Mutual Fund Competition, Managerial Skill, and Alpha Persistence

Gerard Hoberg, Nitin Kumar, and Nagpurnanand Prabhala*

April 9, 2014

*Hoberg is from University of Maryland, and can be reached at ghoberg@rhsmith.umd.edu, Kumar is from Indian School of Business, and can be reached at nitin_kumar@isb.edu, and Prabhala is from University of Maryland, can be reached at prabhala@umd.edu. We thank Albert Kyle, Georgios Skoulakis, Russ Wermers, and seminar participants at NUS, Indian School of Business, University of Sydney and UTS Business School for helpful comments. Any remaining errors are ours alone.

Mutual Fund Competition, Managerial Skill, and Alpha Persistence

Abstract

Whether fund managers can generate positive alpha and do so persistently are key questions in the mutual fund literature. We propose a new economic force that limits persistence in alpha: *competition* from other funds that cater to similar segments of investor demand. We make three contributions. First, we use new spatial methods to identify the dynamic competition faced by funds. Second, we develop a new measure of fund manager skill, viz., the ability of a fund to beat its spatially close rivals. The skill measure predicts alphas for at least four quarters ahead. Finally, we show that alpha is persistent only when a fund has few rivals. This new persistence is not driven by diseconomies of scale, is economically large, and lasts up to four quarters. Thus, besides the scale diseconomies emphasized by Berk and Green (2004), competition between funds is a potent force that limits the persistence of alpha.

1 Introduction

Money managers in the U.S. manage close to \$15 trillion in assets, of which \$13 trillion is held in open-ended mutual funds. As of December 2012, there are 8,752 mutual funds, 4,514 of which are long-term equity funds. The shares held by mutual funds represent 28% of outstanding shares in the U.S. market (ICI Factbook, 2013).

Can mutual fund managers generate positive alpha? If so, does alpha persist? These questions are of fundamental interest in the mutual funds literature. Research on these issues dates back to at least Jensen (1968), who finds that neither the mutual funds in aggregate, nor individual funds, perform better than what would be expected by random chance. Jensen's skepticism finds support in work, such as Elton, Gruber, Das, and Hlavka (1993), Carhart (1997), Busse, Goyal, and Wahal (2010) and Fama and French (2010). However, Bollen and Busse (2005), Kosowski, Timmermann, Wermers, and White (2006), and Cremers and Petajisto (2009) find evidence of performance predictability.

What economic forces limit the ability of managers to generate sustained alpha? Berk and Green (2004) – henceforth BG – articulate perhaps the most influential line of thought on this issue. Competition between investors and scale diseconomies in asset management are the key drivers in their model. Specifically, BG argue that fund manager talent is in short supply. Talented managers attract additional money flows from investors, resulting in growth in fund size to the point where diseconomies of scale kick in and eliminate alpha. Thus, in the BG equilibrium, no fund manager earns positive alpha. The theory is consistent with stylized facts in the fund industry.[1]

Our study proposes an alternative axiomatic foundation for understanding alpha and its persistence. Specifically, we examine the role played by the competition between *funds* catering to similar slices of investor demand. We make three main contributions in this regard. First, we construct new measures of the competition faced by funds. Our competition

[1]These facts include evidence that (a) fund flows chase past returns (Gruber (1996)); (b) fund alphas decrease in size (Chen, Hong, Huang, and Kubik (2004)); and (c) the average fund does not have persistent alpha.

measure is dynamic: it adapts to changes in portfolios held by funds and their rivals over time. Second, we propose a new measure of fund manager skill, "customized peer alpha." The measure is based on a fund's performance relative to spatially proximate rivals catering to similar segments of investor demand. We show that our new skill measure predicts future fund alpha with economically meaningful spreads. Finally, we show that competition between funds can explain alpha persistence. Alpha persists when funds face low competition. This new persistence is both statistically and economically significant.

Our focus on competition between funds has two motivations, one economic and another empirical. From an economic perspective, we draw on theories of industrial organization. From an investor's perspective, a mutual fund offers a particular combination of risk exposures or "styles." Some funds face competition from many other funds who offer a similar combination. Other funds may occupy portions of the style space where there are few rivals. These funds should be more likely to preserve rents from good ideas that a manager generates. This leads to our main hypothesis: competition between funds limits the ability of managers to generate persistent alpha.

Competition is likely to be especially significant in contestable markets characterized by few barriers to entry and less differentiated products (Baumol, Panzar, and Willig (1982)). These characteristics describe the mutual fund industry quite well as entry and exit do not entail high cost, so incumbent funds vigorously compete with each other. We emphasize that our framework and that of Berk and Green (2004) (BG) are not mutually exclusive. The key forces in BG are scale diseconomies and competition between *investors*. We consider competition between *funds*, and while we do not explicitly require exogenous scale diseconomies, we do not preclude them either. Our approach complements that in BG, just as diseconomies of scale and competition are complementary forces in industrial organization that coexist and determine rents to incumbents.

An empirical motivation for our study comes from the mixed evidence on the relation between fund size and alpha. Chen, Hong, Huang, and Kubik (2004) find that alpha and size are negatively related. However, Elton, Gruber, and Blake (2012) report a positive relation between size and alpha. The absence of a negative relation between size and alpha is also a theme in more recent studies that employ tools for causal identification. Using an instrumental variables method that relies on changes in holding period returns reported by funds, Phillips, Pukthuanthong, and Rau (2013) find no evidence of a negative size-alpha relation. Using regression discontinuity methods that rely on rules employed for Morningstar ratings, Reuter and Zitzewitz (2013) reach similar conclusions. Collectively, these results question whether exogenous diseconomies of scale exist in fund management. The evidence calls for alternative micro foundations for understanding alpha persistence. Our study contributes towards filling in this gap.

The key focus of our study is the competition between funds. We construct new measures of competition motivated by insights from portfolio theory and industrial organization. Portfolio theory provides the demand-side foundations for our approach. Investors demand portfolios that provide them exposures to a common set of k risk factors (or, analogously, k styles). Because most funds are well-diversified, idiosyncratic risks are likely immaterial to this choice. The optimal mix of risk exposures sought by a particular investor depends, for instance, on her unique hedging needs and risk aversion. Given this view of demand, the competitive environment confronting a mutual fund has a simple spatial representation. Each fund locates itself in a k-dimensional space where each dimension represents a style attribute relevant to investor demand. An investor's demand is thus a point in this space that represents her ideal exposure to the k styles or risk exposures. In turn, a fund's location in this k-dimensional space reflects the market a fund manager caters to. The competition faced by a fund is then simply the set of funds that occupy proximate locations in this space. This spatial approach has a rich tradition in the economics literature on product choice (Hotelling (1929), Chamberlin (1933)).

To empirically implement our spatial approach, we must define three items: the spatial product market dimensions in which funds reside (a spatial basis), a norm function that defines distances between funds in space, and the spatial distance cutoff that is likely to identify a fund's competitors. Our choice of a spatial basis follows the asset pricing literature (e.g., Daniel, Grinblatt, Titman, and Wermers (1997)). Our main results are based on a $k = 3$ characteristic style space whose axes are size, value-growth orientation, and momentum. We then consider both a narrower ($k = 2$) space that excludes momentum, and an expanded space ($k = 4$) that includes the dividend yield. The first is motivated by a suggestion in Chan, Dimmock, and Lakonishok (2009), while the latter is motivated by potentially different clientele or preferences for funds that produce income. For robustness, we also consider a space where individual stock investment weights form the spatial basis. We view such a specification as a placebo definition of competition. If received asset pricing models are correct, and funds should compete based on the risk-based style dimensions modeled, and the placebo result should be weaker. We define the style-based axes in terms of percentiles and levels, and consider different norms. We discuss these technical details later in the paper.

We place stocks in a k-dimensional space and let funds inherit the value weighted style characteristics of their individual stocks (Grinblatt and Titman (1989), Daniel, Grinblatt, Titman, and Wermers (1997), Chan, Chen, and Lakonishok (2002), Chan, Dimmock, and Lakonishok (2009), Brown, Harlow, and Zhang (2009)). Fund j is then a competitor of fund i in quarter t if the spatial distance $d_{i,j,t} \leq d^*$, where d^* is a fixed radius specified by the researcher. Using a low value of d^* generates tight definitions of competition while a larger radius d^* permits more distant funds to be defined as competitors. To avoid ad-hoc choices, we choose d^* to calibrate our network's granularity to match the granularity of the Lipper classification system.

Our approach has three important features. First, we do not impose any constraints on the number of competitors of a fund. Some funds have over 50 competitors within the spatial radius d^* while others have less than 10 competitors. Second, a fund's competition can be dynamic. As funds change their holdings over time, they confront new competitors in the parts of the investment space they move to. For instance, if a fund tries to game its style (Sensoy (2009)), or becomes conservative to lock in early gains (Brown, Harlow, and Starks (1996)), then its closest competitors might change. We allow for this possibility. Finally, the sets of rivals are intransitive. If fund A is a competitor of fund B and fund

B is a competitor of fund C, A is not necessarily a competitor of C. The final product of our competitor classifications is a dynamic network of a fund's competitors with each fund facing a customized and time-varying set of competitors. The network is analogous to the dynamic product market network of publicly traded U.S. firms in Hoberg and Phillips (2010) and Hoberg and Phillips (2013).[2]

We turn to the empirical results and first characterize the competition faced by funds. An interesting question is whether our network of rivals overlaps with the widely-used Lipper system peers. We find some overlap although it is not substantial. For instance, less than one quarter of our customized rivals are also peer funds according to the Lipper classification. We compute the Euclidean distance in style space between funds and their rivals. Figure 1 shows that funds are significantly closer to rivals we identify than they are to Lipper peers, and both are closer than peers assigned randomly. The number of rivals also varies significantly over time. Only about one half of a fund's rivals in quarter t continue to be rivals in the quarter $t + 1$. In out of sample cross-sectional regressions of fund returns on returns of rivals, the regression R-squared ranges from 27% to 36% depending on how we specify the dimensions of the style space. These diagnostics suggest that our approach identifies economically meaningful rivals, and that we capture changes in the network as they occur.

Our main tests are about the economic effects of competition between funds. We examine the salience of competition in two ways. First, we hypothesize that if skill exists, it is best identified as outperformance relative to spatially proximate rivals. For example, consider a fund that outperforms its rivals in our network. This fund is effectively making superior investment choices relative to closely-matched funds that cater to the *same* segment of investor demand. If persistent skill exists, it is likely to reside in such a fund. Moreover, if competitive pressures originate from proximate rivals, and this diminishes alpha, then the ability to beat these close rivals should identify a manager's potential for generating future

[2] An important technical difference is that Hoberg and Phillips treat each product word as a separate spatial dimension. An analog might be to implement their procedure by treating each stock as a separate dimension. We intentionally shrink the relevant space to the style dimensions related to investor demand, thereby recognizing that some pairs of stocks are closer substitutes to each other in fulfilling investor demand than others.

alpha.

We find that funds that outperform their rivals in our network exhibit superior future alpha. We measure alpha, or risk-adjusted return, using the standard approaches advocated in the funds literature. Our main results are based on excess returns over style matched portfolios (Daniel, Grinblatt, Titman, and Wermers (1997)) but the Carhart (1997) approach gives similar results. We also report results using univariate sorts, two-way sorts that control for past risk-adjusted returns, and multivariate regressions that include other controls such as fund size. Outperformance compared to competitors derived from our network is a reliable predictor of future alpha in all models. The 10-1 decile spread is about 256 basis points of predictable future returns per year. To further understand the source of future outperformance, we decompose fund returns following Wermers (2000). We find that positive future alpha largely comes from the ability of managers to beat their rivals in our network, and skill comes from stock selection rather than style timing or average style.

We then turn to the link between competition and alpha persistence. The starting point for our hypothesis is the observation that spatially proximate rivals pose greater threats to funds than distant ones. Proximate rivals can mimic good ideas without making extensive changes in the intrinsic styles they promise to their investors, and they should be able to do so with lower turnover. Our basic economic hypothesis follows. Outperformance is more likely to last when a fund resides in a spatially concentrated market populated by relatively fewer rivals. We note that the source of alpha-producing skill is not important. It could obtain from intrinsic ability, superior analysis in a particular market segment, or access to privileged information perhaps through connections (Cohen, Frazzini, and Malloy (2008)). Whatever the source of the alpha, funds with many nearby rivals should find it hard to sustain returns from alpha-generating ideas.[3] We find empirical support for our competition hypothesis in the data. Persistence entirely vanishes in high competition markets. In the low competition markets, the 10-1 alpha spread is about 450 basis points. Competition between *funds* is economically important in determining whether funds can generate persistent alpha.

[3]Thus, managerial talent is necessary but not sufficient for long-lasting alpha. Competition in the talented manager's market determines the durability of alpha.

The rest of the paper is organized as follows. Section 2 provides some institutional background and reviews other approaches in the literature that identify a fund's benchmarks or competitors. Section 3 describes the data. Section 4 describes our methods for identifying competition in detail and Section 5 provides descriptive statistics. Section 6 discusses the structure of our rival networks and the predictive value of outperformance relative to the competitors we identify. Section 7 examines the role of competition and alpha persistence. Section 8 concludes.

2 Literature

Our approach to identify a fund's competitors is related to a literature on fund styles. The traditional approaches of inferring fund styles are based on fund prospectuses (Sensoy (2009)), return-based style analysis (Sharpe (1988), Sharpe (1992), Brown and Goetzmann (1997)), or the actual fund holdings (Grinblatt and Titman (1989), Daniel, Grinblatt, Titman, and Wermers (1997), Chan, Chen, and Lakonishok (2002), Chan, Dimmock, and Lakonishok (2009), Brown, Harlow, and Zhang (2009)). The holdings based approach is also extensively used in practice. For instance, the Thomson Reuters Lipper classification uses fund holdings data to construct 13 style groups for U.S. diversified equity funds, excluding the S&P 500 index funds. We discuss each approach in detail next.

We also note that our focus is on industrial organization, specifically the construction of dynamic measures of competition in the fund style space, and our analytic focus is on the resulting economic effects on alpha and alpha persistence. This differentiates us from other recent work on peers. For instance, Blocher (2014) and Lou (2012) identify peers and examine flows, and do not consider a style-based approach. Similarly, our focus is on dynamic measures of competition and its effects on alpha persistence, which also differs from the use of more static Russell fund buckets in Hunter, Kandel, Kandel, and Wermers (2014), who focus on benchmarking.

