Mutual Fund Competition, Managerial Skill, and Alpha Persistence

Gerard Hoberg, Nitin Kumar, and N. R. Prabhala*

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Abstract

What economic forces limit mutual fund managers from generating consistent outperformance? We propose and test the hypothesis that competition from *other funds* catering to similar segments of investor demand limits alpha persistence. We make three contributions. First, we use spatial methods to identify the dynamic competition faced by funds. Second, we develop a new measure of skill, which is the ability of a fund to beat its spatially close rivals. Third, we show that performance is persistent only when a fund faces less competition in its style space. This new persistence is economically significant and lasts for over four quarters.

*Hoberg is at the University of Southern California, and can be reached at hoberg@marshall.usc.edu, Kumar is at the Indian School of Business, and can be reached at nitin_kumar@isb.edu, Prabhala is at CAFRAL and the University of Maryland, College Park and can be reached at prabhala@umd.edu. We thank Jonathan Berk, Clifton Green (FIRS discussant), Albert Kyle, Fabio Moneta (NFA discussant), Lubos Pastor, Clemens Sialm (ABFER discussant), Georgios Skoulakis, Juan Sotes-Paladino (FDU discussant), Allan Timmerman, Sheridan Titman (AFA discussant), Charles Trzcinka (CFEA discussant), Russ Wermers, and seminar participants at NUS, Indian School of Business, University of Sydney, UTS Business School, 2014 ABFER Annual Conference, 2014 Conference on Financial Economics and Accounting, 2014 NFA Annual Conference and 2015 AFA Annual Conference, 2015 Finance Down Under Conference and 2015 FIRS Conference for helpful comments. Any remaining errors are ours alone.

1 Introduction

As of December 2013, US mutual funds manage close to $15 trillion in assets. Of these, 4,540 are open ended equity funds with assets worth $7.7 trillion. The shares held by mutual funds represent 96 million households and account for 29% of the value of the outstanding shares in the U.S. market (ICI Factbook, 2014).

Can mutual fund managers generate positive alpha? If so, does alpha persist? These are fundamental questions in the mutual funds literature. Research on these issues dates back to at least Jensen (1968), who finds that neither 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), Cremers and Petajisto (2009), and Kacperczyk, Nieuwerburgh, and Veldkamp (2014) find evidence of performance persistence.

What forces limit the ability of managers to generate alpha consistently? Berk and Green (2004) (BG) articulate perhaps the most influential line of thought on this issue. They emphasize scale diseconomies in asset management. BG argue that fund manager talent is in short supply. Talented managers attract additional money flows from investors, which increases the assets under management. Under diseconomies of scale, fund alpha decreases to zero in equilibrium. This view is consistent with stylized facts in the fund industry. Predictions that find support include (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. Pastor and Stambaugh (2012) and Pastor, Stambaugh, and Taylor (2015) argue that diseconomies operate at the aggregate fund industry level rather than the individual fund level.

We propose an alternative axiomatic foundation for understanding alpha persistence, viz. the competition between *funds*. Our hypothesis draws on classical theories of industrial organization. Mutual funds offer investors particular combinations of risk exposures or "styles." A fund faces more competition when many rivals offer similar packages of style exposures as its investing ideas are under greater scrutiny and are more easily mimicked by rivals without extensive changes in styles promised to their investing clientele. Following Duffie (2010) or Mitchell, Pedersen, and Pulvino (2007), when funds face fewer spatially proximate rivals, relevant arbitrage capital is more slow moving and alpha can last longer. The relative immobility of distant capital in the style space is discussed in He and Xiong (2013), who point out that funds operate with "... narrow mandates and tight tracking error constraints." Alternatively, when firms face more proximate rivals, faster trading dissipates alpha quickly, reducing the ability to accumulate mispriced shares (Foster and Viswanathan (1996)).[1]

We make three contributions in characterizing the role of competition and alpha persistence. First, we construct new measures of competition faced by funds. Our competition measures are dynamic and adapt to changes in portfolios held by funds and their rivals over time. Second, we propose a new measure of manager skill, "customized peer alpha." Intuitively, a fund is skilled when it outperforms its spatially proximate competitors. Finally, we show that competition explains alpha persistence. In particular, a fund's alpha persists if it faces low competition. This new persistence is both statistically and economically significant.

Our focus on competition is motivated by the observation of Baumol, Panzar, and Willig (1982) that competition is likely to be an important force in contestable markets with few barriers to entry and less differentiated products. These characteristics describe the mutual fund industry quite well, where funds vigorously compete with each other, offering similar styles to investors. Competition does not, however, preclude other forces such as diseconomies of scale. Both forces can coexist, just as scale diseconomies and competition are distinct forces in industrial organization that can limit rents to incumbents.

Our focus on competition also has an empirical motivation. There is mixed evidence on the relation between fund size and alpha. Chen, Hong, Huang, and Kubik (2004) find a

[1]The idea that greater competition dissipates alpha sooner is also consistent with textbook descriptions of financial market efficiency. For instance, Cochrane (2005) writes (p. 390) that,"...Informational efficiency in turn derives from competition." See also Berk and Demarzo (2005) p.295-296.

negative relation between alpha and fund size while Elton, Gruber, and Blake (2012) report a positive relation. Pastor, Stambaugh, and Taylor (2015) find that individual funds may not have diseconomies of scale although these can exist at the aggregate industry level. Studies employing tools for causal identification also fail to find a relation between individual fund size and alpha. Phillips, Pukthuanthong, and Rau (2013) employ an instrumental variables method that relies on changes in holding period returns reported by funds. They find no evidence of a negative size-alpha relation. Using regression discontinuity methods that rely on rules used in Morningstar ratings, Reuter and Zitzewitz (2013) reach similar conclusions. Our study is distinct in that we neither rely on scale diseconomies nor preclude them. We propose an alternative micro foundation based on competition between similar-style funds.

Our key RHS variable is the style competition between funds. Portfolio theory provides the demand-side foundations for our competition measure. Investors demand portfolios that provide them exposures to a common set of k risk factors or styles. The 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. An investor's demand is a point in space that represents her ideal exposure to the k styles or risk exposures. In turn, the fund's location reflects the market the fund caters to, and its competitors are simply the set of funds that are spatially close to it. The spatial approach to modeling market structure has a rich tradition dating back to even the early economics literature (Hotelling (1929), Chamberlin (1933)).

Our framework requires us to operationalize three items. One is a spatial basis, or the product market dimensions along which funds compete. The other two are a norm function to define distances between funds and a distance cutoff within which competitors reside. We choose a spatial basis based on the asset pricing literature (e.g. Daniel, Grinblatt, Titman, and Wermers (1997)), in which the style space has $k = 3$ axes, viz., size, value-growth orientation, and momentum. We obtain similar results with an expanded basis with $k = 4$ dimensions that incorporate dividend yield to capture preferences for income stocks. Distances are based on the Euclidean norm. We define the style space using standardized style exposures as explained later in Section 4.2

We place stocks in a k-dimensional space. Funds inherit the value weighted style characteristics of their individual stocks (Daniel, Grinblatt, Titman, and Wermers (1997), Chan, Chen, and Lakonishok (2002), Brown, Harlow, and Zhang (2009), and Chan, Dimmock, and Lakonishok (2009)). Fund j is a competitor of fund i in quarter t if the spatial distance between them $d_{i,j,t}$ is less than a cutoff d^* specified by the researcher. Using a low value of d^* generates highly localized definitions of competition, while a larger radius d^* permits more distant funds to be competitors. To avoid ad-hoc choices, we choose d^* to calibrate our network's granularity to match that of the Lipper classification system. This choice is not critical. We obtain similar results when experimenting with alternate granularities.

Our approach has some important features. First, we do not impose any constraints on the number of competitors of a fund. Thus, some funds may have many competitors while others have few rivals. In Figure 1, Fairholme Fund has 38 peers while JP Morgan Tax Aware US Equity Fund has 335 peers. 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. As our competitive network is updated dynamically every quarter, our approach would fully internalize such shifts. Finally, the set of rivals is intransitive. Consider Figure 2, in which fund X is located at the boundary of two clusters. In a transitive approach, fund X would be assigned to either cluster 1 or cluster 2. If it is assigned to the right cluster 2, we would miss that funds R1 and R5 are also rivals of fund X. Our approach mitigates this boundary mismatch. The output of our analysis is a quarterly updated dynamic network that identifies rivals of each fund. It is analogous to the product market network constructed by Hoberg and Phillips (2010) and Hoberg and Phillips (2015).

We describe the empirical results briefly. An interesting question is whether the rivals we identify overlap with the widely-used Lipper peers. There is some but not substantial overlap. On average, less than a quarter of our customized rivals are Lipper peers. The average style distance between funds and their customized rivals is significantly lower than the distances to Lipper rivals and both sets of rivals 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 $t+1$.

Our main hypothesis is that alpha is less persistent when funds face more competition. We measure alpha, or risk-adjusted return, using the standard approach advocated in the funds literature. Our main results are based on excess returns relative to style matched portfolios (Daniel, Grinblatt, Titman, and Wermers (1997)), although the Carhart (1997) approach gives similar results as does an approach that adjusts for the Pastor and Stambaugh (2003) liquidity factor. In unconditional univariate portfolio sorts based on past performance, the 10-1 decile spread for future alpha ranges from 233 to 264 basis points per year depending on how the past performance portfolios are formed. This persistence is near zero in the subsample of high competition markets, but widens to 450 basis points per year in low competition markets. The results are robust to several tests including controls for assets under management, market size, fund style orientation, flows, whether the analysis employs sorts or multivariate regressions, or when we follow Berk and Van Binsbergen (2015) and examine "value added" as an alternate skill measure. Persistence is more pronounced in low competition style spaces.

Our measure of spatial competition essentially captures the flavor of the slow moving arbitrage capital discussed in Duffie (2010). In the context of a focal mutual fund, greater competition implies that more managers can mimic good ideas without extensive style changes. Spatially distant managers, on the other hand, must gather information about less familiar style stocks, move greater distances in style space and thus incurring more transaction costs, and explain style deviations to investors. Their capital is thus likely to be more slow moving when they are investing near the focal fund. These arguments suggest that it is useful to explore the channels through which competition can reduce profits. To this end, we examine the trading behavior of funds and their rivals before, during, and after the profitable trading opportunities arise in their markets. Funds in low competition markets face slower and less aggressive trading, more favorable liquidity from more distant funds, and are able to accumulate more shares before profitable opportunities experience run-ups. These results have the flavor of competitive trading models with asymmetric information such as Foster and Viswanathan (1996) in which trading becomes faster when competition is higher.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data. Section 4 describes our methods for identifying competition in detail. Section 5 presents the main results, and Section 6 concludes.

2 Related Literature

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.[2] Characterizing competition between actively managed funds is less straightforward as funds differ in style. Each fund offers a 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. Because funds compete with each other on style dimensions (in fact, they are marketed in style buckets, such as large-cap funds), our approach is to measure competition by the number of proximate rival funds in the style space.

Our approach is related to the literature on fund styles. 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,

[2]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), and Cooper, Halling, and Lemmon (2012). Other work on fees includes Khorana, Servaes, and Tufano (2008), Gil-bazo and Ruiz-Verdu (2009), and Stoughton, Wu, and Zechner (2011).

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.

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, 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*

This description leaves managers enormous latitude in their baseline investment choices, and furthermore it explicitly permits managers to deviate from these choices. These attributes are typical, even when funds are specific about their investing philosophies.[3]

Prospectuses also provide another source of data to infer competitors, the self-disclosed benchmarks reported by funds to their investors. However, regulations offer little guidance about which benchmark a fund should pick and why. This flexibility allows for benchmark gaming. Sensoy (2009) finds that the benchmark in a large number of cases does not match actual fund style.[4] Thus, prospectus disclosures are unlikely to be useful in practice.

[3]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.*

[4]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. In a different context, see Faulkender and Yang (2010).

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 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)). Brown and Goetzmann (1997) 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 popular. The widely used Lipper and Morningstar approaches are perhaps the most visible use of holdings based benchmarking. Both agencies divide funds into classes comprised of funds holding similar style stocks. Academic studies such as Chan, Chen, and Lakonishok (2002) and Chan, Dimmock, and Lakonishok (2009) suggest that style classes based on size and book-to-market (BM) are useful in generating performance benchmarks. Hunter, Kandel, Kandel, and Wermers (2014) use Russell style buckets for benchmarking. We embrace the viewpoint of style-based benchmarking based on holdings. However, we compare fund holdings to the holdings of rival *funds* holding similar style stocks. The fund-to-fund comparison is in the spirit of Cohen, Coval, and Pastor (2005) and varies from comparisons with the entire universe of stocks that enter the passive risk benchmarks.

An important question in constructing style based peers is the specification of the style space. Lipper and Morningstar use size and B/M as style axes, a practice supported by academic literature (e.g., Chan, Dimmock, and Lakonishok (2009)). However, other dimensions can drive demand. For instance, returns to momentum investing are known since at least Jegadeesh and Titman (1993), and Grinblatt, Titman, and Wermers (1995) show that active mutual funds are momentum investors. Thus, it is plausible that investor demand, and fund competition, also relies on the momentum dimension. Likewise, investors may have demand for funds producing cash income (see for example Allen, Bernardo, and Welch (2000) and Harris, Hartzmark, and Solomon (Forthcoming)). If so, dividend yield may also be a basis on which firms compete. We consider multiple approaches to assess robustness.

The use of Lipper (or Morningstar) peers to identify fund competitors raises two other issues. One is transitivity. In the Lipper or Morningstar approaches, each fund belongs to a class and peers are transitive. Such a condition is not necessary to identify rivals and we do not employ it. We instead let each fund have its own *customized* peers. A second issue is style drift (Brown, Harlow, and Starks (1996), Wermers (2012)). Because we do not require funds to stay in fixed classes, our approach adapts to a fund's style shift by changing its customized peer group.

2.3 Literature on Identifying Peers

Our work is also related to the broader literature on identifying peers. Our methods are similar to those used in Hoberg and Phillips (2010) and Hoberg and Phillips (2015), who construct networks of product-market competitors based on cosine similarities between product descriptions provided by firms in their 10-K's. There are two important technical distinctions. One is that we do not employ cosine similarity as a distance metric for reasons that we discuss later. A second difference is that Hoberg and Phillips (also Blocher (2014) and Wahal and Wang (2011) in the funds context) treat each product word (or each stock) as a separate spatial dimension. We consider the reduced dimension style space and use style distances to identify peers.

Our emphasis on the style space is based on the nature of investor demand for stocks. Additionally, it also recognizes the economic intuition that some pairs of stocks are closer substitutes for each other in fulfilling investor demand than are others. For instance, two growth firms are more similar to each other than a growth firm and a value firm. Treating each stock as a separate dimension would mask these important differences. As we show in the robustness section, imposing more refined demand-side economics matters.

3 Data

We obtain a sample of actively managed open-ended U.S. equity mutual funds from 1980 to 2012 from the CRSP Survivor-Bias Free US Mutual Fund database. To identify diversified equity 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. If both codes are missing, we pick funds with Wiesenberger objective codes equal to G, G-I, GCI, LTG, MCG, SCG or those with "Policy" code of CS. For the remaining funds, we require that the lifetime average investment in equity is at least 80%. We eliminate index funds using the CRSP index fund flags and by screening fund names for words such as "Index" or "S&P." We also remove funds whose names have words such as "ETF."

We obtain data on net returns from CRSP. To obtain gross returns before expenses, we add one-twelfth the fund expense ratio to the net monthly return. To avoid multiple-counting of funds with more than one class, we value-weight fund-class returns (and other characteristics including expense ratios) using prior month total net assets. Fund size is then 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 first offer-date. We exclude funds with negative age.

We obtain snapshots of quarterly holdings from the Thomson Reuters mutual fund holdings database. Since our focus is on U.S. equity diversified 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.

We also 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. We do this as 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. We then combine the CRSP sample with the Thomson Reuters holdings sample using the MFLINKS dataset developed by Wermers (2000). We further remove fund-quarters that do not have a valid Lipper class in CRSP.[5] Because we are interested in persistency tests, we then remove fund-months for which fund gross return or alpha cannot be computed.[6] Our final sample consists of 387,143 fund-months for 3390 unique funds from July 1980 to June 2012.

3.1 Summary Statistics

Table 1 presents summary statistics for our dataset. There are 3,390 unique funds in our sample. The number of funds varies by year, with 292 funds in 1985, and 1,733 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 $292 million in 1985 to $1,220 million towards the end of the period. The returns, average size and number of funds in our sample are comparable to those in prior studies such as Chan, Chen, and Lakonishok (2002) and Lou (2012), although the samples are not identical because our study includes more recent data.

[5]We implement this screen only for fund-quarters after December 1999 because Lipper classifications are unavailable before that date.

[6]These missing fund-months are due to missing expense-ratios in CRSP or due to missing or unmatched holdings in Thomson Reuters holding database.

4 Methodology

This section describes our four-step algorithm for identifying a fund's competitors. First, we define the attributes that define the style space. Second, we define axes either in terms of ranks or levels, and in each case, we consider raw attributes or an orthogonalized basis. Third, we specify a distance metric and a radius cutoff to identify a fund's rivals. Finally, we construct a metric of the fund competition and relative fund performance by assessing each fund's customized rivals. Each step requires the researcher to make empirical choices. We describe our approach and provide a brief rationale for our final specifications. The key results on alpha persistence versus competition are relatively robust to these choices.

4.1 Spatial Basis

We place stocks into a k-dimensional characteristics space and locate funds based on the value weighted characteristic of the stocks held by the fund. The baseline $k = 3$ spatial basis has 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 (skipping the most recent month). 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. Where necessary (e.g., regressions), we winsorize variables at the 1 and 99 percentile levels. In robustness tests, we also consider an expanded 4-dimensional style space, that includes dividend yield (the dividend in the first fiscal year prior to the current quarter end date divided by the fiscal year end stock price).

4.2 Specifying Axes

We consider several methods for defining the axes in the style space. The baseline follows the asset pricing literature and uses ranks of each attribute of the style space. We also consider z-scores that account for the actual distribution of style characteristics. We consider an orthogonalized basis, which is a better motivated norm for defining distance and also reflects a practice suggested 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.

