, and most important, mutual fund

[5]When a firm has 0 patents, equation (2) is technically undefined (and, as a result, so are equations (5) and (6)). However, when a firm has no patents, its technological overlap with other firms is 0. As a result, equation (6) is unaffected. That is, if firm i has 0 patents, then it has 0 technological overlap with the rest of the portfolio and we set equation (5) equal to 0.

portfolios vary in TS due to their style and mandates, e.g., compared to a growth fund, a value fund may naturally hold firms that have relatively little technological innovation exposure (e.g., few patents) and therefore little technological overlap.[6] Second, a number of theoretical (e.g., Kacperczyk and Seru (2007)) and empirical (e.g., Chen, Jegadeesh, and Wermers (2000), Kothari and Warner (2001), and Baker, Litov, Wachter, and Wurgler (2010)) studies suggest that a manager's trades better capture her informational advantages than portfolio weights. Third, as discussed in the introduction, we hypothesize the relation between technological innovation and returns primarily arises from mutual fund trades that increase the TS of the fund's portfolio.

Specifically, we define 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. We begin by computing a fund's end of quarter weights assuming that the manager had made no trades in quarter q as:

$$(7) \qquad \widetilde{\omega}_{m,i,q} = \frac{\omega_{m,i,q-1}\left(1+\mathrm{RET}_{i,q}\right)}{\sum_i \omega_{m,i,q-1}\left(1+\mathrm{RET}_{i,q}\right)},$$

where $\omega_{m,i,q-1}$ is fund m's weight in stock i at the end of quarter $q-1$ and $\mathrm{RET}_{\mathrm{i,q}}$ is firm i's return in quarter q. Based on these "no-trading" weights ($\widetilde{\omega}_{m,i,q}$) and each stock's TS with the other stocks in the portfolio the manager held at the beginning of the quarter, a fund's "passive" TS (PASSIVE_TS) at the end of quarter q (i.e., what a fund's TS would have been at the end of quarter q had the fund not traded any stocks in quarter q) is given by:

$$(8) \qquad \mathrm{PASSIVE\_TS}_m = \sum_i \widetilde{\omega}_{m,i} \langle T_{m,i} \cdot T_{m,-i,\widetilde{\omega}} \rangle.$$

Note that the value-weighted distribution of patents across a fund's other (i.e., excluding firm i) holdings is a function of the implied weights at the end of the quarter had the fund manager not traded any stocks over the quarter (i.e., $\widetilde{\omega}_m$) rather than the fund's actual (post-trading) weights at the end of the quarter (i.e., ω_m).[7] That is, equation (8) uses $T_{m,-i,\widetilde{\omega}}$, whereas equation (6) uses $T_{m,-i,\omega}$.

The extent to which a fund's quarter q trades shift its portfolio to greater or lesser TS is given by the ATS (i.e., the difference between the fund's TS (equation (6))

[6]Consider, for example, the TS of 2 mutual funds that each holds a value-weighted portfolio of firms in one of 2 industries: Fund A holds a value-weighted portfolio of all firms in the Information Retrieval Services (SIC = 7375) industry, and Fund B holds a value-weighted portfolio of all firms in the Computer Programing Services (SIC = 7371) industry. In the first quarter of 2006, the Information Retrieval Services industry has TS of 0.57, reflecting the fact that patents in that industry are heavily concentrated in 9 patent classes. In contrast, TS for the Computer Programing Services Industry, where patents are diversely populated across 21 patent classes, is only 0.087. Thus, Funds A and B exhibit extremely different TS simply because they focus on different industries. Nonetheless, either manager could increase or decrease the TS of their holdings by deviating from industry weights and concentrating their portfolio in firms that focus on the same patent classes.

[7]Because a fund's passive TS (PASSIVE_TS) is based on the fund's portfolio weights at the end of quarter q had the manager not traded, we use the vector of patent distributions at the end of quarter q. That is, PASSIVE_TS measures what the fund's TS would have been at the end of quarter q had the manager made no trades in quarter q.

and what the fund's TS would have been had the manager not traded any securities (equation (8))):[8]

$$\text{(9)} \quad \text{ATS}_m = \text{TS}_m - \text{PASSIVE\_TS}_m = \sum_i \left(\omega_{m,i} \langle T_{m,i} \cdot T_{m,-i,\omega} \rangle - \tilde{\omega}_{m,i} \langle T_{m,i} \cdot T_{m,-i,\tilde{\omega}} \rangle \right).$$

If a fund's trades during the quarter increase the TS of its holdings, equation (9) will be positive.[9] Alternatively, if the fund's trades increase the technological diversity of the portfolio, equation (9) will be negative.

B. Data

We use the updated CRSP-matched Google patent data from Kogan, Papanikolaou, Seru, and Stoffman (2017) to measure TS. This data set covers 1.94 million patents with application filing dates between 1926 and 2017.[10] Following the literature (e.g., Hall, Jaffe, and Trajtenberg (2001), Hsu (2009)), we use the patent application date (rather than the patent grant date) to better capture the time the technological innovation begins impacting real production.[11] We gather monthly fund returns and characteristics from the CRSP survivor-bias-free mutual fund database and mutual fund holdings from the Thomson Reuters mutual fund holdings database.[12] We use WRDS MFLINKS to merge the CRSP

[8]To reduce notional clutter, we sum over all firms in the market (equations (6), (8), and (9)). Note that if the manager does not hold a given security, its weight is 0.

[9]Because we want to measure how a manager's trades impact TS and given that TS is a function of portfolio weights and the distribution of patents at a point in time, we focus on ATS rather than the quarterly change in raw TS (i.e., the change in equation (6)). That is, TS at the end of the quarter will be different from TS at the beginning of the quarter, even if the manager does not trade, because stocks in the portfolio have different returns (thus resulting in passive portfolio weight changes) and because the patent distribution at the end of the quarter differs from the patent distribution at the beginning of the quarter. Therefore, we focus on ATS that captures how managers' trades impact TS.