2.1 Competitors from Prospectuses

Fund prospectuses provide short descriptions of style. These classifications are used by investors to categorize funds providing equivalent investment opportunities. In practice, however, prospectus descriptions are not specific enough to provide precise quantitative guidance on fund strategies. Moreover, the prospectuses explicitly permit managers to deviate from their stated strategies. For instance, the prospectus of T. Rowe Price Growth Funds says

... The fund seeks to provide long-term capital growth and *... dividend income through investments in the common stocks of well-established growth companies....* and *... the fund has the discretion to deviate from its normal investment criteria*

The description leaves managers enormous latitude in their baseline investment choices. Moreover, it explicitly permits managers to deviate from these choices. This is typical, even when funds are specific about their investing philosophies.[4]

Prospectuses provide another source of data to infer competitors. SEC rules require mutual funds to report a benchmark index. Funds reporting similar benchmarks are potentially competitors to each other. However, the regulations offer little guidance about which benchmark a fund should pick and why. This flexibility makes room for benchmark gaming. Sensoy (2009) finds that the benchmark in a large number of cases does not match actual fund style.[5] Thus, the prospectus disclosed benchmarks are potentially useful in inferring a fund's competitors, but are unlikely to be useful in practice.

[4]See, e.g., T. Rowe Price's diversified midcap growth fund, which states *... The fund seeks to provide long-term capital growth by investing primarily in the common stocks of mid-cap growth companies. The fund defines mid-cap companies as those whose market capitalization falls within the range of either the S&P MidCap 400 Index or the Russell Midcap Growth Index. The fund has the flexibility to purchase some larger and smaller companies ... [and] some securities that do not meet its normal investment criteria.*

[5]See also Brown and Goetzmann (1997), Cremers and Petajisto (2009), Huang, Sialm, and Zhang (2011) or Hunter, Kandel, Kandel, and Wermers (2014) for a summary of problems associated with self-reported benchmarks.

2.2 Competitors from Returns or Holdings

A fund's competitors can also be constructed using quantitative data reported by funds on their returns or their holdings. The "returns based style analysis" approach is pioneered by Sharpe (1988, 1992), who suggests regressing fund returns on benchmark indexes with the restriction that the coefficients are positive and sum to unity. The coefficients can be interpreted as portfolio weights that are used to establish fund benchmarks for performance analysis. A variant of this approach is to regress mutual fund returns on factors suggested in the asset pricing literature (Jensen (1968), Fama and French (1993), Carhart (1997)). Chan, Dimmock, and Lakonishok (2009) find that the procedure is not effective in analyzing performance in their sample of 199 managed equity portfolios. Brown and Goetzmann (1997) suggest an approach to improve return-based analyses by using k-means clustering methods. Over time, as more precise and timely data on fund holdings has become available, holdings-based methods have become more widely-used in the mutual funds literature.

Perhaps the most visible use of holdings data to infer rivals are the Lipper and Morningstar approaches, which are used widely in industry. These agencies assign funds to classes comprised of funds holding similar stocks. A fund's star rating is based on its performance relative to other class members, who can be viewed as its competitors. While the exact process for generating fund classes has varied over time, one constant is the use of size and the value/growth orientation as style dimensions. Both the Lipper and Morningstar classifications use these dimensions to derive fund classes. Academic studies also show that size and book-to-market (B/M) are useful in generating benchmarks for evaluating fund performance. Chan, Chen, and Lakonishok (2002) analyze Morningstar funds from 1979 to 1997 while Chan, Dimmock, and Lakonishok (2009) study actively managed equity portfolios.

The potential use of Lipper (or Morningstar) peers to identify fund competitors raises interesting questions. One issue is transitivity. All funds in a given fund class are rivals of other funds in the same category. As we discuss later, requiring transitivity is equivalent to imposing a mathematical constraint on a clustering problem. It is not economically necessary and considerably increases computational complexity. Not requiring transitivity also allows us to address the dynamics of fund style drift (Brown, Harlow, and Starks (1996), Wermers (2012)). In our approach, drifts in style are met with corresponding changes in a fund's rivals while the industry practice of assigning funds to clusters requires all-or-nothing moves of funds across entire classes or developing new categories. We place no such restriction as rivals are fund-specific and can change from quarter to quarter.

Yet another question is the specification of the style space. Lipper and Morningstar use size and B/M ratios of funds' holdings to classify funds. While academics recognize momentum based returns since at least Jegadeesh and Titman (1993), practitioners in the fund industry tend not to use momentum as a style dimension (Chan, Dimmock, and Lakonishok (2009)). For our purposes, the key issue in the specification of the style space is what drives *investor* demand for funds. The literature on momentum is at least two decades old. It is plausible for example that investor demand accounts for a momentum style dimension, as investors might consider past fund returns or momentum risk exposures when choosing where to invest. Likewise, investors may have demand for an income dimension, i.e., stocks that produce income. If so, funds that pay dividends should be viewed as more relevant competitors to each other. Because it is not clear that there is one correct approach, we consider multiple approaches to assess robustness.

3 Data

We obtain data on actively managed, open-ended U.S. equity mutual funds from CRSP Survivor-Bias Free US Mutual Fund database. Our sample starts from January 1980. We focus on diversified equity funds. To identify such funds, we follow a sequential algorithm similar to that in Kacperczyk, Sialm, and Zheng (2007). We first select funds whose Lipper Classification Code is one of the following: EIEI, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE. If the Lipper classification code is missing, we select funds whose "Strategic Insights" objective code is AGG, GMC, GRI, GRO, ING, or SCG. Where both codes are missing, we pick funds with Wiesenberger objective codes equal to G, G-I, GCI, LTG, MCG, or SCG or "Policy" code of CS. For the remaining funds, we require that the lifetime average invested in equity is at least 80%. We eliminate index funds by using the CRSP-defined index fund flags and by screening the names of funds for words such as "Index" or "S&P." We further remove funds whose names have words such as "ETF."

Our dependent variable in many specifications is the monthly fund return. The net (after-expense) monthly return comes from CRSP. To obtain gross returns before expenses, we add back one-twelfth of the fund expense ratio to the net monthly return. To avoid multiple-counting funds that have more than one class, we then value-weight fund-class returns using prior month total net assets to obtain fund level net and gross returns. Similarly, we also value-weight expense and turnover ratios. Fund size is the sum of total net assets of all fund classes. Fund age is in years, and is computed as of the month end relative to the fund's earliest first offer-date. We exclude funds with negative age and further screen for incubation bias as described later.

We obtain snapshots of the quarterly holdings of funds from the Thomson Reuters mutual fund holdings database. Since our focus is on U.S. equity mutual funds, we exclude all funds whose objective code is one of the following: International, Municipal Bonds, Bond & Preferred, Balanced, and Metals. For funds that do not report quarterly, which is less common in the later years of our sample, we extrapolate the previous quarter holdings to the current quarter. This is done for at most one quarter to avoid excessively stale data. Holdings disclosures before a quarter end are carried forward to the quarter end.

From the fund-quarter portfolios identified through the holdings data, we remove all funds whose total net assets (TNA) are less than $5 million. We do not necessarily eliminate fund-quarters with missing TNA because these observations are sometimes for funds that have large previously disclosed TNA. We eliminate survivorship bias due of newly incubated funds by excluding the first appearance of a fund-quarter in the Thomson Reuters dataset. These funds may appear in the data only if their prior performance has been satisfactory.

Evans (2010) points out that this bias is not eliminated by simply screening on size.

Because our focus is on diversified funds, we eliminate funds with less than 10 stocks in their portfolio. These funds are unlikely to be diversified. We then combine the CRSP sample with the Thomson Reuters holdings sample using the MFLINKS dataset developed by Wermers (2000). After merging the datasets, we further remove fund-quarters that do not have a valid Lipper class in CRSP. We implement this screen only for fund-quarters after December 1999 because Lipper classifications are unavailable before that date. Our final sample consists of 3593 unique funds for which we have at least one disclosed portfolio from quarter 2 of 1980 to quarter 1 of 2012.

4 Methodology

4.1 Spatial Basis

We place stocks into a k-dimensional characteristics space and value weight stocks held by a fund to identify fund locations in the characteristics space. We calculate the characteristic vector of each fund at the end of each quarter based on reported holdings. Our baseline characteristic axes are size, book-to-market (B/M) ratio and momentum. Stock size is based on the quarter-ending market capitalization in millions of dollars from CRSP. B/M is calculated in June of year t using the book equity for the last fiscal year end in year *t-1* and market equity at the end of December in year *t-1.* The B/M ratio thus obtained is applied from July of year t to June of year *t+1.* We calculate book equity as defined in Daniel and Titman (2006). Momentum is the cumulative return of the past 11 months. Thus, we exclude the return for the quarter-ending month when the portfolio is disclosed. We also require a minimum of 10 months of non-missing return data to calculate momentum.

While our main specifications are based on a 3-dimensional space, we also consider a 2-dimensional space that excludes momentum, and a 4-dimensional space that incorporates dividend yield. This is to capture income oriented equity funds. A stock's dividend yield is its previous fiscal year dividend divided by the end of fiscal year stock price. We winsorize yield at 1%. The fiscal year for the yield computation is the first fiscal year prior to the current quarter ending date.

4.2 Specifying Location and Distance

We consider several methods for defining location in the style space. We follow the asset pricing literature and consider ranks of each attribute of the style space. Because ranks do not account for all of the information in the distribution of characteristics, we then consider z-scores for each attribute. Finally, we consider techniques that step-wise orthogonalize attributes prior to computing distances. This method leads to a better motivated norm for defining distance. The orthogonalization also takes into account an important industry practice stressed by Chan, Chen, and Lakonishok (2002). They recommend that researchers should control for size and then sort on other dimensions controlling for size. This procedure reflects, for instance, that a B/M ratio of 3.0 is perhaps less unusual for a small firm than for a large firm. We describe the details of our approach next.

4.2.1 Rank Methods

A stock's characteristic rank is its percentile in the distribution of all NYSE stocks with share codes of 10 or 11. For instance, a firm's size percentile is 0.70 if it is the 70th percentile of the size distribution of all NYSE stocks. A fund's characteristic percentile is based on the weighted average percentiles of the stocks in its portfolio.

The above method takes as input the raw levels of each characteristic. Our second method orthogonalizes the characteristic space in the spirit of the Fama and French (1993) factor computation or Chan, Chen, and Lakonishok (2002) in the context of mutual funds. To obtain an orthogonalized B/M ranking, we regress log $(1+B/M)$, or LBM on log market capitalization $LSIZE$ for all NYSE stocks. The residual from the regression is used as a basis for ranking all NYSE stocks along the residualized book-to-market dimension. For each non-NYSE stock, we assign a stock's percentile based on the NYSE universe. The residual LBM is LBM minus the predicted value based on the NYSE stock regression. The orthogonalized book-to-market rank is based on the distribution of the NYSE residuals.

We use a similar procedure to locate firms in three and higher dimensional spaces. For instance, when the space is defined by size, B/M, and momentum, we assign size and orthogonalized book-to-market ranks as in the previous paragraph. We then regress momentum on size and LBM for NYSE stocks and rank all NYSE residuals. For non-NYSE stocks, the orthogonalized momentum equals past 11-month returns minus the predicted value based on the NYSE regression coefficients. We assign ranks based on NYSE residual rankings.

4.2.2 z-score Methods

Rank based methods do not account for the actual distributions of characteristics. For instance, consider a characteristic that is standard normal. Its 75th percentile corresponds to a value of 0.67. However, its 75th percentile value would be 0.51 if it were instead distributed as $\chi^2(5)$ standardized to zero mean and unit variance. Distances based on ranks would assign zero distance between the two characteristics, while a level-based norm would assign a distance of 0.16. Whether rank suffices or whether we should exploit the information in the levels of a style characteristic is ultimately an empirical issue. Industry practice provides precedent for considering characteristic levels. For instance, the Lipper growth style assignment is based on the actual values of growth proxies (such as BM). Accordingly, we consider style space methods that incorporate data on the actual distributions of characteristics rather than just their ranks.

We proceed as follows. We standardize each characteristic at the end of each quarter to zero mean and unit standard deviation for all NYSE stocks. For instance, for log size, NYSE stock i's z-score equals $\frac{LSIZE_i - mean(LSIZE)}{sd(LSIZE)}$. Non-NYSE stocks are assigned z-scores based on the NYSE mean and standard deviations. A further refinement of this procedure defines style characteristics using orthogonalized z-scores using the methods described in Section 4.2.1. For B/M z-scores, we regress z_{LBM} on z_{LSIZE} for all NYSE stocks. The residual is the

B/M z-score for NYSE stocks. For non-NYSE stocks, the z-score is z_{LBM} minus its predicted level based on the NYSE-only regression coefficients. A fund's characteristic vector is the dollar-weighted average of its stock holdings vector.

4.3 Defining Competitors

We identify competitors based on pairwise comparisons between funds in a style space as in Hoberg and Phillips (2013). However, unlike them, we do *not* rescale the characteristic vector of each fund to unit length before computing distances. The reason is that a fund with low percentiles on characteristics is not a rival for another fund with proportionately higher percentiles. For instance a fund in the 20th B/M percentile and 30th size percentile is not a rival of a fund with 40th B/M and 60th size percentiles, which would be implied by normalization of all vectors to the same scale.

For fund i in quarter t, we denote its N-element characteristic vector of percentiles as V_i. In our main specification, $N = 3$, but we express the methodology with greater generality to illustrate that this computation is not unduly difficult for higher dimensions. We consider a fund j as a rival of fund i if the elements of V_j are all very close to V_i in nominal magnitude. Denote the distance between i and j as d_{ij}. If $V_i[n]$ is the nth element of the vector V_i, the pairwise distance between funds i and j, d_{ij} can be defined as:

$$d_{ij} = \sqrt{\sum_{n=1,\dots,N} \frac{(V_i[n] - V_j[n])^2}{N}} \tag{1}$$

Lower distance scores indicate that funds i and j are likely to be rivals. Further, because d_{ij} is known for every pair of funds, this calculation is intuitively similar to a fund "style network" in which the network is fully described by a pairwise similarity matrix. To complete the process of using this network to construct a peer classification system, we need to specify a cutoff distance $\bar{d}$ such that rivals are funds with $d_{i,j} < \bar{d}$. The selection of $\bar{d}$ is an empirical choice, determined by the target granularity a researcher desires.