4.2.1 Ranks

A stock's characteristic rank is its percentile in the distribution of all NYSE stocks with share codes of 10 or 11. A fund's characteristic percentile is based on the weighted average percentiles of the stocks in its portfolio. We consider an orthogonalized basis in the spirit of the Fama and French (1993) factor computation or Chan, Chen, and Lakonishok (2002) in the context of mutual funds. At the end of each quarter, we regress log $(1 + B/M)$, or LBM on log market capitalization $LSIZE$ for all NYSE stocks. We use the regression residual as a basis for ranking all NYSE stocks along the residualized BM dimension. For non-NYSE stocks, we assign a stock's percentile based the residual LBM, or LBM minus the predicted value based on the NYSE regression parameters. For three and higher dimensional spaces, we use a similar orthogonalization procedure, first sorting by size, then orthogonalizing BM, and then orthogonalizing momentum and finally dividend yield. In each case, ranks are based on NYSE residual rankings.

4.2.2 Z-scores

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 use levels is ultimately an empirical issue. Industry practice provides precedent for considering characteristic levels. For instance, the Lipper style assignment depends on the actual values of growth proxies (such as BM). It seems reasonable to consider characteristic levels as a spatial basis.

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 Identifying Customized Peers

We identify competitors based on pairwise comparisons between funds in a style space as in Hoberg and Phillips (2015). 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:

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

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.[7] To complete the process of using this network to construct a peer classification system, we need to specify a cutoff distance d^* such that rivals are funds with $d_{i,j} < d^*$.

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.[8] 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 is achieved by identifying d^* as the smallest number such that at least 8.858% of all d_{ij} permutations are less than d^*.[9] As a minor refinement, we further require that all funds should 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. For robustness, we experimented with alternate granularities of 5%, 10%, and 15% and obtain similar results.

We note two aspects of our methods. One, each fund has its own unique set of rivals

[7] Similarity between two funds is defined as -1 multiplied by $d_{i,j}$.

[8] 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.

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

and hence the property of rivalry is not transitive. Intuitively, rivals can be visualized as funds in a sphere of fixed radius. Second, our approach scales easily to accommodate higher dimensions or different norm functions to specify distance. We also note that increasing dimensionality may be tempting but it is not necessarily beneficial.[10]

4.4 Competition Measures

We construct two measures of competition. One is just the number of rivals within radius d^*, which we call *(NPeers)*. This measure does not distinguish between rivals packed together within a small radius or scattered across the circumference. Thus, we compute similarity between funds and rivals where $s_{i,j,t} = -d_{i,j,t}$, normalized to positive values by subtracting the minimum similarity in quarter t. Our second measure is the sum of pairwise similarities between a fund and all rivals, *total similarity*, or *(TSIM)*. A fund with greater values of *NPeers* or *TSIM* faces more competition.

4.5 Customized Peer Alpha

We introduce a measure of fund manager skill called "customized peer alpha" *(CPA)*. To motivate the measure, observe that a fund's competitors are other active mutual funds catering to similar slices of investor demand. A skilled fund should beat its spatially proximate rivals who offer similar risk exposures to their investors. Thus, we construct CPA as a fund's return minus the average return of its rivals. As in Cohen, Coval, and Pastor (2005) and Fama and French (2010)), we work with before-expense returns to best capture managerial skill. Thus, we add 1/12th the annual expense ratio to the net returns.[11] For each fund j in month t, customized peer alpha is

$$CPA_{jt} = RFund_{jt} - RPeer_{jt} \tag{2}$$

[10] Spatial proximity on irrelevant dimensions can lead to dilution of weights placed on the relevant dimensions and thus, wrong funds being identified as rivals.

[11] Our results are robust if we use net returns instead of gross returns.

where $RPeer_{jt} = \frac{\sum_{k=1}^{N} RFund_{kt}}{N}$, and fund j has N rivals ($k = 1, 2, ..., N$). *CPA* thus considers each fund relative to the alternate *active* fund with the same risk profile as the focal fund.

4.6 Alternative Spatial Representations

We consider an alternative to our baseline 3-D network based on size, B/M, and momentum: a 4-D network that adds dividend yield to the 3-D network. 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 prefer more income to growth as they reach retirement. The 4-D network is analogous to the 3-D network 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, which is analogous to the Wahal and Wang (2011) measure of overlap between incumbent and entrant portfolio holdings. As discussed earlier, this approach treats each stock as a separate dimension, effectively ignoring, for instance, that General Electric is less similar to Facebook than LinkedIn may be. Thus, we do not necessarily recommend this approach. The relevant dimensions on which funds compete should be the styles sought by investors and targeted by managers (He and Xiong (2013)). We analyze this network as a robustness exercise. It can be viewed as the limiting case of when all style dimensions are ignored. If funds target styles, we expect this approach to yield some, although not particularly strong, information about rivals as He and Xiong argue.

To compute the stock-by-stock 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 fund pairs using one minus the cosine similarity as follows:[12]

$$d_{ij} = 1 - \sqrt{\frac{(V_i \cdot V_j)}{\|V_i\| \ \ \|V_j\|}} \tag{3}$$

5 Competition and Alpha Persistence

In this section, we examine the role of competition. We begin with a summary of the customized peers and then display our baseline results on predicting future alpha. We examine alpha conditional on levels of competition faced by funds (our main result) and then motivate and discuss several additional tests that shed light on our competition hypothesis. We also discuss many robustness tests.

5.1 Properties of Customized Peers

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. The customized peers used here and in the results to follow are derived in the 3-dimensional orthogonalized space using z-score methods.

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

[12] Using the cosine similarity method is warranted in this setting because investment weights sum to one for all funds. We use this measure as 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 $[0, 1]$.

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 3 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 4 illustrates the decay in rival similarity over time. The upper panel compares the similarity distribution of fund pairs in the current quarter to similarities between the same peers one quarter later. If rivals are stable, the similarities and their distribution should be nearly identical. The lower panel compares similarities of current-quarter customized peers with similarities for the same peers one year later. The two panels suggest that customized peers exhibit strong but not perfect overlap. There is decay in similarities and 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 Baseline Persistence Results

Our first tests examine if a fund's future alpha is predicted by its outperformance relative to its spatial peers. We estimate future alpha as "CS" alpha or the fund's holding return minus the return of the corresponding DGTW portfolio (Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004)).[13] We form portfolios based on past customized peer alpha (CPA) and test if they predict next-period CS alpha. While we focus on predicting future CS alpha for consistency with the mutual funds literature, the results are similar if we instead predict future CPA.

Table 3 reports the results of sorts at 3-, 6-, and 12-month horizons. At each horizon, we report two columns of results. In the first column, funds are sorted into decile portfolios based on the past 12-month average CS alpha. In the second column, the sorts are based on the past 12-month average CPA.[14] In both cases, the number reported in the table is the future CS alpha, or the fund's risk-adjusted return. We find that a fund's past CPA is a reliable predictor of its future risk-adjusted returns with a 10-1 decile spread of 264 basis points for the three month horizon. The spread is 257 basis points and 179 basis points at 6- and 12-month horizons, respectively. We conclude that CPA, which measures how funds perform relative to spatially proximate rivals, reflects durable skill.

5.2.1 Robustness of Baseline Results

We conduct additional tests to better understand the predictive power of past CPA. The detailed tables are in the Appendix but we briefly overview the motivation and bottom line of the tests here. The first tests examine whether CPA predicts Carhart (1997) and Pastor and Stambaugh (2003) alphas. We report affirmative results in Tables A1 and A2 in the Appendix. Second, we test whether the ability of CPA to predict future alpha simply reflects its correlation with past CS alpha: if winners (losers) are more likely to remain

[13]Data are from http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

[14]Because our sample starts from July 1980, for 3- and 6-month horizons, our first decile portfolios are formed at the end of June 1981. For 12-month horizon, we form portfolios at the end of each calendar year as in DGTW, so that the first decile portfolios are formed at the end of December 1981.

winners (losers). In multivariate regressions, we find that CPA predicts future CS alpha even after controlling for past CS alpha. Table A3 in the appendix presents the detailed results.

The third test examines whether high CPA funds perform better because they are better stock pickers or whether they are better at style timing. We employ an approach akin to that in Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2000) and decompose a fund's gross return for month t, r_{ft} into three components.

$$r_{ft} = (r_{ft} - r_{pt}) + (r_{pt} - r_{pt,q4}) + r_{pt,q4} \tag{4}$$

r_{pt} is the average return of the fund's current peers and $r_{pt,q4}$ is the average time t return of the 4-quarter back peers. The first term in Equation (4) reflects selection while the second term comparing current and past rivals reflects style timing. Table A4 in the Appendix shows that fund performance is largely due to stock selection skills rather than style timing.

Finally, we consider "activeness" of a fund. Kacperczyk, Sialm, and Zheng (2005) show that the industry concentration index *(ICI)*, the sum of the squared deviation between the fund's weights of holdings in various industries and the weights of these industries in the market portfolio, predicts future performance. Other papers such as Kacperczyk, Sialm, and Zheng (2007), Cremers and Petajisto (2009), Petajisto (2013), and Amihud and Goyenko (2013) build on and develop this intuition to generate related measures. We follow Huang, Sialm, and Zhang (2011), and use sequential sorts. At the beginning of each quarter, we first sort funds into terciles by activeness and then by past CPA. Table A5 in the Appendix reports the results. We find that the 3-1 tercile spread based on CPA remains economically and statistically significant across a range of activeness measures. Customized peer alpha appears to contain information about future alpha beyond activeness.

5.3 The Role of Competition

We turn to the central hypothesis that alpha is less persistent when funds face more competition in their spatial location. The intuition for this hypothesis is straightforward. When a fund faces many spatially proximate rivals, the stocks comprising the focal fund's portfolio are under greater scrutiny from more managers with greater overlaps in portfolio styles. These managers can act faster to exploit the same opportunities as spotted by the focal fund. As He and Xiong (2013) point out, narrow investing mandates and attention to tracking error tend to restrict mobility of capital to local style spaces. For spatially distant managers, gathering such information, evaluating it, taking active decisions based on it, and persuading investors about the need for an unfamiliar habitat away from core investing mandates, are all significant barriers that reduce the likelihood of quick action.

Two other questions arise. One, does migration by investors who move wealth to rival managers matter? This form of competition faces similar, if not higher hurdles as it requires investors to take actions that managers would have. Indeed, the very purpose of delegating investment to such managers is to delegate such information production and avoid second-guessing manager choices. Another question is whether a similar channel can arise from having more invested *capital* – rather than a greater number of competing *funds* – in the spatial vicinity of the focal fund. While this is an empirical question, there is good reason to believe that information and competitive pressures from one large fund can be quite different from that from multiple funds (thus managers) with equivalent capital. For instance, Foster and Viswanathan (1996) argue that information and profit-making trajectories can vary when there are multiple differently informed competitors. We take up this point later in tests that control for local market size and in Section 5.9 where we address the competitive mechanism by which fund managers generate and retain investing rents.

Table 4 reports results consistent with the competition hypothesis. Here, we sort portfolios by competition levels and customized peer alpha (CPA) and report future alphas in each category at 3-, 6- and 12-month horizons. Both competition and CPA are measured over the past year and as discussed in Section 4.4. We consider two measures of competition. In Panel A, competition is based on the number of rivals. We form terciles of high, medium, and low competition based on the number of rivals, which are recomputed every quarter with updated holdings data. In Panel B, competition is based on total similarity to rivals (also recomputed every quarter). Funds with higher total similarity face more competition.

At each horizon, we find a significant degradation in alpha persistence when competition increases. For instance, in the one quarter-ahead results in Panel A of Table 4, the 10-1 spread is close to an annualized 450 basis points in the low competition tercile. This drops to 96 basis points when competition is high. This pattern persists at longer horizons although the 10-1 differences are attenuated. For instance, at a 12-month horizon, the 10-1 spreads are 288 and 86 basis points in the high and low competition terciles, respectively. In Panel B of Table 4, which measures competition as total similarity, the results are similar.

We conduct additional robustness tests whose results are collected in the Appendix. Table A6 report results when funds are independently sorted into competition terciles and past CPA performance deciles. In panel A, the 3-month ahead 10-1 decile spread for low competition tercile is now about 343 basis points, while the corresponding spread for the high competition tercile is an statistically insignificant 54 basis points. In unreported results, we further confirm these results based on independent sorting in a regression framework.

In Table A7, we show that the results are robust to measuring ex-ante decile rankings by CS alpha instead of CPA. For instance, at the 3-month horizon, the 10-1 spread for low competition tercile is 338 basis points versus 98 basis points for the high competition tercile. We also consider alternative granularities for defining rivals and find robust results. In the baseline results, two funds have an 8.858% probability of being rivals. In Table A8, we find that the results are robust to alternative granularities in which the probability is 5%, 10%, or 15%.

We rerun the competition tests using individual stocks as a spatial basis. A stock based spatial basis may seem attractive at first sight. However, it does not identify rivals investing in similar style stocks. Table A9 in the Appendix reports the results. While low competition spreads are consistently higher than high competition spreads at all three intervals, the high minus low differences are muted relative to the baseline results in Table 4.

A question that often comes up is whether competition predicts the level of alpha rather than alpha persistence. We do not have strong priors on this question. One perspective on this issue is that funds are unlikely to earn positive alpha simply by virtue of being located in particular locations in the style space. For an opposite view, one could argue that following Merton (1987), funds in low competition spaces may invest in neglected stocks that may have higher expected returns. We examine the alpha versus competition issue in Table A10. We find that managers who operate in less competitive markets earn roughly 0.9% higher alphas on average. The results are marginally significant indicating that there exists significant variation around the average alpha.

5.4 Size

We next consider whether persistency depends on fund size. There are two motivations for this test. One is that competition can be correlated with fund size. Second, in the Berk and Green (2004) equilibrium, alpha decreases in fund size. Their model does not depend on particular dynamics by which fund size grows in response to alpha. However, if the growth of a small outperforming fund to a large fund is not instantaneous, alpha persistence should be greater for small funds. Industry size may also help predict fund persistence. However, our tests are cross-sectional across funds and thus control for year-level heterogeneity that controls for the aggregate industry size (Pastor and Stambaugh (2012), Pastor, Stambaugh, and Taylor (2015)). We test the hypothesis that alpha persists more in small funds.

At the beginning of each quarter, we sort funds into small and large categories by median size cutoff. We then sort funds into low, medium and high competition terciles and finally into quintiles within terciles by past CPA. This process maintains the number of portfolios at 30, as in the basic competition tests. Table 5 reports the results. In Panel A of Table 5, competition is measured by the number of rivals. Here, the 5-1 quintile spread is an annualized 359 basis points for small funds when competition is low and 103 basis points when competition is high. The corresponding spreads for large funds are 269 and 65 basis points, respectively. We find similar results in Panel B, when competition is measured by total similarity. Thus, we find some evidence that alpha persistency is lesser in larger funds. The finding is consistent with a version of BG in which fund size does not instantaneously adjust to its alpha-eliminating equilibrium size. More importantly, however, competition matters even after controlling for fund size.

We next consider whether persistency depends on market size. At the beginning of each quarter, we first divide the style axes by median z-score. This results in eight sub-markets.[15] We compute the market size of each of these sub-markets as the sum of AUM of all funds that populate a sub-market. All funds within a particular sub-market inherit the same sub-market size. We then proceed as usual. We sort funds into small and large market sizes by median market size cutoff. We then sort funds into low, medium and high competition terciles and finally into quintiles within terciles by past CPA. This process results in 30 portfolios. Table 6 reports the results on market size.

Panel A reports results when competition is measured by the number of rivals. We find that the 5-1 quintile spread is an annualized 294 basis points for funds located in the small market size locations, when competition is low and an statistically insignificant 64 basis points when competition is high. The corresponding spreads for funds located in the large market locations are 299 and 101 basis points, respectively. We find similar results in Panel B, when competition is measured by total similarity. Overall, we find that competition matters for persistency, even after we control for local market size.

5.5 Style

One measure of competition we use is the number of funds within a specified radius in the style space. As large stocks are more widely held, funds focusing on large cap stocks may

[15]Our results are robust if we divide the style axes into three parts. This results in 27 sub-markets.

face more funds in their spatial location. Thus, we test whether competition is related to a fund's size orientation.

Panel A of Table 7 reports competition in the large and small size orientation portions of the style space. We sort funds into small-cap and large-cap oriented fund categories based on whether the fund size z (see Section 4.2.2) exceeds the median z statistic. We then sort funds competition terciles and quintiles by prior CPA, leading to 30 portfolios. In the small cap style space, the 5-1 quintile spread is 328 basis points in low competition space and 154 basis points in high competition space. In the large cap style space, the 5-1 quintile spread for low and high competition spaces are 202 and 42 basis points, respectively. In Panels B and C, we repeat the analysis for other style dimensions. Competition limits persistency for a range of fund style orientations.

5.6 Flows

Lou (2012) argues that past winners receive flows and expand holdings, while past losers must sell to meet redemptions. Thus, flows can predict future alpha. While our competition hypothesis does not preclude flow based persistence, it is useful to test whether competition limits alpha persistence in high and low flow categories. We report the results in Table 8.

We sort funds into low and high flow categories.[16] We then sort funds into CPA quintiles and competition terciles to produce 30 portfolios. The average monthly flow in the low flow sample is -2.23%, while the average flow in the high flow subsample is 3.96%. The average past performance in the low flow subsample is -0.07%, while the average past performance in the high flow subsample is 0.13%. For the low flow samples, the 5-1 quintile alpha spread is 230 basis points and 63 basis points in the low and high competition samples, respectively. The corresponding spreads for high flow funds are 254 basis points and 64 basis points, respectively. We find similar results in Panel B, when competition is measured by total

[16] The flow for a fund i in month $t+1$ is obtained as $Flow_{i,t+1} = \frac{TNA_{i,t+1} - TNA_{i,t}(1+RFund_{i,t+1})}{TNA_{i,t}}$, where $TNA_{i,t}$ represents the total net assets of fund i at the end of month t and $RFund_{i,t+1}$ is the CRSP reported net return of the fund i in month $t+1$.

similarity. Competition limits persistency in both samples.