[10]The data are downloaded from Noah Stoffman's website at (https://host.kelley.iu.edu/nstoffma/). We thank the authors for making the data available. Earlier version of these data has been used by a number of previous studies (e.g., Kogan et al. (2017), Qiu et al. (2018)). As Lee et al. (2019) point out, this data set is substantially more comprehensive than the National Bureau of Economic Research patent data set. Note that this data set contains 2.95 million patents. We limit our analysis to patents with nonmissing filing/application dates and CPC classifications. We obtain patent filing/application dates from the full set of 2019 data files hosted in the patent assignment data set (https://bulkdata.uspto.gov/data/patent/assignment/economics/2019/dta.zip). The CPC classification data for all patents (applied retrospectively to all patents) are extracted from PatentsView at http://data.patentsview.org/20200630/download/cpc_current.tsv.zip.

[11]Application date is the date a patent is submitted to the USPTO; grant date (typically 2–3 years after the application date) is the date a patent is granted. As pointed out by the literature (Pakes and Griliches (1984), Pakes (1985), Shea (1998), Hall et al. (2001), and Hsu (2009)), relative to grant dates, application dates better capture when new technologies begin to impact real production. By using patent application dates (following the most relevant literature), our study does not suggest that an investor could identify managers' increasing technological concentration in real time. Rather, our economic question is whether expertise in technological innovation is a meaningful channel that some managers exploit. Regardless, as shown in Appendix A.1 in the Supplementary Material, our results are nearly identical when using patent grant dates to measure similarity.

[12]The Thomson Reuters mutual fund holdings database is based on mandatory and voluntary fund holding disclosures. Prior to 2004, mutual funds were required to disclose their holdings semiannually; many funds voluntarily disclosed their holdings quarterly. The U.S. Securities and Exchange Commission increased the mandatory disclosure frequency from semiannually to quarterly in May 2004.

fund data and the Thomson Reuters holdings data. We employ the "follow the money" approach of Elton, Gruber, and Blake (1996) and Gruber (1996) to address merged funds. This method mitigates the survivorship bias and assumes that investors in merged funds put their money in the surviving fund and continue to earn the surviving fund's return. We also follow Lou (2012) to identify and exclude flows from fund mergers.

Our analysis focuses on actively managed domestic equity mutual funds. Thus, following Huang, Sialm, and Zhang (2011), we eliminate balanced, bond, money market, international, and index funds.[13] We remove the first 2 years of return data to eliminate incubation bias (Evans (2010)) and exclude funds with total net assets (TNA) less than \$15 million. We also drop funds with a total market value of reported holdings under 80% or over 120% of the TNA. For funds with multiple share classes, we follow Wermers (2000) and compute value-weighted fund characteristics, with the exception of fund age, which is based on the oldest share class. To generate factor loadings and abnormal return estimates, we also require funds to have at least 20 monthly returns over the previous 2 years. Turnover is the minimum of a fund's sales and purchases normalized by net assets averaged over the past year. Following the literature (e.g., Sirri and Tufano (1998)), we compute fund flow as:

$$\text{FLOW}_{m,t} = \frac{\text{TNA}_{m,t} - (1+\text{RET}_{m,t-2:t}) \times \text{TNA}_{m,t-3}}{\text{TNA}_{m,t-3}}, \tag{10}$$

where $\text{RET}_{m,t-2:t}$ is fund m's return over the quarter ending in month t (i.e., months $t-2$ to t). Fund TNA is winsorized at the 99% level. Fund flow, expense ratio, and ATS are winsorized at the 1% and 99% levels to minimize the impact of outliers.

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. Table 1 reports the time-series means of the cross-sectional summary statistics. Results are similar to those reported in earlier work (e.g., Amihud and Goyenko (2013)).

III. Empirical Results

A. ATS and Fund Characteristics

We begin our empirical analysis by examining the relation between fund ATS and fund characteristics. Specifically, we predict that high-ATS funds will tend to be

[13]CRSP uses 3 sources for fund style: Wiesenberger objective codes, Strategic Insights objective codes, and Lipper objective codes. We follow Huang et al. (2011) and use funds with Lipper objectives codes of CA, CG, CS, EI, FS, G, GI, H, ID, LCCE, LCGE, LCVE, MC, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, MR, NR, S, SCCE, SCGE, SCVE, SG, SP, TK, TL, and UT. If Lipper codes are not available, we select funds with Strategic Insights objective codes of AGG, ENV, FIN, GMC, GRI, GRO, HLT, ING, NTR, SCG, SEC, TEC, UTI, GLD, and RLE. If neither Lipper nor Strategic Insights codes are available, we use the Wiesenberger objective codes of G, G-I, G-S, GCI, IEQ, ENR, FIN, GRI, HLT, LTG, MCG, SCG, TCH, UTL, and GPM to select funds. Finally, further following Huang et al., if a fund does not have Lipper, Strategic Insights, or Wiesenberger code, then the fund is included if it has a Common Stocks policy or holds more than 80% of its value in common stocks. Names are used to identify index funds.

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TABLE 1

Summary Statistics

Table 1 reports the time-series means of the cross-sectional summary statistics of fund active technological similarity (ATS) and characteristics. ATS is calculated at the end of each quarter using equations (1)–(9). FLOW is calculated quarterly using equation (10). Expense ratio (EXP_RATIO) and TURNOVER are provided by the Center for Research in Security Prices at the annual frequency. ATS, FLOW, and EXP_RATIO are winsorized at the 1% and 99% levels. Total net assets (TNA) is winsorized at the 99% level. The sample size is 87,804 fund-quarter observations for ATS between 1983:Q4 and 2017:Q4 and 263,412 fund-month observations for other variables.