To avoid an arbitrary choice of granularity, we specify the target granularity based on the observed granularity of the Lipper classification widely used in the fund industry. Under the Lipper classification, 8.858% of all fund pairs are in the same Lipper class.[6] Thus, we require that our classification is equally granular such that 8.858% of fund pairs will be members of one another's customized peer groups. This target granularity of 8.858% is achieved by identifying a maximum distance $\bar{d}$ such that i and j are deemed to be peers if $d_{ij} \leq \bar{d}$. $\bar{d}$ is thus the smallest number such that 8.858% of all d_{ij} permutations are less than $\bar{d}$.[7] As a minor refinement, we further require that any particular fund have at least five rivals. This refinement does not materially affect our results, but has the added benefit of ensuring that any given fund can be compared to a reasonably populated set of competitors. As the target granularity of 8.858% is relatively coarse, most funds have 100 or more rivals. The minimum of five is binding only for a very small number of "unique" funds.

We note that our methods yield intransitive rivals. Intuitively, the geometry of our space illustrates this point. In the 3-D attribute space, rivals can be visualized as funds within a sphere of a fixed radius. If two funds A and B lie within a sphere surrounding fund C, it is not necessary that B lies within a sphere of similar radius surrounding A. We also note that our specification is flexible while preserving parsimony. We can use different norm functions to specify distance and also expand the dimensions of the style space. Increasing dimensionality is not computationally burdensome but is not necessarily an improvement. The economics of the specification matters because adding irrelevant dimensions can make us identify rivals close on the irrelevant dimensions but far on the relevant ones.[8]

We briefly highlight the differences in our approach compared to the other approaches to infer rivals used in the literature. Sharpe (1992) and Brown and Goetzmann (1997) use historical returns to cluster funds into styles. Our approach uses current holdings rather

[6]We compute this figure by computing the actual fraction all possible fund pairs that are in fact Lipper peers. We compute this figure separately in each quarter, and 8.858% is the average over all quarters. We use this parsimonious sample wide average as quarterly granularities do not vary materially over time.

[7]More succinctly, we simply take the 8.858% of actual fund pairs with the highest similarities, and these pairs then constitute our intransitive peer network.

[8]We also do not further utilize information regarding the distance of each rival j relative to a focal fund i. For example, some rivals are closer to a given fund i than others. We leave these analyses for future work.

than historical return patterns to infer rivals. Furthermore, clustering results in transitive measures of competition while we focus on more general fund-specific intransitive rivals. The focus on intransitive fund-specific rivals also differentiates our methods from the Lipper or Morningstar classifications used in the industry.

Our analysis is also distinct from the Daniel, Grinblatt, Titman, and Wermers (1997) approach, which focuses on the universe of all stocks by value, growth, and momentum to generate benchmarks (see also Chan, Chen, and Lakonishok (2002) and Chan, Dimmock, and Lakonishok (2009)). We complement this line of work in two ways. One, we relax the assumption of transitivity in fund peers by allowing each fund to have its own set of peers. More importantly, our measure compares fund holdings to holdings of other *funds*, in the spirit of Cohen, Coval, and Pastor (2005) rather than the entire universe of stocks that enter the passive risk benchmarks.

4.4 Alternative Spatial Basis

We consider two alternatives to our baseline 3-D network based on size, B/M, and momentum: a 2-D network based on size and B/M and a 4-D network that adds dividend yield to the 3-D network. The 2-D network is computed in a fully analogous fashion as in equation 1, except that we only compute vector distances using two dimensions instead of three. Our consideration of dividend yield as a spatial basis is motivated by the view that income-oriented stock investors consider dividend yield in their demand functions. For example, older investors might be concerned with dividend yield in order to construct a portfolio with both income and growth as they reach retirement. The 4-D network is computed sequentially analogous to the 3-D network in equation 1, except that we compute vector distances using all four dimensions instead of three.

We also consider a spatial basis that employs the actual stock holdings of each fund. Using each stock as a dimension is also analogous to the Wahal and Wang (2011) measure of overlap between incumbent and entrant portfolio holdings. Treating each stock as a separate dimension ignores the fact that some pairs of stocks are more similar to each other than others. For instance, General Electric is less similar to Facebook than LinkedIn is, but treating each of them as a separate dimension ignores this distinction.

To compute the stock holdings-based network, we first compute for each fund in each quarter a vector V_i that represents a fund's market value weighted investment in each stock. We then compute the distance between each fund using one minus the cosine similarity as follows:

$$d_{ij} = 1 - \sqrt{\frac{(V_i \cdot V_j)}{\|V_i\| \quad \|V_j\|}} \tag{2}$$

This metric is based on the cosine similarity measure as used in Hoberg and Phillips (2013), which is the cosine of the angle between two vectors that reside on a unit sphere. We use the cosine similarity method here because all that matters is the relative difference in percentages allocated to different stocks. In contrast, for style designations as discussed in the Section 4.3, cosine similarities are inappropriate. Scaling matters when considering locations in style dimensions but not when considering investment weights in $[0, 1]$.

5 Descriptive Statistics

Table 1 presents summary statistics for our dataset. There are 3,593 unique funds in our sample. The number of funds varies by year, with 505 funds in 1980, and 2,220 funds in 2010. There is a decline in the number of funds between 2005 and 2010, reflecting exit in the industry after the 2008 financial crisis. The average fund size increases from \$212 million in 1985 to \$1,182 million towards the end of the period. The returns for the funds in our sample are comparable to those in prior studies such as Chan, Chen, and Lakonishok (2002), although the samples are not identical because our study includes more recent data.

5.1 Properties of Customized Rivals

Table 2 examines the differences between rivals identified by us relative to style peers identified by the Lipper classification methods. Holding granularity constant, we ask whether the two methods designate similar funds as rivals. For convenience, we call the rivals identified by our methods as *customized peers*. The table reports two panels. Panel A represents a Venn diagram of the customized peer (CP) and the Lipper peer (LP) classifications while Panel B displays data on the intersection of current and past customized peers.

Panel A lists three categories of funds, viz., customized peers that are not Lipper peers $j_{qt}(CP \notin LP)$, common peers $j_{qt}(CP \cap LP)$, and Lipper peers that are not customized peers $j_{qt}(LP \notin CP)$. We add these numbers across all funds j and divide by the sum to normalize them into percentages. We then average these percentages for all four quarters $q = 1, 2, 3, 4$ for year t and report the average for each year. The table shows that there is little overlap between the different types of peers. The overlapping peers constitute only about 20% of the total number of peers.

Panel B of Table 2 examines the churn in rival groups over time. We examine all pairs of funds in two successive quarters within the same year and report averages within a year. The results suggest that about one half of peers in one quarter are likely to remain peers in the next quarter (the column labeled "Common" in Panel B). However, quite remarkably, few funds have *exactly* the same set of rivals even between two successive quarters as 99.8% of funds experience some churn in rivals from one quarter to another. A fund's rival in quarter t has between a quarter and a third chance of not being a rival in quarter $t + 1$.

To further assess the quality of our rival identification method, Figure 1 shows the distribution of the similarity scores for customized peers, using the baseline 3-D style space and z-scores to define the axes. (see Section 4.2). The figure shows that customized peers have leftward shifted similarity distributions and the distribution discretely drops to zero at a fund distance of 0.35. For interpretation, we also display similarity distributions for Lipper peers and the distribution for all fund pairs. Both distributions are to the right of customized peers, suggesting that funds are closer to the rivals generated by our spatial methods.

Figure 2 illustrates the decay in rival similarity over time. The upper figure compares the similarity distribution of fund pairs in the current quarter to the same distribution of these current-quarter defined customized peers one quarter later. The lower figure reports an analogous comparison for the scenario in which the current-quarter customized peers are compared to the same customized peers one year later. We find that customized peers exhibit a strong but also an imperfect level of persistence over time. The extent of peer decay after one year is notably stronger than that after one quarter. Thus, we adopt the practice of updating a fund's rivals every quarter.

5.2 Return on Return Regressions

If the competitors we identify are economically meaningful, fund returns should be related to the returns of portfolios of rivals. Table 3 examines this proposition. For each fund j in month t, we compute the average month t return of the fund's customized peer group, where the peers are identified at the end of the previous quarter. In each month, we regress a fund's net return on the average net return of customized peers derived from rank and z-score based methods in 2, 3 and 4-dimensional investment spaces, and then report average R-squared across all months.

Panel A of Table 3 reports the average fund-on-peer regression using two-dimensional customized peers in which size and B/M define the style space. This R-squared ranges from 26.56% to 27.30%, depending on whether we use rank, $z - scores$, or their orthogonalized counterparts that correspond to sorting first on size and then on B/M. Panels B and C present results for our baseline 3-D peers that include momentum, and also 4-D peers that further include the dividend yield, respectively. The R-squared is between 33% and 36% under these specifications. The improvement in R-squared when incorporating momentum is not surprising. There is likely to be commonality in movements in stocks with similar momentum and yield characteristics. For example, stocks with high or low momentum have moved together in the past. Thus, accounting for momentum helps pick up unobserved co-movement and improves fit.

6 Competition and CPA: A New Measure of Skill

This section reports our main empirical results. We test two main hypotheses on the relevance of competition. First, we test whether outperformance relative to spatially proximate competitors, or "customized peer alpha," predicts future fund alpha. We also test the hypothesis that funds facing many rivals are less likely to have persistent alpha.

6.1 Portfolio Analysis

As in Busse, Goyal, and Wahal (2010), at the start of each time period (quarter, semi-annual and annual), we form portfolios of funds. We call a fund's outperformance relative to spatial peers as CPA or "customized peer alpha." We call a fund's excess return over the 125 DGTW style portfolios the "CS alpha," which measures a fund's risk-adjusted return. Our basic hypothesis is that a fund's ex-ante customized peer alpha, CPA_t, should predict its next-period risk-adjusted return, or the DGTW CS alpha. We focus on predicting CS alpha to ensure that our results are easily compared to those in the literature, which also focuses on predicting ex-post CS alpha. We get similar results when we predict future CPA.We consider both one-way and two-way sorts. In the one-way sorts, we divide funds into deciles based on past CPA and examine the future alpha of each decile portfolio. In the two-way sorts, we condition on both the past CPA and past CS alpha.[9] In each case, we consider predictions at 3-month, 6-month, and 1-year horizons.

Table 4 reports the results of the one way sorts. At each horizon, there are two columns of results. In the first column, funds are sorted based on past CPA and in the second column, the sorts are based on past CS alpha. In both cases, the number reported in the table is the

[9]We remove all fund-months for which either CS or CPA is missing. We then calculate past alphas as the average monthly alpha over the past 12-month period.

future CS alpha, the risk-adjusted return. The key result in the table is that a fund's past CPA is a reliable predictor of its future risk-adjusted returns with a 10-1 decile spread of 256 basis points for the three month horizon.[10] The spread is 252 basis points and 177 basis points at 6- and 12-month horizons, respectively. Table 4 also shows that a fund's past CS alpha predicts future CS alpha. However, the predictive power of CS alpha is less robust than that of CPA at longer horizons. For instance, at a 1-year horizon, the 10-1 spread based on the CS alpha is no longer statistically significant although the spread based on CPA continues to be statistically and economically significant.

Table 5 presents bivariate sort results. In Panel A, we first sort funds based on their most recent CS alphas and form portfolios of funds in each quintile. Each such quintile corresponds to a row in Panel A. CPA quintiles form the columns in Panel A. The table reports the future CS alpha over 3, 6, and 12 months and the quintile 5 minus quintile 1 (Q5-Q1) spread with p-values. Panel A suggests that past CPA has predictive power even after controlling for past CS alpha. The predictive value of CPA is most pronounced in the best and worst performing funds, and customized peer alpha predicts future performance for up to one year. For example, in CS quintile 1, corresponding to the currently worst performing funds, funds in quintile 5 of CPA outperform quintile 1 CPA funds by (an annualized) 200, 227, and 210 basis points over 3, 6, and 12 month horizons. Likewise, among the currently best performing funds in CS quintile 5, funds in quintile 5 of current CPA outperform funds in quintile 1 current CPA by 235, 224, and 218 basis points over 3, 6, and 12 months. Thus, even conditional on current CS alpha, CPA can predict future fund performance.

For completeness, we also present complementary evidence with sequential sorting by CPA and then by CS alpha. Panel B of Table 5 presents the evidence. The findings are first order similar to those in Panel A: conditional on current CS alpha (which is a column in Panel B), the Q5-Q1 spread is significant at 3, 6, and 12 month horizons, with the effects most pronounced in the currently best and worst performing funds. The Q5-Q1 spread ranges from 154 to 203 basis points for the current loser funds and 208 to 254 basis points

[10]We get a spread of 264 bps if we calculate ex-ante CPA using gross returns instead of net returns.

for the current winner funds. In short, performance relative to our rivals can predict future fund performance at relatively long intervals.

An auxiliary question is whether whether holding CPA constant, current CS alphas predict future CS alphas. Panel B of Table 5 shows that there is little evidence of such an effect. In fact, three of the Q5-Q1 spreads in the last column in Panel B for 12-month horizon are negative. There are two potential explanations for why past CS alpha loses its predictive power when controlling for CPA. First, CS alphas reflect performance relative to the universe of stocks with similar characteristics. CPA reflects performance relative to other *funds* holding stocks with similar characteristics. The ability of funds to beat other similar funds is more predictive of future performance. Second, we update customized peers every quarter, while DGTW update their matrix once a year. As Figure 2 shows, the quality of peers deteriorate over time because their similarity goes down.

6.2 Regression Analysis

Table 6 supplements the bivariate sorts with regression results. The regressions control for additional explanatory variables that can predict future alphas. The dependent variable is the average 3-, 6-, or 12-month ahead CS alpha. The independent variables are past CPA, past CS alphas, and other controls such as fund's expense ratios, assets under management, and age. We also include past flows because if money is smart, flows can predict future alphas.[11] We control for fund return volatility and the size of the fund's family (Gaspar, Massa, and Matos (2006)). All regressions include time fixed effects and standard errors are clustered by fund.