5.7 Value Added

Berk and Van Binsbergen (2015) suggest that skill in the mutual fund industry is measured as the dollar value generated by a fund. Their measure is, in essence, a fund's excess return times assets under management. Dollar value represents the value extracted from the market. We consider whether competition between funds is related to value added. Specifically, we test whether dollar value added is higher when funds face less competition.

Our measure of value added is based on a fund's holding return minus the return of the corresponding DGTW style matched portfolio. We multiply the DGTW-adjusted return for period t by assets under management at $t-1$ to produce the dollar value added.[17] Before comparing the value added when competition is high or low, we note that dollar figures are likely to increase in fund size. Thus, we measure dollar value added separately for large and small funds.

We proceed as follows. At the start of each quarter, we sort funds into small and large categories by median size cutoff. We then sort funds into low, medium and high competition terciles and finally into quintiles within terciles by past CPA. This results in 30 portfolios as before. We hold these portfolios for the next 3 months and then re-balance the portfolios. During the holding stage, we obtain the value added by the median fund in each of the 30 portfolios. Thus, we have a time-series of value added by the median fund for each of the 30 portfolios. Finally, we take the average of the time-series to obtain the value added by the median fund. Table 9 reports the results.

Panel A in Table 9 shows that when competition from proximate peers is low, past winners add \$2.63 million/year more than the value added by past losers. This figure drops to \$0.71 millions, when competition is high. Not surprisingly, the low-high difference in value added is greater for large funds. We find similar results in Panel B, when competition

[17] Using customized peer adjusted return instead of DGTW-adjusted return produces similar results.

is measured by total similarity. Funds that perform well have greater value added when competition is low.

5.8 Regressions

Table 10 revisits the hypothesis that competition determines alpha persistency but now in a regression context. We regress future CS alphas on past CPA deciles and controls. We report separate regressions for funds facing low, medium, and high competition. This analysis effectively mimics the portfolio results of Table 4 but lets us include additional controls such as fund size, expenses, or age. Standard errors are clustered by fund and we winsorize variables at the 1% level. We include dummy variables for past CPA in the 1st and the 10th decile to make results comparable to the portfolio results in Table 4.

We find that in Table 10, the 1-quarter ahead 10-1 spread in future alpha is 26.7 basis points per month, or about 320 basis points per year when competition is low in Model 1. This spread declines to 15.7 basis points per month or 188 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 12-month horizons. Table A11 shows that we get similar results when the dependent variable is the Carhart alpha rather than the DGTW based CS alpha. We get slightly stronger results when the dependent variable is the Pastor-Stambaugh alpha that further adjusts for the liquidity risk. Table A12 shows that the annual spread between the deciles is about 232 basis points in Model 3.[18]

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 horizon fully reflects the updated peer groups. However, the longer horizon tests do *not* update rivals from quarter to quarter during the ex-post period. Thus, the stronger quarterly results

[18]For brevity, we display results for when peers are formed and alphas predicted one quarter ahead. The 6- and 12-month results display similar patterns as those for CS alpha.

relative to the annual results reflects the value of controlling for dynamic "customized peers" rather than fixed peers based on more deeply lagged style classifications. This suggests that using more frequently updated customized peers is important for understanding competition. Such dynamic competition measures should be more important when there is more flux in product-markets as is likely to be the case in the funds industry.

5.9 Mechanisms

Our results thus far establish that competition moderates alpha persistence. An interesting question concerns the mechanism by which this moderation occurs. In this section, we present some evidence on this channel. Our analysis is informed by models of competition between funds in settings where funds compete with each other, as is likely when funds occupy similar portions of the style space. The essential intuition is that competition should operate through the channel of faster trading responses and price adjustments. For instance, Foster and Viswanathan (1996) further develop Kyle (1985) to argue that when competition is greater, funds have stronger incentives to try to accumulate shares before rival funds do so. This results in faster trading, more informationally efficient prices, and lower rents to informed trading as competition increases.

We conduct the following test to assess the competitive mechanism. We first identify a set of very profitable investments in high and low competition markets. We examine trading patterns before, during, and after the profitable investments are realized. We test whether funds in low competition markets can accumulate more shares at a more gradual pace before information is fully disseminated. Accordingly, we consider markets grouped ex ante by high and low competition. Within each market, we identify focal winner funds as the top decile of high-performing funds based on past CPA in the four quarters from $t = -3$ to $t = 0$. The top decile stocks in each portfolio based on stock returns is the set of highly profitable investment opportunities in the relevant market. We then assess buying and selling patterns for the 12 quarter period ranging from $t = -7$ to $t = +4$. This 12-quarter period brackets the measurement window. We consider four sets of funds: the focal winner fund, its rivals, its rivals of rivals (distant rivals), and all remaining funds (non-rival funds).

Table 11 displays the results. We report the total trade imbalance for each of the four groups of funds in the low competition market and the high competition market. We first calculate the quarterly trades of funds at the start of each quarter. Trade imbalance for stock i at the start of quarter $t+1$ is thus

$$TI_{i,t+1} = \frac{NBuys_{i,t+1} - NSells_{i,t+1}}{NBuys_{i,t+1} + NSells_{i,t+1}}, \tag{5}$$

where $NBuys_{i,t+1}$ ($NSells_{i,t+1}$) is the total number of shares of stock i purchased (sold) by all funds at the start of quarter $t+1$. To isolate the trade imbalances due to focal fund, its rivals, distant rivals and non-rivals, we decompose the numerator of trade imbalance due to the four groups as follows

$$TI_{i,t+1} = \frac{\sum_{j=1}^{4} NBuys_{i,j,t+1} - NSells_{i,j,t+1}}{NBuys_{i,t+1} + NSells_{i,t+1}}, \tag{6}$$

where $NBuys_{i,j,t+1}$ ($NSells_{i,j,t+1}$) is the total number of shares of stock i purchased (sold) by funds in group j at the start of quarter $t+1$. We then obtain the cross-sectional average of trade imbalance for each group j, $(NBuys_{i,j,t+1} - NSells_{i,j,t+1})/(NBuys_{i,t+1} + NSells_{i,t+1})$, across all stocks. Finally, we obtain time-series averages of the resulting time series. We report these averages in Table 11.

When comparing the low competition market in Panel A to the high competition market in Panel B, we observe three distinct patterns. First, when faced with profitable opportunities, a focal fund in the low competition market can accumulate substantially more shares than a similar fund in high competition markets. Second, for the focal fund and also its rivals in low competition markets, trading is gradual and funds are able to accumulate substantial shares prior to the price run-up that occurs by design in $t = -3$ to $t = 0$. In contrast, in high competition markets, trading is fast and is largely focused in the period of the price run up itself.

In the low competition markets, non-rival funds sell shares prior to the run-up, potentially generating liquidity for the focal and rival funds who wish to accumulate shares. We do not observe this for high competition markets, where the evidence suggests that even non-competing funds also trade in the same direction.

Figure 5 illustrates the results visually. We depict the cumulative trade imbalance for all four groups of funds during the 12 quarter period discussed above. Low competition funds are reported as solid lines, and high competition funds are dotted lines. The top figure clearly illustrates that funds in low competition markets are able to accumulate substantially more shares than funds in high competition markets, especially in the four quarters prior to the run-up. The second and third figures more directly show that the gradient of share accumulation is steeper in low competition markets prior to the period of the price run-up. In contrast, the there is a flat slope in this window for high competition markets (see, especially, the third figure). There is little opportunity to identify profitable opportunities before prices ramp up in high competition markets.

The bottom-most figure illustrates that non-rival funds in distant markets appear to sell exactly when informed investors in the low competition markets should find it optimal to be buyers (the quarters before the run-up). This outside selling pressure generates favorable liquidity and allows for the funds in these markets to accumulate more shares over time before price run-ups occur.

The trend lines in the ex post period after the price run-up (quarters t=1 to t=4) once again indicate favorable conditions for funds in low competition markets for liquidation of the ex-ante accumulated shares. In these periods, we observe non-rival funds buying stock in these low competition markets exactly when the low competition managers seek to liquidate and realize their profits. This allows for exit with higher ex-post profits without the need to strongly demand liquidity. We do not observe this pattern in high competition markets, as non-rival funds are neither strong buyers nor strong sellers in t=1 to t=4. We conclude that the basic trading patterns illustrate a channel through which competition modulates alpha persistence. In low competition markets, we observe (1) slower trading speed allowing for more ex-ante share accumulation and (2) superior liquidity conditions allowing informed funds to enter and exit without excessive price pressure. The results are broadly consistent with models of competition among informed traders such as Foster and Viswanathan (1996).

6 Conclusion

A key issue in the mutual fund industry is whether fund managers are skilled. If so, what forces limit the ability of skilled managers to consistently earn positive risk-adjusted returns over long periods of time? Our study highlights the role played by competition between *funds* in limiting the persistence of alpha. We make three contributions in this regard. 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 spatially proximate competitors. Our third contribution is to show that the competition faced by a fund predicts whether the fund's alpha persists.

Our central result is that competition between funds limits alpha persistence. The role played by similar-style competitors is economically sensible. When more rivals are present in the vicinity of a fund's chosen style, there are more active funds monitoring investments in the local style space. These funds can move to exploit alpha generating opportunities without extensive disruption to the styles they promise their own investors. Building on Duffie (2010), Mitchell, Pedersen, and Pulvino (2007), He and Xiong (2013) and Foster and Viswanathan (1996), the greater presence of spatially proximate rivals implies that there is more swift-moving arbitrage capital to eliminate alpha. We explore the mechanisms through which competition can reduce fund profits. These tests indicate that trading becomes faster for each competing fund when competition is higher. In particular, funds in low competition markets are able to accumulate more shares before profitable opportunities experience run-ups in these low competition markets.

It is not surprising that competition between funds is economically important. 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.

Our results also have implications for measuring fund manager skill. A goal of fund managers is to generate positive alpha 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. We offer a different perspective on skill. In the mutual fund industry, skilled individuals compete with each other to generate alpha. In this environment, it is difficult for a fund manager to beat other active managers. Thus, outperformance relative to other managers can serve as a signal of skill. Our evidence is consistent with this view. The broader point of these results is that peer comparisons provide unique signals of manager talent. The extension of these methods to other asset classes or other types of funds represents an interesting avenue for future research.

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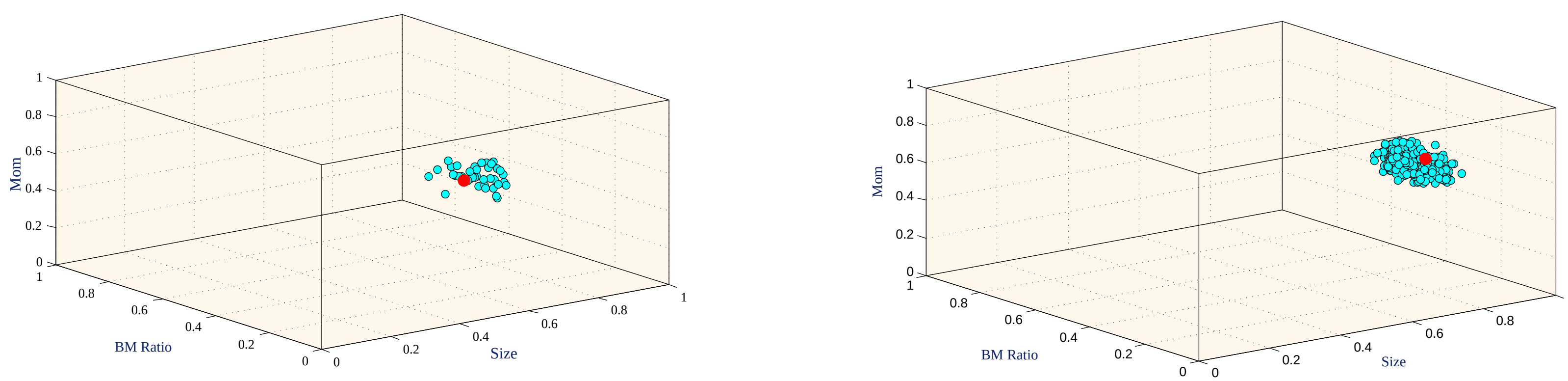
Figure 1: **Visualizing fund competition in the style space**
This figure shows spatial locations of two funds and their peers in the style space for 2005:Q4.



(a) Fund in low competition space

(b) Fund in high competition space

Figure 2: **Understanding fund competition: transitivity**
This figure illustrates that peer information is lost by imposing transitivity constraint.

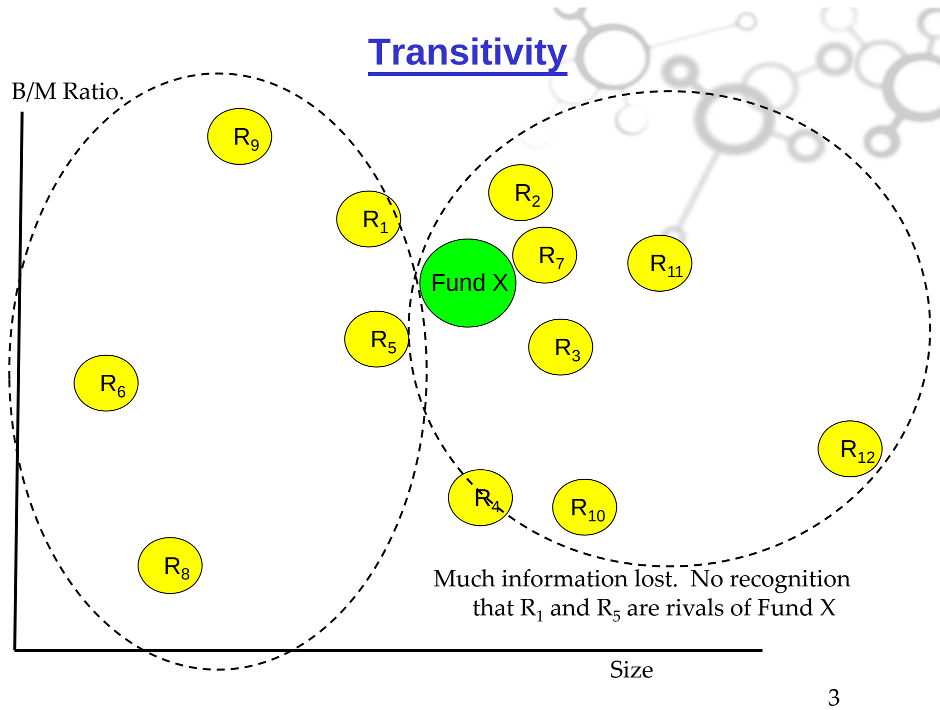


Figure 3: **Similarity distribution for customized peers, Lipper peers, and randomly drawn funds**

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.

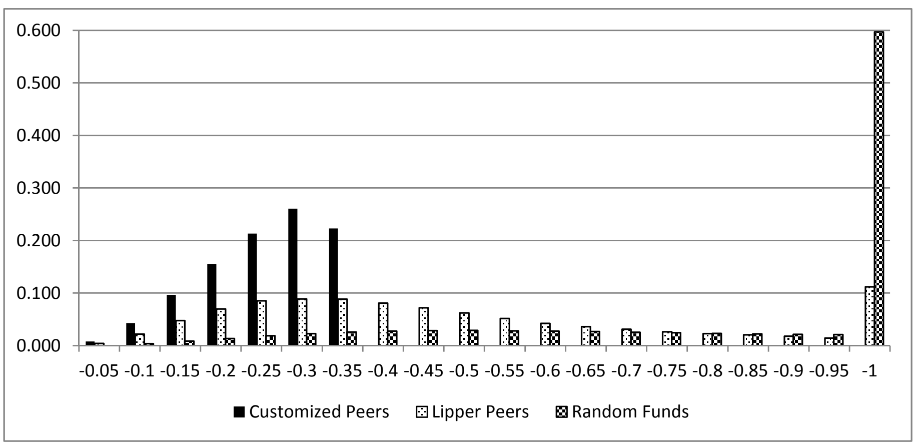


Figure 4: **Similarity distribution for customized peers in a given quarter compared to the distribution of similarities for one-quarter lagged customized peers (upper panel) and one year lagged customized peers (lower panel)**
All similarities are computed for the year 2003 for a pair of funds, and 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.

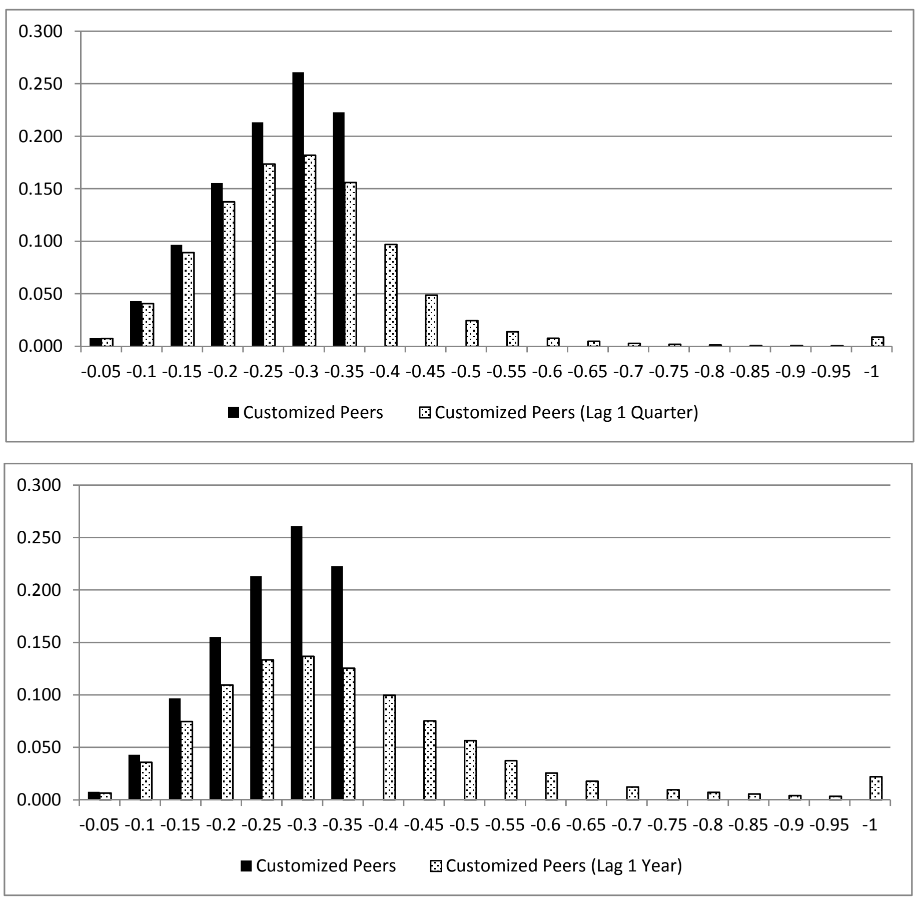


Figure 5: **Cumulative Trade Imbalance for low and high competition markets** The figure reports cumulative trade imbalance for extreme-winner stocks in low competition (solid line) and high competition (dotted line) markets. The extreme-winner stocks are the top decile stocks in the portfolio of funds that were in the top decile of performance in a given year. For these stocks, we report cumulative trade imbalance over the 12 quarter period beginning four quarters before these extreme winners experience their run-up in value. The figure thus shows the accumulation of trade imbalance before, during and after run-ups. We report the contributions to trade imbalance of the focal funds themselves, its rival funds, the rivals of its rivals, and the remaining set of non-competing funds.