	Mean	Median	Std. Dev.	25th Percentile	75th Percentile
ATS (%)	−0.084	−0.135	2.776	−1.145	0.809
TNA ($million)	595	226	824	75	718
AGE (in years)	17	15	10	11	21
EXP_RATIO (annual, %)	1.17	1.15	0.42	0.92	1.43
TURNOVER (annual, %)	83	63	81	35	107
FAMILY_SIZE($million)	6,999	2,527	12,024	477	8,118
FLOW (quarterly, %)	1.30	−0.54	10.94	−3.86	4.42

smaller, younger, exhibit higher expense ratio, and have higher turnover.[14] Because our focus is on funds that have substantial increases in ATS, we estimate a logistic regression, each quarter, where the dependent variable is an indicator for whether a fund is in the top ATS quintile in that quarter:

$$\text{(11)} \quad \text{logit}\left(\text{Top ATS}_{m,q}\,\text{quintile}\right) = \alpha_{style} + \beta_1 \log\left(\text{TNA}_{m,q}\right) + \beta_2 \log\left(\text{AGE}_{m,q}\right) + \beta_3 \text{EXP\_RATIO}_{m,q} + \beta_4 \text{TURNOVER}_{m,q} + \varepsilon_{m,q},$$

where log(TNA) and log(AGE) are the natural logarithms of fund TNA (in millions of dollars) and 1 plus fund age (in months), respectively. EXP_RATIO and TURNOVER are the fund's expense ratio and turnover, respectively, measured over the previous year, and α_{style} are indicator variables based on the CRSP fund style codes.[15]

The first column of Table 2 reports the time-series mean coefficients and associated t-statistics (computed from the time-series standard errors as in Fama and MacBeth (1973)) from the quarterly logistic regressions. As predicted, high-ATS funds tend to be smaller, exhibit higher turnover, and charge higher fees. We find little evidence of a meaningful relation between ATS and fund age.

We also expect that high-ATS funds will tend to exhibit greater "activeness." Thus, the remaining columns of Table 2 add the three concentration/activeness measures (individually and collectively). Specifically, we follow Kacperczyk et al. (2005) and measure industry concentration for each fund (at the end of each quarter) as the sum of the squared differences between the fund's industry weights and the market's industry weights.[16] Our active share data come from Antti Petajiso's

[14]As pointed out by Cremers and Petajisto (2009), some of these variables are clearly endogenous. For instance, a fund determines its ATS as well as its expense ratio and turnover.

[15]We use CRSP mutual fund objective codes that allow for continuous classification codes based on the 3 sources used by CRSP (Wiesenberger, Strategic Insights, and Lipper) to identify fund style. Specifically, the CRSP fund style codes are based on Wiesenberger objective codes between 1962 and 1993, Strategic Insights objective codes between 1993 and 1998, and Lipper objective codes beginning in 1998 and include objectives of growth, income, growth and income, large, mid, small, and micro (for additional details, see http://www.crsp.org/products/documentation/crsp-style-code-0).

[16]We use 10 industry classifications following Kacperczyk et al. (2005).

TABLE 2

Fund Characteristic and ATS

Column 1 of Table 2 reports the time-series mean coefficients from quarterly cross-sectional logistic regressions of an indicator for funds in the top active technological similarity (ATS) quintile on fund characteristics including the natural logarithm of total net assets (TNA), the natural logarithm of fund age (months + 1), expense ratio, turnover, and indicators for the Center for Research in Security Prices fund styles. The remaining columns add, individually and collectively, 3 measures of fund activeness – industry concentration, active share, and fund R^2. The *t*-statistics reported in parentheses are based on Fama–MacBeth standard errors computed from the time series of coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	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	Yes	Yes	Yes	Yes	Yes
No. of quarters	137	137	126	137	126
Observations	86,832	86,355	53,320	86,832	53,279

website (petajisto.net/data.html) for the period between the first quarter of 1984 and the last quarter of 2015. Active share is one-half the sum, across stocks, of the absolute values of the difference in a fund's portfolio weights and the associated index weights (see Petajisto (2013) for details). We follow Amihud and Goyenko (2013) and compute fund R^2 from a time-series regression of fund returns on market, size, value, and momentum factors. We winsorize industry concentration, active share, and fund R^2 at the 1% and 99% levels to minimize the impact of outliers. Further consistent with our hypothesis, the last 4 columns of Table 2 reveal that high-ATS funds tend to be more active/concentrated as they exhibit greater industry concentration, higher active share, and lower fund R^2. However, when including all three activeness measures, high-ATS funds only remain materially related to active share.

B. Portfolio Sorts

We begin to investigate the relation between ATS and future fund performance by sorting funds to the extent that their trades move their portfolio toward technologically similar firms. Specifically, we sort funds into ATS quintiles at the end of each quarter q (i.e., based on their trading in quarter q). We then compute the average mutual fund gross (pre-expense) and net (post-expense) monthly returns over the subsequent quarter (i.e., months $m+1$, $m+2$, and $m+3$) for funds within each ATS quintile.[17] We collect the contemporaneous monthly excess returns of the

[17]Following previous work, we compute the gross monthly mutual fund return as the CRSP reported net monthly return plus monthly expense ratio (i.e., 1/12th of the fund expense ratio reported by CRSP).

market portfolio as well as the 0-investment factor mimicking portfolios for size, book-to-market, and momentum from Kenneth French's website. Finally, following previous work (e.g., Kacperczyk et al. (2005), Cremers and Petajisto (2009), and Amihud and Goyenko (2013)), we estimate the Carhart (1997) 4-factor alpha as the intercept from a time-series regression of the cross-sectional average monthly return of funds within each ATS quintile portfolio P (portfolios are rebalanced each quarter) on market, size, value, and momentum factors:

$$\text{RET}_{P,t} - r_{f,t} = \alpha_P + \beta_{\text{MKT},P}\left(\text{MKT}_t - r_{f,t}\right) + \beta_{\text{SMB},P}\text{SMB}_t + \beta_{\text{HML},P}\text{HML}_t + \beta_{\text{UMD},P}\text{UMD}_t + \varepsilon_{P,t}. \tag{12}$$

The first column of Panel A of Table 3 reports the average monthly mutual fund net return (in percentage) for funds within each ATS quintile over the following quarter. The next 2 columns report the Carhart 4-factor monthly alphas based on gross and net fund returns, respectively, over the following quarter. Consistent with our hypothesis that expertise in understanding technological innovation is an informational advantage source for some fund managers, we find that funds increasing their technological concentration garner positive abnormal returns. Specifically, the difference between the top and bottom quintiles is positive; the monthly performance difference is 0.236% for net returns, 0.240% for gross return alphas, and 0.235% for net return alphas, implying annualized return differences of 283 basis points (i.e., 0.236×12) for net returns, 288 basis points for gross return alphas, and 282 basis points for net return alphas.[18] Moreover, as shown in the bottom row of Panel A, all three performance measures generate differences that are statistically significant at the 1% level.[19,20]

Further consistent with our hypothesis, the results suggest that managers increasing the TS of their holdings primarily drive the relation between ATS and subsequent abnormal returns. For instance, the second column of Panel A of Table 3

[18]In Appendix A.2 in the Supplementary Material, we provide estimates for quarters +2, +3, and +4. The results reveal that although ATS is most strongly related to returns the following quarter (i.e., the results reported in Table 3), ATS is also positively related to longer-term returns.