We find that CP alpha is significant in all specifications, whether included singly or with other controls. Although past CS alpha is significant in univariate regressions, it loses significance and its coefficient drops to near zero or changes sign in multivariate specifications that include both CP alpha and CS alpha. We conclude that CS alpha offers little additional

[11] Unlike sorts that form portfolios to characterize portfolio returns, regressions can be sensitive to outliers. We winsorize all variables at the 1% level to control for outliers.

information beyond CP alpha. As indicated by the additional controls, funds with high expense ratios have higher alphas, and funds with more assets under management or more volatile past returns have lower alphas. However, these controls have little effect on the significance and the magnitudes of the coefficients for CP alpha.[12]

6.3 Stock Selection or Style Timing Effects?

The previous results suggest that past CPA predicts future fund performance. We next ask whether this reflects the ability of high CPA funds to select stocks better or whether these funds are better style timers. To answer this question, we decompose fund returns using a similar return decomposition as Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2000). We decompose total fund return for month t, as reported in CRSP into three components.

$$RFund_t = (RFund_t - RPeer_t^T) + (RPeer_t^T - RPeer_t^{T-4}) + RPeer_t^{T-4} \tag{3}$$

$RFund_t$ is the month t return of a fund, $RPeer_t^T$ is the average month t return of the fund's rivals derived at the end of the immediate past quarter T preceding month t, and $RPeer_t^{T-4}$ is the average month t return of the fund's rivals derived at the end of the fourth quarter $T-4$ preceding month t, i.e. the average month t return of the rivals derived 1 year before the immediate preceding quarter end.

The above decomposition has an intuitive interpretation. The first term, $RFund_t - RPeer_t^T$, captures the excess return of a fund as compared to its peers in its immediate vicinity in the style space. Because the focal fund and its peers are very similar in terms of characteristics that matter for co-movement of returns, the only way the manager of the focal fund can generate excess returns is through better within-style stock selection. This is our customized peer alpha (CPA). The second term, $RPeer_t^T - RPeer_t^{T-4}$ captures the gain in return due to change in overall style, or returns due to style drift over the past one year.

[12] We find similar results with Carhart (1997) measures over 3-, 6-, or 12-month horizons.

Intuitively, it captures the return accruing to a fund due to its movement from one style location at time $T-4$ to the new location at time T in the style space. As in DGTW, we label this *Style Timing*, ST. The third and the final term, $RPeer_t^{T-4}$, captures the overall style of the fund. We call it *Average Style*, AS.

As before, we sort funds into deciles based on past CPA, ST and AS return components, and then calculate the average CS performance over the next three months for each decile. Finally, we compute the average monthly *CS* post-ranking portfolio performance by taking the average over the entire time-series. 10-1 represents a zero-investment long-short portfolio that is long on decile ten and short on decile one. Returns are annualized. We also perform the same analysis for 6- and 12-month horizons.

The results show that the ability of CPA to predict future alpha reflects selection skill. The 10-1 decile spread due to ST and AS of a fund are positive, but are not statistically significant at any horizon. However, we note that for the past winners, decile 10, ST generates 121 and 117 basis points at the 3- and 6-month horizons, respectively. The ex-post CS alpha is same as in Table 4, but is included for comparison. In summary, the customized peer alpha captures stock selection skills of the manager.

6.4 Controlling for Activeness

The mutual fund literature shows that active share, or the difference in a fund's holdings relative to benchmarks predicts future performance. Related work includes Kacperczyk, Sialm, and Zheng (2005), Kacperczyk, Sialm, and Zheng (2007), Cremers and Petajisto (2009), and Amihud and Goyenko (2013).[13] In Table 8, we test whether CP alphas reflect fund activeness. Following Huang, Sialm, and Zhang (2011), we use sequential sorts. At the beginning of each quarter, we first sort funds into terciles by activeness measures and then sort funds within activeness terciles into terciles by past CPA. The last column shows that the 3-1 tercile spread is economically and statistically significant. Customized peer alpha

[13]Data on Active Share is obtained from http://www.petajisto.net/data.html. Also see Petajisto (2013).

appears to contain information beyond activeness.

7 Competition and Alpha Persistence

7.1 Hypothesis

While the literature on mutual funds is vast, work on the industrial organization of the fund industry is less developed. An interesting exception is the market for index funds, where industrial organization issues have been researched because competitors are more easily identified in this marketplace. Funds that aim to replicate the same index cater to the same segment of investor demand and are thus rivals.[14]

Characterizing competition between actively managed funds is less straightforward than for index funds due to style differences between funds. Each fund offers a particular configuration of exposures to investors. Thus, identifying a fund's competitors is the problem of identifying other funds that offer similar risk-return tradeoffs. Our spatial methods are, of course, designed to identify precisely these rivals. Under the joint hypothesis that (a) funds compete on style dimensions; and (b) this competition is captured by the number of spatially proximate rivals, we can test hypotheses concerning competition in the actively managed fund industry.

We consider two hypotheses concerning alpha and competition. The first hypothesis comes from the industrial organization viewpoint that competition should be negatively related to rents. The analogous prediction is that alpha should be negatively related to competition. However, the economic assumptions of this initial hypothesis are likely harder to justify in the funds setting. For example, superior investment ideas do not necessarily concentrate in sparsely populated regions of the style space. We focus on a more compelling

[14]Because the risk-return profiles of similar-target index funds are first order identical, competitive effects should be reflected in fees charged by funds (see Elton, Gruber, and Busse (2004), Hortacsu and Syverson (2004), or Cooper, Halling, and Lemmon (2012)). Other work on fees includes Khorana, Servaes, and Tufano (2008) and Gil-bazo and Ruiz-Verdu (2009).

hypothesis regarding the *persistence* of alpha.[15]

Our persistence hypothesis starts with the view that low competition is not a sufficient condition for earning persistent alpha. However, low competition when paired with skill can generate persistent alpha. Managers in all parts of the fund industry can have high value investment ideas. However, if a fund faces many proximate competitors, it is less likely to maintain significant alpha for long because it is under watch by many nearby rivals. Equivalently, in the terminology of Duffie (2010), arbitrage capital reacts more quickly when a fund has many close rivals. These arguments predict that *persistence* of alpha should be greater in concentrated markets. We test this proposition.

7.2 Results

Tables 9 and 10 analyze the persistence of alpha in relation to competition. In Table 9, we sort funds into high, medium, and low competition categories and then by time t customized peer alpha CPA_t. We then predict future outperformance, or the CS alpha α_{t+1}, over horizons ranging from one quarter to one year. In Panel A, the initial sort for competition is by the number of rivals. In Panel B, the high, medium, and low competition brackets are formed based on the "total similarity" competition measure (the sum of pairwise similarities between a focal fund and all of its rivals). Our motivation is that some funds may have proximate rivals who are less similar to themselves while other funds may have rivals who are relatively closer. We capture this heterogeneity through similarity, or the cosine dot product between funds and their peers. Funds with more similar rivals face more competition.

At each horizon, we find significant degradation in the persistence of alpha when competition increases. For instance, in the one quarter results in Panel A of Table 9, we find that the 10-1 spread is close to an annualized 450 basis points in the low competition tercile, but this drops to 98 basis points when competition is high. This pattern persists at longer

[15] In unreported results, we find that high competition funds underperform low competition funds if funds are small to middle sized. Controlling for competition attenuates the relation between size and alpha but not the other way around.

horizons although the 10-1 differences are attenuated. For instance, at a 12-month horizon, the 10-1 spreads are 283 and 95 basis points, respectively. Panel B of Table 9 reports results on alpha persistency when competition is measured using total similarity. The results are similar. Funds with more similar rivals, who face more intense competition, have less persistent alphas.

Table 10 presents the persistence results using regression methods. Here, we regress future CS alphas on past customized peer alpha deciles and controls . We report separate regressions for funds facing low, medium, and high competition. This analysis effectively mimics the portfolio results of Table 9 except for the additional controls such as fund size, expenses, age, and family characteristics. We note that the regression coefficients can be interpreted as basis points per month. In Table 10, the 1-quarter ahead 10-1 spread in future alpha is 26.3 basis points per month, or about 315 basis points per year when competition is low in Model 1. This spread declines to 17.5 basis points per month or 210 basis points per year in the multivariate specification for funds facing low competition in Model 3. We observe a similar pattern at the 6-month and one year horizons.

The longer horizon results are particularly interesting because of the conservative manner in which we classify competitors at longer horizons. Funds move portfolios from quarter to quarter as do their competitors. Thus, the closest competitors of funds likely change from quarter to quarter due to changing allocations of funds and their rivals. The quarterly results fully reflect the updated peer groups. However, in the longer horizon tests, we do *not* update rivals from quarter to quarter during the ex-post period. Thus, the differences between the quarterly and annual results reflect the value of controlling for "customized peers" rather than passive peers based on historical classifications of fund styles. The greater magnitudes of the 10-1 spreads at short horizons suggest that using customized peers is important for understanding competition. More generally, dynamic competition measures are likely to be more important when there is flux in the product space, which is more typical in the funds industry than, for example, the market for real assets.

7.3 Individual Stocks As Spatial Basis

We also consider a measure of competition that uses individual stocks as a spatial basis. Two funds that invest in similar stocks are likely close in style, but funds investing in similar styles are not necessarily close in the stock space. For instance, consider two funds investing in four large cap value stocks. If both funds invest 50% in stocks 1 and 2, using the stock based space identifies the funds as close rivals. However, if one fund invests in stocks 1 and 2 but the other invests in stocks 3 and 4, the two funds will no longer be identified as rivals in the stock space. However, the two funds will be identified as rivals if we define rivals based on styles, which is the appropriate classification. Stock based competition measures are thus not without merit, but omit rivals investing in similar style through similar but different stocks.

We place funds into the stock-based style space based on their investment weights in each stock. Then we choose a spatial radii to define rivals in the stock space such that the rival network achieves the same granularity as our style-based network. This process leads to the "stock-based" customized peers of each focal fund. We identify funds facing high, medium, or low competition levels in this space and rerun the tests of Table 4 and Table 9. We report these analogous stock-based peer results in Tables 11 and 12.

Table 11 shows that the univariate sorts in the stock space give 10-1 decile spreads of 190, 177, and 87 basis points. These are smaller than the 233, 213, and 97 basis points we found using style peers. Table 12 reports the results of alpha persistence sorted by the level of competition. Low competition spreads are consistently higher than high competition spreads at 3-month, 6-month, and 12-month intervals. For example, at the 3-month interval, low competition segments show a 272 basis point 10-1 decile spread versus 147 basis points for high competition segments. Overall, these differences are muted relative to our style based peers reported in Table 9. For example, at the 3-month interval for style-based peers, the 10-1 spread is about 450 basis points in the low competition segment, compared to 98 basis points for the high competition segments. The difference, 350 basis points, is roughly 3 times the difference of 125 basis points produced by the firm-investment-weight peer classifications. We conclude that style based peers produce stronger spreads in alpha predictability than stock-based peers.

8 Conclusion

A key issue in the mutual fund industry is whether fund managers have durable investing skills. If so, what forces limit the ability of skilled managers to earn positive risk-adjusted returns? Our study highlights the role played by competition between *funds* in explaining the returns earned by fund managers. We make three contributions. First, we develop a new measure of competition between funds based on their spatial locations in style space. Second, we develop a new measure of fund manager skill that reflects performance relative to spatial competitors. We show that it predicts the future alpha of funds. Our third contribution is to show that the competition faced by a fund predicts whether the fund's alpha persists.

Our results have implications for the area of measuring fund manager skill. A goal of fund managers is to generate positive risk-adjusted returns for investors. Which fund managers possess the skills to do so? The existing literature examines a number of variables that explain manager skill such as fund size or active portfolio weights relative to benchmarks. Our paper offers a different perspective on this issue. We show that the ability to beat *other funds* with similar styles indicates talent and the ability to generate future alpha. These results fit well with theoretical predictions. In the mutual fund industry, skilled individuals compete with each other to generate alpha. In this environment, it is difficult to consistently outperform peers, and managers who do so appear to have durable talent. Our results further suggest that manager talent lies in stock selection rather than style rotation. The broader point is that peer fund-to-fund return comparisons provide unique signals of manager talent beyond that in investment weights or performance relative to passive benchmarks. The extension of these methods to other asset classes or other types of funds represents an interesting avenue for future research.

Our results also suggest that competition limits sustainable investing rents in the mutual fund industry. When funds face more rivals, even funds that can find ways to generate alpha likely cannot sustain it for long as there are more rivals who can adjust their portfolios to compete away alpha-generating ideas. These results complement the viewpoint of Berk and Green (2004), who focus on the role of scale diseconomies. In their model, investors with "smart" money reallocate their wealth to funds that do well and grow to the point where scale diseconomies eliminate alpha. The two viewpoints are not mutually exclusive, as in industrial organization, scale economies and competition are both important forces that limit rents. We find that competition matters even after controlling for fund size, and thus provide an alternative economic foundation for the limited nature of rents in the fund industry.

It is not surprising that competition is important and that it produces economically significant dispersion in the predictability of alpha. Competition matters when markets are contestable, which occurs when there are few barriers to entry and less differentiated products (Baumol, Panzar, and Willig (1982)). This description is quite apt for the funds industry, where entry and exit are unrestricted, leading to vigorous competition between incumbent funds for investor flows. We regard our study as one step in understanding competition between funds. We provide a method of characterizing competition and study its economic effects. However, several open questions remain. Further consideration of the dynamics of competitor strategies, in terms of moves within a region of the style space, and also across regions of the style space, are promising avenues for future research.

References

Amihud, Y., and R. Goyenko, 2013, Mutual fund's r2 as predictor of performance, *Review of Financial Studies* 26, 667–694.

Baumol, W., J. Panzar, and R. Willig, 1982, *Contestable Markets and the Theory of Iindustrial Structure* (Harcourt College Publishing: New York).

Berk, J. B., and R. C. Green, 2004, Mutual Fund Flows and Performance in Rational Markets, *Journal of Political Economy* 112, 1269–1295.

Blocher, Jesse, 2014, Peer effects in mutual funds, *Vanderbilt University working paper.*

Bollen, N., and J. Busse, 2005, Short-Term Persistence in Mutual Find Pperformance, *Review of Financial Studies* 18, 569–597.

Brown, K. C., W. V. Harlow, and L. T. Starks, 1996, Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual Fund Industry, *Journal of Finance* 51, 85–110.

Brown, Keith C., W. Van Harlow, and Hanjiang Zhang, 2009, Staying the course: The role of investment style consistency in the performance of mutual funds, *Working Paper.*

Brown, S., and W. N. Goetzmann, 1997, Mutual fund styles, *Journal of Financial Economics* 79, 373–399.

Busse, J., A. Goyal, and S. Wahal, 2010, Performance and persistence in institutional investment management, *Journal of Finance* 65, 765–790.

Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance* 52, 57–82.

Chamberlin, EH, 1933, *The Theory of Monopolistic Competition* (Harvard University Press: Cambridge).

Chan, Louis K. C., Hsiu-Lang Chen, and Joseph Lakonishok, 2002, On Mutual Fund Investment Styles, *Review of Financial Studies* 15, 1407–1437.