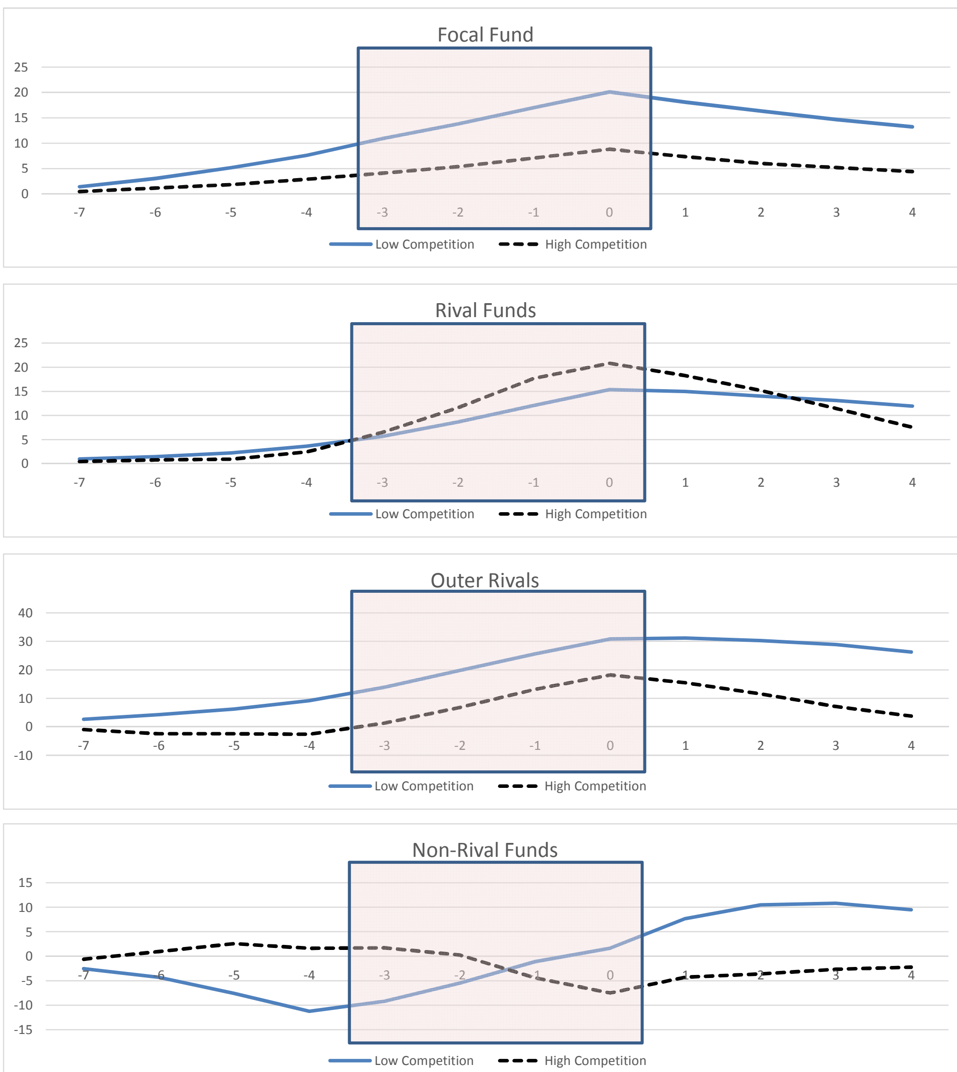


TABLE 1: **Summary Statistics**

We report descriptive statistics for our sample. For select years, we report averages of the 12-monthly observations per year of fund-month observations of total net assets (TNA), fund age, expense ratio, turnover ratio and raw return. For the full period, statistics are averages of all such annual averages. *Nfunds* represents average number of funds in the sample per year. *Total Funds* represents total unique funds in the sample.

Mean Statistics By Year						
Year	Nfunds	TNA ($M)	Fund Age (Years)	Expense Ratio (%)	Turnover Ratio (%)	Raw Ret (%)
1985	292	292	21.347	0.977	0.736	2.271
1990	494	348	18.167	1.272	0.767	-0.530
1995	1125	652	12.371	1.277	0.857	2.231
2000	1615	1466	11.348	1.300	0.995	0.007
2005	1855	1299	13.105	1.324	0.869	0.568
2010	1733	1220	15.877	1.241	0.935	1.514
1980-2012	1110	800	15.907	1.197	0.856	0.998
Total Funds	3390					

TABLE 2: **Fund Peer Comparisons**

This table compares peers from our approach with Lipper peers as well as our peers with once-lagged peers for the sample of all active mutual funds from 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: Predicting Future Alpha: Unconditional Results

This table reports future Characteristic-Selectivity (CS) alphas for 10 deciles of past CS alphas and past customized peer alpha *(CPA)*. 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* alpha over the next three months after portfolio formation. Portfolios are updated every quarter in this fashion and the table reports the average portfolio alpha over the entire time-series. The 6- and 12-month portfolio results are obtained similarly but portfolios are updated at the relevant lower frequencies. The 10-1 decile spread is the zero-investment long-short portfolio that is long on decile ten and short on decile one. Returns are annualized. p-values are reported in parentheses.

	3 Month		6 Month		12 Month	
Decile	CS	CPA	CS	CPA	CS	CPA
1	-0.478	-0.757	-0.332	-0.690	0.148	-0.098
	(0.529)	(0.287)	(0.625)	(0.285)	(0.834)	(0.876)
2	-0.027	0.101	0.063	-0.032	0.480	0.266
	(0.956)	(0.812)	(0.889)	(0.937)	(0.305)	(0.523)
3	0.428	-0.117	0.460	0.168	0.579	0.229
	(0.271)	(0.749)	(0.225)	(0.636)	(0.111)	(0.520)
4	0.008	0.123	0.134	0.266	0.387	0.261
	(0.981)	(0.723)	(0.682)	(0.431)	(0.239)	(0.451)
5	0.350	0.488	0.441	0.540	0.350	0.537
	(0.248)	(0.128)	(0.198)	(0.089)	(0.267)	(0.087)
6	0.586	0.583	0.483	0.476	0.388	0.262
	(0.040)	(0.052)	(0.088)	(0.152)	(0.170)	(0.400)
7	0.510	0.707	0.450	0.523	0.541	0.445
	(0.113)	(0.020)	(0.163)	(0.085)	(0.089)	(0.183)
8	0.599	0.842	0.610	1.082	0.421	0.946
	(0.096)	(0.013)	(0.093)	(0.002)	(0.249)	(0.009)
9	1.132	1.109	1.069	0.990	0.738	0.600
	(0.011)	(0.006)	(0.012)	(0.008)	(0.076)	(0.119)
10	1.858	1.887	1.805	1.884	1.113	1.694
	(0.014)	(0.002)	(0.011)	(0.002)	(0.120)	(0.005)
10-1	2.336	2.644	2.138	2.574	0.965	1.792
	(0.045)	(0.004)	(0.035)	(0.002)	(0.348)	(0.023)

TABLE 4: **Competition and Persistency**

This table reports future Characteristic-Selectivity *(CS)* alphas for decile portfolios based on past customized peer alpha *(CPA)* further classified into high, low, and medium levels of competition. Panel A shows results when competition is measured by the average number of customized peers *(NPeers)* over the past 12 months, while Panel B shows results when competition is measured by average of *Total Similarity* between a fund and its customized peers over the past 12 months. At the start of each calendar quarter, we first sort funds into terciles by competition measures. 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 annualized. p-values are reported in parentheses.

Panel A: Competition and Persistency (NPeers)									
	3 Month			6 Month			12 Month		
Decile	Low	Med	High	Low	Med	High	Low	Med	High
1	-0.843	-0.873	-0.804	-0.901	-0.735	-0.687	-0.354	-0.176	-0.629
	(0.441)	(0.198)	(0.072)	(0.368)	(0.234)	(0.100)	(0.718)	(0.769)	(0.132)
2	0.275	-0.031	-0.261	0.169	0.115	-0.422	1.079	0.344	-0.176
	(0.682)	(0.950)	(0.455)	(0.801)	(0.813)	(0.205)	(0.122)	(0.467)	(0.577)
3	0.388	-0.194	0.046	0.383	0.005	0.083	-0.004	0.119	0.304
	(0.503)	(0.668)	(0.885)	(0.513)	(0.991)	(0.784)	(0.995)	(0.794)	(0.368)
4	0.369	-0.214	0.372	0.639	0.174	0.263	0.513	0.013	0.513
	(0.545)	(0.585)	(0.194)	(0.275)	(0.657)	(0.339)	(0.376)	(0.974)	(0.093)
5	1.318	-0.157	0.330	1.460	0.215	0.336	0.970	0.572	0.440
	(0.021)	(0.704)	(0.254)	(0.011)	(0.594)	(0.276)	(0.089)	(0.140)	(0.132)
6	0.808	0.254	0.161	0.637	0.045	0.038	0.831	0.053	0.044
	(0.136)	(0.487)	(0.562)	(0.248)	(0.911)	(0.903)	(0.107)	(0.900)	(0.870)
7	1.478	1.084	0.421	1.490	0.951	0.022	0.908	0.768	-0.251
	(0.009)	(0.002)	(0.150)	(0.014)	(0.011)	(0.940)	(0.150)	(0.084)	(0.405)
8	1.296	0.931	0.620	1.613	1.087	0.811	1.531	1.359	0.225
	(0.036)	(0.016)	(0.048)	(0.006)	(0.006)	(0.007)	(0.010)	(0.001)	(0.461)
9	1.857	1.039	0.328	1.694	0.880	0.214	1.231	0.518	0.308
	(0.009)	(0.027)	(0.307)	(0.023)	(0.037)	(0.496)	(0.109)	(0.223)	(0.318)
10	3.643	1.008	0.158	3.389	1.190	0.385	2.527	1.310	0.240
	(0.000)	(0.075)	(0.671)	(0.000)	(0.032)	(0.325)	(0.004)	(0.011)	(0.540)
10-1	4.486	1.881	0.963	4.290	1.925	1.072	2.882	1.486	0.869
	(0.001)	(0.040)	(0.100)	(0.000)	(0.019)	(0.061)	(0.013)	(0.067)	(0.124)

Panel B: Competition and Persistency (Total Similarity)									
	3 Month			6 Month			12 Month		
Decile	Low	Med	High	Low	Med	High	Low	Med	High
1	-0.829	-0.788	-0.842	-0.731	-0.815	-0.610	-0.242	-0.335	-0.586
	(0.446)	(0.244)	(0.058)	(0.465)	(0.193)	(0.142)	(0.808)	(0.584)	(0.156)
2	0.383	-0.141	-0.253	0.333	-0.028	-0.484	1.004	0.389	-0.156
	(0.565)	(0.771)	(0.469)	(0.611)	(0.954)	(0.144)	(0.138)	(0.403)	(0.620)
3	0.096	-0.005	0.077	0.057	0.098	0.229	0.208	0.255	0.410
	(0.870)	(0.991)	(0.800)	(0.922)	(0.826)	(0.450)	(0.731)	(0.585)	(0.219)
4	0.366	-0.131	0.500	0.622	0.060	0.293	0.375	0.004	0.414
	(0.550)	(0.744)	(0.079)	(0.303)	(0.873)	(0.292)	(0.508)	(0.992)	(0.172)
5	1.095	-0.067	0.132	1.383	0.439	0.245	1.082	0.489	0.442
	(0.047)	(0.863)	(0.655)	(0.013)	(0.278)	(0.423)	(0.060)	(0.194)	(0.140)
6	1.057	0.266	0.240	0.774	0.036	0.029	0.734	0.030	0.095
	(0.057)	(0.477)	(0.381)	(0.173)	(0.933)	(0.925)	(0.149)	(0.945)	(0.719)
7	1.336	0.922	0.430	1.379	0.905	0.103	0.684	1.007	-0.314
	(0.018)	(0.010)	(0.134)	(0.019)	(0.016)	(0.733)	(0.287)	(0.020)	(0.287)
8	1.374	0.828	0.462	1.729	0.994	0.759	1.615	1.231	0.227
	(0.023)	(0.038)	(0.146)	(0.003)	(0.012)	(0.011)	(0.007)	(0.002)	(0.457)
9	1.827	1.033	0.479	1.596	0.790	0.253	1.232	0.421	0.397
	(0.010)	(0.022)	(0.146)	(0.033)	(0.058)	(0.424)	(0.113)	(0.328)	(0.210)
10	3.597	1.066	0.222	3.345	1.413	0.347	2.418	1.426	0.298
	(0.000)	(0.052)	(0.566)	(0.000)	(0.010)	(0.379)	(0.005)	(0.006)	(0.448)
10-1	4.426	1.854	1.064	4.076	2.228	0.958	2.660	1.761	0.884
	(0.001)	(0.040)	(0.078)	(0.001)	(0.008)	(0.095)	(0.020)	(0.035)	(0.116)

TABLE 5: **Competition and Persistency By AUM**

This table reports future Characteristic-Selectivity *(CS)* alphas for quintile portfolios based on past customized peer alpha *(CPA)* further classified by fund size, or Assets Under Management (AUM), and by levels of competition. Panel A shows results when competition is measured by the average number of customized peers *(NPeers)* over the past 12 months, while Panel B shows results when competition is measured by average of *Total Similarity* between a fund and its customized peers over the past 12 months. At the start of each calendar quarter, we first sort funds into small and large categories based on the median fund size cutoff. Then, funds are further sorted into terciles by competition measures. These terciles are represented by *Low*, *Med* and *High*. Finally, we sort funds into quintiles 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. 5-1 represents zero-investment long-short portfolio that is long on quintile five and short on quintile one. Returns are annualized. p-values are reported in parentheses.

Panel A: Competition (NPeers)

	Small				Large			
Quintile	Low	Med	High	Low-High	Low	Med	High	Low-High
1	-0.517	-0.566	-0.369	-0.149	-0.138	-0.179	-0.571	0.433
	(0.579)	(0.358)	(0.340)	(0.852)	(0.866)	(0.758)	(0.155)	(0.545)
2	0.506	0.175	0.183	0.323	0.126	-0.233	-0.043	0.168
	(0.440)	(0.720)	(0.560)	(0.605)	(0.832)	(0.578)	(0.894)	(0.745)
3	1.247	0.133	-0.127	1.374	0.965	-0.018	0.512	0.452
	(0.020)	(0.768)	(0.658)	(0.011)	(0.051)	(0.958)	(0.090)	(0.342)
4	1.708	0.583	0.458	1.250	0.879	0.984	0.715	0.164
	(0.010)	(0.149)	(0.121)	(0.039)	(0.144)	(0.005)	(0.023)	(0.766)
5	3.076	1.017	0.670	2.406	2.560	1.052	0.086	2.474
	(0.000)	(0.037)	(0.071)	(0.001)	(0.002)	(0.031)	(0.811)	(0.001)
5-1	3.593	1.583	1.039	2.555	2.698	1.231	0.657	2.041
	(0.001)	(0.033)	(0.040)	(0.006)	(0.006)	(0.077)	(0.200)	(0.011)

Panel B: Competition (Total Similarity)

	Small				Large			
Quintile	Low	Med	High	Low-High	Low	Med	High	Low-High
1	-0.420	-0.670	-0.372	-0.048	-0.242	-0.082	-0.528	0.286
	(0.651)	(0.292)	(0.340)	(0.953)	(0.767)	(0.888)	(0.192)	(0.688)
2	0.594	0.162	0.139	0.455	0.145	-0.303	0.032	0.113
	(0.356)	(0.735)	(0.655)	(0.462)	(0.801)	(0.471)	(0.919)	(0.826)
3	1.052	0.210	-0.044	1.096	1.069	-0.095	0.555	0.515
	(0.054)	(0.622)	(0.878)	(0.045)	(0.035)	(0.791)	(0.056)	(0.276)
4	1.665	0.631	0.479	1.186	0.789	1.075	0.611	0.177
	(0.011)	(0.123)	(0.109)	(0.052)	(0.188)	(0.002)	(0.059)	(0.745)
5	2.964	1.190	0.546	2.417	2.513	1.049	0.159	2.355
	(0.000)	(0.016)	(0.137)	(0.001)	(0.003)	(0.030)	(0.669)	(0.002)
5-1	3.383	1.859	0.918	2.465	2.755	1.131	0.687	2.069
	(0.002)	(0.014)	(0.075)	(0.007)	(0.005)	(0.103)	(0.188)	(0.011)

TABLE 6: **Competition and Persistency By Market Size**

This table reports future Characteristic-Selectivity *(CS)* alphas for quintile portfolios based on past customized peer alpha *(CPA)* further classified by market size, and by levels of competition. Panel A shows results when competition is measured by the average number of customized peers *(NPeers)* over the past 12 months, while Panel B shows results when competition is measured by average of *Total Similarity* between a fund and its customized peers over the past 12 months. At the start of each calendar quarter, we first sort funds into small and large market size categories based on the median market size cutoff. Then, funds are further sorted into terciles by competition measures. These terciles are represented by *Low*, *Med* and *High*. Finally, we sort funds into quintiles 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. 5-1 represents zero-investment long-short portfolio that is long on quintile five and short on quintile one. Returns are annualized. p-values are reported in parentheses.