[19]As detailed in Appendix A.3 in the Supplementary Material, we find qualitatively identical results when using Capital Asset Pricing Model alphas (Sharpe (1964), Lintner (1965)), Fama–French 3-factor alphas (Fama and French (1993)), or Daniel, Grinblatt, Titman, and Wermers (DGTW) (2012) characteristic benchmark-adjusted returns to measure fund performance.

[20]One potential concern is that TS is a property of any, including passive, portfolios. We thank an anonymous referee for suggesting 2 tests to address this concern. First, we repeat our tests using (passive) industry portfolios rather than (active) mutual fund portfolios. Specifically, we repeat the analysis in Table 3 for the Fama and French industry portfolios (formed following the procedure described on Ken French's website). Given ATS is the difference between the TS at the end of the quarter and what the TS at the end of the quarter would be if the "manager" did not trade, the ATSs for industry portfolios are driven by changes in industry membership (e.g., Dell going private in the third quarter of 2013 changed the composition of the computer industry; Fama–French industry number = 35). Given that quarterly changes in industry membership are typically relatively minor, industry ATS is generally close to 0. Consistent with hypothesis that ATS captures skill associated with active management, we find no evidence (details shown in Appendix A.4 in the Supplementary Material) that "industry ATS" predicts passive industry returns. Second, we repeat our tests sorting on TS (i.e., equation (6)) rather than active TS (i.e., equation (8)). As shown in Appendix A.5 in the Supplementary Material, we find no evidence of a material relation between TS and subsequent returns.

TABLE 3

ATS and Future Performance: Portfolio Analysis

At the end of each quarter between 1983:Q4 and 2017:Q4, we sort mutual funds into quintile portfolios based on their active technological similarity (ATS) and evaluate three measures of monthly fund performance over the following quarter: monthly net return, monthly gross Carhart alpha, and monthly net Carhart alpha. The Carhart alphas (and associated *t*-statistics) are estimated from a time-series regression of the average excess monthly fund return on the contemporaneous monthly factor portfolio returns (excess monthly market returns, size, value, and momentum). All performance measures are in percentage per month. The bottom row of Panel A of Table 3 reports the mean monthly return differences between the portfolios of high- (top quintile) and low-ATS (bottom quintile) funds. Panel B reports analogous net alpha statistics for the top and bottom quintiles, as well as their difference, between mutual funds with i) high-vs.-low industry concentration, ii) high-vs.-low active share, iii) high-vs.-low fund R^2, and iv) high-vs.-low lag alpha (in all 4 cases, high-vs.-low refers to top quintile less bottom quintile). Standard errors are adjusted for heteroscedasticity and autocorrelation. *t*-Statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. ATS Quintiles

	Net Return	Gross Carhart Alpha	Net Carhart Alpha		
Quintile			All	Early Period (1984–2000)	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: High − Low	0.236***	0.240***	0.235***	0.210***	0.246***
	(7.71)	(7.86)	(7.72)	(3.99)	(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)

reveals that, prior to expenses, funds that strongly increase the TS of their portfolio (i.e., top ATS quintile) garner monthly abnormal returns of 0.187% over the following quarter (statistically significant at the 1% level). In contrast, funds that strongly decrease the TS of their holdings (i.e., bottom ATS quintile) average monthly gross Carhart alphas of −0.053% (not meaningfully different from 0). We find some evidence that mutual fund investors are able to earn positive abnormal returns after fees. That is, as shown in the third column, the annualized net Carhart alpha for the high-ATS quintile is 88 basis points (i.e., 0.073 × 12) and marginally significant. Regardless, investors in high-ATS funds are substantially better off than investors in low-ATS funds, as the latter, on average, suffer post-expense negative abnormal returns (statistically significant at the 1% level) and the difference in net Carhart alpha between high- and low-ATS funds (reported in the bottom row of Panel A) remains statistically significant at the 1% level.

The last 2 columns of Panel A of Table 3 examine the net Carhart alphas for the first (1984–2000) and second (2001–2018) halves of our sample period. Although the high–low portfolio return is substantial in both periods, the point estimate (and associated t-statistic) is larger in the post-2000 period when technological innovation becomes a more important part of the economy (e.g., Fagerberg and Srholec (2008), Qiu and Wan (2015), and Bekkerman et al. (2020)).

To better gauge the economic magnitude of the relation between ATS and subsequent returns, we repeat the sorting exercise but sort, at the end of each quarter q, on industry concentration, active shares, fund R^2, and lag fund alpha. Specifically, directly corresponding to the third column of Panel A of Table 3 (based on ATS), the first row of Panel B reports the net Carhart alpha for mutual funds in the top quintile of industry concentration, active share, fund R^2, or lag fund alpha. Analogously, the second row reports the net Carhart alpha for the bottom quintile, and the bottom row reports the net Carhart alpha for a portfolio of long high-quintile funds and short low-quintile funds.

The results are consistent with previous work, as abnormal returns are positively related to industry concentration, active share, and lag alpha and are inversely related to fund R^2. The results also reveal that point estimates for ATS are larger than the analogous values for 4 other metrics. Specifically, the difference in net Carhart alphas for high- and low-ATS funds (2.82% annualized) is 53% larger than the industry concentration spread (1.85%), 101% larger than the active share spread (1.40%), 12% larger than the fund R^2 spread (2.52%), and 56% larger than the lag alpha spread (1.81%).