Chan, L. K. C., S. G. Dimmock, and J. Lakonishok, 2009, Benchmarking Money Manager Performance: Issues and Evidence, *Review of Financial Studies* 22, 4553–4599.

Chen, J., H. Hong, M. Huang, and J. D. Kubik, 2004, Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization, *American Economic Review* 94, 1276–1302.

Cohen, L., A. Frazzini, and C. Malloy, 2008, The Small World of Inesting: Board Connections and Mutual Fund Returns, *Journal of Political Economy* 116, 951–979.

Cohen, Randolph B., Joushua D. Coval, and Lubos Pastor, 2005, Judging fund managers by the company they keep, *Journal of Finance* 60, 1057–1096.

Cooper, M., M. Halling, and M. Lemmon, 2012, Fee Dispersion and Persistence in The Mutual Fund Industry, *University of Utah working paper.*

Cremers, K. J. M., and A. Petajisto, 2009, How Active Is Your Fund Manager? A New Measure That Predicts Performance, *Review of Financial Studies* 22, 3329–3365.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997, Measuring Mutual Fund Performance with Characteristic-Based Benchmarks, *Journal of Finance* 52, 1035–1058.

Daniel, K., and S. Titman, 2006, Market Reactions to Tangible and Intangible Information, *Journal of Finance* 61, 1605–1643.

Duffie, D., 2010, Asset Price Dynamics with Slow Moving Capital, *Journal of Finance* 65, 1237–1267.

Elton, E., M. Gruber, and C. Blake, 2012, Does Mutual Fund Size Matter? the Relationship Between Size and Performance, *Review of Asset Pricing Studies* 2, 31–55.

Elton, E., M. Gruber, S. Das, and M. Hlavka, 1993, Efficiency with costly information: A reinterpretation of evidence from managed portfolios, *Review of Financial Studies* 6, 1–22.

Elton, E. J., M. J. Gruber, and J. A Busse, 2004, Are Investors Rational? Choices among Index Funds, *Journal of Finance* 59, 261–288.

Evans, Richard B., 2010, Mutual fund incubation, *Journal of Finance* 65, 15811611.

Fama, E. F., and K. R. French, 1993, Common Risk Factors in the Return on Bonds and Stocks, *Journal of Financial Economics* 33, 3–53.

Fama, Eugene F., and Kenneth R. French, 2010, Luck versus Skill in the Cross-Section of Mutual Fund Returns, *Journal of Finance* 65, 1915–1947.

Gaspar, J., M. Massa, and P. Matos, 2006, Favoritism in mutual fund families? evidence on strategic cross-fund subsidization, *Journal of Finance* 61, 73–104.

Gil-bazo, J., and P. Ruiz-Verdu, 2009, The Relation between Price and Performance in the Mutual Fund Industry, *Journal of Finance* 64, 2153–2183.

Grinblatt, M., and S. Titman, 1989, Adverse Risk Incentives and the Design of Performance-Based Contracts, *Management Science* 35, 807 – 822.

Gruber, M. J., 1996, Another Puzzle: The Growth in Actively Managed Mutual Funds, *Journal of Finance* 59, 261–288.

Hoberg, Gerard, and Gordon Phillips, 2010, Product market synergies and competition in mergers and acquisitions: A text-based analysis, *Review of Financial Studies* 23, 3773–3811.

——— , 2013, Text-based network industries and endogenous product differentiation, *University of Maryland working paper*.

Hortacsu, A., and C. Syverson, 2004, Product differentiation, search costs, and competition in the mutual fund industry: A case study of s&p 500 index funds, *Quarterly Journal of Economics* 119, 403–456.

Hotelling, H., 1929, Stability in competition, *Economic Journal* pp. 41–57.

Huang, J., C. Sialm, and H. Zhang, 2011, Risk Shifting and Mutual Fund Performance, *Review of Financial Studies* 24, 1–42.

Hunter, D., E. Kandel, S. Kandel, and R. Wermers, 2014, Mutual fund performance evaluation with active peer benchmarks, *Journal of Financial Economics* 112, 1–29.

Jegadeesh, N., and S. Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Jensen, M. C., 1968, The Performance of Mutual Funds in the Period 1945-1964, *Journal of Finance* 23, 389–416.

Kacperczyk, M., C. Sialm, and L. Zheng, 2005, On the Industry Concentration of Actively Managed Equity Mutual Funds, *Journal of Finance* 60, 1983–2011.

——— , 2007, Unobserved Actions of Mutual Funds, *Review of Financial Studies* 21, 2379–2416.

Khorana, A., H. Servaes, and P. Tufano, 2008, Mutual Fund Fees Around the World, *Review of Financial Studies* 22, 1279–1310.

Kosowski, Robert, Allan Timmermann, Russ Wermers, and Hal White, 2006, Can Mutual Fund "Stars" Really Pick Stocks? New Evidence from a Bootstrap Analysis, *Journal of Finance* 61, 2551–2595.

Lou, Dong, 2012, A flow-based explanation for return predictability, *Review of Financial Studies* 25, 3457–3489.

Petajisto, A., 2013, Active share and mutual fund performance, *Financial Analysts Journal* 69, 73–93.

Phillips, B., K. Pukthuanthong, and R. Rau, 2013, Size Doesn't Matter: Ddiseconomies of Scale in the Musual Fund Iindustry, *CambridgeUniversity Working Paper*.

Reuter, J., and E. Zitzewitz, 2013, How Much Does Size Erode Fund Performance? a Regression Discontinuity Approach, *Dartmouth University Working Paper*.

Sensoy, B. A., 2009, Performance Evaluation and Self-Designated Benchmark Indexes in the Mutual Fund Industry, *Journal of Financial Economics* 92, 25–39.

Sharpe, William F., 1988, Determining a fund's effective asset mix, *Investment Management Review* 2, 59–69.

——— , 1992, Asset allocation: Management style and performance measurement, *Journal of Portfolio Management* 18, 7–19.

Wahal, Sunil, and Yan Wang, 2011, Competition among mutual funds, *Journal of Financial Economics* 99, 41–59.

Wermers, Russ, 2000, Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses, *Journal of Finance* 55, 1655–1703.

———, 2012, Matter of style: The causes and consequences of style drift in institutional portfolios, *University of Maryland Working Paper* http://dx.doi.org/10.2139/ssrn.2024259.

Figure 1: **Similarity distribution for customized peers, Lipper peers, and randomly drawn funds**
All similarities are computed for the year 2003 for a pair of funds, and similarity is equal to minus one multiplied by the Euclidean spatial distance between the vectors of style attributes of the two funds in each pair. We then report the distribution of fund-pair similarities for three sets of funds: (1) fund pairs deemed to be rivals using our intransitive network peer methodology, (2) fund pairs deemed to be rivals by the Lipper peer classification, and (3) randomly drawn fund pairs. As the figure shows, randomly drawn funds are not highly similar, but serve as a benchmark for comparing similarities of peer classifications. For compactness, we assign all distributional mass associated with values less than minus one to last bin on the right. The large mass on the right for random peers thus reflects the fact that a large fraction of the distribution for this group lies to the right of minus one.

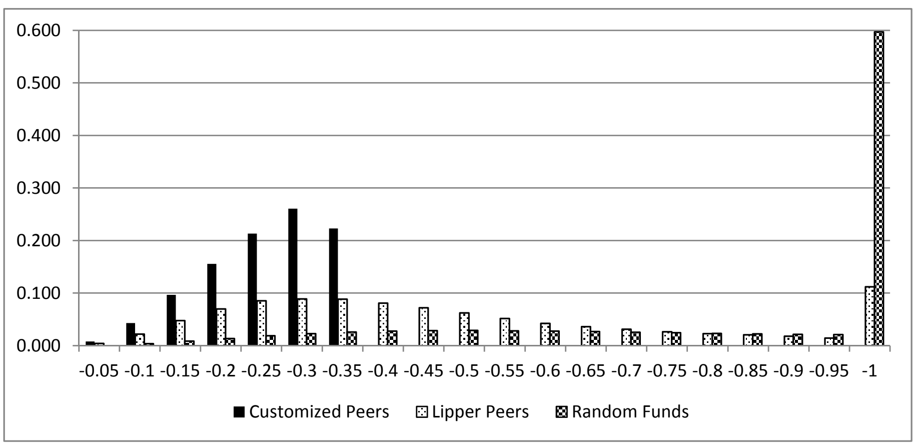

Figure 2: **Similarity distribution for customized peers in a given quarter compared to the distribution of similarities for one-quarter lagged customized peers (upper panel) and one year lagged customized peers (lower panel)**
All similarities are computed for the year 2003 for a pair of funds, and similarity is equal to minus one multiplied by the Euclidean spatial distance between the vectors of style attributes of the two funds in each pair. We then report the distribution of fund-pair similarities for three sets of funds: (1) fund pairs deemed to be rivals using our intransitive network peer methodology (baseline in both graphs), (2) the same fund peers lagged one quarter (upper graph), and (3) the same fund peers lagged one year (lower graph). As the figures show, peer similarities decline over time as funds move in the style space and become more distant.

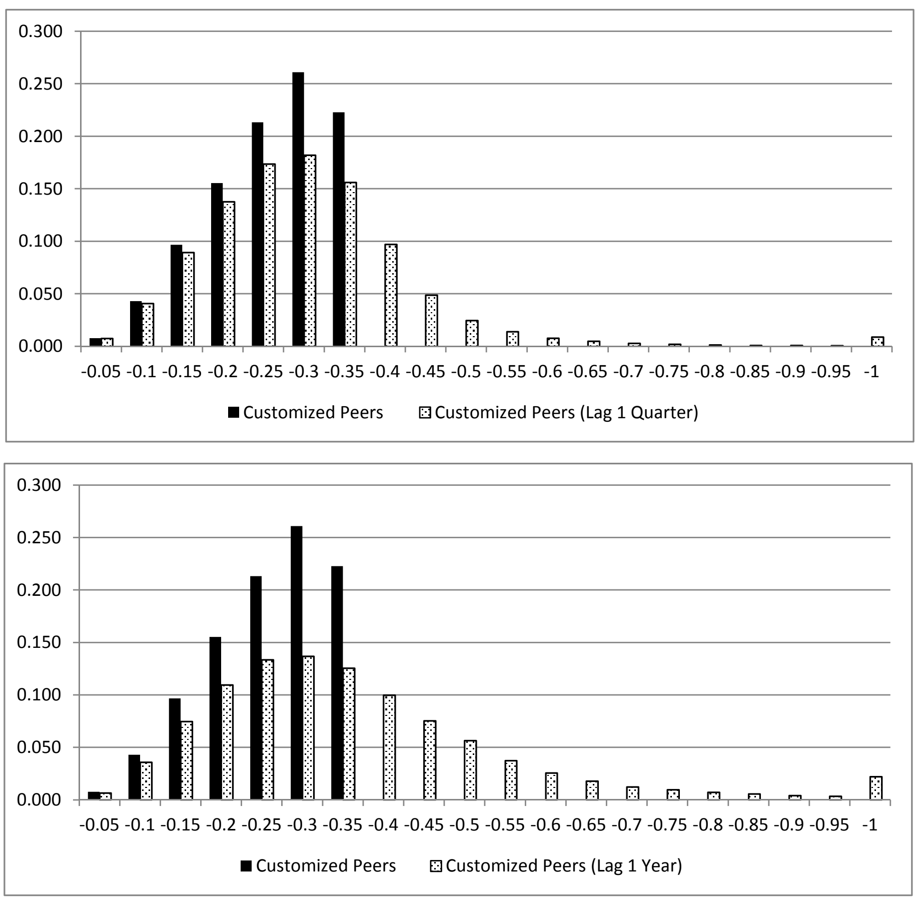

TABLE 1: **Summary Statistics**

This table reports mean statistics by year. First, from the full sample of fund-month observations from July 1980 to June 2012, observations at the fund-year level are obtained by averaging monthly total net assets (TNA), fund age, expense ratio, turnover ratio and raw return for each fund and for each year. Then, for each year, averages are taken over the funds in the sample in that year. Finally, averages are taken over all years. *Nfunds* represents average number of funds in the sample per year. *Total funds* represents total unique funds in the sample.

Year	Nfunds	TNA ($M)	Fund Age (Years)	Expense Ratio (%)	Turnover Ratio (%)	Raw Ret (%)
1985	505	212	16.18	0.913	0.766	2.349
1990	854	268	13.32	1.153	0.783	-0.449
1995	1495	559	10.56	1.315	0.852	2.264
2000	2311	1,212	10.07	1.368	1.032	0.062
2005	2466	1,134	12.28	1.372	0.894	0.619
2010	2220	1,182	15.84	1.260	0.977	1.530
1980-2012	1,526	692	13.67	1.202	0.884	1.023
Total Funds	3,593					

TABLE 2: Peer Comparisons

This table reports average statistics from peer comparisons (Lipper peers Vs customized peers) and customized peers (*t-1 Vs t*) for the years 2000 to 2011. In Panel A, for each quarter t and each fund i, we first calculate the number of customized peers that are not Lipper peers *(CP(t,i) Minus LP(t,i))*, the common peers *(Common(t,i))*, and the Lipper peers that are not customized peers *(LP(t,i) Minus CP(t,i))*. We then obtain sum of these numbers across across all funds in quarter t and obtain *CP(t) Minus LP(t)*, *Common(t)* and *LP(t) Minus CP(t)*. For each quarter t, we normalize *CP(t) Minus LP(t)*, *Common(t)* and *LP(t) Minus CP(t)* by dividing these numbers by the sum of [*CP(t) Minus LP(t)* + *Common(t)* + *LP(t) Minus CP(t)*]. Finally, we report average for each year across four quarters. In Panel B, we compare customized peers across two consecutive quarters, *t-1* and t. We only include funds that have customized peers in both quarters, *t-1* and t. We first report the fraction of funds that have same peers in both the quarters, *t-1* and t. This is obtained by normalizing the number of funds that have same peers in consecutive quarters with the total number of funds in quarter t. We report the average for each year across four quarters. This number is represented by *SamePeer*. We also calculate for each quarter t and each fund i, the number of old customized peers in quarter *t-1* that are no longer peers in the current quarter t, the number of common peers in *t-1* and t, and the number of new peers in quarter t that were not peers in the last quarter *t-1*. We then obtain a ratio for each fund i in quarter t by dividing the old peers, common peers and new peers by the sum of old, common and new peers. Next, we calculate the average for each quarter, and finally report the average for each year across four quarters.