Panel A: Competition (NPeers)

	Small				Large			
Quintile	Low	Med	High	Low-High	Low	Med	High	Low-High
1	-0.775	-0.429	-0.258	-0.517	0.134	-0.380	-0.551	0.686
	(0.431)	(0.502)	(0.634)	(0.518)	(0.857)	(0.397)	(0.111)	(0.340)
2	-0.045	0.287	0.280	-0.325	0.779	-0.246	0.118	0.662
	(0.940)	(0.579)	(0.518)	(0.565)	(0.214)	(0.476)	(0.685)	(0.278)
3	0.927	0.143	0.225	0.702	1.066	0.747	0.255	0.811
	(0.073)	(0.750)	(0.588)	(0.170)	(0.075)	(0.027)	(0.372)	(0.179)
4	0.773	0.685	0.593	0.180	1.894	0.613	0.258	1.635
	(0.165)	(0.119)	(0.155)	(0.760)	(0.003)	(0.097)	(0.364)	(0.010)
5	2.173	1.230	0.389	1.783	3.128	0.786	0.460	2.668
	(0.004)	(0.025)	(0.406)	(0.015)	(0.000)	(0.084)	(0.133)	(0.002)
5-1	2.948	1.659	0.647	2.301	2.994	1.165	1.012	1.982
	(0.015)	(0.035)	(0.279)	(0.019)	(0.001)	(0.040)	(0.011)	(0.009)

Panel B: Competition (Total Similarity)

	Small				Large			
Quintile	Low	Med	High	Low-High	Low	Med	High	Low-High
1	-0.837	-0.526	-0.164	-0.672	0.184	-0.318	-0.512	0.695
	(0.398)	(0.416)	(0.765)	(0.399)	(0.810)	(0.483)	(0.146)	(0.330)
2	-0.129	0.461	0.117	-0.247	0.838	-0.232	-0.046	0.884
	(0.828)	(0.367)	(0.787)	(0.659)	(0.158)	(0.491)	(0.876)	(0.131)
3	0.997	0.124	0.149	0.848	1.072	0.564	0.291	0.782
	(0.057)	(0.778)	(0.718)	(0.100)	(0.074)	(0.094)	(0.283)	(0.189)
4	0.807	0.773	0.659	0.149	1.809	0.618	0.349	1.460
	(0.138)	(0.082)	(0.113)	(0.796)	(0.004)	(0.089)	(0.211)	(0.022)
5	2.066	1.372	0.334	1.732	3.039	0.927	0.502	2.537
	(0.007)	(0.011)	(0.480)	(0.017)	(0.000)	(0.046)	(0.103)	(0.003)
5-1	2.902	1.899	0.498	2.404	2.855	1.245	1.014	1.841
	(0.017)	(0.015)	(0.416)	(0.013)	(0.001)	(0.029)	(0.010)	(0.013)

TABLE 7: **Competition and Persistency By Style Classes**

This table reports future Characteristic-Selectivity *(CS)* alphas for quintile portfolios based on past customized peer alpha *(CPA)*, further classified by style and by levels of competition. We measure competition by the average number of customized peers *(NPeers)* over the past 12 months. Style is measured by orthognalized z-scores as described in the text. At the start of each calendar quarter, we first sort funds by median size, book-to-market ratio, and momentum z-score, in panels A, B and C, respectively. Then, funds are further sorted into terciles by the competition measure. These terciles are represented by *Low*, *Med* and *High*. Finally, we sort funds into quintiles 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. 5-1 represents zero-investment long-short portfolio that is long on quintile five and short on quintile one. Returns are annualized. p-values are reported in parentheses.

Panel A: Size

	Small				Large			
Quintile	Low	Med	High	Low-High	Low	Med	High	Low-High
1	-0.864	-0.145	-0.500	-0.364	-0.282	-0.464	-0.264	-0.018
	(0.390)	(0.851)	(0.407)	(0.650)	(0.611)	(0.247)	(0.479)	(0.973)
2	0.346	0.956	0.146	0.200	-0.287	0.065	0.061	-0.347
	(0.596)	(0.110)	(0.768)	(0.743)	(0.459)	(0.830)	(0.835)	(0.356)
3	0.722	1.044	0.363	0.360	-0.117	0.305	0.125	-0.243
	(0.269)	(0.052)	(0.439)	(0.561)	(0.731)	(0.321)	(0.625)	(0.516)
4	1.318	1.444	1.037	0.281	0.817	0.451	0.482	0.335
	(0.055)	(0.008)	(0.030)	(0.702)	(0.046)	(0.139)	(0.097)	(0.399)
5	2.420	2.103	1.050	1.370	1.740	0.624	0.161	1.580
	(0.006)	(0.001)	(0.029)	(0.079)	(0.007)	(0.101)	(0.634)	(0.012)
5-1	3.284	2.248	1.549	1.734	2.022	1.088	0.424	1.598
	(0.004)	(0.007)	(0.022)	(0.064)	(0.015)	(0.051)	(0.338)	(0.023)

Panel B: BM Ratio

	Growth				Value			
Quintile	Low	Med	High	Low-High	Low	Med	High	Low-High
1	-0.426	-0.462	-0.445	0.020	-0.030	-0.433	-0.313	0.282
	(0.701)	(0.553)	(0.464)	(0.981)	(0.964)	(0.338)	(0.403)	(0.662)
2	0.126	0.426	-0.004	0.130	0.370	-0.132	-0.005	0.375
	(0.881)	(0.507)	(0.992)	(0.843)	(0.460)	(0.691)	(0.985)	(0.388)
3	1.221	0.803	0.223	0.998	0.347	0.081	0.164	0.184
	(0.132)	(0.166)	(0.601)	(0.119)	(0.380)	(0.789)	(0.522)	(0.653)
4	1.446	1.126	0.407	1.039	0.963	0.424	0.599	0.364
	(0.113)	(0.063)	(0.352)	(0.175)	(0.018)	(0.155)	(0.034)	(0.381)
5	2.579	2.176	1.051	1.528	2.087	0.512	0.080	2.006
	(0.019)	(0.002)	(0.035)	(0.077)	(0.000)	(0.212)	(0.814)	(0.000)
5-1	3.004	2.637	1.496	1.508	2.117	0.945	0.393	1.724
	(0.010)	(0.001)	(0.024)	(0.076)	(0.017)	(0.122)	(0.390)	(0.032)

Panel C: Momentum

	Low Momentum				High Momentum			
Quintile	Low	Med	High	Low-High	Low	Med	High	Low-High
1	-1.065	-0.566	-0.400	-0.666	-0.312	0.138	0.287	-0.599
	(0.336)	(0.253)	(0.301)	(0.485)	(0.713)	(0.851)	(0.542)	(0.391)
2	0.126	-0.726	-0.005	0.130	0.786	0.497	0.214	0.572
	(0.851)	(0.041)	(0.988)	(0.820)	(0.288)	(0.402)	(0.623)	(0.324)
3	-0.018	0.279	0.308	-0.326	0.853	1.298	0.687	0.166
	(0.975)	(0.417)	(0.252)	(0.518)	(0.212)	(0.025)	(0.092)	(0.767)
4	0.501	0.210	0.160	0.341	1.730	1.302	0.857	0.874
	(0.312)	(0.470)	(0.563)	(0.468)	(0.035)	(0.028)	(0.059)	(0.191)
5	1.296	-0.072	0.318	0.978	3.170	2.132	0.875	2.296
	(0.006)	(0.827)	(0.277)	(0.050)	(0.001)	(0.002)	(0.094)	(0.004)
5-1	2.361	0.494	0.717	1.644	3.483	1.993	0.588	2.895
	(0.019)	(0.339)	(0.091)	(0.060)	(0.000)	(0.007)	(0.247)	(0.000)

TABLE 8: Competition and Persistency By Flow Levels

This table reports future Characteristic-Selectivity *(CS)* alphas for quintile portfolios based on past customized peer alpha *(CPA)*, further classified by fund flows and by levels of competition. Panel A shows results when competition is measured by the average number of customized peers *(NPeers)* over the past 12 months, while Panel B shows results when competition is measured by average of *Total Similarity* between a fund and its customized peers over the past 12 months. At the start of each calendar quarter, we first sort funds into low and high flow categories based on the median flow cutoff. Then, funds are further sorted into terciles by competition measures. These terciles are represented by *Low*, *Med* and *High*. Finally, we sort funds into quintiles 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. 5-1 represents zero-investment long-short portfolio that is long on quintile five and short on quintile one. Returns are annualized. p-values are reported in parentheses.

Panel A: Competition (NPeers)

	Low				High			
Quintile	Low	Med	High	Low-High	Low	Med	High	Low-High
1	-1.143	-0.796	-0.495	-0.648	0.613	-0.368	-0.491	1.104
	(0.358)	(0.316)	(0.306)	(0.521)	(0.463)	(0.502)	(0.174)	(0.138)
2	0.168	0.192	-0.040	0.207	0.217	0.049	0.113	0.104
	(0.821)	(0.732)	(0.909)	(0.744)	(0.738)	(0.908)	(0.676)	(0.871)
3	-0.078	-0.154	-0.024	-0.055	0.651	0.594	0.332	0.320
	(0.911)	(0.749)	(0.940)	(0.931)	(0.289)	(0.127)	(0.209)	(0.582)
4	0.535	0.024	0.335	0.200	1.226	0.979	0.183	1.043
	(0.337)	(0.955)	(0.245)	(0.703)	(0.107)	(0.032)	(0.520)	(0.179)
5	1.164	0.667	0.138	1.027	3.155	1.433	0.152	3.003
	(0.178)	(0.159)	(0.657)	(0.224)	(0.003)	(0.012)	(0.676)	(0.002)
5-1	2.308	1.463	0.633	1.675	2.542	1.802	0.643	1.899
	(0.073)	(0.063)	(0.243)	(0.104)	(0.015)	(0.023)	(0.213)	(0.023)

Panel B: Competition (Total Similarity)

	Low				High			
Quintile	Low	Med	High	Low-High	Low	Med	High	Low-High
1	-1.205	-0.696	-0.546	-0.660	0.617	-0.402	-0.492	1.109
	(0.335)	(0.382)	(0.271)	(0.514)	(0.461)	(0.467)	(0.178)	(0.135)
2	0.136	0.124	-0.076	0.212	0.230	0.005	0.115	0.115
	(0.853)	(0.828)	(0.824)	(0.736)	(0.719)	(0.990)	(0.671)	(0.857)
3	-0.110	0.015	0.062	-0.173	0.569	0.812	0.325	0.244
	(0.876)	(0.976)	(0.839)	(0.787)	(0.352)	(0.037)	(0.213)	(0.675)
4	0.643	-0.035	0.281	0.362	1.222	0.844	0.177	1.046
	(0.251)	(0.934)	(0.335)	(0.505)	(0.104)	(0.070)	(0.525)	(0.168)
5	0.947	0.773	0.200	0.746	3.082	1.556	0.174	2.908
	(0.276)	(0.105)	(0.516)	(0.378)	(0.004)	(0.008)	(0.636)	(0.003)
5-1	2.152	1.469	0.746	1.406	2.465	1.958	0.666	1.799
	(0.093)	(0.065)	(0.179)	(0.165)	(0.019)	(0.014)	(0.206)	(0.029)

TABLE 9: Value Added By Competition Levels

This table reports future value added for quintile portfolios based on past customized peer alpha *(CPA)*, controlling for fund size, for competition tercile subsamples. Panel A shows results when competition is measured by the average number of customized peers *(NPeers)* over the past 12 months, while Panel B shows results when competition is measured by average of *Total Similarity* between a fund and its customized peers over the past 12 months. At the start of each calendar quarter, we first sort funds into small and large fund categories based on the median size cutoff. Then, funds are further sorted into terciles by competition measures. These terciles are represented by *Low*, *Med* and *High*. Finally, we sort funds into quintiles based on the past 12 months average *CPA* performance to arrive at 30 portfolios. Next, we obtain median value added over the next three months after portfolio formation, and then re-balance the portfolios. Finally, we obtain average monthly value added post-ranking portfolio performance by taking average over the entire time-series. 5-1 represents zero-investment long-short portfolio that is long on quintile five and short on quintile one. Value added is annualized. p-values are reported in parentheses.

Panel A: Competition (NPeers)

	Small				Large			
Quintile	Low	Med	High	Low-High	Low	Med	High	Low-High
1	-0.716	-0.762	-0.570	-0.146	-4.842	-2.275	-5.340	0.498
	(0.125)	(0.064)	(0.021)	(0.705)	(0.381)	(0.532)	(0.145)	(0.919)
2	0.115	-0.095	-0.157	0.271	-0.392	-3.294	-3.979	3.586
	(0.791)	(0.770)	(0.419)	(0.489)	(0.921)	(0.292)	(0.199)	(0.427)
3	0.550	0.064	-0.211	0.761	4.492	-0.747	-0.362	4.855
	(0.169)	(0.864)	(0.259)	(0.065)	(0.136)	(0.800)	(0.884)	(0.131)
4	0.527	0.107	0.058	0.469	2.831	2.939	2.239	0.593
	(0.260)	(0.738)	(0.781)	(0.296)	(0.473)	(0.380)	(0.380)	(0.887)
5	1.918	0.642	0.147	1.771	10.172	5.769	-1.079	11.250
	(0.001)	(0.059)	(0.550)	(0.002)	(0.060)	(0.129)	(0.729)	(0.038)
5-1	2.634	1.403	0.717	1.917	15.014	8.044	4.262	10.752
	(0.000)	(0.006)	(0.033)	(0.001)	(0.020)	(0.107)	(0.349)	(0.034)

Panel B: Competition (Total Similarity)

	Small				Large			
Quintile	Low	Med	High	Low-High	Low	Med	High	Low-High
1	-0.685	-0.723	-0.545	-0.140	-5.040	-2.925	-4.645	-0.395
	(0.146)	(0.090)	(0.034)	(0.730)	(0.358)	(0.434)	(0.196)	(0.935)
2	0.230	-0.135	-0.153	0.384	0.360	-3.714	-3.783	4.143
	(0.561)	(0.672)	(0.413)	(0.291)	(0.922)	(0.230)	(0.216)	(0.337)
3	0.505	-0.045	-0.145	0.650	4.315	-1.338	-0.053	4.368
	(0.207)	(0.901)	(0.432)	(0.116)	(0.154)	(0.629)	(0.983)	(0.190)
4	0.576	0.111	0.099	0.477	2.121	3.562	1.610	0.511
	(0.238)	(0.729)	(0.647)	(0.299)	(0.592)	(0.278)	(0.551)	(0.902)
5	1.923	0.846	0.148	1.775	10.239	4.617	-1.075	11.314
	(0.001)	(0.013)	(0.542)	(0.001)	(0.058)	(0.201)	(0.744)	(0.041)
5-1	2.608	1.569	0.693	1.915	15.279	7.543	3.570	11.709
	(0.000)	(0.002)	(0.046)	(0.002)	(0.018)	(0.130)	(0.437)	(0.026)

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 deciles 1 and 10, 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*. $ExpRatio_t$ and $TurnRatio_t$ represent the expense ratio and turnover ratio at the end of month *t*, respectively. $LogFundAge_t$ and $LogFundSize_t$ represent natural logarithm of fund age (years) and fund size ($millions) at the end of month *t*, respectively. $Flow_t$ represents monthly flow in month *t*. $StdDev_{t\text{-}11,t}$ is the standard deviation of monthly raw returns over the months *t-11* to *t*. $LogFamSize_t$ represents natural logarithm of family size ($millions) at the end of month *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	-0.138	-0.713	-0.715	-0.211	0.435	0.427	-0.245	0.027	0.023
	(0.350)	(0.116)	(0.116)	(0.070)	(0.000)	(0.000)	(0.002)	(0.862)	(0.881)
CPA_Decile1	-0.080	-0.030	-0.010	-0.071	-0.048	-0.042	-0.046	-0.043	-0.039
	(0.008)	(0.339)	(0.777)	(0.000)	(0.026)	(0.067)	(0.001)	(0.004)	(0.012)
CPA_Decile10	0.187	0.168	0.147	0.057	0.072	0.065	-0.025	-0.024	-0.028
	(0.000)	(0.000)	(0.000)	(0.006)	(0.002)	(0.006)	(0.048)	(0.090)	(0.058)
$CS_{t\text{-}11,t}$			0.029			0.012			0.011
			(0.074)			(0.458)			(0.520)
$ExpRatio_t$		0.035	0.034		-0.008	-0.008		0.013	0.013
		(0.154)	(0.160)		(0.618)	(0.618)		(0.217)	(0.214)
$TurnRatio_t$		0.007	0.007		-0.001	-0.000		-0.017	-0.016
		(0.531)	(0.533)		(0.933)	(0.976)		(0.024)	(0.027)
$LogFundAge_t$		0.011	0.011		0.017	0.017		0.006	0.006
		(0.424)	(0.412)		(0.050)	(0.051)		(0.264)	(0.260)
$LogFundSize_t$		-0.003	-0.005		-0.006	-0.006		-0.003	-0.003
		(0.619)	(0.473)		(0.227)	(0.214)		(0.377)	(0.363)
$Flow_t$		0.008	0.008		0.003	0.003		0.001	0.001
		(0.000)	(0.000)		(0.030)	(0.042)		(0.461)	(0.505)
$StdDev_{t\text{-}11,t}$		-3.043	-3.059		-3.933	-3.891		-2.008	-1.966
		(0.000)	(0.000)		(0.000)	(0.000)		(0.005)	(0.007)
$LogFamSize_t$		-0.000	0.000		0.004	0.004		-0.001	-0.001
		(0.920)	(0.973)		(0.264)	(0.253)		(0.716)	(0.737)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	35734	29277	29277	35794	29057	29057	35752	29151	29151
AdjRSQ	0.081	0.076	0.076	0.065	0.066	0.066	0.061	0.064	0.064