C. Multivariate Analysis

Analogous to the tests in Cremers and Petajisto (2009) and Amihud and Goyenko (2013), we next examine whether other fund characteristics subsume ATS's power to predict fund returns. Specifically, each month, we estimate a cross-sectional regression of monthly fund performance the following quarter on lag ATS and fund characteristics:[21]

$$
\begin{aligned}
(13)\quad \alpha_{m,t} = {} & \beta_0 + \beta_1 \mathrm{ATS}_{m,t-1} + \beta_2 \log(\mathrm{TNA}_{m,t-1}) + \beta_3 \log(\mathrm{AGE}_{m,t-1}) \\
& + \beta_4 \mathrm{EXP\_RATIO}_{m,t-1} + \beta_5 \mathrm{TURNOVER}_{m,t-1} + \beta_6 \log(\mathrm{FAMILY\_SIZE}_{m,t-1}) \\
& + \beta_7 \mathrm{LAG\_FUND\_ALPHA}_{m,t-1} + \beta_8 \mathrm{FLOW}_{m,t-1} \\
& + \beta_9 \sigma(\mathrm{FUND\_RETURN}_{m,t-1}) + \varepsilon_{m,t},
\end{aligned}
$$

where the dependent variable is fund m's net monthly Carhart alpha (in percentage).[22] Specifically, following Kacperczyk et al. (2005), Cremers and Petajisto (2009), and Amihud and Goyenko (2013), we compute monthly fund net Carhart alphas as the difference between a fund's net return in month t and the fund's 4-factor expected return in month t. The fund's month t expected return is the sum of the products of the fund's factor loadings (estimated over the previous 24 months

[21]Because patent data are quarterly, ATS is measured at the end of the previous quarter. Other variables (e.g., fund size) that are available monthly are measured at the end of the previous month.

[22]As shown in Appendix A.6 in the Supplementary Material, we find nearly identical results when using gross alphas as the dependent variable. Note also that because the results of Table 4 are based on monthly returns, the number of observations is approximately 3 times that reported in the quarterly regressions in Table 2 explaining cross-sectional variation in quarterly ATS.

for funds with at least 20 months of return data) and the market, size, value, and momentum factor realizations in month *t*.

We include a set of lagged fund characteristics that could affect fund performance as suggested in previous studies (e.g., Cremers and Petajisto (2009), Amihud and Goyenko (2015)). Specifically, log(TNA), log(AGE), EXP_RATIO, and TURNOVER are as defined in Section III.A and measured at the end of the previous month. log(FAMILY_SIZE) is the natural logarithm of 1 plus the aggregate TNA of all the funds under fund family management less the focal fund's TNA measured at the end of the previous month.[23] LAG_FUND_ALPHA is the fund's Carhart (1997) 4-factor alpha at the end of the previous month estimated over the previous 24 months (minimum of 20 months observation). FLOW is the ratio of net flows to assets over the previous quarter (see equation (10)). σ(FUND_RETURN) is the volatility (standard deviation) of fund net returns at the end of the previous month (computed over the previous 12 months). ATS is the fund's ATS measured at the end of the previous quarter.

Table 4 reports the time-series mean coefficients from the monthly cross-sectional regressions (and associated *t*-statistics computed from the time-series

TABLE 4

Fund Characteristics, ATS, and Future Performance

Table 4 reports the average coefficients from cross-sectional regressions of monthly (1984:M1–2018:M3) net Carhart alphas in quarter $q+1$ on fund characteristics measured at the end of the previous month and active technological similarity (ATS) measured at the end of quarter q. Alphas are in percentage per month. Fund characteristics include the natural logarithm of total net assets (TNA), the natural logarithm of fund age (months + 1), the natural logarithm of total fund family net assets, expense ratio, turnover, past fund performance (the fund's Carhart (1997) 4-factor alpha estimated over the previous 24 months), fund flow over the previous 3 months (see equation (10)), and the standard deviation of fund net returns over the previous year. Column 1 reports the results of a univariate regression. Column 2 includes fund characteristics as controls. Column 3 includes fund style indicator variables. Column 4 is limited to the first half of our sample period (1984:M1–2000:M12, 204 months), and column 5 is limited to the second half of the sample period (2001:M1–2018:M3, 207 months). *t*-Statistics (reported parenthetically) are computed from the time series of monthly estimates (i.e., Fama–MacBeth) with Newey–West standard errors with 3 lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	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	No	No	Yes	Yes	Yes
No. of months	411	411	411	204	207
Average R^2	0.005	0.097	0.119	0.121	0.116

[23]We use CRSP variable MGMT_CD to identify fund family. We backfill missing fund family identifier using the most recent available identifier.

standard error). Consistent with the portfolio sorts, the results in the first column reveal a strong positive relation (statistically significant at the 1% level) between monthly fund net abnormal returns in quarter $q+1$ and the extent that a manager shifted the fund portfolio toward more technologically similar firms in quarter q. Moreover, the results are economically meaningful – given that the standard deviation of ATS is 2.775% (see Table 1), the coefficient in the first column suggests that a 1-standard-deviation higher ATS is associated with an annualized 93 basis points higher return ($0.028 \times 0.02775 \times 12 = 0.93\%$).

The second column of Table 4 adds fund characteristics to the regression. The coefficients are largely consistent with previous work. For instance, consistent with Amihud and Goyenko (2013), fund performance is positively related to lag fund alpha. Importantly, however, the additional fund characteristics do not subsume the role of ATS – in fact, the point estimate of the coefficient associated with ATS is slightly greater (and remains statistically significant at the 1% level) when including other fund characteristics. The regression reported in column 3 includes indicator variables for CRSP fund styles (as defined previously). The results remain virtually unchanged.

The final 2 columns of Table 4 repeat the regression in column 3 for the early (1984–2000) and more recent (2001–2018) periods. Consistent with the last 2 columns of Panel A of Table 3, the results are stronger in the second half of our sample period. In short, the cross-sectional regressions confirm the portfolio sorts analysis – funds whose trades increase the TS of their holdings subsequently garner larger abnormal returns.