	Panel A: Fraction			Panel B: Customized Peers (t Vs t+1)			
Year	CP Minus LP	Common	LP Minus CP	SamePeer	Old Rival	Common	New Rival
2000	0.423	0.173	0.404	0.0002	0.329	0.353	0.319
2001	0.396	0.184	0.420	0.0002	0.300	0.367	0.333
2002	0.386	0.214	0.400	0.0002	0.277	0.426	0.297
2003	0.367	0.247	0.385	0.0000	0.261	0.457	0.282
2004	0.371	0.246	0.383	0.0009	0.245	0.495	0.260
2005	0.385	0.231	0.383	0.0011	0.221	0.546	0.234
2006	0.400	0.214	0.387	0.0010	0.235	0.537	0.228
2007	0.404	0.212	0.384	0.0007	0.220	0.533	0.247
2008	0.409	0.209	0.382	0.0004	0.258	0.486	0.256
2009	0.397	0.225	0.377	0.0011	0.272	0.467	0.261
2010	0.377	0.237	0.386	0.0007	0.252	0.507	0.241
2011	0.354	0.267	0.380	0.0017	0.227	0.560	0.214

TABLE 3: **Comparison of Fund Classifications**

This table reports R-squared and adjusted R-squared from cross-sectional monthly regressions of a fund's monthly return on its monthly benchmark return obtained from four methods described in the text. Monthly benchmark return is the average return of a fund's customized peers (excluding own fund return). Customized peers are obtained at the start of each quarter and carried over the next three months. For each of these three months, only the surviving funds are considered to be peers. For instance, if a fund has 100 peers based on its disclosed portfolio on March 2004 and if 2 funds do not have return data for April 2004, then this fund has 98 peers in April 2004. The table also reports average number of monthly observations (*NObs/Mon*) used in cross-sectional regressions. The monthly period used in regressions is from 1980:07 to 2012:06.

Panel A: Customized 2D Peers			
Classification Method	Nobs/Mon	RSQ	ADJRSQ
Rank	1044	26.56%	26.43%
Rank_Ortho	1044	26.84%	26.70%
Zscore	1044	27.29%	27.16%
Zscore_Ortho	1044	27.30%	27.17%

Panel B: Customized 3D Peers			
Classification Method	Nobs/Mon	RSQ	ADJRSQ
Rank	1044	33.19%	33.07%
Rank_Ortho	1044	33.26%	33.14%
Zscore	1044	33.60%	33.48%
Zscore_Ortho	1044	33.49%	33.37%

Panel C: Customized 4D Peers			
Classification Method	Nobs/Mon	RSQ	ADJRSQ
Rank	1044	36.67%	36.55%
Rank_Ortho	1044	35.96%	35.84%
Zscore	1044	36.10%	35.98%
Zscore_Ortho	1044	35.92%	35.80%

TABLE 4: **Future Performance Prediction from Past Characteristic Adjusted and Customized Peer Alpha Performance**

This table reports future Characteristic-Selectivity alphas based on deciles of past Characteristic-Selectivity *(CS)* and past customized peer alpha *(CPA)* performance. At the start of each calendar quarter, we sort funds into decile portfolios based on the past 12 month average *CS* and *CPA* performance. Next, we calculate equal-weighted *CS* performance over the next three months after portfolio formation, and then re-balance the portfolios. Finally, we obtain average monthly *CS* post-ranking portfolio performance by taking average over the entire time-series. Similarly, we form portfolios at the start of each half-year (year) and then re-balance portfolios after six (twelve) months and obtain future *CS* performance. 10-1 represents zero-investment long-short portfolio that is long on decile ten and short on decile one. Returns are percentage annual (monthly return multiplied by 12). p-values are reported in parentheses.

	3 Month		6 Month		12 Month	
Decile	CS	CPA	CS	CPA	CS	CPA
1	-0.478	-0.638	-0.332	-0.589	0.148	-0.075
	(0.529)	(0.362)	(0.625)	(0.359)	(0.834)	(0.906)
2	-0.027	-0.032	0.063	-0.091	0.480	0.306
	(0.956)	(0.942)	(0.889)	(0.828)	(0.305)	(0.469)
3	0.428	-0.097	0.460	0.190	0.579	0.051
	(0.271)	(0.788)	(0.225)	(0.611)	(0.111)	(0.881)
4	0.008	0.249	0.134	0.322	0.387	0.393
	(0.981)	(0.477)	(0.682)	(0.338)	(0.239)	(0.279)
5	0.350	0.263	0.441	0.346	0.350	0.431
	(0.248)	(0.419)	(0.198)	(0.287)	(0.267)	(0.156)
6	0.586	0.684	0.483	0.582	0.388	0.397
	(0.040)	(0.020)	(0.088)	(0.067)	(0.170)	(0.202)
7	0.510	0.727	0.450	0.641	0.541	0.464
	(0.113)	(0.019)	(0.163)	(0.043)	(0.089)	(0.146)
8	0.599	0.838	0.610	0.959	0.421	0.829
	(0.096)	(0.013)	(0.093)	(0.004)	(0.249)	(0.019)
9	1.132	1.051	1.069	0.906	0.738	0.631
	(0.011)	(0.010)	(0.012)	(0.019)	(0.076)	(0.106)
10	1.858	1.927	1.805	1.939	1.113	1.700
	(0.014)	(0.002)	(0.011)	(0.001)	(0.120)	(0.004)
10-1	2.336	2.565	2.138	2.528	0.965	1.776
	(0.045)	(0.005)	(0.035)	(0.002)	(0.348)	(0.025)

TABLE 5: Bivariate Sorts Comparing Characteristic-Selectivity and Customized Peer Alpha Performance

This table reports future Characteristic-Selectivity alphas for quintile groups based on past Characteristic-Selectivity *(CS)* and past customized peer alpha *(CPA)* performance, using bivariate sequential sorts. At the start of each calendar quarter, we form 25 portfolios using sequential sorts. We next calculate equal-weighted *CS* performance over the next three months after portfolio formation in Panels A1 and B1, and then re-balance the portfolios. Finally, we obtain average monthly *CS* post-ranking portfolio performance by taking average over the entire time-series. Similarly, we form portfolios at the start of each half-year (year) and then re-balance portfolios after six (twelve) months and obtain future *CS* performance. 5-1 represents zero-investment long-short portfolio that is long on quintile five and short on quintile one. Returns are percentage annual (monthly return multiplied by 12). p-values are reported in parentheses.

Panel A: First sort by CS, second sort by CPA

Panel A1: 3 Months

CS Quintile	CPA Quintile 1	2	3	4	5	5-1
1	-1.317	-0.155	-0.476	-0.009	0.684	2.000
	(0.218)	(0.805)	(0.419)	(0.986)	(0.271)	(0.018)
2	-0.102	0.121	-0.001	0.518	0.539	0.641
	(0.833)	(0.751)	(0.998)	(0.160)	(0.228)	(0.167)
3	0.023	0.282	0.495	0.602	0.935	0.911
	(0.959)	(0.395)	(0.098)	(0.031)	(0.017)	(0.040)
4	0.030	0.437	0.765	0.523	1.000	0.970
	(0.949)	(0.233)	(0.025)	(0.136)	(0.026)	(0.041)
5	0.634	1.250	1.305	1.314	2.989	2.355
	(0.347)	(0.021)	(0.025)	(0.036)	(0.000)	(0.000)
5-1	1.951	1.405	1.781	1.323	2.305	
	(0.109)	(0.102)	(0.041)	(0.113)	(0.020)	

Panel A2: 6 Months

CS Quintile	CPA Quintile 1	2	3	4	5	5-1
1	-1.513	0.094	-0.251	0.230	0.764	2.277
	(0.112)	(0.872)	(0.647)	(0.651)	(0.191)	(0.003)
2	0.022	0.032	-0.018	0.700	0.721	0.699
	(0.964)	(0.927)	(0.960)	(0.064)	(0.120)	(0.159)
3	0.327	0.133	0.314	0.524	1.048	0.721
	(0.487)	(0.689)	(0.324)	(0.072)	(0.010)	(0.093)
4	0.111	0.195	0.914	0.449	0.949	0.838
	(0.810)	(0.592)	(0.006)	(0.177)	(0.058)	(0.092)
5	0.665	1.039	1.121	1.465	2.913	2.247
	(0.318)	(0.052)	(0.028)	(0.017)	(0.000)	(0.001)
5-1	2.178	0.945	1.372	1.235	2.148	
	(0.039)	(0.236)	(0.078)	(0.100)	(0.019)	

Panel A3: 12 Months

CS Quintile	CPA Quintile 1	2	3	4	5	5-1
1	-0.654	0.204	0.102	0.442	1.454	2.108
	(0.483)	(0.729)	(0.851)	(0.422)	(0.021)	(0.004)
2	0.937	0.287	0.228	0.464	0.486	-0.451
	(0.049)	(0.399)	(0.572)	(0.210)	(0.266)	(0.338)
3	0.196	-0.025	0.366	0.439	0.872	0.675
	(0.661)	(0.940)	(0.225)	(0.142)	(0.031)	(0.110)
4	0.004	0.322	0.668	0.827	0.541	0.537
	(0.993)	(0.398)	(0.062)	(0.028)	(0.224)	(0.309)
5	-0.188	0.483	0.849	1.406	2.000	2.187
	(0.769)	(0.354)	(0.089)	(0.032)	(0.010)	(0.000)
5-1	0.467	0.279	0.748	0.964	0.546	
	(0.646)	(0.718)	(0.313)	(0.250)	(0.547)	

Panel B: First sort by CPA, second sort by CS

Panel B1: 3 Months

CPA Quintile	CS Quintile 1	2	3	4	5	5-1
1	-0.994	-0.486	-0.301	-0.064	0.145	1.139
	(0.350)	(0.438)	(0.581)	(0.888)	(0.814)	(0.289)
2	-0.102	0.218	-0.183	0.329	0.087	0.189
	(0.861)	(0.604)	(0.609)	(0.325)	(0.852)	(0.764)
3	0.142	0.282	0.308	0.834	0.781	0.639
	(0.763)	(0.392)	(0.309)	(0.016)	(0.116)	(0.302)
4	1.117	0.467	0.781	0.594	0.974	-0.143
	(0.016)	(0.205)	(0.012)	(0.097)	(0.084)	(0.831)
5	0.962	0.986	1.145	1.925	2.426	1.464
	(0.071)	(0.027)	(0.013)	(0.002)	(0.009)	(0.108)
5-1	1.956	1.472	1.446	1.989	2.281	
	(0.047)	(0.045)	(0.032)	(0.003)	(0.005)	

Panel B2: 6 Months

CPA Quintile	CS Quintile 1	2	3	4	5	5-1
1	-1.066	-0.655	-0.008	0.068	-0.073	0.994
	(0.247)	(0.274)	(0.988)	(0.885)	(0.906)	(0.296)
2	0.110	0.141	0.109	0.449	0.433	0.324
	(0.841)	(0.720)	(0.761)	(0.166)	(0.360)	(0.579)
3	0.385	0.553	0.063	0.532	0.757	0.372
	(0.429)	(0.101)	(0.854)	(0.107)	(0.098)	(0.506)
4	1.296	0.533	0.832	0.544	0.808	-0.488
	(0.007)	(0.111)	(0.007)	(0.120)	(0.154)	(0.446)
5	0.972	0.986	1.150	1.500	2.476	1.503
	(0.058)	(0.044)	(0.009)	(0.008)	(0.005)	(0.059)
5-1	2.039	1.641	1.157	1.432	2.548	
	(0.022)	(0.024)	(0.068)	(0.023)	(0.001)	

Panel B3: 12 Months

CPA Quintile	CS Quintile 1	2	3	4	5	5-1
1	-0.300	-0.270	0.524	1.132	-0.410	-0.110
	(0.747)	(0.652)	(0.247)	(0.025)	(0.520)	(0.909)
2	0.360	0.342	0.450	0.065	-0.051	-0.411
	(0.543)	(0.383)	(0.181)	(0.850)	(0.911)	(0.507)
3	0.427	0.458	0.301	0.403	0.478	0.052
	(0.373)	(0.181)	(0.299)	(0.228)	(0.311)	(0.928)
4	1.004	0.420	0.770	0.585	0.540	-0.464
	(0.034)	(0.270)	(0.023)	(0.122)	(0.319)	(0.483)
5	1.246	0.394	1.174	1.398	1.674	0.428
	(0.018)	(0.303)	(0.014)	(0.013)	(0.057)	(0.600)
5-1	1.546	0.664	0.649	0.266	2.084	
	(0.083)	(0.310)	(0.265)	(0.669)	(0.003)	

TABLE 6: CS Future Performance Prediction: Regression Analysis

This table reports coefficients from regressions of future Characteristic-Selectivity alpha on past customized peer alpha *(CPA)*, past Characteristic-Selectivity *(CS)* alpha, and other controls. The dependent variable is $CS_{t+i,t+j}$, which represents the average *CS* performance over the months *t+i* to *t+j*. $CPA_{t\text{-}11,t}$ represents average *CPA* performance over the months *t-11* to *t*. $CS_{t\text{-}11,t}$ represents average *CS* performance over the months *t-11* to *t*. $ExpRatio_{t\text{-}11,t}$ and $TurnRatio_{t\text{-}11,t}$ represent the average expense ratio and turnover ratio over the months *t-11* to *t*, respectively. $LogFundAge_{t\text{-}11,t}$ and $LogFundSize_{t\text{-}11,t}$ represent average natural logarithm of fund age (years) and fund size ($millions) over the months *t-11* to *t*, respectively. $Flow_{t\text{-}11,t}$ represents average monthly flow over the months *t-11* to *t*. $StdDev_{t\text{-}11,t}$ is the standard deviation of monthly investor returns over the months *t-11* to *t*. $LogFamSize_{t\text{-}11,t}$ represents average natural logarithm of family size ($millions) over the months *t-11* to *t*. All regressions include time *t* dummies. *N* and *AdjRSQ* represent number of observations and adjusted-Rsquared, respectively. Standard errors are clustered by fund. *p*-values are reported in parentheses.