Panel B: Dep Var = $CS_{t+1,t+6}$									
	Low			Med			High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.118	0.137	0.133	-0.011	0.096	0.085	-0.039	-0.304	-0.297
	(0.291)	(0.671)	(0.685)	(0.881)	(0.018)	(0.045)	(0.548)	(0.102)	(0.114)
CPA_Decile1	-0.083	-0.012	0.022	-0.078	-0.054	-0.046	-0.034	-0.029	-0.035
	(0.007)	(0.701)	(0.511)	(0.000)	(0.017)	(0.051)	(0.019)	(0.057)	(0.024)
CPA_Decile10	0.158	0.154	0.119	0.060	0.064	0.055	-0.015	-0.013	-0.006
	(0.000)	(0.000)	(0.001)	(0.004)	(0.005)	(0.019)	(0.283)	(0.402)	(0.714)
$CS_{t-11,t}$			0.048			0.015			-0.019
			(0.004)			(0.357)			(0.260)
$ExpRatio_t$		0.039	0.038		-0.001	-0.001		0.012	0.012
		(0.125)	(0.126)		(0.958)	(0.959)		(0.249)	(0.258)
$TurnRatio_t$		0.011	0.011		0.000	0.001		-0.021	-0.021
		(0.330)	(0.330)		(0.985)	(0.922)		(0.005)	(0.004)
$LogFundAge_t$		0.004	0.004		0.013	0.012		0.003	0.003
		(0.788)	(0.770)		(0.157)	(0.163)		(0.558)	(0.566)
$LogFundSize_t$		-0.004	-0.006		-0.005	-0.005		-0.002	-0.002
		(0.594)	(0.381)		(0.357)	(0.336)		(0.519)	(0.548)
$Flow_t$		0.004	0.003		0.004	0.003		0.000	0.000
		(0.017)	(0.059)		(0.017)	(0.025)		(0.878)	(0.783)
$StdDev_{t-11,t}$		-3.889	-3.922		-3.908	-3.855		-1.438	-1.527
		(0.000)	(0.000)		(0.000)	(0.000)		(0.051)	(0.041)
$LogFamSize_t$		0.003	0.004		0.001	0.001		-0.001	-0.002
		(0.614)	(0.448)		(0.699)	(0.674)		(0.531)	(0.500)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	17844	14605	14605	17879	14515	14515	17856	14576	14576
AdjRSQ	0.067	0.072	0.072	0.051	0.057	0.057	0.054	0.059	0.059

Panel C: Dep Var = $CS_{t+1,t+12}$									
	Low			Med			High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.178	-0.085	-0.317	-0.092	0.401	0.418	-0.026	0.011	0.025
	(0.012)	(0.163)	(0.000)	(0.102)	(0.000)	(0.000)	(0.566)	(0.812)	(0.636)
CPA_Decile1	-0.052	0.016	0.017	-0.019	-0.009	-0.021	-0.018	-0.006	-0.020
	(0.153)	(0.674)	(0.677)	(0.368)	(0.699)	(0.407)	(0.220)	(0.694)	(0.231)
CPA_Decile10	0.111	0.098	0.098	0.062	0.070	0.081	-0.026	-0.022	-0.007
	(0.001)	(0.008)	(0.012)	(0.006)	(0.006)	(0.002)	(0.059)	(0.147)	(0.674)
$CS_{t-11,t}$			0.000			-0.021			-0.040
			(0.979)			(0.240)			(0.021)
$ExpRatio_t$		0.028	0.028		-0.009	-0.008		0.009	0.010
		(0.321)	(0.321)		(0.642)	(0.652)		(0.405)	(0.404)
$TurnRatio_t$		0.014	0.014		-0.009	-0.010		-0.019	-0.021
		(0.275)	(0.275)		(0.419)	(0.368)		(0.020)	(0.014)
$LogFundAge_t$		0.001	0.001		0.009	0.009		0.005	0.005
		(0.946)	(0.946)		(0.352)	(0.341)		(0.310)	(0.315)
$LogFundSize_t$		-0.008	-0.009		-0.008	-0.007		-0.001	-0.000
		(0.264)	(0.264)		(0.171)	(0.189)		(0.858)	(0.906)
$Flow_t$		0.004	0.004		0.001	0.001		-0.001	-0.001
		(0.017)	(0.019)		(0.492)	(0.400)		(0.304)	(0.447)
$StdDev_{t-11,t}$		-2.699	-2.699		-1.488	-1.552		0.152	-0.016
		(0.000)	(0.000)		(0.035)	(0.029)		(0.830)	(0.982)
$LogFamSize_t$		0.006	0.006		-0.002	-0.002		-0.002	-0.002
		(0.274)	(0.274)		(0.642)	(0.614)		(0.508)	(0.458)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9162	7405	7405	9185	7398	7398	9171	7432	7432
AdjRSQ	0.082	0.095	0.095	0.058	0.068	0.069	0.060	0.070	0.071

TABLE 11: **Trade Imbalance**

This table reports trade imbalances of portfolio holdings of funds in low and high competition spaces in Panels A and B, respectively. At the end of each quarter t, we first identify the winner holdings of winner funds. Winner funds are the funds in decile 10 based on past 12-month average CPA performance, and winner holdings are the top decile stocks in a fund's portfolio based on past 12 month's of cumulative return performance. We then divide the fund universe into four groups. Group 4 funds are the winner funds that hold the winner stocks. Group 3 funds are rivals of winner funds. Group 2 funds are the rivals of rivals (outer rivals), and finally group 1 consists of non-rival funds (rest of all funds). We then calculate the trade imbalance in a stock due to the four groups. Trade imbalance in stock i due to the funds in group j at the start of quarter $t+1$ is defined as $TI_{i,j,t+1} = (NBuys_{i,j,t+1} - NSells_{i,j,t+1})/(NBuys_{i,t+1} + NSells_{i,t+1})$, where $NBuys_{i,j,t+1}$ ($NSells_{i,j,t+1}$) is the total number of stock i purchased (sold) by funds in group j at the start of quarter $t+1$. $NBuys_{i,t+1}$ ($NSells_{i,t+1}$) is the total number of stock i purchased (sold) by all funds at the start of quarter $t+1$. We then obtain cross-sectional average of $TI_{i,j,t+1}$ for each group j across all stocks. Finally, we obtain time-series averages of the resulting series. We report these averages in percentage. p-values are reported in parentheses.

Low Competition												
Group	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
1	-2.530	-1.757	-3.302	-3.669	2.074	3.691	4.382	2.748	6.050	2.816	0.332	-1.339
	(0.027)	(0.069)	(0.000)	(0.000)	(0.029)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.616)	(0.034)
2	2.646	1.597	1.983	2.974	4.751	5.864	5.799	5.281	0.285	-0.903	-1.404	-2.634
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.460)	(0.010)	(0.001)	(0.000)
3	0.965	0.480	0.765	1.411	2.058	2.953	3.447	3.272	-0.349	-0.981	-0.942	-1.152
	(0.001)	(0.086)	(0.012)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.172)	(0.000)	(0.000)	(0.000)
4	1.397	1.611	2.167	2.448	3.283	2.905	3.217	3.078	-2.034	-1.734	-1.720	-1.404
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

High Competition												
Group	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
1	-0.609	1.599	1.597	-0.948	0.091	-1.466	-4.653	-3.098	3.240	0.666	0.937	0.436
	(0.538)	(0.145)	(0.135)	(0.345)	(0.926)	(0.175)	(0.000)	(0.003)	(0.001)	(0.451)	(0.333)	(0.705)
2	-1.005	-1.443	0.029	-0.191	3.898	5.500	6.412	5.017	-2.777	-3.858	-4.451	-3.390
	(0.235)	(0.092)	(0.971)	(0.816)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)
3	0.442	0.347	0.150	1.486	4.059	5.097	6.106	3.128	-2.535	-3.123	-3.765	-3.832
	(0.524)	(0.652)	(0.838)	(0.044)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
4	0.443	0.692	0.678	1.047	1.221	1.274	1.713	1.732	-1.476	-1.326	-0.813	-0.804
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

A Appendix

The Appendix reports results of several robustness tests that are briefly described in the text. Additional details are available from the authors upon request.

TABLE A1: Future Carhart Alpha: Unconditional Results

This table reports coefficients from regression of future 4-factor adjusted performance on past customized peer alpha *(CPA)* performance, past Characteristic-Selectivity *(CS)* and other controls. The dependent variable is $Carhart_{t+i,t+j}$, which represents the average 4-factor adjusted performance over the months *t+i* to *t+j*. For each month in *(t+i, t+j)*, we obtain monthly *Carhart* alpha by subtracting the estimated monthly return from the fund's raw return reported in CRSP. We estimate monthly return by multiplying the estimated factor loadings (obtained from past 36 month regression, with a minimum of 30 observations) with factor returns. $CPA_{t\text{-}11,t}$ 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*. $ExpRatio_t$ and $TurnRatio_t$ represent the expense ratio and turnover ratio at the end of month *t*, respectively. $LogFundAge_t$ and $LogFundSize_t$ represent natural logarithm of fund age (years) and fund size ($millions) at the end of month *t*, respectively. $Flow_t$ represents monthly flow in month *t*. $StdDev_{t\text{-}11,t}$ is the standard deviation of monthly raw returns over the months *t-11* to *t*. $LogFamSize_t$ represents natural logarithm of family size ($millions) at the end of month *t*. All regressions include time *t* dummy. *N* and *AdjRSQ* represent number of observations and adjusted-Rsquared. Standard errors are clustered by fund. *p*-values are reported in parentheses.

Dep Var	$Carhart_{t+1,t+3}$				$Carhart_{t+1,t+6}$				$Carhart_{t+1,t+12}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.266	0.261	0.278	1.543	0.148	0.141	0.158	0.642	-0.374	-0.373	-0.367	-0.094
	(0.011)	(0.014)	(0.008)	(0.000)	(0.016)	(0.023)	(0.010)	(0.001)	(0.000)	(0.000)	(0.000)	(0.021)
$CPA_{t\text{-}11,\,t}$	0.070		0.104	0.082	0.072		0.103	0.080	0.040		0.081	0.058
	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
$CS_{t\text{-}11,\,t}$		0.010	-0.053	-0.062		0.014	-0.049	-0.056		-0.015	-0.065	-0.065
		(0.285)	(0.000)	(0.000)		(0.145)	(0.000)	(0.000)		(0.108)	(0.000)	(0.000)
$ExpRatio_t$				-0.058				-0.063				-0.072
				(0.000)				(0.000)				(0.000)
$TurnRatio_t$				-0.017				-0.020				-0.027
				(0.031)				(0.011)				(0.001)
$LogFundAge_t$				-0.008				-0.008				-0.008
				(0.197)				(0.182)				(0.197)
$LogFundSize_t$				-0.019				-0.018				-0.020
				(0.000)				(0.000)				(0.000)
$Flow_t$				0.002				0.001				0.001
				(0.032)				(0.235)				(0.295)
$StdDev_{t\text{-}11,\,t}$				-2.297				-1.838				-1.433
				(0.000)				(0.000)				(0.001)
$LogFamSize_t$				0.009				0.009				0.011
				(0.000)				(0.000)				(0.000)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	104759	104759	104759	85644	52766	52766	52766	43169	27433	27433	27433	22208
AdjRSQ	0.071	0.070	0.071	0.080	0.085	0.083	0.086	0.096	0.093	0.092	0.095	0.112

TABLE A2: Future Pastor-Stambaugh Alpha: Unconditional Results

This table reports coefficients from regression of future 5-factor adjusted performance on past customized peer alpha *(CPA)* performance, past Characteristic-Selectivity *(CS)* and other controls. The dependent variable is $PS_{t+i,t+j}$, which represents the average 5-factor adjusted performance over the months $t+i$ to $t+j$. For each month in $(t+i,\ t+j)$, we obtain monthly *PS* alpha by subtracting the estimated monthly return from the fund's raw return reported in CRSP. We estimate monthly return by multiplying the estimated factor loadings (obtained from past 36 month regression, with a minimum of 30 observations) with factor returns. $CPA_{t\text{-}11,t}$ 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*. $ExpRatio_t$ and $TurnRatio_t$ represent the expense ratio and turnover ratio at the end of month *t*, respectively. $LogFundAge_t$ and $LogFundSize_t$ represent natural logarithm of fund age (years) and fund size ($millions) at the end of month *t*, respectively. $Flow_t$ represents monthly flow in month *t*. $StdDev_{t\text{-}11,t}$ is the standard deviation of monthly raw returns over the months *t-11* to *t*. $LogFamSize_t$ represents natural logarithm of family size ($millions) at the end of month *t*. All regressions include time *t* dummy. *N* and *AdjRSQ* represent number of observations and adjusted-Rsquared. Standard errors are clustered by fund. *p*-values are reported in parentheses.

Dep Var	$PS_{t+1,t+3}$				$PS_{t+1,t+6}$				$PS_{t+1,t+12}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.389	0.380	0.401	1.546	0.243	0.235	0.255	0.591	-0.381	-0.381	-0.375	-0.093
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.014)	(0.000)	(0.000)	(0.000)	(0.015)
$CPA_{t\text{-}11,\ t}$	0.094		0.127	0.106	0.087		0.120	0.101	0.061		0.099	0.076
	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
$CS_{t\text{-}11,\ t}$		0.025	-0.052	-0.060		0.021	-0.053	-0.056		-0.000	-0.061	-0.055
		(0.008)	(0.000)	(0.000)		(0.028)	(0.000)	(0.000)		(0.977)	(0.000)	(0.000)
$ExpRatio_t$				-0.056				-0.063				-0.068
				(0.000)				(0.000)				(0.000)
$TurnRatio_t$				-0.020				-0.022				-0.030
				(0.012)				(0.004)				(0.000)
$LogFundAge_t$				-0.006				-0.006				-0.005
				(0.325)				(0.322)				(0.434)
$LogFundSize_t$				-0.021				-0.020				-0.022
				(0.000)				(0.000)				(0.000)
$Flow_t$				0.002				0.000				0.001
				(0.084)				(0.701)				(0.610)
$StdDev_{t\text{-}11,\ t}$				-2.789				-2.351				-2.356
				(0.000)				(0.000)				(0.000)
$LogFamSize_t$				0.009				0.008				0.011
				(0.000)				(0.001)				(0.000)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	104759	104759	104759	85644	52766	52766	52766	43169	27433	27433	27433	22208
AdjRSQ	0.062	0.060	0.062	0.069	0.063	0.060	0.064	0.070	0.061	0.059	0.063	0.073

TABLE A3: **Future CS Alpha Versus CPA: 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*. $ExpRatio_t$ and $TurnRatio_t$ represent the expense ratio and turnover ratio at the end of month *t*, respectively. $LogFundAge_t$ and $LogFundSize_t$ represent natural logarithm of fund age (years) and fund size ($millions) at the end of month *t*, respectively. $Flow_t$ represents monthly flow in month *t*. $StdDev_{t\text{-}11,t}$ is the standard deviation of monthly raw returns over the months *t-11* to *t*. $LogFamSize_t$ represents natural logarithm of family size ($millions) at the end of month *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	-0.194	-0.209	-0.196	-0.140	0.026	0.010	0.023	-0.164	-0.096	-0.097	-0.093	-0.062
	(0.004)	(0.002)	(0.004)	(0.496)	(0.610)	(0.836)	(0.645)	(0.298)	(0.005)	(0.004)	(0.006)	(0.391)
$CPA_{t\text{-}11,\,t}$	0.083		0.076	0.072	0.083		0.076	0.065	0.046		0.063	0.052
	(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	0.010		0.011	-0.028	-0.030
		(0.000)	(0.299)	(0.708)		(0.000)	(0.306)	(0.403)		(0.224)	(0.010)	(0.013)
$ExpRatio_t$				0.030				0.031				0.023
				(0.006)				(0.004)				(0.048)
$TurnRatio_t$				-0.000				0.001				-0.001
				(0.991)				(0.824)				(0.829)
$LogFundAge_t$				0.006				0.002				0.004
				(0.230)				(0.673)				(0.494)
$LogFundSize_t$				-0.006				-0.005				-0.006
				(0.042)				(0.079)				(0.044)
$Flow_t$				0.004				0.002				0.002
				(0.000)				(0.015)				(0.034)
$StdDev_{t\text{-}11,\,t}$				-1.473				-1.898				-0.685
				(0.000)				(0.000)				(0.106)
$LogFamSize_t$				0.000				0.000				-0.000
				(0.917)				(0.904)				(0.882)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	107280	107280	107280	87485	53579	53579	53579	43696	27518	27518	27518	22235
AdjRSQ	0.052	0.051	0.052	0.050	0.045	0.044	0.046	0.047	0.055	0.054	0.056	0.063

TABLE A4: Decomposition of CPA Into Selectivity and Style Timing

This table reports the average future Characteristic-Selectivity (CS) alpha for 10 portfolios sorted by past customized peer alpha *(CPA)* , style timing *(ST)* and average style *(AS)*. At the start of each calendar quarter, we sort funds into deciles based on the past 12 months average *CPA*, *ST* and *AS*. Next, we calculate *CS* alpha for each of the next three months after portfolio formation. The process is repeated with rebalanced portfolios each quarter. Finally, we obtain average monthly *CS* post-ranking portfolio alpha by averaging over the entire time-series of alphas. The 6- and 12-month results are based on similar methods except for the rebalancing frequency. The 10-1 decile spread is the return of a zero-investment long-short portfolio that is long on decile 10 and short on decile 1 portfolios. Returns are annualized. p-values are reported in parentheses.