D. ATS, Fund Activeness, and Lag Fund Alpha

Previous work reveals that fund performance is related to both lag fund alpha (e.g., Amihud and Goyenko (2013)) and measures of fund portfolio concentration/activeness – industry concentration (Kacperczyk et al. (2005)), active share (Cremers and Petajisto (2009)), and fund R^2 (Amihud and Goyenko (2013)). ATS, however, is fundamentally different from measures of portfolio concentration/activeness, because ATS is a trade-based measure (i.e., changes in positions), whereas the concentration/activeness metrics are levels-based measures. For example, although TS is stronger for firms within the same industry than firms within different industries, the ATS for a manager who buys and holds any portfolio (including an industry portfolio) is always 0 in contrast to industry concentration, active share, fund R^2, and lag fund alpha. That is, ATS measures changes in a fund's portfolio TS due to changes in the manager's holdings (i.e., their trades).[24]

[24]Consider a simple example – if a manager holds only 2 stocks, the fund's TS would be determined by the similarity between the 2 stocks. If the manager does not trade either stock, the ATS is 0. For a nonzero ATS, the manager would have to trade – buying or selling shares of either of the securities held or any other security. We verify the relation between industries and TS, by computing the TS (i.e., equation (6)) for every pair of firms in each quarter in our sample period. The average TS between firms in the same industry (using the Fama and French 48 industry classifications) is 0.17 (n = 9.2 million same-industry firm-pair-quarter observations) vs. 0.03 for firms in different industries (n = 148.9 million different-industry firm-pair-quarter observations).

TABLE 5

Correlation Between ATS, Lag Fund Alphas, and Fund Activeness

Table 5 reports the time-series means of the cross-sectional quarterly correlation between mutual funds' active technological similarity (ATS), 3 measures of fund activeness, and lag fund alpha. The 3 active measures include industry concentration (Kacperczyk et al. (2005)), active share (Cremers and Petajisto (2009)), and fund R^2 (Amihud and Goyenko (2013)). Spearman (Pearson) correlations are reported above (below) the diagonal. The sample period is 1984:Q1–2017:Q4 except active share (1984:Q1–2013:Q4). p-Values (computed from the time series of correlation estimates) are reported parenthetically.

	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_CONCENTRATION	−0.022	1	0.453	−0.405	0.071
	(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_ALPHA	−0.005	0.051	0.089	−0.060	1
	(0.49)	(0.01)	(0.01)	(0.01)	

Given ATS is fundamentally different from the fund concentration/activeness measures and lag alpha, it is likely that ATS can be combined with other measures to increase the ability to identify managers with superior skills. Thus, in this section, we begin by computing the cross-sectional correlation between ATS, the 3 concentration/activeness measures, and lag fund alpha. Table 5 reports the Spearman (above the diagonal) and Pearson (below the diagonal) correlations between ATS, industry concentration, active share, fund R^2, and lag fund alpha. Not surprisingly, the three activeness measures are strongly related to averaging (absolute value) Spearman correlations of 0.45 and Pearson correlations of 0.38. ATS, however, is largely orthogonal to lag fund alpha and the three concentration/activeness measures (averaging absolute Spearman and Pearson correlations of 0.02).

We begin to investigate whether one can better identify high-skill managers by combining ATS with the other metrics by double-sorting funds by ATS and each of the other four measures. Specifically, at the end of each quarter q, we independently sort funds into ATS quintiles, lag alpha quintiles, industry concentration quintiles, active share quintiles, and fund R^2 quintiles. Panel A of Table 6 reports monthly net Carhart alphas (in percentage) over the following quarter (i.e., analogous to Table 3, we report monthly alphas for portfolios that are updated quarterly) for funds within each of the 25 portfolios sorted by ATS and lag fund alpha. The last column of Panel A reports the difference in monthly net Carhart alphas (and associated t-statistics) for the high- and low-ATS quintiles within each lag alpha quintile. Analogously, the bottom row of Panel A reports the difference in monthly alphas (and associated t-statistics) for high- and low-lag fund alpha portfolios within each ATS quintile. The bottom 3 panels report analogous statistics for ATS and industry concentration portfolios (Panel B), ATS and active share portfolios (Panel C), and ATS and fund R^2 portfolios (Panel D).

The results in Table 6 suggest that ATS captures information that is unique from the information captured by lag fund alpha, industry concentration, active share, or fund R^2. As a result, using ATS in combination with the other metrics