Dep Var	$CS_{t+1,t+3}$				$CS_{t+1,t+6}$				$CS_{t+1,t+12}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	-0.195	-0.209	-0.197	-0.143	0.024	0.010	0.022	-0.165	-0.096	-0.097	-0.094	0.424
	(0.004)	(0.002)	(0.004)	(0.487)	(0.626)	(0.836)	(0.660)	(0.296)	(0.005)	(0.004)	(0.006)	(0.003)
$CPA_{t\text{-}11,t}$	0.084		0.077	0.077	0.083		0.076	0.070	0.045		0.063	0.055
	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
$CS_{t\text{-}11,t}$		0.057	0.011	0.004		0.057	0.011	0.007		0.011	-0.028	-0.030
		(0.000)	(0.331)	(0.738)		(0.000)	(0.317)	(0.536)		(0.224)	(0.012)	(0.015)
$ExpRatio_{t\text{-}11,t}$				0.038				0.035				0.025
				(0.000)				(0.001)				(0.026)
$TurnRatio_{t\text{-}11,t}$				-0.003				-0.002				-0.006
				(0.672)				(0.758)				(0.407)
$LogFundAge_{t\text{-}11,t}$				0.006				0.004				0.003
				(0.232)				(0.403)				(0.606)
$LogFundSize_{t\text{-}11,t}$				-0.008				-0.008				-0.008
				(0.005)				(0.007)				(0.008)
$Flow_{t\text{-}11,t}$				0.001				0.001				-0.002
				(0.350)				(0.265)				(0.200)
$StdDev_{t\text{-}11,t}$				-1.640				-1.924				-0.829
				(0.000)				(0.000)				(0.046)
$LogFamSize_{t\text{-}11,t}$				0.002				0.001				0.000
				(0.402)				(0.636)				(0.918)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	107280	107280	107280	91442	53579	53579	53579	45315	27518	27518	27518	22885
AdjRSQ	0.052	0.051	0.052	0.050	0.045	0.044	0.045	0.048	0.055	0.054	0.056	0.063

TABLE 7: Return Decomposition and Future Performance

This table reports the average future Characteristic-Selectivity alpha for decile portfolios based on past customized peer alpha *(CPA)* performance, style timing *(ST)* and average style *(AS)*. At the start of each calendar quarter, we sort funds into decile portfolios based on the past 12 months average *CPA*, *ST* and *AS*. Next, we calculate equal-weighted *CS* performance over the next three months after portfolio formation, and then re-balance the portfolios. Finally, we obtain average monthly *CS* post-ranking portfolio performance by taking average over the entire time-series. Similarly, we form portfolios at the start of each half-year (year) and then re-balance portfolios after six (twelve) months and obtain future *CS* performance. 10-1 represents zero-investment long-short portfolio that is long on decile ten and short on decile one. Returns are percentage annual (monthly return multiplied by 12). p-values are reported in parentheses.

	3 Month			6 Month			12 Month		
Decile	CPA	ST	AS	CPA	ST	AS	CPA	ST	AS
1	-0.638	0.582	0.382	-0.589	0.554	0.297	-0.075	0.351	-0.225
	(0.362)	(0.267)	(0.587)	(0.359)	(0.301)	(0.676)	(0.906)	(0.502)	(0.732)
2	-0.032	0.515	0.367	-0.091	0.747	0.589	0.306	0.479	0.383
	(0.942)	(0.220)	(0.472)	(0.828)	(0.075)	(0.260)	(0.469)	(0.290)	(0.475)
3	-0.097	0.528	0.647	0.190	0.618	0.397	0.051	0.237	0.270
	(0.788)	(0.156)	(0.124)	(0.611)	(0.091)	(0.333)	(0.881)	(0.500)	(0.539)
4	0.249	0.605	0.472	0.322	0.461	0.454	0.393	0.411	0.293
	(0.477)	(0.080)	(0.176)	(0.338)	(0.183)	(0.177)	(0.279)	(0.214)	(0.437)
5	0.263	0.377	0.365	0.346	0.333	0.183	0.431	0.605	0.303
	(0.419)	(0.224)	(0.281)	(0.287)	(0.322)	(0.583)	(0.156)	(0.051)	(0.395)
6	0.684	0.387	0.495	0.582	0.305	0.376	0.397	0.251	0.470
	(0.020)	(0.186)	(0.147)	(0.067)	(0.275)	(0.252)	(0.202)	(0.377)	(0.152)
7	0.727	0.257	0.433	0.641	0.370	0.704	0.464	0.315	0.577
	(0.019)	(0.416)	(0.186)	(0.043)	(0.259)	(0.035)	(0.146)	(0.389)	(0.082)
8	0.838	0.518	0.506	0.959	0.525	0.542	0.829	0.393	0.444
	(0.013)	(0.155)	(0.205)	(0.004)	(0.123)	(0.150)	(0.019)	(0.246)	(0.223)
9	1.051	0.506	0.641	0.906	0.302	0.903	0.631	0.476	0.708
	(0.010)	(0.283)	(0.194)	(0.019)	(0.503)	(0.071)	(0.106)	(0.292)	(0.128)
10	1.927	1.213	1.184	1.939	1.175	0.958	1.700	0.716	1.023
	(0.002)	(0.073)	(0.101)	(0.001)	(0.065)	(0.169)	(0.004)	(0.267)	(0.132)
10-1	2.565	0.631	0.801	2.528	0.621	0.661	1.776	0.365	1.249
	(0.005)	(0.340)	(0.455)	(0.002)	(0.309)	(0.525)	(0.025)	(0.549)	(0.205)

TABLE 8: Activeness and Customized Peer Alpha

At the start of each calendar quarter, we form 9 portfolios using sequential sorts, first by the activeness measure and then by customized peer alpha performance. We next calculate equal-weighted *CS* performance over the next three months after portfolio formation and then re-balance the portfolios. Finally, we obtain average monthly *CS* post-ranking portfolio performance by taking the average over the entire time-series. 3-1 represents a zero-investment long-short portfolio that is long on tercile three and short on tercile one. Reported returns are percentage annual returns (monthly return multiplied by 12). p-values are reported in parentheses.

Panel A: ICI

	CPA			
ICI	1	2	3	3-1
1	-0.143	0.410	0.953	1.096
	(0.639)	(0.089)	(0.002)	(0.000)
2	-0.033	0.501	1.040	1.073
	(0.942)	(0.154)	(0.011)	(0.016)
3	-0.041	0.757	1.408	1.448
	(0.955)	(0.148)	(0.024)	(0.062)

Panel B: Active Share

	CPA			
Active Share	1	2	3	3-1
1	-0.210	0.361	0.684	0.894
	(0.488)	(0.124)	(0.030)	(0.013)
2	-0.019	0.484	0.775	0.794
	(0.968)	(0.187)	(0.086)	(0.134)
3	0.015	0.964	1.803	1.788
	(0.983)	(0.076)	(0.002)	(0.007)

Panel C: RetGap

	CPA			
RetGap	1	2	3	3-1
1	-0.002	0.673	1.193	1.195
	(0.997)	(0.049)	(0.006)	(0.023)
2	-0.112	0.442	1.130	1.242
	(0.792)	(0.184)	(0.003)	(0.008)
3	-0.285	0.727	1.089	1.374
	(0.640)	(0.067)	(0.048)	(0.020)

Panel D: RSQ

	CPA			
RSQ	1	2	3	3-1
1	0.291	0.921	1.693	1.402
	(0.574)	(0.026)	(0.002)	(0.026)
2	0.057	0.585	1.141	1.084
	(0.919)	(0.121)	(0.011)	(0.024)
3	-0.538	0.291	0.401	0.939
	(0.202)	(0.288)	(0.252)	(0.016)

TABLE 9: Competition and Performance Prediction: Portfolio Analysis

This table reports future Characteristic-Selectivity *(CS)* alphas for decile portfolios based on past customized peer alpha *(CPA)* for tercile subsamples based on measures of ex-ante peer competition. Panel A shows results when competition is measured by the number of customized peers *(NPeers)*, while Panel B shows results when competition is measured by *Total Similarity* between a fund and its customized peers. At the start of each calendar quarter, we first sort funds into terciles by *NPeers* in Panel A and by *Total Similarity* in Panel B. These terciles are represented by *Low*, *Med* and *High*. Then we sort funds within terciles into deciles based on the past 12 months average *CPA* performance to arrive at 30 portfolios. Next, we calculate equal-weighted *CS* performance over the next three months after portfolio formation, and then re-balance the portfolios. Finally, we obtain average monthly *CS* post-ranking portfolio performance by taking average over the entire time-series. Similarly, we form portfolios at the start of each half-year (year) and then re-balance portfolios after six (twelve) months and obtain future *CS* performance. 10-1 represents zero-investment long-short portfolio that is long on decile ten and short on decile one. Returns are percentage annual (monthly return multiplied by 12). p-values are reported in parentheses.

Panel A: Competition and Persistency (NPeer)									
	3 Month			6 Month			12 Month		
Decile	Low	Med	High	Low	Med	High	Low	Med	High
1	-1.003	-0.922	-0.757	-1.025	-0.754	-0.614	-0.423	-0.149	-0.616
	(0.356)	(0.169)	(0.096)	(0.310)	(0.221)	(0.154)	(0.674)	(0.804)	(0.161)
2	0.651	-0.063	-0.322	0.269	-0.007	-0.444	0.865	0.205	-0.201
	(0.335)	(0.901)	(0.362)	(0.686)	(0.989)	(0.178)	(0.200)	(0.666)	(0.511)
3	-0.102	-0.194	0.171	0.135	0.072	0.147	0.225	-0.002	0.432
	(0.864)	(0.659)	(0.587)	(0.822)	(0.865)	(0.629)	(0.713)	(0.996)	(0.207)
4	0.660	-0.168	0.271	0.776	0.335	0.092	0.510	0.264	0.331
	(0.272)	(0.695)	(0.350)	(0.189)	(0.435)	(0.748)	(0.378)	(0.528)	(0.241)
5	1.352	-0.141	0.188	1.856	0.169	0.217	0.965	0.521	0.242
	(0.017)	(0.723)	(0.529)	(0.002)	(0.664)	(0.488)	(0.120)	(0.167)	(0.399)
6	0.986	0.435	0.072	0.740	0.317	-0.075	0.787	0.227	-0.129
	(0.063)	(0.250)	(0.802)	(0.166)	(0.443)	(0.811)	(0.127)	(0.611)	(0.675)
7	1.252	0.935	0.444	1.256	0.727	0.217	1.113	0.792	0.181
	(0.025)	(0.007)	(0.133)	(0.031)	(0.036)	(0.471)	(0.064)	(0.066)	(0.524)
8	1.401	0.917	0.717	1.256	0.954	0.837	1.195	1.002	0.350
	(0.025)	(0.019)	(0.022)	(0.038)	(0.017)	(0.007)	(0.048)	(0.011)	(0.277)
9	1.935	1.021	0.342	1.961	0.960	0.204	1.519	0.628	0.070
	(0.006)	(0.032)	(0.295)	(0.008)	(0.028)	(0.524)	(0.048)	(0.163)	(0.824)
10	3.500	1.009	0.226	3.341	1.152	0.467	2.403	1.351	0.337
	(0.000)	(0.071)	(0.544)	(0.000)	(0.033)	(0.231)	(0.006)	(0.008)	(0.394)
10-1	4.503	1.931	0.983	4.366	1.905	1.081	2.826	1.500	0.952
	(0.001)	(0.035)	(0.099)	(0.000)	(0.021)	(0.065)	(0.016)	(0.068)	(0.102)

Panel B: Competition and Persistency (Total Similarity)									
	3 Month			6 Month			12 Month		
Decile	Low	Med	High	Low	Med	High	Low	Med	High
1	-1.021	-0.693	-0.743	-0.894	-0.838	-0.532	-0.538	-0.300	-0.420
	(0.346)	(0.301)	(0.100)	(0.374)	(0.183)	(0.212)	(0.587)	(0.630)	(0.336)
2	0.696	-0.241	-0.230	0.483	-0.027	-0.421	1.002	0.345	-0.219
	(0.297)	(0.637)	(0.521)	(0.463)	(0.957)	(0.207)	(0.135)	(0.464)	(0.473)
3	-0.187	-0.043	0.081	0.068	0.067	0.182	0.255	0.047	0.425
	(0.758)	(0.923)	(0.794)	(0.909)	(0.876)	(0.553)	(0.669)	(0.916)	(0.227)
4	0.614	-0.069	0.382	0.546	0.295	0.155	0.480	0.250	0.361
	(0.306)	(0.868)	(0.189)	(0.357)	(0.472)	(0.600)	(0.399)	(0.537)	(0.196)
5	1.127	-0.145	-0.003	1.631	0.118	0.126	0.823	0.443	0.108
	(0.043)	(0.714)	(0.992)	(0.004)	(0.773)	(0.675)	(0.196)	(0.250)	(0.714)
6	1.036	0.391	0.170	0.782	0.235	-0.035	0.822	0.163	-0.044
	(0.056)	(0.306)	(0.547)	(0.130)	(0.571)	(0.910)	(0.103)	(0.712)	(0.879)
7	1.452	0.905	0.509	1.501	0.873	0.232	1.252	0.939	0.171
	(0.008)	(0.010)	(0.086)	(0.010)	(0.009)	(0.437)	(0.040)	(0.030)	(0.550)
8	1.153	0.756	0.606	1.194	0.951	0.837	1.128	1.121	0.303
	(0.061)	(0.051)	(0.056)	(0.051)	(0.021)	(0.006)	(0.065)	(0.005)	(0.351)
9	1.964	1.046	0.390	1.827	0.900	0.227	1.473	0.525	0.161
	(0.005)	(0.021)	(0.248)	(0.013)	(0.035)	(0.486)	(0.053)	(0.234)	(0.613)
10	3.513	1.099	0.279	3.346	1.256	0.377	2.265	1.350	0.393
	(0.000)	(0.046)	(0.470)	(0.000)	(0.019)	(0.340)	(0.010)	(0.009)	(0.319)
10-1	4.534	1.792	1.023	4.240	2.094	0.909	2.803	1.650	0.813
	(0.001)	(0.048)	(0.093)	(0.001)	(0.014)	(0.118)	(0.015)	(0.053)	(0.159)

TABLE 10: **Competition and CS Performance Prediction: Regression Analysis**

This table reports coefficients from regressions of future Characteristic-Selectivity alpha on past customized peer alpha *(CPA)* performance and other controls for low, medium and high competition sub-samples. We consider three horizons of future CS alpha as the dependent variable: 3 months (Panel A), 6 months (Panel B), and 12 months (Panel C). At the start of each time period (three months, six months and twelve months), we first sort funds into terciles depending upon the average number of monthly peers in the past one year. We refer to the samples in the lowest, medium and highest terciles as as *Low*, *Med* and *High* competition sub-samples, respectively. We then sort funds into deciles within terciles based on the past 12 month *(t-11,t)* average CPA performance. *CPA_Decile1* and *CPA_Decile10* are dummy variables for funds corresponding to the funds in the bottom and top decile, respectively. The dependent variable is $CS_{t+i,t+j}$, which represents the average *CS* performance over the months *t+i* to *t+j*. $CS_{t\text{-}11,t}$ represents average *CS* performance over the months *t-11* to *t*. $ExpRatio_{t\text{-}11,t}$ and $TurnRatio_{t\text{-}11,t}$ represent average expense ratio and turnover ratio over the months *t-11* to *t*, respectively. $LogFundAge_{t\text{-}11,t}$ and $LogFundSize_{t\text{-}11,t}$ represent average natural logarithm of fund age (years) and fund size ($millions) over the months *t-11* to *t*, respectively. $Flow_{t\text{-}11,t}$ represents average monthly flow over the months *t-11* to *t*. $StdDev_{t\text{-}11,t}$ is the standard deviation of monthly investor returns over the months *t-11* to *t*. $LogFamSize_{t\text{-}11,t}$ represents average natural logarithm of family size ($millions) over the months *t-11* to *t*. All regressions include time *t* dummy. *N* and *AdjRSQ* represent number of observations and adjusted-Rsquared, respectively. Standard errors are clustered by fund. *p*-values are reported in parentheses.