	3 Month			6 Month			12 Month		
Decile	CPA	ST	AS	CPA	ST	AS	CPA	ST	AS
1	-0.757	0.605	0.375	-0.690	0.669	0.327	-0.098	0.446	-0.247
	(0.287)	(0.264)	(0.591)	(0.285)	(0.223)	(0.643)	(0.876)	(0.406)	(0.707)
2	0.101	0.687	0.454	-0.032	0.727	0.594	0.266	0.241	0.460
	(0.812)	(0.087)	(0.362)	(0.937)	(0.087)	(0.236)	(0.523)	(0.589)	(0.368)
3	-0.117	0.542	0.413	0.168	0.650	0.325	0.229	0.412	0.075
	(0.749)	(0.149)	(0.336)	(0.636)	(0.073)	(0.444)	(0.520)	(0.257)	(0.867)
4	0.123	0.291	0.546	0.266	0.395	0.476	0.261	0.594	0.337
	(0.723)	(0.387)	(0.124)	(0.431)	(0.249)	(0.165)	(0.451)	(0.044)	(0.377)
5	0.488	0.476	0.391	0.540	0.389	0.234	0.537	0.420	0.511
	(0.128)	(0.133)	(0.250)	(0.089)	(0.230)	(0.468)	(0.087)	(0.220)	(0.123)
6	0.583	0.299	0.393	0.476	0.179	0.241	0.262	0.244	0.354
	(0.052)	(0.286)	(0.232)	(0.152)	(0.538)	(0.457)	(0.400)	(0.382)	(0.298)
7	0.707	0.505	0.573	0.523	0.449	0.618	0.445	0.252	0.353
	(0.020)	(0.129)	(0.099)	(0.085)	(0.167)	(0.079)	(0.183)	(0.475)	(0.303)
8	0.842	0.428	0.515	1.082	0.491	0.665	0.946	0.549	0.658
	(0.013)	(0.248)	(0.193)	(0.002)	(0.156)	(0.083)	(0.009)	(0.107)	(0.074)
9	1.109	0.393	0.592	0.990	0.235	0.811	0.600	0.396	0.763
	(0.006)	(0.392)	(0.226)	(0.008)	(0.604)	(0.108)	(0.119)	(0.372)	(0.105)
10	1.887	1.265	1.238	1.884	1.204	1.109	1.694	0.688	1.000
	(0.002)	(0.061)	(0.090)	(0.002)	(0.058)	(0.113)	(0.005)	(0.282)	(0.142)
10-1	2.644	0.660	0.863	2.574	0.535	0.782	1.792	0.243	1.247
	(0.004)	(0.319)	(0.424)	(0.002)	(0.389)	(0.453)	(0.023)	(0.698)	(0.205)

TABLE A5: Customized Peer Alpha Versus Activeness

At the start of each calendar quarter, we form nine portfolios using sequential sorts, first by the past activeness measure and then by past 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 of CPA. Returns are annualized. p-values are reported in parentheses.

Panel A: ICI

	CPA			
ICI	1	2	3	3-1
1	-0.117	0.395	0.941	1.058
	(0.700)	(0.096)	(0.002)	(0.000)
2	-0.024	0.535	0.994	1.018
	(0.959)	(0.125)	(0.016)	(0.023)
3	-0.090	0.845	1.369	1.459
	(0.901)	(0.104)	(0.028)	(0.057)

Panel B: Active Share

	CPA			
Active Share	1	2	3	3-1
1	-0.188	0.303	0.721	0.909
	(0.538)	(0.199)	(0.021)	(0.012)
2	-0.030	0.488	0.782	0.813
	(0.949)	(0.181)	(0.082)	(0.126)
3	0.010	0.953	1.822	1.812
	(0.989)	(0.078)	(0.002)	(0.006)

Panel C: RetGap

	CPA			
RetGap	1	2	3	3-1
1	-0.006	0.717	1.152	1.158
	(0.990)	(0.036)	(0.008)	(0.027)
2	-0.116	0.397	1.180	1.297
	(0.788)	(0.230)	(0.002)	(0.006)
3	-0.261	0.732	1.056	1.317
	(0.665)	(0.067)	(0.055)	(0.025)

Panel D: RSQ

	CPA			
RSQ	1	2	3	3-1
1	0.277	0.948	1.684	1.408
	(0.598)	(0.020)	(0.002)	(0.027)
2	0.092	0.505	1.187	1.095
	(0.869)	(0.179)	(0.009)	(0.024)
3	-0.536	0.251	0.438	0.974
	(0.200)	(0.369)	(0.206)	(0.013)

TABLE A6: Competition and Persistency: Independent Sorts

This table reports future Characteristic-Selectivity *(CS)* alphas for decile portfolios based on past customized peer alpha *(CPA)* further classified into high, low, and medium levels of competition. Panel A shows results when competition is measured by the average number of customized peers *(NPeers)* over the past 12 months, while Panel B shows results when competition is measured by average of *Total Similarity* between a fund and its customized peers over the past 12 months. At the start of each calendar quarter, we independently sort funds into competition terciles and past performance deciles. The terciles are represented by *Low*, *Med* and *High*. The past performance deciles are 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 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 annualized. p-values are reported in parentheses.

Panel A: Competition and Persistency (NPeers)									
	3 Month			6 Month			12 Month		
Decile	Low	Med	High	Low	Med	High	Low	Med	High
1	-0.783	-0.936	-0.699	-0.661	-0.625	-0.799	0.010	-0.035	-0.919
	(0.395)	(0.186)	(0.222)	(0.440)	(0.334)	(0.154)	(0.991)	(0.954)	(0.102)
2	0.952	-0.268	-0.634	0.479	-0.164	-0.554	0.860	0.177	-0.329
	(0.108)	(0.578)	(0.132)	(0.415)	(0.727)	(0.162)	(0.163)	(0.704)	(0.397)
3	-0.367	0.002	-0.277	0.287	0.306	-0.197	0.135	0.065	0.092
	(0.548)	(0.996)	(0.392)	(0.633)	(0.463)	(0.523)	(0.826)	(0.881)	(0.785)
4	0.606	-0.444	0.252	0.680	0.019	0.170	0.472	0.071	0.237
	(0.366)	(0.287)	(0.397)	(0.322)	(0.963)	(0.555)	(0.444)	(0.867)	(0.478)
5	1.468	0.138	0.282	1.329	0.362	0.388	0.981	0.494	0.550
	(0.016)	(0.738)	(0.300)	(0.039)	(0.360)	(0.166)	(0.150)	(0.208)	(0.045)
6	1.170	0.625	0.169	1.492	0.298	-0.168	0.726	0.256	-0.170
	(0.052)	(0.097)	(0.551)	(0.012)	(0.482)	(0.596)	(0.203)	(0.562)	(0.549)
7	1.160	1.040	0.523	0.547	0.830	0.349	0.340	1.035	0.126
	(0.056)	(0.007)	(0.067)	(0.370)	(0.022)	(0.226)	(0.589)	(0.020)	(0.663)
8	1.383	0.728	0.654	1.830	1.153	0.557	1.810	1.181	0.275
	(0.017)	(0.066)	(0.055)	(0.003)	(0.007)	(0.080)	(0.006)	(0.003)	(0.396)
9	1.688	1.186	0.301	1.710	0.983	0.229	1.054	0.422	0.119
	(0.011)	(0.009)	(0.401)	(0.005)	(0.016)	(0.527)	(0.081)	(0.341)	(0.731)
10	2.642	1.151	-0.159	2.506	1.295	0.319	2.121	1.406	0.635
	(0.001)	(0.053)	(0.766)	(0.002)	(0.020)	(0.554)	(0.009)	(0.009)	(0.337)
10-1	3.425	2.087	0.540	3.167	1.920	1.118	2.112	1.441	1.554
	(0.002)	(0.030)	(0.509)	(0.002)	(0.025)	(0.160)	(0.028)	(0.090)	(0.075)

Panel B: Competition and Persistency (Total Similarity)

	3 Month			6 Month			12 Month		
Decile	Low	Med	High	Low	Med	High	Low	Med	High
1	-0.751	-0.838	-0.734	-0.569	-0.750	-0.686	0.078	-0.220	-0.809
	(0.416)	(0.226)	(0.188)	(0.504)	(0.237)	(0.192)	(0.926)	(0.719)	(0.129)
2	0.913	-0.325	-0.536	0.458	-0.195	-0.421	0.821	0.208	-0.301
	(0.122)	(0.500)	(0.199)	(0.432)	(0.682)	(0.281)	(0.179)	(0.663)	(0.432)
3	-0.408	0.152	-0.302	0.335	0.336	-0.147	0.255	0.224	0.063
	(0.494)	(0.729)	(0.352)	(0.569)	(0.417)	(0.645)	(0.666)	(0.603)	(0.856)
4	0.418	-0.442	0.309	0.594	-0.037	0.202	0.462	-0.064	0.285
	(0.519)	(0.290)	(0.305)	(0.379)	(0.927)	(0.489)	(0.450)	(0.877)	(0.393)
5	1.385	0.249	0.256	1.324	0.408	0.350	0.979	0.597	0.480
	(0.022)	(0.544)	(0.344)	(0.036)	(0.314)	(0.206)	(0.148)	(0.129)	(0.077)
6	1.052	0.540	0.206	1.459	0.155	-0.078	0.672	0.163	-0.106
	(0.081)	(0.151)	(0.460)	(0.014)	(0.727)	(0.802)	(0.243)	(0.705)	(0.704)
7	1.227	0.937	0.466	0.509	0.910	0.302	0.440	1.035	0.112
	(0.046)	(0.014)	(0.098)	(0.403)	(0.010)	(0.297)	(0.496)	(0.013)	(0.698)
8	1.529	0.567	0.671	2.020	1.037	0.518	1.761	1.230	0.299
	(0.007)	(0.149)	(0.052)	(0.001)	(0.012)	(0.102)	(0.007)	(0.002)	(0.361)
9	1.603	1.359	0.353	1.703	1.154	0.185	1.143	0.418	0.151
	(0.016)	(0.003)	(0.333)	(0.006)	(0.004)	(0.609)	(0.057)	(0.354)	(0.665)
10	2.774	1.105	-0.160	2.497	1.427	0.336	2.028	1.638	0.874
	(0.001)	(0.060)	(0.765)	(0.002)	(0.012)	(0.535)	(0.012)	(0.003)	(0.199)
10-1	3.525	1.943	0.574	3.067	2.177	1.022	1.949	1.858	1.683
	(0.001)	(0.041)	(0.484)	(0.002)	(0.012)	(0.183)	(0.039)	(0.033)	(0.050)

TABLE A7: Competition and Persistency By Prior CS Alpha

This table reports future Characteristic-Selectivity *(CS)* alphas for decile portfolios based on past *CS* alphas further classified by levels of competition. Panel A shows results when competition is measured by the average number of customized peers *(NPeers)* over the past 12 months, while Panel B shows results when competition is measured by average of *Total Similarity* between a fund and its customized peers over the past 12 months. At the start of each calendar quarter, we first sort funds into terciles by the competition measure. These terciles are represented by *Low*, *Med* and *High*. Then we sort funds within terciles into deciles based on the past 12 months average *CS* 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 annualized. p-values are reported in parentheses.

Panel A: Competition and CS Persistency (NPeers)									
	3 Month			6 Month			12 Month		
Decile	Low	Med	High	Low	Med	High	Low	Med	High
1	-0.523	-0.923	-0.559	-0.931	-0.516	-0.193	0.135	-0.118	-0.131
	(0.660)	(0.193)	(0.237)	(0.383)	(0.430)	(0.672)	(0.901)	(0.863)	(0.765)
2	0.275	0.042	0.058	0.347	0.202	-0.168	0.806	0.233	-0.027
	(0.693)	(0.938)	(0.875)	(0.602)	(0.701)	(0.631)	(0.238)	(0.655)	(0.940)
3	0.494	0.124	0.355	0.947	0.142	0.239	1.122	0.464	0.307
	(0.460)	(0.791)	(0.297)	(0.170)	(0.759)	(0.470)	(0.105)	(0.285)	(0.377)
4	0.249	0.161	-0.033	0.833	0.154	-0.016	0.814	0.584	0.322
	(0.672)	(0.691)	(0.905)	(0.142)	(0.705)	(0.953)	(0.151)	(0.166)	(0.296)
5	1.039	0.395	0.067	0.701	0.682	0.258	1.446	0.551	-0.091
	(0.079)	(0.288)	(0.816)	(0.238)	(0.066)	(0.343)	(0.006)	(0.182)	(0.751)
6	0.820	0.891	-0.135	0.928	0.586	-0.131	0.329	0.472	-0.206
	(0.112)	(0.026)	(0.639)	(0.110)	(0.116)	(0.674)	(0.555)	(0.232)	(0.482)
7	1.169	-0.061	0.045	0.955	0.381	0.002	0.632	0.465	0.159
	(0.044)	(0.874)	(0.884)	(0.104)	(0.345)	(0.995)	(0.298)	(0.237)	(0.570)
8	1.912	0.808	0.394	2.066	0.614	0.205	1.859	0.645	0.186
	(0.005)	(0.064)	(0.179)	(0.002)	(0.122)	(0.475)	(0.007)	(0.130)	(0.547)
9	2.277	0.681	0.754	2.088	0.741	0.429	0.843	0.594	0.045
	(0.007)	(0.142)	(0.019)	(0.009)	(0.087)	(0.193)	(0.276)	(0.135)	(0.889)
10	2.866	0.622	0.429	2.500	0.861	0.459	1.445	1.051	0.431
	(0.007)	(0.273)	(0.286)	(0.014)	(0.116)	(0.257)	(0.173)	(0.041)	(0.284)
10-1	3.389	1.546	0.988	3.432	1.377	0.652	1.310	1.168	0.562
	(0.050)	(0.113)	(0.134)	(0.025)	(0.107)	(0.306)	(0.396)	(0.182)	(0.347)

Panel B: Competition and CS Persistency (Total Similarity)									
	3 Month			6 Month			12 Month		
Decile	Low	Med	High	Low	Med	High	Low	Med	High
1	-0.515	-0.793	-0.565	-0.664	-0.487	-0.126	0.369	-0.090	-0.146
	(0.664)	(0.262)	(0.235)	(0.536)	(0.458)	(0.782)	(0.734)	(0.896)	(0.736)
2	0.149	0.127	0.011	0.320	0.116	-0.187	0.506	0.025	0.138
	(0.833)	(0.818)	(0.976)	(0.634)	(0.827)	(0.578)	(0.458)	(0.962)	(0.698)
3	0.529	0.107	0.358	0.841	0.220	0.216	1.236	0.564	0.277
	(0.439)	(0.816)	(0.280)	(0.225)	(0.629)	(0.505)	(0.076)	(0.190)	(0.414)
4	0.167	0.334	-0.082	0.715	0.239	0.035	0.675	0.644	0.320
	(0.776)	(0.402)	(0.772)	(0.220)	(0.550)	(0.904)	(0.223)	(0.116)	(0.293)
5	0.978	0.212	0.224	0.700	0.596	0.284	1.497	0.601	-0.101
	(0.094)	(0.570)	(0.432)	(0.228)	(0.111)	(0.299)	(0.005)	(0.147)	(0.729)
6	0.913	0.862	-0.123	1.134	0.654	-0.124	0.506	0.348	-0.156
	(0.087)	(0.023)	(0.669)	(0.057)	(0.084)	(0.686)	(0.374)	(0.367)	(0.587)
7	1.230	-0.024	0.043	1.170	0.048	0.131	0.484	0.559	0.081
	(0.027)	(0.952)	(0.885)	(0.046)	(0.897)	(0.673)	(0.421)	(0.171)	(0.780)
8	1.783	0.766	0.541	1.724	0.728	0.212	1.739	0.525	0.265
	(0.010)	(0.078)	(0.058)	(0.008)	(0.076)	(0.465)	(0.010)	(0.219)	(0.373)
9	2.072	0.629	0.685	2.079	0.753	0.454	0.819	0.674	0.251
	(0.011)	(0.164)	(0.045)	(0.010)	(0.079)	(0.170)	(0.287)	(0.089)	(0.465)
10	3.110	0.781	0.343	2.529	1.051	0.276	1.405	1.091	0.254
	(0.004)	(0.166)	(0.402)	(0.013)	(0.051)	(0.495)	(0.186)	(0.034)	(0.522)
10-1	3.625	1.574	0.908	3.192	1.538	0.401	1.035	1.181	0.400
	(0.036)	(0.110)	(0.176)	(0.037)	(0.077)	(0.523)	(0.501)	(0.188)	(0.497)

TABLE A8: **Competition and Persistence: Alternate Granularities**

This table reports future Characteristic-Selectivity *(CS)* alphas for decile portfolios based on past customized peer alpha *(CPA)* further classified by levels of competition. We measure competition as the average number of customized peers *(NPeers)* over the past 12 months. Customized peers are formed such that n% of two randomly picked funds are peers where n= 5, 10, and 15 in panels A, B, and C, respectively. At the start of each calendar quarter, we first sort funds into terciles by the competition measure and by levels of the past 12 months average *CPA*. We compute equal-weighted *CS* performance over the next three months. Portfolios are re-formed after every quarter. The *CS* post-ranking portfolio performance is averaged over the entire time-series. The 6- and 12-month results are based on rebalancing at the respective horizons. The 10-1 spread is a zero-investment long-short portfolio that is long on decile ten and short on decile one. Returns are annualized. p-values are reported in parentheses.