TABLE 6

Portfolios Double-Sorted by ATS, Lag Fund Alpha, and Fund Activeness

Table 6 reports the average monthly net Carhart alphas for mutual funds independently double-sorted by active technological similarity (ATS) and lag fund alpha (Panel A), ATS and industry concentration (Panel B), ATS and active share (Panel C), and ATS and fund R^2 (Panel D). ATS, lag alpha, and fund activeness are all measured at the end of quarter q, and portfolios are updated quarterly. Alphas are in percentage per month. The last column of each panel reports the average monthly performance difference between the top and bottom ATS quintiles within each lag fund alpha or concentration/activeness quintile, and the bottom row of each panel reports the average monthly performance difference between the top and bottom lag fund alpha or concentration/activeness quintiles within each ATS quintile. Standard errors are adjusted for heteroscedasticity and autocorrelation. t-Statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	ATS Quintile					
Quintile	5 (High)	4	3	2	1 (Low)	ATS Difference: 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: High − Low	0.187***	0.118	0.266***	0.167**	0.128*	
	(2.59)	(1.64)	(3.76)	(2.31)	(1.95)	
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: High − Low	0.384***	0.189**	0.131**	0.264***	−0.190***	
	(4.69)	(2.57)	(2.03)	(3.48)	(−2.96)	
Panel C. Active Share and ATS						
5 (High)	0.263**	0.108	0.064	0.024	−0.265***	0.501***
	(2.31)	(1.10)	(0.74)	(0.24)	(−3.29)	(4.77)
4	0.214**	−0.024	−0.161**	−0.025	−0.224***	0.432***
	(2.10)	(−0.30)	(−1.99)	(−0.31)	(−2.84)	(4.60)
3	0.056	−0.034	−0.113	−0.023	−0.166**	0.223***
	(0.69)	(−0.50)	(−1.55)	(−0.36)	(−2.56)	(2.98)
2	−0.076	−0.099*	−0.094*	−0.119**	−0.101**	0.027
	(−1.25)	(−1.95)	(−1.72)	(−2.59)	(−1.97)	(0.45)
1 (Low)	−0.102*	−0.079**	−0.020	−0.086**	−0.049	−0.053
	(−1.97)	(−2.18)	(−0.49)	(−2.21)	(−1.09)	(−0.89)
Difference: High − Low	0.367***	0.193*	0.076	0.101	−0.211**	
	(2.96)	(1.96)	(0.83)	(0.98)	(−2.50)	
Panel D. Fund R^2 and ATS						
5 (High)	−0.114**	−0.104**	−0.096**	−0.144***	−0.134***	0.016
	(−2.26)	(−2.44)	(−2.47)	(−3.59)	(−3.30)	(0.30)
4	0.035	−0.123***	−0.172***	−0.069*	−0.198***	0.228***
	(0.69)	(−2.72)	(−3.58)	(−1.76)	(−3.74)	(3.40)
3	0.007	−0.046	−0.090*	−0.093*	−0.216***	0.221***
	(0.13)	(−0.98)	(−1.74)	(−1.82)	(−4.69)	(3.69)
2	0.118*	−0.016	−0.072	−0.052	−0.193***	0.308***
	(1.96)	(−0.28)	(−1.22)	(−0.87)	(−3.58)	(6.16)
1 (Low)	0.249***	0.112	0.186***	0.045	−0.112**	0.360***
	(3.49)	(1.61)	(2.79)	(0.70)	(−2.14)	(5.09)
Difference: High − Low	−0.362***	−0.216***	−0.282***	−0.189***	−0.016	
	(−4.31)	(−3.20)	(−4.08)	(−2.84)	(−0.28)	

yields substantially stronger results. First, recognize that both ATS and the second dimension (in each panel) discriminate between high- and low-alpha funds when controlling for the other. Specifically, as shown in the bottom row of each panel (and consistent with previous work), holding ATS constant, funds with higher lag returns (Panel A), greater industry concentration (Panel B), higher active share (Panel C), and lower fund R^2 (Panel D) tend to earn larger abnormal returns in the following quarter. Analogously, as shown in the last column of each panel, funds with high ATS meaningfully outperform funds with low ATS, holding lag fund alpha, industry concentration, active share, or fund R^2 constant.

Second, consistent with our hypothesis, the results suggest that ATS's independence means it can be combined with the other measures to better identify funds with superior performance. For example, as shown in the top-left cell of Panel A of Table 6, a portfolio of long high-ATS/high-lag alpha funds averages an annualized net alpha of 2.54% (i.e., 0.212×12; statistically significant at the 1% level). Similarly, as shown in the bottom-right cell, a portfolio of low-ATS/low-lag alpha funds averages an annualized net alpha of −2.78% (-0.232×12; statistically significant at the 1% level). Thus, the high-ATS/high-lag alpha portfolio outperforms the low-ATS/low-lag alpha portfolio by an annualized net alpha of 5.33% (i.e., $(0.212 - (-0.232)) \times 12$).

We find similar results when combining ATS with the concentration/activeness metrics. For instance, as shown in the top-left cell of Panel B of Table 6, a portfolio of long high-ATS/high-industry concentration funds garners an annualized net alpha of 4.10% (0.342×12; statistically significant at the 1% level), and the long–short ATS/industry concentration portfolio garners an annualized net alpha of 4.84% (i.e., $(0.342 - (-0.061)) \times 12$). Panels C (ATS/active share) and D (ATS/fund R^2) generate similar results. Specifically, the associated long–short portfolios garner annualized net alphas of 3.74% for ATS/active share (i.e., $(0.263 - (-0.049)) \times 12$) and 4.60% for ATS/fund R^2 (i.e., $(0.249 - (-0.134)) \times 12$).

As discussed previously, unlike the levels-based activeness/concentration measures, ATS is a trade-based measure (i.e., changes in positions).[25] One potential concern, therefore, is that perhaps the ability of ATS to predict fund returns beyond that captured by activeness/concentration measures arises from targeting mutual funds' trades rather than their portfolio holdings. To investigate this possibility, we repeat the analysis in Table 6 but double-sort on ATS and changes in industry concentration, ATS and changes in active share, and ATS and changes in fund R^2. As detailed in Appendix A.7 in the Supplementary Material, inconsistent with the concentration/activeness levels results in Table 6, we find little evidence that changes in fund concentration or fund activeness are related to future fund performance. Consistent with Table 6, however, we continue to document a strong relation between ATS and subsequent returns even when controlling for changes in industry concentration, active share, or fund R^2.

As a final test, we estimate monthly cross-sectional regressions of monthly net Carhart alphas in quarter $q + 1$ on ATS, industry concentration, and active share at

[25]Industry concentration and active share are levels-based measures. Although likely primarily driven by holdings, fund R^2 could be impacted by trades.

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TABLE 7

Regression Analysis: ATS, Lag Fund Alpha, and Fund Activeness

Table 7 reports the results of mean coefficient from cross-sectional regressions of monthly (n = 381–411 months depending on measure) net Carhart alphas in quarter $q+1$ (i.e., months $m+1$, $m+2$, and $m+3$) on lag fund characteristics, active technological similarity (ATS) measured at the end of quarter q, lag fund alpha (the fund's Carhart (1997) 4-factor alpha estimated over the previous 24 months), and three measures of fund concentration/activeness: industry concentration, active share, and fund R^2. Industry concentration and active share are measured at the end of quarter q; fund R^2 and lag fund alpha are measured at the end of the previous month. Alphas are in percentage per month. Fund characteristics include the natural logarithm of total net assets (TNA), the natural logarithm of fund age (months + 1), the natural logarithm of total fund family net assets, expense ratio, turnover, fund flow over the previous 3 months (see equation (10)), and the standard deviation of fund net returns over the previous year. The regressions also include indicator variables for fund styles. Standard errors are based on the time series of cross-sectional coefficients and adjust for heteroscedasticity and autocorrelation (Newey–West with 3 lags). t-Statistics are in parentheses. *** indicates statistical significance at the 1% level.