Panel A: Dep Var = $CS_{t+1,t+3}$									
	Low			Med			High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.134	-0.716	-0.715	-0.210	0.440	0.432	-0.246	0.026	0.023
	(0.365)	(0.117)	(0.119)	(0.070)	(0.000)	(0.000)	(0.002)	(0.868)	(0.881)
CPA_Decile1	-0.097	-0.057	-0.033	-0.069	-0.043	-0.035	-0.043	-0.040	-0.037
	(0.001)	(0.078)	(0.326)	(0.001)	(0.052)	(0.125)	(0.001)	(0.006)	(0.015)
CPA_Decile10	0.166	0.164	0.142	0.054	0.076	0.068	-0.021	-0.022	-0.025
	(0.000)	(0.000)	(0.000)	(0.009)	(0.001)	(0.003)	(0.095)	(0.108)	(0.080)
CS (t-11,t)			0.033			0.013			0.008
			(0.043)			(0.422)			(0.619)
$ExpRatio_{t\text{-}11,t}$		0.039	0.036		0.004	0.004		0.016	0.016
		(0.115)	(0.130)		(0.802)	(0.822)		(0.107)	(0.110)
$TurnRatio_{t\text{-}11,t}$		0.001	0.000		0.003	0.004		-0.019	-0.018
		(0.957)	(0.963)		(0.745)	(0.712)		(0.010)	(0.011)
$LogFundAge_{t\text{-}11,t}$		0.014	0.013		0.015	0.014		0.006	0.006
		(0.268)	(0.301)		(0.082)	(0.088)		(0.210)	(0.211)
$LogFundSize_{t\text{-}11,t}$		-0.011	-0.012		-0.007	-0.007		-0.003	-0.003
		(0.110)	(0.081)		(0.174)	(0.167)		(0.367)	(0.361)
$Flow_{t\text{-}11,t}$		0.004	0.003		0.000	-0.000		0.002	0.002
		(0.054)	(0.141)		(0.977)	(0.927)		(0.145)	(0.155)
$StdDev_{t\text{-}11,t}$		-3.240	-3.248		-4.147	-4.099		-2.171	-2.138
		(0.000)	(0.000)		(0.000)	(0.000)		(0.002)	(0.002)
$LogFamSize_{t\text{-}11,t}$		0.003	0.004		0.004	0.005		-0.000	-0.000
		(0.554)	(0.467)		(0.181)	(0.173)		(0.882)	(0.897)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	35734	30570	30570	35794	30411	30411	35752	30461	30461
AdjRSQ	0.081	0.077	0.077	0.065	0.065	0.065	0.061	0.065	0.065

Panel B: Dep Var = $CS_{t+1,t+6}$									
	Low			Med			High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.121	0.137	0.138	-0.011	0.095	0.082	-0.041	-0.301	-0.294
	(0.283)	(0.675)	(0.675)	(0.885)	(0.017)	(0.045)	(0.532)	(0.106)	(0.119)
CPA_Decile1	-0.101	-0.048	-0.014	-0.078	-0.055	-0.044	-0.024	-0.021	-0.028
	(0.001)	(0.147)	(0.682)	(0.000)	(0.016)	(0.059)	(0.102)	(0.178)	(0.081)
CPA_Decile10	0.145	0.142	0.111	0.057	0.068	0.058	-0.007	-0.009	-0.001
	(0.000)	(0.000)	(0.001)	(0.006)	(0.002)	(0.010)	(0.585)	(0.555)	(0.938)
CS (t-11,t)			0.045			0.019			-0.020
			(0.007)			(0.264)			(0.228)
$ExpRatio_{t-11,t}$		0.039	0.036		0.001	0.000		0.014	0.015
		(0.126)	(0.145)		(0.956)	(0.988)		(0.187)	(0.167)
$TurnRatio_{t-11,t}$		0.004	0.004		0.001	0.001		-0.023	-0.024
		(0.687)	(0.696)		(0.955)	(0.894)		(0.002)	(0.002)
$LogFundAge_{t-11,t}$		0.011	0.009		0.014	0.014		0.003	0.003
		(0.395)	(0.453)		(0.101)	(0.112)		(0.601)	(0.593)
$LogFundSize_{t-11,t}$		-0.013	-0.014		-0.007	-0.007		-0.002	-0.002
		(0.078)	(0.049)		(0.168)	(0.159)		(0.622)	(0.644)
$Flow_{t-11,t}$		0.005	0.003		0.001	0.001		0.001	0.002
		(0.066)	(0.214)		(0.592)	(0.719)		(0.249)	(0.213)
$StdDev_{t-11,t}$		-3.925	-3.946		-3.809	-3.741		-1.540	-1.640
		(0.000)	(0.000)		(0.000)	(0.000)		(0.032)	(0.024)
$LogFamSize_{t-11,t}$		0.004	0.005		0.002	0.002		-0.002	-0.002
		(0.393)	(0.288)		(0.565)	(0.539)		(0.422)	(0.398)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	17844	15140	15140	17879	15076	15076	17856	15099	15099
AdjRSQ	0.067	0.073	0.074	0.051	0.056	0.056	0.054	0.059	0.060

Panel C: Dep Var = $CS_{t+1,t+12}$									
	Low			Med			High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.175	-0.079	-0.282	-0.092	0.385	0.386	-0.028	0.261	0.266
	(0.013)	(0.190)	(0.000)	(0.098)	(0.000)	(0.000)	(0.549)	(0.000)	(0.000)
CPA_Decile1	-0.066	-0.018	-0.017	-0.012	0.002	-0.005	-0.014	0.002	-0.014
	(0.077)	(0.642)	(0.670)	(0.584)	(0.933)	(0.849)	(0.336)	(0.892)	(0.429)
CPA_Decile10	0.097	0.086	0.085	0.061	0.073	0.079	-0.018	-0.020	-0.004
	(0.005)	(0.024)	(0.032)	(0.007)	(0.003)	(0.002)	(0.188)	(0.167)	(0.814)
CS (t-11,t)			0.001			-0.012			-0.044
			(0.951)			(0.512)			(0.012)
$ExpRatio_{t-11,t}$		0.027	0.027		-0.010	-0.009		0.006	0.008
		(0.315)	(0.316)		(0.591)	(0.614)		(0.590)	(0.476)
$TurnRatio_{t-11,t}$		0.004	0.004		-0.005	-0.005		-0.023	-0.024
		(0.745)	(0.746)		(0.659)	(0.626)		(0.004)	(0.003)
$LogFundAge_{t-11,t}$		0.001	0.001		0.006	0.007		0.005	0.005
		(0.921)	(0.923)		(0.491)	(0.473)		(0.324)	(0.312)
$LogFundSize_{t-11,t}$		-0.015	-0.015		-0.007	-0.007		-0.001	-0.001
		(0.055)	(0.055)		(0.192)	(0.199)		(0.796)	(0.832)
$Flow_{t-11,t}$		-0.001	-0.001		-0.003	-0.003		-0.000	0.000
		(0.799)	(0.794)		(0.120)	(0.143)		(0.943)	(0.896)
$StdDev_{t-11,t}$		-2.850	-2.851		-1.743	-1.781		-0.206	-0.399
		(0.000)	(0.000)		(0.012)	(0.011)		(0.769)	(0.574)
$LogFamSize_{t-11,t}$		0.007	0.007		-0.002	-0.002		-0.002	-0.002
		(0.169)	(0.168)		(0.599)	(0.587)		(0.496)	(0.455)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9162	7624	7624	9185	7631	7631	9171	7630	7630
AdjRSQ	0.081	0.094	0.093	0.058	0.067	0.067	0.060	0.069	0.070

TABLE 11: **Future Performance Prediction from Past Customized Peer Alpha Performance (Firm Portfolio Weights)**

This table reports results on future Characteristic-Selectivity alpha for deciles based on past alternative customized peer alpha *(CPA)*, derived from firm-portfolio-weights (instead of style vectors). At the start of each calendar quarter, we sort funds into decile portfolios based on the past 12 months average *CPA* performance. Next, we calculate equal-weighted *CS* performance over the next three months after portfolio formation, and then re-balance the portfolios. Finally, we obtain average monthly *CS* post-ranking portfolio performance by taking the average over the entire time-series. Similarly, we form portfolios at the start of each half-year (year) and then re-balance portfolios after six (twelve) months and obtain future *CS* performance. 10-1 represents a zero-investment long-short portfolio that is long on decile ten and short on decile one. Reported returns are percentage annual returns (monthly return multiplied by 12). p-values are reported in parentheses.

Decile	3 Month	6 Month	12 Month
1	-0.285	-0.229	0.161
	(0.658)	(0.708)	(0.795)
2	-0.250	0.038	0.375
	(0.560)	(0.928)	(0.385)
3	0.166	0.091	0.016
	(0.645)	(0.786)	(0.963)
4	0.187	0.274	0.158
	(0.579)	(0.432)	(0.616)
5	0.079	0.320	0.446
	(0.799)	(0.317)	(0.176)
6	0.672	0.709	0.720
	(0.036)	(0.035)	(0.030)
7	0.830	0.611	0.414
	(0.008)	(0.035)	(0.192)
8	0.853	0.742	0.727
	(0.013)	(0.026)	(0.024)
9	1.080	1.069	1.098
	(0.007)	(0.008)	(0.009)
10	1.619	1.543	1.035
	(0.007)	(0.010)	(0.071)
10-1	1.904	1.772	0.874
	(0.012)	(0.011)	(0.192)

TABLE 12: Competition and Performance Prediction: Portfolio Analysis (Firm Portfolio Weights)

This table reports results on future Characteristic-Selectivity alpha for deciles based on past alternative customized peer alpha *(CPA)*, derived from firm-portfolio-weights (instead of style vectors), for tercile subsamples based on past peer competition (also based on firm-portfolio-weight peers). At the start of each calendar quarter, we first sort funds into terciles by *NPeers*. These terciles are represented by *Low*, *Med* and *High*. Then we sort funds within each tercile into deciles based on the past 12 months average *CPA* performance to arrive at 30 portfolios. Next, we calculate equal-weighted *CS* alpha over the next three months after portfolio formation, and then re-balance the portfolios. Finally, we obtain average monthly *CS* post-ranking portfolio performance by taking average over the entire time-series. Similarly, we form portfolios at the start of each half-year (year) and then re-balance portfolios after six (twelve) months and obtain future *CS* performance. 10-1 represents a zero-investment long-short portfolio that is long on decile ten and short on decile one. Reported returns are percentage annual returns (monthly return multiplied by 12). p-values are reported in parentheses.

Competition and Persistency (Firm Based Peers)									
	3 Month			6 Month			12 Month		
Decile	Low	Med	High	Low	Med	High	Low	Med	High
1	-0.635	-0.213	-0.709	-0.250	-0.368	-0.554	-0.171	0.344	-0.082
	(0.442)	(0.789)	(0.141)	(0.757)	(0.613)	(0.243)	(0.838)	(0.642)	(0.859)
2	0.053	0.151	-0.632	0.293	0.293	-0.426	0.760	0.633	-0.320
	(0.932)	(0.777)	(0.102)	(0.638)	(0.593)	(0.253)	(0.246)	(0.174)	(0.389)
3	0.661	0.255	-0.187	0.345	0.320	-0.072	0.363	0.108	0.095
	(0.276)	(0.591)	(0.557)	(0.543)	(0.468)	(0.816)	(0.527)	(0.808)	(0.772)
4	0.204	0.369	-0.104	0.321	0.120	-0.079	0.118	0.003	-0.068
	(0.684)	(0.404)	(0.717)	(0.524)	(0.779)	(0.795)	(0.825)	(0.995)	(0.812)
5	0.577	0.358	0.122	0.787	0.883	0.082	1.040	0.733	0.265
	(0.228)	(0.420)	(0.687)	(0.116)	(0.064)	(0.783)	(0.035)	(0.105)	(0.401)
6	0.673	0.751	0.451	0.943	0.394	0.314	0.962	0.468	0.089
	(0.204)	(0.097)	(0.155)	(0.072)	(0.336)	(0.304)	(0.072)	(0.278)	(0.774)
7	1.218	0.577	0.353	1.320	0.663	0.616	0.999	0.864	0.261
	(0.017)	(0.133)	(0.224)	(0.006)	(0.100)	(0.060)	(0.046)	(0.060)	(0.365)
8	1.070	0.648	0.658	0.717	0.513	0.642	0.786	0.513	0.468
	(0.033)	(0.127)	(0.051)	(0.115)	(0.232)	(0.052)	(0.114)	(0.246)	(0.148)
9	1.443	1.072	0.573	1.720	1.232	0.173	1.250	1.423	0.176
	(0.003)	(0.064)	(0.112)	(0.001)	(0.040)	(0.612)	(0.007)	(0.016)	(0.634)
10	2.083	1.907	0.757	1.756	1.687	0.745	1.439	1.468	0.345
	(0.001)	(0.033)	(0.174)	(0.008)	(0.050)	(0.183)	(0.031)	(0.087)	(0.521)
10-1	2.718	2.121	1.466	2.006	2.055	1.299	1.610	1.125	0.427
	(0.002)	(0.038)	(0.036)	(0.018)	(0.023)	(0.052)	(0.044)	(0.201)	(0.512)