Panel A: 5% Granularity									
	3 Month			6 Month			12 Month		
Decile	Low	Med	High	Low	Med	High	Low	Med	High
1	-0.963	-0.516	-0.669	-0.605	-0.628	-0.572	0.343	-0.093	-0.679
	(0.358)	(0.436)	(0.127)	(0.543)	(0.295)	(0.166)	(0.729)	(0.874)	(0.097)
2	0.203	-0.110	-0.268	-0.150	0.121	-0.502	0.402	0.366	-0.192
	(0.770)	(0.820)	(0.432)	(0.823)	(0.793)	(0.136)	(0.540)	(0.414)	(0.566)
3	0.260	-0.519	0.061	0.141	0.044	0.073	0.641	0.207	0.221
	(0.654)	(0.234)	(0.843)	(0.800)	(0.923)	(0.806)	(0.256)	(0.640)	(0.465)
4	0.406	0.143	0.063	1.168	0.323	-0.002	0.585	0.243	0.295
	(0.466)	(0.730)	(0.824)	(0.048)	(0.417)	(0.995)	(0.344)	(0.560)	(0.349)
5	1.312	0.193	0.516	1.505	0.194	0.443	1.153	0.245	0.328
	(0.021)	(0.640)	(0.069)	(0.010)	(0.622)	(0.143)	(0.060)	(0.563)	(0.267)
6	0.766	0.293	0.208	0.511	0.310	0.121	0.856	0.300	0.027
	(0.149)	(0.449)	(0.444)	(0.326)	(0.449)	(0.658)	(0.083)	(0.455)	(0.923)
7	1.450	0.947	0.385	1.246	0.521	0.200	0.039	0.689	-0.082
	(0.007)	(0.009)	(0.166)	(0.027)	(0.158)	(0.509)	(0.946)	(0.110)	(0.765)
8	1.172	0.870	0.556	1.412	1.177	0.538	1.252	0.967	0.265
	(0.045)	(0.045)	(0.064)	(0.009)	(0.006)	(0.076)	(0.023)	(0.026)	(0.363)
9	1.995	0.743	0.441	2.119	0.393	0.407	1.777	0.548	0.587
	(0.006)	(0.101)	(0.182)	(0.005)	(0.349)	(0.214)	(0.019)	(0.217)	(0.056)
10	3.478	1.136	0.113	3.212	1.398	0.412	2.496	1.388	0.217
	(0.000)	(0.041)	(0.759)	(0.000)	(0.016)	(0.265)	(0.005)	(0.011)	(0.583)
10-1	4.441	1.652	0.782	3.817	2.027	0.983	2.153	1.482	0.895
	(0.000)	(0.059)	(0.157)	(0.001)	(0.012)	(0.065)	(0.053)	(0.062)	(0.094)

Panel B: 10% Granularity									
	3 Month			6 Month			12 Month		
Decile	Low	Med	High	Low	Med	High	Low	Med	High
1	-0.847	-0.957	-0.785	-1.154	-0.574	-0.678	-0.554	-0.146	-0.500
	(0.440)	(0.145)	(0.085)	(0.253)	(0.360)	(0.106)	(0.571)	(0.804)	(0.225)
2	0.334	-0.149	-0.212	0.309	0.083	-0.316	0.973	0.315	-0.234
	(0.635)	(0.763)	(0.549)	(0.654)	(0.867)	(0.360)	(0.180)	(0.517)	(0.466)
3	0.162	0.006	-0.042	0.148	0.020	0.102	0.244	0.180	0.369
	(0.782)	(0.989)	(0.894)	(0.793)	(0.965)	(0.741)	(0.666)	(0.691)	(0.267)
4	0.599	-0.205	0.403	0.876	0.013	0.277	0.804	-0.017	0.454
	(0.323)	(0.600)	(0.172)	(0.154)	(0.971)	(0.330)	(0.164)	(0.965)	(0.114)
5	1.263	0.059	0.360	1.104	0.451	0.131	0.638	0.669	0.173
	(0.022)	(0.886)	(0.212)	(0.041)	(0.277)	(0.662)	(0.246)	(0.125)	(0.553)
6	0.675	-0.157	0.225	1.081	-0.199	0.170	0.718	-0.096	0.077
	(0.222)	(0.676)	(0.431)	(0.056)	(0.624)	(0.582)	(0.180)	(0.810)	(0.792)
7	1.304	0.874	0.432	1.151	0.761	0.275	1.296	0.642	0.031
	(0.024)	(0.015)	(0.125)	(0.054)	(0.035)	(0.347)	(0.040)	(0.104)	(0.910)
8	1.304	1.198	0.505	1.454	1.223	0.745	1.169	1.128	0.238
	(0.037)	(0.005)	(0.116)	(0.020)	(0.003)	(0.015)	(0.057)	(0.007)	(0.440)
9	2.070	1.003	0.356	2.069	0.868	0.195	1.663	0.612	0.364
	(0.003)	(0.026)	(0.276)	(0.004)	(0.040)	(0.535)	(0.030)	(0.160)	(0.263)
10	3.591	1.159	0.249	3.235	1.365	0.275	2.224	1.432	0.211
	(0.000)	(0.040)	(0.519)	(0.000)	(0.012)	(0.495)	(0.012)	(0.005)	(0.583)
10-1	4.438	2.116	1.033	4.389	1.939	0.953	2.777	1.578	0.711
	(0.001)	(0.019)	(0.092)	(0.000)	(0.020)	(0.105)	(0.017)	(0.047)	(0.202)

Panel C: 15% Granularity									
	3 Month			6 Month			12 Month		
Decile	Low	Med	High	Low	Med	High	Low	Med	High
1	-1.297	-0.985	-0.772	-1.081	-0.524	-0.512	-0.280	-0.150	-0.366
	(0.252)	(0.138)	(0.102)	(0.310)	(0.411)	(0.245)	(0.782)	(0.808)	(0.413)
2	0.360	0.010	-0.312	0.097	-0.138	-0.617	0.430	0.204	-0.309
	(0.616)	(0.983)	(0.376)	(0.893)	(0.775)	(0.072)	(0.557)	(0.673)	(0.343)
3	0.430	-0.124	-0.020	0.158	0.114	0.144	0.525	0.187	0.406
	(0.472)	(0.785)	(0.950)	(0.786)	(0.796)	(0.616)	(0.387)	(0.687)	(0.192)
4	0.583	-0.277	0.301	0.801	0.111	0.175	0.654	0.421	0.233
	(0.338)	(0.510)	(0.299)	(0.180)	(0.791)	(0.554)	(0.247)	(0.299)	(0.451)
5	0.944	-0.068	0.143	0.944	0.346	0.106	0.066	0.241	0.281
	(0.077)	(0.855)	(0.620)	(0.097)	(0.387)	(0.704)	(0.907)	(0.542)	(0.311)
6	0.484	0.547	0.402	0.680	0.143	0.316	1.121	0.334	0.109
	(0.363)	(0.129)	(0.174)	(0.226)	(0.699)	(0.324)	(0.038)	(0.364)	(0.721)
7	1.690	0.632	0.248	1.751	0.687	0.243	1.617	0.588	-0.112
	(0.009)	(0.078)	(0.387)	(0.004)	(0.055)	(0.409)	(0.013)	(0.105)	(0.681)
8	1.851	0.831	0.540	1.772	0.610	0.679	0.811	0.739	0.429
	(0.005)	(0.028)	(0.088)	(0.007)	(0.120)	(0.032)	(0.209)	(0.077)	(0.157)
9	1.804	1.272	0.470	2.138	0.957	0.447	1.733	0.737	0.391
	(0.013)	(0.004)	(0.137)	(0.005)	(0.017)	(0.171)	(0.030)	(0.077)	(0.247)
10	3.467	1.383	0.207	3.180	1.662	0.203	2.297	1.508	0.422
	(0.000)	(0.011)	(0.625)	(0.001)	(0.002)	(0.631)	(0.008)	(0.003)	(0.312)
10-1	4.764	2.369	0.980	4.261	2.186	0.715	2.577	1.658	0.789
	(0.001)	(0.010)	(0.128)	(0.001)	(0.012)	(0.222)	(0.029)	(0.049)	(0.178)

TABLE A9: **Using Stocks as Spatial Basis**

This table reports results on future Characteristic-Selectivity alpha for deciles based on past alternative customized peer alpha *(CPA)*, derived from firm-portfolio-weights further classified by competitors derived in the stock space. At the start of each calendar quarter, we first sort funds into terciles by the competition measure. 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. Returns are annualized. 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	-0.529	-0.274	-0.737	-0.373	-0.407	-0.615	-0.255	0.272	-0.230
	(0.508)	(0.733)	(0.119)	(0.633)	(0.579)	(0.184)	(0.752)	(0.709)	(0.619)
2	-0.459	0.372	-0.428	0.216	0.469	-0.336	0.555	0.754	-0.125
	(0.483)	(0.487)	(0.274)	(0.735)	(0.387)	(0.375)	(0.388)	(0.097)	(0.738)
3	1.012	0.004	-0.298	0.623	-0.113	0.019	0.505	-0.031	0.057
	(0.064)	(0.993)	(0.339)	(0.240)	(0.785)	(0.951)	(0.377)	(0.943)	(0.859)
4	0.359	0.466	-0.124	0.659	0.490	-0.188	0.630	0.395	-0.010
	(0.513)	(0.290)	(0.667)	(0.227)	(0.266)	(0.516)	(0.256)	(0.372)	(0.971)
5	0.286	0.263	0.108	0.241	0.469	0.101	0.762	0.490	0.185
	(0.551)	(0.581)	(0.708)	(0.620)	(0.325)	(0.722)	(0.120)	(0.319)	(0.574)
6	0.920	0.764	0.334	1.210	0.754	0.282	1.075	0.453	0.131
	(0.088)	(0.082)	(0.308)	(0.026)	(0.086)	(0.379)	(0.049)	(0.239)	(0.688)
7	1.205	0.598	0.303	1.328	0.448	0.512	1.263	0.594	0.160
	(0.010)	(0.139)	(0.291)	(0.006)	(0.288)	(0.094)	(0.009)	(0.255)	(0.541)
8	0.921	0.873	0.691	0.825	0.950	0.642	0.505	0.784	0.531
	(0.096)	(0.049)	(0.037)	(0.110)	(0.026)	(0.056)	(0.324)	(0.065)	(0.109)
9	1.500	0.947	0.802	1.353	0.994	0.366	1.136	1.499	0.199
	(0.003)	(0.101)	(0.035)	(0.007)	(0.094)	(0.301)	(0.021)	(0.012)	(0.589)
10	2.166	1.873	0.606	2.019	1.694	0.614	1.324	1.261	0.302
	(0.001)	(0.034)	(0.268)	(0.002)	(0.050)	(0.268)	(0.042)	(0.140)	(0.577)
10-1	2.695	2.146	1.343	2.392	2.101	1.229	1.579	0.989	0.532
	(0.002)	(0.033)	(0.052)	(0.005)	(0.019)	(0.061)	(0.052)	(0.253)	(0.408)

TABLE A10: **Competition and Alpha**

This table reports future Characteristic-Selectivity *(CS)* alphas for tercile portfolios by levels of competition. Panel A shows results when competition is measured by the average number of customized peers *(NPeers)* over the past 12 months, while Panel B shows results when competition is measured by average of *Total Similarity* between a fund and its customized peers over the past 12 months. At the start of each calendar quarter, we first sort funds into terciles by competition measures. These terciles are represented by *Low*, *Med* and *High*. 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. The 6- and 12-month portfolio results are obtained similarly but portfolios are updated at the relevant lower frequencies. Low-High represents zero-investment long-short portfolio that is long on tercile *Low* and short on tercile *High*. Returns are annualized. p-values are reported in parentheses.

	Panel A: NPeers			Panel B: TSIM		
Comp Tercile	3 Month	6 Month	12 Month	3 Month	6 Month	12 Month
Low	1.062	1.059	0.944	1.041	1.053	0.922
	(0.041)	(0.041)	(0.073)	(0.046)	(0.043)	(0.081)
Med	0.287	0.395	0.490	0.303	0.393	0.492
	(0.372)	(0.216)	(0.133)	(0.343)	(0.218)	(0.128)
High	0.142	0.111	0.102	0.147	0.119	0.123
	(0.546)	(0.636)	(0.665)	(0.534)	(0.611)	(0.599)
Low-High	0.920	0.949	0.842	0.894	0.934	0.799
	(0.039)	(0.032)	(0.063)	(0.045)	(0.035)	(0.079)

TABLE A11: Competition and Carhart Alpha: Regression Analysis

This table reports coefficients from regression of future Carhart alpha on past customized peer alpha *(CPA)* performance and other controls for low, medium and high competition sub-samples. At the start of each quarter, 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 deciles 1 and 10, respectively. The dependent variable is $Carhart_{t+i,t+j}$, which represents the average *Carhart* performance over the months $t+i$ to $t+j$. For each month in $(t+i,\ t+j)$, we obtain monthly *Carhart* alpha by subtracting the estimated monthly return from the fund's raw return. We estimate monthly return by multiplying the estimated factor loadings (obtained from past 36 month regression, with a minimum of 30 observations) with factor returns. $CS_{t\text{-}11,t}$ represents average *CS* performance over the months *t-11* to *t*. $ExpRatio_t$ and $TurnRatio_t$ represent the expense ratio and turnover ratio at the end of month *t*, respectively. $LogFundAge_t$ and $LogFundSize_t$ represent natural logarithm of fund age (years) and fund size ($millions) at the end of month *t*, respectively. $Flow_t$ represents monthly flow in month *t*. $StdDev_{t\text{-}11,t}$ is the standard deviation of monthly raw returns over the months *t-11* to *t*. $LogFamSize_t$ represents natural logarithm of family size ($millions) at the end of month *t*. All regressions include time *t* dummy. *N* and *AdjRSQ* represent number of observations and adjusted-Rsquared. Standard errors are clustered by fund. *p*-values are reported in parentheses.

	Dep Var = $\mathrm{Carhart}_{t+1,t+3}$								
	Low			Med			High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.335	2.985	2.986	0.360	0.790	0.831	0.144	1.173	1.220
	(0.179)	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)	(0.331)	(0.000)	(0.000)
CPA_Decile1	-0.161	-0.054	-0.062	-0.064	-0.026	-0.059	-0.027	0.007	-0.038
	(0.000)	(0.099)	(0.066)	(0.004)	(0.284)	(0.023)	(0.108)	(0.710)	(0.047)
CPA_Decile10	0.070	0.083	0.092	0.113	0.131	0.165	-0.049	-0.063	-0.014
	(0.018)	(0.011)	(0.008)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.436)
$\mathrm{CS}_{t\text{-}11,\ t}$			-0.012			-0.059			-0.136
			(0.496)			(0.001)			(0.000)
$\mathrm{ExpRatio}_t$		-0.062	-0.062		-0.086	-0.086		-0.083	-0.083
		(0.019)	(0.020)		(0.000)	(0.000)		(0.000)	(0.000)
$\mathrm{TurnRatio}_t$		-0.026	-0.026		-0.017	-0.019		-0.011	-0.015
		(0.052)	(0.053)		(0.210)	(0.153)		(0.292)	(0.135)
$\mathrm{LogFundAge}_t$		-0.007	-0.007		0.000	0.001		-0.006	-0.006
		(0.673)	(0.667)		(0.990)	(0.908)		(0.366)	(0.357)
$\mathrm{LogFundSize}_t$		-0.032	-0.031		-0.019	-0.018		-0.006	-0.006
		(0.000)	(0.000)		(0.001)	(0.002)		(0.090)	(0.142)
Flow_t		0.004	0.004		0.000	0.001		0.000	0.001
		(0.054)	(0.041)		(0.805)	(0.454)		(0.820)	(0.293)
$\mathrm{StdDev}_{t\text{-}11,\ t}$		-4.604	-4.597		-3.145	-3.345		-2.471	-2.985
		(0.000)	(0.000)		(0.000)	(0.000)		(0.002)	(0.000)
$\mathrm{LogFamSize}_t$		0.017	0.017		0.007	0.007		0.003	0.002
		(0.001)	(0.001)		(0.063)	(0.079)		(0.269)	(0.432)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	34624	28483	28483	35011	28466	28466	35124	28695	28695
AdjRSQ	0.105	0.119	0.119	0.088	0.097	0.097	0.089	0.100	0.103

TABLE A12: **Competition and Pastor-Stambaugh Alpha: Regression Analysis**

This table reports coefficients from regression of future Pastor-Stambaugh alpha on past customized peer alpha *(CPA)* performance and other controls for low, medium and high competition sub-samples. At the start of each quarter, 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 deciles 1 and 10, respectively. The dependent variable is $PS_{t+i,t+j}$, which represents the average *PS* performance over the months $t+i$ to $t+j$. For each month in $(t+i,\ t+j)$, we obtain monthly *PS* alpha by subtracting the estimated monthly return from the fund's raw return. We estimate monthly return by multiplying the estimated factor loadings (obtained from past 36 month regression, with a minimum of 30 observations) with factor returns. $CS_{t\text{-}11,t}$ represents average *CS* performance over the months *t-11* to *t*. $ExpRatio_t$ and $TurnRatio_t$ represent the expense ratio and turnover ratio at the end of month *t*, respectively. $LogFundAge_t$ and $LogFundSize_t$ represent natural logarithm of fund age (years) and fund size ($millions) at the end of month *t*, respectively. $Flow_t$ represents monthly flow in month *t*. $StdDev_{t\text{-}11,t}$ is the standard deviation of monthly raw returns over the months *t-11* to *t*. $LogFamSize_t$ represents natural logarithm of family size ($millions) at the end of month *t*. All regressions include time *t* dummy. *N* and *AdjRSQ* represent number of observations and adjusted-Rsquared. Standard errors are clustered by fund. *p*-values are reported in parentheses.

	Dep Var = $PS_{t+1,t+3}$								
	Low			Med			High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.490	3.374	3.375	0.511	0.517	0.548	0.223	1.137	1.182
	(0.051)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.132)	(0.000)	(0.000)
CPA_Decile1	-0.174	-0.068	-0.072	-0.079	-0.041	-0.066	-0.032	0.002	-0.041
	(0.000)	(0.038)	(0.032)	(0.000)	(0.096)	(0.011)	(0.051)	(0.930)	(0.032)
CPA_Decile10	0.102	0.116	0.121	0.127	0.148	0.174	-0.037	-0.054	-0.007
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.021)	(0.002)	(0.685)
CS_t			-0.007			-0.045			-0.130
			(0.696)			(0.009)			(0.000)
$ExpRatio_t$		-0.053	-0.053		-0.084	-0.084		-0.080	-0.080
		(0.050)	(0.052)		(0.000)	(0.000)		(0.000)	(0.000)
$TurnRatio_t$		-0.030	-0.030		-0.018	-0.020		-0.015	-0.020
		(0.026)	(0.026)		(0.182)	(0.143)		(0.134)	(0.055)
$LogFundAge_t$		-0.005	-0.005		-0.003	-0.003		-0.002	-0.002
		(0.765)	(0.762)		(0.736)	(0.799)		(0.794)	(0.774)
$LogFundSize_t$		-0.037	-0.037		-0.021	-0.020		-0.009	-0.008
		(0.000)	(0.000)		(0.000)	(0.001)		(0.020)	(0.035)
$Flow_t$		0.004	0.004		-0.000	0.001		-0.000	0.001
		(0.031)	(0.027)		(0.949)	(0.750)		(0.801)	(0.588)
$StdDev_{t\text{-}11,\ t}$		-4.883	-4.879		-3.791	-3.945		-2.601	-3.094
		(0.000)	(0.000)		(0.000)	(0.000)		(0.001)	(0.000)
$LogFamSize_t$		0.018	0.017		0.008	0.008		0.004	0.003
		(0.001)	(0.001)		(0.052)	(0.062)		(0.176)	(0.297)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	34624	28483	28483	35011	28466	28466	35124	28695	28695
AdjRSQ	0.099	0.112	0.112	0.079	0.086	0.086	0.072	0.081	0.083