	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_CONCENTRATION (×100)		0.013***			0.003
		(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	Yes	Yes	Yes	Yes	Yes
Fund characteristics	Yes	Yes	Yes	Yes	Yes
No. of months	411	411	381	411	381
Avg. no. of funds	641	622	415	641	403
Average R^2	0.119	0.129	0.139	0.127	0.159

the end of quarter q, and on 1-month lag fund R^2, 1-month lag fund alpha, and other fund characteristics.[26] That is, we add industry concentration, active share, or fund R^2 to the regression given in equation (13). Consistent with the evidence in Table 6, the results reported in the first 4 columns of Table 7 reveal the relation between ATS and subsequent returns remains robust when controlling for fund characteristics including lag fund alpha and any of the three activeness measures. Moreover, consistent with the hypothesis that combining ATS with fund concentration metrics or lag fund alpha can generate better identification of funds that outperform, ATS, lag fund alpha, greater industry concentration, higher active share, or lower fund R^2 are all associated with higher subsequent returns. As shown in the final column, when we include all three activeness measures in the same regression, fund R^2 subsumes the power of industry concentration and active share, but ATS remains strongly related to future performance.

E. ATS-Increasing and ATS-Decreasing Trades

As shown in the right-hand side of equation (9), the ATS for fund m in quarter q is the sum of the change in ATS attributed to each trade by fund m in quarter q

[26]ATS, industry concentration, and active share data are updated quarterly and therefore measured at the end of the previous quarter. Fund R^2 and lag fund alpha are updated monthly and therefore measured at the end of the previous month in these regressions. As detailed in Appendix A.8 in the Supplementary Material, we find nearly identical results when focusing on gross alphas.

(i.e., ATS is computed by summing over all securities).[27] Therefore, a given trade either increases the fund's ATS:

$$(14) \qquad \omega_{m,i}\langle T_{m,i} \cdot T_{m,-i,\omega}\rangle - \widetilde{\omega}_{m,i}\langle T_{m,i} \cdot T_{m,-i,\widetilde{\omega}}\rangle > 0,$$

or decreases the fund's ATS:

$$(15) \qquad \omega_{m,i}\langle T_{m,i} \cdot T_{m,-i,\omega}\rangle - \widetilde{\omega}_{m,i}\langle T_{m,i} \cdot T_{m,-i,\widetilde{\omega}}\rangle < 0.$$

As discussed in the introduction, we expect that ATS-increasing trades will be associated with positive abnormal returns, while ATS-decreasing trades will not be associated with abnormal returns. Thus, we partition the trades of funds in each ATS quintile into ATS-increasing trades and ATS-*decreasing* trades in quarter q. We then compute both market-adjusted (using the CRSP value-weighted index) and abnormal monthly returns for each security in the following quarter. Specifically, we calculate the stock's abnormal return as the stock's gross return less the DGTW benchmark return. We next compute the cross-sectional average market-adjusted and abnormal returns across ATS-increasing trades and ATS-decreasing trades for each fund and then average across funds in each quarter. Table 8 reports the time-series mean market-adjusted (Panel A) and DGTW-adjusted (Panel B) returns for each group. Consistent with our hypothesis, ATS-increasing trades outperform ATS-decreasing trades for funds in the top ATS quintile. Moreover, as shown in

TABLE 8

ATS-Increasing Trades Versus ATS-Decreasing Trades

Using equation (9), we classify each mutual fund's trade during quarter q as either ATS-increasing or ATS-decreasing (see equations (14) and (15)). We next compute the average market-adjusted and abnormal monthly returns (in percentage) for each fund-quarter's ATS-increasing and ATS-decreasing trades and then average across funds in each quarter. Panel A of Table 8 reports the time-series mean market-adjusted monthly returns for ATS-increasing and ATS-decreasing trades for funds within each ATS quintile. Panel B reports the time-series mean Daniel, Grinblatt, Titman, and Wermers (DGTW) (2012)-adjusted monthly returns averaged across funds. DGTW-adjusted return is the gross return less the average return for a portfolio of securities matched by size, value, and momentum characteristics. *t*-Statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	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)

[27] As detailed in Section II.A, if fund m does not hold a given stock i during the quarter, the weight in the stock is 0, and the stock's contribution to the fund's ATS is 0.

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the final column, the ability of high-ATS funds to outperform low-ATS funds primarily arises from ATS-increasing trades.

IV. Conclusion

Previous work demonstrates that markets are slow to incorporate information regarding technological innovation. We propose that some fund managers' superior understanding of the role of technological innovation is a source of positive abnormal returns. Specifically, we hypothesize that a manager who better understands a technology space will increase her concentration toward that space when i) the space is undervalued or ii) the manager can identify undervalued firms in that space. As a result, we hypothesize that increases in the mutual fund's technological concentration will be associated with subsequent positive abnormal returns.

The empirical tests support our hypothesis – funds that increase the TS of their holdings earn larger subsequent returns. The relation is robust to standard asset pricing variables, fund characteristics, lag fund performance, industry concentration, active share, and fund R^2. For our sample period, ATS sorts yield stronger results than analogous sorts based on industry concentration, active share, fund R^2, or lag fund alpha.

Because ATS is largely orthogonal to other predictors of fund performance, it can be combined with lag fund alpha, industry concentration, active share, or fund R^2 to better identify skilled managers. That is, the combination of ATS and these other measures to explain subsequent fund performance is greater than the ability of any of the measures to do so independently. Finally, further consistent with our hypothesis, the ability of high-ATS funds to garner abnormal returns primarily arises from ATS-increasing trades. In short, our analysis adds a new dimension to the nascent literature identifying the types of information (besides better connections such as links to alumni or investment banks) that successful mutual fund managers use. Specifically, superior knowledge regarding technological innovation is a previously unidentified and important source of some managers' ability to outperform.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109021000685.

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